Environmental Impact Assessment Report
Volume 3, Appendix 12.5: Offshore Ornithology MRSea Modelling Report

MarramWind Offshore Wind Farm

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MarramWind

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Checked by:	WSP UK Limited
Approved by:	MarramWind Limited

Contents

1. Introduction

1.1 Project background

1.1.1.1 This Appendix presents the findings of a study of offshore ornithology features that characterise the area that may be influenced by the MarramWind Offshore Wind Farm (hereafter, referred to as 'the Project'). This Appendix specifically relates to modelled, through the MRSea package developed in R (R Core Team, 2024), spatial and temporal distribution and densities of the pre-construction digital aerial survey data (DAS) collected between April 2021 and March 2023 within the Offshore Array Area (OAA) and a 4 km buffer.

1.1.1.2 A separate report (**Appendix 12.1: Offshore and Intertidal Ornithology Baseline Report**) provides the baseline characterisation of the OAA through the data obtained from digital aerial surveys (DAS) with which the MRSea model-based estimates can be compared. This MRSea analysis technical Appendix has been produced to support **Volume 1, Chapter 12: Offshore and Intertidal Ornithology**.

1.2 MRSea analysis scope

1.2.1.1 MRSea is a package developed in R (R Core Team, 2024) used for identifying spatially explicit changes in the spatial distribution and abundance of seabirds over time and across an offshore development site (Scott-Hayward *et al*., 2013a, 2013b). MRSea modelling is recommended on the basis that it may offer greater facility in understanding the variation in distribution in response to environmental variables. Examples of environmental variables which could be used include distance to shore or distance to Special Protection Areas (as proxies of distance to nearest colony); sea depth (as a proxy for foraging suitability for bottom feeders); or sea surface temperature (related to fish density and therefore foraging quality for pursuit feeders). Where bird distribution is influenced by environmental variables that vary spatially across a given study region, inclusion of those environmental variables as covariates in the modelling approach has two advantages. Firstly, it should make the model results more accurate. Secondly, it is useful from an ecological perspective to understand the drivers in a species distribution. Whilst it is possible to fit "Complex Region Spatial Smoother" (CReSS) models purely spatially and without any environmental covariables, doing so will produce a model that does not provide any information on why that distribution is observed.

1.2.1.2 The seabird species to be initially considered for MRSea modelling are summarised below based on their known presence within the 24 months of DAS collected:

- Atlantic puffin (*Fratercula arctica*);
- black-legged kittiwake (*Rissa tridactyla*);
- common guillemot (*Uria aalge*);
- herring gull (*Larus argentatus*);
- lesser black-backed gull (*Larus fuscus*);
- fulmar (*Fulmarus glacialis*);
- gannet (*Morus bassanus*); and
- great black-backed gull (*Larus marinus*).

1.2.1.3 Due to the statistical methods used with the MRSea framework, species with low records of DAS observations across multiple months, or highly clustered low count data within a month, are not suitable for modelling. Therefore, any species with fewer than 10 observations in a given month, or with an inadequate number of months to be representative of a given season were removed for analysis, as per relevant guidance (NatureScot, 2023) and described in Table 12.1 in **Volume 1, Chapter 12: Offshore and Intertidal Ornithology**. Therefore, only the following species met the criteria for analysis using MRSea:

- common guillemot;
- Atlantic puffin (breeding only);
- black-legged kittiwake;
- gannet (breeding only); and
- fulmar.

2. Methods

2.1 Data collection

2.1.1.1 Flight planning software determined the required altitude and speed based on the camera specifications, lens configuration, and target pixel resolution. Digital still imagery was acquired at a Ground Sampling Distance of 2 centimetres (cm).

2.1.1.2 Survey data were analysed to generate maps depicting species distribution and density within a Geographic Information System (GIS) framework. Photographs were geo-referenced using the WGS84 coordinate system, and the following data were recorded:

- count and identification of each individual species;
- behavioural state (flying, resting, submerged, or surfacing);
- position (latitude / longitude or utm easting / northing);
- morphometric data (body length, wingspan);
- ageing of birds (where possible based on species which show seasonal variation in plumage);
- heading (degrees); and
- date and time of image capture.

2.1.1.3 For MRSea analysis, only species identification, count, position, date, and time stamp were utilised, along with relevant effort information.

2.2 Survey information

2.2.1.1 The OAA is 684km^2, with the OAA plus a 2km and 4km buffer being 920km^2 and 1,180km^2 respectively. DAS surveys were carried out across the OAA plus the 4km buffer. Detailed survey information for the DAS surveys used within MRSea analysis can be found in **Appendix 12.1**.

2.2.1.2 A programme of 24 monthly DAS took place between April 2021 to March 2023 (**Table 2.1**). The poor weather conditions off the north-east coast of Scotland, particularly during the winter months, interrupted the scheduled, consecutive monthly DAS programme as follows:

- On five occasions (Survey 8, 9, 10, 12 and 19) the monthly DAS had to be flown the following month.
- Three surveys (Survey 2, 8 and 9) were collected over multiple days due to unsuitable weather conditions partway through the survey. Further details are available within the specific survey reports.
- Prolonged periods of sustained poor weather meant no DAS was flown in November 2021, February, June and December 2022 and January 2023.

2.2.1.3 Instead, DAS was conducted in each of the 12 calendar months across the 24-month survey period, and 24 DAS were flown within 24 successive months (two DAS flown in July and November 2022, and March 2023, three DAS flown in February 2023) (**Table 2.1**); an approach presented to and agreed by NatureScot.

2.2.1.4 For **Appendix 12.3: Offshore Ornithology Collision Risk Modelling**, surveys were allocated to provide continuous 24 months DAS as outlined in **Table 2.1**. Here, we present the outputs at the survey level with no allocation for clarity across the survey and modelling information.

Table 2.1 Survey months flown and surveys assigned values

Survey	Month flown	Date flown	Assigned month and year
1	April 2021.	15 April 2021.	April 2021.
2	May 2021.	15 May 2021 and 16 May 2021.	May 2021.
3	June 2021.	06 June 2021.	June 2021.
4	July 2021.	24 July 2021.	July 2021.
5	August 2021.	13 August 2021.	August 2021.
6	September 2021.	20 September 2021.	September 2021.
7	October 2021.	04 October 2021.	October 2021.
8	December 2021.	13 December 2021 and 15 December 2021.	December 2021.
9	January 2022.	15 January 2022 and 18 January 2022.	January 2022.
10	March 2022.	01 March 2022.	March 2022.
11	April 2022.	14 April 2022.	April 2022.
12	May 2022.	02 May 2022.	May 2022.
13	July number 1 of 2022.	05 July 2022.	June 2022.
14	July number 2 of 2022.	18 July 2022.	July 2022.
15	August 2022.	11 August 2022.	August 2022.
16	September 2022.	24 September 2022.	September 2022.
17	October 2022.	13 October 2022.	October 2022.
18	November number 1 of 2022.	09 November 2022.	November 2021 and November 2022.
19	November number 2 of 2022.	21 November 2022.	December 2022.
20	February number 1 of 2023.	05 February 2023.	January 2023.
21	February number 2 of 2023.	12 February 2023.	February 2023.
22	February number 3 of 2023.	18 February 2023.	February 2023.

Survey	Month flown	Date flown	Assigned month and year
23	March number 1 of 2023.	09 March 2023.	March 2023.
24	March number 2 of 2023.	19 March 2023.	March 2023.

2.3 Model-based data analysis

2.3.1.1 To provide a greater understanding of species distribution within the OAA plus a 2km buffer zone, model-based data analysis was conducted. MRSea analysis was utilised to provide statistically robust estimates of species distribution and abundance, underpinned by observations recorded in the DAS imagery (Scott-Hayward *et al.*, 2013b). MRSea enables the incorporation of environmental variables into the analysis, enhancing the predictions of abundance and density distributions within the array and survey areas. Models were constructed using all collected data from the OAA plus 4km buffer before being clipped to OAA plus 2km buffer for outputs. This provides a robust approach to modelling distributions across a small area by minimising edge effects.

2.3.1.2 MRSea is a statistical analysis package for R (R Core Team, 2024), developed by the Centre for Research into Ecological and Environmental Modelling (CREEM). It supports baseline site characterisation and, where data allows, pre- and post-construction analysis when assessing changes in bird distributions following offshore wind farm development. MRSea uses a CReSS and a "Spatially Adaptive Local Smoothing" algorithm (SALSA) within a Generalised Additive Model (GAM) framework (Scott-Hayward *et al.*, 2013a) to estimate bird distributions. Designed for spatial abundance data, it effectively handles spatial autocorrelation and zero inflation, making it well-suited for evaluating environmental changes such as wind farm impacts (Scott-Hayward *et al.*, 2021).

2.4 Modelling approach details

2.4.1.1 Specific model configurations and environmental variables differ by species. All species' behaviours were included, with additional models for flying only of gannet and kittiwake to allow for consideration of use within collision risk modelling.

2.4.1.2 A spatially adaptive GAM was used to model non-linear relationships for each covariate (see **Table 2.2**). Collinearity was assessed using Generalised Variance Inflation Factors (GVIF) in R (Fox and Weisberg, 2019). GVIF values and correlation plots identified interdependencies. GVIF values were assessed as within acceptable limits if they were below 20, indicate no adverse effects on model performance (Scott-Hayward *et al.*, 2021). Model selection was based on Quasi-Bayesian Information Criterion (QBIC) scores, removing non-informative terms and comparing linear and smoothed terms. Full model validation and selection process is described in **Appendix D**.

2.4.1.3 X and Y coordinates were included as a two-dimensional spatial smoother. The survey variable was added as a factor with an interaction term between the survey variable and smoothed spatial terms (X and Y), allowing knot coefficients to vary across surveys.

2.5 Model specifications

2.5.1.1 Seabird count data typically follows an over-dispersed Poisson distribution. Model assessment was performed visually to identify the appropriate error structure. Temporal correlation in data collected across transects and repeated surveys was evaluated using runs tests and autocorrelation function (ACF) plots.

2.5.1.2 A CReSS basis was used to fit the spatial density surface. Model flexibility was determined by the number of knots (anchor points) and the effective range (r) of the basis function for each knot. A two-dimensional SALSA model optimized knot placement and r parameters, with QBIC used for model selection.

2.6 Spatially explicit inference

2.6.1.1 Data for the modelling were collected as part of the Project's DAS programme between April 2021 and March 2023. In spatial analyses, geo-referenced locations close together often show more similar counts than those further apart in time and space. Omission of key environmental variables affecting species abundance can lead to residual patterns, violating the error independence assumption of statistical analyses like GAMs. This violation can undermine model precision and reduce the reliability of abundance predictions.

2.6.1.2 If residual correlation was detected, robust standard errors were applied to account for autocorrelation and provide accurate uncertainty estimates. To manage residual correlation, a blocking structure was used, correlating residuals within blocks while maintaining independence between them. The blocking structure was defined by Survey ID (month as a numeric variable) and Transect ID, ensuring data from the same transect within a survey were treated as correlated, while data from different transects and surveys were independent. These assumptions were validated through visual assessment of ACF plots (**Appendix B**).

2.7 Model covariates

2.7.1.1 Along with survey information, environmental covariates were spatially attributed to the locations of all observations of the species to be modelled. Iterative steps of model selection were then undertaken as detailed in **Section 2.4**.

2.7.1.2 Selection for all species initially included covariates for survey, boat presence, depth, distance to coast, distance to colony, distance to oil rig, mean prey density, mean prey presence, smoothed X and Y coordinates (spatial term), an interaction term between survey and the spatial term, and an area offset. Distance to coast was excluded for all species due to high GVIF values (> 20) during the initial model selection process.

2.7.1.3 The covariates considered for each species are listed in **Table 2.2**. Due to collinearity identified during the modelling process, highly correlated covariates were assessed based on species ecology. Distance to colony was selected over distance to coast for gannet, while distance to coast was selected over distance to colony for fulmar, guillemot, puffin and kittiwake. Additionally, bathymetric slope was considered initially in the modelling process however on review of the available data and the depth trend across the OAA, it was decided that depth was the more appropriate variable to carry forward as the two were highly correlated for all species.

Table 2.2 Candidate model covariates considered for each species and behaviour model

Covariate	Description
Survey information (various)	Year, month, survey and transect ID from the survey effort data. Treated as factors.
Depth	Mean depth (m) of prediction grid cell.
Distance to coast	Distance (m) to nearest coastline from observed individual.
Distance to colony	Distance (m) to nearest colony from observed individual.
Distance to oil rig	Distance (m) to nearest oil rig from observed individual.
Mean prey density	Mean prey density (g/km^2) for the prediction grid cell of sandeel. Data sourced from Langston *et. al*. (2019).
Mean prey presence	Mean prey density for the prediction grid cell of sandeel. Data sourced from Langston *et. al*. (2019). Data is a percentage of total prey presence bounded between 0 and 1.
Boat presence	Accounting for fishing vessels within the survey data boat presence was treated as a factor variable.

2.8 Model selection

2.8.1.1 In the initial one-dimensional SALSA model, a knot was placed at the median of the variable range. Additional knots were added in regions requiring more model flexibility during the optimisation process. For the two-dimensional SALSA model, initial knot locations were distributed to maximize spatial coverage, and their positions were refined through the model selection process. QBIC was used to determine optimal model flexibility, adding or removing knots based on spatial variability.

2.8.1.2 Model fit was evaluated by assessing residual autocorrelation with ACF plots and run tests. Model selection was guided by an analysis of variance to examine p-values for each term. Two-dimensional relationships were plotted for biological plausibility, and an F-test on cumulative residual plots assessed the adequacy of covariate modelling. A ten-fold cross-validation was conducted to compare the final two-dimensional model to the previous iterations (one-dimensional and initial general linear model) to confirm its selection was appropriate. Final models for each species are summarised in **Table 2.3** with model description presented in **Appendix A**.

Table 2.3 Final MRSea model (simplified) for each assessed species

Species	Model specifics	Final model
Guillemot	(all seasons, all behaviours).	count ~ Survey + depth + LRF.g + offset.
Kittiwake	(all seasons, all behaviours).	count ~ Survey + depth + LRF.g + offset.
Kittiwake	(all seasons, flying only).	count ~ Survey + depth + LRF.g + offset.
Gannet	(breeding only, all behaviours).	count ~ Survey + LRF.g + offset.
Gannet	(breeding only, flying only).	count ~ Survey + LRF.g + offset.
Puffin	(breeding only, all behaviours).	count ~ Survey + depth + LRF.g + offset.
Fulmar	(all seasons, all behaviours).	count ~ Survey + LRF.g + offset.

LRF.g is the spatial smoothing model term created within the salse2D modelling process.

2.9 Prediction grid

2.9.1.1 To allow for the inclusion of environmental variables and to visualise model outputs a prediction grid was generated by overlaying a 1km² grid onto the survey area and clipping it to the defined spatial extent (QGIS Development Team, 2024). Each grid cell was assigned values for each environmental covariate, derived from the geospatial information collected during survey observations and spatial joins.

2.10 Model distribution

2.10.1.1 Abundance estimates, density per km², and lower and upper confidence intervals (CIs) were calculated for the survey area. The 95 per cent CIs were derived from 1,000 bootstrap replicates generated during the modelling process. Abundance estimate values were used to visualise species density across the multiple areas of interest (AoI).

2.10.1.2 Model outputs were produced for both the OAA and the OAA with a 2km buffer zone by clipping them to the appropriate AoI shapefile and are presented in **Section 3**.

2.10.1.3 Apportioned model outputs were based on the values provided by the design-based estimates. Availability bias was accounted for by using the standard approach (Dunn *et al.*, 2024; Thaxter *et al.*, 2010; and Spencer, 2012) with the method described in detail in the **Appendix 12.1**. The numbers apportioned to each species was based on the ratio of similar species within each individual survey.

3. Results

3.1.1.1 MRSea modelling was completed for five species: guillemot, puffin (breeding season only), kittiwake (both all behaviours and flying only), gannet (both all behaviours and flying only for the breeding season only) and fulmar. Species seasonal definitions can be found in **Appendix 12.3**.

3.1.1.2 The model diagnostics for all reveal deviations from the underlying assumptions (see **Appendix B**). However, in most cases these deviations are minor and are unlikely to significantly alter the robustness of the model conclusions. Therefore, the model outputs are considered acceptable.

3.2 Guillemot

3.2.1 Abundance estimates

3.2.1.1 Guillemot were recorded in all surveys, with the peak raw count within the OAA and 2 km buffer in April 2021 (1,827 individuals). Raw counts for each month are presented in **Table 3.1.**

3.2.1.2 Apportioned and unapportioned model-based population estimates are presented in **Table 3.1** alongside the design-based population estimates.

3.2.1.3 The peak apportioned abundance estimates for guillemot in the OAA plus 2km buffer were:

- Design-based: 19,891 in April 2021; and
- MRSea based: 11,545 in April 2021.

3.2.1.4 The peak apportioned abundance estimates for guillemot within the OAA excluding the 2km buffer were:

- Design-based: 15,898 in April 2021; and
- MRSea based: 9,077 in April 2021.

3.2.2 Density plots

3.2.2.1 Density of guillemot was nominally evenly spread throughout the site. Guillemots were continually observed across the site, with variation between months primarily occurring across the site rather than increases or decreases in the numbers of birds in specific clusters, with a few exceptions (**Figure 1** and **Figure 2**).

3.2.2.2 Peak density of guillemot occurred in April 2021 (Survey 1), in the northern limit of the survey area, and is likely linked to return migration aggregations that are normally observed offshore. The exception to this was Surveys 1 and 15, which showed higher levels of clustering. While a fishing vessel was present during Survey 15, boat presence was not retained within the model (**Plate 3.1**). High levels of clustering in this survey are caused by post breeding moult aggregations.

Plate 3.1 Snip from DAS imagery showing a concentration of gannet following a fishing vessel

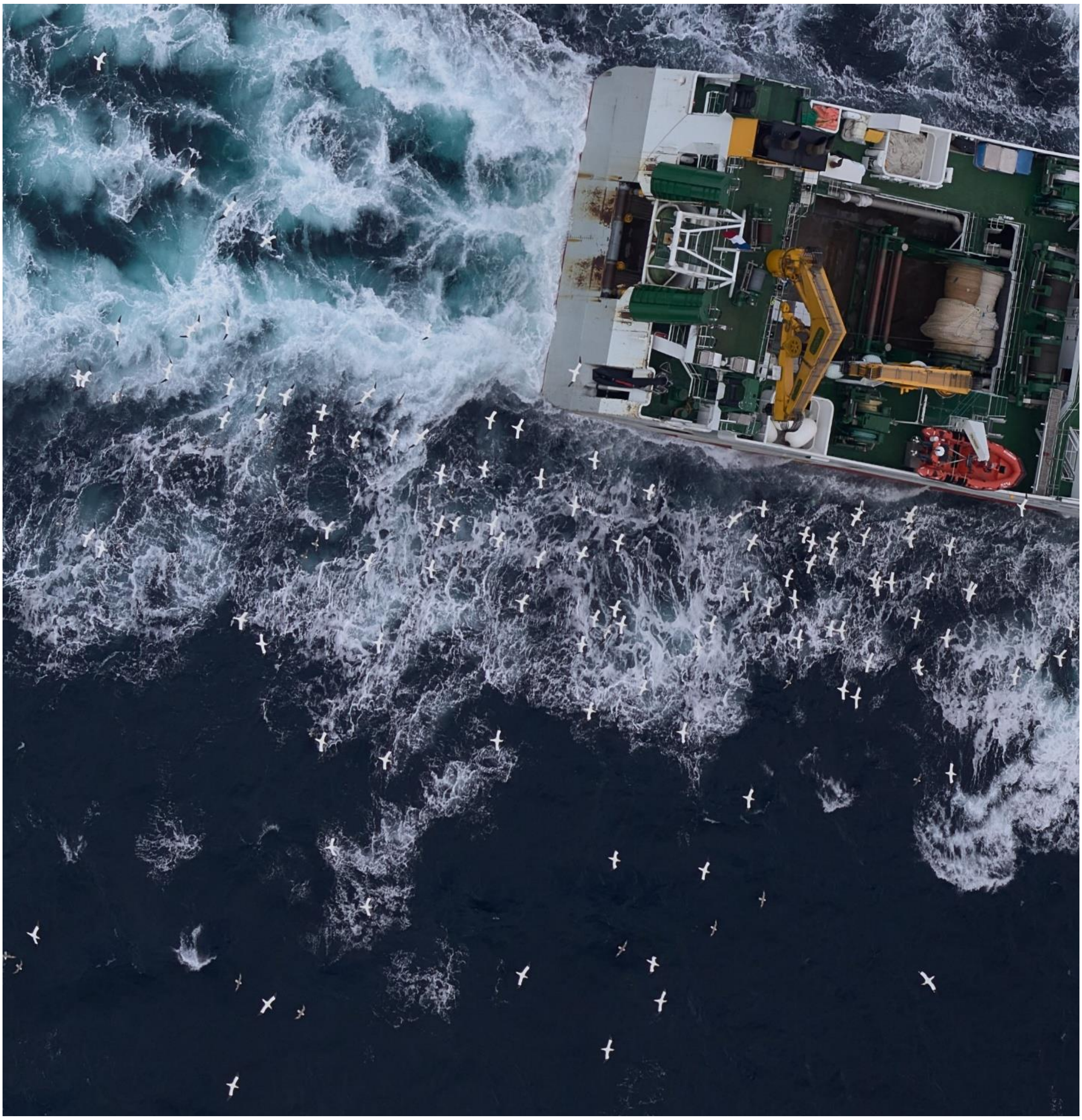


Table 3.1 Comparison between design based and modelled estimates for OAA and OAA plus 2km for the Project for guillemot

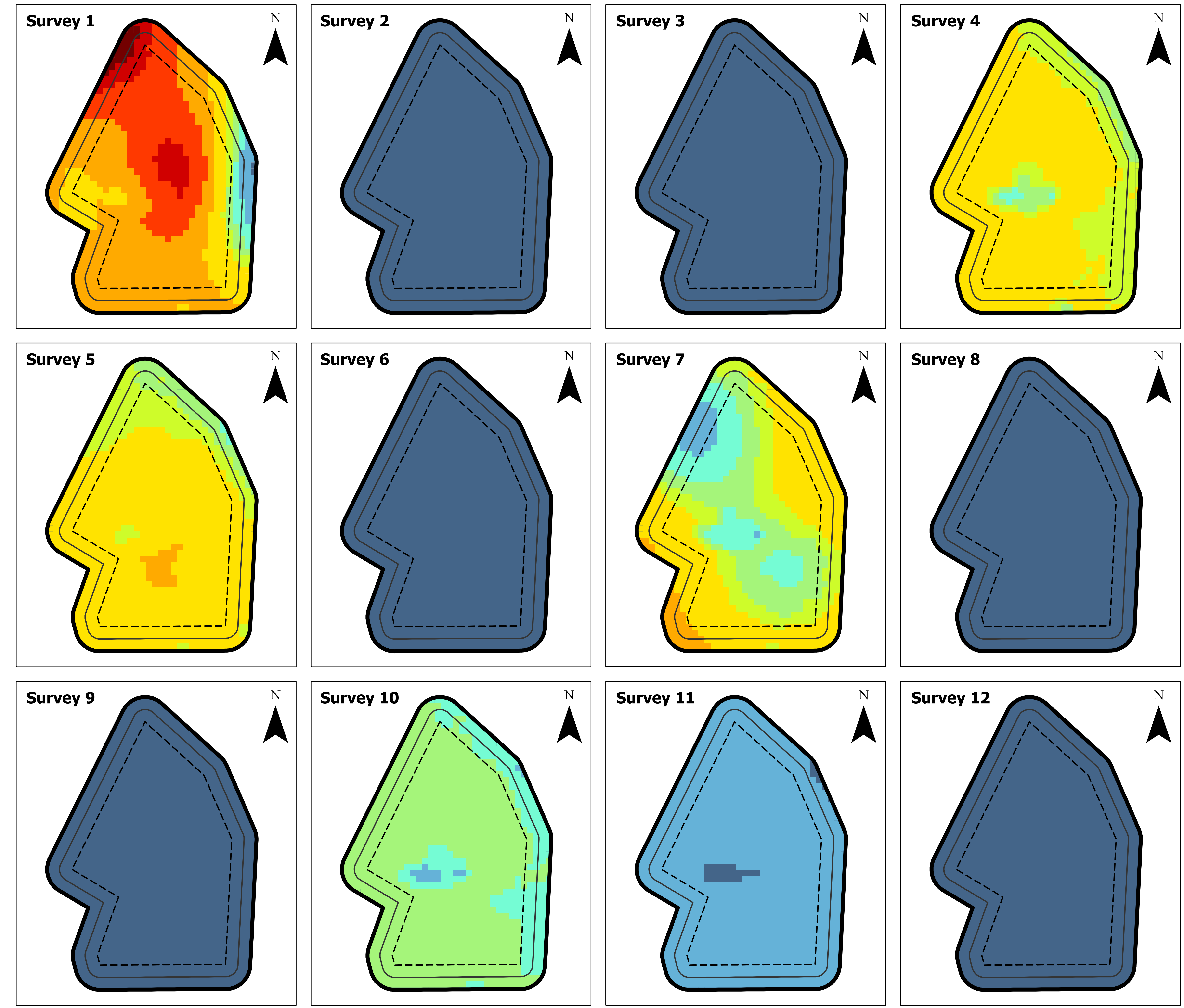
Survey number	Survey date	DAS data raw count - OAA	DAS data raw count - OAA plus 2km buffer	Design-based abundance estimate - OAA apportioned and corrected for availability bias) (95% CIs)	MRSea abundance estimate - OAA (unapportioned) (95% CIs)	MRSea abundance estimate - OAA (apportioned and corrected for availability bias) (95% CIs)	Design-based abundance estimate - OAA plus 2km buffer apportioned and corrected for availability bias) (95% CIs)	MRSea abundance estimate - OAA plus 2km buffer (unapportioned) (95% CIs)	MRSea abundance estimate - OAA plus 2km buffer (apportioned and corrected for availability bias) (95% CIs)
1	April 2021.	1,464	1,827	15,898 (13,994, 18,159)	6,838 (5,381, 8,665)	9,077 (7,154, 11,507)	19,891 (17,856, 22,296)	8,699 (6,853, 11,046)	11,545 (9,110, 14,660)
2	May 2021.	31	47	366 (241, 496)	237 (168, 335)	317 (225, 452)	551 (396, 724)	319 (225, 451)	429 (303, 612)
3	June 2021.	32	42	333 (208, 487)	201 (158, 253)	264 (207, 332)	454 (293, 667)	270 (213, 340)	355 (279, 450)
4	July 2021.	372	456	3,588 (3,033, 4,157)	1,772 (1,549, 2,015)	2,090 (1,822, 2,392)	4,382 (3,790, 5,004)	2,384 (2,086, 2,710)	2,806 (2,451, 3,206)
5	August 2021.	410	525	3,883 (3,309, 4,498)	2,421 (1,962, 2,989)	2,780 (2,252, 3,438)	5,018 (4,405, 5,729)	3,112 (2,530, 3,823)	3,573 (2,903, 4,395)
6	September 2021.	40	53	1,865 (1,433, 2,308)	247 (183, 341)	484 (393, 636)	2,413 (1,931, 2,909)	332 (246,459)	640 (520, 836)
7	October 2021.	232	374	2,802 (2,378, 3,202)	1,430 (1,163, 1,777)	1,809 (1,476, 2,249)	4,442 (3,792, 5,077)	2,122 (1,727, 2,636)	2,682 (2,191, 3,330)

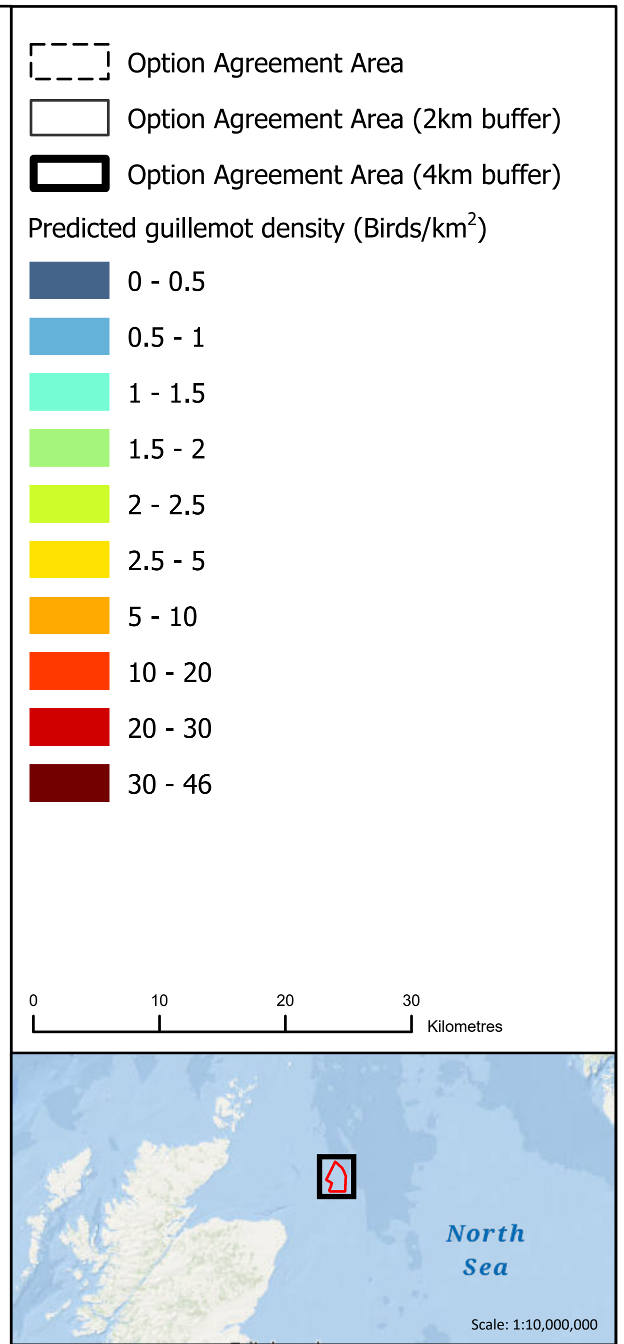
Survey number	Survey date	DAS data raw count - OAA	DAS data raw count - OAA plus 2km buffer	Design-based abundance estimate - OAA apportioned and corrected for availability bias) (95% CIs)	MRSea abundance estimate - OAA (unapportioned) (95% CIs)	MRSea abundance estimate - OAA (apportioned and corrected for availability bias) (95% CIs)	Design-based abundance estimate - OAA plus 2km buffer apportioned and corrected for availability bias) (95% CIs)	MRSea abundance estimate - OAA plus 2km buffer (unapportioned) (95% CIs)	MRSea abundance estimate - OAA plus 2km buffer (apportioned and corrected for availability bias) (95% CIs)
8	December 2021.	14	21	1,668 (1,355, 2,009)	121 (65, 220)	358 (265, 532)	2,285 (1,948, 2,628)	163 (88, 296)	482 (361, 710)
9	January 2022.	16	23	1,641 (1,292, 2,000)	128 (86,194)	362 (288, 491)	2,145 (1,677, 2,608)	173 (115, 261)	477 (377, 645)
10	March 2022.	189	244	2,724 (2,313, 3,152)	1,118 (970, 1,295)	1,740 (1,510, 2,023)	3,658 (3,206, 4,153)	1,505 (1,307, 1,738)	2,355 (2,049, 2,726)
11	April 2022.	81	95	928 (726, 1,142)	506 (418, 606)	676 (557, 815)	1,107 (876, 1,337)	681 (563, 813)	909 (749, 1,095)
12	May 2022.	7	18	120 (46, 208)	119 (74, 198)	214 (132, 273)	288 (162, 425)	160 (99, 267)	223 (140, 372)
13	July number 1 of 2022.	154	201	1,664 (1,336, 2,028)	852 (730, 1,004)	1,018 (869, 1,212)	2,156 (1,795, 2,563)	1,146 (983, 1,350)	1,365 (1,169, 1,620)
14	July number 2 of 2022.	380	493	3,892 (3,103, 4,795)	1,992 (1,658, 2,394)	2,356 (1,959, 2,847)	5,067 (4,211, 6,021)	2,682 (2,233, 3,219)	3,173 (2,640, 3,822)
15	August 2022.	1,016	1,525	9,225 (7,569, 11,027)	6,539 (5,385, 7,936)	7,506 (6,179, 9,121)	14,087 (11,939, 16,291)	8,825 (7,204, 10,801)	10,145 (8,282, 12,432)

Survey number	Survey date	DAS data raw count - OAA	DAS data raw count - OAA plus 2km buffer	Design-based abundance estimate - OAA apportioned and corrected for availability bias) (95% CIs)	MRSea abundance estimate - OAA (unapportioned) (95% CIs)	MRSea abundance estimate - OAA (apportioned and corrected for availability bias) (95% CIs)	Design-based abundance estimate - OAA plus 2km buffer apportioned and corrected for availability bias) (95% CIs)	MRSea abundance estimate - OAA plus 2km buffer (unapportioned) (95% CIs)	MRSea abundance estimate - OAA plus 2km buffer (apportioned and corrected for availability bias) (95% CIs)
16	September 2022.	199	288	2,290 (1,823, 2,796)	1,232 (1,001,1531)	1,472 (1,199, 1,836)	3,428 (2,835, 4,060)	1,734 (1,399, 2,170)	2,088 (1,691, 2,614)
17	October 2022.	134	240	1,576 (1,227, 1,957)	702 (564, 876)	894 (719, 1,119)	3,055 (2,511, 3,595)	1,245 (1,013, 1,531)	1,613 (1,317, 1,993)
18	November number 1 of 2022.	153	210	2,247 (1,766, 2,741)	817 (656, 1,033)	1,156 (933, 1,467)	3,033 (2,515, 3,588)	1,119 (901, 1,410)	1,575 (1,275, 1,986)
19	November number 2 of 2022.	373	433	5,065 (4,403, 5,683)	1,725 (1,406, 2,119)	2,397 (1,967, 2,944)	6,031 (5,339, 6,740)	2,201 (1,788, 2,717)	3,060 (2,505, 3,770)
20	February number 1 of 2023.	76	95	1,021 (781, 1,276)	448 (364, 563)	666 (540, 842)	1,299 (1,036, 1,589)	603 (490, 757)	897 (729, 1,129)
21	February number 2 of 2023.	132	174	1,759 (1,457, 2,109)	884 (726, 1,063)	1,305 (1,071, 1,575)	2,335 (1,966, 2,721)	1,190 (978, 1,428)	1,757 (1,444, 2,114)
22	February number 3 of 2023.	99	129	1,147 (918, 1,360)	710 (609, 826)	1,030 (881, 1,204)	1,510 (1,249, 1,791)	956 (821, 1,110)	1,386 (1,187, 1,616)

Survey number	Survey date	DAS data raw count - OAA	DAS data raw count - OAA plus 2km buffer	Design-based abundance estimate - OAA apportioned and corrected for availability bias) (95% CIs)	MRSea abundance estimate - OAA (unapportioned) (95% CIs)	MRSea abundance estimate - OAA (apportioned and corrected for availability bias) (95% CIs)	Design-based abundance estimate - OAA plus 2km buffer apportioned and corrected for availability bias) (95% CIs)	MRSea abundance estimate - OAA plus 2km buffer (unapportioned) (95% CIs)	MRSea abundance estimate - OAA plus 2km buffer (apportioned and corrected for availability bias) (95% CIs)
23	March number 1 of 2023.	89	120	1,152 (894, 1,418)	653 (555, 775)	992 (841, 1,186)	1,568 (1,302, 1,827)	879 (748, 1,041)	1,336 (1,135, 1,590)
24	March number 2 of 2023.	51	86	622 (424, 852)	508 (378, 671)	765 (569, 1,013)	1,059 (748, 1,411)	684 (509, 903)	1,031 (767, 1,364)

Table note: Light green indicates breeding season, grey-blue indicates non-breeding season.
N/A in MRSea columns indicates months not modelled.





REV	REV DATE	GIS CREATOR	GIS REVIEWER	TECHNICAL CHECKER	TECHNICAL APPROVER
3	12/11/2025	BB	GB	MB	LG
2	30/10/2025	BB	GB	MB	LG
1	13/08/2025	BB	GB	MP	LG

WSP DRAWING NUMBER	808368-WEIS-IA-FG-O6-18288
MarramWind DRAWING NUMBER	MAR-GEN-ENV-MAP-WSP-000459

DATUM	ETRS 89	PROJECTION	UTM Zone 30N
SCALE	1:600,000	PAGE SIZE	A3

PROJECT TITLE

MarramWind Offshore Wind Farm

DRAWING TITLE

Figure 1 Model-based density plot of guillemot distribution to highlight peak areas of potential abundance in the OAA plus 4km buffer extent – Survey 1 to Survey 12 (all behaviours)

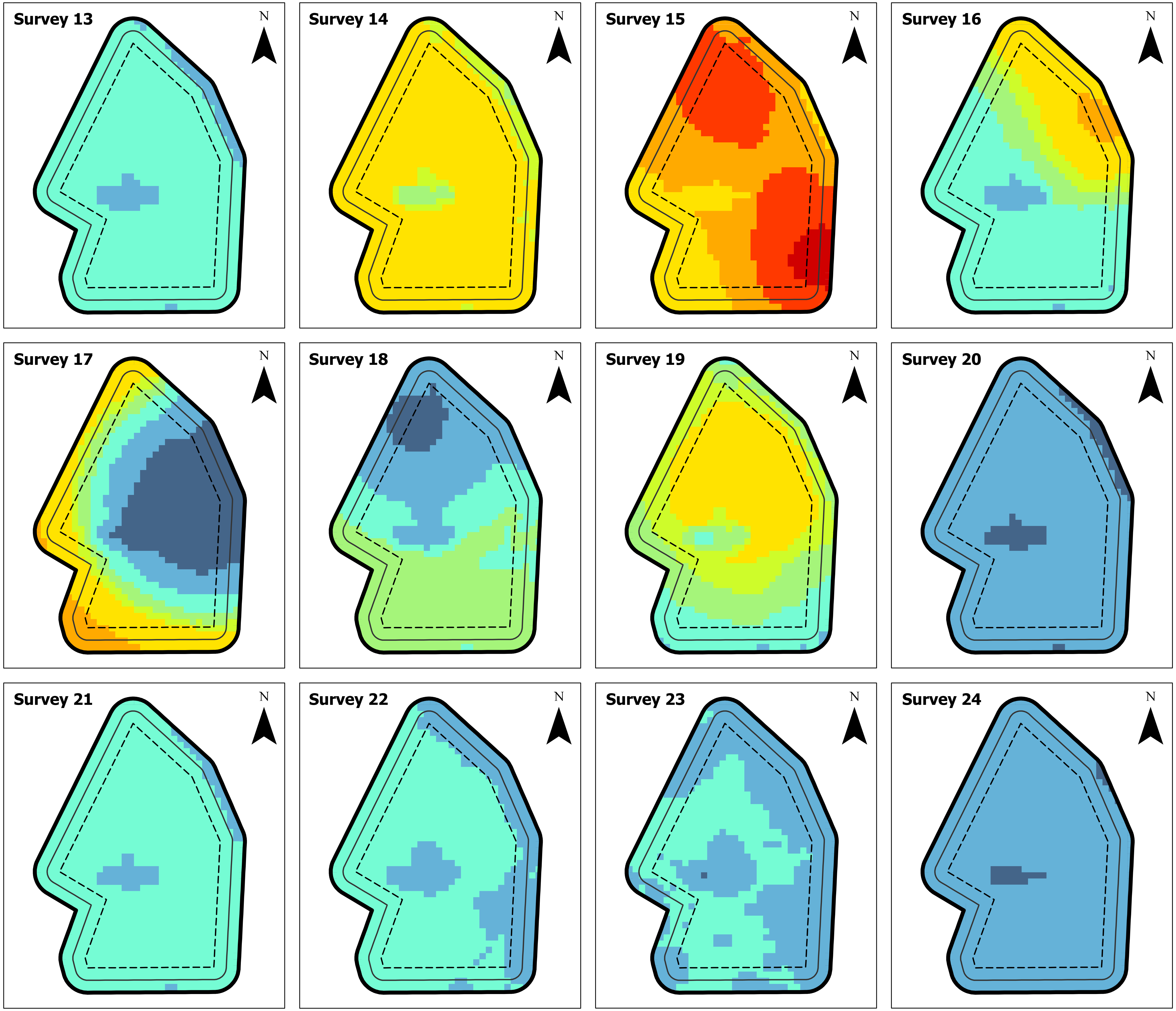
Environmental Impact Assessment Report

Appendix 12.5

NOT TO BE USED FOR NAVIGATION

APEM Group

MarramWind

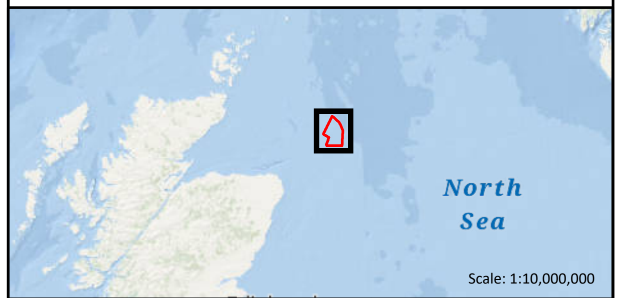


Option Agreement Area
Option Agreement Area (2km buffer)
Option Agreement Area (4km buffer)

Predicted Guillemot Density (Birds/km^2)

- 0 - 0.5
- 0.5 - 1
- 1 - 1.5
- 1.5 - 2
- 2 - 2.5
- 2.5 - 5
- 5 - 10
- 10 - 20
- 20 - 30
- 30 - 46

0 10 20 30 Kilometres



REV	REV DATE	GIS CREATOR	GIS REVIEWER	TECHNICAL CHECKER	TECHNICAL APPROVER
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2	30/10/2025	BB	GB	MB	LG
1	13/08/2025	BB	GB	MP	LG

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PROJECT TITLE
MarramWind Offshore Wind Farm

DRAWING TITLE
Figure 2 Model-based density plot of guillemot distribution to highlight peak areas of potential abundance in the OAA plus 4km buffer extent – Survey 13 to Survey 24 (all behaviours)
Environmental Impact Assessment Report
Appendix 12.5

NOT TO BE USED FOR NAVIGATION

APEM Group
MarramWind

3.3 Puffin

3.3.1.1 MRSea modelling was carried out for the breeding season only due to low DAS raw counts in the non-breeding season (**Table 3.2**).

3.3.2 Abundance estimates

3.3.2.1 Puffin were recorded in 13 of 24 surveys, with the peak raw count within the OAA and 2km buffer area in May 2022 80 individuals). Raw counts for each month are presented in **Table 3.2**.

3.3.2.2 Apportioned and unapportioned model-based population estimates are presented in **Table 3.2** alongside the design-based population estimates.

3.3.2.3 The peak apportioned abundance estimates for puffin in the OAA plus 2km buffer were:

- Design-based: 782 in May 2022; and
- MRSea based: 850 in May 2022..

3.3.2.4 The peak apportioned abundance estimates for puffin within the OAA excluding the 2km buffer were:

- Design-based: 635 in May 2022; and
- MRSea based: 471 in May 2022.

3.3.3 Density plots

3.3.3.1 Density of puffin was nominally evenly spread throughout the site (**Figure 3**).

3.3.3.2 Peak density of puffin occurred in May 2021 (Survey 2), in the southern west limit of the survey area. The direct cause of this increase is unknown and it is possible that this is a modelling edge effect trait, although as this is a single occurrence it is thought unlikely. It is therefore considered that this captures the edge of a potential temporary clustering of puffin linked to surface prey availability. It is highlighted that it is outside of the OAA plus 4km buffer.

Table 3.2 Comparison between design based and modelled estimates for OAA and OAA plus 2km for the Project for puffin

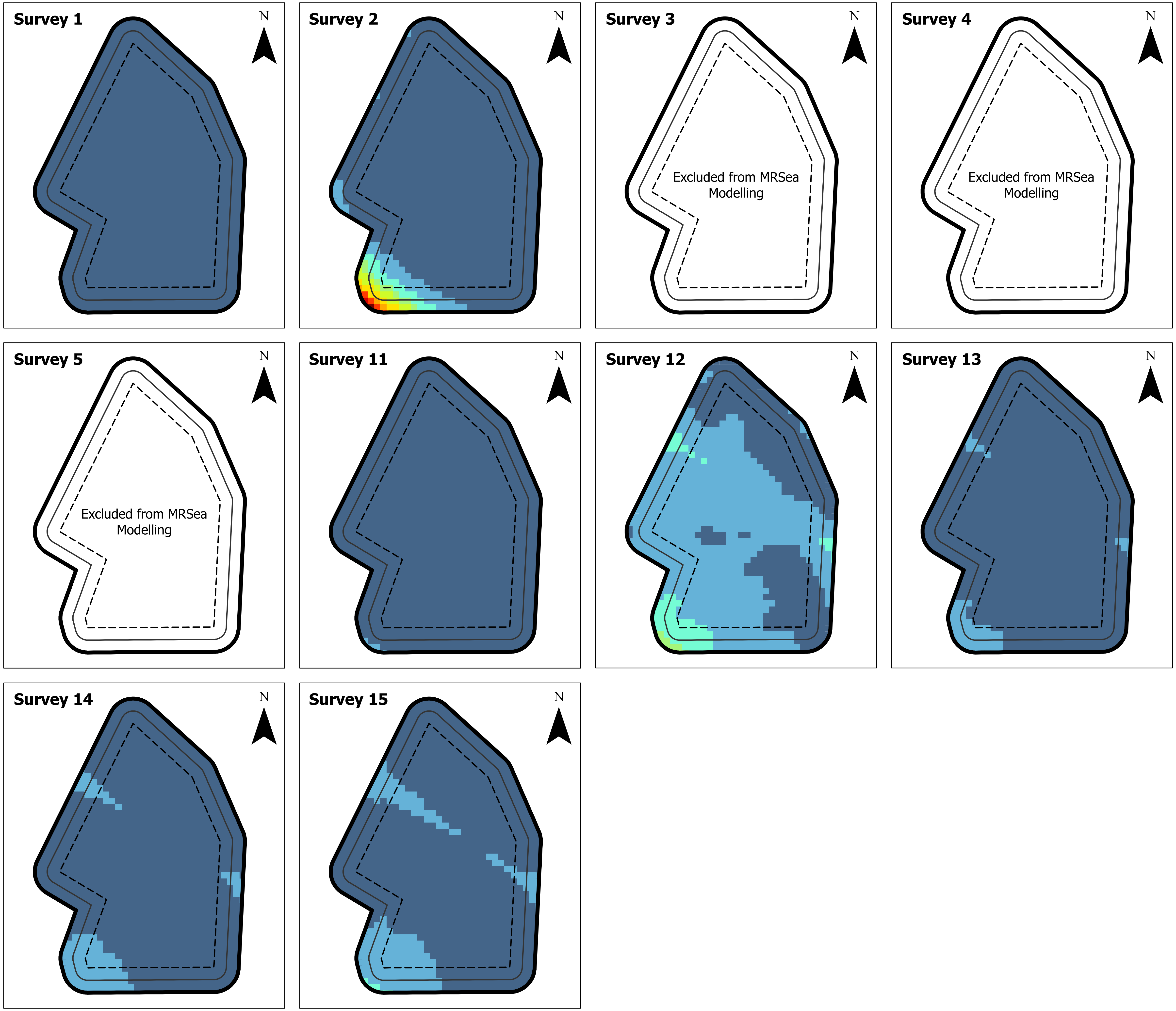
Survey number	Survey date	DAS data raw count - OAA	DAS data raw count - OAA plus 2km buffer	Design-based abundance estimate - OAA (apportioned) (95% CIs)	MRSea abundance estimate - OAA (unapportioned) (95% CIs)	MRSea abundance estimate - OAA (apportioned and corrected for availability bias) (95% CIs)	Design-based abundance estimate - OAA plus 2km buffer (apportioned) (95% CIs)	MRSea abundance estimate - OAA plus 2km buffer (unapportioned) (95% CIs)	MRSea abundance estimate - OAA plus 2km buffer (apportioned and corrected for availability bias) (95% CIs)
1	April 2021.	18	23	164 (74, 263)	68 (36, 131)	79 (42, 154)	214 (103, 343)	123 (64, 239)	143 (75, 280)
2	May 2021.	11	34	104 (36, 189)	54 (26, 116)	64 (30, 136)	325 (184, 491)	297 (124, 784)	348 (146, 917)
3	June 2021.	2	2	17 (2, 44)	n/a	n/a	18 (2, 45)	n/a	n/a
4	July 2021.	6	6	54 (6, 118)	n/a	n/a	55 (9, 118)	n/a	n/a
5	August 2021.	0	0	-	-	-	-	-	-
6	September 2021.	2	3	19 (2, 51)	n/a	n/a	29 (3, 68)	n/a	n/a
7	October 2021.	0	0	-	-	-	-	-	-
8	December 2021.	0	0	-	-	-	-	-	-

Survey number	Survey date	DAS data raw count - OAA	DAS data raw count - OAA plus 2km buffer	Design-based abundance estimate - OAA (apportioned) (95% CIs)	MRSea abundance estimate - OAA (unapportioned) (95% CIs)	MRSea abundance estimate - OAA (apportioned and corrected for availability bias) (95% CIs)	Design-based abundance estimate - OAA plus 2km buffer (apportioned) (95% CIs)	MRSea abundance estimate - OAA plus 2km buffer (unapportioned) (95% CIs)	MRSea abundance estimate - OAA plus 2km buffer (apportioned and corrected for availability bias) (95% CIs)
9	January 2022.	0	0	-	-	-	-	-	-
10	March 2022.	0	0	-	-	-	-	-	-
11	April 2022.	20	25	186 (95, 295)	107 (63, 192)	125 (73, 225)	242 (140, 358)	188 (108, 341)	220 (126, 400)
12	May 2022.	66	80	635 (445, 842)	401 (287, 565)	471 (337, 664)	782 (568, 1,010)	726 (503, 1,060)	850 (589, 1,244)
13	July number 1 of 2022.	32	42	313 (183, 469)	190 (130, 282)	223 (153, 332)	410 (257, 595)	344 (230, 522)	403 (269, 612)
14	July number 2 of 2022.	33	49	317 (183, 475)	220 (151, 328)	257 (177, 384)	471 (280, 680)	398 (267, 609)	465 (312, 712)
15	August 2022.	54	71	474 (290, 693)	256 (162, 394)	289 (183, 445)	625 (413, 872)	462 (294, 717)	522 (332, 811)
16	September 2022.	0	0	-	-	-	-	-	-

Survey number	Survey date	DAS data raw count - OAA	DAS data raw count - OAA plus 2km buffer	Design-based abundance estimate - OAA (apportioned) (95% CIs)	MRSea abundance estimate - OAA (unapportioned) (95% CIs)	MRSea abundance estimate - OAA (apportioned and corrected for availability bias) (95% CIs)	Design-based abundance estimate - OAA plus 2km buffer (apportioned) (95% CIs)	MRSea abundance estimate - OAA plus 2km buffer (unapportioned) (95% CIs)	MRSea abundance estimate - OAA plus 2km buffer (apportioned and corrected for availability bias) (95% CIs)
17	October 2022.	4	7	40 (10, 88)	n/a	n/a	70 (20, 140)	n/a	n/a
18	November number 1 of 2022.	0	1	-	n/a	n/a	10 (1, 30)	n/a	n/a
19	November number 2 of 2022.	5	5	52 (11, 98)		n/a	54 (11, 106)	n/a	n/a
20	February number 1 of 2023.	0	0	-	-	-	-	-	-
21	February number 2 of 2023.	0	0	-	-	-	-	-	-
22	February number 3 of 2023.	1	1	10 (1, 31)	n/a	n/a	11 (1, 40)	n/a	n/a

Survey number	Survey date	DAS data raw count - OAA	DAS data raw count - OAA plus 2km buffer	Design-based abundance estimate - OAA (apportioned) (95% CIs)	MRSea abundance estimate - OAA (unapportioned) (95% CIs)	MRSea abundance estimate - OAA (apportioned and corrected for availability bias) (95% CIs)	Design-based abundance estimate - OAA plus 2km buffer (apportioned) (95% CIs)	MRSea abundance estimate - OAA plus 2km buffer (unapportioned) (95% CIs)	MRSea abundance estimate - OAA plus 2km buffer (apportioned and corrected for availability bias) (95% CIs)
23	March number 1 of 2023.	0	0	-	-	-	-	-	-
24	March number 2 of 2023.	0	0	-	-	-	-	-	-

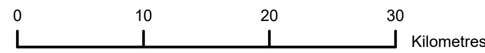
Table note: Light green indicates breeding season, grey-blue indicates non-breeding season.
N/A in MRSea columns indicates months not modelled.

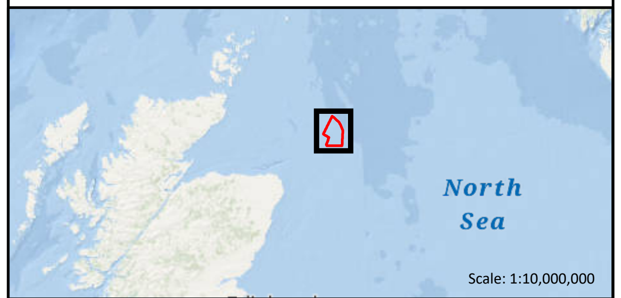


Option Agreement Area
Option Agreement Area (2km buffer)
Option Agreement Area (4km buffer)

Predicted Puffin Density (Birds/km^2)

0 - 0.5
0.5 - 1
1 - 1.5
1.5 - 2
2 - 3
3 - 4
4 - 5
5 - 6
6 - 7
7 - 8





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1	13/08/2025	BB	GB	MP	LG
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WSP DRAWING NUMBER 808368-WEIS-IA-FG-O6-94190

MarramWind DRAWING NUMBER MAR-GEN-ENV-MAP-WSP-000465

DATUM	ETRS 89	PROJECTION	UTM Zone 30N
SCALE	1:600,000	PAGE SIZE	A3

PROJECT TITLE
MarramWind Offshore Wind Farm

DRAWING TITLE
Figure 3 Model-based density plot of puffin distribution to highlight peak areas of potential abundance in the OAA plus 4km buffer extent – Surveys 1-5 and 11-15 (all behaviours - breeding)
Environmental Impact Assessment Report
Appendix 12.5

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MarramWind

3.4 Kittiwake

3.4.1 All behaviours

Abundance estimates

3.4.1.1 Kittiwake were recorded in all surveys, with the peak raw count within the OAA plus 2km buffer in July 2022 second survey (185 individuals). Raw counts for each month are presented in **Table 3.3**.

3.4.1.2 Apportioned and unapportioned model-based population estimates are presented in **Table 3.3** alongside the design-based population estimates.

3.4.1.3 The peak apportioned abundance estimates for kittiwake in the OAA plus 2km buffer were:

- Design-based: 1,479 in July 2022; and
- MRSea based: 957 in July 2022.

3.4.1.4 The peak apportioned abundance estimates for kittiwake within the OAA excluding the 2km buffer were:

- Design-based: 1,230 in July 2022; and
- MRSea based: 720 in July 2022.

Density plots

3.4.1.5 Kittiwake showed highly variable patterns in occurrence, in both density and distribution (**Figure 4** and **Figure 5**).

3.4.1.6 Peak density of kittiwake occurred in April 2021 (Survey 1), with a hotspot of kittiwake densities within the southern area of the site. This is potentially due to localised prey availability aggregations, within the survey area.

3.4.1.7 Increases in uncertainty within the model indicate a hotspot to the southern edge of the site within the same survey of April 2021. It is likely that this is due to this model containing all behaviours, and as can be seen in the kittiwake flying only model, this is an area of increased flying kittiwake presence. The mixture of behaviours is likely driving the model uncertainty. Behaviour was considered but was excluded due to correlation with other candidate model variables, as was boat presence. Both behaviour and boat presence exclusion are thought to be due to the correlation of boat presence with survey with boat presence also driving the number of flying birds.

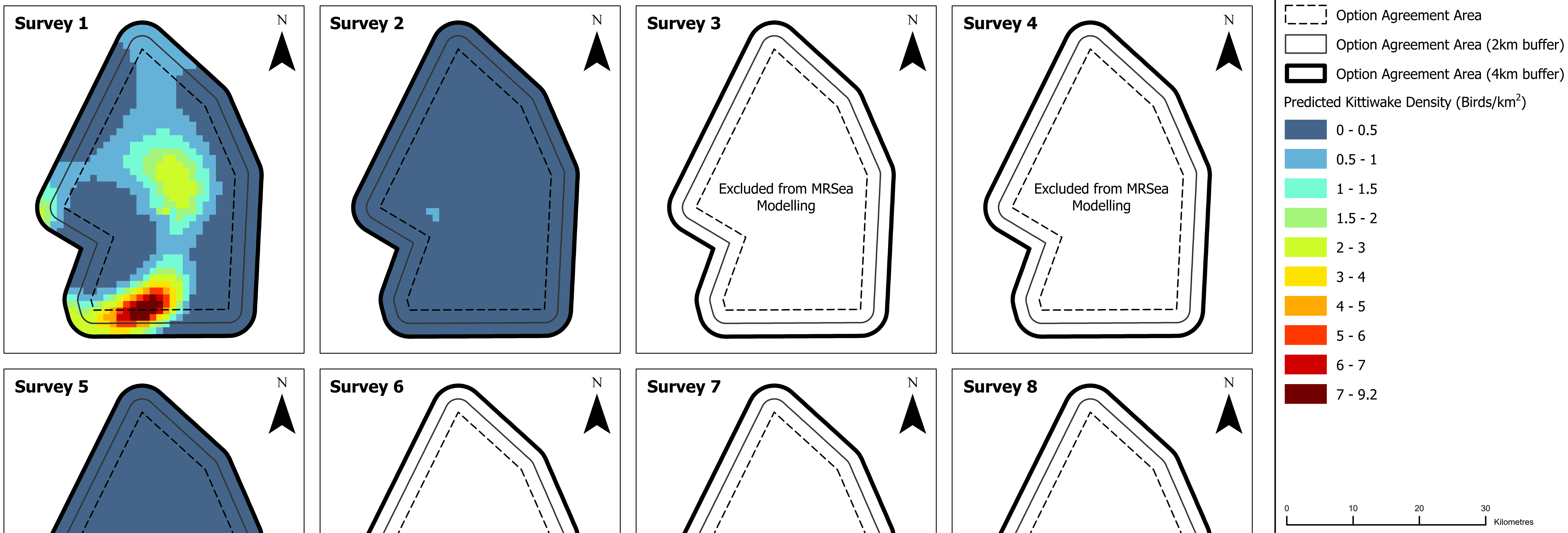
Table 3.3 Comparison between design based and modelled estimates for OAA and OAA plus 2km for the Project for kittiwake all behaviours

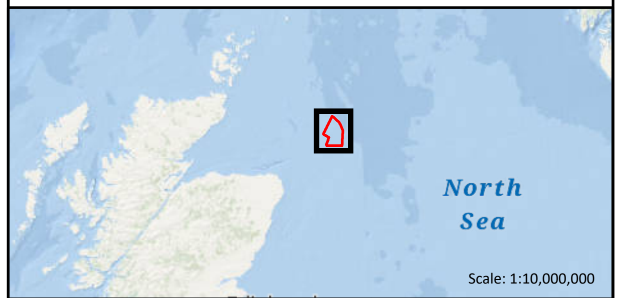
Survey number	Survey date	DAS data raw count - OAA	DAS data raw count - OAA plus 2km buffer	Design-based abundance estimate - OAA (apportioned) (95% CIs)	MRSea abundance estimate - OAA (unapportioned) (95% CIs)	MRSea abundance estimate - OAA (apportioned) (95% CIs)	Design-based abundance estimate - OAA plus 2km buffer (apportioned) (95% CIs)	MRSea abundance estimate - OAA plus 2km buffer (unapportioned) (95% CIs)	MRSea abundance estimate - OAA plus 2km buffer (apportioned) (95% CIs)
1	April 2021.	146	171	1,137 (614, 1,905)	622 (273, 1,557)	622 (273, 1,557)	1,351 (805, 2,139)	823 (354, 2,089)	823 (354, 2,089)
2	May 2021.	34	40	266 (150, 394)	182 (112, 300)	182 (112, 300)	315 (190, 458)	241 (148, 396)	241 (148, 396)
3	June 2021.	3	3	25 (3, 64)	n/a	n/a	24 (3, 64)	n/a	n/a
4	July 2021.	2	2	14 (2, 46)	n/a	n/a	15 (2, 46)	n/a	n/a
5	August 2021.	24	31	193 (105, 314)	122 (72, 198)	122 (72, 198)	252 (138, 389)	161 (96, 261)	161 (96, 261)
6	September 2021.	1	1	8 (1, 23)	n/a	n/a	8 (1, 23)	n/a	n/a
7	October 2021.	6	7	48 (6, 128)	n/a	n/a	66 (8, 153)	n/a	n/a
8	December 2021.	0	3	-	n/a	n/a	24 (3, 56)	n/a	n/a

Survey number	Survey date	DAS data raw count - OAA	DAS data raw count - OAA plus 2km buffer	Design-based abundance estimate - OAA (apportioned) (95% CIs)	MRSea abundance estimate - OAA (unapportioned) (95% CIs)	MRSea abundance estimate - OAA (apportioned) (95% CIs)	Design-based abundance estimate - OAA plus 2km buffer (apportioned) (95% CIs)	MRSea abundance estimate - OAA plus 2km buffer (unapportioned) (95% CIs)	MRSea abundance estimate - OAA plus 2km buffer (apportioned) (95% CIs)
9	January 2022.	8	12	62 (24, 104)	47 (28, 81)	47 (28, 81)	98 (48, 152)	62 (36, 106)	62 (36, 106)
10	March 2022.	11	14	87 (39, 142)	64 (38, 108)	64 (38, 108)	111 (56, 182)	85 (50, 142)	85 (50, 142)
11	April 2022.	1	16	8 (1, 24)	43 (18, 109)	43 (18, 109)	124 (16, 309)	91 (34, 259)	91 (34, 259)
12	May 2022.	12	14	95 (48, 151)	74 (42, 129)	74 (42, 129)	112 (56, 175)	97 (56, 170)	97 (56, 170)
13	July number 1 of 2022.	1	1	8 (1, 24)	n/a	n/a	8 (1, 24)	n/a	n/a
14	July number 2 of 2022.	156	185	1,230 (758, 1,793)	720 (407, 1,331)	720 (407, 1,331)	1,479 (960, 2,071)	957 (524, 1,860)	957 (524, 1,860)
15	August 2022.	11	16	86 (39, 147)	79 (47, 136)	79 (47, 136)	124 (70, 195)	105 (62, 178)	105 (62, 178)
16	September 2022.	0	1	-	-	-	8 (1, 24)	n/a	n/a
17	October 2022.	8	9	64 (24, 118)	47 (25, 86)	47 (25, 86)	72 (24, 126)	62 (34, 114)	62 (34, 114)

Survey number	Survey date	DAS data raw count - OAA	DAS data raw count - OAA plus 2km buffer	Design-based abundance estimate - OAA (apportioned) (95% CIs)	MRSea abundance estimate - OAA (unapportioned) (95% CIs)	MRSea abundance estimate - OAA (apportioned) (95% CIs)	Design-based abundance estimate - OAA plus 2km buffer (apportioned) (95% CIs)	MRSea abundance estimate - OAA plus 2km buffer (unapportioned) (95% CIs)	MRSea abundance estimate - OAA plus 2km buffer (apportioned) (95% CIs)
18	November number 1 of 2022.	7	11	55 (16, 102)	65 (37, 111)	65 (37, 111)	87 (39, 142)	86 (49, 146)	86 (49, 146)
19	November number 2 of 2022.	13	19	105 (41, 186)	57 (33, 100)	58 (33, 100)	154 (81, 235)	75 (44, 132)	75 (44, 132)
20	February number 1 of 2023.	3	5	24 (3, 56)	n/a	n/a	40 (8, 80)	n/a	n/a
21	February number 2 of 2023.	20	22	161 (88, 240)	118 (77, 186)	118 (77, 186)	177 (112, 265)	156 (102, 245)	156 (102, 245)
22	February number 3 of 2023.	4	14	32 (8, 63)	28 (9, 118)	28 (9, 118)	111 (55, 165)	64 (25, 209)	64 (25, 209)
23	March number 1 of 2023.	7	10	56 (24, 95)	42 (21, 82)	43 (21, 82)	81 (32, 135)	55 (27, 109)	56 (27, 109)
24	March number 2 of 2023.	9	11	70 (24, 118)	48 (26, 89)	48 (26, 89)	88 (32, 150)	64 (35, 117)	64 (35, 117)

Table note: Light green indicates breeding season, grey-blue indicates non-breeding season.
N/A in MRSea columns indicates months not modelled.





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MarramWind DRAWING NUMBER	MAR-GEN-ENV-MAP-WSP-000466
DATUM	ETRS 89
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PROJECT TITLE

MarramWind Offshore Wind Farm

DRAWING TITLE

Figure 4 Model-based density plot of kittiwake distribution to highlight peak areas of potential abundance in the OAA plus 4km buffer extent – Survey 1 to Survey 12 (all behaviours)

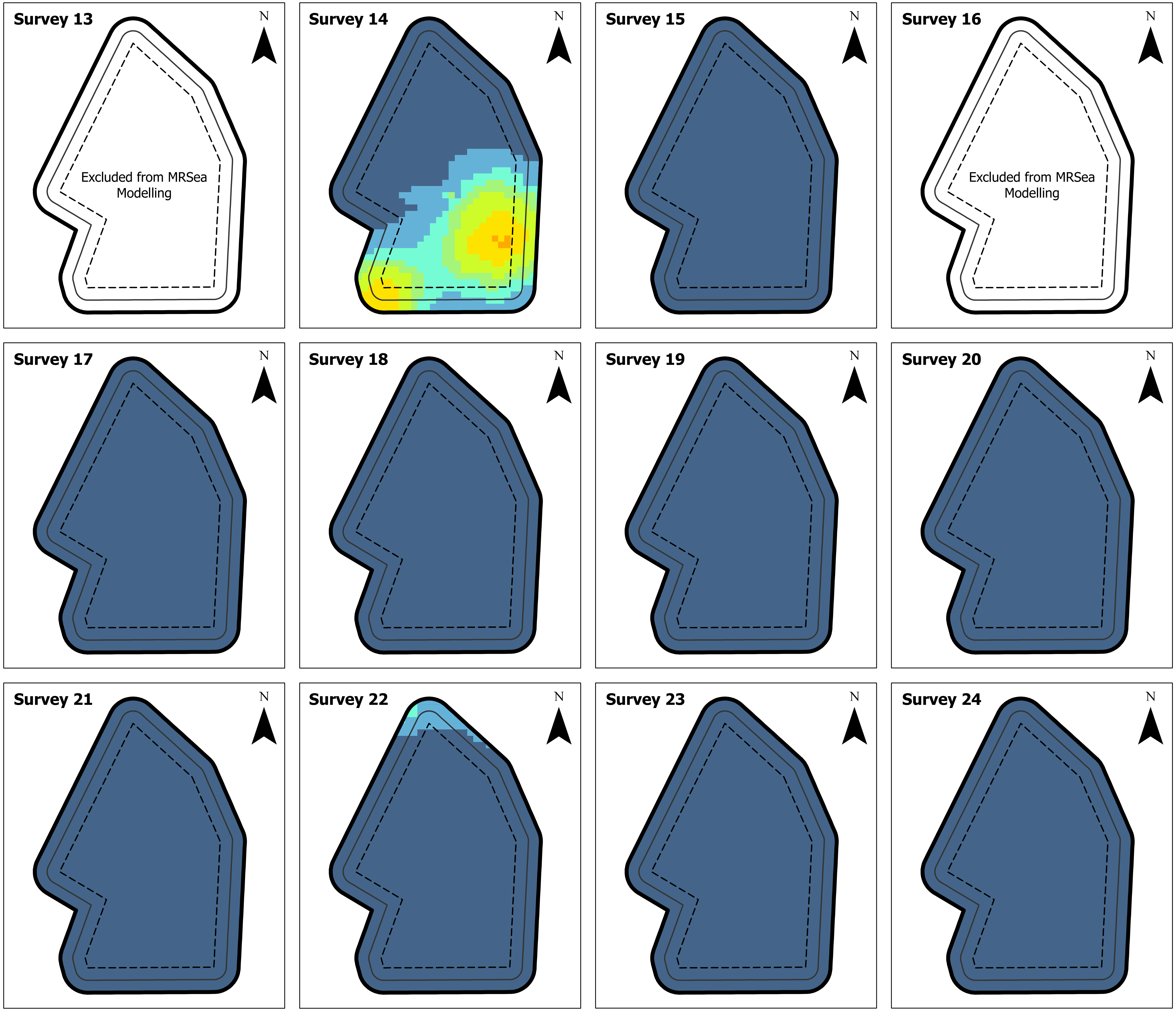
Environmental Impact Assessment Report

Appendix 12.5

NOT TO BE USED FOR NAVIGATION

APEM APEM Group

MarramWind

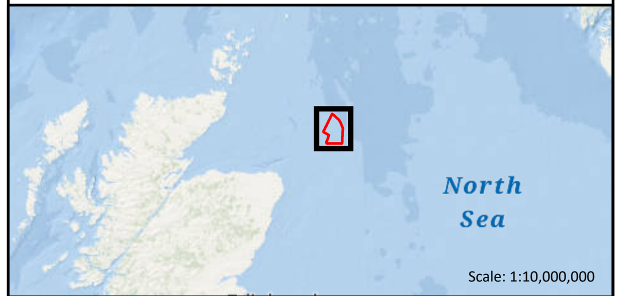


Option Agreement Area
Option Agreement Area (2km buffer)
Option Agreement Area (4km buffer)

Predicted Kittiwake Density (Birds/km^2)

- 0 - 0.5
- 0.5 - 1
- 1 - 1.5
- 1.5 - 2
- 2 - 3
- 3 - 4
- 4 - 5
- 5 - 6
- 6 - 7
- 7 - 9.2

0 10 20 30 Kilometres



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1	13/08/2025	BB	GB	MP	LG

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PROJECTION	UTM Zone 30N
SCALE	1:600,000
PAGE SIZE	A3

PROJECT TITLE
MarramWind Offshore Wind Farm

DRAWING TITLE
Figure 5 Model-based density plot of kittiwake distribution to highlight peak areas of potential abundance in the OAA plus 4km buffer extent – Survey 13 to Survey 24 (all behaviours)
Environmental Impact Assessment Report
Appendix 12.5

NOT TO BE USED FOR NAVIGATION

APEM APEMGroup MarramWind

3.4.2 Flying only

Abundance estimates

3.4.2.1 Flying kittiwake were recorded in all surveys, with the peak raw count within the OAA in April 2021 (47 individuals). Raw counts for each month are presented in **Table 3.4.**

3.4.2.2 Apportioned and unapportioned model-based population estimates are presented in **Table 3.4** alongside the design-based population estimates.

3.4.2.3 The peak apportioned abundance estimates for flying kittiwake in the OAA plus 2km buffer were:

- Design-based: 517 in April 2021; and
- MRSea based: 297 in April 2021.

3.4.2.4 The peak apportioned abundance estimates for flying kittiwake within the OAA excluding the 2km buffer were:

- Design-based: 370 in April 2021; and
- MRSea based: 212 in April 2021.

Density plots

3.4.2.5 Peak density of flying kittiwake occurred in April 2021 (Survey 1), in the southern limit of the survey area **(Figure 6** and **Figure 7**).

3.4.2.6 Occurrence of flying kittiwakes was highly varied throughout the site and between surveys. This is thought to be predominantly driven by localised prey availability and fishing vessel presence, however statistically boat presence was dropped as a covariate within the model due to correlation with other candidate variables. When forced through, the model failed to run. Boat presence exclusion is thought to be due to the correlation of boat presence with survey. The model variation was spatially consistent with the upper confidence interval of the estimated densities, indicating uncertainty in the model upper estimates.

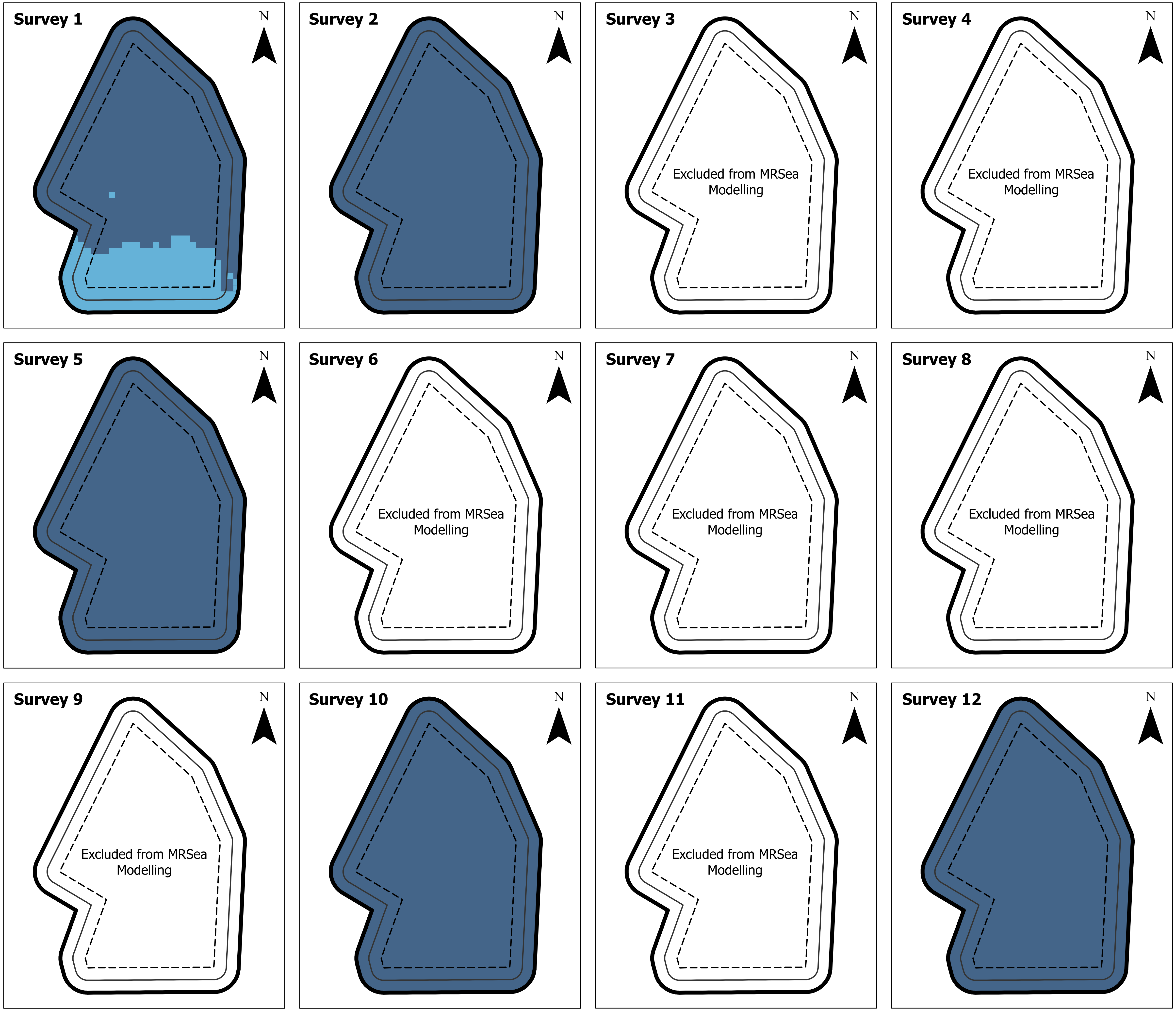
Table 3.4 Comparison between design based and modelled estimates for OAA and OAA plus 2km for the Project for kittiwake flying

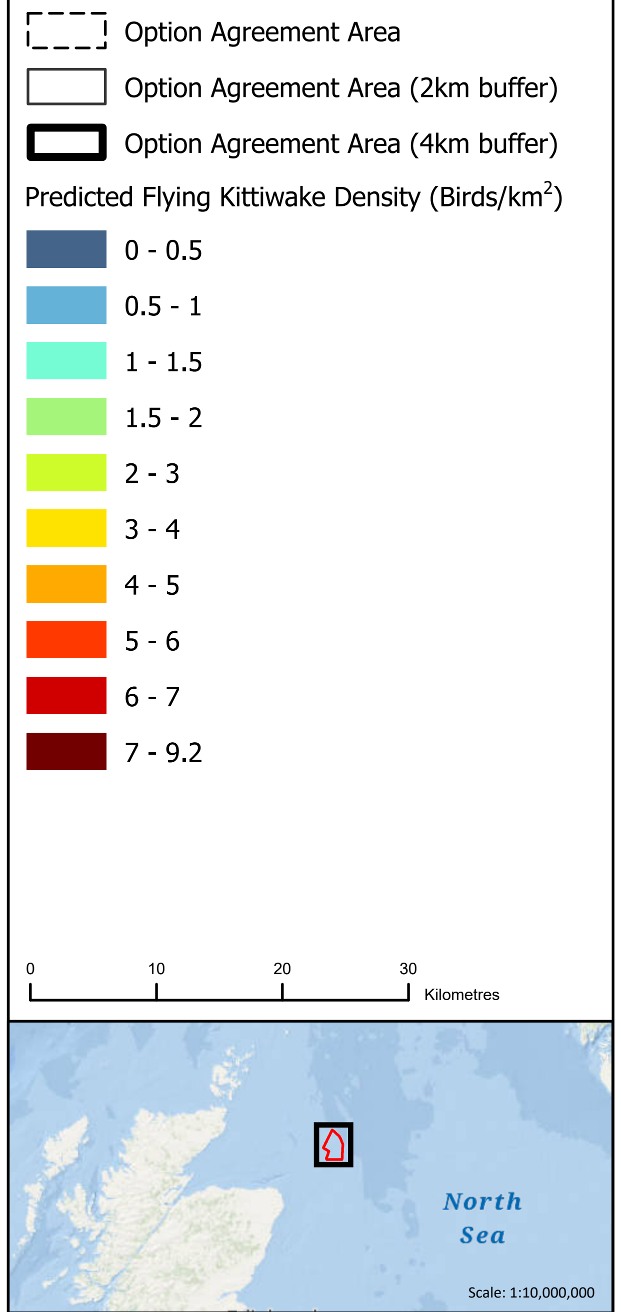
Survey number	Survey date	DAS data raw count - OAA	DAS data raw count - OAA plus 2km buffer	Design-based abundance estimate - OAA (apportioned) (95% CIs)	MRSea abundance estimate - OAA (unapportioned) (95% CIs)	MRSea abundance estimate - OAA (apportioned) (95% CIs)	Design-based abundance estimate - OAA plus 2km buffer (apportioned) (95% CIs)	MRSea abundance estimate - OAA plus 2km buffer (unapportioned) (95% CIs)	MRSea abundance estimate - OAA plus 2km buffer (apportioned) (95% CIs)
1	April 2021.	47	66	370 (244, 527)	212 (119, 372)	212 (119, 372)	517 (355, 703)	297 (165, 525)	297 (165, 525)
2	May 2021.	27	33	212 (111, 323)	151 (89, 258)	151 (89, 258)	260 (150, 379)	200 (118, 343)	200 (118, 343)
3	June 2021.	1	1	8 (1, 24)	n/a	n/a	8 (1,24)	n/a	n/a
4	July 2021.	0	0	-	-	-	-	-	-
5	August 2021.	22	27	177 (89, 290)	109 (63, 186)	109 (63, 186)	220 (113, 348)	145 (84, 247)	145 (84, 247)
6	September 2021.	1	1	8 (1,23)	n/a	n/a	8 (1, 23)	n/a	n/a
7	October 2021.	6	7	48 (6, 128)	n/a	n/a	66 (8, 153)	n/a	n/a
8	December 2021.	0	2	-	n/a	n/a	16 (2, 40)	n/a	n/a
9	January 2022.	5	8	39 (8, 72)	n/a	n/a	66 (24, 112)	n/a	n/a

Survey number	Survey date	DAS data raw count - OAA	DAS data raw count - OAA plus 2km buffer	Design-based abundance estimate - OAA (apportioned) (95% CIs)	MRSea abundance estimate - OAA (unapportioned) (95% CIs)	MRSea abundance estimate - OAA (apportioned) (95% CIs)	Design-based abundance estimate - OAA plus 2km buffer (apportioned) (95% CIs)	MRSea abundance estimate - OAA plus 2km buffer (unapportioned) (95% CIs)	MRSea abundance estimate - OAA plus 2km buffer (apportioned) (95% CIs)
10	March 2022.	7	8	56 (16, 103)	43 (25, 73)	43 (25, 73)	64 (24, 111)	57 (33, 96)	57 (33, 96)
11	April 2022.	0	3	-	-	-	23 (3, 55)	-	-
12	May 2022.	10	12	79 (32, 135)	62 (35, 110)	62 (35, 110)	96 (48, 151)	83 (46, 147)	83 (46, 147)
13	July number 1 of 2022.	0	0	-	-	-	-	-	-
14	July number 2 of 2022.	35	47	278 (191, 375)	211 (144, 316)	211 (144, 316)	377 (272, 504)	267 (181, 400)	267 (181, 400)
15	August 2022.	8	11	63 (16, 116)	57 (32,103)	57 (32, 103)	86 (39, 140)	76 (43, 136)	76 (43, 136)
16	September 2022.	0	1	-	-	-	8 (1, 24)	-	-
17	October 2022.	5	6	40 (8, 79)	n/a	n/a	48 (16, 95)	n/a	n/a
18	November number 1 of 2022.	7	11	55 (16, 102)	65 (38, 114)	65 (38, 114)	87 (39, 142)	87 (50, 151)	87 (50, 151)

Survey number	Survey date	DAS data raw count - OAA	DAS data raw count - OAA plus 2km buffer	Design-based abundance estimate - OAA (apportioned) (95% CIs)	MRSea abundance estimate - OAA (unapportioned) (95% CIs)	MRSea abundance estimate - OAA (apportioned) (95% CIs)	Design-based abundance estimate - OAA plus 2km buffer (apportioned) (95% CIs)	MRSea abundance estimate - OAA plus 2km buffer (unapportioned) (95% CIs)	MRSea abundance estimate - OAA plus 2km buffer (apportioned) (95% CIs)
19	November number 2 of 2022.	12	18	97 (40, 171)	54 (30, 97)	54 (30, 97)	145 (73, 222)	72 (40, 129)	72 (40, 129)
20	February number 1 of 2023.	2	4	16 (2, 40)	n/a	n/a	32 (8, 64)	n/a	n/a
21	February number 2 of 2023.	17	19	137 (72, 208)	92 (58, 148)	92 (58, 148)	152 (88, 233)	123 (78, 195)	123 (78, 195)
22	February number 3 of 2023.	4	13	32 (8, 63)	42 (19, 89)	42 (19, 89)	103 (47, 157)	71 (33, 148)	71 (33, 148)
23	March number 1 of 2023.	7	10	56 (24, 95)	42 (22, 84)	42 (22, 84)	81 (32, 135)	56 (29, 111)	56 (29, 111)
24	March number 2 of 2023.	8	10	62 (24, 110)	45 (25, 83)	45 (25, 83)	80 (32, 143)	59 (34, 110)	59 (34, 110)

Table note: Light green indicates breeding season, grey-blue indicates non-breeding season. N/A in MRSea columns indicates months not modelled.





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2	30/10/2025	BB	GB	MB	LG
1	13/08/2025	BB	GB	MP	LG
REV	REV DATE	GIS CREATOR	GIS REVIEWER	TECHNICAL CHECKER	TECHNICAL APPROVER

WSP DRAWING NUMBER 808368-WEIS-IA-FG-O6-96544

MarramWind DRAWING NUMBER MAR-GEN-ENV-MAP-WSP-000468

DATUM	ETRS 89	PROJECTION	UTM Zone 30N
SCALE	1:600,000	PAGE SIZE	A3

PROJECT TITLE
MarramWind Offshore Wind Farm

DRAWING TITLE
Figure 6 Model-based density plot of kittiwake distribution to highlight peak areas of potential abundance in the OAA plus 4km buffer extent – Survey 1 to Survey 12 (flying)
Environmental Impact Assessment Report
Appendix 12.5

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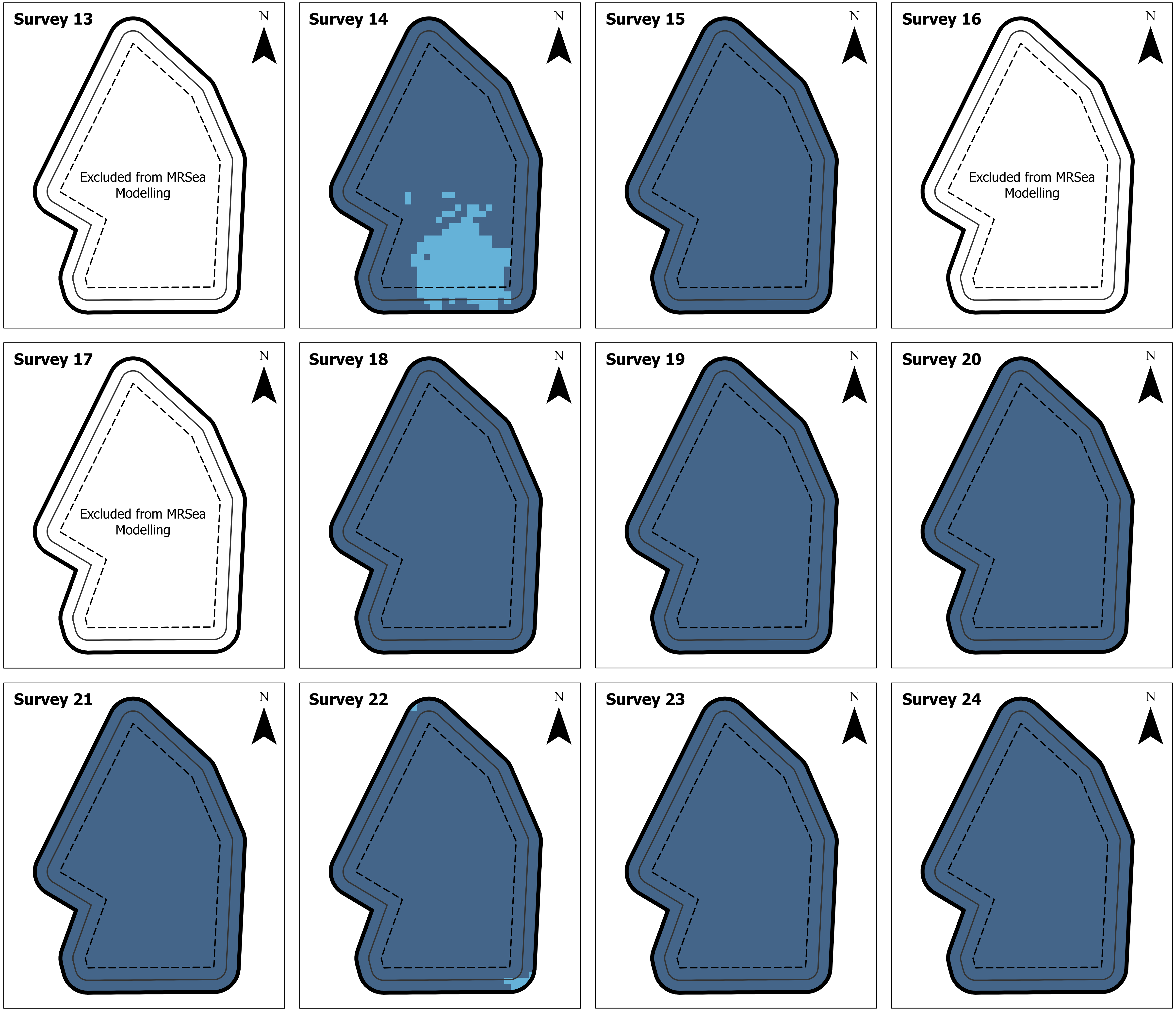
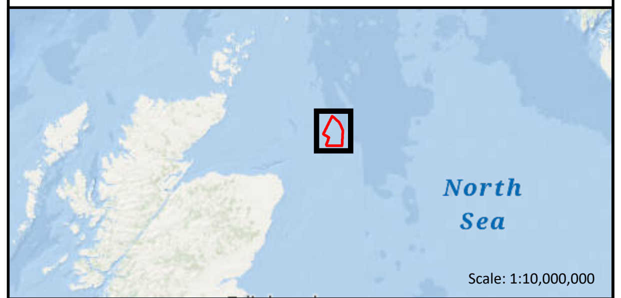


Option Agreement Area
Option Agreement Area (2km buffer)
Option Agreement Area (4km buffer)

Predicted Flying Kittiwake Density (Birds/km^2)

- 0 - 0.5
- 0.5 - 1
- 1 - 1.5
- 1.5 - 2
- 2 - 3
- 3 - 4
- 4 - 5
- 5 - 6
- 6 - 7
- 7 - 9.2

0 10 20 30 Kilometres



REV	REV DATE	GIS CREATOR	GIS REVIEWER	TECHNICAL CHECKER	TECHNICAL APPROVER
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2	30/10/2025	BB	GB	MB	LG
1	13/08/2025	BB	GB	MP	LG

WSP DRAWING NUMBER	808368-WEIS-IA-FG-O6-74004
MarramWind DRAWING NUMBER	MAR-GEN-ENV-MAP-WSP-000469

DATUM	ETRS 89	PROJECTION	UTM Zone 30N
SCALE	1:600,000	PAGE SIZE	A3

PROJECT TITLE
MarramWind Offshore Wind Farm

DRAWING TITLE
Figure 7 Model-based density plot of kittiwake distribution to highlight peak areas of potential abundance in the OAA plus 4km buffer extent – Survey 13 to Survey 24 (flying)
Environmental Impact Assessment Report
Appendix 12.5

NOT TO BE USED FOR NAVIGATION

APEM
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MarramWind

3.5 Gannet

3.5.1.1 MRSea modelling was carried out for breeding season only due to low raw counts in the DAS data during ten of the 14 non-breeding season months.

3.5.2 All behaviours

Abundance estimates

3.5.2.1 Gannet were recorded in all surveys, with the peak raw count within the OAA plus 2km in August 2021 (332 individuals). Raw counts for each month are presented in **Table 3.5**.

3.5.2.2 Apportioned and unapportioned model-based population estimates are presented in **Table 3.5**.alongside the design-based population estimates.

3.5.2.3 The peak apportioned abundance estimates for gannet in the OAA plus 2km buffer were:

- Design-based: 2,724 in August 2021; and
- MRSea based: 1,778 in August 2021.

3.5.2.4 The peak apportioned abundance estimates for kittiwake within the OAA excluding the 2km buffer were:

- Design-based: 2,542 in August 2021; and
- MRSea based: 1,672 in August 2021.

Density plots

3.5.2.5 Occurrence of gannet was highly varied throughout the site, and between surveys, with peak density of gannet observed in August 2021 (Survey 5), near the centre of the survey area (**Figure 8** and **Figure 9**).

3.5.2.6 Densities are thought to be predominantly driven by fishing vessel presence, however statistically boat presence was dropped as a covariate within the model. When forced through the model failed to run. The model variation was spatially consistent with the upper confidence interval of the estimated densities, indicating uncertainty in the model upper estimates.

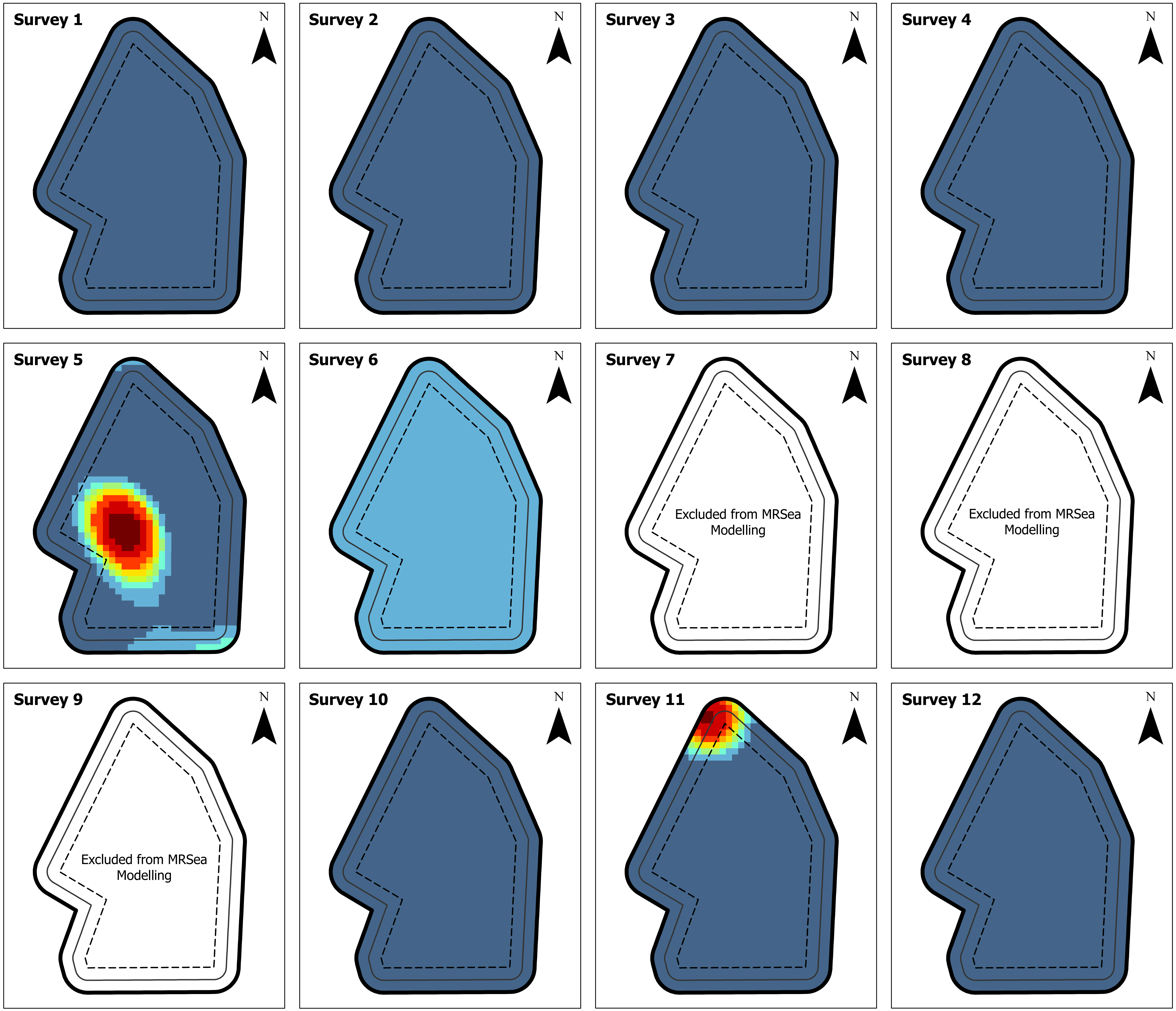
Table 3.5 Comparison between design based and modelled estimates for OAA and OAA plus 2km for the Project for gannet all behaviours

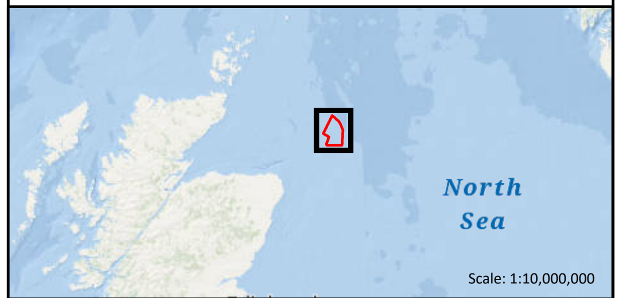
Survey number	Survey date	DAS data raw count - OAA	DAS data raw count - OAA plus 2km buffer	Design-based abundance estimate - OAA (apportioned) (95% CIs)	MRSea abundance estimate - OAA (unapportioned) (95% CIs)	MRSea abundance estimate - OAA (apportioned) (95% CIs)	Design-based abundance estimate - OAA plus 2km buffer (apportioned) (95% CIs)	MRSea abundance estimate - OAA plus 2km buffer (unapportioned) (95% CIs)	MRSea abundance estimate - OAA plus 2km buffer (apportioned) (95% CIs)
1	April 2021.	74	98	582 (417, 764)	283 (133, 589)	283 (133, 589)	772 (584, 979)	494 (232, 1028)	494 (232, 1,028)
2	May 2021.	27	30	214 (134, 300)	158 (119, 206)	158 (119, 206)	237 (158, 331)	276 (208, 359)	276 (208, 359)
3	June 2021.	35	44	278 (191, 373)	212 (158, 278)	212 (158, 278)	348 (248, 455)	370 (276, 486)	370 (276, 486)
4	July 2021.	9	16	68 (23, 123)	67 (42, 104)	67 (42, 104)	123 (62, 200)	117 (73, 181)	117 (73, 181)
5	August 2021.	315	332	2,542 (726, 5,970)	1,672 (450, 7,786)	1,672 (450, 7,786)	2,724 (859, 5,980)	1,778 (483, 8,506)	1,778 (483, 8,506)
6	September 2021.	51	74	390 (268, 529)	399 (301, 534)	399 (301, 534)	570 (423, 746)	696 (526, 932)	696 (526, 932)
7	October 2021.	42	55	337 (241, 449)	n/a	n/a	442 (322, 572)	n/a	n/a
8	December 2021.	2	2	16 (2,48)	n/a	n/a	17 (2, 48)	n/a	n/a
9	January 2022.	2	2	16 (2, 40)	n/a	n/a	16 (2, 40)	n/a	n/a

Survey number	Survey date	DAS data raw count - OAA	DAS data raw count - OAA plus 2km buffer	Design-based abundance estimate - OAA (apportioned) (95% CIs)	MRSea abundance estimate - OAA (unapportioned) (95% CIs)	MRSea abundance estimate - OAA (apportioned) (95% CIs)	Design-based abundance estimate - OAA plus 2km buffer (apportioned) (95% CIs)	MRSea abundance estimate - OAA plus 2km buffer (unapportioned) (95% CIs)	MRSea abundance estimate - OAA plus 2km buffer (apportioned) (95% CIs)
10	March 2022.	5	8	40 (5, 111)	37 (16, 91)	37 (16, 91)	63 (8, 135)	65 (27, 158)	65 (27, 158)
11	April 2022.	9	75	71 (24, 126)	78 (26, 241)	78 (26, 241)	615 (75, 1,647)	555 (130, 2,598)	555 (130, 2,598)
12	May 2022.	49	65	390 (279, 517)	325 (262, 406)	325 (262, 406)	520 (399, 654)	567 (457, 709)	567 (457, 709)
13	July number 1 of 2022.	9	16	70 (24, 127)	80 (53, 120)	80 (53, 120)	129 (56, 208)	140 (92, 209)	140 (92, 209)
14	July number 2 of 2022.	12	16	96 (48, 151)	66 (44, 96)	66 (44, 96)	127 (64, 200)	115 (77, 167)	115 (77, 167)
15	August 2022.	15	24	117 (62, 186)	105 (70, 161)	105 (70, 161)	186 (117, 272)	184 (123, 281)	184 (123, 281)
16	September 2022.	52	65	414 (211, 731)	336 (212, 554)	336 (212, 554)	526 (301, 855)	587 (369, 966)	587 (369, 966)
17	October 2022.	15	21	118 (63, 181)	n/a	n/a	165 (103, 237)	n/a	n/a
18	November number 1 of 2022.	5	10	40 (8, 78)	n/a	n/a	79 (32, 126)	n/a	n/a
19	November number 2 of 2022.	3	4	25 (3, 57)	n/a	n/a	33 (8, 73)	n/a	n/a

Survey number	Survey date	DAS data raw count - OAA	DAS data raw count - OAA plus 2km buffer	Design-based abundance estimate - OAA (apportioned) (95% CIs)	MRSea abundance estimate - OAA (unapportioned) (95% CIs)	MRSea abundance estimate - OAA (apportioned) (95% CIs)	Design-based abundance estimate - OAA plus 2km buffer (apportioned) (95% CIs)	MRSea abundance estimate - OAA plus 2km buffer (unapportioned) (95% CIs)	MRSea abundance estimate - OAA plus 2km buffer (apportioned) (95% CIs)
20	February number 1 of 2023.	1	1	8 (1, 24)	n/a	n/a	8 (1, 24)	n/a	n/a
21	February number 2 of 2023.	2	8	16 (2, 40)	n/a	n/a	65 (8, 177)	n/a	n/a
22	February number 3 of 2023.	6	8	48 (8, 94)	n/a	n/a	63 (24, 118)	n/a	n/a
23	March number 1 of 2023.	1	2	8 (1, 24)	n/a	n/a	16 (2, 40)	n/a	n/a
24	March number 2 of 2023.	7	10	55 (24, 95)	50 (29, 84)	50 (29, 84)	81 (32, 135)	87 (50, 147)	87 (50, 147)

Table note: Light green indicates breeding season, grey-blue indicates non-breeding season.
N/A in MRSea columns indicates months not modelled.





REV	REV DATE	GIS CREATOR	GIS REVIEWER	TECHNICAL CHECKER	TECHNICAL APPROVER
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2	30/10/2025	BB	GB	MB	LG
1	13/08/2025	BB	GB	MP	LG

WSP DRAWING NUMBER	808368-WEIS-IA-FG-O6-39826
MarramWind DRAWING NUMBER	MAR-GEN-ENV-MAP-WSP-000470

DATUM	ETRS 89	PROJECTION	UTM Zone 30N
SCALE	1:600,000	PAGE SIZE	A3

PROJECT TITLE

MarramWind Offshore Wind Farm

DRAWING TITLE

Figure 8 Model-based density plot of gannet distribution to highlight peak areas of potential abundance in the OAA plus 4km buffer extent – Survey 1 to Survey 12 (all behaviours - breeding)

Environmental Impact Assessment Report

Appendix 12.5

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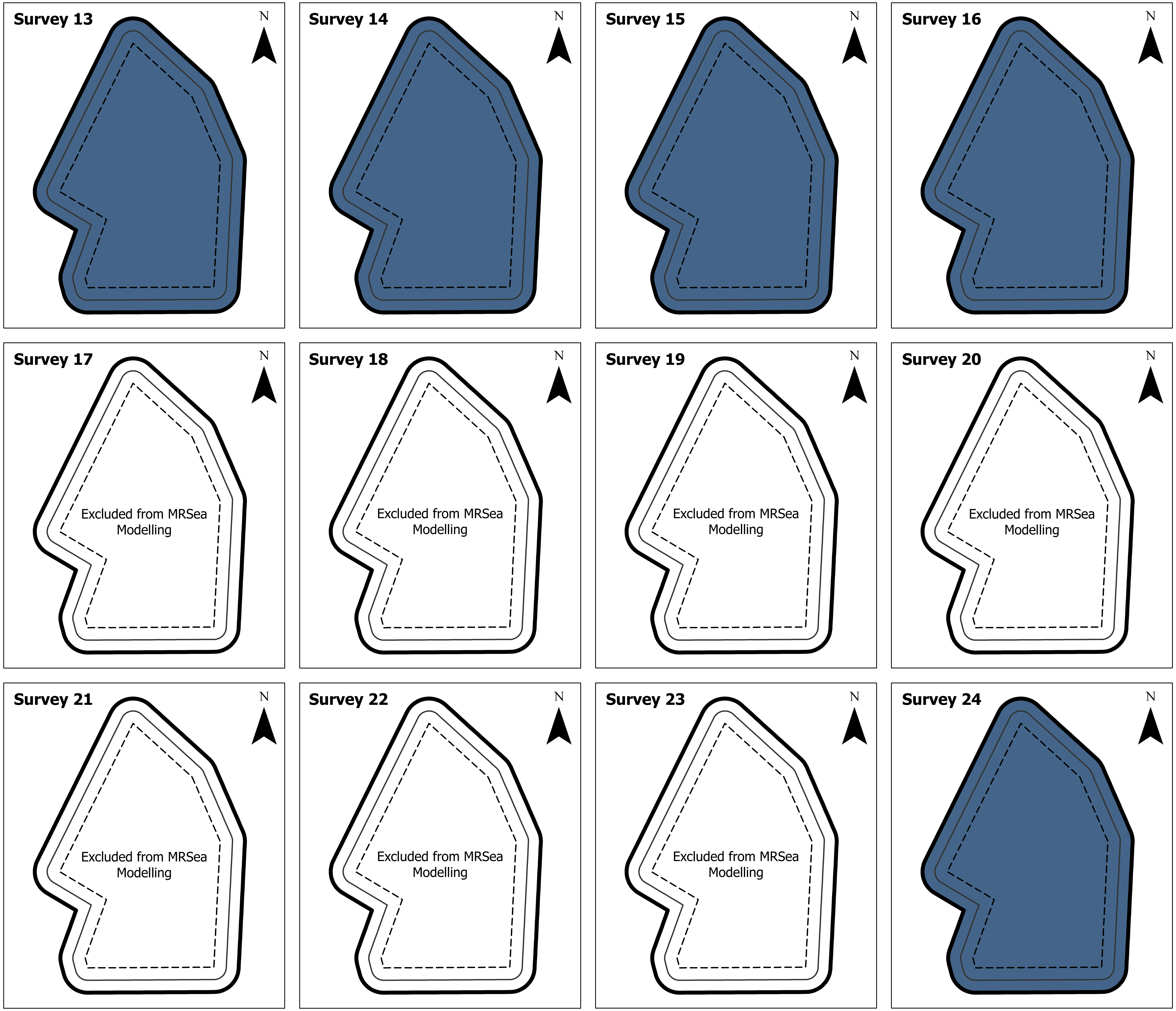
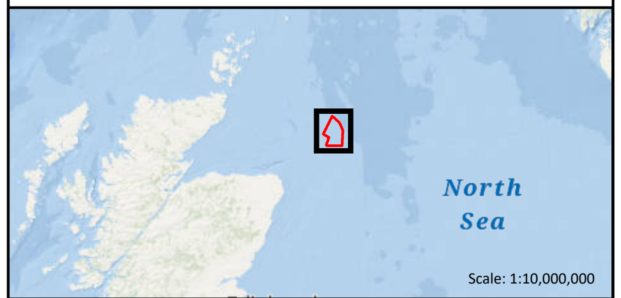


Option Agreement Area
Option Agreement Area (2km buffer)
Option Agreement Area (4km buffer)

Predicted Gannet Density (Birds/km^2)

- 0 - 0.5
- 0.5 - 1
- 1 - 1.5
- 1.5 - 2
- 2 - 3
- 3 - 4
- 4 - 5
- 5 - 10
- 10 - 20
- 20 - 40

0 10 20 30 Kilometres



REV	REV DATE	GIS CREATOR	GIS REVIEWER	TECHNICAL CHECKER	TECHNICAL APPROVER
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2	30/10/2025	BB	GB	MB	LG
1	13/08/2025	BB	GB	MP	LG

WSP DRAWING NUMBER	808368-WEIS-IA-FG-O6-47325
MarramWind DRAWING NUMBER	MAR-GEN-ENV-MAP-WSP-000471

DATUM	ETRS 89	PROJECTION	UTM Zone 30N
SCALE	1:600,000	PAGE SIZE	A3

PROJECT TITLE
MarramWind Offshore Wind Farm

DRAWING TITLE
Figure 9 Model-based density plot of gannet distribution to highlight peak areas of potential abundance in the OAA plus 4km buffer extent – Survey 13 to Survey 24 (all behaviours - breeding)
Environmental Impact Assessment Report
Appendix 12.5

NOT TO BE USED FOR NAVIGATION

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MarramWind

3.5.3 Flying only

Abundance estimates

3.5.3.1 Flying gannet were recorded in all surveys, with the peak raw count within the OAA in August 2021 (244 individuals). Raw counts for each month are presented in **Table 3.6.**

3.5.3.2 Apportioned and unapportioned model-based population estimates are presented in **Table 3.6.**

3.5.3.3 The peak apportioned abundance estimates for flying gannet in the OAA plus 2km buffer were:

- Design-based: 2,140 in August 2021; and
- MRSea based: 1,341 in August 2021.

3.5.3.4 The peak apportioned abundance estimates for flying gannet within the OAA excluding the 2km buffer were:

- Design-based: 1,972 in August 2021; and
- MRSea based: 1,312 in August 2021.

Density plots

3.5.3.5 Flying gannet had an even distribution in all surveys except August 2021 (**Figure 10** and **Figure 11**). This is likely due to the presence of a fishing vessel within the area (**Plate 3.1**), generating a hotspot of flying birds. Occurrence was sporadic throughout the rest of the survey area during other surveys; therefore, the density estimates are comparatively low.

3.5.3.6 Models containing the covariate boat presence were highly correlated with survey-based variables and therefore statistically were dropped from the models. For the models where boat presence was forced through, many failed to converge. Any models that did converge produced exceptionally high and unrealistic results on their upper estimate. Therefore, these models were deemed not appropriate for use.

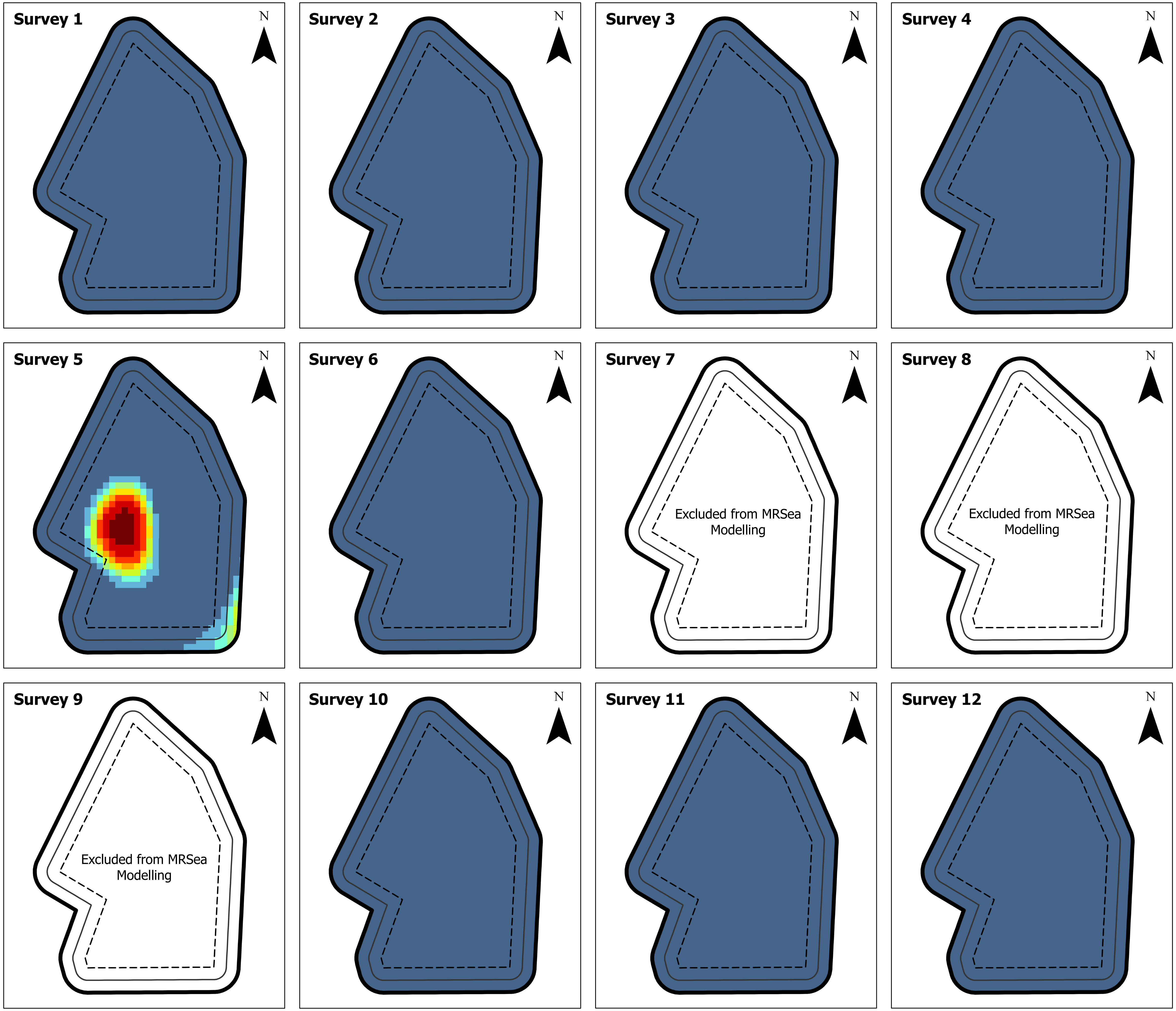
Table 3.6 Comparison between design based and modelled estimates for OAA and OAA plus 2km for the Project for gannet flying

Survey number	Survey date	DAS data raw count - OAA	DAS data raw count - OAA plus 2km buffer	Design-based abundance estimate - OAA (apportioned) (95% CIs)	MRSea abundance estimate - OAA (unapportioned) (95% CIs)	MRSea abundance estimate - OAA (apportioned) (95% CIs)	Design-based abundance estimate - OAA plus 2km buffer (apportioned) (95% CIs)	MRSea abundance estimate - OAA plus 2km buffer (unapportioned) (95% CIs)	MRSea abundance estimate - OAA plus 2km buffer (apportioned) (95% CIs)
1	April 2021.	18	32	142 (79, 213)	92 (36, 221)	92 (36, 221)	252 (142, 379)	124 (49, 300)	124 (49, 300)
2	May 2021.	16	18	126 (63, 189)	81 (54, 119)	81 (54, 119)	143 (79, 221)	110 (73, 161)	110 (73, 161)
3	June 2021.	11	15	88 (40, 143)	69 (43, 109)	69 (43, 109)	120 (64, 184)	94 (59, 147)	94 (59, 147)
4	July 2021.	7	9	53 (15, 100)	37 (20, 63)	37 (20, 63)	69 (31, 115)	50 (27, 85)	50 (27, 85)
5	August 2021.	244	260	1,972 (339, 5,042)	1,312 (289, 8,238)	1,312 (289, 8,238)	2,140 (462, 5,267)	1,341 (295, 8,798)	1,341 (295, 8,798)
6	September 2021.	35	45	266 (184, 360)	224 (163, 311)	224 (163, 311)	348 (246, 454)	304 (220, 421)	304 (220, 421)
7	October 2021.	31	41	249 (160, 345)	n/a	n/a	329 (226, 451)	n/a	n/a
8	December 2021.	2	2	16 (2,48)	n/a	n/a	17 (2,48)	n/a	n/a
9	January 2022.	2	2	16 (2,40)	n/a	n/a	16 (2,40)	n/a	n/a

Survey number	Survey date	DAS data raw count - OAA	DAS data raw count - OAA plus 2km buffer	Design-based abundance estimate - OAA (apportioned) (95% CIs)	MRSea abundance estimate - OAA (unapportioned) (95% CIs)	MRSea abundance estimate - OAA (apportioned) (95% CIs)	Design-based abundance estimate - OAA plus 2km buffer (apportioned) (95% CIs)	MRSea abundance estimate - OAA plus 2km buffer (unapportioned) (95% CIs)	MRSea abundance estimate - OAA plus 2km buffer (apportioned) (95% CIs)
10	March 2022.	5	8	40 (5, 111)	37 (15, 89)	37 (15, 89)	63 (8, 135)	50 (21, 121)	50 (21, 121)
11	April 2022.	7	8	55 (16, 110)	45 (21, 94)	45 (21, 94)	64 (24, 119)	61 (29, 128)	61 (29, 128)
12	May 2022.	28	37	222 (135, 310)	207 (154, 283)	207 (154, 283)	297 (207, 399)	280 (208, 383)	280 (208, 383)
13	July number 1 of 2022.	5	8	38 (8, 80)	35 (18, 71)	35 (18, 71)	64 (16, 128)	48 (24, 96)	48 (24, 96)
14	July number 2 of 2022.	6	8	48 (16, 88)	30 (14, 60)	30 (14, 60)	63 (24, 120)	41 (19, 81)	41 (19, 81)
15	August 2022.	7	10	54 (16, 101)	42 (23, 80)	42 (23, 80)	78 (31, 132)	57 (31, 109)	57 (31, 109)
16	September 2022.	17	21	138 (73, 203)	125 (82, 200)	125 (82, 200)	172 (106, 252)	170 (111, 271)	170 (111, 271)
17	October 2022.	11	12	86 (39, 142)	n/a	n/a	94 (47, 150)	n/a	n/a
18	November number 1 of 2022.	3	5	24 (3, 55)	n/a	n/a	40 (8, 79)	n/a	n/a
19	November number 2 of 2022.	2	3	17 (2, 48)	n/a	n/a	25 (3, 57)	n/a	n/a

Survey number	Survey date	DAS data raw count - OAA	DAS data raw count - OAA plus 2km buffer	Design-based abundance estimate - OAA (apportioned) (95% CIs)	MRSea abundance estimate - OAA (unapportioned) (95% CIs)	MRSea abundance estimate - OAA (apportioned) (95% CIs)	Design-based abundance estimate - OAA plus 2km buffer (apportioned) (95% CIs)	MRSea abundance estimate - OAA plus 2km buffer (unapportioned) (95% CIs)	MRSea abundance estimate - OAA plus 2km buffer (apportioned) (95% CIs)
20	February number 1 of 2023.	1	1	8 (1, 24)	n/a	n/a	8 (1, 24)	n/a	n/a
21	February number 2 of 2023.	2	2	16 (2, 40)	n/a	n/a	16 (2, 40)	n/a	n/a
22	February number 3 of 2023.	6	8	48 (8, 94)	n/a	n/a	63 (24, 118)	n/a	n/a
23	March number 1 of 2023.	1	2	8 (1, 24)	n/a	n/a	16 (2, 40)	n/a	n/a
24	March number 2 of 2023.	4	6	32 (8, 71)	27 (12, 56)	27 (12, 56)	48 (16, 87)	36 (17, 76)	36 (17, 76)

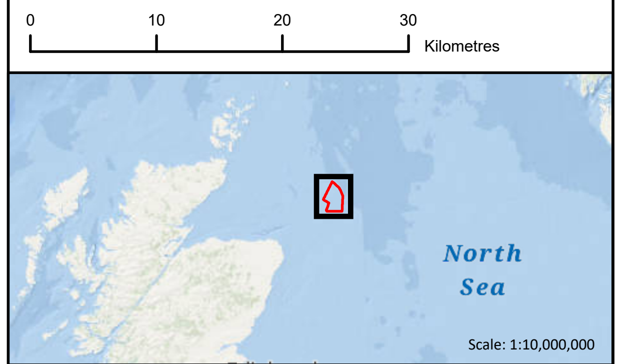
Table note: Light green indicates breeding season, grey-blue indicates non-breeding season. N/A in MRSea columns indicates months not modelled.



Option Agreement Area
Option Agreement Area (2km buffer)
Option Agreement Area (4km buffer)

Predicted Flying Gannet Density (Birds/km^2)

- 0 - 0.5
- 0.5 - 1
- 1 - 1.5
- 1.5 - 2
- 2 - 3
- 3 - 4
- 4 - 5
- 5 - 10
- 10 - 20
- 20 - 40



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2	30/10/2025	BB	GB	MB	LG
1	13/08/2025	BB	GB	MP	LG
REV	REV DATE	GIS CREATOR	GIS REVIEWER	TECHNICAL CHECKER	TECHNICAL APPROVER

WSP DRAWING NUMBER 808368-WEIS-IA-FG-O6-74710

MarramWind DRAWING NUMBER MAR-GEN-ENV-MAP-WSP-000460

DATUM	ETRS 89	PROJECTION	UTM Zone 30N
SCALE	1:600,000	PAGE SIZE	A3

PROJECT TITLE
MarramWind Offshore Wind Farm

DRAWING TITLE
Figure 10 Model-based density plot of gannet distribution to highlight peak areas of potential abundance in the OAA plus 4km buffer extent – Survey 1 to Survey 12 (flying - breeding)
Environmental Impact Assessment Report
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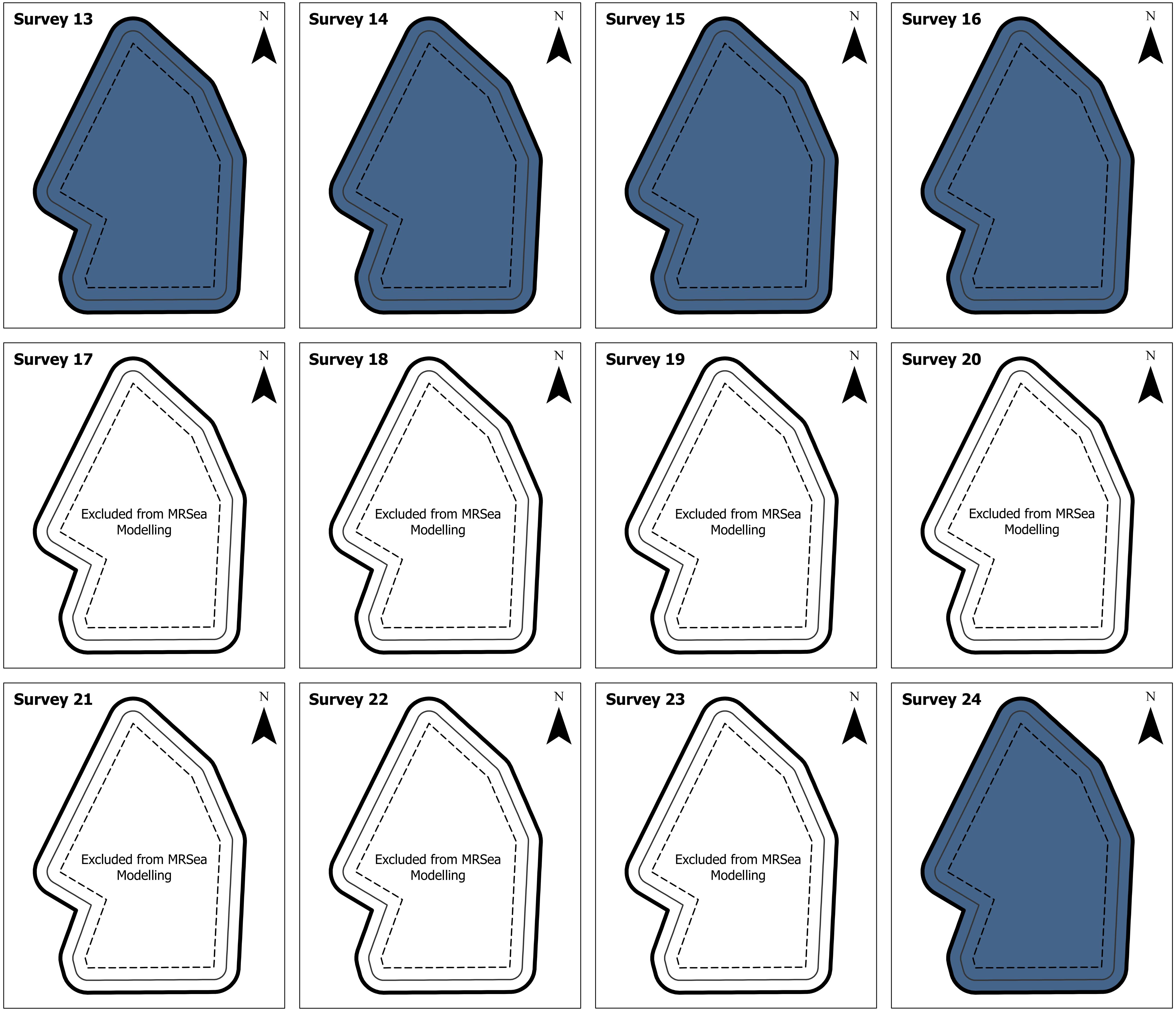
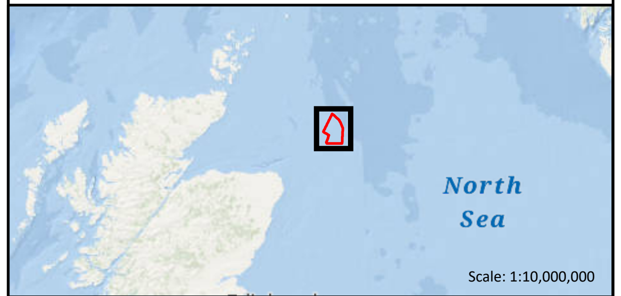


Option Agreement Area
Option Agreement Area (2km buffer)
Option Agreement Area (4km buffer)

Predicted Flying Gannet Density (Birds/km^2)

- 0 - 0.5
- 0.5 - 1
- 1 - 1.5
- 1.5 - 2
- 2 - 3
- 3 - 4
- 4 - 5
- 5 - 10
- 10 - 20
- 20 - 40

0 10 20 30 Kilometres



REV	REV DATE	GIS CREATOR	GIS REVIEWER	TECHNICAL CHECKER	TECHNICAL APPROVER
3	12/11/2025	BB	GB	MB	LG
2	30/10/2025	BB	GB	MB	LG
1	13/08/2025	BB	GB	MP	LG

WSP DRAWING NUMBER	808368-WEIS-IA-FG-O6-27130
MarramWind DRAWING NUMBER	MAR-GEN-ENV-MAP-WSP-000461

DATUM	ETRS 89	PROJECTION	UTM Zone 30N
SCALE	1:600,000	PAGE SIZE	A3

PROJECT TITLE
MarramWind Offshore Wind Farm

DRAWING TITLE
Figure 11 Model-based density plot of gannet distribution to highlight peak areas of potential abundance in the OAA plus 4km buffer extent – Survey 13 to Survey 24 (flying - breeding)
Environmental Impact Assessment Report
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3.6 Fulmar

3.6.1 Abundance estimates

3.6.1.1 Fulmar were recorded in all surveys with the peak raw count within the OAA plus 2km buffer in August 2021 (447 individuals). Raw counts for each month are presented in **Table 3.7**.

3.6.1.2 Apportioned and unapportioned model-based population estimates are presented in **Table 3.7** alongside the design-based population estimates.

3.6.1.3 The peak apportioned abundance estimates for fulmar in the OAA plus 2km buffer were:

- Design-based: 3,702 in August 2021; and
- MRSea based: 2,709 in August 2021.

3.6.1.4 The peak apportioned abundance estimates for fulmar within the OAA excluding the 2km buffer were:

- Design-based: 3,331 in August 2021; and
- MRSea based: 2,296 in August 2021.

3.6.2 Density plots

3.6.2.1 The two surveys showing increases in densities were Survey 5 (August 2021) and survey 16 (September 2022) (**Figure 12** and **Figure 13**). Fulmars are highly associated with fishing vessels and their tracks, as can be seen clearly in Survey 5. An image from the DAS showing the vessel and the attracted birds is provided within **Plate 3.1**. Clustering of fulmar into the hotspot recorded in survey 16 may likely be associated with localised prey availability.

3.6.2.2 Throughout surveys where fishing vessels were not present, the model variation is indicated as low, however this is likely partially caused by the fishing vessel influenced values present in other months. Models where boat presence was forced into the model were deemed not suitable for use due to unrealistic estimates. There is no clear trend of occurrence across the survey area other than those influenced by the fishing vessel.

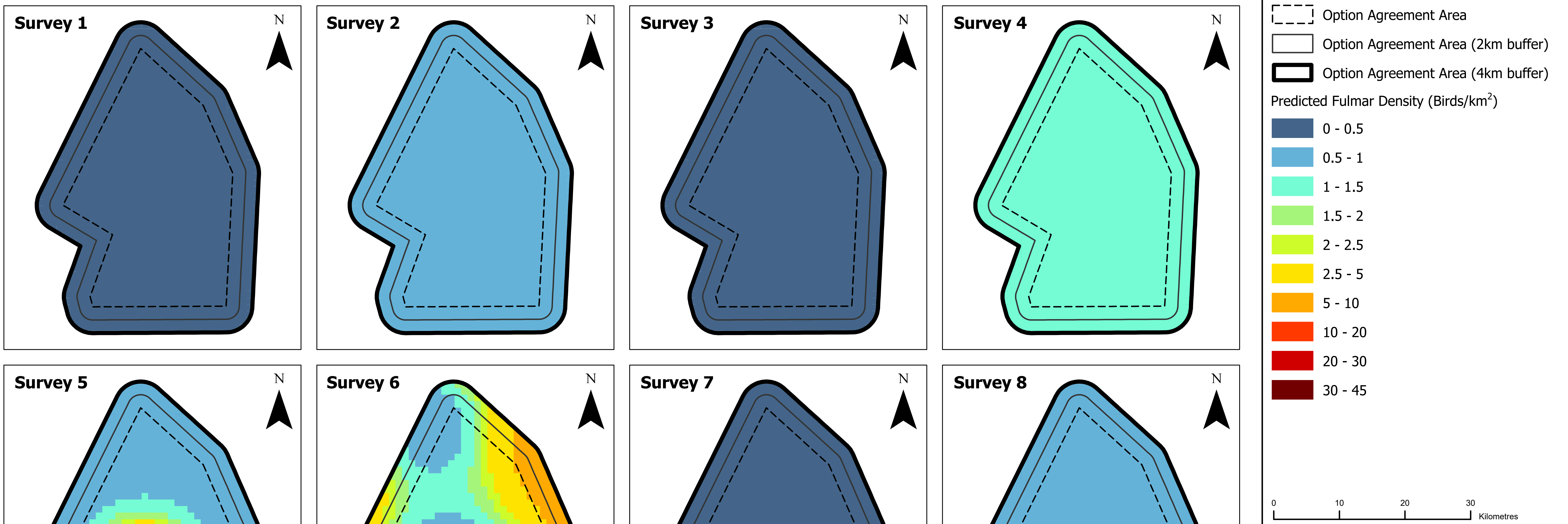
Table 3.7 Comparison between design based and modelled estimates for OAA and OAA plus 2km for the Project for fulmar

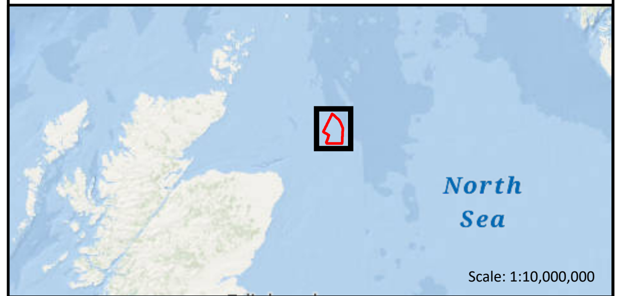
Survey number	Survey date	DAS data raw count - OAA	DAS data raw count - OAA plus 2km buffer	Design-based abundance estimate - OAA (apportioned) (95% CIs)	MRSea abundance estimate - OAA (unapportioned) (95% CIs)	MRSea abundance estimate - OAA (apportioned) (95% CIs)	Design-based abundance estimate - OAA plus 2km buffer (apportioned) (95% CIs)	MRSea abundance estimate - OAA plus 2km buffer (unapportioned) (95% CIs)	MRSea abundance estimate - OAA plus 2km buffer (apportioned) (95% CIs)
1	April 2021.	81	92	641 (386, 984)	289 (152, 569)	289 (152, 569)	720 (450, 1,082)	504 (265, 993)	504 (265, 993)
2	May 2021.	38	54	302 (213, 410)	342 (263, 445)	342 (263, 445)	424 (316, 536)	597 (459, 776)	597 (459, 776)
3	June 2021.	22	28	175 (111, 254)	189 (128, 276)	189 (128, 276)	223 (136, 319)	330 (223, 481)	330 (223, 481)
4	July 2021.	143	211	1,104 (922, 1,299)	941 (806, 1,091)	941 (806, 1,091)	1,627 (1,407, 1,861)	1,641 (1,406, 1,903)	1,641 (1,406, 1,903)
5	August 2021.	407	447	3,331 (1,356, 6,728)	2,296 (1,062, 5,098)	2,296 (1,062, 5,098)	3,702 (1,661, 7,477)	2,709 (1,319, 5,763)	2,709 (1,319, 5,763)
6	September 2021.	190	243	1,430 (736, 2,684)	816 (437, 1,584)	816 (437, 1,584)	1,865 (1,115, 3,022)	2,277 (1,093, 4,917)	2,277 (1,093, 4,917)
7	October 2021.	67	86	544 (305, 914)	334 (226, 500)	334 (226, 500)	705 (443, 1,111)	582 (394, 873)	582 (394, 873)
8	December 2021.	99	125	797 (627, 989)	598 (439, 807)	598 (439, 807)	1,007 (807, 1,218)	1,043 (765, 1,407)	1,043 (765, 1,407)

Survey number	Survey date	DAS data raw count - OAA	DAS data raw count - OAA plus 2km buffer	Design-based abundance estimate - OAA (apportioned) (95% CIs)	MRSea abundance estimate - OAA (unapportioned) (95% CIs)	MRSea abundance estimate - OAA (apportioned) (95% CIs)	Design-based abundance estimate - OAA plus 2km buffer (apportioned) (95% CIs)	MRSea abundance estimate - OAA plus 2km buffer (unapportioned) (95% CIs)	MRSea abundance estimate - OAA plus 2km buffer (apportioned) (95% CIs)
9	January 2022.	77	98	617 (462, 780)	440 (357, 551)	440 (357, 551)	784 (633, 962)	767 (623, 962)	767 (623, 962)
10	March 2022.	21	29	167 (103, 245)	166 (127, 221)	166 (127, 221)	227 (143, 317)	290 (221, 385)	290 (221, 385)
11	April 2022.	23	32	181 (103, 268)	180 (137, 230)	180 (137, 230)	253 (166, 356)	314 (239, 401)	314 (239, 401)
12	May 2022.	13	25	103 (48, 167)	129 (93,186)	129 (93,186)	199 (120, 287)	225 (162, 324)	225 (162, 324)
13	July number 1 of 2022.	164	312	1,302 (1,099, 1,498)	1,025 (613, 1,839)	1,025 (613, 1,839)	2,518 (1,855, 3,583)	2,634 (1,402, 6,154)	2,634 (1,402, 6,154)
14	July number 2 of 2022.	216	312	1,723 (1,459, 2,025)	1,268 (1,085, 1,478)	1,268 (1,085, 1,478)	2,482 (2,151, 2,846)	2,212 (1,893, 2,578)	2,212 (1,893, 2,578)
15	August 2022.	106	151	821 (660, 993)	649 (565, 746)	649 (565, 746)	1,174 (981, 1,378)	1,133 (985, 1,301)	1,133 (985, 1,301)
16	September 2022.	402	423	3,164 (691, 7,150)	2,583 (525, 22,026)	2,583 (525, 22,026)	3425 (953, 7,093)	3,109 (676, 27,196)	3,109 (676, 27,196)
17	October 2022.	183	231	1,433 (1,181, 1,701)	948 (811, 1,107)	948 (811, 1,107)	1,822 (1,538, 2,130)	1,653 (1,415, 1,932)	1,653 (1,415, 1,932)

Survey number	Survey date	DAS data raw count - OAA	DAS data raw count - OAA plus 2km buffer	Design-based abundance estimate - OAA (apportioned) (95% CIs)	MRSea abundance estimate - OAA (unapportioned) (95% CIs)	MRSea abundance estimate - OAA (apportioned) (95% CIs)	Design-based abundance estimate - OAA plus 2km buffer (apportioned) (95% CIs)	MRSea abundance estimate - OAA plus 2km buffer (unapportioned) (95% CIs)	MRSea abundance estimate - OAA plus 2km buffer (apportioned) (95% CIs)
18	November number 1 of 2022.	163	242	1,282 (1,027, 1,575)	1,225 (912, 1,621)	1,225 (912, 1,621)	1,920 (1,615, 2,276)	2,136 (1,590, 2,829)	2,136 (1,590, 2,829)
19	November number 2 of 2022.	270	352	2,212 (1,927, 2,526)	1,298 (1,104, 1,517)	1,302 (1,102, 1,524)	2,887 (2,551, 3,254)	2,265 (1,926, 2,646)	2,269 (1,929, 2,653)
20	February number 1 of 2023.	54	86	430 (311, 550)	561 (400, 804)	561 (400, 804)	686 (535, 839)	979 (698,1,403)	979 (698, 1,403)
21	February number 2 of 2023.	55	76	442 (312, 577)	464 (340, 600)	464 (340, 600)	610 (442, 779)	810 (593, 1,047)	810 (593, 1,047)
22	February number 3 of 2023.	91	138	712 (557, 871)	1,083 (730, 1,610)	1,083 (730, 1,610)	1,085 (889, 1,283)	1,889 (1,274, 2,808)	1,889 (1,274, 2,808)
23	March number 1 of 2023.	83	105	670 (485, 881)	561 (432, 734)	562 (432, 737)	840 (645, 1,042)	979 (753, 1,281)	980 (753, 1,284)
24	March number 2 of 2023.	42	53	333 (213, 466)	261 (183, 362)	261 (183, 362)	418 (293, 570)	455 (319, 631)	455 (319, 631)

Table note: Light green indicates breeding season, grey-blue indicates non-breeding season.
N/A in MRSea columns indicates months not modelled.





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2	30/10/2025	BB	GB	MB	LG
1	13/08/2025	BB	GB	MP	LG

WSP DRAWING NUMBER	808368-WEIS-IA-FG-O6-91775
MarramWind DRAWING NUMBER	MAR-GEN-ENV-MAP-WSP-000462

DATUM	ETRS 89	PROJECTION	UTM Zone 30N
SCALE	1:600,000	PAGE SIZE	A3

PROJECT TITLE

MarramWind Offshore Wind Farm

DRAWING TITLE

Figure 12 Model-based density plot of fulmar distribution to highlight peak areas of potential abundance in the OAA plus 4km buffer extent – Survey 1 to Survey 12 (all behaviours)

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Appendix 12.5

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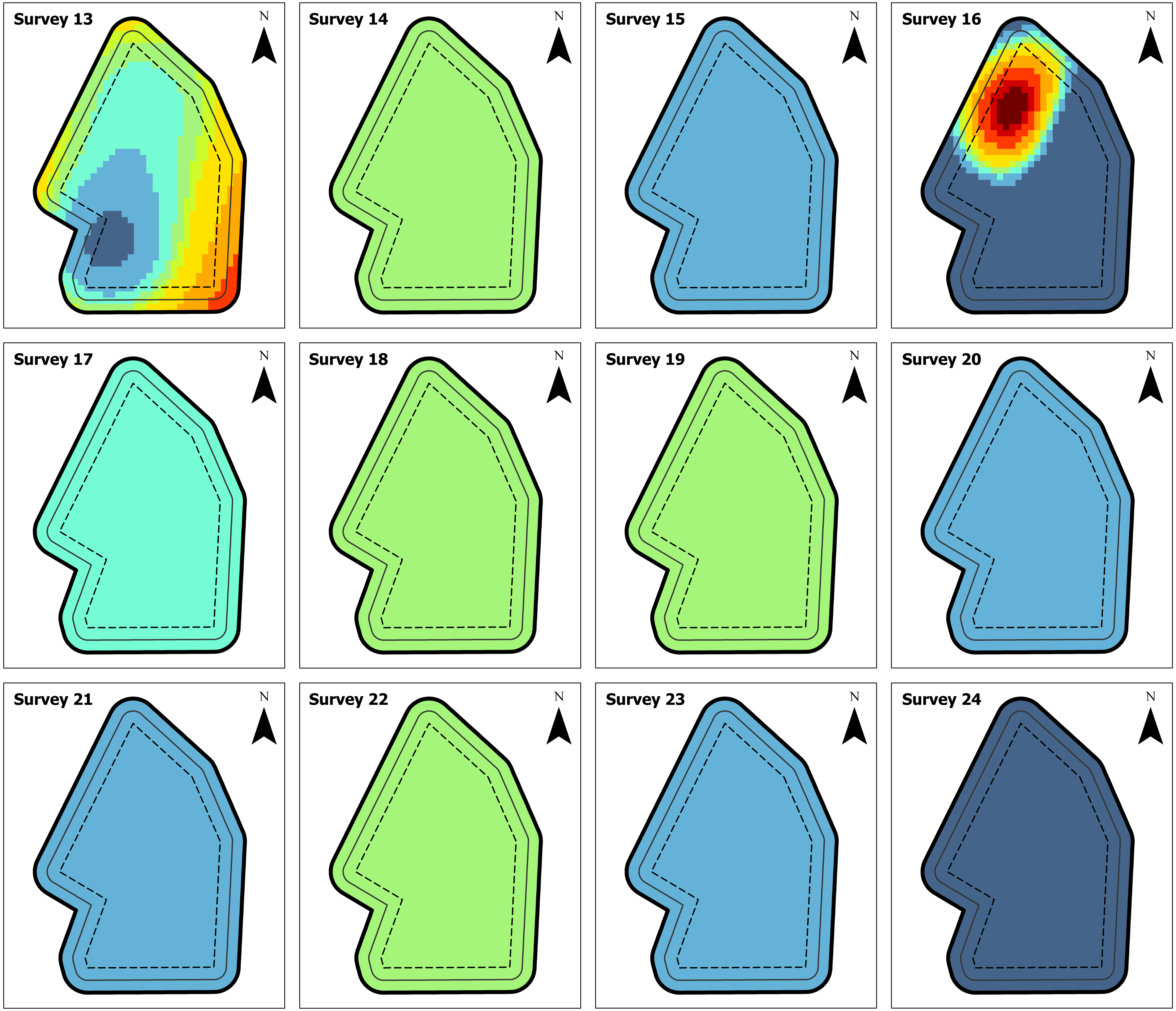
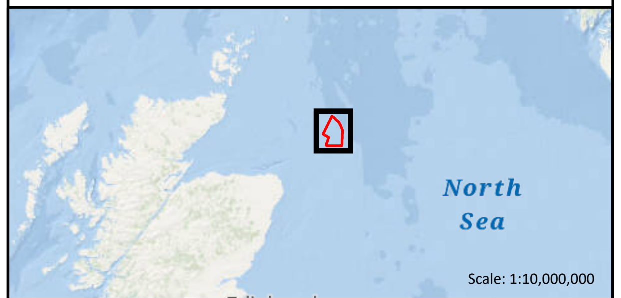


Option Agreement Area
Option Agreement Area (2km buffer)
Option Agreement Area (4km buffer)

Predicted Fulmar Density (Birds/km^2)

- 0 - 0.5
- 0.5 - 1
- 1 - 1.5
- 1.5 - 2
- 2 - 2.5
- 2.5 - 5
- 5 - 10
- 10 - 20
- 20 - 30
- 30 - 45

0 10 20 30 Kilometres



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2	30/10/2025	BB	GB	MB	LG
1	13/08/2025	BB	GB	MP	LG
REV	REV DATE	GIS CREATOR	GIS REVIEWER	TECHNICAL CHECKER	TECHNICAL APPROVER

WSP DRAWING NUMBER 808368-WEIS-IA-FG-O6-30840

MarramWind DRAWING NUMBER MAR-GEN-ENV-MAP-WSP-000463

DATUM	ETRS 89	PROJECTION	UTM Zone 30N
SCALE	1:600,000	PAGE SIZE	A3

PROJECT TITLE
MarramWind Offshore Wind Farm

DRAWING TITLE
Figure 13 Model-based density plot of fulmar distribution to highlight peak areas of potential abundance in the OAA plus 4km buffer extent – Survey 13 to Survey 24 (all behaviours)
Environmental Impact Assessment Report
Appendix 12.5

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4. Discussion on design-based vs model-based estimated abundances

4.1.1.1 The appropriateness of the design-based vs model-based abundances were reviewed. For species with unusually high counts in a single survey, some of which were artificially inflated by the presence of fishing vessels, model-based abundances were used. Seasonal mean abundance estimates were calculated by averaging the abundance estimates for each season. Calculating seasonal abundance in such a way is highly precautionary, as it is highly unlikely that the abundance within a given season remains consistent across the entire season, especially when considering such peaks are usually characterised by temporary passage movements or moulting flocks.

4.2 Guillemot

4.2.1.1 Design-based abundance estimates were used across the survey period in both the breeding and non-breeding seasons for guillemot due to underprediction in the model-based abundance estimates which were not representative of the raw data or design-based abundance estimates. In this case the model-based abundance estimates often fell outwith the confidence intervals of the design-based abundance estimates and were significantly lower (**Table 4.1**).

Table 4.1 Selection of abundance estimate method used for further assessment of potential impacts on guillemot

Survey number	Survey date	DAS data raw count - OAA plus 2km buffer	Design-based abundance estimate - OAA plus 2km buffer (apportioned) (95% CIs)	MRSea abundance estimate - OAA plus 2km buffer (apportioned and corrected for availability bias) (95% CIs)	Method outputs selected for assessments going forward	Seasonal mean abundance estimate
1	April 2021.	1,827	19,891 (17,856, 22,296)	11,545 (9,110, 14,660)	Design	6,319
2	May 2021.	47	551 (396, 724)	429 (303, 612)	Design	
3	June 2021.	42	454 (293, 667)	355 (279, 450)	Design	
4	July 2021.	456	4,382 (3,790, 5,004)	2,806 (2,451, 3,206)	Design	
5	August 2021.	525	5,018 (4,405, 5,729)	3,573 (2,903, 4,395)	Design	
6	September 2021.	53	2,413 (1,931, 2,909)	640 (520, 836)	Design	2,964
7	October 2021.	374	4,442 (3,792, 5,077)	2,682 (2,191, 3,330)	Design	
8	December 2021.	21	2,285 (1,948, 2,628)	482 (361, 710)	Design	
9	January 2022.	23	2,145 (1,677, 2,608)	477 (377, 645)	Design	
10	March 2022.	244	3,658 (3,206, 4,153)	2,355 (2,049, 2,726)	Design	
11	April 2022.	95	1,107 (876, 1,337)	909 (749, 1,095)	Design	5,137
12	May 2022.	18	288 (162, 425)	223 (140, 372)	Design	
13	July number 1 of 2022.	201	2,156 (1,795, 2,563)	1,365 (1,169, 1,620)	Design	

Survey number	Survey date	DAS data raw count - OAA plus 2km buffer	Design-based abundance estimate - OAA plus 2km buffer (apportioned) (95% CIs)	MRSea abundance estimate - OAA plus 2km buffer (apportioned and corrected for availability bias) (95% CIs)	Method outputs selected for assessments going forward	Seasonal mean abundance estimate
14	July number 2 of 2022.	493	5,067 (4,211, 6,021)	3,173 (2,640, 3,822)	Design	
15	August 2022.	1,525	14,087 (11,939, 16,291)	10,145 (8,282, 12,432)	Design	
16	September 2022.	288	3,428 (2,835, 4,060)	2,088 (1,691, 2,614)	Design	2,558
17	October 2022.	240	3,055 (2,511, 3,595)	1,613 (1,317, 1,993)	Design	
18	November number 1 of 2022.	210	3,033 (2,515, 3,588)	1,575 (1,275, 1,986)	Design	
19	November number 2 of 2022.	433	6,031 (5,339, 6,740)	3,060 (2,505, 3,770)	Design	
20	February number 1 of 2023.	95	1,299 (1,036, 1,589)	897 (729, 1,129)	Design	
21	February number 2 of 2023.	174	2,335 (1,966, 2,721)	1,757 (1,444, 2,114)	Design	
22	February number 3 of 2023.	129	1,510 (1,249, 1,791)	1,386 (1,187, 1,616)	Design	
23	March number 1 of 2023.	120	1,568 (1,302, 1,827)	1,336 (1,135, 1,590)	Design	
24	March number 2 of 2023.	86	1,059 (748, 1,411)	1,031 (767, 1,364)	Design	

4.3 Puffin

4.3.1.1 Design-based abundance estimates were deemed most appropriate for the puffin breeding seasons due to a complete seasonal dataset, whereas model-based estimates could not be generated for several months. The design-based abundances were within a reasonable range of the model-based estimates (**Table 4.2**).

Table 4.2 Selection of abundance estimate method used for further assessment of potential impacts on puffin

Survey number	Survey date	DAS data raw count - OAA plus 2km buffer	Design-based abundance estimate - OAA plus 2km buffer (apportioned) (95% CIs)	MRSea abundance estimate - OAA plus 2km buffer (apportioned and corrected for availability bias) (95% CIs)	Method outputs selected for assessments going forward	Seasonal mean abundance estimate
1	April 2021.	23	214 (103, 343)	143 (75, 280)	Design	153
2	May 2021.	34	325 (184, 491)	348 (146, 917)	Design	
3	June 2021.	2	18 (2, 45)	n/a	Design	
4	July 2021.	6	55 (9, 118)	n/a	Design	
5	August 2021.	0	-	-	Design	
6	September 2021.	3	29 (3, 68)	n/a	-	-
7	October 2021.	0	-	-	-	
8	December 2021.	0	-	-	-	
9	January 2022.	0	-	-	-	
10	March 2022.	0	-	-	-	
11	April 2022.	25	242 (140, 358)	220 (126, 400)	Design	510
12	May 2022.	80	782 (568, 1,010)	850 (589, 1,244)	Design	
13	July number 1 of 2022.	42	410 (257, 595)	403 (269, 612)	Design	

Survey number	Survey date	DAS data raw count - OAA plus 2km buffer	Design-based abundance estimate - OAA plus 2km buffer (apportioned) (95% CIs)	MRSea abundance estimate - OAA plus 2km buffer (apportioned and corrected for availability bias) (95% CIs)	Method outputs selected for assessments going forward	Seasonal mean abundance estimate
14	July number 2 of 2022.	49	471 (280, 680)	465 (312, 712)	Design	
15	August 2022.	71	625 (413, 872)	522 (332, 811)	Design	
16	September 2022.	0	-	-	-	-
17	October 2022.	7	70 (20, 140)	n/a	-	
18	November number 1 of 2022.	1	10 (1, 30)	n/a	-	
19	November number 2 of 2022.	5	54 (11, 106)	n/a	-	
20	February number 1 of 2023.	0	-	-	-	
21	February number 2 of 2023.	0	-	-	-	
22	February number 3 of 2023.	1	11 (1, 40)	n/a	-	
23	March number 1 of 2023.	0	-	-	-	
24	March number 2 of 2023.	0	-	-	-	

4.4 Kittiwake

4.4.1.1 Model-based abundance estimates were used for the kittiwake breeding season in both all behaviour and flying estimates due to the larger variance surrounding the design-based peak abundance estimates where notable hotspots were observed. However, design-based abundance estimates were used for the non-breeding season as they fell within a reasonable range of the model-based estimates and were available for all months for this period (**Table 4.3** and **Table 4.4**).

Table 4.3 Selection of abundance estimate method used for further assessment of potential impacts on kittiwake – all behaviours

Survey number	Survey date	DAS data raw count - OAA plus 2km buffer	Design-based abundance estimate - OAA plus 2km buffer (apportioned) (95% CIs)	MRSea abundance estimate - OAA plus 2km buffer (apportioned) (95% CIs)	Method outputs selected for assessments going forward	Seasonal mean abundance estimate
1	April 2021.	171	1,351 (805, 2,139)	823 (354, 2,089)	MRSea	245
2	May 2021.	40	315 (190, 458)	241 (148, 396)	MRSea	
3	June 2021.	3	24 (3, 64)	n/a	MRSea	
4	July 2021.	2	15 (2, 46)	n/a	MRSea	
5	August 2021.	31	252 (138, 389)	161 (96, 261)	MRSea	
6	September 2021.	1	8 (1, 23)	n/a	Design	62
7	October 2021.	7	66 (8, 153)	n/a	Design	
8	December 2021.	3	24 (3,56)	n/a	Design	
9	January 2022.	12	98 (48, 152)	62 (36, 106)	Design	
10	March 2022.	14	111 (56, 182)	85 (50, 142)	Design	
11	April 2022.	16	124 (16, 309)	91 (34, 259)	MRSea	250
12	May 2022.	14	112 (56, 175)	97 (56, 170)	MRSea	
13	July number 1 of 2022.	1	8 (1, 24)	n/a	MRSea	

Survey number	Survey date	DAS data raw count - OAA plus 2km buffer	Design-based abundance estimate - OAA plus 2km buffer (apportioned) (95% CIs)	MRSea abundance estimate - OAA plus 2km buffer (apportioned) (95% CIs)	Method outputs selected for assessments going forward	Seasonal mean abundance estimate
14	July number 2 of 2022.	185	1,479 (960, 2,071)	957 (524, 1,860)	MRSea	
15	August 2022.	16	124 (70, 195)	105 (62, 178)	MRSea	
16	September 2022.	1	8 (1, 24)	n/a	Design	91
17	October 2022.	9	72 (24, 126)	62 (34, 114)	Design	
18	November number 1 of 2022.	11	87 (39, 142)	86 (49, 146)	Design	
19	November number 2 of 2022.	19	154 (81, 235)	75 (44, 132)	Design	
20	February number 1 of 2023.	5	40 (8, 80)	n/a	Design	
21	February number 2 of 2023.	22	177 (112, 265)	156 (102, 245)	Design	
22	February number 3 of 2023.	14	111 (55, 165)	64 (25, 209)	Design	
23	March number 1 of 2023.	10	81 (32, 135)	56 (27, 109)	Design	
24	March number 2 of 2023.	11	88 (32, 150)	64 (35, 117)	Design	

Table 4.4 Selection of abundance estimate method used for further assessment of potential impacts on flying kittiwake – flying only

Survey number	Survey date	DAS data raw count - OAA plus 2km buffer	Design-based abundance estimate - OAA plus 2km buffer (apportioned) (95% CIs)	MRSea abundance estimate - OAA plus 2km buffer (apportioned) (95% CIs)	Method outputs selected for assessments going forward	Seasonal mean abundance estimate
1	April 2021.	66	517 (355, 703)	297 (165, 525)	MRSea	129
2	May 2021.	33	260 (150, 379)	200 (118, 343)	MRSea	
3	June 2021.	1	8 (1,24)	n/a	MRSea	
4	July 2021.	0	-	-	MRSea	
5	August 2021.	27	220 (113, 348)	145 (84, 247)	MRSea	
6	September 2021.	1	8 (1, 23)	n/a	Design	44
7	October 2021.	7	66 (8, 153)	n/a	Design	
8	December 2021.	2	16 (2, 40)	n/a	Design	
9	January 2022.	8	66 (24, 112)	n/a	Design	
10	March 2022.	8	64 (24, 111)	57 (33, 96)	Design	
11	April 2022.	3	23 (3, 55)	-	MRSea	86
12	May 2022.	12	96 (48, 151)	83 (46, 147)	MRSea	
13	July number 1 of 2022.	0	-	-	MRSea	

Survey number	Survey date	DAS data raw count - OAA plus 2km buffer	Design-based abundance estimate - OAA plus 2km buffer (apportioned) (95% CIs)	MRSea abundance estimate - OAA plus 2km buffer (apportioned) (95% CIs)	Method outputs selected for assessments going forward	Seasonal mean abundance estimate
14	July number 2 of 2022.	47	377 (272, 504)	267 (181, 400)	MRSea	
15	August 2022.	11	86 (39, 140)	76 (43, 136)	MRSea	
16	September 2022.	1	8 (1, 24)	-	Design	82
17	October 2022.	6	48 (16, 95)	n/a	Design	
18	November number 1 of 2022.	11	87 (39, 142)	87 (50, 151)	Design	
19	November number 2 of 2022.	18	145 (73, 222)	72 (40, 129)	Design	
20	February number 1 of 2023.	4	32 (8, 64)	n/a	Design	
21	February number 2 of 2023.	19	152 (88, 233)	123 (78, 195)	Design	
22	February number 3 of 2023.	13	103 (47, 157)	71 (33, 148)	Design	
23	March number 1 of 2023.	10	81 (32, 135)	56 (29, 111)	Design	
24	March number 2 of 2023.	10	80 (32, 143)	59 (34, 110)	Design	

4.5 Gannet

4.5.1.1 Model-based abundance estimates were used for the gannet breeding season in both all behaviour and flying estimates. However, design-based abundance estimates were used for the non-breeding season due to low raw counts in the DAS data during ten of the 14 non-breeding season months (**Table 4.5** and **Table 4.6**).

Table 4.5 Selection of abundance estimate method used for further assessment of potential impacts on gannet – all behaviours

Survey number	Survey date	DAS data raw count - OAA plus 2km buffer	Design-based abundance estimate - OAA plus 2km buffer (apportioned) (95% CIs)	MRSea abundance estimate - OAA plus 2km buffer (apportioned) (95% CIs)	Method outputs selected for assessments going forward	Seasonal mean abundance estimate
1	April 2021.	98	772 (584,979)	494 (232, 1,028)	MRSea	607
2	May 2021.	30	237 (158,331)	276 (208, 359)	MRSea	
3	June 2021.	44	348 (248,455)	370 (276, 486)	MRSea	
4	July 2021.	16	123 (62,200)	117 (73, 181)	MRSea	
5	August 2021.	332	2,724 (859, 5,980)	1,778 (483, 8,506)	MRSea	
6	September 2021.	74	570 (423,746)	696 (526, 932)	Design	222
7	October 2021.	55	442 (322, 572)	n/a	Design	
8	December 2021.	2	17 (2, 48)	n/a	Design	
9	January 2022.	2	16 (2, 40)	n/a	Design	
10	March 2022.	8	63 (8, 135)	65 (27, 158)	Design	
11	April 2022.	75	615 (75, 1,647)	555 (130, 2,598)	MRSea	313
12	May 2022.	65	520 (399, 654)	567 (457, 709)	MRSea	
13	July number 1 of 2022.	16	129 (56, 208)	140 (92, 209)	MRSea	
14	July number 2 of 2022.	16	127 (64, 200)	115 (77, 167)	MRSea	

Survey number	Survey date	DAS data raw count - OAA plus 2km buffer	Design-based abundance estimate - OAA plus 2km buffer (apportioned) (95% CIs)	MRSea abundance estimate - OAA plus 2km buffer (apportioned) (95% CIs)	Method outputs selected for assessments going forward	Seasonal mean abundance estimate
15	August 2022.	24	186 (117, 272)	184 (123, 281)	MRSea	
16	September 2022.	65	526 (301, 855)	587 (369, 966)	Design	116
17	October 2022.	21	165 (103, 237)	n/a	Design	
18	November number 1 of 2022.	10	79 (32, 126)	n/a	Design	
19	November number 2 of 2022.	4	33 (8,73)	n/a	Design	
20	February number 1 of 2023.	1	8 (1, 24)	n/a	Design	
21	February number 2 of 2023.	8	65 (8, 177)	n/a	Design	
22	February number 3 of 2023.	8	63 (24, 118)	n/a	Design	
23	March number 1 of 2023.	2	16 (2, 40)	n/a	Design	
24	March number 2 of 2023.	10	81 (32, 135)	87 (50, 147)	Design	

Table 4.6 Selection of abundance estimate method used for further assessment of potential impacts on flying gannet – flying only

Survey number	Survey date	DAS data raw count - OAA plus 2km buffer	Design-based abundance estimate - OAA plus 2km buffer (apportioned) (95% CIs)	MRSea abundance estimate - OAA plus 2km buffer (apportioned) (95% CIs)	Method outputs selected for assessments going forward	Seasonal mean abundance estimate
1	April 2021.	32	252 (142, 379)	124 (49, 300)	MRSea	344
2	May 2021.	18	143 (79, 221)	110 (73, 161)	MRSea	
3	June 2021.	15	120 (64, 184)	94 (59, 147)	MRSea	
4	July 2021.	9	69 (31, 115)	50 (27, 85)	MRSea	
5	August 2021.	260	2,140 (462, 5,267)	1,341 (295, 8,798)	MRSea	
6	September 2021.	45	348 (246, 454)	304 (220, 421)	Design	155
7	October 2021.	41	329 (226, 451)	n/a	Design	
8	December 2021.	2	17 (2,48)	n/a	Design	
9	January 2022.	2	16 (2,40)	n/a	Design	
10	March 2022.	8	63 (8, 135)	50 (21, 121)	Design	
11	April 2022.	8	64 (24, 119)	61 (29, 128)	MRSea	98
12	May 2022.	37	297 (207, 399)	280 (208, 383)	MRSea	
13	July number 1 of 2022.	8	64 (16, 128)	48 (24, 96)	MRSea	

Survey number	Survey date	DAS data raw count - OAA plus 2km buffer	Design-based abundance estimate - OAA plus 2km buffer (apportioned) (95% CIs)	MRSea abundance estimate - OAA plus 2km buffer (apportioned) (95% CIs)	Method outputs selected for assessments going forward	Seasonal mean abundance estimate
14	July number 2 of 2022.	8	63 (24, 120)	41 (19, 81)	MRSea	
15	August 2022.	10	78 (31, 132)	57 (31, 109)	MRSea	
16	September 2022.	21	172 (106, 252)	170 (111, 271)	Design	54
17	October 2022.	12	94 (47,150)	n/a	Design	
18	November number 1 of 2022.	5	40 (8,79)	n/a	Design	
19	November number 2 of 2022.	3	25 (3,57)	n/a	Design	
20	February number 1 of 2023.	1	8 (1, 24)	n/a	Design	
21	February number 2 of 2023.	2	16 (2, 40)	n/a	Design	
22	February number 3 of 2023.	8	63 (24, 118)	n/a	Design	
23	March number 1 of 2023.	2	16 (2, 40)	n/a	Design	
24	March number 2 of 2023.	6	48 (16, 87)	36 (17, 76)	Design	

4.6 Fulmar

4.6.1.1 Model-based abundance estimates were used across the survey period in both the breeding and non-breeding seasons for fulmar due to the larger variance surrounding the design-based peak abundance estimates where notable hotspots were observed (**Table 4.7**).

Table 4.7 Selection of abundance estimate method used for further assessment of potential impacts on puffin

Survey number	Survey date	DAS data raw count - OAA plus 2km buffer	Design-based abundance estimate - OAA plus 2km buffer (apportioned) (95% CIs)	MRSea abundance estimate - OAA plus 2km buffer (apportioned) (95% CIs)	Method outputs selected for assessments going forward	Seasonal mean abundance estimate
1	April 2021.	92	720 (450, 1,082)	504 (265, 993)	MRSea	1,157
2	May 2021.	54	424 (316, 536)	597 (459, 776)	MRSea	
3	June 2021.	28	223 (136, 319)	330 (223, 481)	MRSea	
4	July 2021.	211	1,627 (1,407, 1,861)	1,641 (1,406, 1,903)	MRSea	
5	August 2021.	447	3,702 (1,661, 7,477)	2,709 (1,319, 5,763)	MRSea	
6	September 2021.	243	1,865 (1,115, 3,022)	2,277 (1,093, 4,917)	MRSea	992
7	October 2021.	86	705 (443, 1,111)	582 (394, 873)	MRSea	
8	December 2021.	125	1,007 (807, 1,218)	1,043 (765, 1,407)	MRSea	
9	January 2022.	98	784 (633, 962)	767 (623, 962)	MRSea	
10	March 2022.	29	227 (143, 317)	290 (221, 385)	MRSea	
11	April 2022.	32	253 (166, 356)	314 (239, 401)	MRSea	1,304
12	May 2022.	25	199 (120, 287)	225 (162, 324)	MRSea	
13	July number 1 of 2022.	312	2,518 (1,855, 3,583)	2,634 (1,402, 6,154)	MRSea	
14	July number 2 of 2022.	312	2,482 (2,151, 2,846)	2,212 (1,893, 2,578)	MRSea	

Survey number	Survey date	DAS data raw count - OAA plus 2km buffer	Design-based abundance estimate - OAA plus 2km buffer (apportioned) (95% CIs)	MRSea abundance estimate - OAA plus 2km buffer (apportioned) (95% CIs)	Method outputs selected for assessments going forward	Seasonal mean abundance estimate
15	August 2022.	151	1,174 (981, 1,378)	1,133 (985, 1,301)	MRSea	
16	September 2022.	423	3,425 (953, 7,093)	3,109 (676, 27,196)	MRSea	1,587
17	October 2022.	231	1,822 (1,538, 2,130)	1,653 (1,415, 1,932)	MRSea	
18	November number 1 of 2022.	242	1,920 (1,615, 2,276)	2,136 (1,590, 2,829)	MRSea	
19	November number 2 of 2022.	352	2,887 (2,551, 3,254)	2,269 (1,929, 2,653)	MRSea	
20	February number 1 of 2023.	86	686 (535, 839)	979 (698, 1,403)	MRSea	
21	February number 2 of 2023.	76	610 (442, 779)	810 (593, 1,047)	MRSea	
22	February number 3 of 2023.	138	1,085 (889, 1,283)	1,889 (1,274, 2,808)	MRSea	
23	March number 1 of 2023.	105	840 (645, 1,042)	980 (753, 1,284)	MRSea	
24	March number 2 of 2023.	53	418 (293, 570)	455 (319, 631)	MRSea	

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6. Glossary and Abbreviations

6.1 Abbreviations

Acronym	Definition
ACF	Autocorrelation Function
AoI	Area of Interest
CI	Confidence Interval
CReSS	Complex Region Spatial Smoother
DAS	Digital aerial survey
GAM	Generalised Additive Model
GIS	Geographic Information System
GVIF	Generalised Variance Inflation Factors
MLWS	Mean Low Water Springs
NE7	Northeast 7
OAA	Option Area Agreement
QBIC	Quasi-Bayesian Information Criterion
SALSA	Spatially Adaptive Local Smoothing Algorithm
SSEN	Scottish and Southern Electricity Networks

6.2 Glossary

Term	Definition
Digital aerial survey	Digital photography surveys carried out by aeroplane.
MRSea	MRSea is a package developed in R (R Core Team, 2024) used for identifying spatially explicit changes in the spatial distribution and abundance of seabirds over time and across an offshore development site. MRSea modelling is recommended on the basis that it may offer greater facility in understanding the variation in distribution in response to environmental variables.

Appendix A
Full species model

Species	Model specifics	Final model
Guillemot	(all seasons, all behaviours).	(response) ~ Survey + bs(mean_depth, knots = splineParams[[2]]$knots, degree = splineParams[[2]]$degree, Boundary.knots = splineParams[[2]]$bd) + LRF.g(radiusIndices, dists, radii, aR) + offset(log(area)), family = quasipoisson(link = log), data = model_data, splineParams = splineParams)
Kittiwake	(all seasons, all behaviours).	response) ~ Survey + bs(mean_depth, knots = splineParams[[2]]$knots, degree = splineParams[[2]]$degree, Boundary.knots = splineParams[[2]]$bd) + LRF.g(radiusIndices, dists, radii, aR) + offset(log(area)), family = quasipoisson(link = log), data = model_data, splineParams = splineParams)
Kittiwake	(all seasons, flying only).	response) ~ Survey + bs(mean_depth, knots = splineParams[[2]]$knots, degree = splineParams[[2]]$degree, Boundary.knots = splineParams[[2]]$bd) + dist_oilrig + LRF.g(radiusIndices, dists, radii, aR) + offset(log(area)), family = quasipoisson(link = log), data = model_data, splineParams = splineParams)
Gannet	(breeding only, all behaviours).	response) ~ Survey + LRF.g(radiusIndices, dists, radii, aR) + offset(log(area)), family = quasipoisson(link = log), data = model_data, splineParams = splineParams)
Gannet	(breeding only, flying only).	response) ~ Survey + LRF.g(radiusIndices, dists, radii, aR) + offset(log(area)), family = quasipoisson(link = log), data = model_data, splineParams = splineParams)
Puffin	(breeding only, all behaviours).	response) ~ Survey + bs(mean_depth, knots = splineParams[[2]]$knots, degree = splineParams[[2]]$degree,

Species	**Model specifics**	**Final model**
		Boundary.knots = splineParams[[2]]$bd) + bs(dist_oilrig, knots = splineParams[[3]]$knots, degree = splineParams[[3]]$degree, Boundary.knots = splineParams[[3]]$bd) + LRF.g(radiusIndices, dists, radii, aR) + offset(log(area)), family = quasipoisson(link = log), data = model_data, splineParams = splineParams)
Fulmar	(all seasons, all behaviours).	response ~ Survey + LRF.g(radiusIndices, dists, radii, aR) + offset(log(area)), family = "quasipoisson", data = model_data, splineParams = splineParams)

Appendix B
MRSea Model validation

Guillemot

Initial Set-up

The co-linearity of explanatory variables was initially assessed by observing Generalised Variance Inflation Factors (GVIFs). Covariates were removed if strong collinearity was detected (GVIF value over 20). All adjusted GVIF values were below this threshold except for distance to coast (**Plate B1**). Despite using a non-linear approach to account for collinearity, distance to coast was excluded from the 1D and 2D smoothed models.

Plate B1 Code snippet detailing testing for co-linearity

```
> vif_out <- car::vif(test_model)
> vif_out
                      GVIF Df GVIF^(1/(2*Df))
Survey        6.943368e+06  4        7.164671
mean_depth    1.842132e+00  1        1.357252
mean_prey_pres 1.105342e+00 1        1.051353
dist_col      5.526249e+02  1       23.507975
dist_oilrig   2.718944e+00  1        1.648922
boat_presence 6.925423e+06  1     2631.619925
x.pos         2.230324e+02  1       14.934268
y.pos         2.652717e+02  1       16.287163
```

To fit the model, it was necessary for all levels of any categorical variables to have non-zero counts. Two categorical (factor) variables were considered, survey and boat presence (**Plate B2**).

Plate B2 Code snippet verifying non-zero counts for all factor levels

```
> checkfactorlevelcounts(factorlist = c("Survey", "boat_presence"),
+                        data = model_data,
+                        response = model_data$response)
[1] "Survey will be fitted as a factor variable; there are non-zero counts for all levels"
[1] "boat_presence will be fitted as a factor variable; there are non-zero counts for all levels"
```

Generalised Linear Model

Before creating more complex models, a simple Generalised Linear Model (GLM) was developed and run as an initial model (**Plate B3**).

Plate B3 Code snippet summarising the initial GLM

```
Call:
glm(formula = response ~ Survey + mean_depth + mean_prey_pres +
    dist_col + dist_oilrig + boat_presence + x.pos + y.pos +
    offset(log(area)), family = "quasipoisson", data = model_data)

Coefficients:
                       Estimate        Std. Error t value            Pr(>|t|)
(Intercept)         614.83392626      117.10634105   5.250   0.0000001526000791 ***
Survey6               0.03553771        0.24733203   0.144             0.885750
Survey7               2.05706147        0.19352696  10.629 < 0.0000000000000002 ***
Survey9              -0.61265430        0.30283649  -2.023             0.043074 *
Survey14              2.12944713        0.19221905  11.078 < 0.0000000000000002 ***
Survey15            -14.04232844      110.02880114  -0.128             0.898447
Survey20              0.63125280        0.22702789   2.781             0.005430 **
Survey21              1.31304641        0.20563242   6.385   0.0000000001725897 ***
Survey24              0.75668522        0.22391129   3.379             0.000727 ***
Survey1               3.35399322        0.18594977  18.037 < 0.0000000000000002 ***
Survey3              -0.16715766        0.27470651  -0.608             0.542862
Survey4               2.00951316        0.19344129  10.388 < 0.0000000000000002 ***
Survey5             -15.10720866      110.02881051  -0.137             0.890792
Survey8              -0.67688594        0.31142340  -2.174             0.029746 *
Survey10              1.55185174        0.20064275   7.734   0.0000000000000106 ***
Survey11              0.75697424        0.22306241   3.394             0.000691 ***
Survey12             -0.69032904        0.31791133  -2.171             0.029902 *
Survey13            -15.95939696      110.02883278  -0.145             0.884674
Survey16              1.82436232        0.19739605   9.242 < 0.0000000000000002 ***
Survey17              1.71913932        0.19739390   8.709 < 0.0000000000000002 ***
Survey18              1.30419746        0.20449171   6.378   0.0000000001814281 ***
Survey19              1.87940967        0.19412464   9.681 < 0.0000000000000002 ***
Survey22              1.09353036        0.20995432   5.208   0.0000001912832909 ***
Survey23              1.00951937        0.21376072   4.723   0.0000023347276291 ***
mean_depth            0.00528842        0.00252785   2.092             0.036439 *
mean_prey_pres -3413807.66316999  2702992.15835450  -1.263             0.206605
dist_col              0.13741218        0.02594041   5.297   0.0000001181221042 ***
dist_oilrig           0.00675643        0.00274376   2.462             0.013802 *
boat_presence1       18.58226540      110.02864969   0.169             0.865887
x.pos                -0.00010633        0.00001973  -5.388   0.0000000714731227 ***
y.pos                -0.00008692        0.00001658  -5.242   0.0000001598777607 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for quasipoisson family taken to be 2.088718)

    Null deviance: 54817  on 45486  degrees of freedom
Residual deviance: 36287  on 45456  degrees of freedom
AIC: NA

Number of Fisher Scoring iterations: 16
```

Residual correlation in the selected model was examined with an empirical Runs Test which indicated no significant residual correlation due to the insignificant p-value (**Plate B4**).

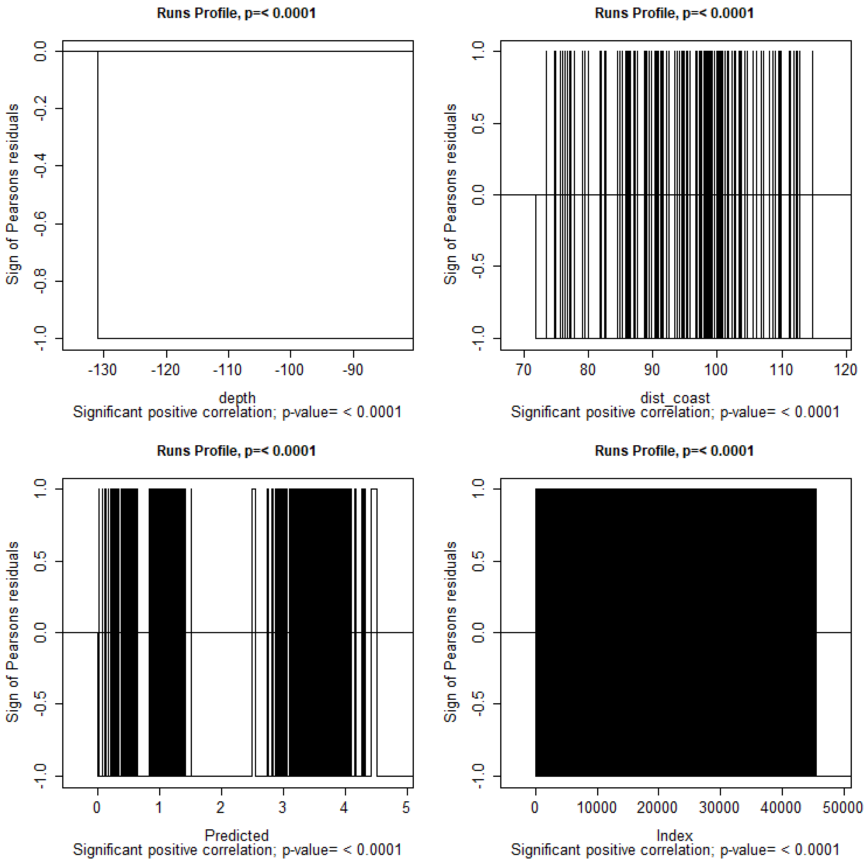
Plate B4 Code snippet highlighting the runs test results

```
        Runs Test - Two sided; Empirical Distribution

data:  residuals(best_model_salsa2dOutput, type = "pearson")
Standardized Runs Statistic = -124.06, p-value = 0.07
```

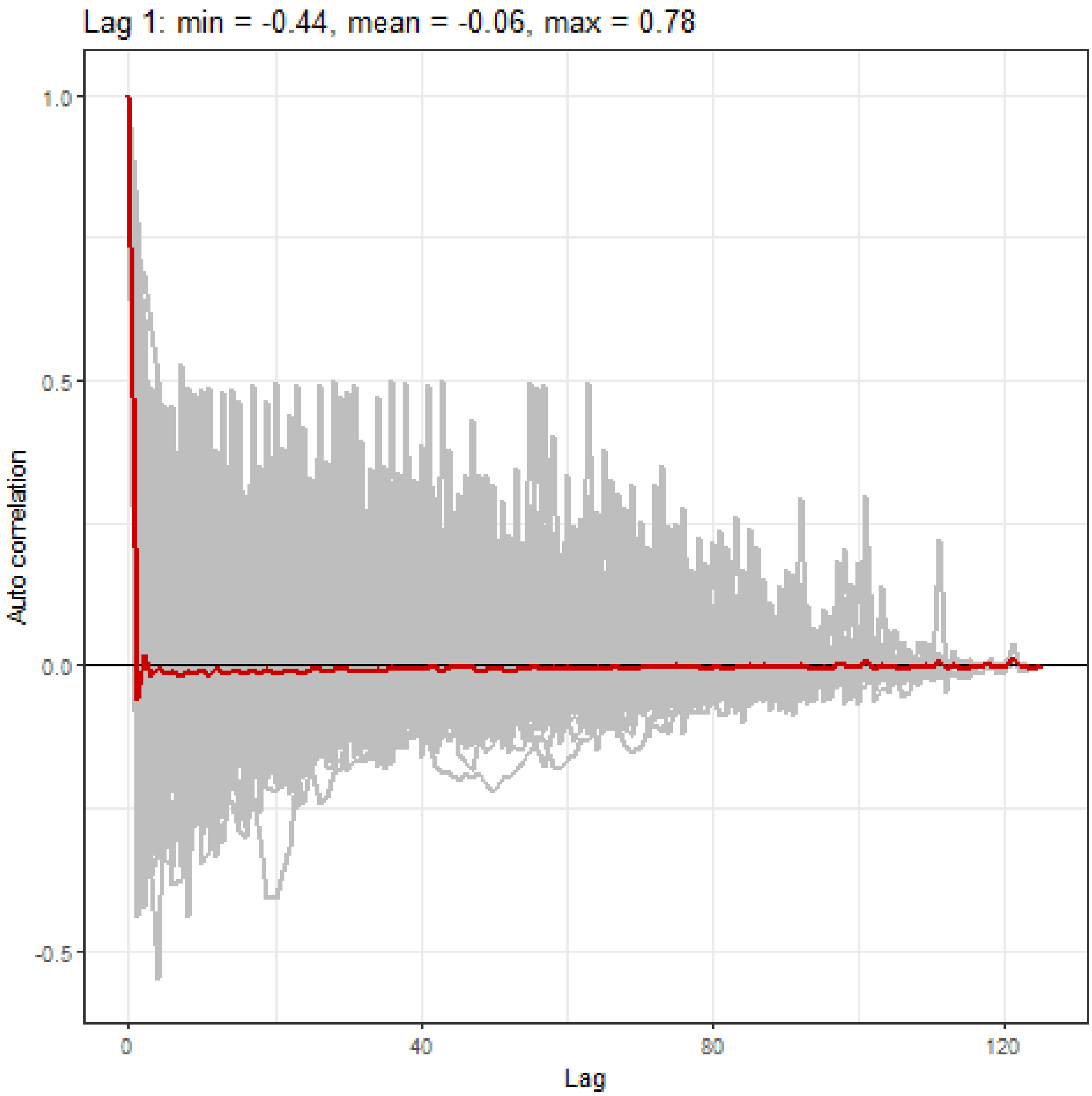
Non-randomness was observed in the runs profiles (Plate B5).

Plate B5 Runs profile for the initial GLM. Black lines display the sequence of positive and negative residuals. It is expected to see random distribution of lines in the absence of correlated residuals. Significance of correlation within each variable



Given the presence of correlation, it was deemed appropriate to incorporate a blocking structure moving forward (**Plate B5**). The blocking structure was based on the combination of Survey ID and Transect ID, allowing the model to treat data from each transect within a survey as correlated while assuming independence between different transects and surveys. An Auto-Correlation Function (ACF) plot was used to assess the effectiveness of the blocking structure (**Plate B6**). Both the mean correlation in residuals (red line) and correlation in residuals within each block (grey lines) quickly moved to zero, indicating that the blocking structure was fit for purpose.

Plate B6 ACF plot used for the initial GLM. The grey lines represent the correlation of residuals within each block, while the red line indicates the average correlation of the residuals



Cumulative residuals were plotted for explanatory variables (**Plate B7** and **Plate B8**).

Plate B7 Cumulative residuals for initial GLM structured by distance to oil rig. The black line shows the modelled cumulative residuals, while they grey line shows expected model fit

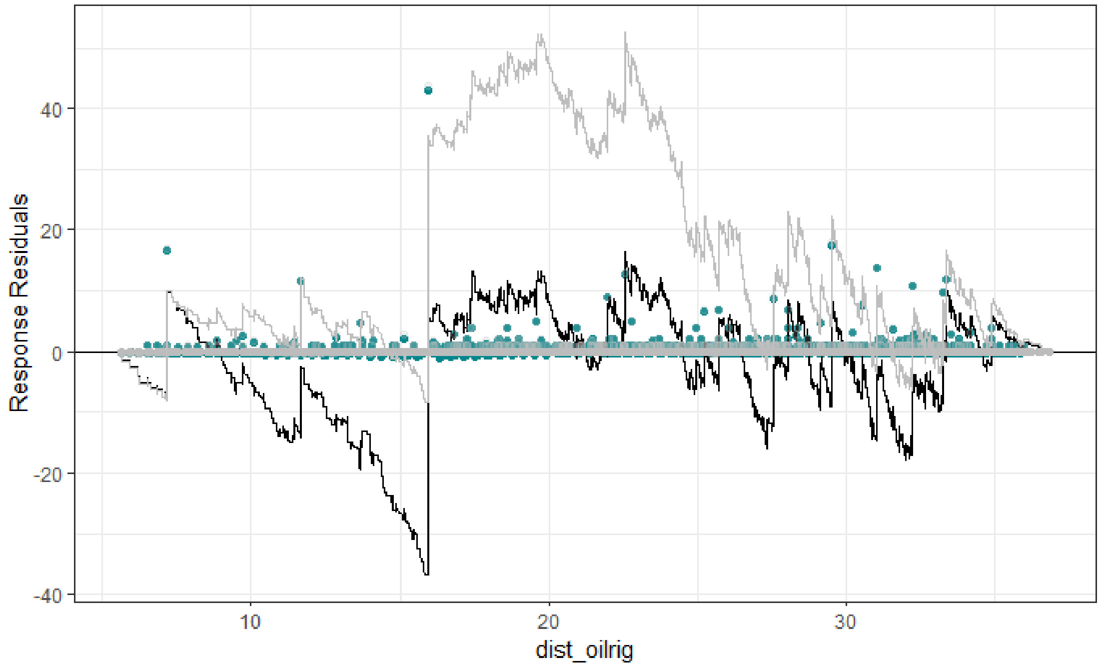
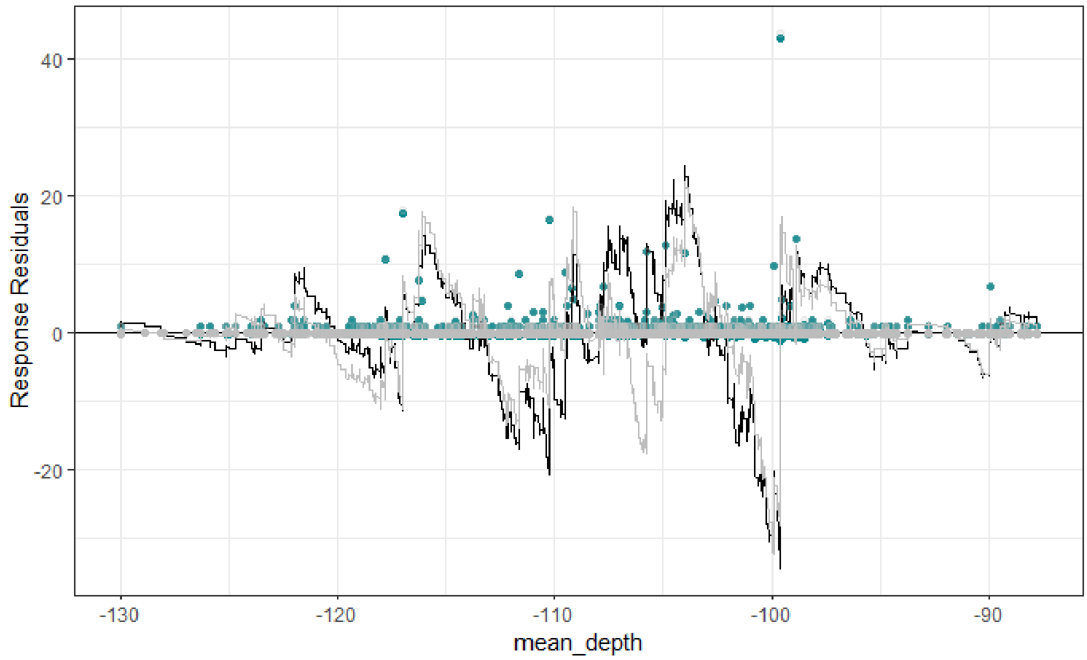


Plate B8 Cumulative residuals for initial GLM structured by depth. The black line shows the modelled cumulative residuals, while they grey line shows expected model fit



2D SALSA Model Diagnostics

The final model was selected according to having the lowest QBIC validation score and the summary can be seen in **Plate B9**. The SALSA 2D function is used to fit a CReSS model to the existing best fit 1D model, where the knot locations were allowed to vary by survey. Bird count served as the response variable, with x.pos and y.pos as spatial coordinates, and log(area) included as an offset. The model employed a quasi-Poisson error distribution with a log link.

Plate B9 Code snippet summarising the final model

```
Call:
gamMRSea(formula = round(response) ~ Survey + bs(mean_depth,
    knots = splineParams[[2]]$knots, degree = splineParams[[2]]$degree,
    Boundary.knots = splineParams[[2]]$bd) + LRF.g(radiusIndices,
    dists, radii, aR) + offset(log(area)), family = quasipoisson(link = log),
    data = model_data, splineParams = splineParams)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-3.0496  -0.6452  -0.4475  -0.2506  18.3372

Coefficients:
                Estimate Std. Error Robust S.E. t value             Pr(>|t|)
(Intercept)      1.48511    0.14145     0.27771   5.348  0.00000008953363678 ***
Survey2         -3.13160    0.22770     0.31603  -9.909 < 0.0000000000000002 ***
Survey3         -3.29853    0.24666     0.29070 -11.347 < 0.0000000000000002 ***
Survey4         -1.12126    0.13616     0.27201  -4.122  0.00003760217803897 ***
Survey5         -1.36396    0.18236     0.30487  -4.474  0.00000769959858634 ***
Survey6         -3.09179    0.21198     0.30723 -10.064 < 0.0000000000000002 ***
Survey7         -0.04142    0.19934     0.30927  -0.134             0.893448
Survey8         -3.80344    0.29112     0.40196  -9.462 < 0.0000000000000002 ***
Survey9         -3.74679    0.28092     0.33962 -11.032 < 0.0000000000000002 ***
Survey10        -1.58123    0.14727     0.27372  -5.777  0.00000000766646569 ***
Survey11        -2.37443    0.17961     0.28086  -8.454 < 0.0000000000000002 ***
Survey12        -3.82225    0.29886     0.36581 -10.449 < 0.0000000000000002 ***
Survey13        -1.85367    0.15323     0.27670  -6.699  0.00000000002119825 ***
Survey14        -1.00383    0.13419     0.27991  -3.586             0.000336 ***
Survey15        -1.11868    0.16889     0.33997  -3.291             0.001001 **
Survey16        -1.94082    0.17512     0.29680  -6.539  0.00000000006252770 ***
Survey17         0.86118    0.24046     0.32592   2.642             0.008238 **
Survey18        -1.50832    0.16817     0.28219  -5.345  0.00000009084827497 ***
Survey19        -2.95351    0.41977     0.59187  -4.990  0.00000060549605611 ***
Survey20        -2.49634    0.18499     0.28480  -8.765 < 0.0000000000000002 ***
Survey21        -1.81603    0.15473     0.28062  -6.472  0.00000000009799213 ***
Survey22        -2.03574    0.16101     0.27464  -7.412  0.00000000000012624 ***
Survey23        -2.11913    0.16649     0.27608  -7.676  0.00000000000001676 ***
Survey24        -2.37078    0.18074     0.30462  -7.783  0.00000000000000725 ***
s(mean_depth)1   0.65806    0.15417     0.20955   3.140             0.001689 **
s(mean_depth)2   0.67427    0.09350     0.13400   5.032  0.00000048771939339 ***
s(mean_depth)3  -0.19132    0.21678     0.30091  -0.636             0.524906
s(x,y)b1         3.54759    0.22679     0.38002   9.335 < 0.0000000000000002 ***
s(x,y)b2       -19.74425    1.80789     3.29782  -5.987  0.00000000215269966 ***
s(x,y)b3        -4.17239    0.33320     0.59266  -7.040  0.00000000000194747 ***
s(x,y)b4        -8.56313    0.94163     1.63184  -5.248  0.00000015483895572 ***
s(x,y)b5         2.35782    0.16567     0.27119   8.694 < 0.0000000000000002 ***
```

```
s(x,y)b6         1.60560    0.16345     0.21211    7.570  0.00000000000003810 ***
s(x,y)b7         1.49647    0.28568     0.19244    7.776  0.00000000000000763 ***
s(x,y)b8         1.92969    0.24997     0.26183    7.370  0.00000000000017346 ***
s(x,y)b9        -4.49324    0.45610     0.37458  -11.995 < 0.0000000000000002 ***
s(x,y)b10       -1.43102    0.39479     0.33212   -4.309  0.00001645744615023 ***
s(x,y)b11        2.09826    0.47752     0.61789    3.396             0.000685 ***
s(x,y)b12       28.00062    2.51439     4.57279    6.123  0.00000000092398637 ***
s(x,y)b13        0.87013    0.22257     0.26468    3.287             0.001012 **
s(x,y)b14       -2.19389    0.35831     0.40894   -5.365  0.00000008143993662 ***
s(x,y)b15       -1.63911    0.30575     0.25547   -6.416  0.00000000014112279 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for quasipoisson family taken to be 2.322657)

    Null deviance: 54817  on 45486  degrees of freedom
Residual deviance: 41582  on 45445  degrees of freedom
AIC:  NA

Max Panel Size = 126; Number of panels = 624
Number of Fisher Scoring iterations: 7
```

Additional model diagnostics for the best fitting SALSA 2D model are displayed below (**Plate B10** and **Plate B11**). The first diagnostic plot compares observed versus fitted values (**Plate B10**). The second diagnostic plot shows the mean variance relationship comparing mean variance from the model with the assumed mean-variance relationship (**Plate B11**). This plot indicates a generally good fit; however, variance is underestimated for the larger fitted values.

Plate B10 Observed versus predicted values for the best fitting 2D smoothed model

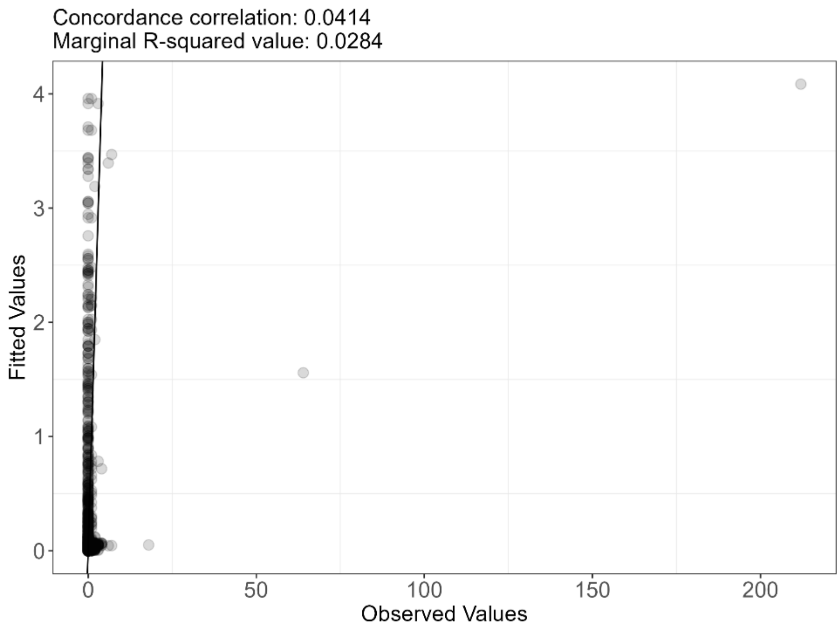
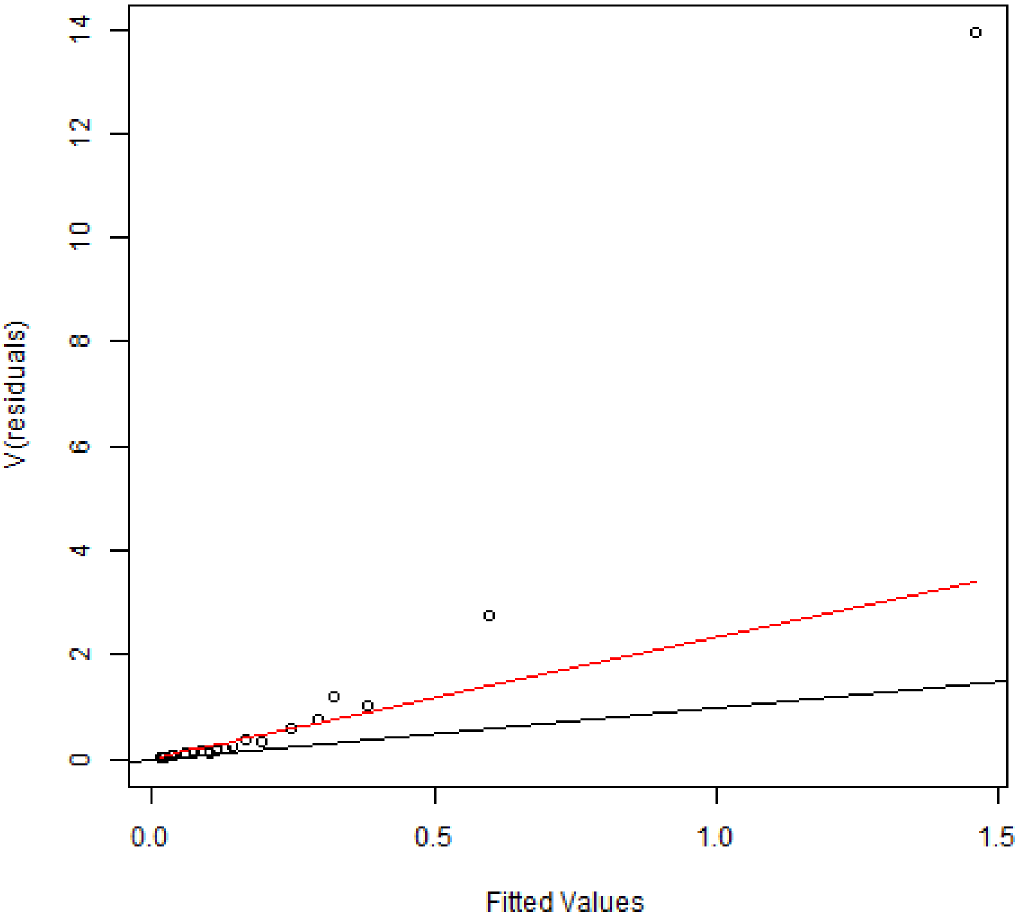


Plate B11 Mean-variance relationship plot. The red line shows the estimates mean variance relationship from the model and the black line represents what would be expected in a perfect Poisson distribution (variance = mean)



Puffin

Initial set-up

The co-linearity of explanatory variables was initially assessed by observing GVIFs. Covariates were removed if strong collinearity was detected (GVIF value over 20). All adjusted GVIF values were below this threshold except for distance to coast (**Plate B12**). Despite using a non-linear approach to account for collinearity, distance to coast was excluded from the 1D and 2D smoothed models.

Plate B12 Code snippet detailing testing for co-linearity

```
> vif_out <- car::vif(test_model)
> vif_out
                        GVIF Df GVIF^(1/(2*Df))
Survey         7683137.406082  6        3.747959
mean_depth           1.820045  1        1.349090
mean_prey_pres       1.110676  1        1.053886
dist_col           533.211245  1       23.091367
dist_oilrig          2.665102  1        1.632514
boat_presence  7660310.941094  1     2767.726674
x.pos              218.661792  1       14.787217
y.pos              262.151601  1       16.191096
```

To fit the model, it was necessary for all levels of any categorical variables to have non-zero counts. Two categorical (factor) variables were considered, survey and boat presence (**Plate B13**).

Plate B13 Code snippet verifying non-zero counts for all factor levels

```
> checkfactorlevelcounts(factorlist = c("Survey", "boat_presence"),
+                        data = model_data,
+                        response = model_data$response)
[1] "Survey will be fitted as a factor variable; there are non-zero counts for all levels"
[1] "boat_presence will be fitted as a factor variable; there are non-zero counts for all levels"
```

Generalised linear model

Before creating more complex models, a simple GLM was developed and run as an initial model (**Plate B14**).

Plate B14 Code snippet summarising the initial GLM

```
> summary (test_model)

Call:
glm(formula = response ~ Survey + mean_depth + mean_prey_pres +
    dist_col + dist_oilrig + boat_presence + x.pos + y.pos +
    offset(log(area)), family = "quasipoisson", data = model_data)

Coefficients:
                         Estimate          Std. Error t value         Pr(>|t|)
(Intercept)         -1138.69210224        564.30472984  -2.018         0.043625 *
Survey2                 1.04224275          0.28793561   3.620         0.000296 ***
Survey11                0.39734478          0.32837701   1.210         0.226290
Survey12                1.76973798          0.26379074   6.709 0.0000000000204 ***
Survey13              -15.84365377        331.57368327  -0.048         0.961890
Survey14                1.15813695          0.27522540   4.208 0.0000259353213 ***
Survey15              -15.66140203        331.57367691  -0.047         0.962328
mean_depth             -0.02195649          0.01038695  -2.114         0.034546 *
mean_prey_pres -22934478.61240605   33949208.50198425  -0.676         0.499336
dist_col               -0.30412339          0.12628334  -2.408         0.016042 *
dist_oilrig             0.01044994          0.01205330   0.867         0.385970
boat_presence1         18.22247846        331.57359362   0.055         0.956173
x.pos                   0.00019211          0.00009692   1.982         0.047477 *
y.pos                   0.00016122          0.00007975   2.022         0.043226 *
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for quasipoisson family taken to be 1.424037)

    Null deviance: 3564.2  on 13524  degrees of freedom
Residual deviance: 2973.3  on 13511  degrees of freedom
AIC: NA

Number of Fisher Scoring iterations: 18
```

Residual correlation in the selected model was examined with an empirical Runs Test which indicated no significant residual correlation due to the insignificant p-value (**Plate B15**).

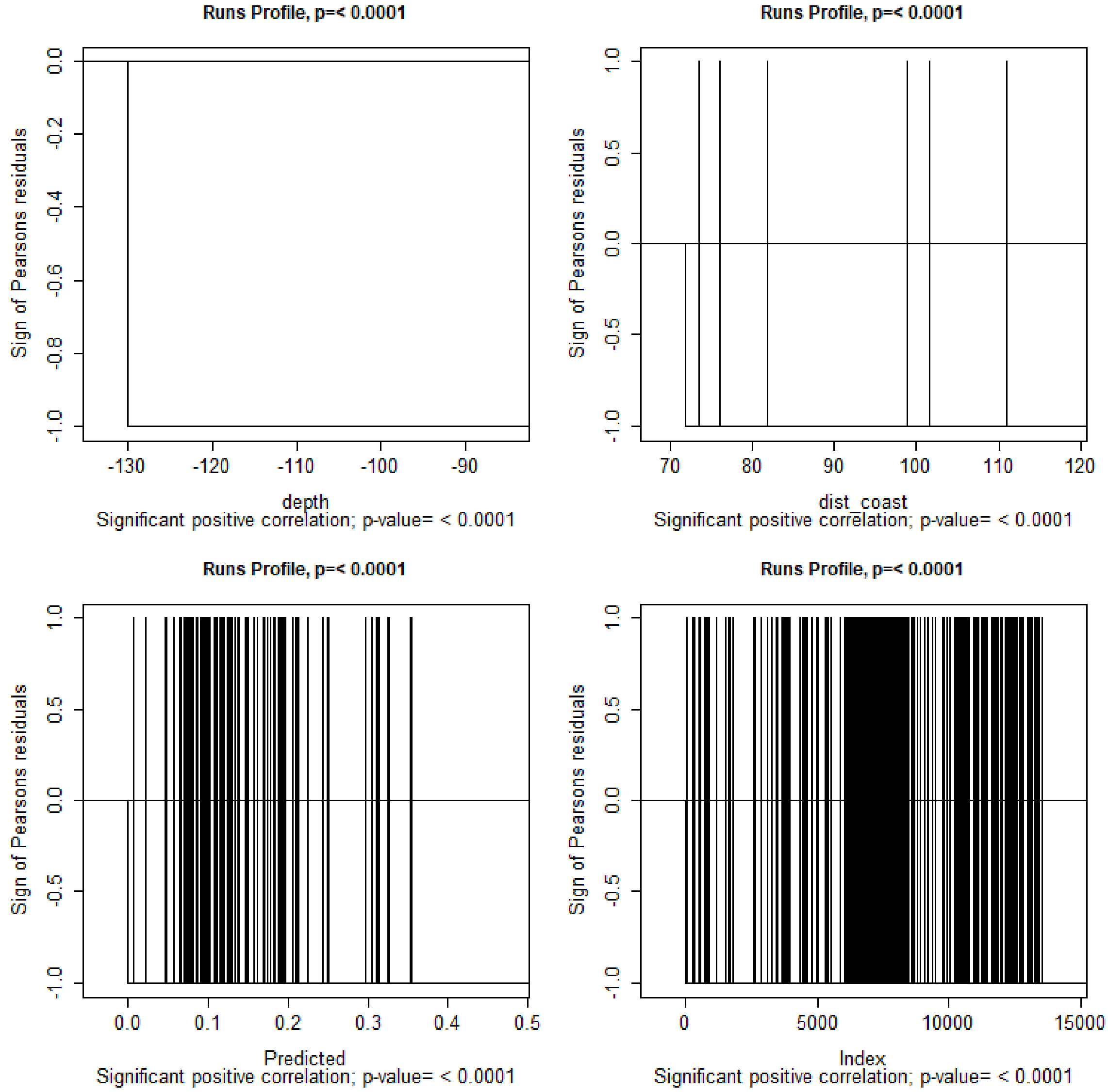
Plate B15 Code snippet highlighting the runs test results

```
    Runs Test - Two sided; Empirical Distribution

data:  residuals(best_model_salsa2dOutput, type = "pearson")
Standardized Runs Statistic = -85.19, p-value = 0.6
```

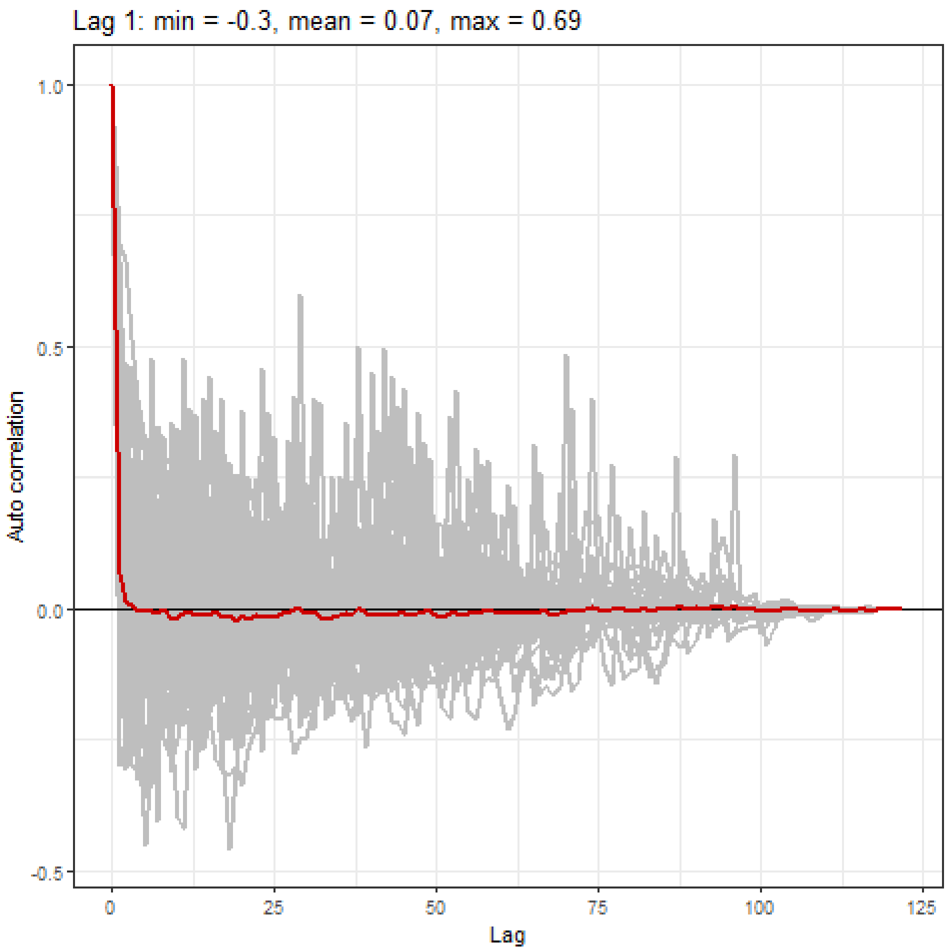
Non-randomness was observed in the runs profiles (**Plate B16**).

Plate B16 Runs profile for the initial GLM. Black lines display the sequence of positive and negative residuals. It is expected to see random distribution of lines in the absence of correlated residuals. Significance of correlation within each variable



Given the presence of correlation, it was deemed appropriate to incorporate a blocking structure moving forward. The blocking structure was based on the combination of Survey ID and Transect ID, allowing the model to treat data from each transect within a survey as correlated while assuming independence between different transects and surveys. An ACF plot was used to assess the effectiveness of the blocking structure (**Plate B17**). Both the mean correlation in residuals (red line) and correlation in residuals within each block (grey lines) quickly moved to zero, indicating that the blocking structure was fit for purpose.

Plate B17 ACF plot used for the initial GLM. The grey lines represent the correlation of residuals within each block, while the red line indicates the average correlation of the residuals



Cumulative residuals were plotted for explanatory variables (**Plate B18** and **Plate B19**).

Plate B18 Cumulative residuals for initial GLM structured by distance to oil rig. The black line shows the modelled cumulative residuals, while they grey line shows expected model fit

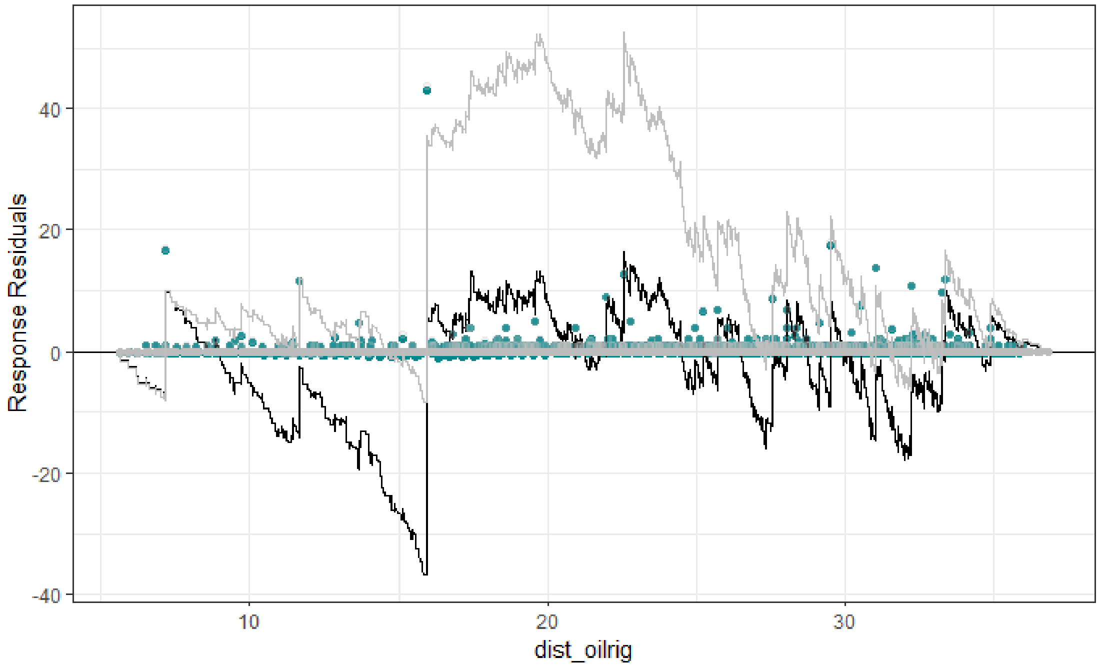
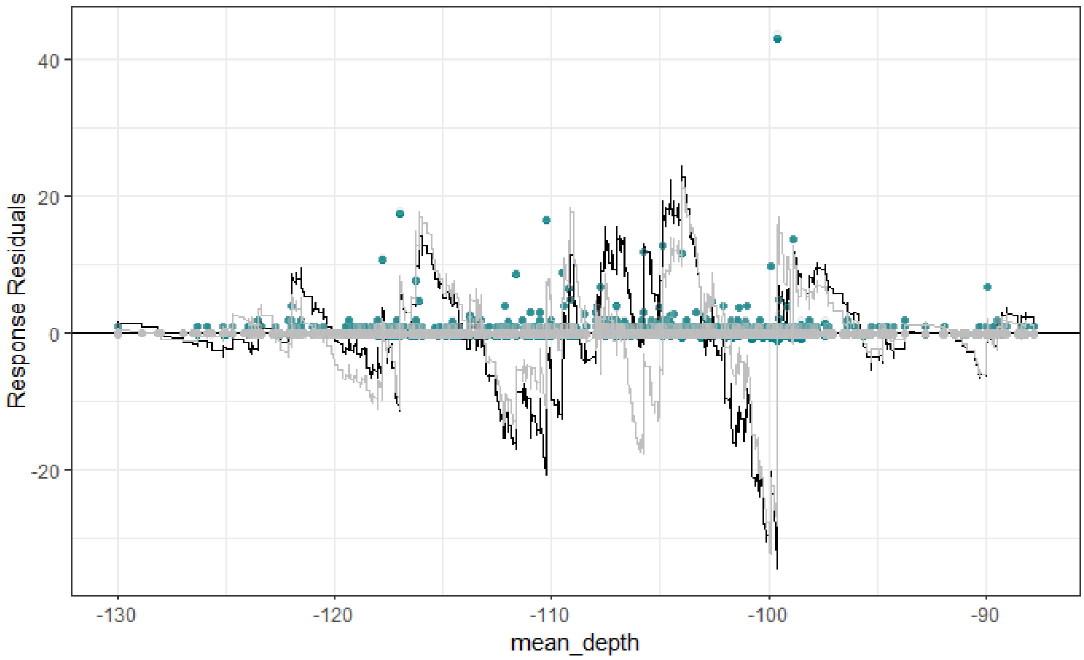


Plate B19 Cumulative residuals for initial GLM structured by depth. The black line shows the modelled cumulative residuals, while they grey line shows expected model fit



2D SALSA model diagnostics

The final model was selected according to having the lowest QBIC validation score and the summary can be seen in **Plate B20**. The SALSA 2D function is used to fit a CReSS model to the existing best fit 1D model, where the knot locations were allowed to vary by survey. Bird count served as the response variable, with x.pos and y.pos as spatial coordinates, and log(area) included as an offset. The model employed a quasi-Poisson error distribution with a log link.

Plate B20 Code snippet summarising the final model

```
Call:
gamMRSea(formula = round(response) ~ Survey + bs(mean_depth,
    knots = splineParams[[2]]$knots, degree = splineParams[[2]]$degree,
    Boundary.knots = splineParams[[2]]$bd) + bs(dist_oilrig,
    knots = splineParams[[3]]$knots, degree = splineParams[[3]]$degree,
    Boundary.knots = splineParams[[3]]$bd) + LRF.g(radiusIndices,
    dists, radii, aR) + offset(log(area)), family = quasipoisson(link = log),
    data = model_data, splineParams = splineParams)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.2290  -0.2886  -0.2345  -0.1584   7.6449

Coefficients:
                  Estimate Std. Error Robust S.E. t value     Pr(>|t|)
(Intercept)       -1.10374    0.72470     0.67337  -1.639     0.101210
Survey2            7.18632    1.13048     1.72141   4.175 0.0000300284 ***
Survey11           0.60775    0.38018     0.39706   1.531     0.125881
Survey12           1.77869    0.30238     0.32595   5.457 0.0000000493 ***
Survey13           1.03271    0.32489     0.33892   3.047     0.002315 **
Survey14           1.17832    0.31543     0.33568   3.510     0.000449 ***
Survey15           1.32748    0.31006     0.34734   3.822     0.000133 ***
s(mean_depth)1    -0.43540    0.74489     0.69223  -0.629     0.529376
s(mean_depth)2     0.38483    0.48647     0.43138   0.892     0.372370
s(mean_depth)3    -0.08201    0.74341     0.66913  -0.123     0.902455
s(dist_oilrig)1   -1.69091    0.56331     0.59787  -2.828     0.004688 **
s(dist_oilrig)2   -1.19663    0.30545     0.33187  -3.606     0.000312 ***
s(dist_oilrig)3   -0.09042    0.62367     0.65792  -0.137     0.890684
s(x,y)b1        -570.78816  817.32624   277.88107  -2.054     0.039988 *
s(x,y)b2          -9.56137    1.86300     2.52821  -3.782     0.000156 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for quasipoisson family taken to be 1.871246)

    Null deviance: 3564.2  on 13524  degrees of freedom
Residual deviance: 3270.9  on 13510  degrees of freedom
AIC:  NA

Max Panel Size = 123; Number of panels = 182
Number of Fisher Scoring iterations: 15
```

Additional model diagnostics for the best fitting SALSA 2D model are displayed below (**Plate B21** and **Plate B22**). The first diagnostic plot compares observed versus fitted values (**Plate B21**). The second diagnostic plot shows the mean variance relationship comparing mean variance from the model with the assumed mean-variance relationship (**Plate B22**). This plot indicates a generally good fit; however, variance is underestimated for the larger fitted values.

Plate B21 Observed versus predicted values for the best fitting 2D smoothed model

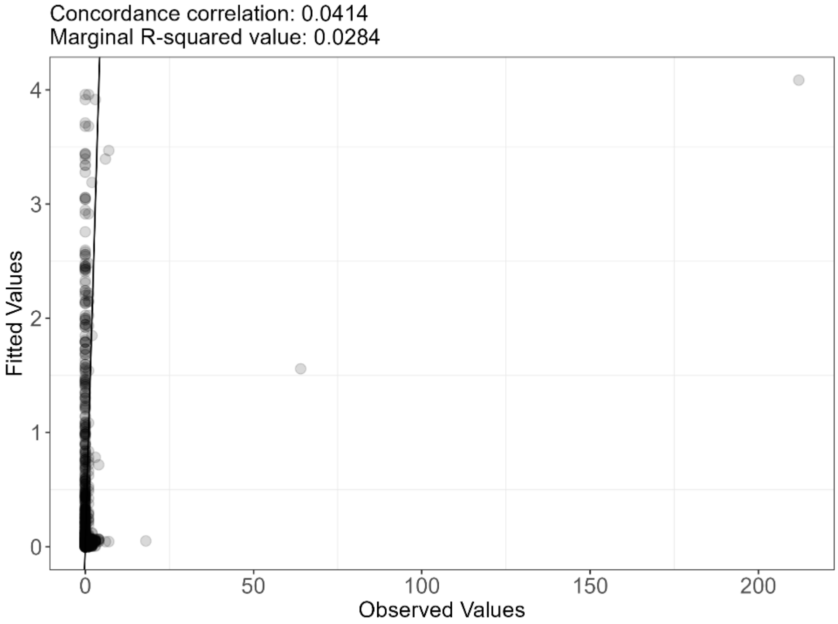
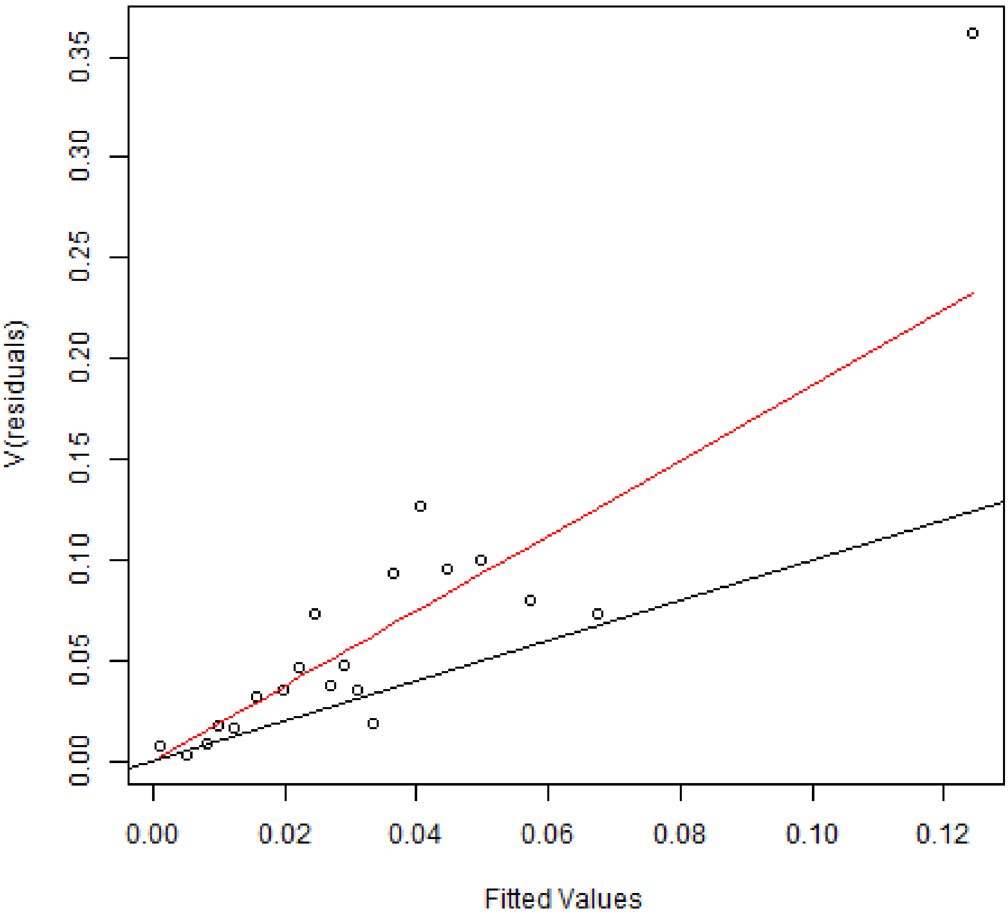


Plate B22 Mean-variance relationship plot. The red line shows the estimates mean variance relationship from the model and the black line represents what would be expected in a perfect Poisson distribution (variance = mean)



Kittiwake all behaviours

Initial set-up

The co-linearity of explanatory variables was initially assessed by observing GVIFs. Covariates were removed if strong collinearity was detected (GVIF value over 20). All adjusted GVIF values were below this threshold except for distance to coast (**Plate B23**) Despite using a non-linear approach to account for collinearity, distance to coast was excluded from the 1D and 2D smoothed models.

Plate B23 Code snippet detailing testing for co-linearity

```
> vif_out <- car::vif(test_model)
> vif_out
                      GVIF Df GVIF^(1/(2*Df))
Survey        6.943368e+06  4        7.164671
mean_depth    1.842132e+00  1        1.357252
mean_prey_pres 1.105342e+00  1        1.051353
dist_col      5.526249e+02  1       23.507975
dist_oilrig   2.718944e+00  1        1.648922
boat_presence 6.925423e+06  1     2631.619925
x.pos         2.230324e+02  1       14.934268
y.pos         2.652717e+02  1       16.287163
```

To fit the model, it was necessary for all levels of any categorical variables to have non-zero counts. Two categorical (factor) variables were considered, survey and boat presence (**Plate B24**).

Plate B24 Code snippet verifying non-zero counts for all factor levels

```
> checkfactorlevelcounts(factorlist = c("Survey", "boat_presence"),
+                        data = model_data,
+                        response = model_data$response)
[1] "Survey will be fitted as a factor variable; there are non-zero counts for all levels"
[1] "boat_presence will be fitted as a factor variable; there are non-zero counts for all levels"
```

Generalised Linear Model

Before creating more complex models, a simple GLM was developed and run as an initial model (**Plate B25**).

Plate B25 Code snippet summarising the initial GLM

```
> summary (test_model)

Call:
glm(formula = response ~ Survey + mean_depth + mean_prey_pres +
    dist_col + dist_oilrig + boat_presence + x.pos + y.pos +
    offset(log(area)), family = "quasipoisson", data = model_data)

Coefficients:
                         Estimate          Std. Error t value          Pr(>|t|)
(Intercept)         -1138.69210224        564.30472984  -2.018          0.043625 *
Survey2                 1.04224275          0.28793561   3.620          0.000296 ***
Survey11                0.39734478          0.32837701   1.210          0.226290
Survey12                1.76973798          0.26379074   6.709 0.0000000000204 ***
Survey13              -15.84365377        331.57368327  -0.048          0.961890
Survey14                1.15813695          0.27522540   4.208 0.0000259353213 ***
Survey15              -15.66140203        331.57367691  -0.047          0.962328
mean_depth             -0.02195649          0.01038695  -2.114          0.034546 *
mean_prey_pres -22934478.61240605   33949208.50198425  -0.676          0.499336
dist_col               -0.30412339          0.12628334  -2.408          0.016042 *
dist_oilrig             0.01044994          0.01205330   0.867          0.385970
boat_presence1         18.22247846        331.57359362   0.055          0.956173
x.pos                   0.00019211          0.00009692   1.982          0.047477 *
y.pos                   0.00016122          0.00007975   2.022          0.043226 *
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for quasipoisson family taken to be 1.424037)

    Null deviance: 3564.2  on 13524  degrees of freedom
Residual deviance: 2973.3  on 13511  degrees of freedom
AIC: NA

Number of Fisher Scoring iterations: 18
```

Residual correlation in the selected model was examined with an empirical Runs Test which indicated no significant residual correlation due to the insignificant p-value (**Plate B26**).

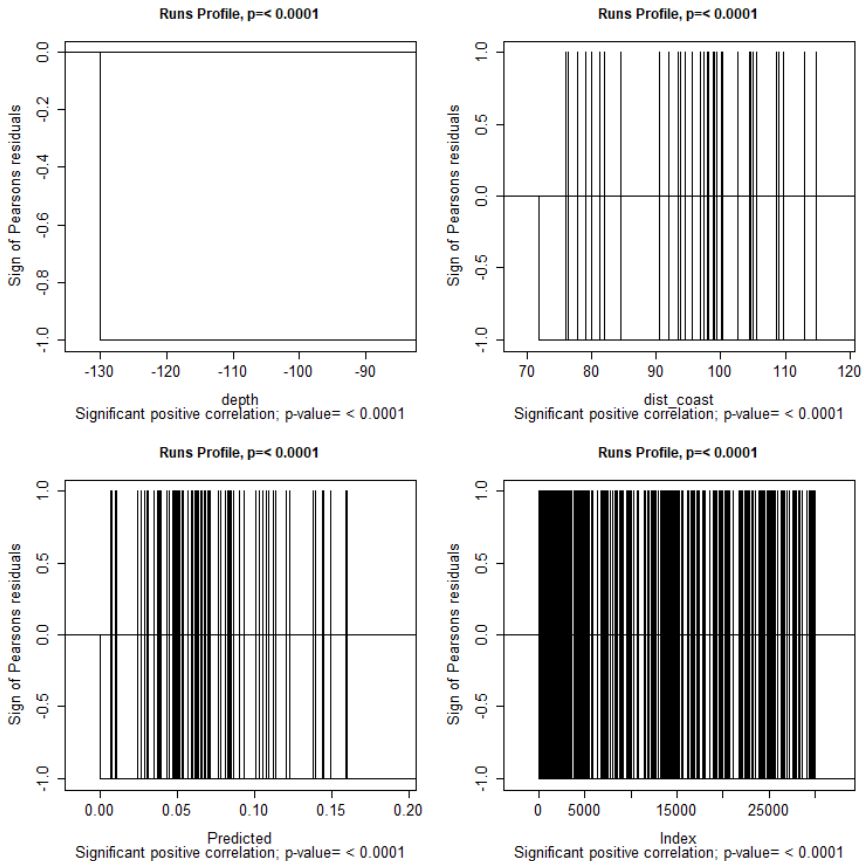
Plate B26 Code snippet highlighting the runs test results

```
    Runs Test - Two sided; Empirical Distribution

data:  residuals(best_model_salsa2dOutput, type = "pearson")
Standardized Runs Statistic = -130.66, p-value = 0.87
```

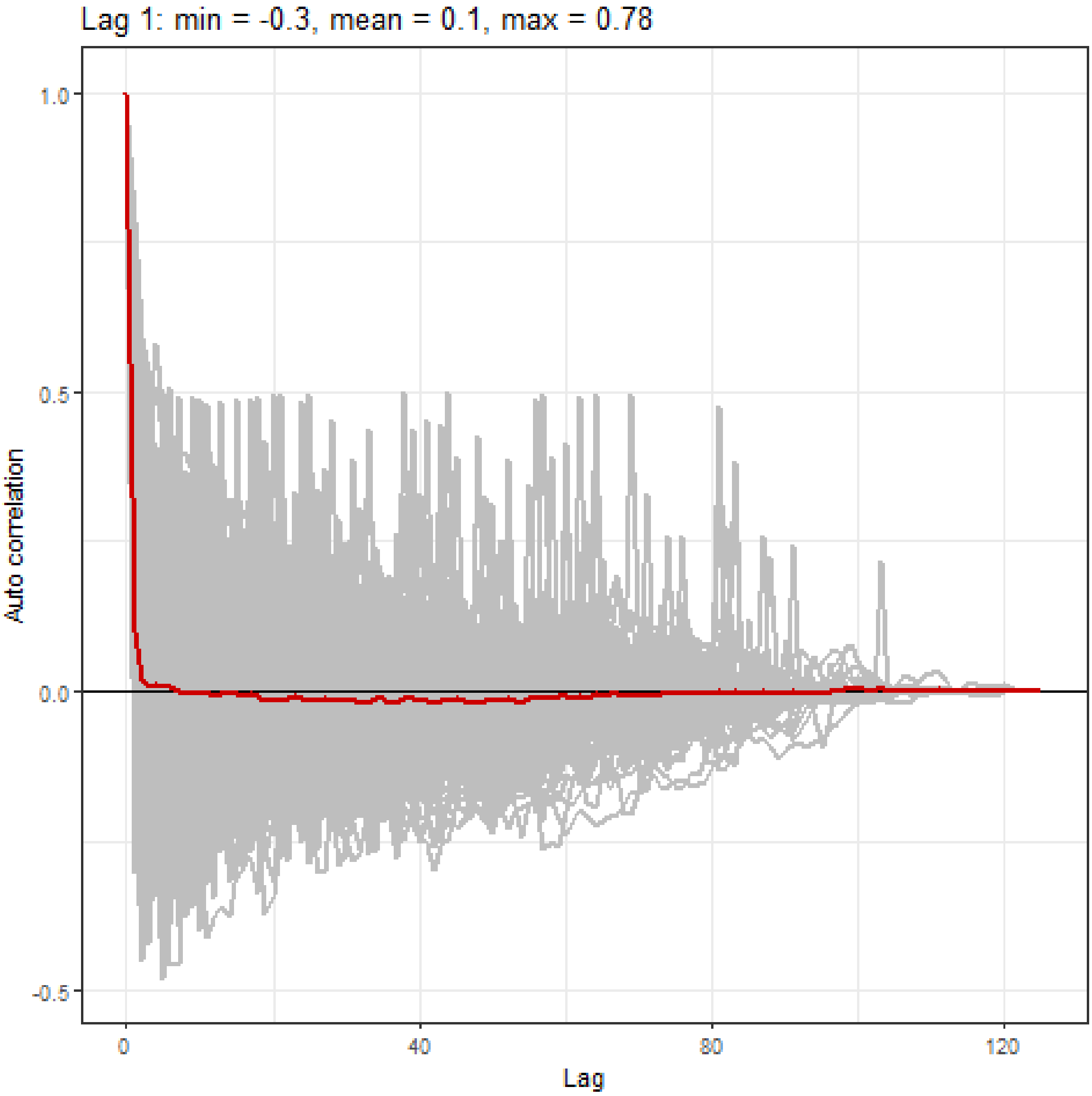
Non-randomness was observed in the runs profiles (**Plate B27**).

Plate B27 Runs profile for the initial GLM. Black lines display the sequence of positive and negative residuals. It is expected to see random distribution of lines in the absence of correlated residuals. Significance of correlation within each variable



Given the presence of correlation, it was deemed appropriate to incorporate a blocking structure moving forward (**Plate B27**). The blocking structure was based on the combination of Survey ID and Transect ID, allowing the model to treat data from each transect within a survey as correlated while assuming independence between different transects and surveys. An ACF plot was used to assess the effectiveness of the blocking structure (**Plate B28**). Both the mean correlation in residuals (red line) and correlation in residuals within each block (grey lines) quickly moved to zero, indicating that the blocking structure was fit for purpose.

Plate B28 ACF plot used for the initial GLM. The grey lines represent the correlation of residuals within each block, while the red line indicates the average correlation of the residuals



Cumulative residuals were plotted for explanatory variables (**Plate B29** and **Plate B30**). The black line represents the modelled cumulative residuals, while the grey line highlights the expected model fit. Systematic over- and under-prediction were evident for both depth and distance to oil rig, necessitating the use of a more complex, non-linear model.

Plate B29 Cumulative residuals for initial GLM structured by distance to oil rig. The black line shows the modelled cumulative residuals, while they grey line shows expected model fit

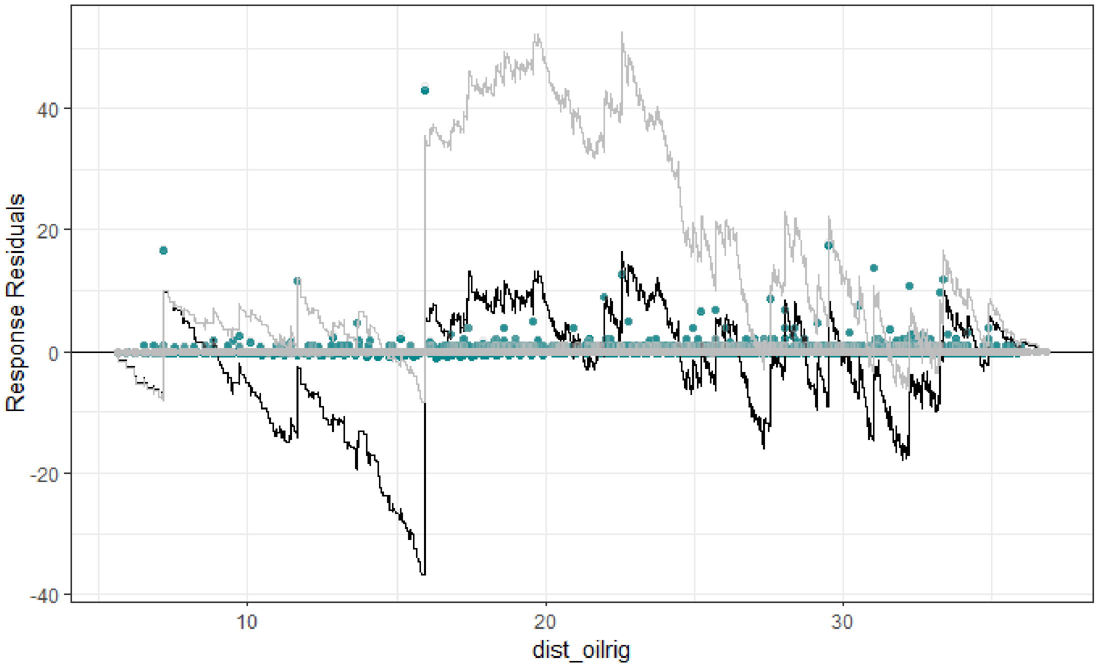
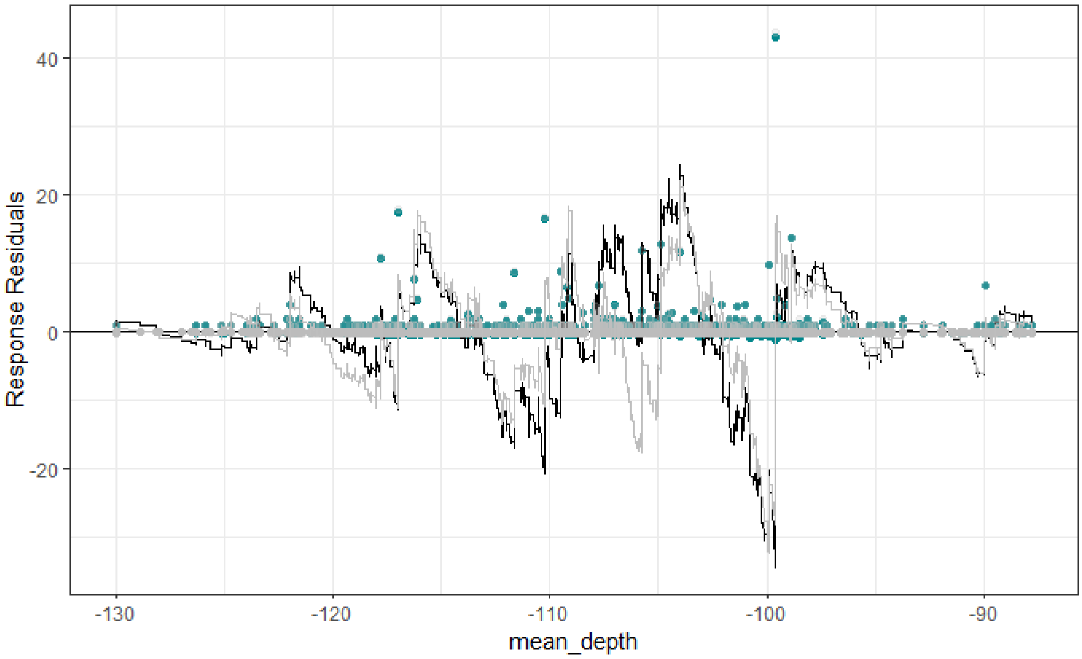


Plate B30 Cumulative residuals for initial GLM structured by depth. The black line shows the modelled cumulative residuals, while they grey line shows expected model fit



2D SALSA model diagnostics

The final model was selected according to having the lowest QBIC validation score and the summary can be seen in **Plate B31**. The SALSA 2D function is used to fit a CReSS model to the existing best fit 1D model, where the knot locations were allowed to vary by survey. Bird count served as the response variable, with x.pos and y.pos as spatial coordinates, and log(area) included as an offset. The model employed a quasi-Poisson error distribution with a log link.

Plate B31 Code snippet summarising the final model

```
Call:
gamMRSea(formula = round(response) ~ Survey + bs(mean_depth,
    knots = splineParams[[2]]$knots, degree = splineParams[[2]]$degree,
    Boundary.knots = splineParams[[2]]$bd) + LRF.g(radiusIndices,
    dists, radii, aR) + offset(log(area)), family = quasipoisson(link = log),
    data = model_data, splineParams = splineParams)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.4266  -0.1937  -0.1409  -0.1196  15.6877

Coefficients:
                Estimate Std. Error Robust S.E. t value     Pr(>|t|)
(Intercept)      -5.6928     1.4579      1.7005  -3.348     0.000816 ***
Survey2           3.3516     0.8744      1.2280   2.729     0.006353 **
Survey5           2.9480     0.8803      1.2335   2.390     0.016856 *
Survey9           1.9946     0.9290      1.2322   1.619     0.105498
Survey10          2.3095     0.9086      1.2324   1.874     0.060947 .
Survey11          1.1122     1.0292      1.3002   0.855     0.392314
Survey12          2.4459     0.9057      1.2320   1.985     0.047115 *
Survey14          3.2200     0.8807      1.2851   2.506     0.012226 *
Survey15          2.5193     0.8932      1.2338   2.042     0.041174 *
Survey17          1.9987     0.9237      1.2395   1.613     0.106850
Survey18          2.3240     0.9056      1.2338   1.884     0.059630 .
Survey19          2.1882     0.9055      1.2349   1.772     0.076416 .
Survey21          2.9154     0.8845      1.2251   2.380     0.017331 *
Survey22          5.1338     0.9576      1.3171   3.898 0.0000972521 ***
Survey23          1.8815     0.9426      1.2535   1.501     0.133359
Survey24          2.0286     0.9353      1.2399   1.636     0.101821
s(mean_depth)1    1.0479     1.5181      1.6205   0.647     0.517875
s(mean_depth)2    0.6196     1.1966      1.1713   0.529     0.596817
s(mean_depth)3    0.9021     1.2370      1.2596   0.716     0.473888
s(mean_depth)4    1.1316     1.2154      1.2532   0.903     0.366552
s(mean_depth)5    1.0689     1.2343      1.2631   0.846     0.397411
s(mean_depth)6    0.5382     1.3315      1.3699   0.393     0.694448
s(mean_depth)7    1.8524     1.3552      1.3140   1.410     0.158635
s(x,y)b1         39.2371     6.1511      9.3783   4.184 0.0000287442 ***
s(x,y)b2          4.9330     1.0840      1.3995   3.525     0.000425 ***
s(x,y)b3          4.8859     0.7982      0.9995   4.888 0.0000010225 ***
s(x,y)b4          2.7522     0.3632      0.9041   3.044     0.002335 **
s(x,y)b5        734.6629   105.8283    187.7935   3.912 0.0000917035 ***
s(x,y)b6        584.9660    81.8988    162.1439   3.608     0.000309 ***
s(x,y)b7       -850.1399   121.4930    218.7400  -3.887     0.000102 ***
s(x,y)b8          3.1372     0.3485      0.5706   5.498 0.0000000387 ***
s(x,y)b9       -296.6328    44.0848     88.2713  -3.360     0.000779 ***
```

```
s(x,y)b10        -3.1641     0.8311      0.8358  -3.786     0.000153 ***
s(x,y)b11        -9.9210     3.3724      3.8578  -2.572     0.010125 *
s(x,y)b12       674.9217    99.2279    215.0771   3.138     0.001702 **
s(x,y)b13      -886.0925   126.4024    268.0528  -3.306     0.000949 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for quasipoisson family taken to be 1.778632)

    Null deviance: 7053.2  on 30505  degrees of freedom
Residual deviance: 5634.3  on 30470  degrees of freedom
AIC:  NA

Max Panel Size = 126; Number of panels = 416
Number of Fisher Scoring iterations: 8
```

Additional model diagnostics for the best fitting SALSA 2D model are displayed below (**Plate B32** and **Plate B33**). The first diagnostic plot compares observed versus fitted values (**Plate B32**). This plot indicates the model fit is adequate, and no substantial residual pattern is apparent, however relatively little of the observed variability is explained by the selected model. The second diagnostic plot shows the mean variance relationship comparing mean variance from the model with the assumed mean-variance relationship (**Plate B33**). This plot indicates a generally good fit; however, variance is underestimated for the larger fitted values.

Plate B32 Observed versus predicted values for the best fitting 2D smoothed model

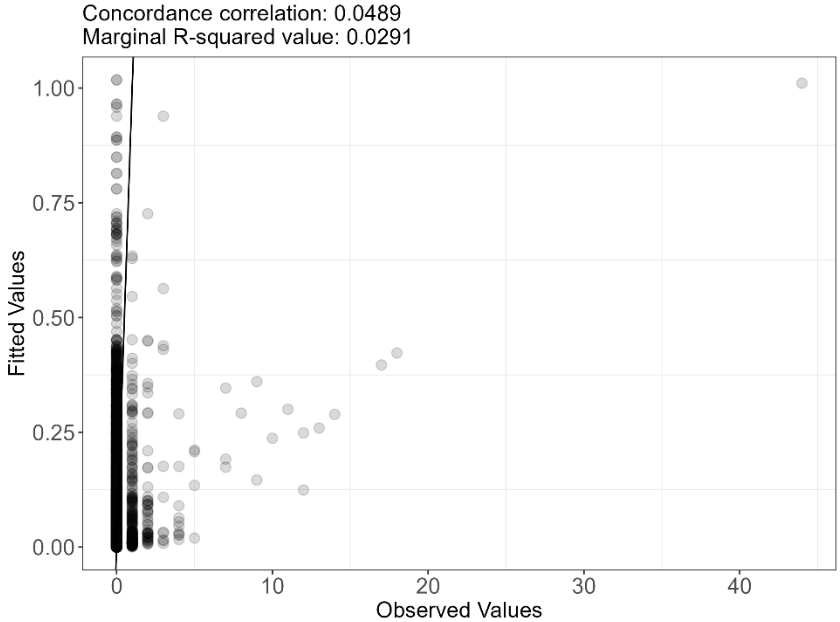
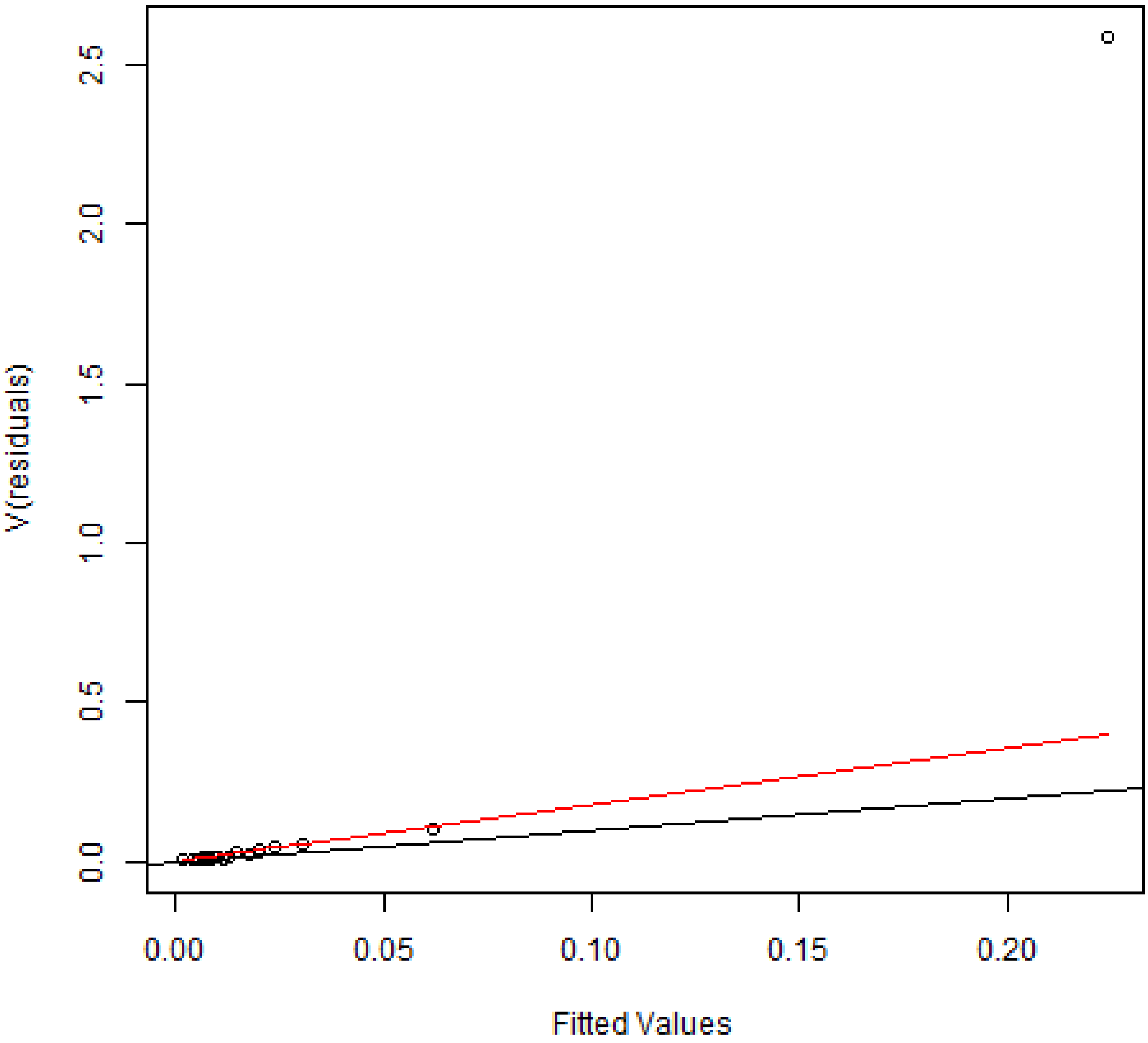


Plate B33 Mean-variance relationship plot. The red line shows the estimates mean variance relationship from the model and the black line represents what would be expected in a perfect Poisson distribution (variance = mean)



Kittiwake flying

Initial set-up

The co-linearity of explanatory variables was initially assessed by observing GVIFs. Covariates were removed if strong collinearity was detected (GVIF value over 20). All adjusted GVIF values were below this threshold except for distance to coast (**Plate B34**). Despite using a non-linear approach to account for collinearity, distance to coast was excluded from the 1D and 2D smoothed models.

Plate B34 Code snippet detailing testing for co-linearity

```
> vif_out <- car::vif(test_model)
> vif_out
                        GVIF Df GVIF^(1/(2*Df))
survey         3612788.369216 12        1.876046
mean_depth           1.966804  1        1.402428
mean_prey_dens       1.092756  1        1.045350
dist_coast         698.282554  1       26.425037
dist_oilrig          2.123237  1        1.457133
boat_presence  3595578.295769  1     1896.201017
x.pos              257.793273  1       16.055942
y.pos              391.465294  1       19.785482
```

To fit the model, it was necessary for all levels of any categorical variables to have non-zero counts. Two categorical (factor) variables were considered, survey and boat presence (**Plate B35**).

Plate B35 Code snippet verifying non-zero counts for all factor levels

```
> checkfactorlevelcounts(factorlist = c("survey"),
+                        data = model_data,
+                        response = model_data$response)
[1] "survey will be fitted as a factor variable; there are non-zero counts for all levels"
```

Generalised Linear Model

Before creating more complex models, a simple GLM was developed and run as an initial model (**Plate B36**).

Plate B36 Code snippet summarising the initial GLM

```
> summary (test_model)

Call:
glm(formula = response ~ Survey + mean_depth + mean_prey_pres +
    dist_col + dist_oilrig + boat_presence + x.pos + y.pos +
    offset(log(area)), family = "quasipoisson", data = model_data)

Coefficients:
                        Estimate         Std. Error t value         Pr(>|t|)
(Intercept)          -1138.69210224       564.30472984  -2.018         0.043625 *
Survey2                  1.04224275         0.28793561   3.620         0.000296 ***
Survey11                 0.39734478         0.32837701   1.210         0.226290
Survey12                 1.76973798         0.26379074   6.709 0.0000000000204 ***
Survey13               -15.84365377       331.57368327  -0.048         0.961890
Survey14                 1.15813695         0.27522540   4.208 0.0000259353213 ***
Survey15               -15.66140203       331.57367691  -0.047         0.962328
mean_depth              -0.02195649         0.01038695  -2.114         0.034546 *
mean_prey_pres -22934478.61240605   33949208.50198425  -0.676         0.499336
dist_col                -0.30412339         0.12628334  -2.408         0.016042 *
dist_oilrig              0.01044994         0.01205330   0.867         0.385970
boat_presence1          18.22247846       331.57359362   0.055         0.956173
x.pos                    0.00019211         0.00009692   1.982         0.047477 *
y.pos                    0.00016122         0.00007975   2.022         0.043226 *
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for quasipoisson family taken to be 1.424037)

    Null deviance: 3564.2  on 13524  degrees of freedom
Residual deviance: 2973.3  on 13511  degrees of freedom
AIC: NA

Number of Fisher Scoring iterations: 18
```

Residual correlation in the selected model was examined with an empirical Runs Test which indicated no significant residual correlation due to the insignificant p-value (**Plate B37**).

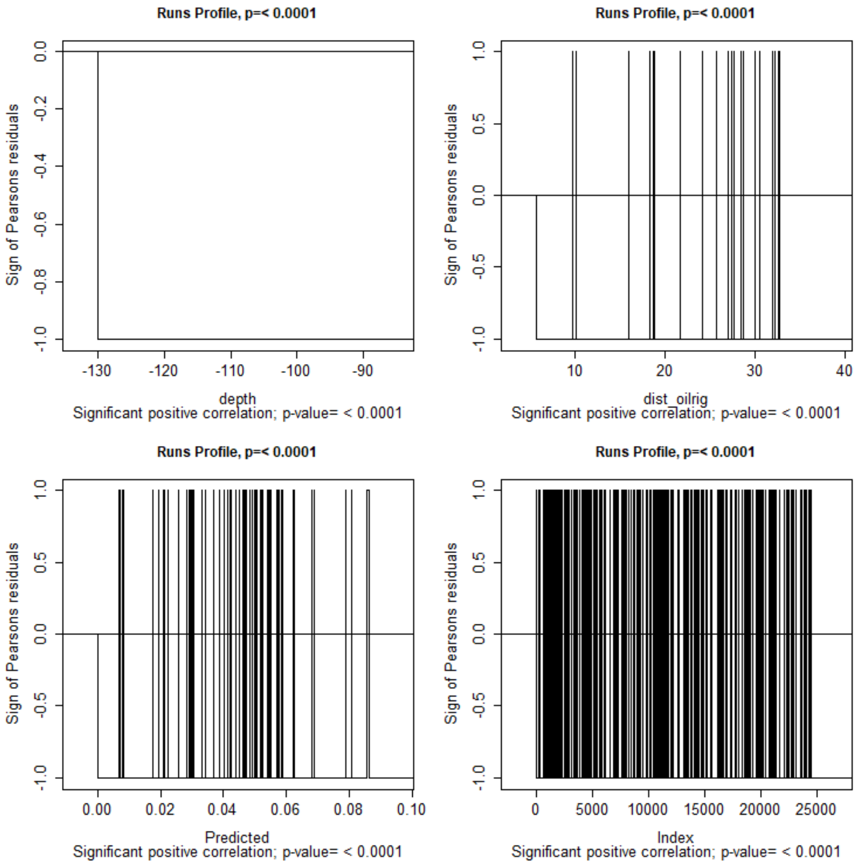
Plate B37 Code snippet highlighting the runs test results

```
	Runs Test - Two sided; Empirical Distribution

data:  residuals(best_model_salsa2dOutput, type = "pearson")
Standardized Runs Statistic = -118.83, p-value = 0.7
```

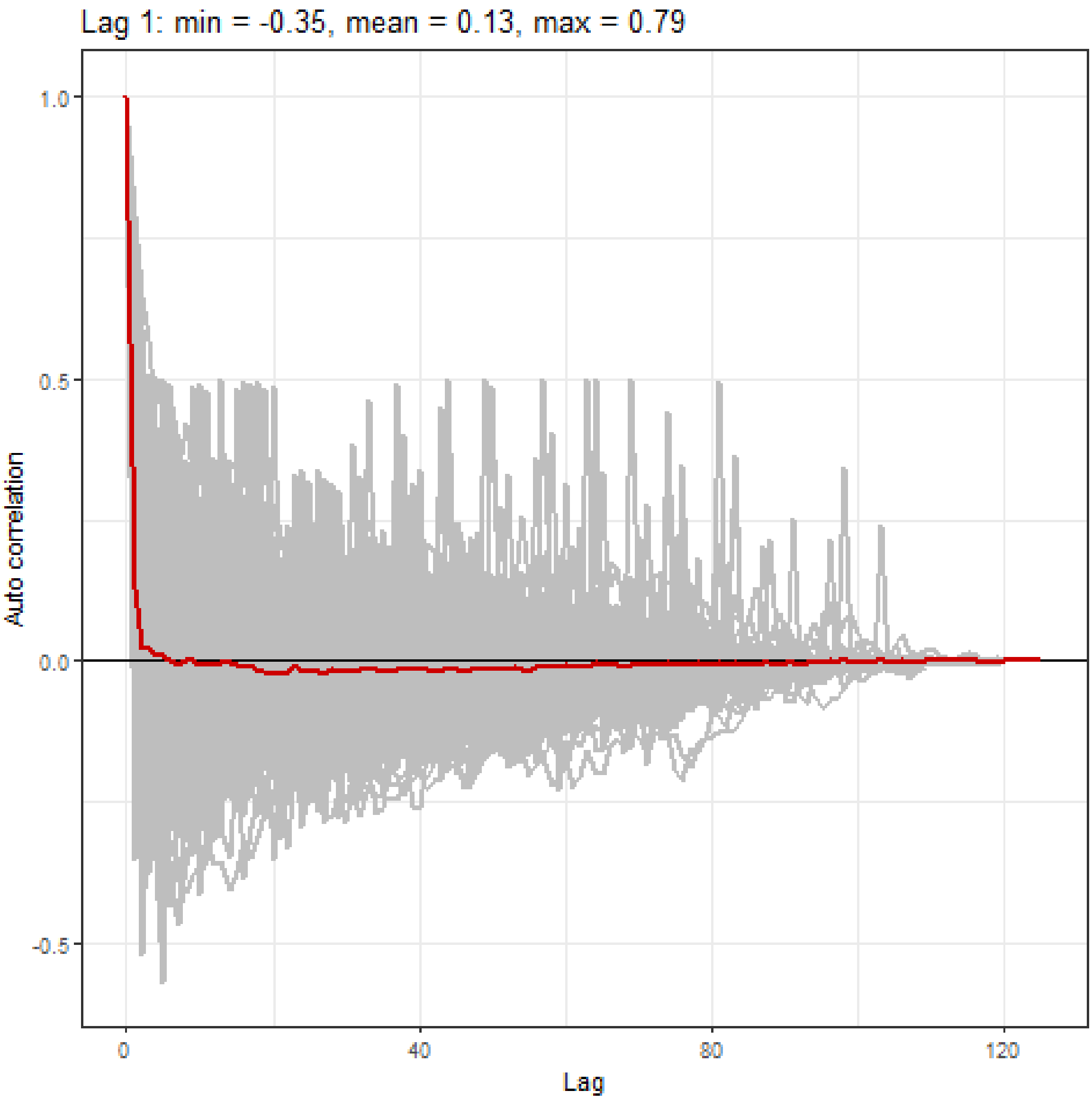
Non-randomness was observed in the runs profiles (**Plate B38**).

Plate B38 Runs profile for the initial GLM. Black lines display the sequence of positive and negative residuals. It is expected to see random distribution of lines in the absence of correlated residuals. Significance of correlation within each variable



Given the presence of correlation, it was deemed appropriate to incorporate a blocking structure moving forward (**Plate B38**). The blocking structure was based on the combination of Survey ID and Transect ID, allowing the model to treat data from each transect within a survey as correlated while assuming independence between different transects and surveys. An ACF plot was used to assess the effectiveness of the blocking structure (**Plate B39**). Both the mean correlation in residuals (red line) and correlation in residuals within each block (grey lines) quickly moved to zero, indicating that the blocking structure was fit for purpose.

Plate B39 ACF plot used for the initial GLM. The grey lines represent the correlation of residuals within each block, while the red line indicates the average correlation of the residuals



Cumulative residuals were plotted for explanatory variables (**Plate B40** and **Plate B41**). The black line represents the modelled cumulative residuals, while the grey line highlights the expected model fit. Systematic over- and under-prediction were evident for both depth and distance to oil rig, necessitating the use of a more complex, non-linear model.

Plate B40 Cumulative residuals for initial GLM structured by distance to oil rig. The black line shows the modelled cumulative residuals, while they grey line shows expected model fit

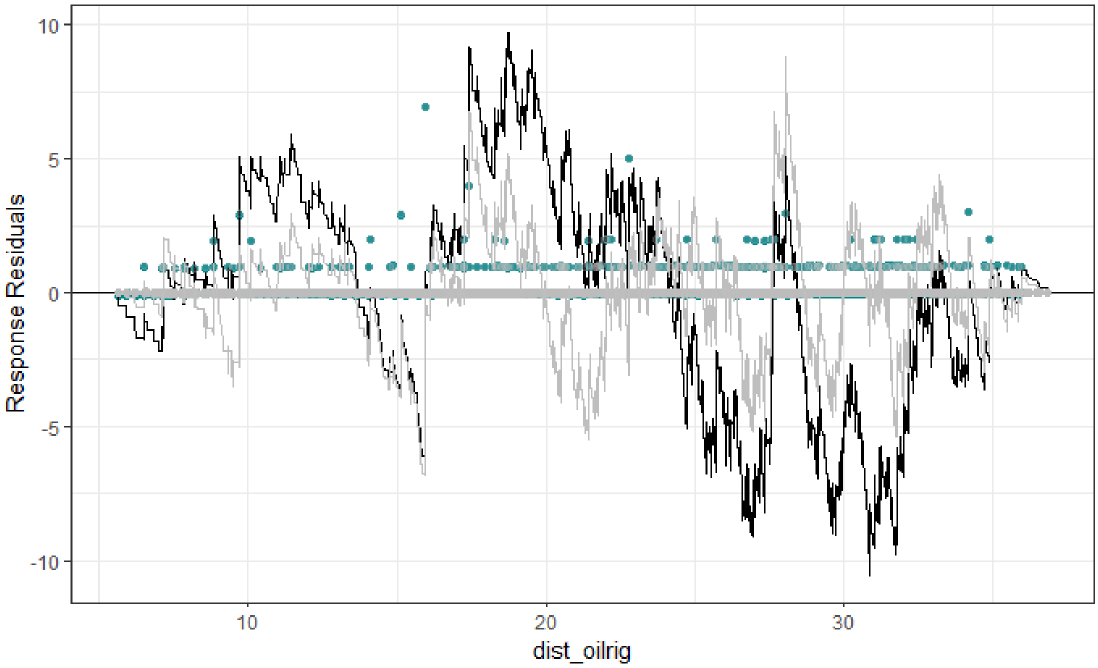
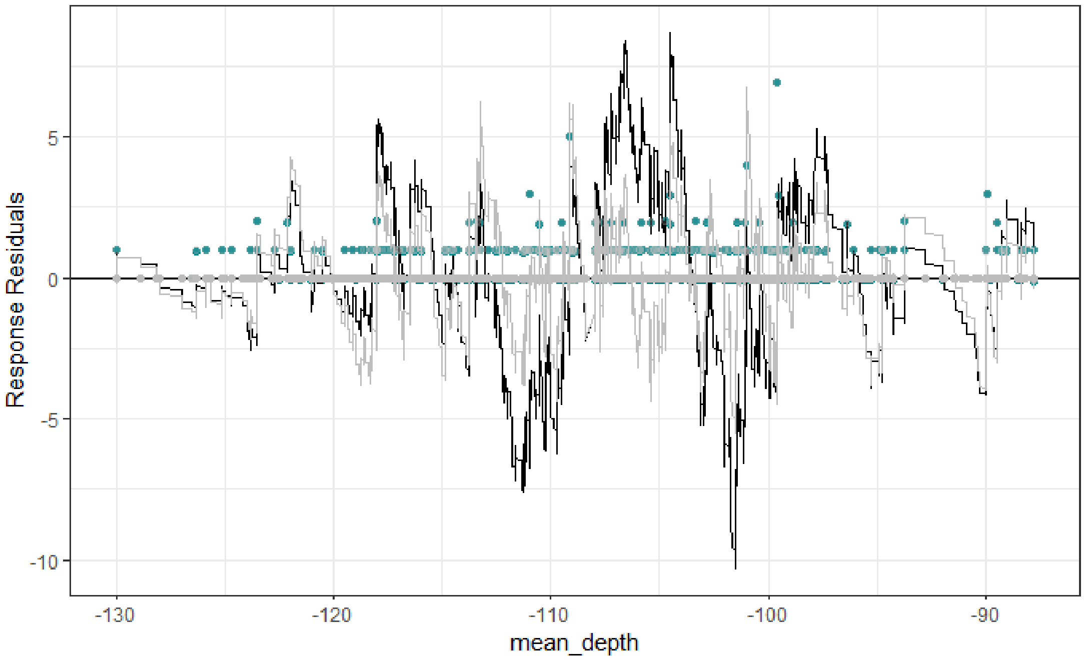


Plate B41 Cumulative residuals for initial GLM structured by depth. The black line shows the modelled cumulative residuals, while they grey line shows expected model fit



2D SALSA model diagnostics

The final model was selected according to having the lowest QBIC validation score and the summary can be seen in **Plate B42**. The SALSA 2D function is used to fit a CReSS model to the existing best fit 1D model, where the knot locations were allowed to vary by survey. Bird count served as the response variable, with x.pos and y.pos as spatial coordinates, and log(area) included as an offset. The model employed a quasi-Poisson error distribution with a log link.

Plate B42 Code snippet summarising the final model

```
Call:
gamMRSea(formula = round(response) ~ Survey + bs(mean_depth,
    knots = splineParams[[2]]$knots, degree = splineParams[[2]]$degree,
    Boundary.knots = splineParams[[2]]$bd) + dist_oilrig + LRF.g(radiusIndices,
    dists, radii, aR) + offset(log(area)), family = quasipoisson(link = log),
    data = model_data, splineParams = splineParams)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-0.5382  -0.1804  -0.1397  -0.1189   6.9440

Coefficients:
                Estimate Std. Error Robust S.E. t value       Pr(>|t|)
(Intercept)    -1.196855   1.412356    1.727203  -0.693       0.488351
Survey2        -1.554542   0.309994    0.468942  -3.315       0.000918 ***
Survey5        -1.881548   0.319695    0.464103  -4.054 0.000050468061 ***
Survey10       -2.813261   0.408454    0.454577  -6.189 0.000000000616 ***
Survey12       -2.441499   0.376241    0.470658  -5.187 0.000000214900 ***
Survey14       -4.236683   0.862552    0.792447  -5.346 0.000000090544 ***
Survey15       -2.522202   0.364940    0.467888  -5.391 0.000000070855 ***
Survey18       -2.394409   0.359474    0.466294  -5.135 0.000000284297 ***
Survey19       -2.581049   0.365132    0.467503  -5.521 0.000000034057 ***
Survey21       -2.046294   0.337632    0.433553  -4.720 0.000002373271 ***
Survey22        3.182020   1.137327    1.449546   2.195       0.028160 *
Survey23       -2.834612   0.419773    0.505863  -5.604 0.000000021225 ***
Survey24       -2.772611   0.420113    0.486765  -5.696 0.000000012403 ***
s(mean_depth)1  1.309729   1.742227    2.147695   0.610       0.541980
s(mean_depth)2  0.705950   1.366725    1.602154   0.441       0.659488
s(mean_depth)3  1.718775   1.413879    1.694847   1.014       0.310536
s(mean_depth)4  1.285196   1.387991    1.653144   0.777       0.436915
s(mean_depth)5  1.664312   1.406551    1.695361   0.982       0.326264
s(mean_depth)6  0.946968   1.489104    1.734493   0.546       0.585096
s(mean_depth)7  2.109836   1.499022    1.733922   1.217       0.223692
s(dist_oilrig) -0.007804   0.009228    0.010500  -0.743       0.457350
s(x,y)b1       -2.320025   0.524402    0.697893  -3.324       0.000888 ***
s(x,y)b2        3.689155   0.952127    0.777236   4.747 0.000002081081 ***
s(x,y)b3       -7.675208   1.763355    2.069078  -3.709       0.000208 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for quasipoisson family taken to be 1.221641)

    Null deviance: 3250.4  on 25010  degrees of freedom
Residual deviance: 3027.0  on 24987  degrees of freedom
AIC:  NA

Max Panel Size = 126; Number of panels = 338
Number of Fisher Scoring iterations: 7
```

Additional model diagnostics for the best fitting SALSA 2D model are displayed below (**Plate B43** and **Plate B44**). The first diagnostic plot compares observed versus fitted values (**Plate B43**). This plot indicates the model fit is adequate, and no substantial residual pattern is apparent, however relatively little of the observed variability is explained by the selected model. The second diagnostic plot shows the mean variance relationship comparing mean variance from the model with the assumed mean-variance relationship (**Plate B44**). This plot indicates a generally good fit; however, variance is underestimated for the larger fitted values.

Plate B43 Observed versus predicted values for the best fitting 2D smoothed model

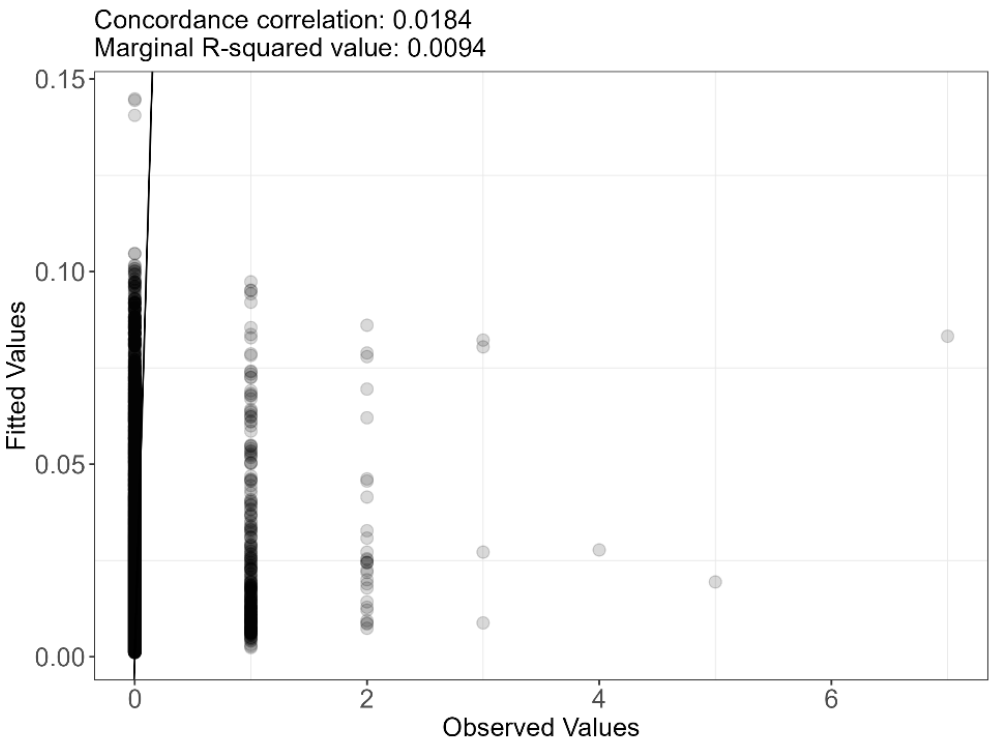
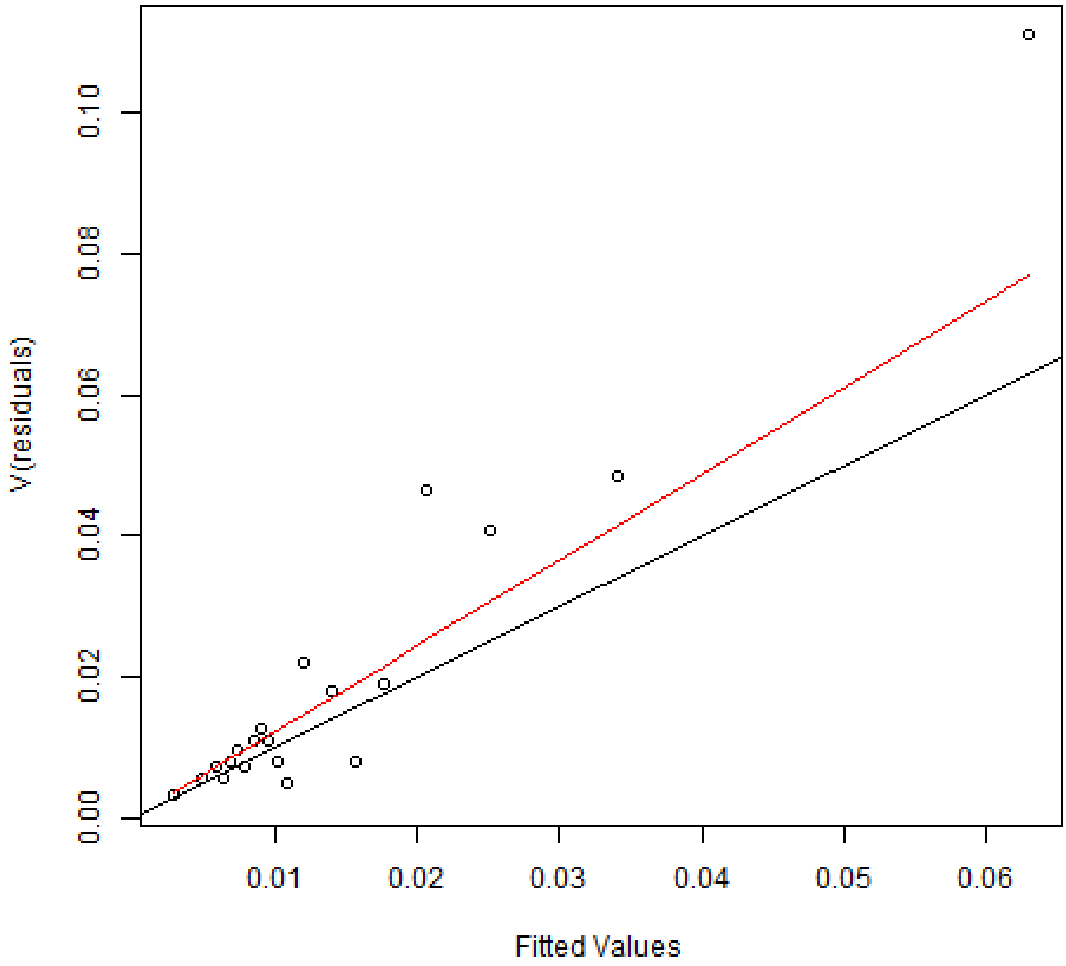


Plate B44 Mean-variance relationship plot. The red line shows the estimates mean variance relationship from the model and the black line represents what would be expected in a perfect Poisson distribution (variance = mean)



Gannet all behaviours

Initial set-up

The co-linearity of explanatory variables was initially assessed by observing GVIFs. Covariates were removed if strong collinearity was detected (GVIF value over 20). All adjusted GVIF values were below this threshold except for distance to coast (**Plate B45**). Despite using a non-linear approach to account for collinearity, distance to coast was excluded from the 1D and 2D smoothed models.

Plate B45 Code snippet detailing testing for co-linearity

```
> vif_out <- car::vif(test_model)
> vif_out
                      GVIF Df GVIF^(1/(2*Df))
survey        6.943368e+06  4        7.164671
mean_depth    1.842132e+00  1        1.357252
mean_prey_pres 1.105342e+00  1        1.051353
dist_col      5.526249e+02  1       23.507975
dist_oilrig   2.718944e+00  1        1.648922
boat_presence 6.925423e+06  1     2631.619925
x.pos         2.230324e+02  1       14.934268
y.pos         2.652717e+02  1       16.287163
```

To fit the model, it was necessary for all levels of any categorical variables to have non-zero counts. Two categorical (factor) variables were considered, survey and boat presence (**Plate B46**).

Plate B46 Code snippet verifying non-zero counts for all factor levels

```
> checkfactorlevelcounts(factorlist = c("Survey", "boat_presence"),
+                        data = model_data,
+                        response = model_data$response)
[1] "Survey will be fitted as a factor variable; there are non-zero counts for all levels"
[1] "boat_presence will be fitted as a factor variable; there are non-zero counts for all levels"
```

Generalised Linear Model

Before creating more complex models, a simple GLM was developed and run as an initial model (**Plate B47**).

Plate B47 Code snippet summarising the initial GLM

```
> summary(test_model)

Call:
glm(formula = response ~ Survey + mean_depth + mean_prey_dens +
    dist_col + dist_oilrig + boat_presence + x.pos + y.pos +
    offset(log(area)), family = "quasipoisson", data = model_data)

Coefficients:
                       Estimate        Std. Error  t value             Pr(>|t|)
(Intercept)       1112.68580485      569.53688996    1.954              0.05075 .
Survey2             -0.56210700        0.39812366   -1.412              0.15799
Survey3             -0.26145794        0.36627810   -0.714              0.47534
Survey4             -1.42577062        0.51461851   -2.771              0.00560 **
Survey5            -15.55509456      365.49804553   -0.043              0.96605
Survey6              0.34971458        0.29059335    1.203              0.22881
Survey10            -2.00474879        0.69473804   -2.886              0.00391 **
Survey11             0.12847810        0.32257726    0.398              0.69042
Survey12             0.16003423        0.31858885    0.502              0.61545
Survey13           -17.97297730      365.49828077   -0.049              0.96078
Survey14            -1.42005837        0.51467426   -2.759              0.00580 **
Survey15           -17.82715611      365.49821194   -0.049              0.96110
Survey16             0.18318849        0.31307943    0.585              0.55847
Survey24            -1.71665291        0.64467414   -2.663              0.00775 **
mean_depth           0.08965299        0.01151967    7.783 0.0000000000000736 ***
mean_prey_dens -1182475.33050710  1318272.67914485   -0.897              0.36973
dist_col             0.30505093        0.12480646    2.444              0.01452 *
dist_oilrig         -0.04618782        0.01465505   -3.152              0.00163 **
boat_presence1      18.14064722      365.49799412    0.050              0.96042
x.pos               -0.00020239        0.00009630   -2.102              0.03560 *
y.pos               -0.00015544        0.00008063   -1.928              0.05388 .
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for quasipoisson family taken to be 4.791669)

    Null deviance: 10222  on 26472  degrees of freedom
Residual deviance:  7973  on 26452  degrees of freedom
AIC: NA

Number of Fisher Scoring iterations: 18
```

Residual correlation in the selected model was examined with an empirical Runs Test which indicated no significant residual correlation due to the insignificant p-value (**Plate B48**).

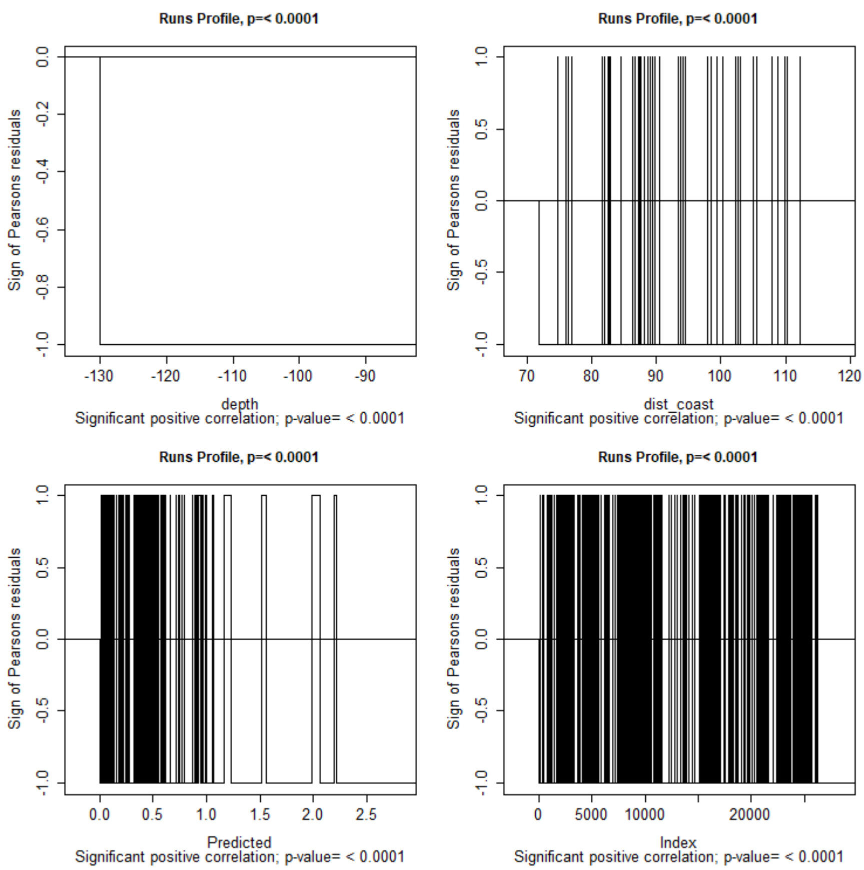
Plate B48 Code snippet highlighting the runs test results

```
    Runs Test - Two sided; Empirical Distribution

data:  residuals(best_model_salsa2dOutput, type = "pearson")
Standardized Runs Statistic = -139.19, p-value = 0.29
```

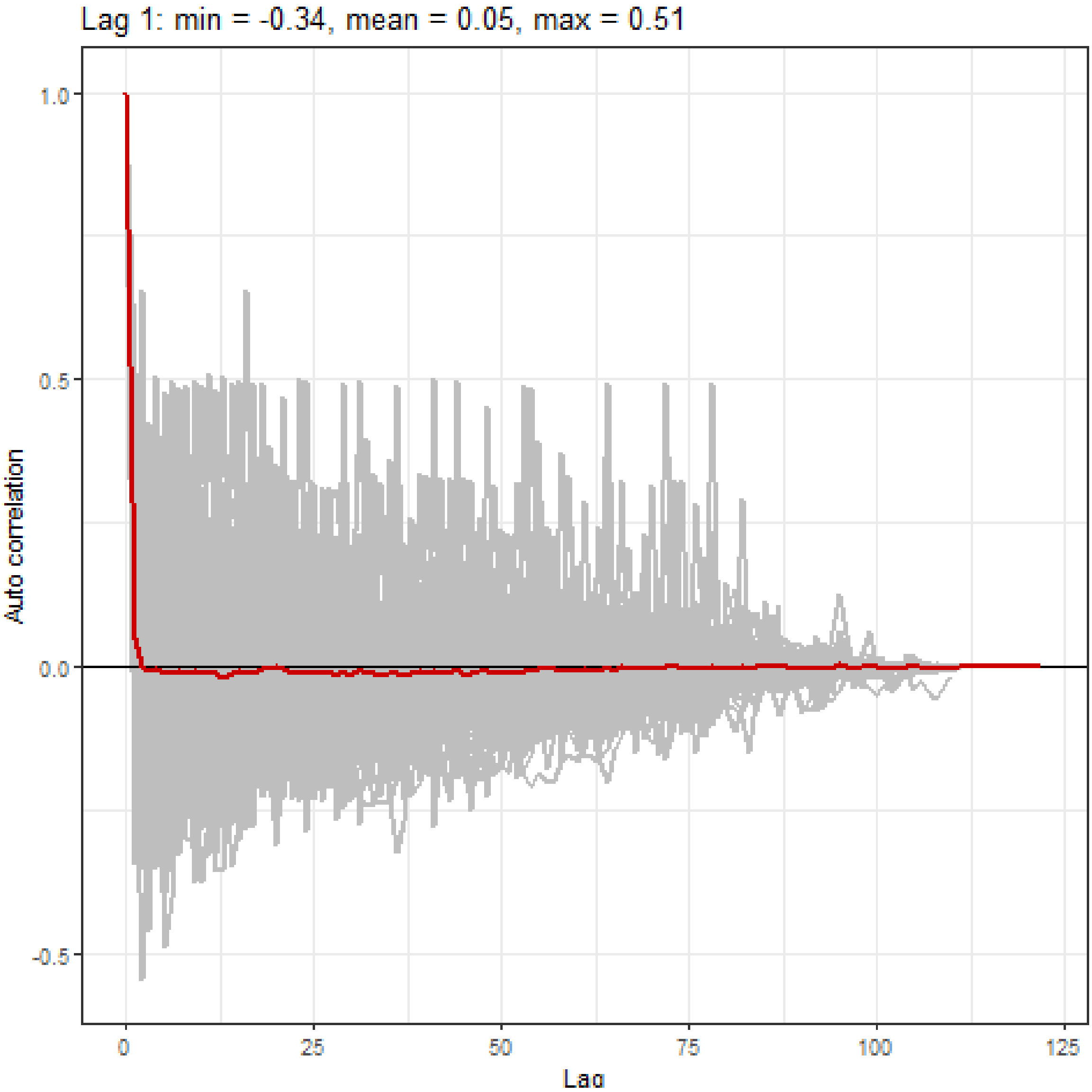
Non-randomness was observed in the runs profiles (**Plate B49**).

Plate B49 Runs profile for the initial GLM. Black lines display the sequence of positive and negative residuals. It is expected to see random distribution of lines in the absence of correlated residuals. Significance of correlation within each variable



Given the presence of correlation, it was deemed appropriate to incorporate a blocking structure moving forward (**Plate B49**). The blocking structure was based on the combination of Survey ID and Transect ID, allowing the model to treat data from each transect within a survey as correlated while assuming independence between different transects and surveys. An ACF plot was used to assess the effectiveness of the blocking structure (**Plate B50**). Both the mean correlation in residuals (red line) and correlation in residuals within each block (grey lines) quickly moved to zero, indicating that the blocking structure was fit for purpose.

Plate B50 ACF plot used for the initial GLM. The grey lines represent the correlation of residuals within each block, while the red line indicates the average correlation of the residuals



Cumulative residuals were plotted for explanatory variables (**Plate B51** and **Plate B52**).

Plate B51 Cumulative residuals for initial GLM structured by distance to oil rig. The black line shows the modelled cumulative residuals, while they grey line shows expected model fit

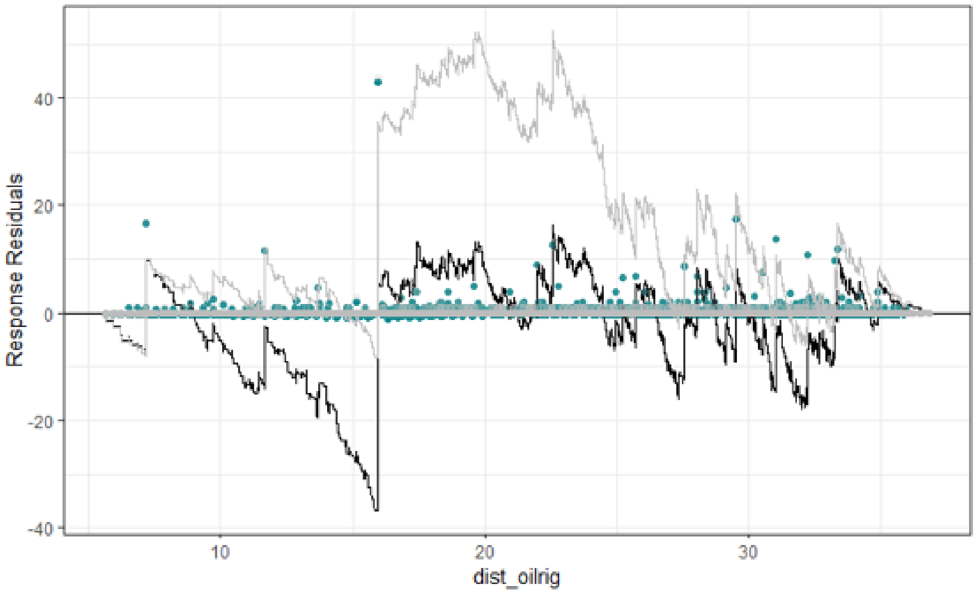
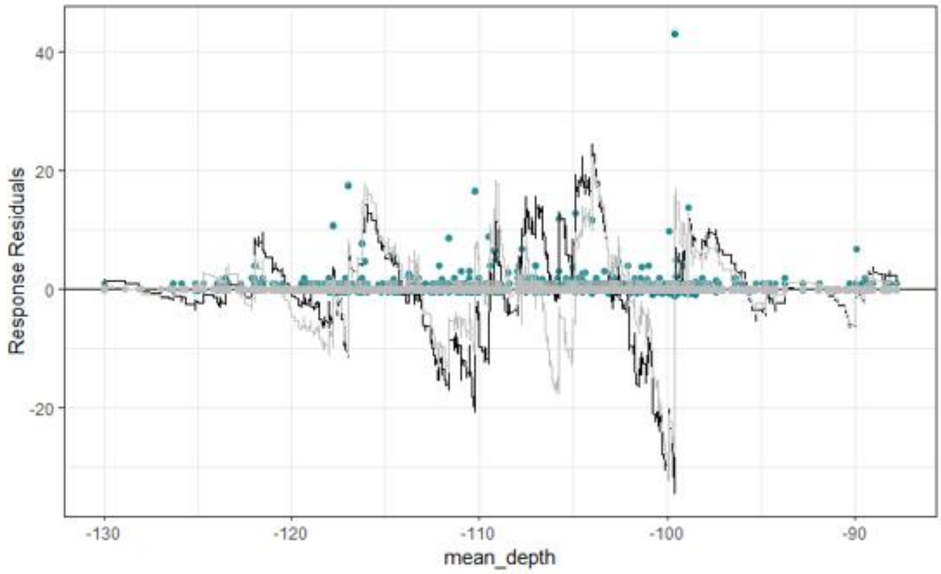


Plate B52 Cumulative residuals for initial GLM structured by depth. The black line shows the modelled cumulative residuals, while they grey line shows expected model fit



2D SALSA model diagnostics

The final model was selected according to having the lowest QBIC validation score and the summary can be seen in **Plate B53**. The SALSA 2D function is used to fit a CReSS model to the existing best fit 1D model, where the knot locations were allowed to vary by survey. Bird count served as the response variable, with x.pos and y.pos as spatial coordinates, and log(area) included as an offset. The model employed a quasi-Poisson error distribution with a log link.

Plate B53 Code snippet summarising the final model

```
Call:
gamMRSea(formula = round(response) ~ Survey + LRF.g(radiusIndices,
    dists, radii, aR) + offset(log(area)), family = quasipoisson(link = log),
    data = model_data, splineParams = splineParams)

Deviance Residuals:
   Min       1Q   Median       3Q      Max
-2.814  -0.303  -0.182  -0.143  35.477

Coefficients:
                                         Estimate Std. Error Robust S.E. t value  Pr(>|t|)
(Intercept)                               -0.8693     0.1594      0.3901  -2.229  0.025854 *
Survey2                                   -0.5834     0.2926      0.4136  -1.411  0.158375
Survey3                                   -0.2890     0.2692      0.4170  -0.693  0.488311
Survey4                                   -1.4424     0.3783      0.4493  -3.211  0.001326 **
Survey5                                    2.6924     0.5321      1.5837   1.700  0.089118 .
Survey6                                    0.3415     0.2136      0.4154   0.822  0.410999
Survey10                                  -2.0291     0.5108      0.5972  -3.398  0.000681 ***
Survey11                                  -2.1589     0.5098      0.7455  -2.896  0.003784 **
Survey12                                   0.1367     0.2342      0.4058   0.337  0.736221
Survey13                                  -1.2639     0.3592      0.4457  -2.836  0.004573 **
Survey14                                  -1.4603     0.3783      0.4385  -3.330  0.000869 ***
Survey15                                  -0.9907     0.3153      0.4462  -2.220  0.026415 *
Survey16                                   0.1716     0.2301      0.4711   0.364  0.715616
Survey24                                  -1.7380     0.4740      0.4761  -3.650  0.000263 ***
LRF.g(radiusIndices, dists, radii, aR)b1 -33.2293     3.5545     18.0806  -1.838  0.066097 .
LRF.g(radiusIndices, dists, radii, aR)b2 173.1149    17.8388     95.1251   1.820  0.068791 .
LRF.g(radiusIndices, dists, radii, aR)b3   6.1414     0.5986      1.4793   4.152 0.0000331 ***
LRF.g(radiusIndices, dists, radii, aR)b4 -84.2976     9.0250     47.3997  -1.778  0.075343 .
LRF.g(radiusIndices, dists, radii, aR)b5 -71.0515     7.4977     39.8825  -1.782  0.074838 .
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for quasipoisson family taken to be 2.590312)

    Null deviance: 10222  on 26472  degrees of freedom
Residual deviance:  7690  on 26454  degrees of freedom
AIC:  NA

Max Panel Size = 123; Number of panels = 364
Number of Fisher Scoring iterations: 8
```

Additional model diagnostics for the best fitting SALSA 2D model are displayed below (**Plate B54** and **Plate B55**). The first diagnostic plot compares observed versus fitted values (**Plate B54**). This plot indicates the model fit is adequate, and no substantial residual pattern is apparent, however relatively little of the observed variability is explained by the selected model. The second diagnostic plot shows the mean variance relationship comparing mean variance from the model with the

assumed mean-variance relationship (**Plate B55**). This plot indicates a generally good fit; however, variance is underestimated for the larger fitted values.

Plate B54 Observed versus predicted values for the best fitting 2D smoothed model

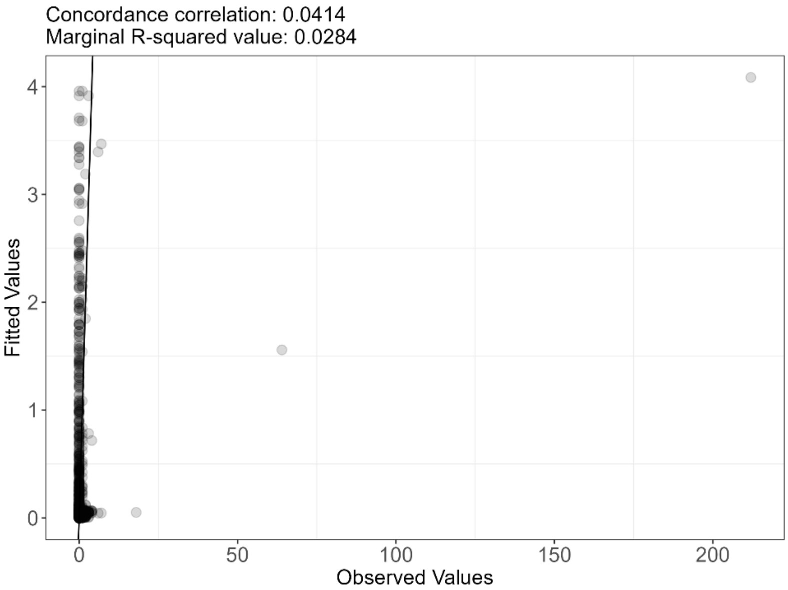
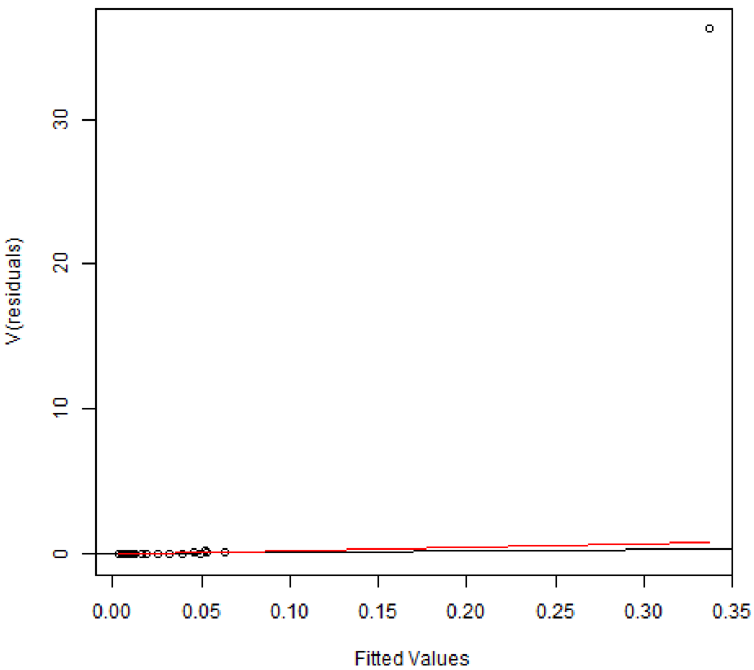


Plate B55 Mean-variance relationship plot. The red line shows the estimates mean variance relationship from the model and the black line represents what would be expected in a perfect Poisson distribution (variance = mean)



Gannet flying

Initial set-up

The co-linearity of explanatory variables was initially assessed by observing GVIFs. Covariates were removed if strong collinearity was detected (GVIF value over 20). All adjusted GVIF values were below this threshold except for distance to coast (**Plate B56**). Despite using a non-linear approach to account for collinearity, distance to coast was excluded from the 1D and 2D smoothed models.

Plate B56 Code snippet detailing testing for co-linearity

```
> vif_out <- car::vif(test_model)
> vif_out
                        GVIF Df GVIF^(1/(2*Df))
survey         4059760.732171 13        1.795449
mean_depth           2.509056  1        1.584000
mean_prey_dens       1.309271  1        1.144234
dist_col           417.073741  1       20.422383
dist_oilrig          2.327452  1        1.525599
boat_presence  4035595.904337  1     2008.879266
x.pos              101.465257  1       10.072996
y.pos              283.764699  1       16.845317
```

To fit the model, it was necessary for all levels of any categorical variables to have non-zero counts. Two categorical (factor) variables were considered, survey and boat presence (**Plate B57**).

Plate B57 Code snippet verifying non-zero counts for all factor levels

```
> checkfactorlevelcounts(factorlist = c("Survey", "boat_presence"),
+                        data = model_data,
+                        response = model_data$response)
[1] "Survey will be fitted as a factor variable; there are non-zero counts for all levels"
[1] "boat_presence will be fitted as a factor variable; there are non-zero counts for all levels"
```

Generalised Linear Model

Before creating more complex models, a simple GLM was developed and run as an initial model (**Plate B58**).

Plate B58 Code snippet summarising the initial GLM

```
> summary(test_model)

Call:
glm(formula = response ~ Survey + mean_depth + mean_prey_dens +
    dist_col + dist_oilrig + boat_presence + x.pos + y.pos +
    offset(log(area)), family = "quasipoisson", data = model_data)

Coefficients:
                      Estimate       Std. Error t value            Pr(>|t|)
(Intercept)        -527.29641275     700.66184885  -0.753             0.45172
Survey2              -0.09962475       0.45936305  -0.217             0.82831
Survey3              -0.24933954       0.48897432  -0.510             0.61011
Survey4              -0.90244372       0.56251538  -1.604             0.10866
Survey5             -14.33499474     277.20330035  -0.052             0.95876
Survey6               0.90802574       0.35081989   2.588             0.00965 **
Survey10             -0.87895980       0.58098098  -1.513             0.13032
Survey11             -0.69022800       0.56249421  -1.227             0.21980
Survey12              0.83388127       0.36627491   2.277             0.02281 *
Survey13            -17.20999181     277.20372455  -0.062             0.95050
Survey14             -1.07733819       0.60238616  -1.788             0.07371 .
Survey15            -17.17780113     277.20363444  -0.062             0.95059
Survey16              0.34203200       0.40493648   0.845             0.39831
Survey24             -1.19601816       0.69436164  -1.722             0.08500 .
mean_depth            0.14056519       0.01295441  10.851 < 0.0000000000000002 ***
mean_prey_dens -7390164.70976338  2624761.78876633  -2.816             0.00487 **
dist_col             -0.03561001       0.15377429  -0.232             0.81687
dist_oilrig          -0.08002728       0.01819928  -4.397            0.000011 ***
boat_presence1       17.72870315     277.20316320   0.064             0.94901
x.pos                 0.00007187       0.00011980   0.600             0.54857
y.pos                 0.00007744       0.00009908   0.782             0.43443
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for quasipoisson family taken to be 2.784081)

    Null deviance: 6556.1  on 26472  degrees of freedom
Residual deviance: 4584.0  on 26452  degrees of freedom
AIC: NA

Number of Fisher Scoring iterations: 18
```

Residual correlation in the selected model was examined with an empirical Runs Test which indicated no significant residual correlation due to the insignificant p-value (**Plate B59**).

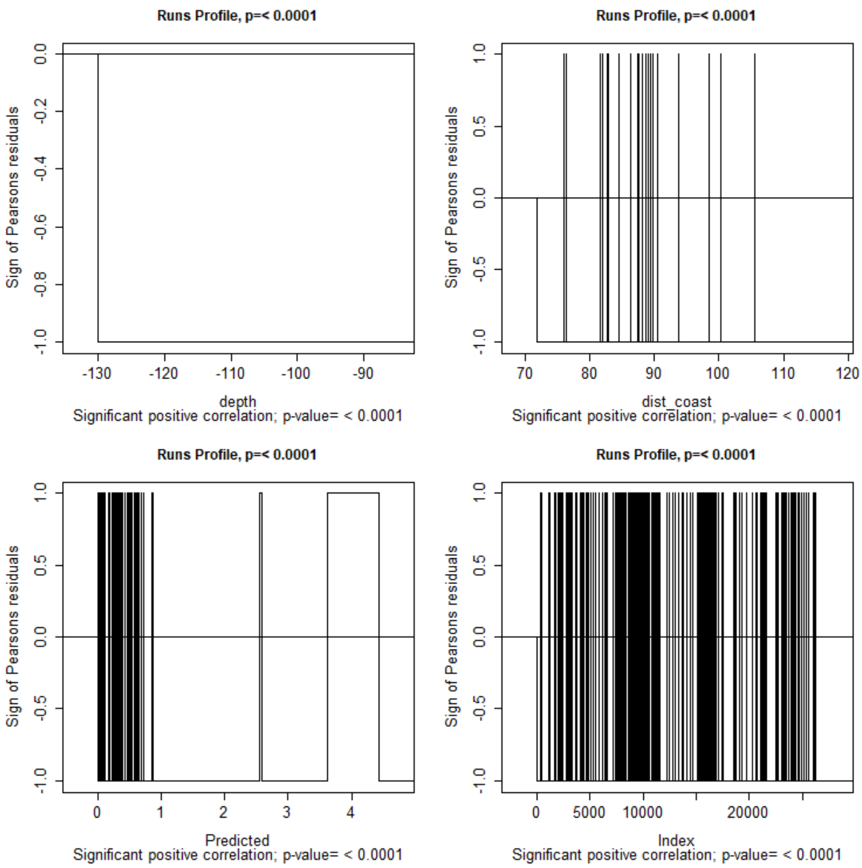
Plate B59 Code snippet highlighting the runs test results

```
	Runs Test - Two sided; Empirical Distribution

data:  residuals(best_model_salsa2dOutput, type = "pearson")
Standardized Runs Statistic = -139.34, p-value = 0.12
```

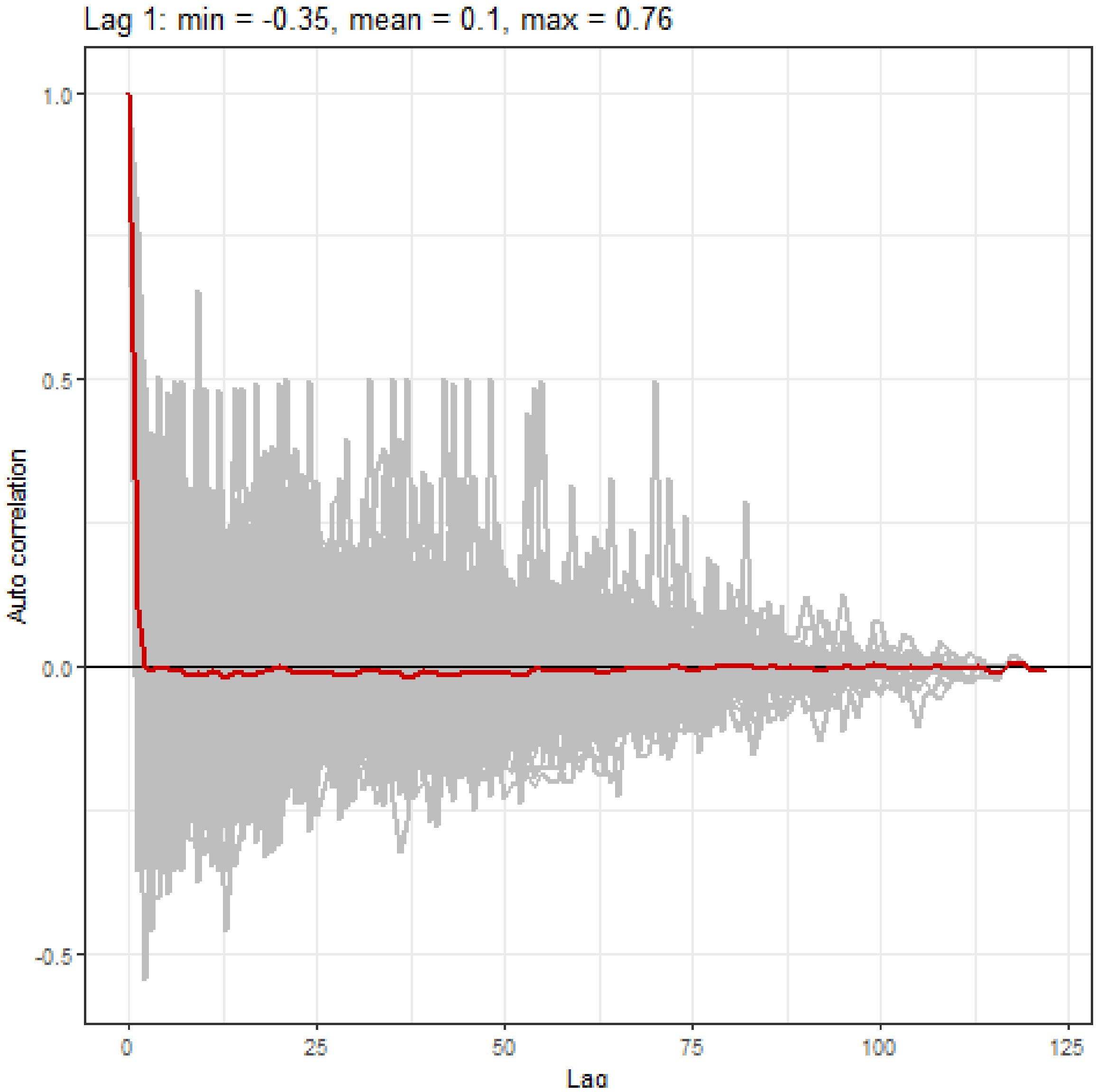
Non-randomness was observed in the runs profiles (**Plate B60**).

Plate B60 Runs profile for the initial GLM. Black lines display the sequence of positive and negative residuals. It is expected to see random distribution of lines in the absence of correlated residuals. Significance of correlation within each variable



Given the presence of correlation, it was deemed appropriate to incorporate a blocking structure moving forward (**Plate B60**). The blocking structure was based on the combination of Survey ID and Transect ID, allowing the model to treat data from each transect within a survey as correlated while assuming independence between different transects and surveys. An ACF plot was used to assess the effectiveness of the blocking structure (**Plate B61**). Both the mean correlation in residuals (red line) and correlation in residuals within each block (grey lines) quickly moved to zero, indicating that the blocking structure was fit for purpose.

Plate B61 ACF plot used for the initial GLM. The grey lines represent the correlation of residuals within each block, while the red line indicates the average correlation of the residuals



Cumulative residuals were plotted for explanatory variables (**Plate B62** and **Plate B63**).

Plate B62 Cumulative residuals for initial GLM structured by distance to oil rig. The black line shows the modelled cumulative residuals, while they grey line shows expected model fit

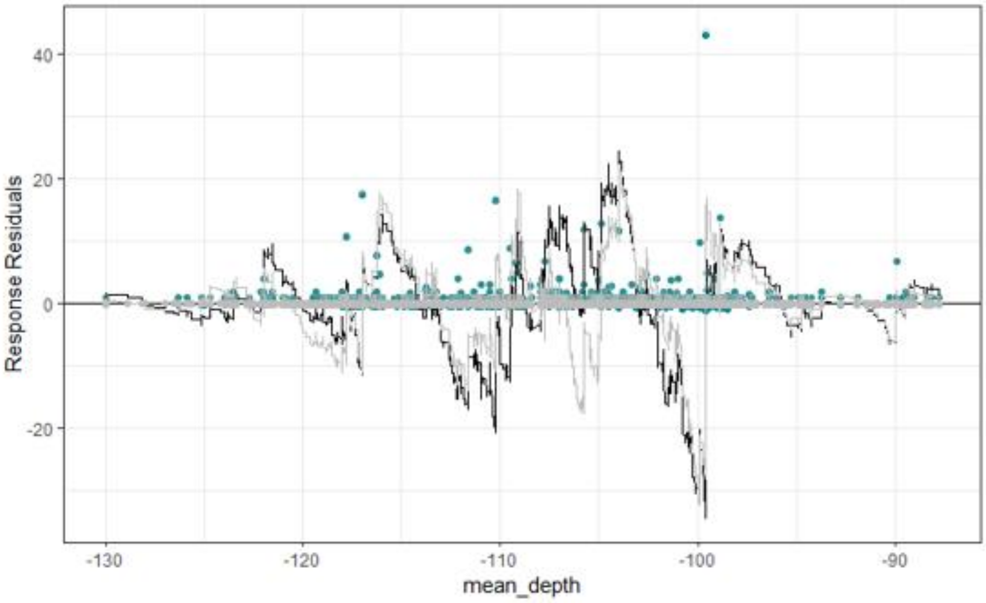
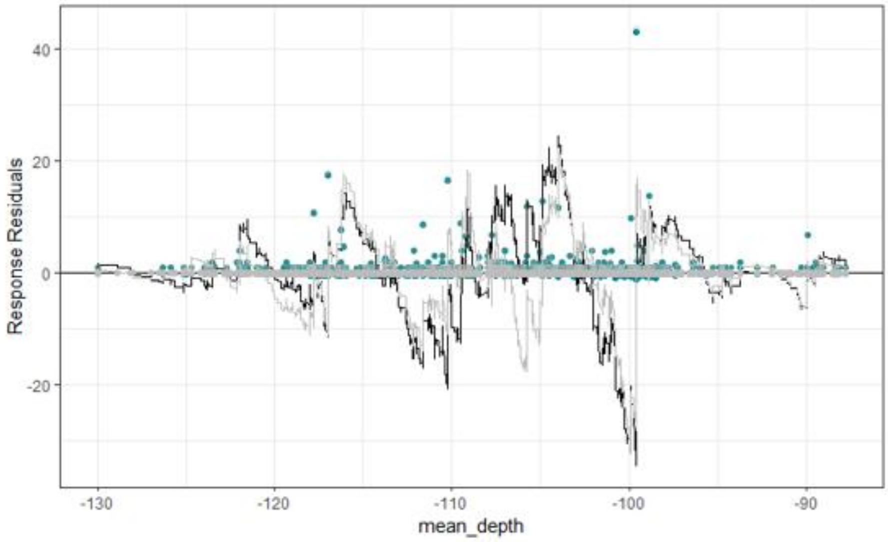


Plate B63 Cumulative residuals for initial GLM structured by depth. The black line shows the modelled cumulative residuals, while they grey line shows expected model fit



2D SALSA model diagnostics

The final model was selected according to having the lowest QBIC validation score and the summary can be seen in **Plate B64**. The SALSA 2D function is used to fit a CReSS model to the existing best fit 1D model, where the knot locations were allowed to vary by survey. Bird count served as the response variable, with x.pos and y.pos as spatial coordinates, and log(area) included as an offset. The model employed a quasi-Poisson error distribution with a log link.

Plate B64 Code snippet summarising the final model

```
Call:
gamMRSea(formula = round(response) ~ Survey + LRF.g(radiusIndices,
    dists, radii, aR) + offset(log(area)), family = quasipoisson(link = log),
    data = model_data, splineParams = splineParams)

Deviance Residuals:
   Min       1Q   Median       3Q      Max
-2.768   -0.172   -0.119   -0.106   32.636

Coefficients:
                                          Estimate Std. Error Robust S.E. t value  Pr(>|t|)
(Intercept)                                -1.9977     0.2704      0.4698  -4.253 0.0000212 ***
Survey2                                    -0.1251     0.4275      0.5106  -0.245    0.8064
Survey3                                    -0.2775     0.4551      0.5288  -0.525    0.5998
Survey4                                    -0.9201     0.5236      0.5467  -1.683    0.0924 .
Survey5                                     2.2523     0.7271      1.1821   1.905    0.0567 .
Survey6                                     0.8946     0.3265      0.4975   1.798    0.0721 .
Survey10                                   -0.9006     0.5408      0.6520  -1.381    0.1672
Survey11                                   -0.7125     0.5236      0.5993  -1.189    0.2345
Survey12                                    0.8132     0.3409      0.4947   1.644    0.1002
Survey13                                   -0.9564     0.5408      0.5932  -1.612    0.1069
Survey14                                   -1.1203     0.5607      0.5963  -1.879    0.0603 .
Survey15                                   -0.7785     0.4954      0.5726  -1.360    0.1740
Survey16                                    0.3121     0.3769      0.5278   0.591    0.5543
Survey24                                   -1.2286     0.6463      0.6052  -2.030    0.0424 *
LRF.g(radiusIndices, dists, radii, aR)b1   57.1802     6.1994     32.8966   1.738    0.0822 .
LRF.g(radiusIndices, dists, radii, aR)b2   81.3171     9.3423     45.9528   1.770    0.0768 .
LRF.g(radiusIndices, dists, radii, aR)b3   29.4713     5.0660     17.8261   1.653    0.0983 .
LRF.g(radiusIndices, dists, radii, aR)b4  -24.5537     3.0707     15.3505  -1.600    0.1097
LRF.g(radiusIndices, dists, radii, aR)b5 -114.8849    12.8478     65.9746  -1.741    0.0816 .
LRF.g(radiusIndices, dists, radii, aR)b6  -32.7838     4.2649     19.9389  -1.644    0.1001
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for quasipoisson family taken to be 2.412506)

    Null deviance: 6556.1  on 26472  degrees of freedom
Residual deviance: 4650.1  on 26453  degrees of freedom
AIC:  NA

Max Panel Size = 123; Number of panels = 364
Number of Fisher Scoring iterations: 8
```

Additional model diagnostics for the best fitting SALSA 2D model are displayed below (**Plate B65** and **Plate B66**). The first diagnostic plot compares observed versus fitted values (**Plate B65**). This plot indicates the model fit is adequate, and no substantial residual pattern is apparent, however relatively little of the observed variability is explained by the selected model. The second diagnostic plot shows the mean variance relationship comparing mean variance from the model with the

assumed mean-variance relationship (**Plate B66**). This plot indicates a generally good fit; however, variance is underestimated for the larger fitted values.

Plate B65 Observed versus predicted values for the best fitting 2D smoothed model

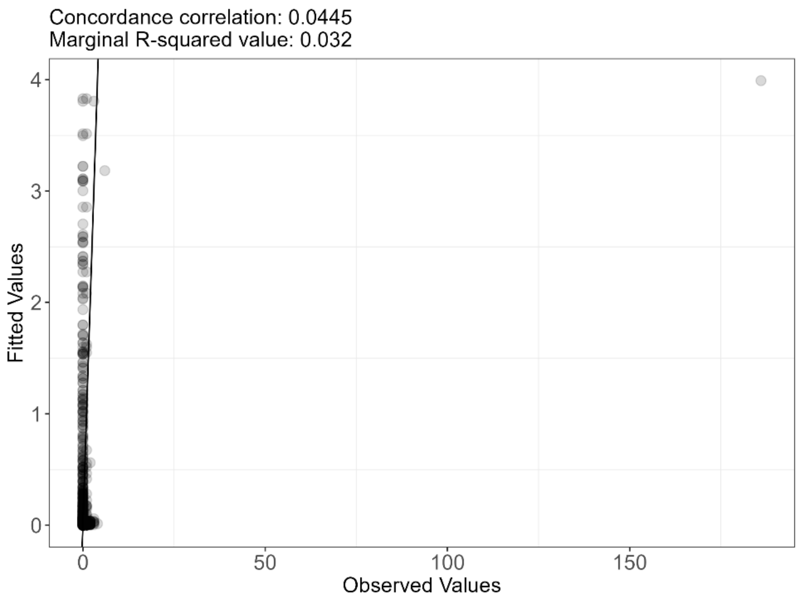
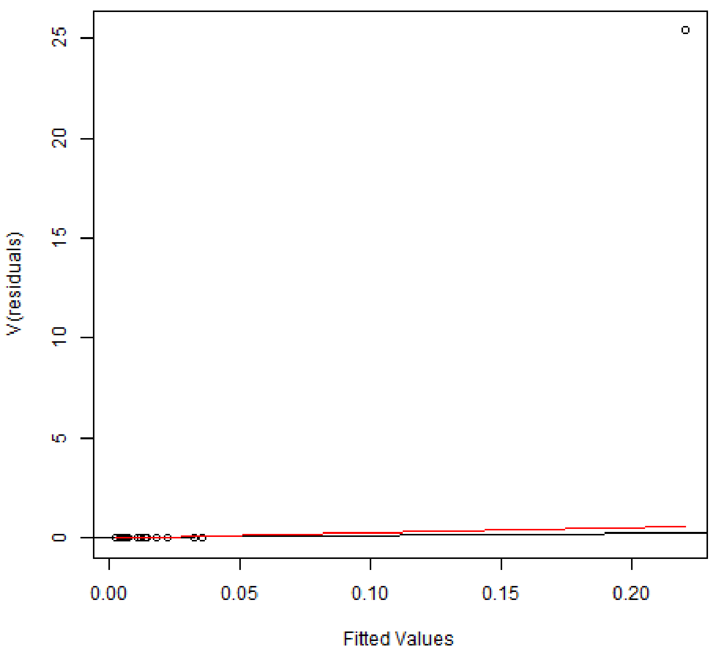


Plate B66 Mean-variance relationship plot. The red line shows the estimates mean variance relationship from the model and the black line represents what would be expected in a perfect Poisson distribution (variance = mean)



Fulmar

Initial set-up

The co-linearity of explanatory variables was initially assessed by observing GVIFs. Covariates were removed if strong collinearity was detected (GVIF value over 20). All adjusted GVIF values were below this threshold except for distance to coast (**Plate B67**). Despite using a non-linear approach to account for collinearity, distance to coast was excluded from the 1D and 2D smoothed models.

Plate B67 Code snippet detailing testing for co-linearity

```
> vif_out <- car::vif(test_model)
> vif_out
                      GVIF Df GVIF^(1/(2*Df))
Survey        6.943368e+06  4        7.164671
mean_depth    1.842132e+00  1        1.357252
mean_prey_pres 1.105342e+00 1        1.051353
dist_col      5.526249e+02  1       23.507975
dist_oilrig   2.718944e+00  1        1.648922
boat_presence 6.925423e+06  1     2631.619925
x.pos         2.230324e+02  1       14.934268
y.pos         2.652717e+02  1       16.287163
```

To fit the model, it was necessary for all levels of any categorical variables to have non-zero counts. Two categorical (factor) variables were considered, survey and boat presence (**Plate B68**).

Plate B68 Code snippet verifying non-zero counts for all factor levels

```
> checkfactorlevelcounts(factorlist = c("Survey", "boat_presence"),
+                        data = model_data,
+                        response = model_data$response)
[1] "Survey will be fitted as a factor variable; there are non-zero counts for all levels"
[1] "boat_presence will be fitted as a factor variable; there are non-zero counts for all levels"
```

Generalised Linear Model

Before creating more complex models, a simple GLM was developed and run as an initial model (**Plate B69**).

Plate B69 Code snippet summarising the initial GLM

```
> summary (test_model)

Call:
glm(formula = response ~ Survey + mean_depth + mean_prey_pres +
    dist_col + dist_oilrig + boat_presence + x.pos + y.pos +
    offset(log(area)), family = "quasipoisson", data = model_data)

Coefficients:
                        Estimate          Std. Error t value         Pr(>|t|)
(Intercept)          -1138.69210224        564.30472984  -2.018         0.043625 *
Survey2                  1.04224275          0.28793561   3.620         0.000296 ***
Survey11                 0.39734478          0.32837701   1.210         0.226290
Survey12                 1.76973798          0.26379074   6.709 0.0000000000204 ***
Survey13               -15.84365377        331.57368327  -0.048         0.961890
Survey14                 1.15813695          0.27522540   4.208 0.0000259353213 ***
Survey15               -15.66140203        331.57367691  -0.047         0.962328
mean_depth              -0.02195649          0.01038695  -2.114         0.034546 *
mean_prey_pres -22934478.61240605  33949208.50198425  -0.676         0.499336
dist_col                -0.30412339          0.12628334  -2.408         0.016042 *
dist_oilrig              0.01044994          0.01205330   0.867         0.385970
boat_presence1          18.22247846        331.57359362   0.055         0.956173
x.pos                    0.00019211          0.00009692   1.982         0.047477 *
y.pos                    0.00016122          0.00007975   2.022         0.043226 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for quasipoisson family taken to be 1.424037)

    Null deviance: 3564.2  on 13524  degrees of freedom
Residual deviance: 2973.3  on 13511  degrees of freedom
AIC: NA

Number of Fisher Scoring iterations: 18
```

Residual correlation in the selected model was examined with an empirical Runs Test which indicated significant residual correlation due to the highly significant p-value (**Plate B70**).

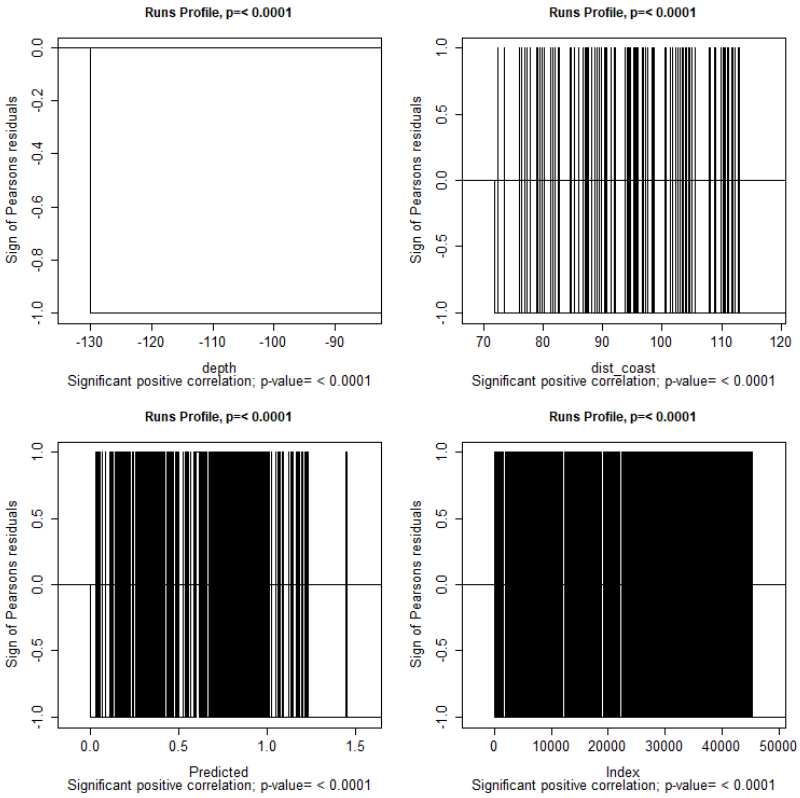
Plate B70 Code snippet highlighting the runs test results

```
	Runs Test - Two sided; Empirical Distribution

data:  residuals(best_model_salsa2dOutput, type = "pearson")
Standardized Runs Statistic = -153.04, p-value < 0.00000000000000022
```

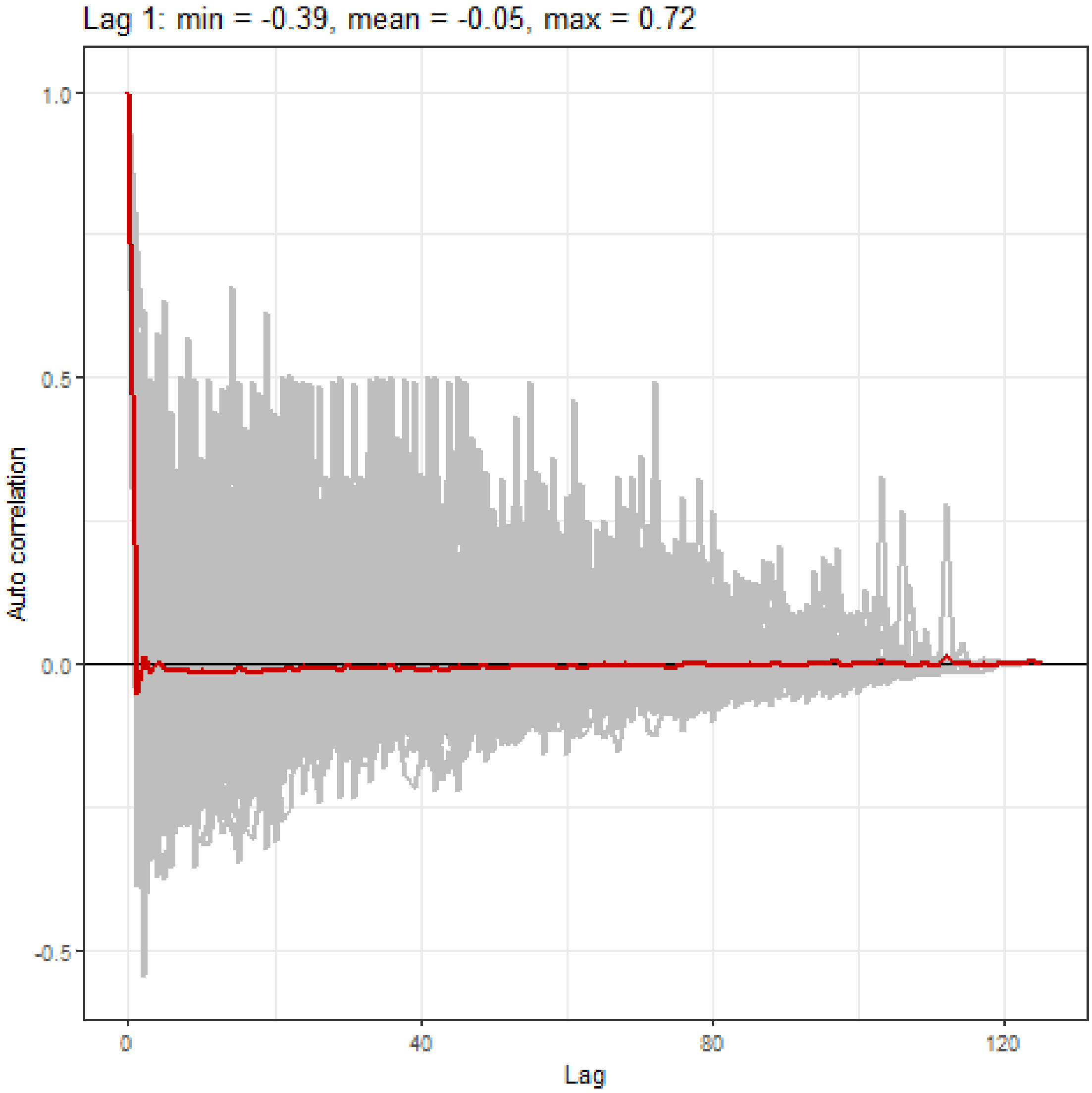
Non-randomness was observed in the runs profiles (**Plate B71**).

Plate B71 Runs profile for the initial GLM. Black lines display the sequence of positive and negative residuals. It is expected to see random distribution of lines in the absence of correlated residuals. Significance of correlation within each variable is displayed



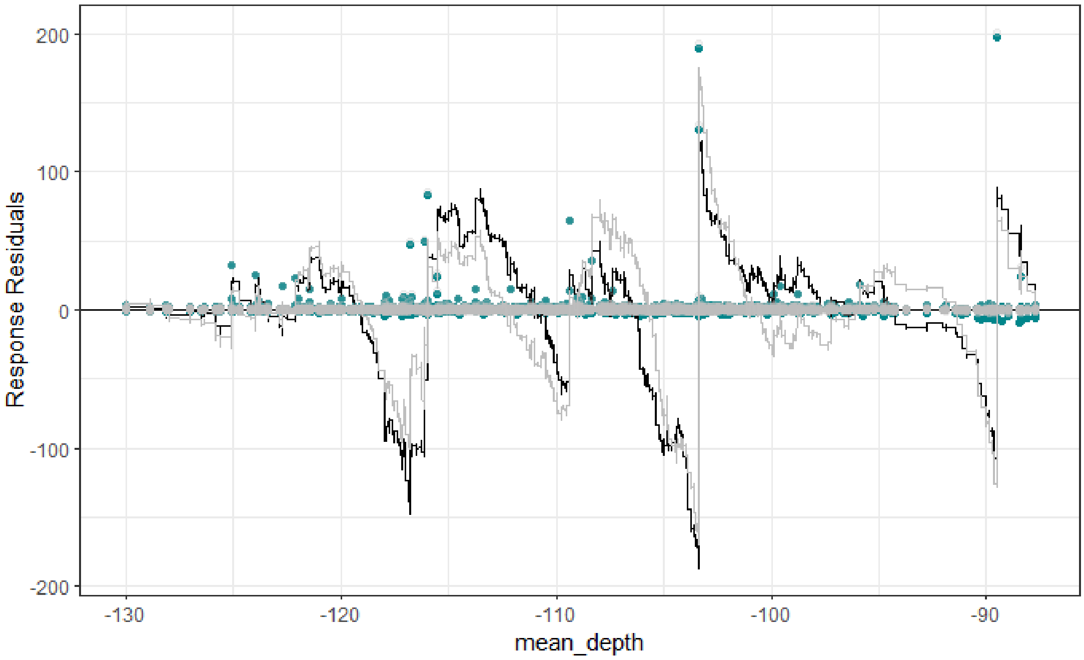
Given the presence of correlation, it was deemed appropriate to incorporate a blocking structure moving forward. The blocking structure was based on the combination of Survey ID and Transect ID, allowing the model to treat data from each transect within a survey as correlated while assuming independence between different transects and surveys. An ACF plot was used to assess the effectiveness of the blocking structure (**Plate B72**). Both the mean correlation in residuals (red line) and correlation in residuals within each block (grey lines) quickly moved to zero, indicating that the blocking structure was fit for purpose.

Plate B72 ACF plot used for the initial GLM. The grey lines represent the correlation of residuals within each block, while the red line indicates the average correlation of the residuals



Cumulative residuals were plotted for explanatory variables (**Plate B73**). The black line represents the modelled cumulative residuals, while the grey line highlights the expected model fit. Systematic over- and under-prediction was evident for depth, necessitating the use of a more complex, non-linear model.

Plate B73 Cumulative residuals for initial GLM structured by depth. The black line shows the modelled cumulative residuals, while they grey line shows expected model fit



2D SALSA model diagnostics

The final model was selected according to having the lowest QBIC validation score and the summary can be seen in **Plate B74**. The SALSA 2D function is used to fit a CReSS model to the existing best fit 1D model, where the knot locations were allowed to vary by survey. Bird count served as the response variable, with x.pos and y.pos as spatial coordinates, and log(area) included as an offset. The model employed a quasi-Poisson error distribution with a log link.

Plate B74 Code snippet summarising the final model

```
Call:
gamMRSea(formula = response ~ Survey + LRF.g(radiusIndices, dists,
    radii, aR) + offset(log(area)), family = "quasipoisson",
    data = model_data, splineParams = splineParams)

Deviance Residuals:
   Min      1Q  Median      3Q     Max
-2.998  -0.553  -0.385  -0.252  38.351

Coefficients:
                                         Estimate Std. Error Robust S.E. t value   Pr(>|t|)
(Intercept)                               -0.8498     0.2760      0.3297  -2.578   0.009950
Survey2                                    0.1685     0.4017      0.3541   0.476   0.634107
Survey3                                   -0.4239     0.4877      0.3885  -1.091   0.275230
Survey4                                    1.1804     0.3191      0.3379   3.494   0.000477
Survey5                                    0.5445     0.3549      0.4203   1.295   0.195160
Survey6                                    3.8222     0.4169      0.8989   4.252 0.00002123
Survey7                                    0.1442     0.3903      0.3898   0.370   0.711378
Survey8                                    0.7273     0.3504      0.3624   2.007   0.044769
Survey9                                    0.4203     0.3716      0.3482   1.207   0.227446
Survey10                                  -0.5546     0.4877      0.3592  -1.544   0.122658
Survey11                                  -0.4741     0.4911      0.3545  -1.337   0.181101
Survey12                                  -0.8047     0.5500      0.3777  -2.130   0.033149
Survey13                                   4.1268     0.4474      1.1891   3.471   0.000520
Survey14                                   1.4790     0.3080      0.3389   4.364 0.00001281
Survey15                                   0.8098     0.3359      0.3373   2.401   0.016344
Survey16                                  -4.7073     1.0770      3.9221  -1.200   0.230075
Survey17                                   1.1876     0.3210      0.3394   3.499   0.000467
Survey18                                   1.4441     0.3119      0.3629   3.979 0.00006924
Survey19                                   1.5024     0.3060      0.3393   4.427 0.00000956
Survey20                                   0.6638     0.3577      0.3710   1.789   0.073584
Survey21                                   0.4745     0.3684      0.3607   1.315   0.188403
Survey22                                   1.3212     0.3177      0.3806   3.472   0.000518
Survey23                                   0.6634     0.3563      0.3558   1.865   0.062203
Survey24                                  -0.1028     0.4389      0.3738  -0.275   0.783252
LRF.g(radiusIndices, dists, radii, aR)b1  -3.3011     0.6663      1.2380  -2.667   0.007667
LRF.g(radiusIndices, dists, radii, aR)b2  -3.0472     0.5113      1.4032  -2.172   0.029890
LRF.g(radiusIndices, dists, radii, aR)b3   7.0369     1.4128      3.5730   1.969   0.048903
LRF.g(radiusIndices, dists, radii, aR)b4 -24.3856     3.7293     14.0519  -1.735   0.082678
LRF.g(radiusIndices, dists, radii, aR)b5  24.4659     3.1583     14.1653   1.727   0.084144
LRF.g(radiusIndices, dists, radii, aR)b6   3.7735     0.3528      0.8517   4.431 0.00000942
LRF.g(radiusIndices, dists, radii, aR)b7  -4.3278     0.7053      1.3462  -3.215   0.001306
LRF.g(radiusIndices, dists, radii, aR)b8  -3.2178     0.7015      1.4635  -2.199   0.027903

(Intercept)                               **
```

```
Survey2
Survey3
Survey4                                 ***
Survey5
Survey6                                 ***
Survey7
Survey8                                 *
Survey9
Survey10
Survey11
Survey12                                *
Survey13                                ***
Survey14                                ***
Survey15                                *
Survey16
Survey17                                ***
Survey18                                ***
Survey19                                ***
Survey20                                .
Survey21
Survey22                                ***
Survey23                                .
Survey24
LRF.g(radiusIndices, dists, radii, aR)b1 **
LRF.g(radiusIndices, dists, radii, aR)b2 *
LRF.g(radiusIndices, dists, radii, aR)b3 *
LRF.g(radiusIndices, dists, radii, aR)b4 .
LRF.g(radiusIndices, dists, radii, aR)b5 .
LRF.g(radiusIndices, dists, radii, aR)b6 ***
LRF.g(radiusIndices, dists, radii, aR)b7 **
LRF.g(radiusIndices, dists, radii, aR)b8 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for quasipoisson family taken to be 7.921662)

    Null deviance: 36707  on 45486  degrees of freedom
Residual deviance: 31031  on 45455  degrees of freedom
AIC:  NA

Max Panel Size = 126; Number of panels = 624
Number of Fisher Scoring iterations: 8
```

Additional model diagnostics for the best fitting SALSA 2D model are displayed below (**Plate B75** and **Plate B76**). The first diagnostic plot compares observed versus fitted values (**Plate B75**). This plot indicates the model fit is adequate, and no substantial residual pattern is apparent, however relatively little of the observed variability is explained by the selected model. The second diagnostic plot shows the mean variance relationship comparing mean variance from the model with the

assumed mean-variance relationship (**Plate B76**). This plot indicates a generally good fit; however, variance is underestimated for the larger fitted values.

Plate B75 Observed versus predicted values for the best fitting 2D smoothed model

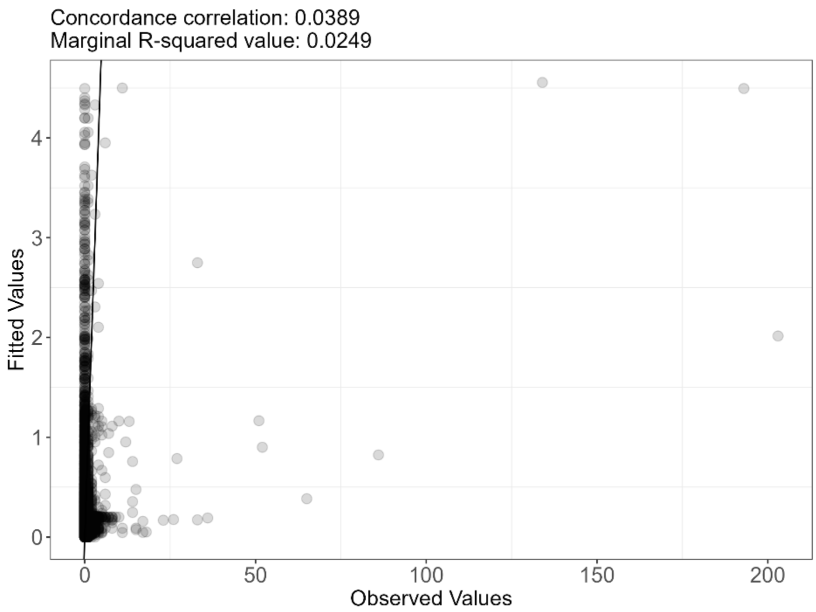
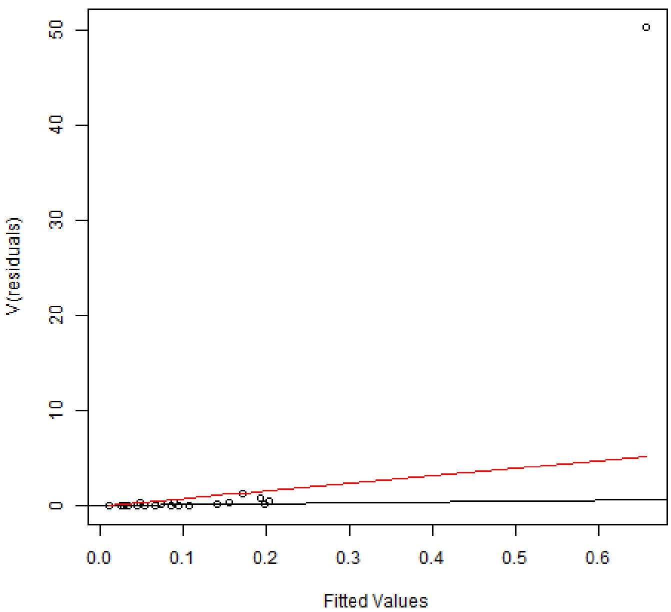


Plate B76 Mean-variance relationship plot. The red line shows the estimates mean variance relationship from the model and the black line represents what would be expected in a perfect Poisson distribution (variance = mean)



MarramWind