Spiorad na Mara Offshore Wind Farm

Offshore Project

Environmental Impact Assessment Report

Annex 14.1.4: MRSea Modelling Report, Volume 2c

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1 INTRODUCTION

1.1 CONTEXT

1.1.1 The Spiorad na Mara Offshore Wind Farm development (hereafter referred to as “the Offshore Project”) is a proposed windfarm to be built off the north-west coast of Scotland/*Alba*. A programme of Digital Aerial Surveys (DAS) was conducted between March 2022 and February 2024 in order to characterise the baseline offshore ornithology interest in the development area. Further details are provided in the main Appendix 14.1: Baseline Characterisation Report, Volume 2c, to which this document is annexed.

1.1.2 The DAS surveys had a coverage of approximately 12% of the Survey Area. Therefore, it is necessary to extrapolate from the survey data to estimate the total abundance of birds present, in order to inform impact analysis. The 2 main methods of extrapolating from the data are referred to as “design-based” and “model-based” estimates. Design-based estimates make the assumption that there is no meaningful spatial pattern underlying bird distribution across the Survey Area, and therefore each DAS image represents an independent, unbiased sample from an identical distribution. A model-based approach does not make this assumption, but instead assumes there is some underlying pattern, and therefore aims to fit a model to explain describe that pattern.

1.1.3 In line with NatureScot Guidance Note 2 (NatureScot, 2023) the recommended approach to model-based abundance estimates is to use the MRSea (Marine Renewables Strategic Environmental Assessment) package (Scott-Hayward *et al.*, 2013) within R (R Core Team, 2024). This report describes the modelling undertaken for to provide the model-based abundance estimate for characterising the baseline of the Offshore Project.

1.1.4 This annex has 4 appendices:

- Appendix 14.1.4.A: Unapportioned and Uncorrected Abundance and Density Estimates, Volume 2c;
- Appendix 14.1.4.B: MRSea Apportioned and Corrected Abundance and Density Estimates, Volume 2c;
- Appendix 14.1.4.C: Model Abundance Confidence Limits and Coefficients of Variation, Volume 2c;
- Appendix 14.1.4.D: Model Diagnostics, Volume 2c.

1.2 INTRODUCTION TO MRSEA

1.2.1 The MRSea package (Scott-Hayward *et al.*, 2013) was developed for analysing data that was collected for assessing potential impacts of renewable developments on marine wildlife. The MRSea package is not a statistical modelling method *per se*, but rather a tool that facilitates modelling. Specifically, the MRSea package enables the user to fit Complex Regional Spatial Splines (CReSS; Scott-Hayward *et al.*, 2014), using a Spatially Adaptive Local Smoothing Algorithm (SALSA; Walker *et al.*, 2010).

2 METHODS

2.1 MRSEA MODELLING

2.1.1 Modelling was carried out for 5 species: gannet, kittiwake, guillemot, razorbill and puffin. These 5 species was selected on the grounds that they would likely represent the key risk species for the Offshore Project, based on an initial review of the DAS report (Appendix 13.1: Digital Aerial Survey Report, Volume 2c) alongside species' sensitivities (e.g. Wade *et al.*, 2016).

2.1.2 The DAS data consisted of abutting digital still imagery, in a transect design. The survey aircraft operates an array of cameras, and each sampling location therefore consists of 3 adjacent images stitched together. Each sampling location (i.e. the 3 images combined) was treated as a single data point for modelling purposes. The sea surface footprint of the images at each sampling location was also provided as a shapefile (note the survey provider supplied these with the 3 individual images at each sampling location already merged, i.e. a single footprint per sampling location was supplied).

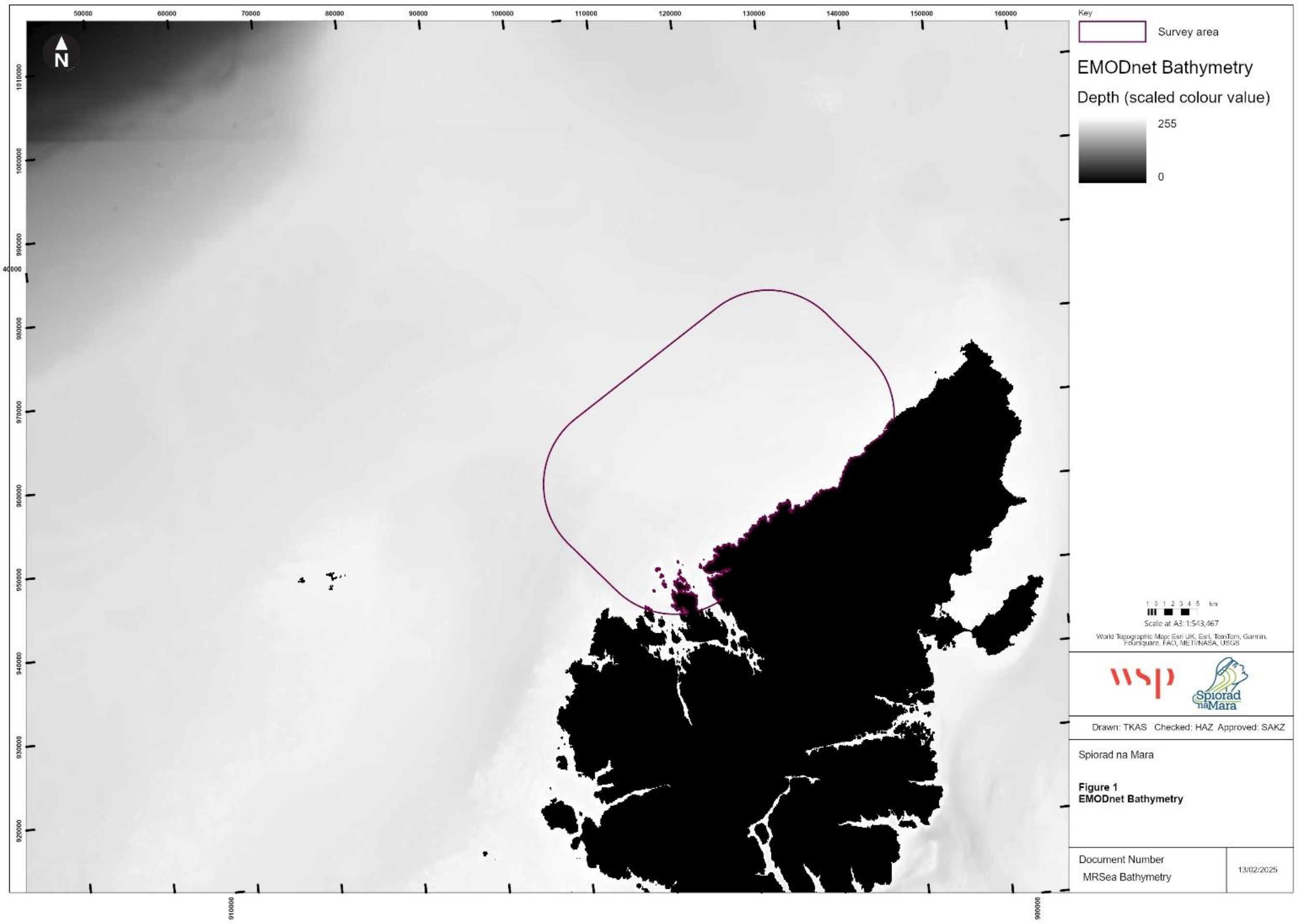
2.1.3 Deceased birds were removed from the data, but otherwise the modelling was carried out for all behaviours together. The majority of birds were recorded as "flying" or "sitting", but a small number of birds were categorised into other behaviours e.g. "diving", "submerged" or "surfacing". Modelling all birds maximises the sample size and therefore ensures that as many surveys as possible can be modelled for each species, and also ensures that these minority behaviours are included in the total abundance estimates.

2.1.4 Modelling was carried out using the entire Survey Area. Modelling was carried out separately for each survey, for each species. Modelling was only carried out for surveys with sufficient observations across the Survey Area. The minimum requirement for modelling to be attempted was a minimum of 10 DAS images with at least one observation of the target species.

2.1.5 One potential advantage of a model-based approach is the ability to include covariates into the model. Covariates are factors that are thought to inform the response variable (i.e. the number of birds present) and therefore including covariates can help improve the accuracy of the model. However, including covariates is not always viable. Firstly, data needs to be obtained at an appropriate spatial and temporal scale. Secondly, including covariates makes it computationally harder to fit the model, requiring more data points, and models can fail to fit properly if there is no relationship between the covariate and the bird distribution, or of the birds present only represent a small portion of the total range of covariate variables. Finally, it is important that each new covariate provides additional information, and is not colinear with existing variables. For example, if the water depth increased in a fairly uniform manner with distance from the coast, then including depth as a covariate would provide no additional information to the spatial coordinates.

2.1.6 Depth was considered as a covariate (Plate 2-1) but there did not appear to be any informative patterns, and therefore it was not taken through to modelling.

Plate 2-1 EMODnet Bathymetry data considered for inclusion as a covariate. Note the depth value is a 8-bit colour scale i.e. a value of 256 represents the minimum depth within the data while a value of 0 represents the maximum depth in the data. Data from EMODnet Bathymetry Consortium (2022).



2.1.7 Other potential covariates (e.g. sea surface temperature, chlorophyll-a concentration) were considered, but it was felt that there were no covariates that were likely to provide statistically useful information, given the scale and location of the Survey Area. Not attempting to fit covariates also maximised the ability to fit models to survey months where the sample size was small. It should also be noted that for the purposes of baseline characterisation, covariates are of less importance in their own right, as the objective is simply to define the baseline abundance and distribution, rather than understand factors that may be influencing this. Therefore, the models were progressed with only spatial terms (x coordinate and y coordinate) as model variables.

2.1.8 Models were fitted using a quasi-poisson error structure, and the log of the area of the image footprint as an offset (to account for variation in effort). For the 2D spatial model, the initial number of knots was set to 10, and a minimum and maximum of 4 and 15 knots was also specified.

Within the SALSA algorithm, the QBIC (quasi-Bayesian Information Criteria) was used for model selection.

2.1.9 The model diagnostics were then reviewed to determine if the model was correctly fitted and suitable. Models that did not conform to expectation were discarded.

2.1.10 The best fitting model was then used to predict abundances within each grid cell of a 1 km by 1 km square grid spanning the survey area. As each grid cell has an area of 1 km^2, the predicted abundance equals the density. The prediction grid can be clipped to a smaller area of interest (e.g. the Offshore Project's Array Area), and where a grid cell is cut, the new abundance in that grid cell can be calculated as the density multiplied by the area of the grid cell within the area of interest. The total abundance for the area of interest can then be calculated as the sum of the abundances within each grid cell.

2.1.11 A parametric bootstrapping process was carried out to estimate the model uncertainty. A parametric bootstrap randomly resamples the model's parameters, and therefore produces potential alternative models. Bootstrapping was carried out with 500 bootstraps, and for each grid cell, the 95% confidence limits and standard deviation of abundance were calculated from the results. The 95% confidence limits and standard deviation of the total abundance within an area of interest were calculated by calculating the total abundance under each bootstrapped run and then extracting the 95% confidence limits and calculating the standard deviation of those results.

2.2 POST-MODELLING PROCESSING

2.2.1 The modelled abundances are for all behaviours combined. To calculate the number of flying and sitting birds, the total abundance was multiplied by the proportion of flying and sitting birds (respectively) within the original raw data for that survey.

2.2.2 The modelled abundances are only for birds identified to species level. Therefore, it is necessary to also account for birds that were not identified to species level. To do this, unidentified birds were apportioned out to species based on the proportion of each species within the original survey data. A hierarchical approach to apportioning was followed, with the following options used in order of preference: observations from the same area and same behaviour; observations from the Study Area and same behaviour; observations from the same area and all behaviours; observations from the Study Area and all behaviours. Note that as apportioning is carried out separately for all behaviours, sitting birds and flying birds, this may lead to slight discrepancies, whereby after apportioning, the total estimate for each species may differ slightly from the sum of the sitting and flying birds. The abundances of unidentified birds were extracted from the design-based abundance estimates as set out in Appendix 13.1, Volume 2c. It should be noted that while other species were necessarily considered when calculating the apportionment, the abundance estimates of those other species were not updated, and therefore the apportioned abundance estimates for those other species presented in the Appendix 14.1Volume 2c are based solely on the design-based approach carried out in Appendix 13.1, Volume 2c. This may also lead to some minor inconsistencies as the same unidentified bird may be apportioned to a different species under each approach. However, such inconsistencies are likely to be small: with the exception of birds identified as “guillemot/razorbill” (both of which were modelled), relatively few birds were not identified to species level.

2.2.3 For guillemot, razorbill and puffin which make foraging dives underwater, a proportion will not be detectable at the surface. As a result, density and abundance estimates need to be adjusted to correct for this availability bias. The correction factors applied to the relative abundance estimates of guillemot, razorbill and puffin sitting on the sea surface are 1.311, 1.211 and 1.165, respectively.

3 RESULTS

3.1.1 A summary of which surveys were modelled for each species (based on the requirement of a minimum of 10 data points) is given in Table 3-1. Kittiwake was modelled in 17 of the 24 surveys, spread across all seasons. Gannet was modelled in 16 surveys, with 8 surveys with insufficient sample sizes largely occurring in the winter period. Guillemot was modelled in all surveys. Razorbill was modelled in 15 of the surveys, spread across the year but with fewer winter surveys modelled. Puffin only had sufficient data to be modelled in 13 of the surveys, spread across the year but with fewer winter surveys modelled.

Table 3-1 Surveys for which modelling was carried out for each species

Survey	Kittiwake	Gannet	Guillemot	Razorbill	Puffin
S01 – March 2022	✓	✓	✓	✓	✗
S02 – April 2022	✓	✓	✓	✓	✓
S03 – May 2022	✓	✓	✓	✓	✗
S04 – June 2022	✗	✓	✓	✗	✗
S05 – July 2022	✓	✓	✓	✓	✓
S06 – August 2022	✗	✓	✓	✗	✓
S07 – September 2022	✗	✓	✓	✓	✓
S08 – October 2022	✓	✓	✓	✗	✗
S09 – November 2022	✓	✗	✓	✗	✗
S10 – December 2022	✓	✗	✓	✗	✓
S11 – January 2023	✓	✓	✓	✗	✗
S12 – February 2023	✓	✗	✓	✓	✗
S13 – March 2023	✓	✓	✓	✓	✗
S14 – April 2023	✗	✓	✓	✓	✓
S15 – May 2023	✓	✓	✓	✓	✓
S16 – June 2023	✓	✓	✓	✓	✓
S17 – July 2023	✓	✓	✓	✗	✓
S18 – August 2023	✗	✓	✓	✓	✓
S19 – September 2023	✗	✓	✓	✓	✓
S20 – October 2023	✓	✗	✓	✓	✓
S21 – November 2023	✓	✗	✓	✗	✓
S22 – December 2023	✓	✗	✓	✗	✗
S23 – January 2024	✗	✗	✓	✓	✗
S24 – February 2024	✓	✗	✓	✓	✗

3.2 KITTIWAKE

3.2.1 Models for kittiwake were fitted in 17 of the 24 surveys. Predicted abundances are shown in Plate 3-1 and Table 3-2. Maps of upper and lower confidence limits, maps coefficient of variation, model diagnostics, and tables of abundance and density for flying and sitting birds, before and after apportioning, are provided in the appendices of this annex.

Plate 3-1 Kittiwake modelled abundance (birds per 1 km2 grid cell). Figure shows model prediction outputs i.e. prior to apportionment and correction.

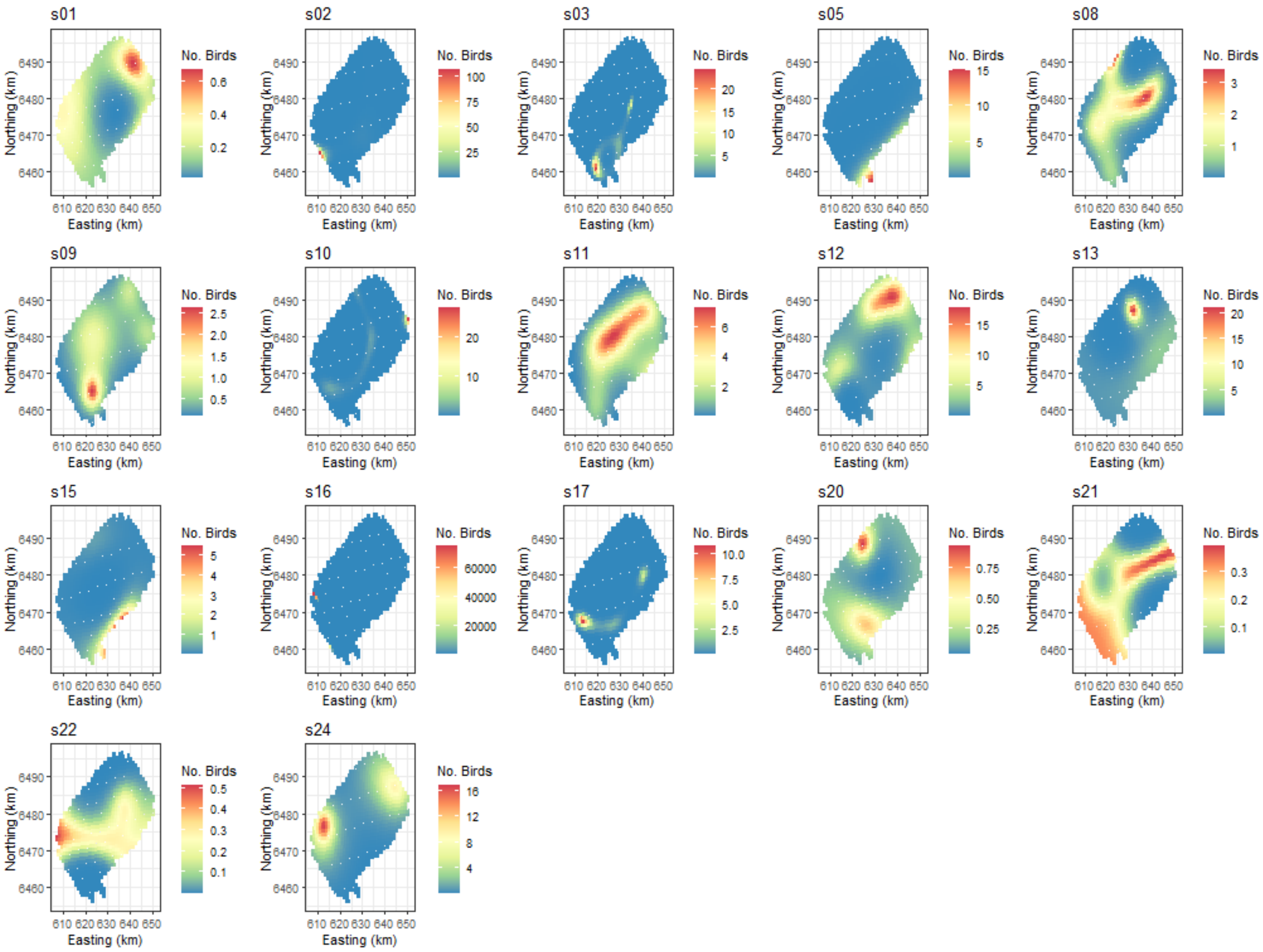


Table 3-2 Estimated abundance and density of kittiwake within the Turbine Area plus 4 km buffer (the Study Area). Estimates are inclusive of apportionment of unidentified birds.

Survey	Total abundance			Average density (birds/km^2)		
	Prediction	LCL	UCL	Prediction	LCL	UCL
S01 – March 2022	41	24	93	0.10	0.06	0.23
S02 – April 2022	51	21	233	0.12	0.05	0.57
S03 – May 2022	67	52	96	0.16	0.13	0.23
S04 – June 2022	NA	NA	NA	NA	NA	NA
S05 – July 2022	33	27	110	0.08	0.07	0.27
S06 – August 2022	NA	NA	NA	NA	NA	NA
S07 – September 2022	NA	NA	NA	NA	NA	NA
S08 – October 2022	478	380	684	1.17	0.93	1.67
S09 – November 2022	285	214	399	0.70	0.52	0.97
S10 – December 2022	52	37	84	0.13	0.09	0.20
S11 – January 2023	1,399	1,176	1,701	3.42	2.87	4.16
S12 – February 2023	921	743	1,146	2.25	1.82	2.80
S13 – March 2023	631	418	1,096	1.54	1.02	2.68
S14 – April 2023	NA	NA	NA	NA	NA	NA
S15 – May 2023	22	10	74	0.05	0.02	0.18
S16 – June 2023	2	1	10	0.00	0.00	0.02
S17 – July 2023	40	19	143	0.10	0.05	0.35
S18 – August 2023	NA	NA	NA	NA	NA	NA
S19 – September 2023	NA	NA	NA	NA	NA	NA
S20 – October 2023	61	35	140	0.15	0.09	0.34
S21 – November 2023	65	45	133	0.16	0.11	0.32
S22 – December 2023	84	58	154	0.21	0.14	0.38
S23 – January 2024	NA	NA	NA	NA	NA	NA
S24 – February 2024	665	541	878	1.62	1.32	2.15

3.3 GANNET

3.3.1 Models for gannet were fitted in 16 of the 24 surveys. Predicted abundances are shown in Plate 3-2 and Table 3-3. Maps of upper and lower confidence limits, maps coefficient of variation, model diagnostics, and tables of abundance and density for flying and sitting birds are provided in the appendices of this annex. Note that no apportionment was carried out for gannets, as no unidentified birds may have been gannets.

Plate 3-2 Gannet modelled abundance (birds per 1 km^2 grid cell). Figure shows model prediction outputs i.e. prior to apportionment and correction.

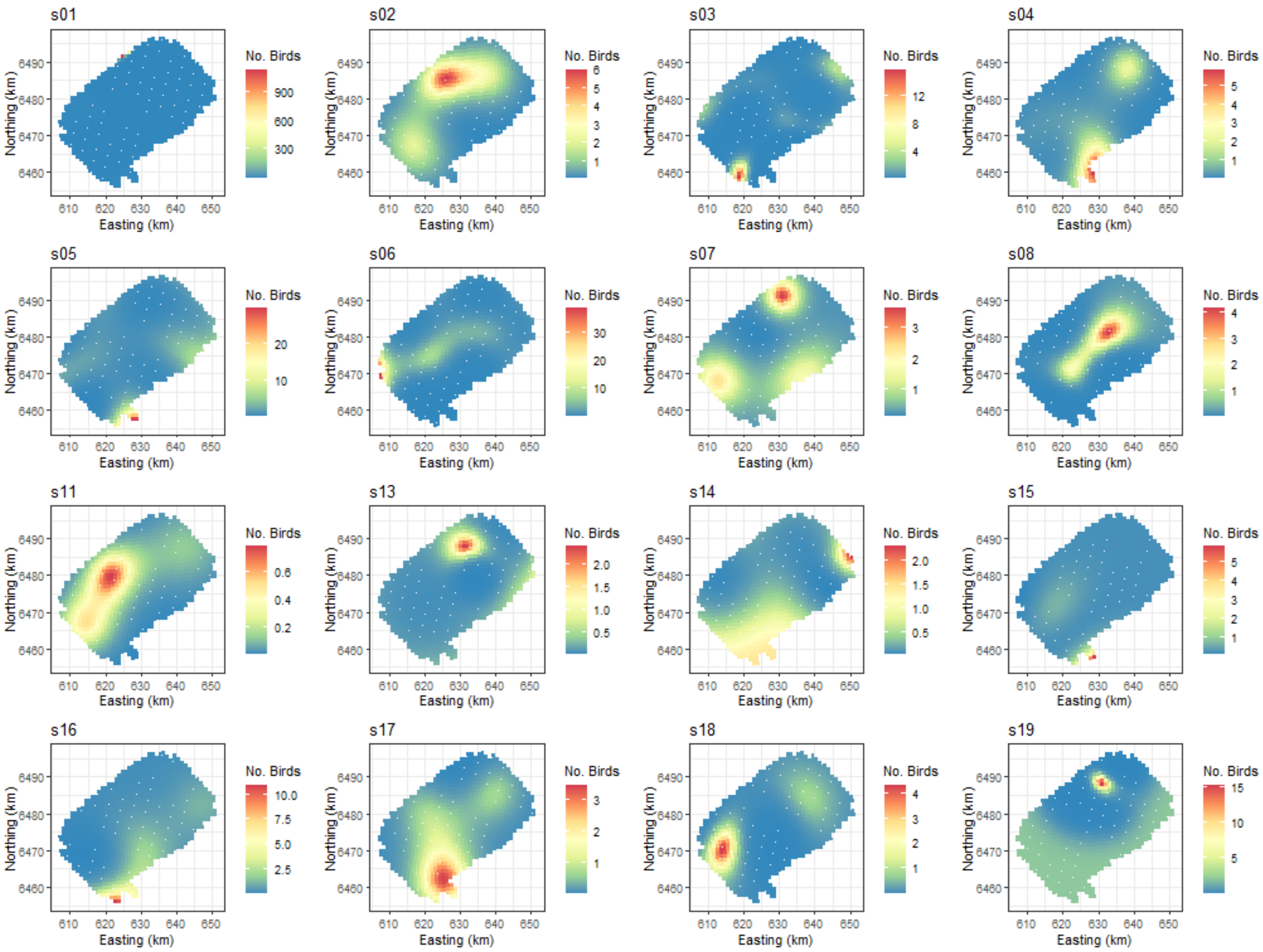


Table 3-3 Estimated abundance and density of gannet within the Turbine Area plus 4 km buffer (the Study Area). Estimates are inclusive of apportionment of unidentified birds.

Survey	Total abundance			Average density (birds/km^2)		
	Prediction	LCL	UCL	Prediction	LCL	UCL
S01 – March 2022	32	19	109	0.08	0.05	0.27
S02 – April 2022	513	404	666	1.25	0.99	1.63
S03 – May 2022	45	21	194	0.11	0.05	0.47
S04 – June 2022	198	146	316	0.48	0.36	0.77
S05 – July 2022	426	314	628	1.04	0.77	1.53
S06 – August 2022	872	542	2,225	2.13	1.33	5.44
S07 – September 2022	222	143	362	0.54	0.35	0.89
S08 – October 2022	360	262	588	0.88	0.64	1.44
S09 – November 2022	NA	NA	NA	NA	NA	NA
S10 – December 2022	NA	NA	NA	NA	NA	NA
S11 – January 2023	82	55	147	0.20	0.13	0.36
S12 – February 2023	NA	NA	NA	NA	NA	NA
S13 – March 2023	56	29	145	0.14	0.07	0.35
S14 – April 2023	107	77	162	0.26	0.19	0.40
S15 – May 2023	117	80	188	0.29	0.20	0.46
S16 – June 2023	275	196	420	0.67	0.48	1.03
S17 – July 2023	273	198	424	0.67	0.48	1.04
S18 – August 2023	137	75	334	0.33	0.18	0.82
S19 – September 2023	355	256	674	0.87	0.62	1.65
S20 – October 2023	NA	NA	NA	NA	NA	NA
S21 – November 2023	NA	NA	NA	NA	NA	NA
S22 – December 2023	NA	NA	NA	NA	NA	NA
S23 – January 2024	NA	NA	NA	NA	NA	NA
S24 – February 2024	NA	NA	NA	NA	NA	NA

3.4 GUILLEMOT

3.4.1 Models for guillemot were fitted in all 24 surveys. Predicted abundances are shown in Plate 3-3 and Table 3-4. Maps of upper and lower confidence limits, maps coefficient of variation, model diagnostics, and tables of abundance and density for flying and sitting birds, before and after apportioning and correction, are provided in the appendices of this annex.

Plate 3-3 Guillemot modelled abundance (birds per 1 km² grid cell). Figure shows model prediction outputs i.e. prior to apportionment and correction.

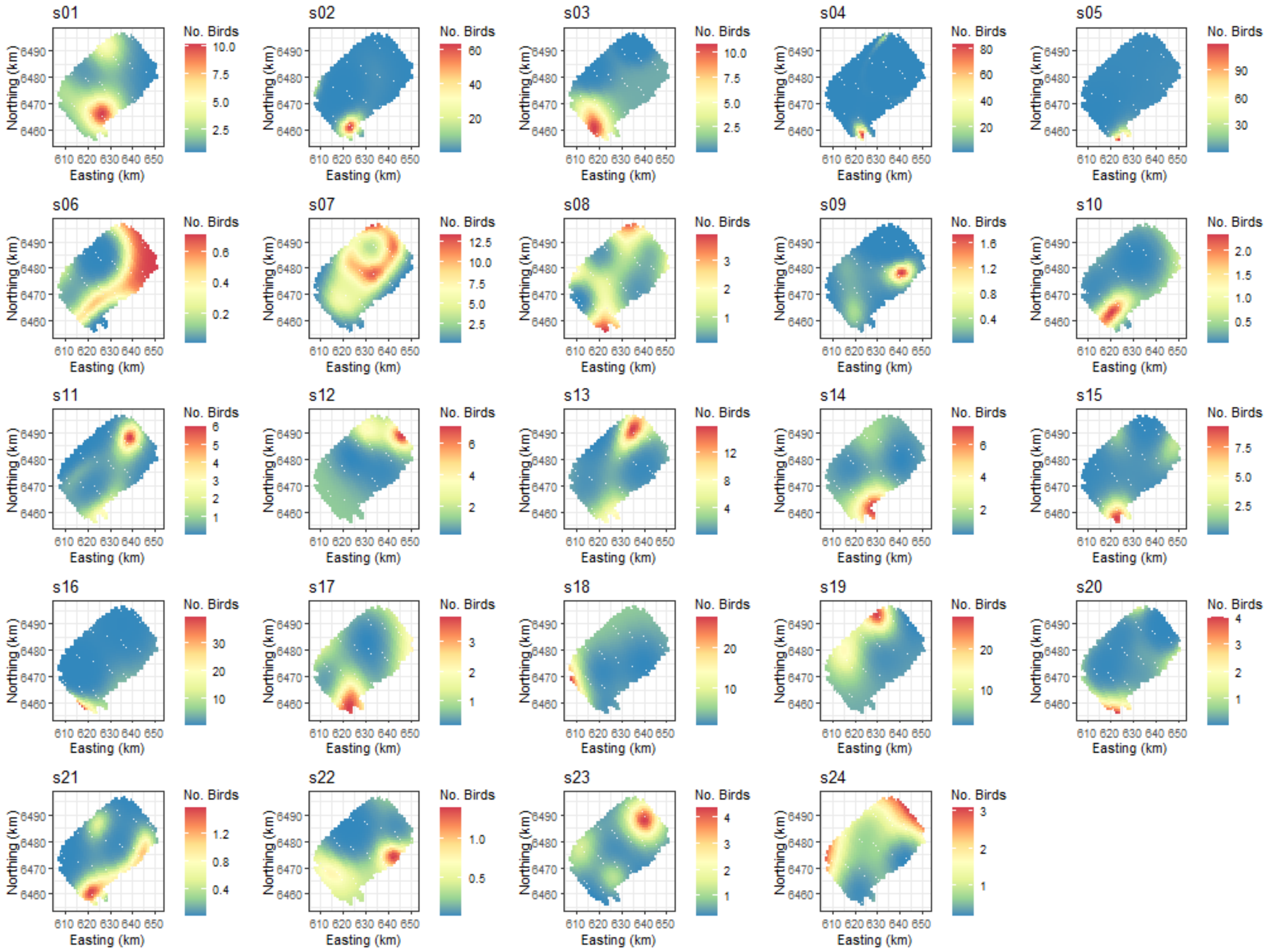


Table 3-4 Estimated abundance and density of guillemot within the Turbine Area plus 4 km buffer (the Study Area). Estimates are inclusive of apportionment of unidentified birds and correction for availability bias.

Survey	Total abundance			Average density (birds/km^2)		
	Prediction	LCL	UCL	Prediction	LCL	UCL
S01 – March 2022	2,181	1,598	4,002	5.33	3.91	9.78
S02 – April 2022	543	278	875	1.33	0.68	2.14
S03 – May 2022	552	442	822	1.35	1.08	2.01
S04 – June 2022	33	9	590	0.08	0.02	1.44
S05 – July 2022	535	354	717	1.31	0.87	1.75
S06 – August 2022	327	175	1,271	0.80	0.43	3.11
S07 – September 2022	5,552	4,510	8,306	13.57	11.02	20.30
S08 – October 2022	501	362	612	1.22	0.88	1.50
S09 – November 2022	132	73	200	0.32	0.18	0.49
S10 – December 2022	123	66	192	0.30	0.16	0.47
S11 – January 2023	475	345	621	1.16	0.84	1.52
S12 – February 2023	426	311	514	1.04	0.76	1.26
S13 – March 2023	1,021	797	1,255	2.49	1.95	3.07
S14 – April 2023	640	425	800	1.57	1.04	1.96
S15 – May 2023	215	118	335	0.53	0.29	0.82
S16 – June 2023	252	107	562	0.62	0.26	1.37
S17 – July 2023	323	176	477	0.79	0.43	1.17
S18 – August 2023	1,058	819	1,307	2.59	2.00	3.19
S19 – September 2023	2,590	2,066	2,824	6.33	5.05	6.90
S20 – October 2023	112	51	206	0.27	0.12	0.50
S21 – November 2023	59	37	123	0.15	0.09	0.30
S22 – December 2023	172	86	272	0.42	0.21	0.67
S23 – January 2024	687	466	909	1.68	1.14	2.22
S24 – February 2024	528	361	725	1.29	0.88	1.77

3.5 RAZORBILL

3.5.1 Models for razorbill were fitted in 15 of the 24 surveys. Predicted abundances are shown in

3.5.2 Plate 3-4 and Table 3-5. Maps of upper and lower confidence limits, maps coefficient of variation, model diagnostics, and tables of abundance and density for flying and sitting birds, before and after apportioning and correction, are provided in the appendices of this annex.

Plate 3-4 Razorbill modelled abundance (birds per 1 km² grid cell). Figure shows model prediction outputs i.e. prior to apportionment and correction.

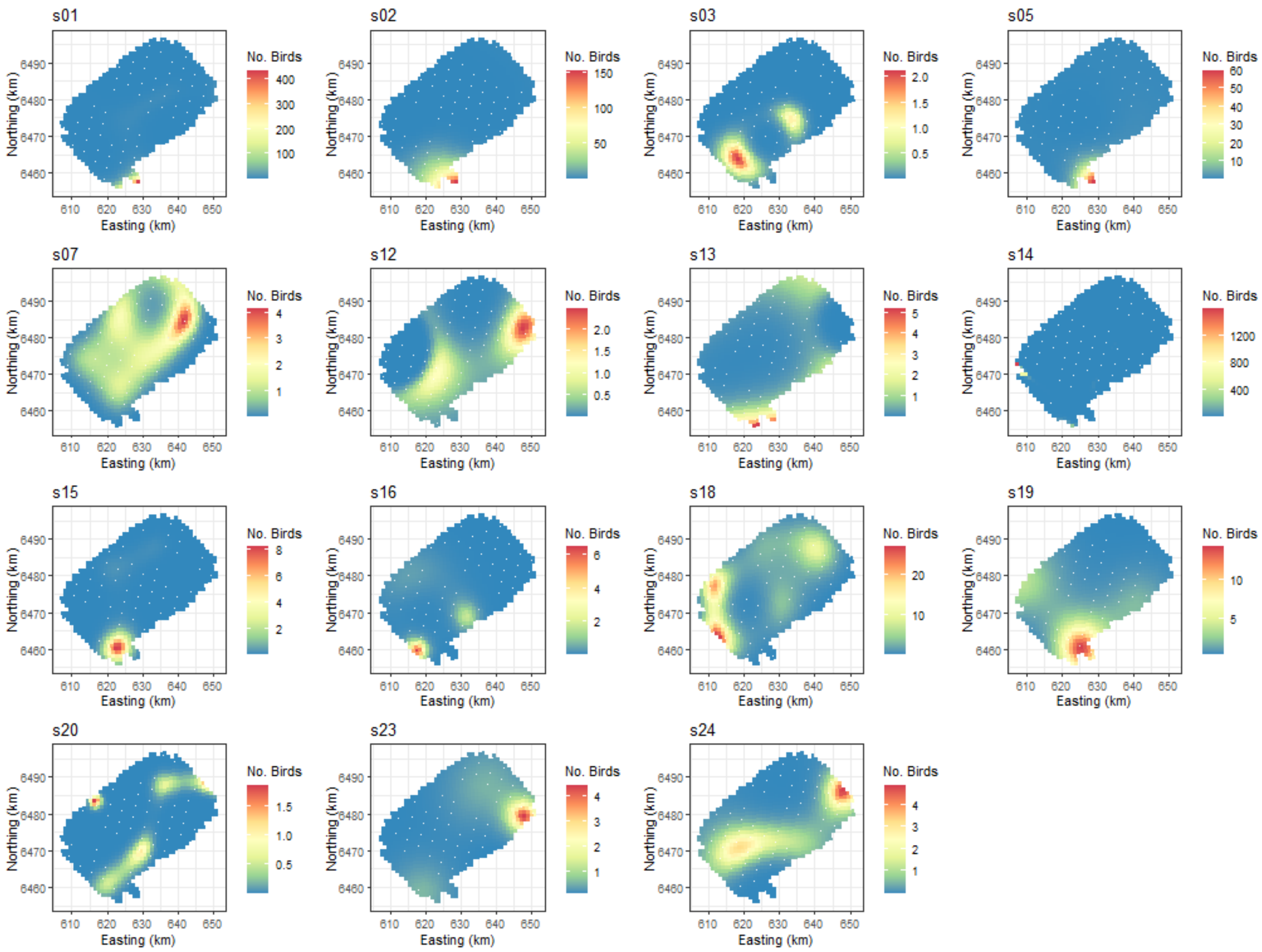


Table 3-5 Estimated abundance and density of razorbill within the Turbine Area plus 4 km buffer (the Study Area). Estimates are inclusive of apportionment of unidentified birds and correction for availability bias.

Survey	Total abundance			Average density (birds/km^2)		
	Prediction	LCL	UCL	Prediction	LCL	UCL
S01 – March 2022	1,065	688	2,288	2.60	1.68	5.59
S02 – April 2022	323	153	653	0.79	0.37	1.59
S03 – May 2022	54	28	136	0.13	0.07	0.33
S04 – June 2022	NA	NA	NA	NA	NA	NA
S05 – July 2022	192	105	282	0.47	0.26	0.69
S06 – August 2022	NA	NA	NA	NA	NA	NA
S07 – September 2022	899	686	1,443	2.20	1.68	3.53
S08 – October 2022	NA	NA	NA	NA	NA	NA
S09 – November 2022	NA	NA	NA	NA	NA	NA
S10 – December 2022	NA	NA	NA	NA	NA	NA
S11 – January 2023	NA	NA	NA	NA	NA	NA
S12 – February 2023	170	105	294	0.42	0.26	0.72
S13 – March 2023	64	38	136	0.16	0.09	0.33
S14 – April 2023	49	38	61	0.12	0.09	0.15
S15 – May 2023	22	10	45	0.05	0.02	0.11
S16 – June 2023	66	36	125	0.16	0.09	0.30
S17 – July 2023	NA	NA	NA	NA	NA	NA
S18 – August 2023	1,221	888	1,638	2.98	2.17	4.00
S19 – September 2023	613	466	730	1.50	1.14	1.78
S20 – October 2023	80	37	155	0.20	0.09	0.38
S21 – November 2023	NA	NA	NA	NA	NA	NA
S22 – December 2023	NA	NA	NA	NA	NA	NA
S23 – January 2024	211	132	315	0.52	0.32	0.77
S24 – February 2024	599	368	925	1.46	0.90	2.26

3.6 PUFFIN

3.6.1 Models for puffin were fitted in 13 of the 24 surveys. Predicted abundances are shown in

3.6.2 Plate 3-5 and Table 3-6. Maps of upper and lower confidence limits, maps coefficient of variation, model diagnostics, and tables of abundance and density for flying and sitting birds, before and after apportioning and correction, are provided in the appendices of this annex.

Plate 3-5 Puffin modelled abundance (birds per 1 km^2 grid cell). Figure shows model prediction outputs i.e. prior to apportionment and correction.

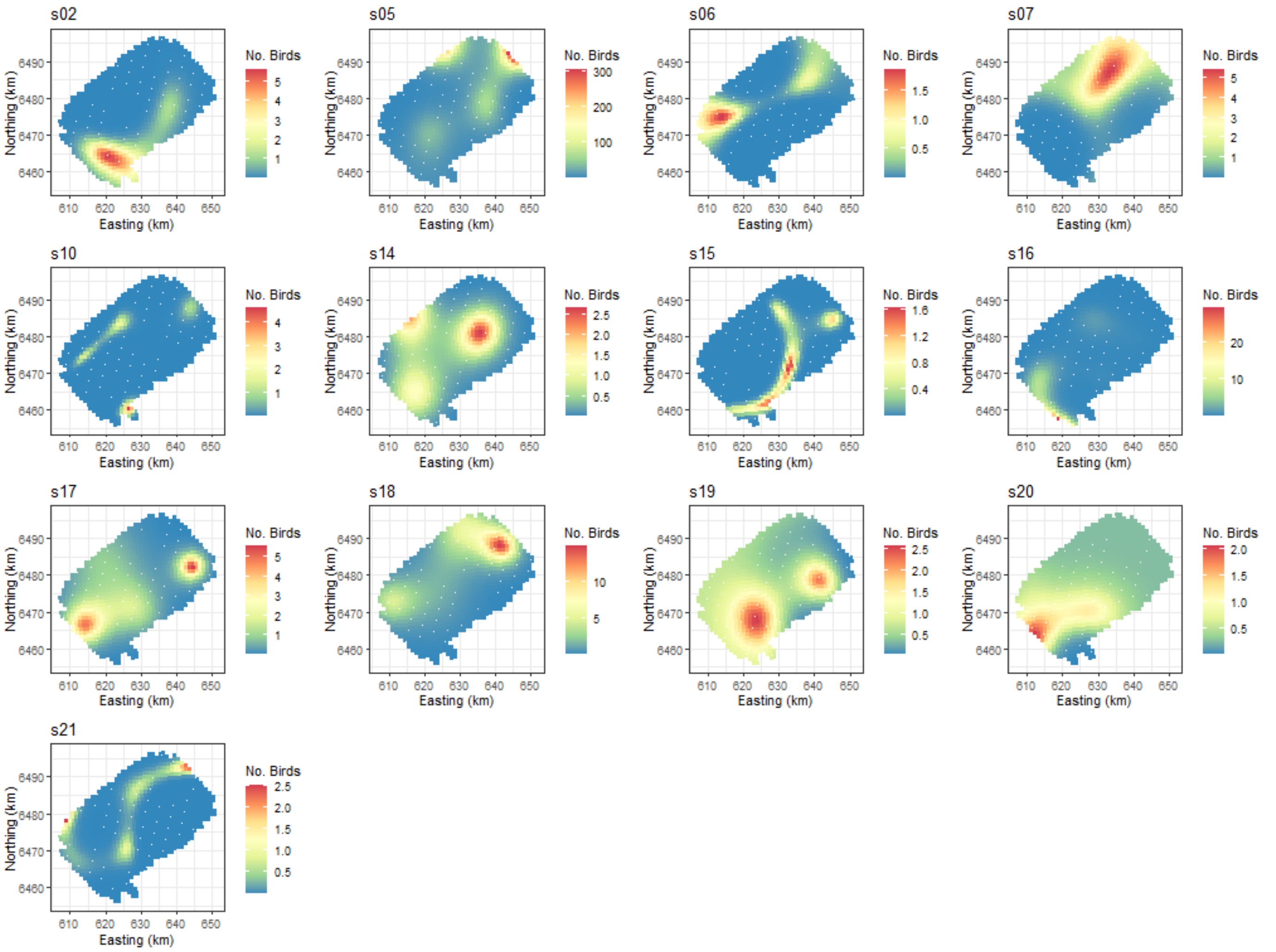


Table 3-6 Estimated abundance and density of puffin within the Turbine Area plus 4 km buffer (the Study Area). Estimates are inclusive of apportionment of unidentified birds and correction for availability bias.

Survey	Total abundance			Average density (birds/km^2)		
	Prediction	LCL	UCL	Prediction	LCL	UCL
S01 – March 2022	NA	NA	NA	NA	NA	NA
S02 – April 2022	152	82	267	0.37	0.20	0.65
S03 – May 2022	NA	NA	NA	NA	NA	NA
S04 – June 2022	NA	NA	NA	NA	NA	NA
S05 – July 2022	10,308	8,209	13,212	25.19	20.06	32.29
S06 – August 2022	67	41	118	0.16	0.10	0.29
S07 – September 2022	683	524	887	1.67	1.28	2.17
S08 – October 2022	NA	NA	NA	NA	NA	NA
S09 – November 2022	NA	NA	NA	NA	NA	NA
S10 – December 2022	10	7	18	0.03	0.02	0.04
S11 – January 2023	NA	NA	NA	NA	NA	NA
S12 – February 2023	NA	NA	NA	NA	NA	NA
S13 – March 2023	NA	NA	NA	NA	NA	NA
S14 – April 2023	354	231	599	0.86	0.57	1.46
S15 – May 2023	59	39	94	0.15	0.09	0.23
S16 – June 2023	225	135	435	0.55	0.33	1.06
S17 – July 2023	488	347	719	1.19	0.85	1.76
S18 – August 2023	870	694	1,140	2.13	1.70	2.79
S19 – September 2023	501	385	674	1.22	0.94	1.65
S20 – October 2023	305	203	434	0.75	0.50	1.06
S21 – November 2023	39	25	78	0.10	0.06	0.19
S22 – December 2023	NA	NA	NA	NA	NA	NA
S23 – January 2024	NA	NA	NA	NA	NA	NA
S24 – February 2024	NA	NA	NA	NA	NA	NA

4 DISCUSSION

4.1.1 Modelling was successfully carried out for the 5 key species in the majority of surveys. The surveys for which modelling was not able to be carried were the surveys with the fewest observations of each species, and therefore the expected abundances in those surveys would be low or zero anyway, so not having modelled abundance estimates for those months is unlikely to materially affect the impact assessment. Further discussion of what these results mean for baseline characterisation is provided in Appendix 14.1, Volume 2c; the discussion in this annex focuses on technical discussion of the modelling process.

4.1.2 In general, the model-based abundance estimates are very similar to the design-based estimates. The model-based results would not be expected to align perfectly with the design-based approach due to the methodological differences. In particular, whilst the estimated abundance/density for the Study Area is very similar, the results for the Turbine Area and Turbine Area + 2 km Buffer show slightly more variation. This is to be expected given the spatial nature of MRSea and the non-uniform distribution of birds within the Study Area.

4.1.3 Overall, therefore, it is concluded that the model-based approach has successfully produced robust abundance and distribution estimates of the key species within the survey area.

5 GLOSSARY OF TERMS AND ABBREVIATIONS

A list of key terms and acronyms used in this annex are provided in Table 5-1 and Table 5-2.

Table 5-1 Acronyms and abbreviations

Term	Definition
DAS	Digital Aerial Surveys
MRSea	Marine Renewables Strategic Environmental Assessment (R package)

Table 5-2 Glossary

Term	Meaning
Array Area	Includes the wind turbine generators, associated foundations, the inter-array cables and offshore substation(s)
MRSea	An R package used to model the abundance of species from survey data.
The Project	To describe the overall development
Study Area	The area over which potentially significant impacts from The Project have the most potential to occur to ornithological receptors, consisting the Turbine Area plus a 4 km buffer (excluding land).
Survey Area	The area covered by DAS, consisting the Array Area plus a 10 km buffer (excluding land)

6 REFERENCES

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