OFFSHORE RENEWABLES JOINT INDUSTRY PROGRAMME (ORJIP) FOR OFFSHORE WIND

CARBON TRUST

WP3: Analysis of existing data

Improving understanding of distributional change for relevant seabird species (ImpUDis)

June 2026

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working to accelerate offshore consenting

ORJIP Offshore Wind

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Abbreviations

Term	Description
OWF	Offshore Wind Farm
DAS	Digital Aerial Survey
DSM	Density Surface Model
ESAS	European Seabirds At Sea
BTO	British Trust for Ornithology
ImpUDis	Improving Understanding of Distributional Change for Relevant Seabird Species
DisNBS	(Effects of) Displacement from offshore renewable developments in the Non-Breeding Season
IBM	Individual-Based Model
BAG	Before After Gradient
BACI	Before After Control Impact
PVA	Population Viability Analysis
GA(M)M	Generalised Additive Model, or Generalised Additive Mixed Model
CRM	Collision Risk Model
WP	Work Package
INLA	Integrated Nested Laplace Approximations

1. Introduction

This document represents the deliverable for work package 3 (WP3) of the ORJIP/Carbon Trust project entitled *Improving Understanding of Distributional Change for Relevant Seabird Species (ImpUDis)*. This project consists of several work-packages, and project goals relevant to work package are:

- Establish agreed methods and sources of evidence to help improve consistency in future assessments and approaches to post-consent monitoring.
- Improve our understanding of seabird distributional change by developing, and applying, standard statistical methods.

This report builds upon initial work within the project, which included:

- WP1 - A comprehensive literature review of studies into the redistribution of seabirds in relation to offshore wind farm (OWF) development (Murrell et al., 2025).
- WP1 - Identification and acquisition of data within these studies, and other OWF developments within UK waters.
- WP2 - A guidance document for analysis of such data for estimating seabird redistribution in response to OWF developments.
- WP2 - An analysis plan for existing data, and associated stage-gate meeting.

This report presents the results of analysis of extant data identified at the stage-gate meeting, using the WP2 analysis plan. This consists of the data obtained under WP1 and deemed usable for estimation of redistribution, following their examination in conjunction with the WP2 guidance. The analyses here also served to inform the WP2 guidance document, offer practical advice, and address research questions confirmed at the stage-gate meeting.

1.1. Research Questions

A series of research questions were proposed during WP2 and presented at the stage-gate meeting.

1. Is there evidence of redistribution of the species in response to OWFs?
2. What is the quantifiable extent of this redistribution?
3. Which candidate analysis methods are practically superior for modelling redistribution based on types of data from WP1?
4. What scale of displacement granularity can be estimated/supported given types of data and methods?
5. What modelled covariates are important drivers of seabird distributions in/around OWF developments and the associated monitoring surveys, outside development effects?
6. Does the OWF developments data support a pooled, transferable, characterisation of redistribution, or does evidence support site-specific effects?

In each instance, these are explored by estimating statistical relationship(s) between animal distributions and developments.

1.2. Data scope

An extensive data gathering process was conducted within WP2, providing substantial data from disparate sources and of varying quality. The initial long list of data was established by identifying data sources fulfilling the following criteria:

- **Identified** – a preference was shown for data sources from the UK, with further preference for any associated with a published investigation into redistribution.
- **Obtainable** – any sources that proved difficult obtain were necessarily excluded
- **Contrasting** – sources were required to contain data collected in both the pre-installation and post-installation periods.
- **Adequate** – sources were required to be well-documented and formatted, without loss of critical attributes (such as spatiotemporal effort)
- **Quality** – data were checked for inconsistencies and those that displayed a gross lack of quality assurance were excluded.

Preliminary data treatments, examination and quality assurance led to eight OWF developments being subject to deeper analysis[1], with eight species/groups with potentially sufficient data for modelling. The OWF and species/groups considered amenable to modelling were († indicates species/groups deemed *a priori* tentative given low abundances over time):

- Beatrice – guillemot, kittiwake, puffin, razorbill, gannet†

[1] Noting some OWF are closely associated with each other

- Gwynt y Mor – Auk sp., kittiwake, guillemot/razorbill, diver sp. †, gannet†
- Inner Dowsing, Lincs, Lynn – auk sp., diver sp., gannet†
- Kentish Flats - diver sp.
- North Hoyle - auk sp., diver sp., kittiwake, Guillemot/Razorbill, gannet†
- Robin Rigg - auk sp., diver sp., gannet, guillemot, razorbill, kittiwake

Initial exploratory plots validated that each instance had sufficient survey effort and associated observations to fit a model. Whilst the initial exploration is omitted from this document, a vignette outlining these steps is available in the GitHub repository, and an outline of the contents and structure of each dataset is provided in Table 1.

Table 1: Overview of installation data scope

Installation	Date Range	Survey Method	Notes
Beatrice	2015-2021	Digital Aerial	
Gwynt y Mor	2010-2018	Digital Aerial	This pertains to a small study area with low counts, and observations are binned into multi-species groups (such as Diver Sp., Cormorant/Shag).
Kentish flats	2002-2007	Visual Aerial	This is JNCC data, covering the wider Thames Estuary. Survey effort varies but consistently contains Kentish Flats.
Lynn, Lincs & Inner Dowsing	2003-2016	Digital Aerial / Visual Aerial	This data is pre-segmented; it has been prepared for a previous analysis.
North Hoyle	2001-2006	Visual Aerial	This is JNCC data, covering the wider Liverpool Bay region. Several installations may be covered spatially and temporally, but North Hoyle has the best coverage.
Robin Rigg	2001-2015	Visual Vessel-Based	

The spatial and temporal extent of all above datasets and sources is provided in an interactive data map: for each individual survey, spatial extent is mapped against a shapefile of any relevant OWF installations. Where possible, the survey tracks have been provided as an overlay. A static map illustrating the outer boundaries of each survey, with relevant OWF installations labelled, is provided in Figure 1. General high-level data summaries are also linked here.

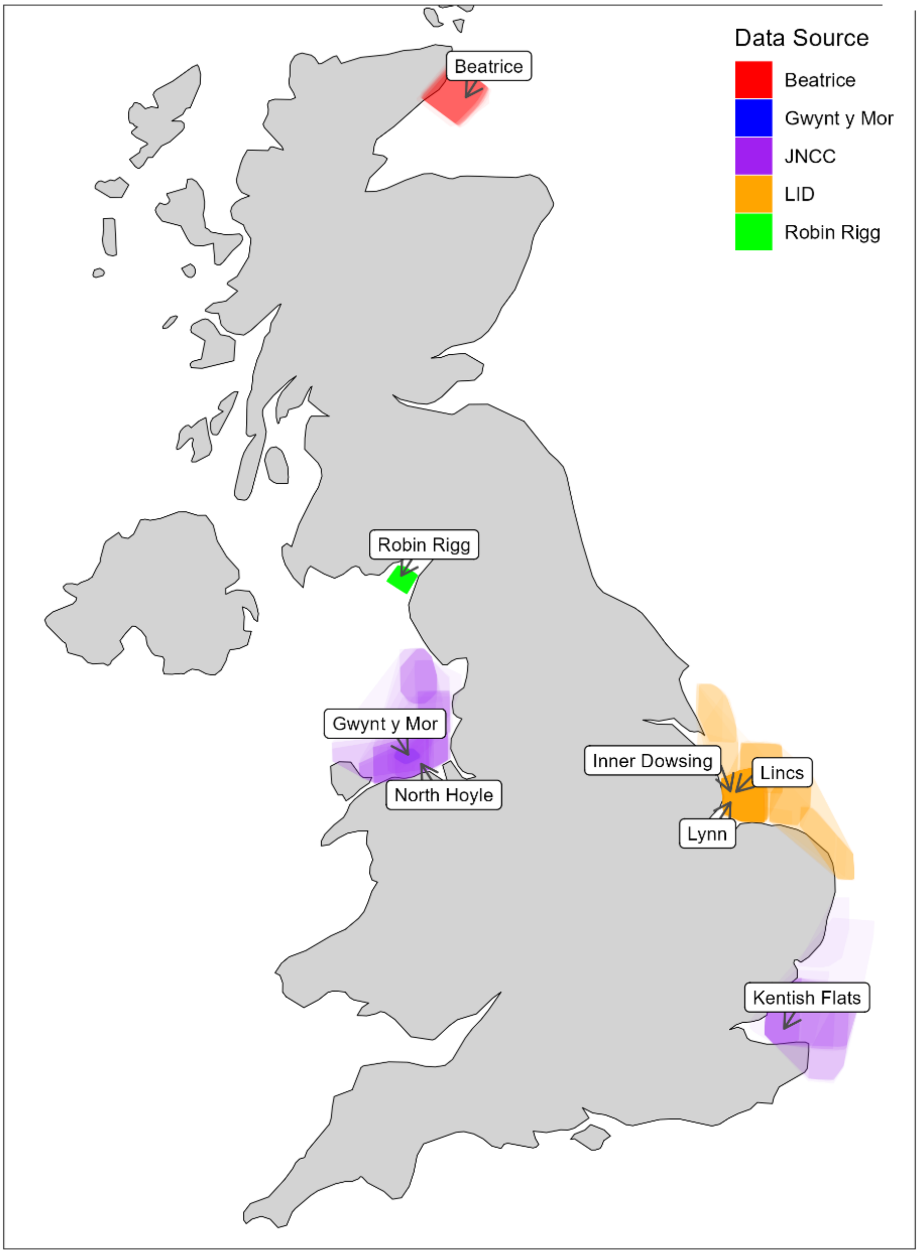

Figure 1: A map of each installation's site, against the relevant survey data. Each survey's polygon is provided as a transparent layer to demonstrate areas of greater survey effort.

1.3. Analysis and report scope

In totality the data obtained and outlined above might permit >100 models, comprising: single species models for each OWF, combined species over developments, and models of simple displacement, displacement as a function of distance to OWF, and more complex spatial redistributions. These might be further fitted at different behavioural levels e.g. flying or sitting.

Modelled data

Modelling of these data in totality is outside scope, and a subset of the data was progressed to detailed analysis in WP3, noting some are excluded on the following basis:

- Species groupings are not necessarily similar over surveys, so ought not be accumulated e.g. the grouping diver sp. evidently covers different species.
- The guillemot/razorbill combined grouping for Gwynt y Mor and North Hoyle is inseparable without species level observations, so cannot be included in a joint guillemot or razorbill analysis.
- Some species with reasonable counts when viewed in aggregate may be entirely excluded at some time-periods due to survey design e.g. was not collected to species level for earlier visual surveys vs later digital aerial.

The resulting short list was given detailed analysis, by species:

- Kittiwake: Beatrice, Gwynt y Mor, North Hoyle, Robin Rigg
- Guillemot: Beatrice, Robin Rigg,
- Guillemot/Razorbill: Gwynt y Mor, North Hoyle
- Puffins: Beatrice
- Razorbill: Beatrice, Robin Rigg
- Auk group[2]: Gwynt y Mor, Lincs, Lincs, Lynn, North Hoyle, Robin Rigg
- Divers group[3]: Gwynt y Mor, Lincs, Lynn and Inner Dowsing, North Hoyle, Robin Rigg

Reporting scope

This document summarises analysis works in line with the WP2 analysis plan and the underpinning WP2 guidance document. Analyses are advised therein to be reproducible and version-controlled, so are presented in detail in the associated github repository. Detailed results for all analyses are not presented in this report, with the full set being voluminous and repetitive – the repository contains documented code for reproducibility of the full set of analysis. One set of analyses is presented here in detail (the *focal* species and development), with the findings of the others summarised.

This document gives:

- high-level descriptions of general data treatment and analysis (sections 2 & 3)
- finer detail on the data treatment and analysis of kittiwake as an exemplar (sections 4 & 0),
- summaries of the analyses and their findings conducted for kittiwake, guillemot, gannet, puffins and some species groupings (section 6)
- a discussion of these analyses in the context of research questions proposed in WP2 (section 7)

This document summarises the state of analysis at time of issue. The repository should be considered definitive and contains fine scale, reproducible, detail.

[2] The definition/contents under this grouping can differ over surveys

[3] The definition/contents under this grouping can differ over surveys

2. Data methodology

The following general data treatments were applied – a detailed treatment vignette is found within the work package repository.

2.1. Initial data treatment

Consistency of format and general QA

All data were broadly checked for errors and placed into a common format. There were typically two components for a survey, although varying in presentation. These were the observations data, giving positions and classification of sighted animals, and the track information, which details where/when areas were surveyed e.g. the GPS vessel tracks. The process was:

- Ingestion of all data in its various formats (spreadsheets, csv, shapefiles, etc)
- Formal spatial representations for coordinates, with projections defined.
- Formal time/date representations for observations
- Alignment of all factor-coding e.g. species codes

A range of fundamental checks (plots and summaries) were conducted to detect and amend obvious errors, including – but not limited to:

- Removing surveyor tracks that were recorded out-of-effort
- Removing observations inexplicably distant from line transects
- Validating that observation and effort data is available for all surveys
- Amending any obvious user-input errors (e.g. excessively large flock sizes)

Derived variables and additional covariates

As the modelling is based on the Before-After-Gradient (BAG) approach, potential confounding factors need to be accounted for to allow estimation of development effects, and better associated power. The following were derived for the data:

- Date information reflecting construction - date of construction/completion
- Distances from the developments - ideally the realized footprint, as opposed to planned. These data were a mix of published footprints, developer-provided, or approximated by convex hulls arounds survey tracks.
- Bathymetry (GEBCO Compilation Group, 2024)

Adjustments for visual observations

All data progressed to analysis were based on designed surveys, where the platform and methodology were either visual boat, visual aerial or digital/photographic aerial. The visual methods, where the sighting of animals is over varying distances, are subject detection bias – so distance analyses were attempted for all such affected species/species groups (Buckland et al., 2015) using the R package Distance (Marshall et al., 2025).

Notably distance analysis requires the assumption that observed individuals are distributed randomly across the width of the transect. This assumption is easily violated, particularly in the case of vessel-based surveys where individuals move away from the observer during the survey (e.g. Figure 2). Distance analysis was not possible for all recorded species, due to these avoidance patterns in vessel data. Counts in these cases are unadjusted, assume equal detection with distance, and reflect relative, rather than absolute, numbers.

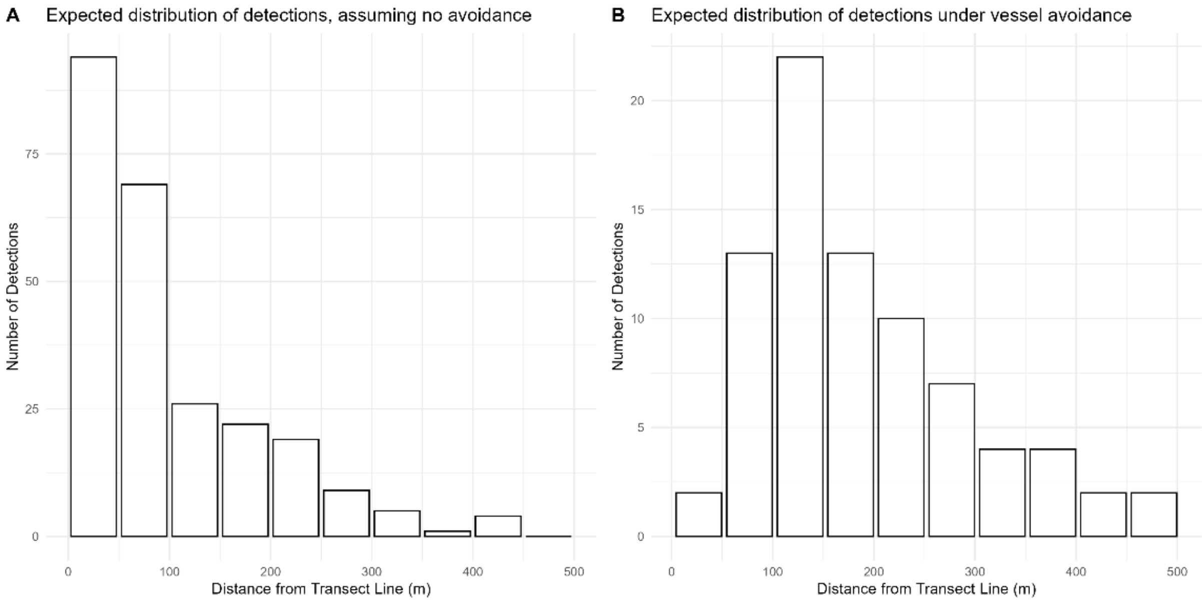

Figure 2: A simulated example comparing the 'expected' distribution of detections to strong avoidance behaviour.

3. Modelling methodology

3.1. General methodology

As described in the WP 2 guidance, the models must allow complex relationships, count responses, random effects, and flexibility in error distributions - both in form and dependencies e.g. cluster, spatio-temporal.

These requirements imply variants of Generalised Additive Mixed Models (GAMMs) when fitted and specified in the frequentist framework, or some Bayesian multi-level model equivalents. The term GAMM will be generally used through the report, while acknowledging this is not strictly accurate for all methods discussed.

GAMMs were fitted to the survey counts, have offset terms to account for variable effort, and with a wide range of predictors. These contained: notable environmental covariates, meso-scale temporal terms to capture seasonality, distance to the realized OWF structures, indicators for development phases, survey type, and development. Interaction terms were important in the testing and model selection phase, to address research questions. Random effects and dependencies in the errors were generally included.

The final models were a product of model selection and amendments in light of model diagnostics – notably many of the species models had a preponderance of zero values, beyond the expectations of simple Poisson models. The stochastic elements of the data were found to be approximated Poisson, quasi-Poisson, negative-binomial, or zero-inflated negative binomial/Poisson.

Modelling was documented in markdown, and version-controlled for its final iteration.

3.2. Modelling tools

There are a number of model fitting tools that are suitable for displacement estimation, depending on the nature of the model. Several were considered during the modelling process, which are listed below, with notes as to their suitability and limitations.

- GAMMs via mcgv (Wood, 2017; Wood et al., 2016) – a well-developed package but with limited zero-inflated offerings when fitting as a mixed model.
- glmmTMB (Brooks et al., 2017; McGillycuddy, Popovic, et al., 2025) – offers a wide range of model types, in particular zero-heavy distributions and associated correlation structures. Notably spline smoothing is generally experimental, with two-dimensional being under-developed.
- Bayesian Regression Models using Stan (brms package Bürkner et al., 2018) – very flexible Bayesian model specification. This uses a Hamiltonian Monte Carlo method for model fitting and can have long computational times to convergence e.g. hours-to-days for complex models.
- INLA via R-INLA and inlabru (Bachl et al., 2019; Martino & Riebler, 2020) - very flexible model specification and fundamentally Bayesian, but it’s quadrature-based Laplace approximation algorithm is substantially faster than traditional Bayesian inference approaches. This is evolving software that lacks many programming conveniences needed to build models quickly. A good theoretical understanding is required and documentation is inconsistent, making it difficult for non-expert users.

- MRSea – a GAM implementation (Scott-Hayward et al., 2013, 2014) based on adaptive splines and GEE fitting for correlated errors. This has been the advised UK method for modelling OWF data in recent years. Can suffer from unstable model fits when densities are low, particularly in terms of its parametric bootstrapped inference.

Methods/tools employed

Modelling here was generally via the glmmTMB and mgcv packages which offered:

- Mixed models with a rich set of family distributions and correlation structures
- Rapid fitting
- Model specification and tools similar to other regression modelling
- Integration with other modelling helpers e.g. Dharma for diagnostics

Model diagnostics and comparisons were via the DHARMA package (Hartig, 2024).

- A particular limitation in glmmTMB is the underdeveloped smoothing functionality, although it integrates with the spline R package and elements of the smoothers from mgcv.

4. Data treatment – focal case

The focal species and development for this report are the kittiwake observed in association with the Beatrice OWF. These are chosen due to the relatively large numbers of animals and consistency of survey methods (digital aerial), giving a relatively clear example – refer to the discussion (section 7) for a range of complexities that enter other cases. Whilst this section will provide a brief overview of data cleaning and preprocessing, a coded example is available in the GitHub repository associated with this document. This example does not incorporate any behavioural differences (e.g. sitting vs flying), to provide a generalised example.

Initial Cleaning & Validation

Prior to modelling, a thorough review was conducted. This involved manual validation of spatial attributes (observation locations, GPS tracks, etc.) and any associated non-spatial data (number of individuals observed, associated timestamps, etc). Figure 3 contains an example of track and observation data for one survey within the Beatrice OWF example.

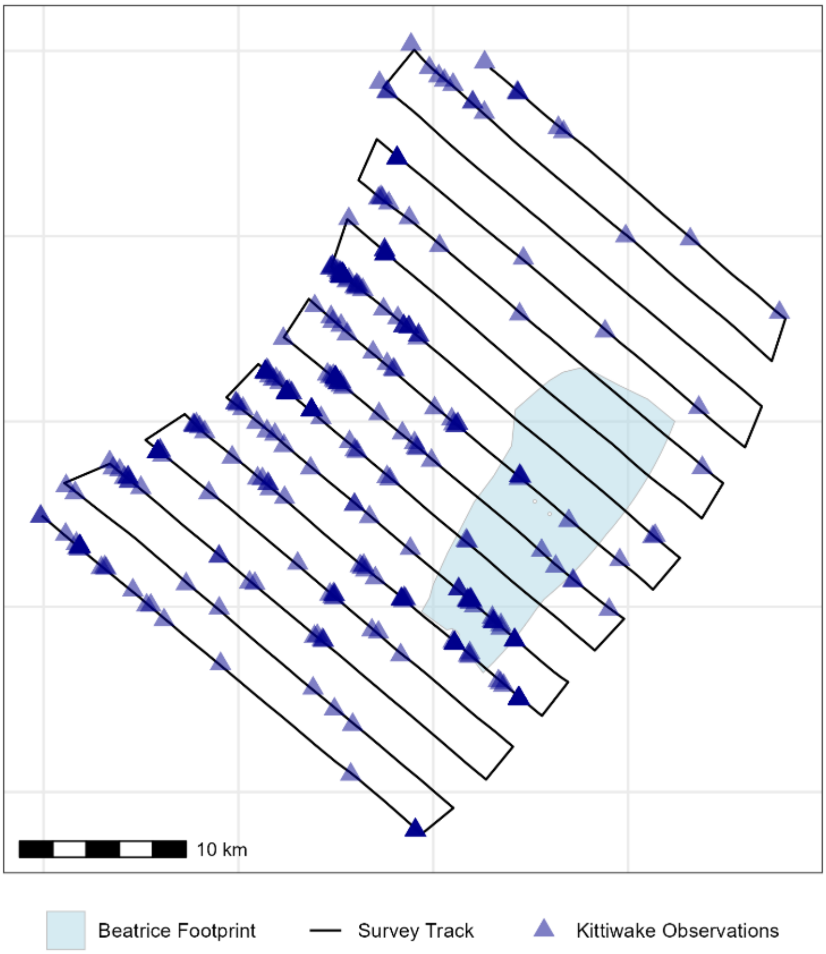

Figure 3: An example of what we expect to see on a review of the data, derived from the Beatrice data – continuous aerial survey tracks with associated observation data. Surveys conducted from fixed wing aircraft, four digital video camera array, approximately 500m altitude, offering up to approximately 500m swath over all cameras.

Analysis here requires both observation data (describing individual birds' locations and characteristics) and track data (describing the tracks followed by the surveyors). In most cases, the track data will need to be cropped to remove out-of-survey or off-effort elements – such as the periods in which the aircraft is turning – as data is not consistently collected in these periods, and effort would otherwise be overestimated.

A further factor to consider is changes to survey design that might have taken place between surveys. This might involve:

a. Changes to survey methodology, such as moving from visual-aerial to digital-aerial surveying – this will require distance analysis on only *part* of the data

b. Changes to survey design, such as adding, removing, or moving a transect

c. Changes to the post-processing of data – for example, in digital-aerial survey data, sometimes only a subset of the cameras are reviewed, affecting the transect width or survey coverage

In the context of the Beatrice example, instance C applies here: two cameras were reviewed for the majority of surveys, but four were reviewed for a subset. Transect width (and, consequently, spatial effort) needs to be increased for the transects that were fully reviewed.

Data Segmentation

Modelling of the structure outlined below requires observations to be summed to spatial 'nodes' or 'segments' along the transect lines – typically 1km resolution. The simplest way to do this is:

1. Sub-divide the survey tracks into equal-length segments
2. Estimate the spatial effort associated with each segment, where $\text{effort} = \text{segment length} \times transect\ \text{width}$
3. For each segment, 'count' the number of observations observed as the surveyor passed through the segment – this is the response variable, *Count*

Figure 4 illustrates an example of the output of survey segmentation for one survey in the Beatrice OWF dataset.

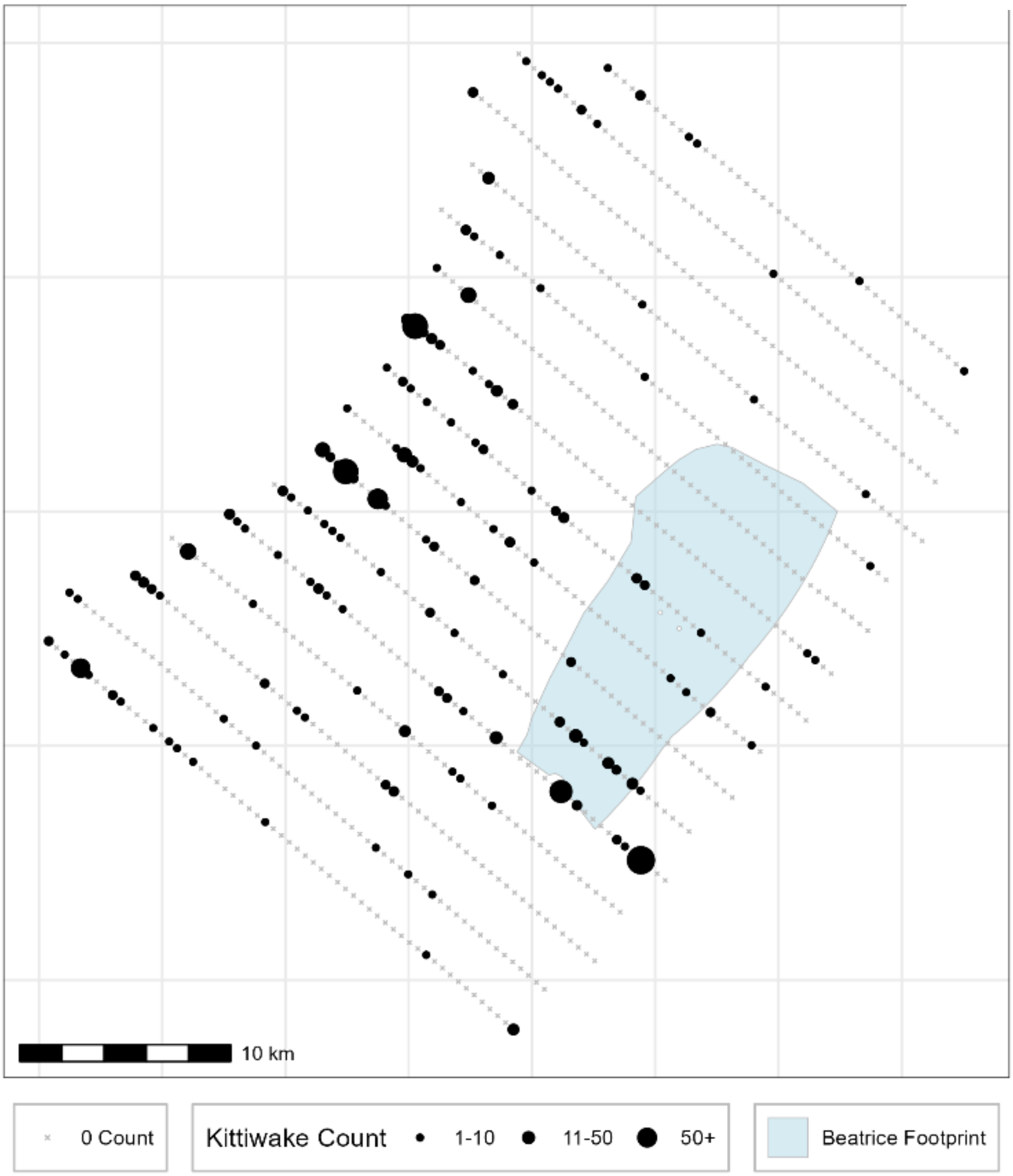

Figure 4: Example of segmented tracks and observations, binned into size groups – 1km segments and 250m – 500m width[4].

[4] Depending on the number of cameras processed in practice – usually 2 to 4.

5. Modelling results – focal case

An account of the redistribution modelling for the focal case is given here, noting that the full details at a reproducible level are given within the associated repository. As for the data preparation, all modelling and post-processing was performed within the R statistical programming environment (R Core Team, 2024).

Three modelling approaches are presented here:

1. Simple redistribution: estimates of the general changes in animal abundance within the development footprint that can be associated with the operational vs pre-construction phases.
2. Functional redistribution (simple): estimates of the general changes in animal abundance as a one-dimensional function of distance from the development, contrasting operational and pre-construction phases.
3. Functional redistribution (complex): estimates of the general changes in animal abundance as a spatial function around the development, contrasting operational and pre-construction phases.

These are generally a reposing of how the redistribution is specified, with many of the surrounding modelling features being the same across approaches. The potential modelling tools required for each case may differ however, due to the increasing complexity. The commonalities are considered first, with case specific details given in their sections. The approach in point 1) is given in section 5.1, whereas approaches 2 & 3 are in section 5.2 as they arise from the same model structure, with differing smooths for the proximity to OWF.

All models contained/accounted for:

- The fundamental response being animal counts at a location (at 1km^2 resolution)
- Changes in animal abundance beyond the development e.g. general temporal changes. All models contain annual terms for general broad-scale abundance changes, as well as monthly elements to capture seasonality.
- Random components in the mixed modelling context: year and surveys date
- Variable effort, captured as an offset term. This is the effective area covered within the survey cell with its associated count. Given the cells are 1km^2 this is equivalent to the proportion covered.
- Residual correlation in the errors/spatial autocorrelation. These are captured here as dependencies along transects.
- A model for the stochasticity of the response, given its expectation e.g. Poisson – the standard base model for count data. Data of this type (seabird counts) is often heavier in zeros than a Poisson and/or with greater variance than expected with a Poisson random variable. Candidates to account for this overdispersion were negative binomial, zero-inflated Poisson or negative binomial. Quasi-Poisson is also considered as it generalises the mean-variance relationship of the Poisson.

5.1. Simple redistribution

The fundamental redistribution measure here is the magnitude of increase or decrease of animal density within the development area, relative to its surrounds. This is a simple "displacement rate" that might be employed in a displacement matrix analysis. To separate out development effects from other influences, in particular general temporal changes, the estimate of an interaction between location (inside/outside the OWF) is of primary interest. This can be interpreted as a change in the relative density inside/outside coincident with the development.

The model was fitted using the glmmTMB package (Brooks et al., 2017; McGillycuddy et al., 2025) with model examination using the DHARMa package (Hartig, 2024). The final model consisted of:

- Log link and negative binomial[5] errors.
- Fixed effects terms for month, random effects for year and survey.
- Fixed effects terms for: pre/post-construction phase (phase), boolean for inside/outside the OWF footprint (OWF), and an interaction between phase and OWF.
- Type 1 autoregressive errors (AR1) where correlation is within ordered blocks along transects, with 5 km to 10 km sufficient to achieve independence.
- An offset term using log effort

Model selection/refinement was made on the basis of AIC[6] and consideration of diagnostic plots. The detailed analysis can be found in markdown form within the project repository, along with those underpinning the general findings in section 6.

Findings and interpretation

The topline result is that there was a relative increase in the predicted density of kittiwakes within the OWF footprint region, when moving from pre- to post-construction and other covariates have been accounted for (**Table 2**). This effect associated with the development alone was estimated to be approximately an 80% increase compared to what we be expected in its absence – as indicated by the interaction term. While significant in the traditional statistical sense ($p = 0.0046$), there is still substantive uncertainty about the estimate, with the increase between 20% and 174%. Additional temporal terms are also presented for additional context e.g. June and July densities are on average much higher than May. The animals appear not to be avoiding the OWF area post-construction but potentially attracted – the reasons for increased numbers being subject to interpretation.

Distributionally, the negative binomial was a good fit to these data. There remains some residual correlation (Figure 5), suggesting uncaptured patterns over a range of several kilometres. This may be genuine spatial autocorrelation, or stem from the model not catering for any systematic spatial structure beyond the OWF boundaries. In the former case modelling could be conducted with explicit spatial autocorrelation, within glmmTMB or INLA, with much greater computational burden given the volume of data. The latter case of more complex spatial structure is addressed in section 5.2.

[5] Specifically, the type 2 negative binomial (quadratic variance) based on nbinom2

[6] Fitted with maximum likelihood

Table 2: Fixed effects estimates (data scale, presented as percentages) for the Beatrice kittiwake simple displacement model. Highlighted term is the primary estimate for redistribution. R^2 = 0.72.

Species	Model term	Estimate	Lower 95% CI	Upper 95% CI
Kittiwake	Month 6 vs Month 5	360.7%	139.5%	932.8%
	Month 7 vs Month 5	368.8%	132.8%	1 023.7%
	Month 8 vs Month 5	186.3%	49.3%	703.6%
	Post installation	64.8%	30.0%	139.9%
	inside OWF footprint	120.7%	85.2%	170.9%
	pre/post OWF footprint interaction	181.7%	120.2%	274.6%

Table 3: Example estimates of density (per km^2) for June contrasting the within OWF footprint to outside, pre- and post-construction (fixed effects predictions).

Species	Model prediction (Month 6)	Estimate	Lower 95% CI	Upper 95% CI
Kittiwake	Within OWF, pre-construction	10.2	8.84	11.9
	Outside OWF, pre-construction	6.55	6.03	7.11
	Within OWF, post-construction	12.2	11.2	13.4
	Outside OWF, post-construction	4.97	4.71	5.25

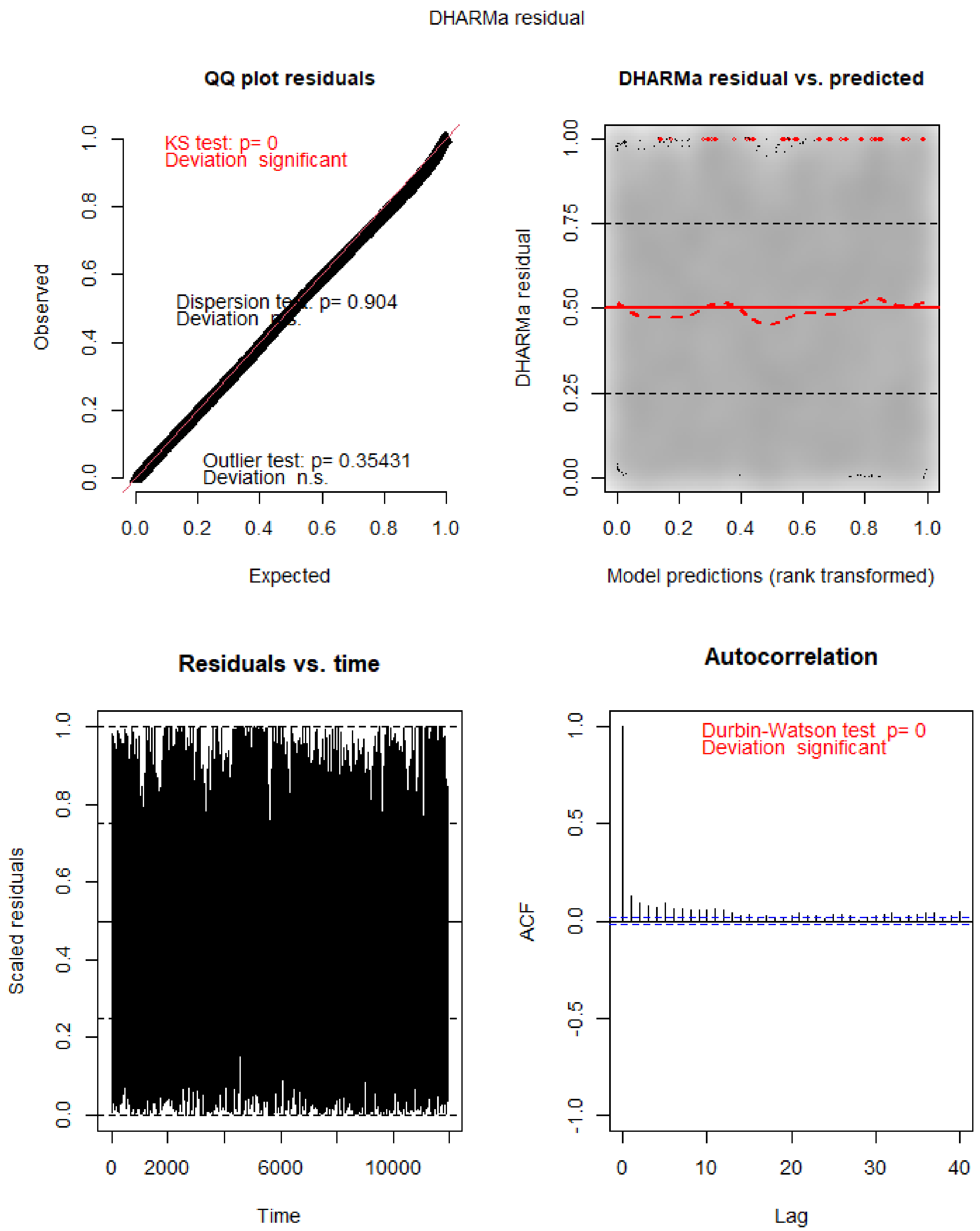

Figure 5: Basic diagnostic plots for the Beatrice kittiwake model. Clockwise from top left: 1. QQ plots showing the consistency of assumed and observed error distributions, 2. Scaled residuals versus magnitude of predictions, 3. Scaled residuals over time and 4. Correlation of residuals at decaying distance (blue lines indicative of effective independence)

5.2. Functional redistribution

Analysis here looks at detailed redistribution, where distance to the OWF development is a covariate. In keeping with the previous analysis of section 6.2, other prospective effects on distribution are included in the model, to isolate the OWF contribution. Focus is again on contrasting the pre- to post-operation distributions, here being either the simple distance to the development (non-directional), or the more general spatial distribution (directional).

The model was fitted using the gamm function within the mgcv package. The final model consisted of:

- Log link and negative binomial errors.
- Fixed effects terms for month and bathymetry (smoothed), random effects for year and survey.
- Fixed effects terms for:
    a. Smooths of distance to OWF, fitted for each of the pre/post-construction phase (phase). The contrast in these functions gives the redistribution effect.
    b. Two-dimensional smooths about OWF, fitted for each of the pre/post-construction phase (phase). The contrast in these functions gives the redistribution effect.
- AR1 correlations in errors within blocks along transects.
- An offset term using log effort

Model selection/refinement was made using AIC and consideration of diagnostic plots. The smooths interacting with phase, with the effects of other covariates partialled out, are of primary focus – which form the basis of pre-to-post-construction contrasts. These are visualised for the two functional models in Figure 6 and Figure 7 for the focal species.

Findings and interpretation

There is evidence of redistribution associated with the completed installation of the OWF for this species. Taken as a simple function of distance, there is a relative increase of animals in near proximity of the OWF, with a concomitant decrease farther away (Figure 6). Examination of the full spatial changes, this corresponds to relative increase in the North-West and decrease to the South-East (Figure 7). Kittiwake abundance at the OWF boundary is approximately 50% higher[7] in the post-construction environment, mirroring the findings of the simpler model. The construction of this model excludes changes internal to the boundary, being only based on distance to the boundary. Calculations to some nominal OWF centre could inform on this further.

Notably the estimated autocorrelation has decreased markedly from previous to a negligible AR1 of 0.08, meaning little association in the errors at 1km scale. This indicates the unresolved correlation in the simpler model was captured by the spatial structure of the added covariates.

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[7] Approximately 0.4, giving a multiplier of exp(0.4) = 1.49.

The redistribution as a simple function of distance is similarly reflected in the more complex spatial smoothing (Figure 7). However, it can be seen here that while there is an estimated increase in kittiwake densities near the OWF, the decline at farther distances is generally at South-East i.e. offshore and at distance from the East Caithness Cliffs SPA, which is found along the adjacent coast.

Some knowledge of the surveyed area should temper the interpretations (refer interactive map linked in section 1.2), given the surveys were conducted from the Eastern shore of far-North Scotland, and lop-sided with regards the OWF location. This means the sample effort at the farther distances in the displacement function in Figure 6 are nearer the shore and North-West. Distances of >6 km would contain some measure of artefact from the survey design, as not all directions from the OWF offer this distance of coverage. In addition, Moray East construction had begun in the last year of the Beatrice survey data (2021), whose position is also coincident with estimated spatial declines (Figure 7) and may be a contributing factor. Future addition of the Moray pre-/post-construction data to models could refine their contributions to redistributions.

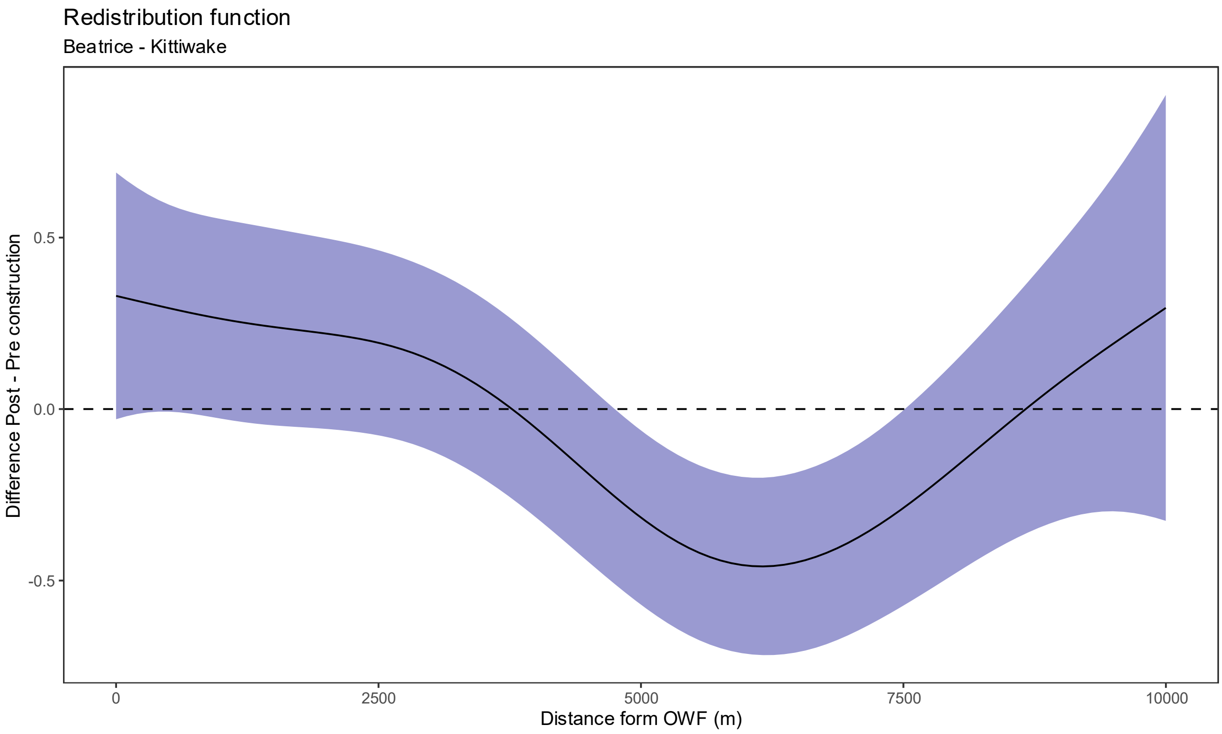

Figure 6: Isolated redistribution function as a function of distance from the OWF.

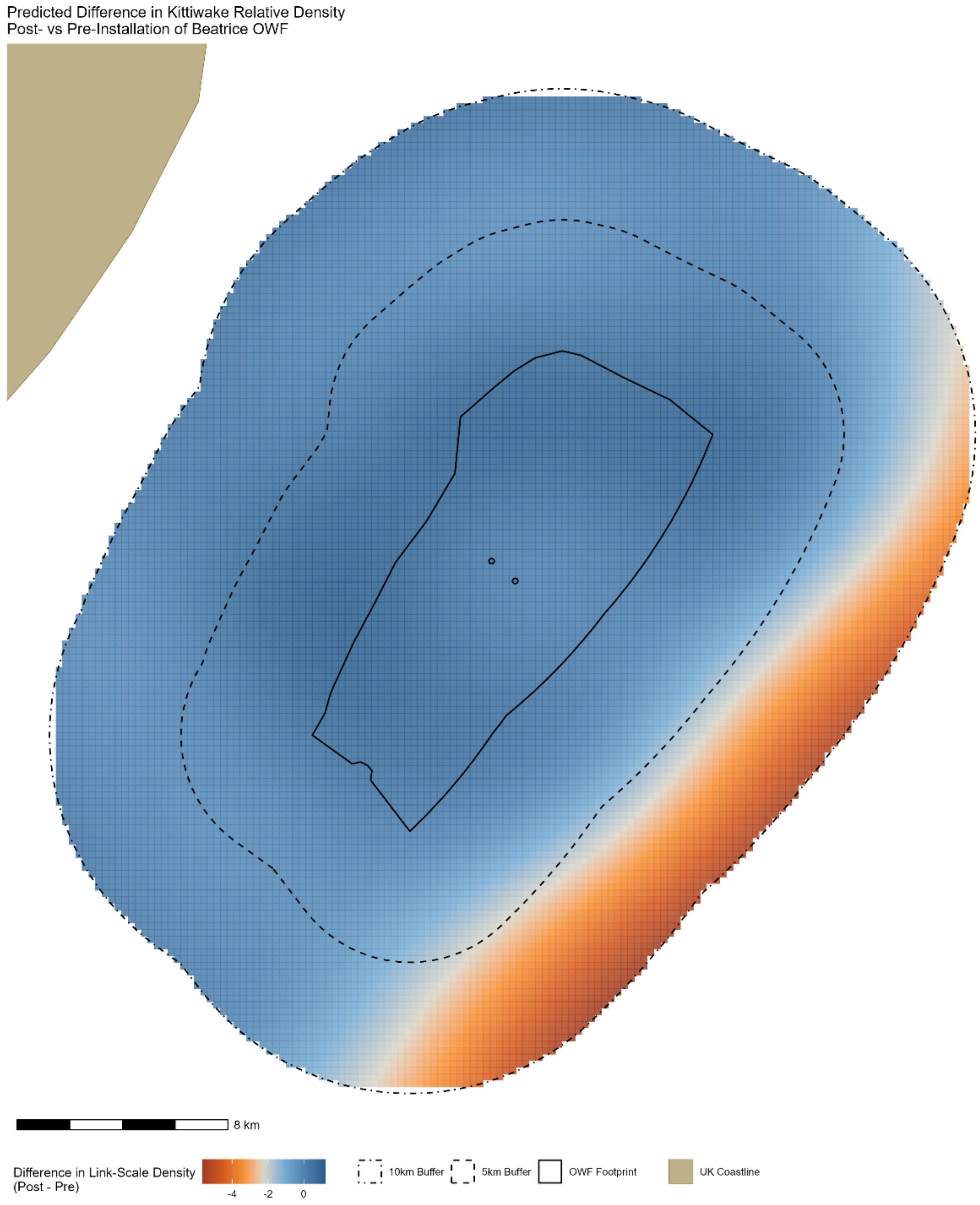

Figure 7: Spatial contrast between kittiwake distributions of construction phases (post – pre). Other covariates have been accounted statistically controlled for within the model.

6. General results

Following similar process to the focal species in 0, the remaining data were modelled. An overview of modelling is given here for the same three model types of increasing complexity:

- An estimation of simple percent reductions in footprint.
- Estimated redistribution as a function of proximity to the OWF footprint, both as simple distance to OWF, and as general spatial surfaces.

6.1. Modelling overview

Despite initial data triage and cleaning, the process of modelling reveals a number of limitations in the data, for example a lack of coincident months over phases. These are structural limitations in estimating model terms, often due to data support. Further restrictions and notable features of the modelling data are given in Table 4.

Table 4: An overview of the OWF-species combinations that are able to be modelled, with reasons for their exclusion or failure to fit.

OWF	Species or group	Summary
Barrow	Auk sp. kittiwakes	• There was no data in hand that clearly covers the operational phase. Reported commissioning year was 2006, coincident with only 1 month of survey data, which may not be during operation. No modelling is possible as there is no clear contrast between pre and post development. • There is variable temporal coverage within years, with winter best represented. Substantial numbers of Auk sp. reported, and kittiwake in double figures in some months.
Beatrice	Gannet Guillemot Kittiwake Puffin Razorbill	• Benefits from consistent survey design and spatio-temporal coverage, albeit with only 3 years coverage. Yearly coverage of May-August. All species able to be modelled.
Gwynt y Mor	Auk sp. Kittiwake Guillemot/razorbill Diver sp Gannet	• Auk and kittiwake unable to be modelled as these lack post construction observations (commission date of 2015). • There is one summer survey but lacks pre/post construction representation. • Essentially provides now two years survey effort, given survey blocks are covered Dec/Jan. • Once thinned to later surveys, gannets (35 in 2017) and divers (low single digits) are sparse. • Only the guillemot/razorbill grouping supports modelling.
Inner dowsing	Diver	• Combined with Lynn given adjacency and commissioning dates.

Lincs	Auk sp Diver sp Gannet	• Very long time-series with wide coverage of months, auk and diver are well-represented, gannets being much sparser. • Given the proximity of Lynn and Inner Dowsing (LID) redistribution for Lincs (commission date 2013) is conditional on these already operating. Data here is restricted to >2009 to provide a separate redistribution conditional on extant OWF. • Divers not present in the summer months, so these are excluded from analysis. • Low gannet presence led to grouping to seasonal levels (autumn and summer) for the modelling.
Lynn	Auk sp Diver sp	• Combined with Inner Dowsing given adjacency and commissioning dates.
North Hoyle	Auk sp. Diver sp. Kittiwake Gannet Guillemot/razorbill	• Very early commissioning date (2003). There is auk sp., diver sp., and kittiwake coverage for months 11/12/1/2 up to 2006. • Gannets have effectively no observations prior to construction or immediately after. • Guill/razorbill have no observations beyond 2002 • Modelling is restricted to auk sp., diver sp. and kittiwake.
Robin Rigg	Auk sp. Diver sp. Gannet Guillemot Kittiwake Razorbill	• Very long time-series with monthly coverage. • Summer not included for divers due to a lack of observations.

6.2. Simple redistribution estimates

Models of the type described in the statistical methods and focal case were fitted to the OWF and taxa in Table 5. The interaction effects isolating the OWF construction are presented, with uncertainty. There are indications that in the OWF footprint region:

- Gannet are present in significantly lower densities after construction (Beatrice and Lincs).
- Kittiwake are present in significantly higher densities after construction for Beatrice, but this is inconclusive at Robin Rigg.
- Puffin are present in significantly lower densities after Beatrice construction.
- Diver sp. Are present in significantly lower densities after Robin Rigg construction (taxa group as per definition for these surveys).

Table 5: Overview of the estimated simple redistribution estimates for all OWF and species progressed to detailed modelling. Grey shading indicates a statistically significant result i.e. a redistribution effect/multiplier that excludes 100% in its confidence bounds (100% representing no change).

Parameter	Species or group	OWF	Estimate	Lower CI	Upper CI
pre/post OWF footprint interaction	Auks sp.	Lincs	77%	44%	136%
		North Hoyle	71%	7%	707%
		Robin Rigg	69%	24%	202%
	Diver sp.	Lincs	21%	1%	637%
		North Hoyle	169%	6%	4990%
		Robin Rigg	41%	18%	93%
	Gannet	Beatrice	20%	7%	57%
		Lincs	4%	0%	64%
	Guillemot	Beatrice	127%	92%	175%
		Robin Rigg	97%	75%	125%
	Guillemot/Razorbill	Gwynt y Mor	34%	13%	90%
	Kittiwake	Beatrice	182%	120%	275%
		Robin Rigg	99%	59%	167%
	Puffin	Beatrice	48%	30%	75%
	Razorbill	Beatrice	137%	76%	247%
		Robin Rigg	90%	50%	163%

6.3. Functional redistribution estimates

Models were fitted to estimate distance and spatial displacement functions in the same fashion as for the focal species in section 5, providing approximately 34 models over the species and OWF. Detailed and reproducible analysis is presented within the WP3 repository, with high-level summaries presented here.

Table 6 gives a broad view of which species displayed evidence of redistribution around the OWF developments, under each modelling approach. Summary plots of the estimated redistribution functions are present in:

- Figure 8 and Figure 9 for redistribution as a function of distance to OWF,
- Figure 10 to Figure 17 for estimated spatial redistribution functions

Results for some taxa and OWF are in line with the simple displacement estimates: puffin, divers, and gannet. Notable differences are that with regards the post-construction OWF:

- Kittiwake at Robin Rigg display some increased densities, as they did for Beatrice
- Guillemot/Razorbill for Gwynt y Mor display no notable redistribution.
- There are indications of guillemots being in higher densities around Beatrice and Robin Rigg
- North Hoyle auks display some redistribution.

Table 6: Functional relationships with the location of the OWF. Two types were fitted (refer section 3 and the focal example 0), here referred to as the distance and spatial redistributions. Table indicates the significance of these terms and whether they generally indicate avoidance or attraction. Grey shading highlights significant findings – purple indicates a result that differs substantially from the simple redistribution estimates of section 5.1.

Parameter	Species or group	OWF	Distance redistribution	Spatial redistribution
pre/post OWF interaction	Auks sp.	Lincs	Not significant	Generally avoidant
		North Hoyle	Attractant	Attractant
		Robin Rigg	Not significant	Not significant
	Diver sp.	Lincs	Not significant	Failure to fit
		North Hoyle	Not significant	Not significant
		Robin Rigg	Avoidant	Generally avoidant
	Gannet	Beatrice	Avoidant	Generally avoidant
		Lincs	Avoidant	Complex spatial relationship
	Guillemot	Beatrice	Not significant	Generally attractant
		Robin Rigg	Attractant	Generally attractant
	Guillemot/Razorbill	Gwynt y Mor	Not significant	Not significant
	Kittiwake	Beatrice	Attractant	Generally attractant
		Robin Rigg	Attractant	Generally attractant
	Puffin	Beatrice	Avoidant	Generally avoidant
	Razorbill	Beatrice	Not significant	Not significant
		Robin Rigg	Not significant	Not significant

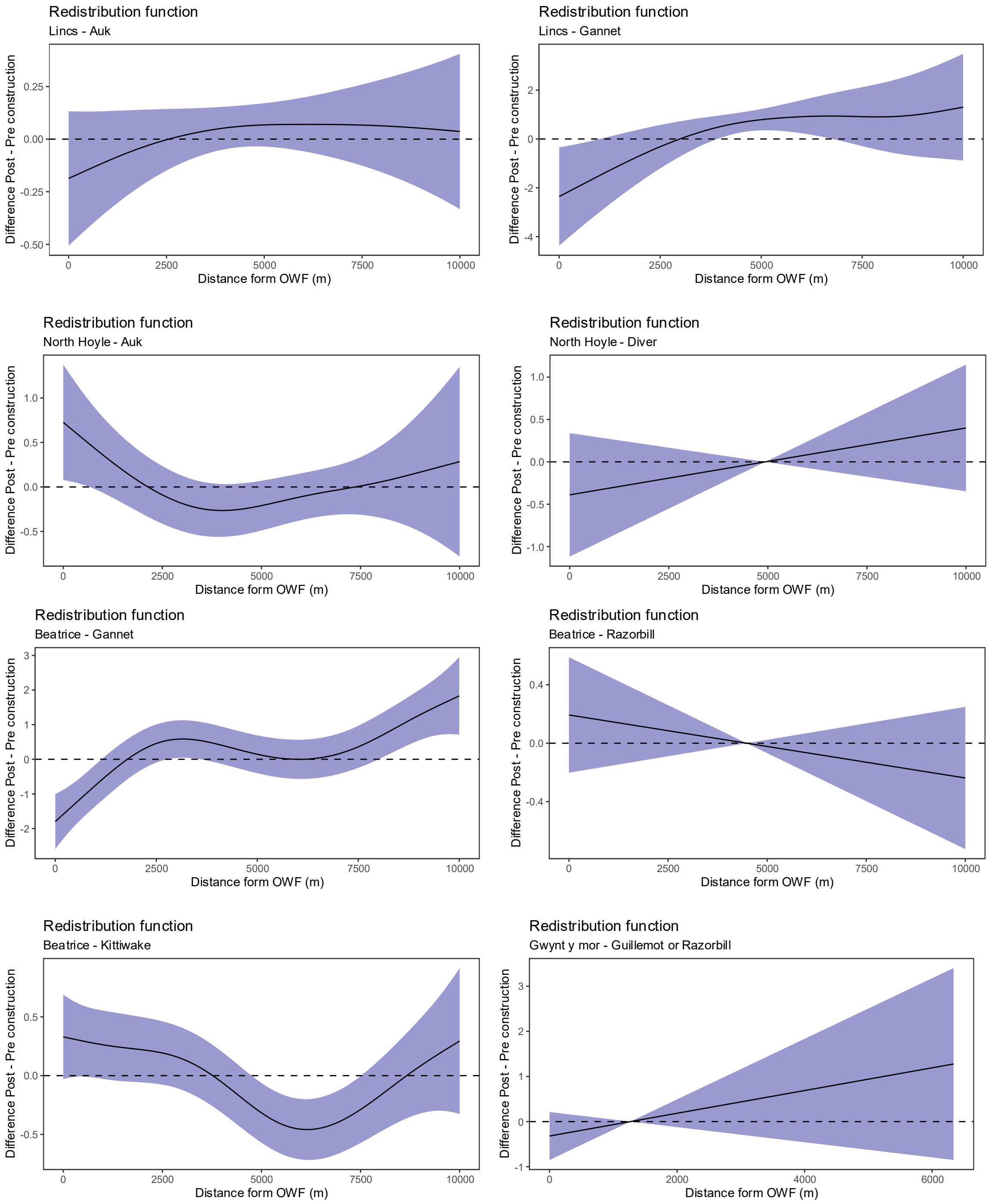

Figure 8: Estimated redistribution as a function of distance from OWF, after other covariates have been accounted for. The purple shading gives the 95% confidence envelope. Estimates are on the link-scale (log), so indicate the relative multiplicative effect[8] - the dashed horizontal line at 0 is a reference for no change, >0 indicates increased animal density and <0 decreased.

8 Specifically, exp(y) give the proportional change in density for a given value of x.

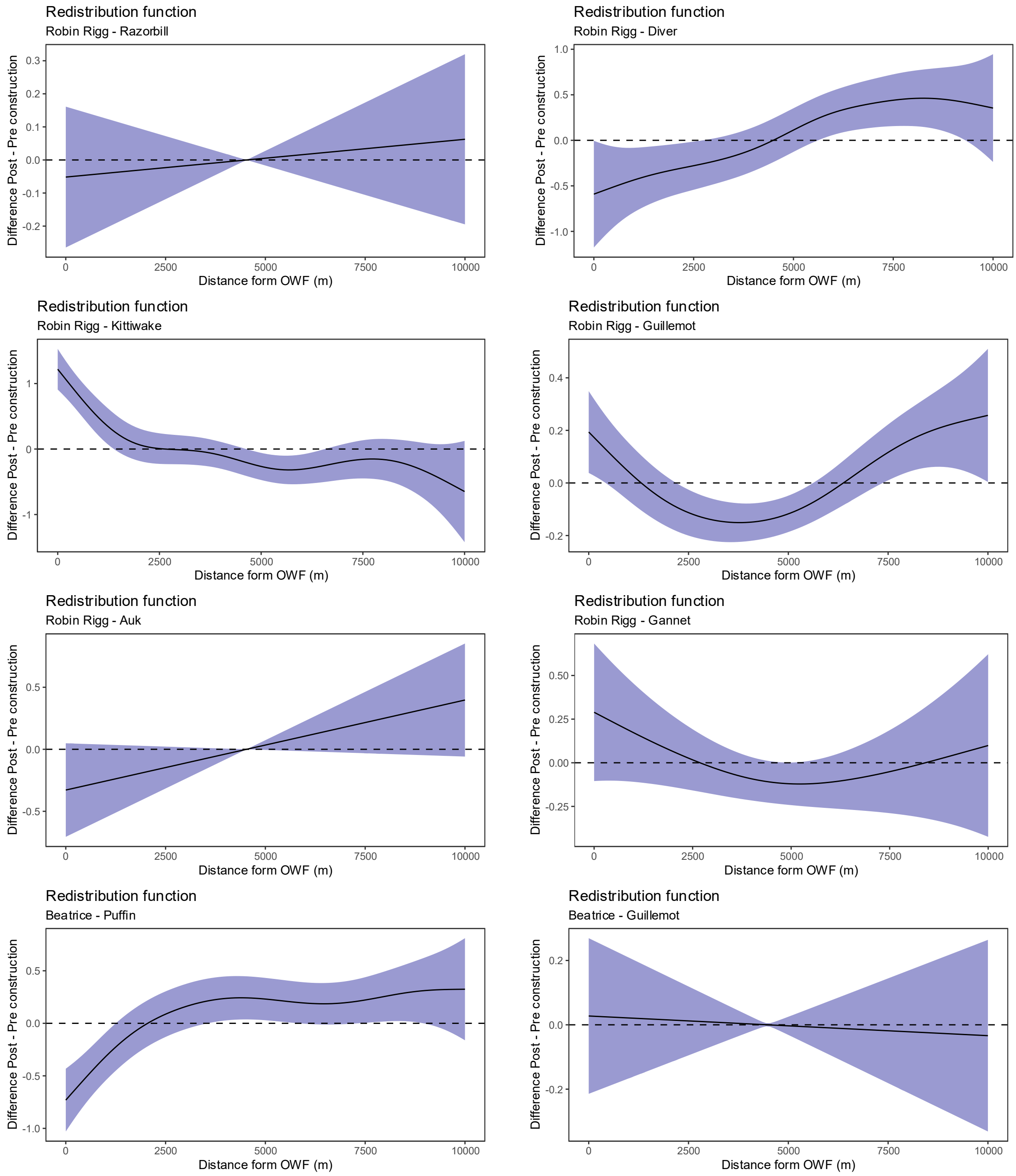

Figure 9: Estimated redistribution as a function of distance from OWF, after other covariates have been accounted for. The purple shading gives the 95% confidence envelope. Estimates are on the link-scale (log), so indicate the relative multiplicative effect - the dashed horizontal line at 0 is a reference for no change, >0 indicates increased animal density and <0 decreased.

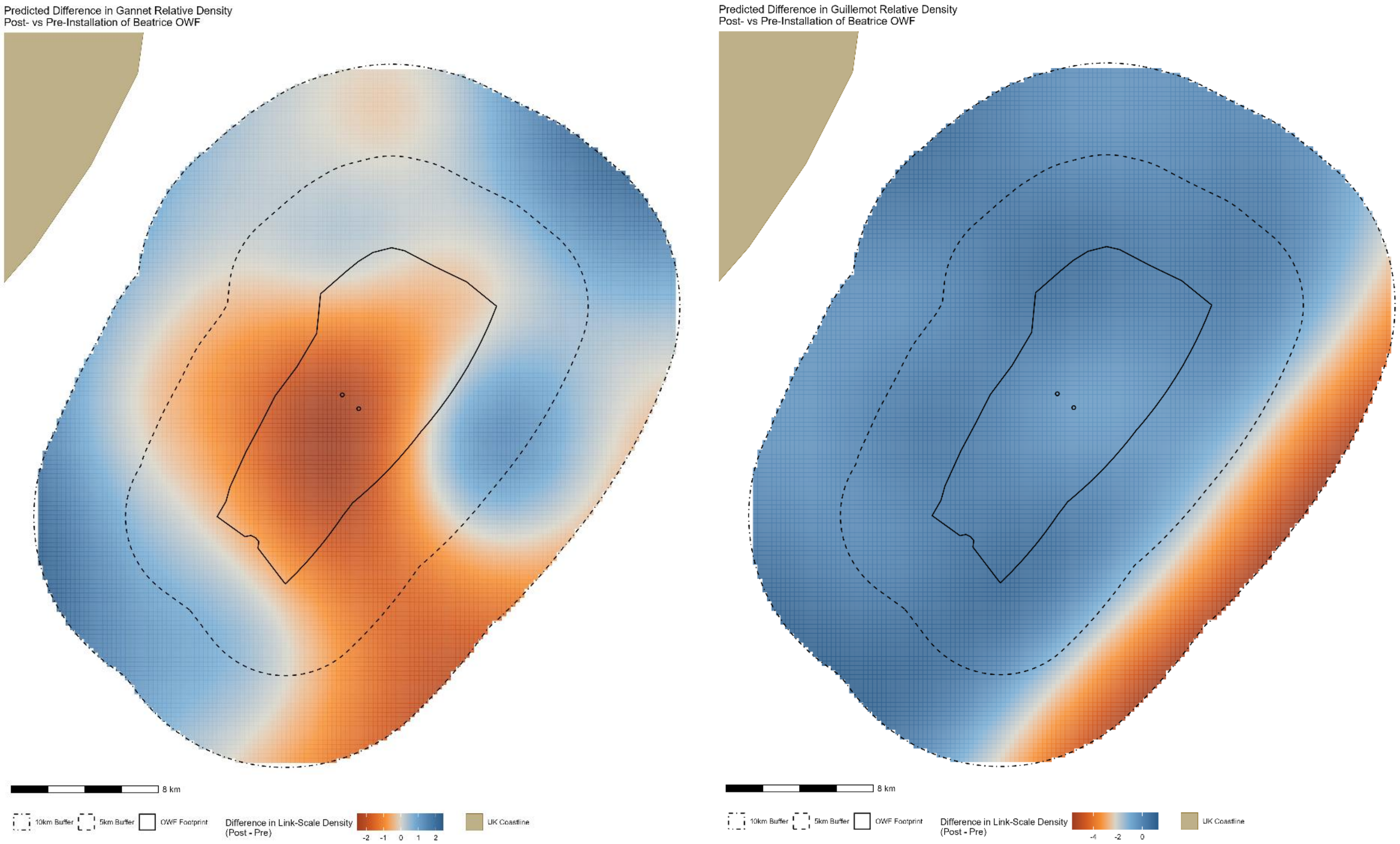

Figure 10: Estimated redistribution as a spatial function about the OWF, after other covariates have been accounted for. Estimates are on the model's link-scale.

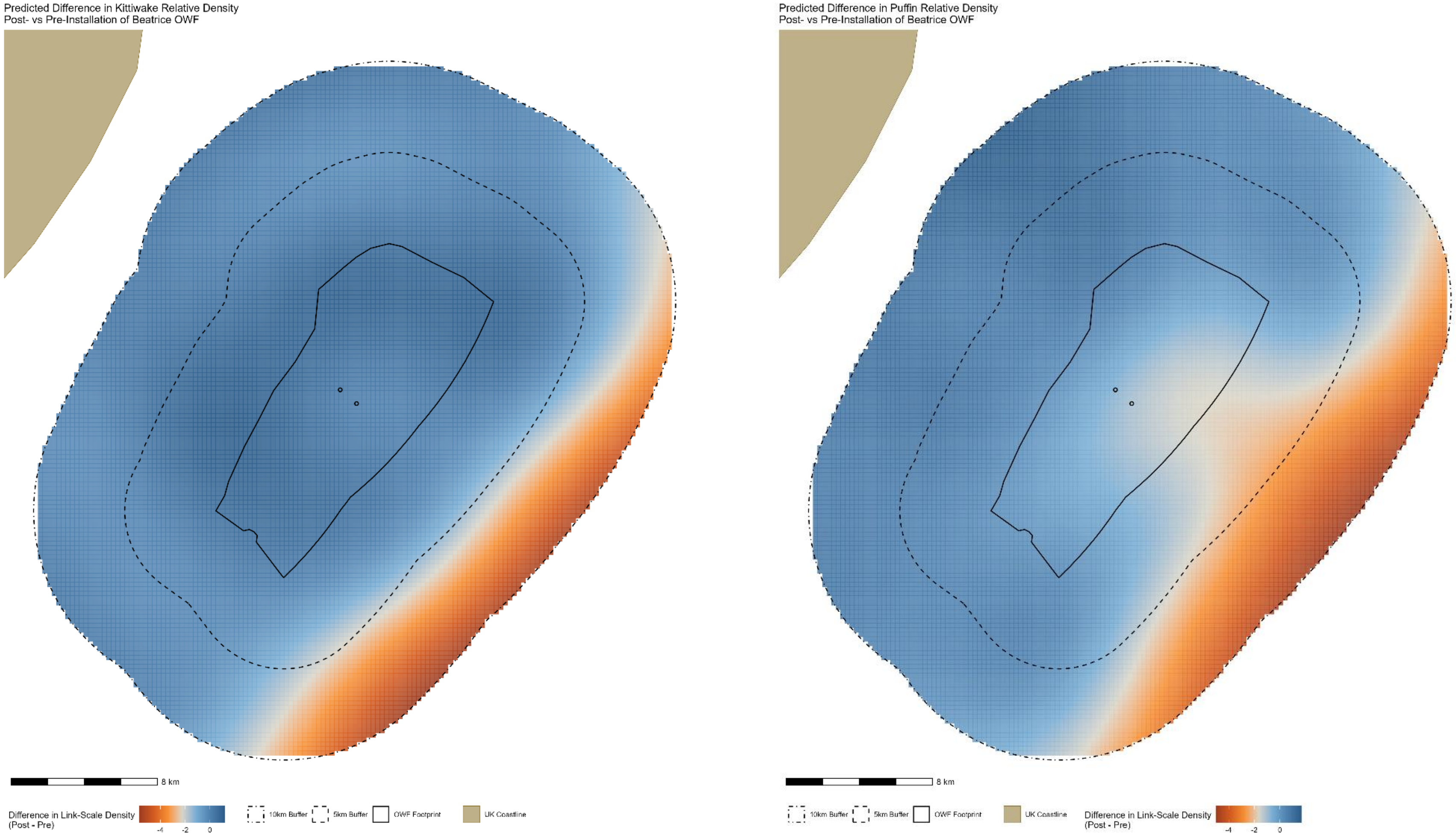

Figure 11: Estimated redistribution as a spatial function about the OWF, after other covariates have been accounted for. Estimates are on the model's link-scale.

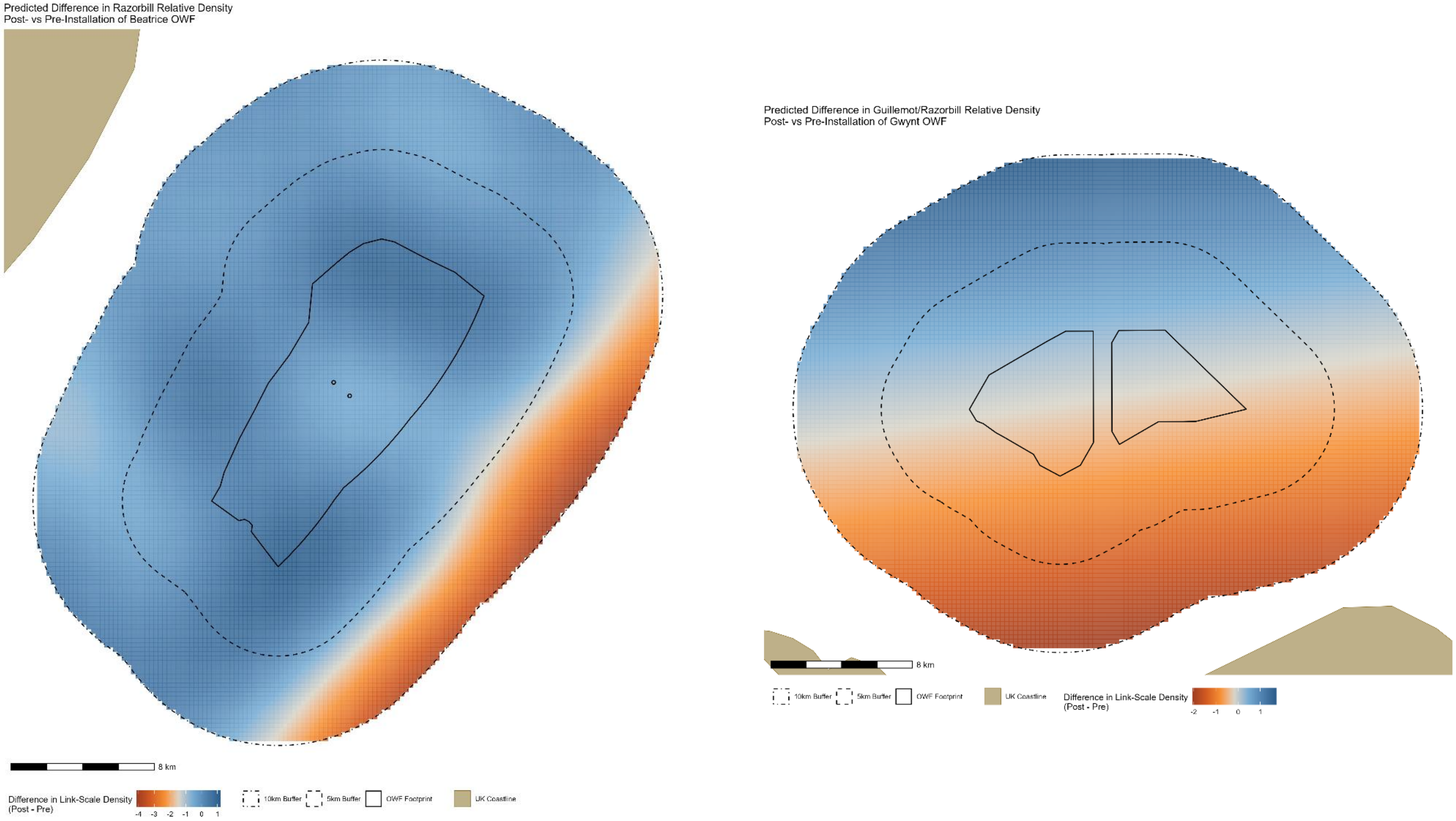

Figure 12: Estimated redistribution as a spatial function about the OWF, after other covariates have been accounted for. Estimates are on the model's link-scale.

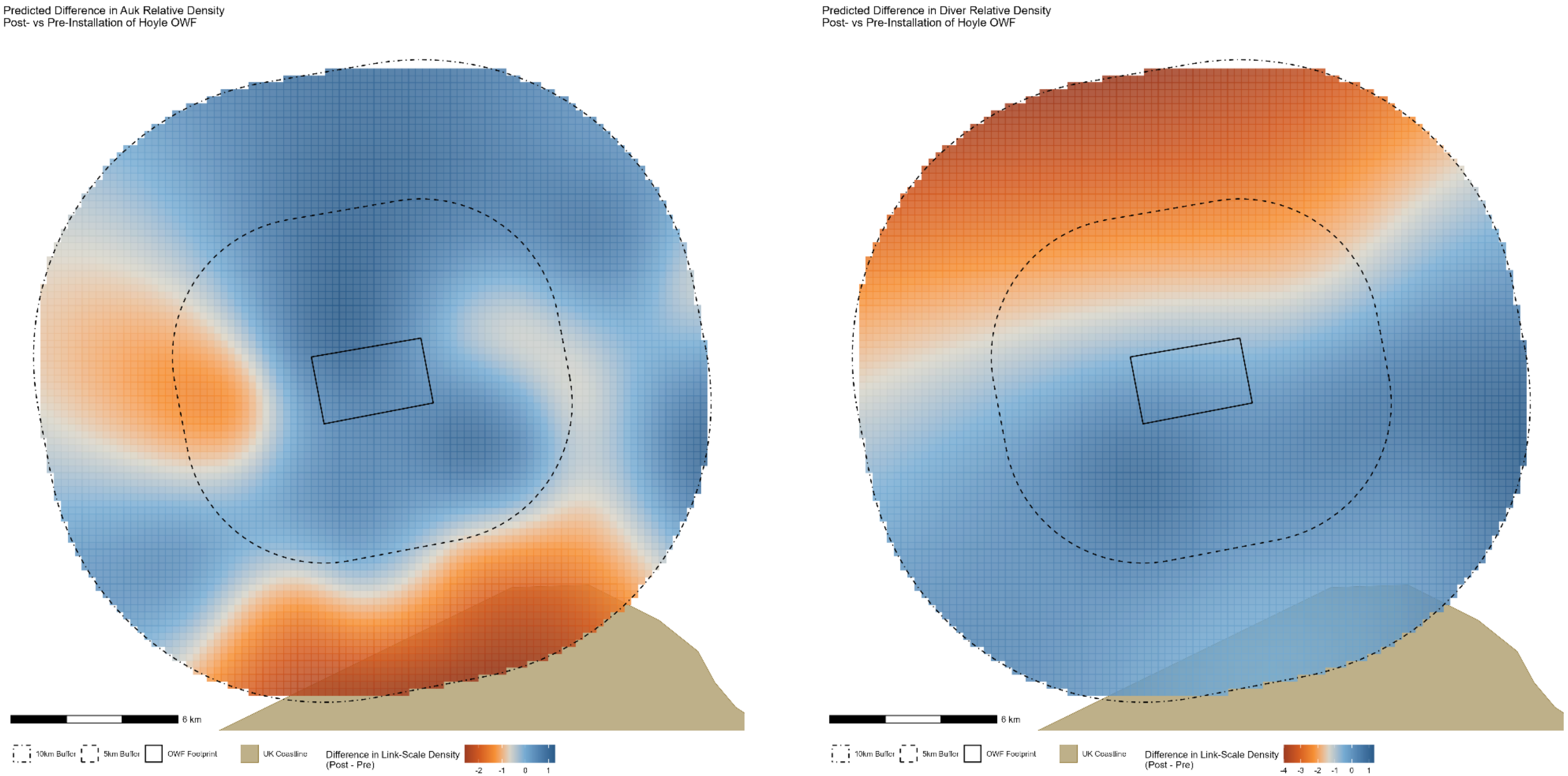

Figure 13: Estimated redistribution as a spatial function about the OWF, after other covariates have been accounted for. Estimates are on the model's link-scale.

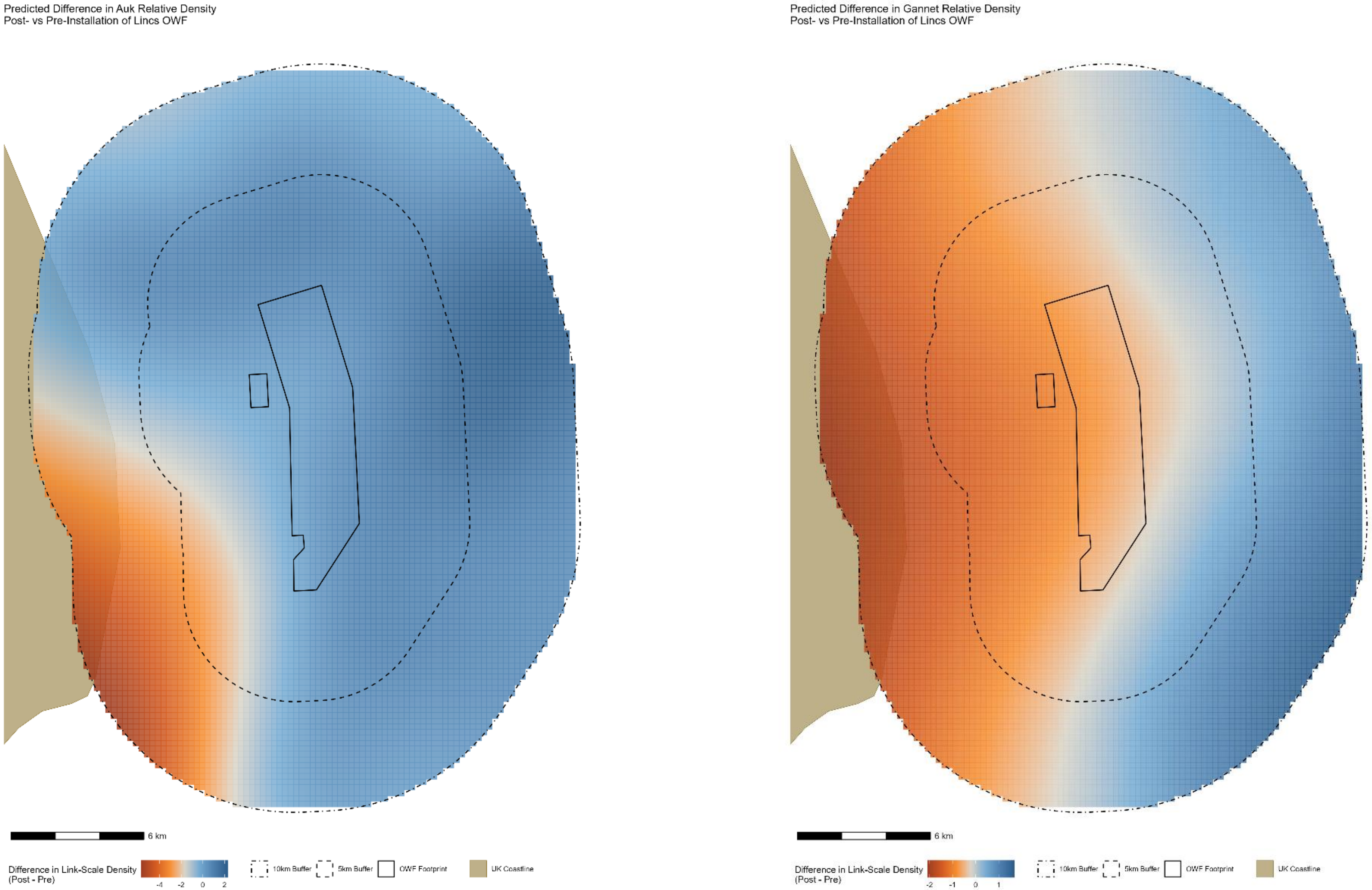

Figure 14: Estimated redistribution as a spatial function about the OWF, after other covariates have been accounted for. Estimates are on the model's link-scale.

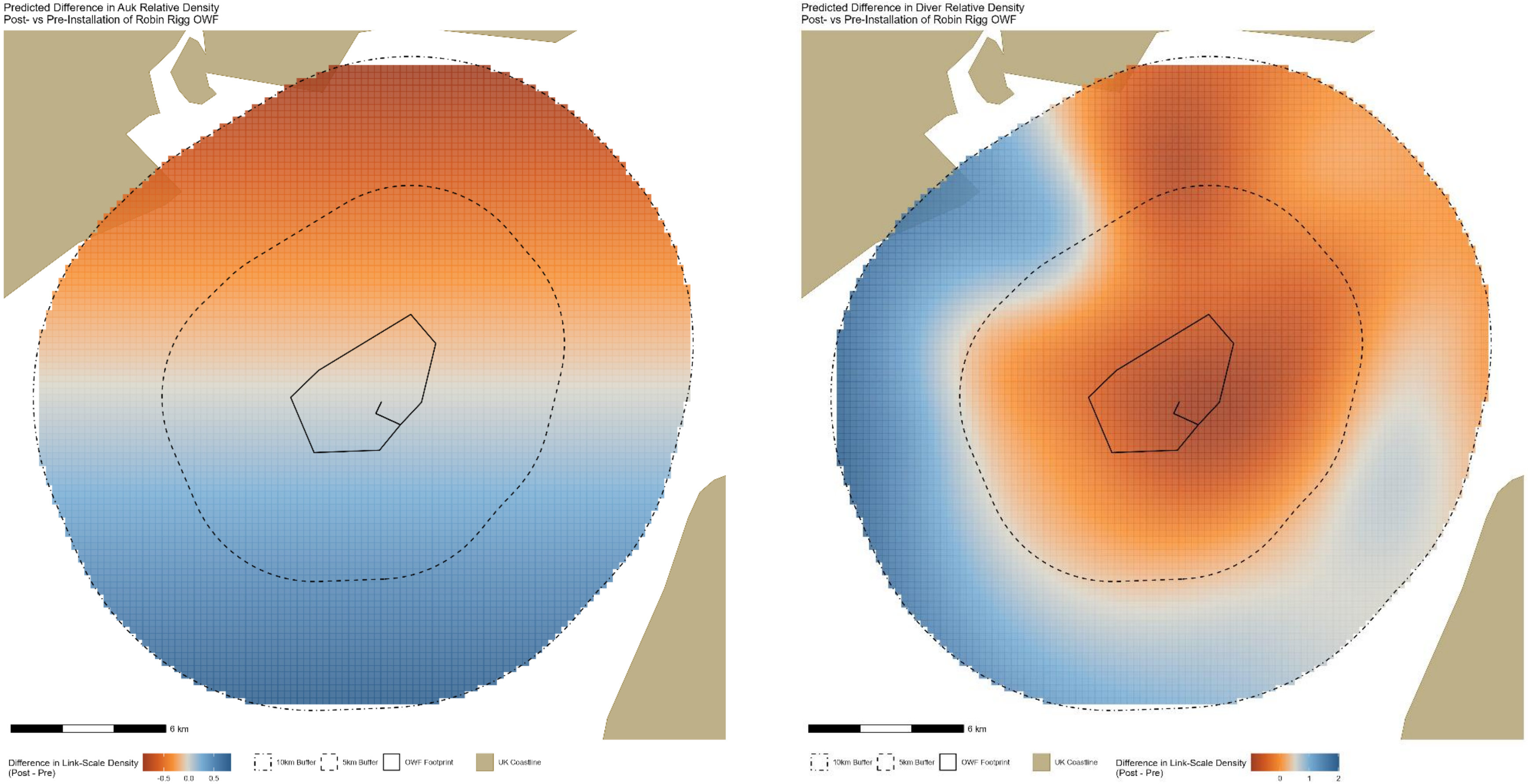

Figure 15: Estimated redistribution as a spatial function about the OWF, after other covariates have been accounted for. Estimates are on the model's link-scale.

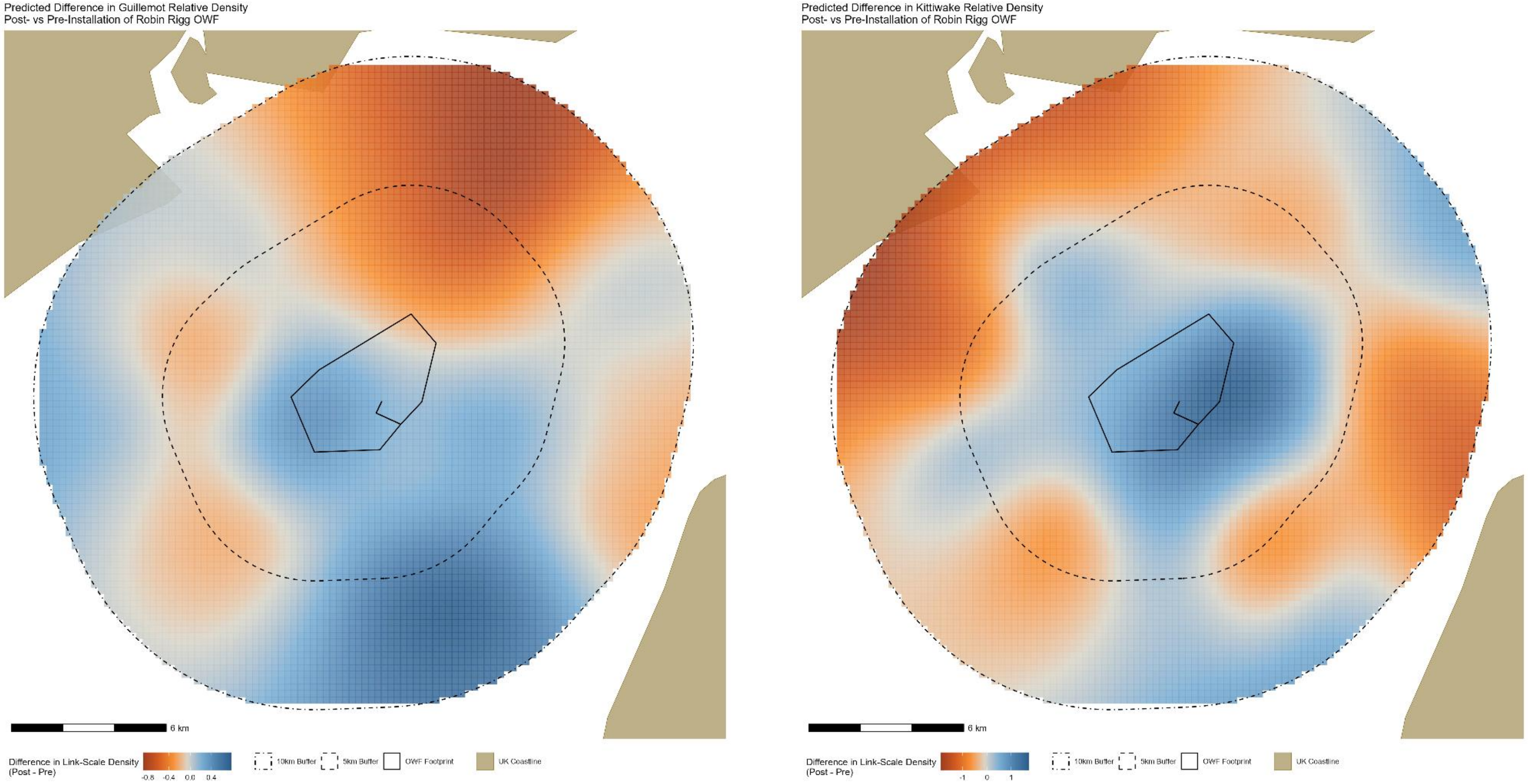

Figure 16: Estimated redistribution as a spatial function about the OWF, after other covariates have been accounted for. Estimates are on the model's link-scale.

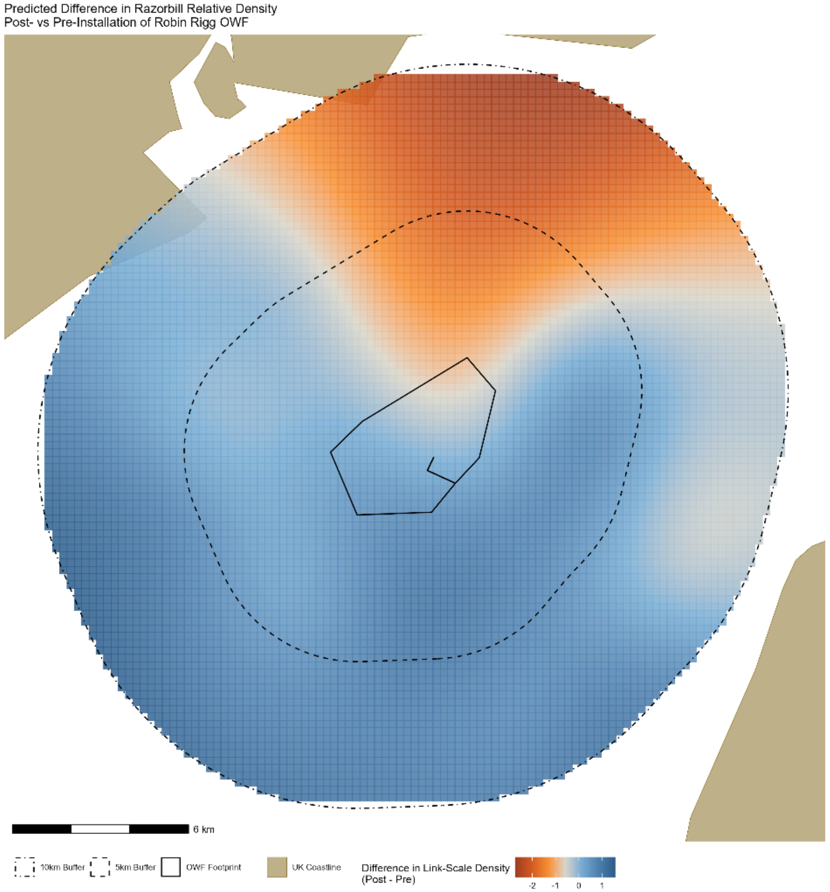

Figure 17: Estimated redistribution as a spatial function about the OWF, after other covariates have been accounted for. Estimates are on the model's link-scale.

7. Discussion

We have presented redistribution estimation from the analysis of data from seven OWF, covering eight species or species groupings. Three model structures were fitted in each case, comprising an estimation of: simple redistribution within the OWF footprint, redistribution as a function of distance from the OWF boundary, and the general changes in space use that are attributable to the OWF installation. In total this represents 54 redistribution models, three of which are presented in some detail in the report body, with the remainder summarised at a high-level. The detailed documentation of analyses is given in the WP3 repository, in the interests of reproducibility, as advised in the WP2 guidance document.

The objectives of this WP are to apply the guidance drawn up for WP2 as far as practicable on the project's accumulated data from UK OWFs. These analyses help refine the guidance, present a template for similar analysis and illuminate many practical analysis issues. The results also serve to address the research questions formulated in WP2. The redistribution estimates here are supported by the data in hand and can be considered indicative of species redistribution in response to OWF, subject to the caveats within this report.

7.1. Caveats on interpretation

The results here should only be considered indicative of redistribution for several reasons. Firstly, the amount of analysis is extensive given the project timeframe and correspondingly not been carefully refined at an individual model level. More 50 models have been fitted – meaning individual model refinement is less than day-level. Coupled with the necessarily complex treatments of data from disparate sources, the time available on a per-model level is small. This also influences the choice of modelling approach, as complex constructions and long fitting times aren't feasible. In contrast, a model for peer-review and publication would warrant days of preparation and scrutiny.

Secondly, the results here may be sensitive to esoteric elements of the data (e.g. individual survey issues) and shouldn't be used uncritically. A deep knowledge of the data collection may offer additional explanation to the patterns observed. For example, significant/influential OWF development phases beyond simple pre-post construction, changes in surveying equipment or methods.

Thirdly, these are observational studies in noisy environments with highly variable animal distributions. The isolation of redistribution effects is fundamentally through statistical, not experimental, control – there is substantial scope for confounding influences on animal distributions coincident with the installation of OWF. For example, changes in prey distributions beyond these covariates, while coincident but not related to the OWF development, would be such a confounding factor. While these distributions are challenging to observe directly, several environmental covariates would be proxies. Conversely, the inherent variability of these systems implies low power to detect redistribution, meaning it may exist but unable to be established with these data and models.

7.2. Research questions

Analysis conducted here offers some insights against the list of proposed research questions from WP2. These are reiterated and addressed in turn.

1. ***Is there evidence of redistribution of the species in response to OWFs?***

Several species appear to show redistribution coincident with OWF developments, when other contributory factors are accounted for. This is consistent in many cases regardless of the complexity of model applied and is indicative of relatively clear changes in distribution associated with the OWF developments. Notably the redistribution can be attractive as well as repulsive. Gannet appeared generally avoidant, as did puffin - noting those were only represented substantially at one OWF (Beatrice) with only 3 years data. Kittiwakes however appeared attracted towards the development.

2. ***What is the quantifiable extent of this redistribution?***

This is heavily influenced by the spatial extent of the survey area around the OWF. In many cases there are dedicated surveys for an OWF and its surrounds, whereas other analyses rely on more opportunistic or historic surveying to give pre-construction coverage. This means there is a complex interplay of survey types (methods and intensity) and surveyed areas over time. Nonetheless, based on broad-scale visual surveys and digital aerial surveys focussed on the OWF, redistribution is estimable to at least 4km from OWF and up to 10km in some cases. Surveys with focus on a particular development are designed to include a few kilometres of buffer about the footprint and provide a good basis for estimation. Beyond this range there is more reliance on chance coverage from other surveys or broad-scale historical data. Therein the data supports broader modelling, but with greater chance of data artefacts, influences of topology and issues with model assumptions and limitations. Within our data specifically there was sufficient power to detect redistribution for gannets out to at least 7km, kittiwakes out to 7.5km, guillemot out to 6km, and puffin out to 5km.

3. ***Which candidate analysis methods are practically superior for modelling redistribution based on types of data from WP1?***

There are broadly two aspects to this: the type of fundamental model being estimated, which differ in the complexity of their representation of redistribution (simple, functional distance or functional spatial), and the method used to fit these.

In the former case, the simple displacement models are easiest to fit but appear to lack power in comparison to the functional redistribution models. The interpretation of the functional distance models is relatively easy, although can disguise complexities in how the animals redistribute in two-dimensions. The end use of the estimates may dictate to an extent, but the recommendation would be to fit the more complex models where the data permits, which can be simplified as required.

In terms of model fitting methodology there are strong practical considerations. At a theoretical level, the flexibility offered by Bayesian methods allows a very general multilevel models to be designed – conducted say through JAGS, STAN or INLA. However, the model construction/specification time can be extensive and fitting times prohibitive. By way of example, models were fitted using STAN with fitting times of 10s of hours to days which precludes model experimentation. For methods that are relatively fast to fit, such as INLA, fitting is still slow compared to frequentist methods and the time required for model construction and experimentation also prohibitive for modelling at volume. This is due in part to the lack of helper functions[9] e.g. the construction of model matrices generally and particularly for smoothers with interactions. The Template Model Builder based methods are however very fast with substantial functionality, but currently with little smoother support. Ultimately

[9] Programming "sugar"

glmmTMB was favoured for simple models, with gamm via mgcv for more complex models. The principal limitation in the latter is a lack of zero-inflated error distributions when fitted mixed modes.

4. ***What level of displacement granularity can be estimated/supported given types of data and methods?***

   From these data, 1km resolution is effectively the lower spatial resolution and temporally, monthly, and perhaps seasonal level for some species. This is imposed in many cases by the data being already aggregated to these resolutions. For the data analysed here, there was sufficient detail and power to estimate redistribution at 1km resolution for gannet, guillemot, kittiwake, and puffin. A finer resolution would be possible for within-OWF distributions of animals via the randomisation tests of Trinder et al., (2024)[10], or if exact location data of animals were used, then as a spatial point process model (e.g. via INLA) that avoids arbitrary gridding/coarsening of the data. Regardless, in the latter it seems unlikely that there would be sufficient power in such noisy data to detect fine scale changes.

5. ***What modelled covariates are important drivers of seabird distributions around OWF developments/within monitoring surveys, outside development effects?***

   Only a small set of covariates were considered in the modelling process, but bathymetry played a clear role, and temporally the month/season were extremely influential (refer analysis vignettes in the project repository).

6. ***Can developments' data be pooled for estimation of redistribution, or does evidence support site-specific effects?***

   Generally, the results indicate site specific effects, and there is a general lack of data support for their combining in this study e.g. few species/OWF combinations that could be fitted within one model for formal testing of site-specific interactions in redistribution. This is also partly evidenced by different findings for different sites for the same species. This is complicated by the lack of consistency in survey methods across different developments – for example the species grouped under Diver/Auk are not certain to be comparable over sites. Other reasons would be the *a priori* lack of comparability of two-dimensional redistributions around developments influenced by site-specific topology and factors e.g. direction and distance to coast or nesting sites. However, there is some notable consistency in the redistribution of kittiwakes and gannets associate with differing OWF, albeit only supported here by 2-3 sites.

7.3. Practical analysis considerations

Data issues

The acquisition and treatment of data was problematic throughout the broader ImpUDis project, and previous WP documents have discussed these in detail. The practical analysis for this WP3 was conducted on a large amount of data that had been subject to triage to ensure the best chance of successful analysis.

[10] Noting this tests for attraction/repulsion given animals are already within the OWF footprint i.e. the null hypothesis does not explore general redistribution.

Despite this data being of relatively high quality for redistribution analysis, there were still substantial complexities. As this WP addresses practicalities, substantive data-level hurdles are discussed here. It should be noted however that this project is ambitious in considering data from many different OWF and surveys, over a long period of time, so accumulates disparate data collection methods and includes visual surveys (boat/aerial) that are less favoured in modern monitoring studies. Regardless, even recent surveys suffer from a lack of consistent collection, treatment, storage and quality assurance.

Poor quality assurance: GPS/tracking data is frequently missing transect IDs and contains incorrectly recorded segments, requiring comprehensive reformatting and/or estimation of transect boundaries. Reconstructing these requires bespoke coding, with various unexpected fail points that can create artefacts.

Inconsistent species-level data: species-level identification is obviously not possible in many cases. The rate with which this occurs is platform dependent, meaning that higher-taxa groupings are difficult to aggregate over sources, as it is unclear they represent the same animals.

Inconsistent survey design: key components might change over time within surveying for a particular site – for example, switching from visual-aerial to digital-aerial surveying, or extending/restricting the survey region. The latter of these is common over longer time frames and redistribution analyses need to focus on those areas consistently covered to avoid artefacts i.e. an intersection of the surveyed regions over time, which can be much smaller than purportedly offered by the broader data.

Poor/no retention of key attributes: certain features or metadata essential to the analysis (for example, transect widths, survey polygons, etc) are omitted from data libraries - these are essential for robust analysis.

Fundamental visual data issues: in the case of visual-aerial and visual-vessel based surveying, detections are inconsistent across distance bands, violating a critical assumption for distance analysis (equal distribution across the transect) and preventing effective detection adjustment. This is a fundamental issue that may arise in visual surveying and only addressed by more complex survey methodology. The general transition to digital surveying makes this less relevant going forwards but affects historical data.

Modelling considerations

The modelling guidance from WP2 is generally agnostic about the model fitting approach, but specific on what the models should contain, should produce, and how they should be presented and stored. The analyses here offer more practical views on approach.

This should be caveated on the timeframes and requirements of the modelling process: a model whose results are of deep importance and with an appropriately generous timeframe, will permit different modelling approaches to those needed at volume. Many approaches were explored in this project, ultimately for a high volume of models. Also, the modelling context is strictly within R, being the pre-eminent statistical modelling environment, but other approaches exist.

Modelling fitting methods: A broad distinction might be drawn between well-established methods with user-focussed statistical functionality and those favouring flexibility. Methods tending towards frequentist linear models are well established and easily used by modestly quantitative users (e.g. mcgv) – conversely Bayesian tools can construct almost any model from their fundamental components but require a high level of statistical competency (e.g. using INLA directly).

Models were fitted in this project from those frequentist-leaning (MRSea, glmmTMB, mgcv) to Bayesian (STAN via brms, INLA via R-INLA/inlabru). Ultimately glmmTMB and mgcv were favoured in this project, partly for practical reasons, but some discussion of these modelling experiences follows.

From a model construction point of view, MRSea, glmmTMB and mgcv are very simple, as they follow a form established over several decades[11] and have largely standard supporting functionality. They are also very fast to fit (seconds to a few minutes for these data), allowing substantial model exploration and modification. In contrast, model construction for STAN and INLA is highly detailed and bespoke, particularly when considering fine scale details of the construction of priors – the improvements in accessibility offered by inlabru not-withstanding. Functionality surrounding the models (querying, predicting, assessing etc) is very package specific and guidance is of varying quality for this type of modelling. INLA is considered relatively fast, but this is within a Bayesian context which here could take hours-to-days, whereas INLA was frequently on the order of hours. In either case, this greatly restricts model exploration.

INLA (within R) was nonetheless promising, with the potential clear benefit of not requiring the specific locations of animals to be gridded. It was deemed currently too underdeveloped to be used at scale: there were substantive fitting times[12], a lack of practical functionality[13], sensitivity to some opaque parameter settings[14] and relatively inaccessible documentation for some functions[15]. This doesn't preclude its smaller scale use with ample time for model construction and fitting.

Within the frequentist-leaning methods, glmmTMB gave good flexibility and speed but with limited smoother support, particularly for >1 dimensional smooths, which limited its use beyond simple displacement modelling. The GAMMs via mgcv are naturally very well developed, mgcv having been continuously developed for over two decades, but with limited zero-inflation options once within the mixed model sphere (with its nlme underpinnings - Pinheiro et al., 2025). The importance of zero-inflation is however frequently overstated[16], given large numbers of zeros are expected for low densities, and models that explain/capture this may not require complex treatment.

Model support: The modelling is complicated by the varying spatio-temporal coverage of the surveys being combined, as well as other fundamental changes in the underlying data. In terms of time, surveys may cover different parts of the year to varying extents. Ideally this is balanced, but where this change coincides with the transition from pre-to-post construction phases, there is complete confounding. The area covered by surveys can fluctuate over time, despite supporting the same OWF development. These must be restricted to the smallest common area covered by the model, unless artefacts arise in the results. In particular, if this is also strongly coincident with the OWF development phases. Further, the apparent change in presence of certain species over time can be coincident with changes in surveys –

[11] Arguably from the late 70s in S from Bell labs – Becker and Chambers, 1984

[12] Many hours for smallish models that scales non-linearly with survey interactions

[13] Construction of design matrices e.g. factor variables and interactions

[14] Mesh construction, cp.priors

[15] Inlabru document sparse, some found within R-INLA while others require fundamental INLA documents

[16] A large proportion of zeros marginally is often mistaken for zero-inflation. Similar to other errors, they ought to be viewed conditional on the systematic component.

possibly as species identifications are not always consistent. As indicated in (Table 4), some data were excluded from models to address these problems and/or time coarsened to season to allow fitting.

Inter-OWF influences: The surveying around a particular OWF might be within close or modest proximity of other developments, whose construction and operation phases are staggered. This complicates the isolation of a redistribution from a simple phase variable in the model. The clear example in these data are the Lincs, Lynn and Inner Dowsing OWFs. Different approaches arise, such as creating multiple "phases", each level of which represents a combination of states from the associated OWF. Here a simple approach was taken with Lynn and Inner Dowsing (LID) treated jointly with an approximate operation date of 2009, allowing some pre-post contrast in the absence of Lincs (nothing that construction phases are being ignored). The modelling of Lincs alternatively is modelled using only post-operational LID data – the contrast in this case is a redistribution attributable to Lincs *conditional* on existing redistribution.

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