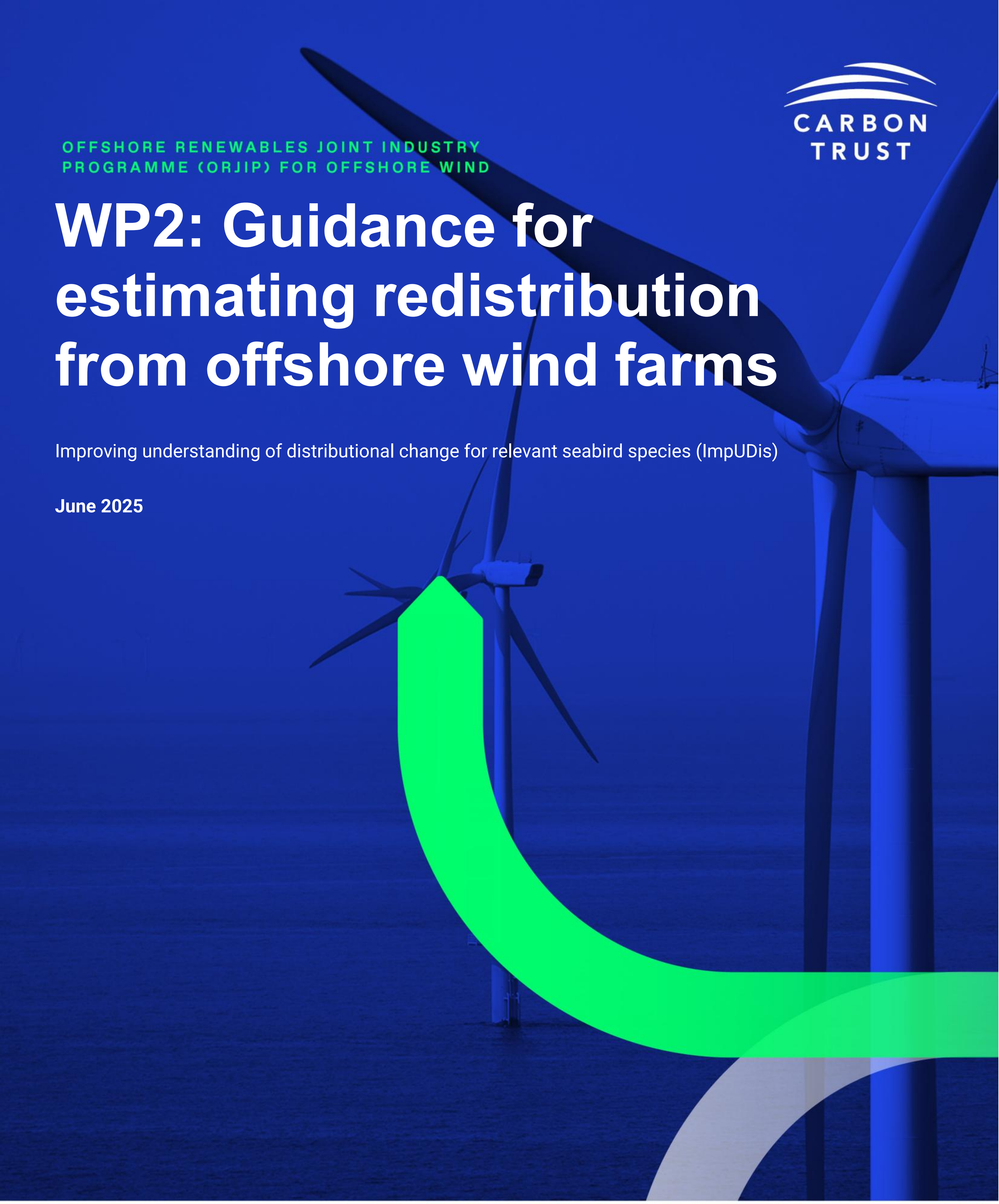

OFFSHORE RENEWABLES JOINT INDUSTRY PROGRAMME (ORJIP) FOR OFFSHORE WIND

WP2: Guidance for estimating redistribution from offshore wind farms

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

June 2025

working to accelerate offshore consenting

ORJIP Offshore Wind

The Offshore Renewables Joint Industry Programme (ORJIP) for Offshore Wind is a collaborative initiative that aims to:

- Fund research to improve our understanding of the effects of offshore wind on the marine environment.
- Reduce the risk of not getting, or delaying consent for, offshore wind developments.
- Reduce the risk of getting consent with conditions that reduce viability of the project.

The programme pools resources from the private sector and public sector bodies to fund projects that provide empirical data to support consenting authorities in evaluating the environmental risk of offshore wind. Projects are prioritised and informed by the ORJIP Advisory Network which includes key stakeholders, including statutory nature conservation bodies, academics, non-governmental organisations and others.

The current stage is a collaboration between the Carbon Trust, EDF Energy Renewables Limited, Ocean Winds UK Limited, Equinor ASA, Ørsted Power (UK) Limited, RWE Offshore Wind GmbH, Shell Global Solutions International B.V., SSE Renewables Services (UK) Limited, TotalEnergies OneTech, Crown Estate Scotland, Scottish Government (acting through the Offshore Wind Directorate and the Marine Directorate) and The Crown Estate Commissioners.

For further information regarding the ORJIP Offshore Wind programme, please refer to the Carbon Trust website, or contact Ivan Savitsky (ivan.savitsky@carbontrust.com) and Žilvinas Valantiejus (zilvinas.valantiejus@carbontrust.com).

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Contents

Abbreviations/glossary

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

1. Introduction

This document presents guidance for the estimation of sea-bird redistribution, as part of the ORJIP/Carbon Trust project entitled *Improving Understanding of Distributional Change for Relevant Seabird Species (ImpUDis)*. This project consists of several work-packages, of which this guidance is part of the second. The project goals relevant to this guidance 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 a comprehensive literature review of studies into the redistribution of seabirds in relation to offshore wind farm (OWF) development. Some elements and ideas are reproduced here – refer to Murrell *et al.* (2025) for full original context. In particular, we adopt their definition of distributional change, where the presence of an OWF has the potential to influence the distribution of seabirds at sea, either through displacement, or attraction – leading to distributional change being "the active selection, or avoidance, of an area following the construction of an OWF".

The ImpUDis literature review was extensive, with 76 studies of seabird redistribution examined, covering 35 OWFs in Europe (Murrell *et al.*, 2025). In totality this addressed >280 redistribution questions for species/species groups over these sites. These research questions were wide ranging, extending from simple tests of redistribution, to the extent of OWF influence, and up to spatially explicit redistribution maps.

Effectively all previous attempts to quantify redistribution in response to OWF have been based on two broad data types: transect surveying and, to a lesser extent, tracking with tags or radar (Murrell *et al.*, 2025). Transect surveys are very dominant, and will continue to be so, due to pre- and post-consenting requirements. In light of this, full guidance is restricted to these data and methods as being both feasible and proven. Tracking data is addressed to a lesser extent, but the substantial lack of consistency in studies to date does not offer a firm basis for complete guidance.

1.1. Scope of guidance

Guidance here covers:

- data collection and its treatment in terms of quality and preparedness for analysis,
- analysis methods,
- modelling outputs, and
- the treatment of data and analysis files for reproducibility and future utility.

Displacement can occur on differing spatial scales and a broad distinction is drawn here between macro and meso-/micro-scale. Macro-scale is considered here to be on the scale of 100s of metres to kilometres, that might be detectable by the large-scale snapshots of bird distributions afforded by boat or plane surveys. Meso-/micro-scale will be treated as being multi-metre scale, such as interactions at turbine-level addressed with GPS tags or radar that track individual animals.

The guidance here focusses on data and analysis that permits the detection and estimation of redistribution that can inform the consenting process. Specifically, any redistribution must be potentially quantifiable to have utility. The outputs of analysis that provide this are given in section 2.3.6. Fixed point observation data is excluded, as these have little utility in this context due to spatial scale - there are situations where this type of data serves well, but not on the scale of OWF.

Guidance here focusses on feasible, proven data collection and methods – hence does not cover emergent data collection technology or analysis that do not have sufficient track record to warrant recommendation as best practice. This does not diminish their potential, and section 7 speaks to such methods and technology.

Note, while this guidance speaks to general redistribution, a distinction can be drawn between questions of displacement (/attraction) and avoidance (/attraction)[1]. This is considered here to be primarily application of the same methods to different data i.e. birds in flight and on the water, versus only birds in flight. Models fitted to these different data would inform fundamentally different downstream analyses e.g. collision risk versus energetics within an Individual Based Model (IBM).

1.2. Objectives of analysis

Guidance here is in support of the consenting process for OWF. The objectives for analysis therefore must translate into population-level[2] estimation problems to determine significance of impacts, and the efficacy of any mitigations. Redistribution estimates may inform several inter-related downstream analyses – notably collision risk (via estimated densities), population viability analyses (contributary mortalities), and other tools (displacement matrices or individual-based models such as SeabORD – Searle *et al.*, 2018).

In light of this, the data and analyses ought to provide:

- **Quantification of redistribution**. This is distinct from solely testing, where evidence of redistribution is established without a measure of magnitude. To have utility, quantification should provide at least the probability of some simple redistribution, and ideally some functional relationship with a development e.g. proportion displaced from within a development footprint, or as a function of distance from it.
- **Quantification of uncertainty**. Estimation of any redistribution will be imprecise – this lack of certainty must be reflected in downstream use. The quantified uncertainty will be ultimately translated to population-level analyses.

Note, the needs of these downstream analyses can be met by the same modelling process but may vary in the details of the data analysed and how the models are queried. For example, the displacement (/attraction) or avoidance (/attraction) may be understood as requiring analysis of birds both in flight and on the water, or only flying birds, respectively.

[1] as per Pavat *et al.* (2023)

[2] "population" is subject to definition, but frequently a colony/site of interest for a particular species.

1.3. Study methodology

The quantification of an effect in a fully controlled experiment would call for pre-treatment measures and a corresponding control throughout – the basis of the BACI design in ecological field experiments. Outside of OWF, establishing suitable control sites is difficult and frequently controversial. Within the context of OWF, control sites are particularly difficult, due to the specific requirements to be a suitable OWF site, and the marked expense and effort required to conduct parallel surveying at any such control.

For this reason, previous studies and those going forwards are/will be predominantly Before-After-Gradient analyses (BAG), which do not require a control site. This is at the cost of no contrast between impacted/unimpacted sites over time, giving less power to separate out confounding temporal changes. Impacts are solely quantified by before-after contrasts (the Before-After), coupled with relationships of the response with distance from the purported impact (the Gradient).

1.4. Analysis methodology

The guidance on analysis is predicated on:

- the types of data in existence and feasibly collected in volume in future,
- the implied study methodology,
- statistical modelling with proven track record for these problems,
- measures of redistribution that will have utility in consenting

Methods without sufficient track-record, or addressing fine-scale turbine-level interactions, are not promoted, but may be discussed in section 7 as having utility.

1.5. Reproducibility and quality assurance

It is recommended that analysis be fully transparent and reproducible. This is covered in in Section 4 with recommendations about process and specific tools.

1.6. Report structure

There are two main sections addressing the two main data types: transect and tracking data (radar or tags). These offer insights at different spatiotemporal resolutions and may demand markedly different analysis approaches.

- Guidance on data collection, treatment, and analysis are addressed for transect surveys (Section 2)
- More limited guidance is given for tracking data in Section 3, due to constraints therein
- Software, reproducibility and quality assurance processes are discussed generally in Section 4
- The storage of data and results is addressed in Section 5
- Emergent data and methods are discussed (Section 7) but cannot strongly inform guidance at this point

2. Survey data

Survey data, in the form boat or aerial transect, is the dominant marine bird data collected to support the consenting of OWF. Current guidance is generally that the surveys be Digital Aerial Survey (DAS), whereby photo or video are taken on flown transects (e.g. Parker *et al.*, 2022a; Natural Resources Wales 2022). The reasons for preferring DAS over other forms are manifold, but general removal of detection issues is sufficiently compelling from an analysis point of view. Specifically, visual observations suffer from decreasing detection probabilities with distance from observer, which adds imprecision and complexity to analyses. This does not apply to downwards-facing images, for birds on or flying near the surface, unless very small.

The problem of availability bias afflicts all these surveys for animals that may dive – when some proportion will be difficult or impossible to count. Minor complications about water clarity aside, the standard practice to address this is to adjust estimates proportionally for the probability an animal is below the surface – being species-specific, based on expected dive times. Another issue facing boat-based or aerial surveys is the reliability of species identification which leads to assumptions needing to be made to generate population estimates (e.g., apportionment of non-identified animals to species level based on proportions of identified species). Both issues add some level of uncertainty which is carried downstream to subsequent analyses.

DAS is expected to continue as the primary source of bird distribution data for OWF and is supported here as best-practice transect surveying. However, there is substantive extant visual data, and these may continue to be collected for logistical reasons. For this reason, visual data treatment and analysis is also covered in this guidance.

Advice here about data treatment is not specific to analysis of animal redistribution, but is general good practice for quality assurance, reproducibility and support of robust analysis. Data collection, treatment and storage is very inconsistent across OWF developments, which is inefficient in terms of re-use of data and validation of results, as well as increasing the likelihood of errors.

The detailed guidance and examples presented in Mackenzie *et al.* (2013) are still broadly applicable to the analysis of survey data, for quantifying redistribution from OWF.

2.1. Data collection

2.1.1. Survey design

The collection of survey data for detecting abundance changes associated with offshore renewable developments, has received substantive guidance in terms of design (Natural England – Parker *et al.*, 2022a; NatureScot 2023; Natural Resources Wales, 2022). An expressed goal for these design recommendations is the detection of displacement effects, in particular the inclusion in the surveys of buffer regions around the development footprints – with 2km, 4km or 10km stipulated, depending on species known or thought to be present.

The guidance here does not further advise on survey design, this being provided in detail elsewhere, and current advice already requires relatively intensive surveying. The sole caveat here, is that survey design advice has been based on some instances of power analysis, focussing on general changes in abundance (Mackenzie *et al.*, 2017, Webb & Nehls 2019). Redistribution may be evidenced in similarly simple abundance shifts, but the power to detect more nuanced redistribution (e.g. small scale, or complex non-linear changes) is expected to be lower.

There is sufficient extant survey data that power analyses could be conducted for redistribution, noting that the problem is generally more complex than those underpinning previous survey effort advice. For example, redistribution can be characterised by simple abundance changes within a speculative OWF region, as justifies current survey advice, or be a more nuanced gradient. Power analyses for these complex situations require:

a) characterisation of variability in the unperturbed system (as provided by existing baseline survey data),

b) simulation of speculative perturbations (e.g. a range of justifiable redistributions), and

c) analysis of these simulations with methods expected to be applied in practice.

These are necessarily species-specific, with the main complexity arising from the myriad ways redistribution might be characterised, and the concomitant influence on analysis methods -which need to be appropriate for the type of perturbation being sought. This is not a trivial exercise but would inform on the power in analysing current data, and how it might be practically increased, noting that digital aerial survey data is collected in some instances but not processed[3]. Tangible outputs would be, under current levels of surveying intensity, the impact of the number of survey years pre-/post-development and the pooling of data across developments.

In brief, transect survey data ought to be generally DAS, and follow the local regulatory guidance for monitoring of seabird populations, with Webb & Nehls (2019) offering a general overview.

2.1.2. Effort and observation data

Two key components to survey data must be available for analysis:

1. Observations data: locations and times that animals were seen. These should be identified to the lowest taxonomic level possible and be as spatiotemporally precise as possible. DAS typically provide precise individual-level recordings, whereas visual recordings will consist of estimated distances from survey platform and estimated group sizes when abundances are high.
2. Effort/track data: the spatiotemporal path of the survey platform from GPS.

Supplementary to these data are platform characteristics, in particular for DAS a measure of the amount of sea-surface observed: the digital video swath, or photo coverage. Visual data will have its (effective) survey width calculated *a posteriori*. Further, for visual data, information on factors that might affect the ability of observers to detect animals should be recorded concurrently with the effort data e.g. sea state. Ultimately visual survey data will be subjected to distance analysis (section 2.2.4), so general advice in Buckland *et al.* (2015) ought to be adhered to.

Effort data is often treated of secondary importance, but no robust analysis can be done without this, and imprecise effort data can lead to levels of uncertainty being passed forward through subsequent analyses.

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[3] e.g. HiDef aerial surveying typically surveys with 4 cameras and processes 2, the remainder being stored. This equates to 250m swathe coverage from a potential 500m.

These effort data are required to make inference on where animals were absent as well as present (i.e., the "zero abundance" information). On-/off-effort information should be clear within the effort data, when applicable, for the same reason.

2.1.3. Data formats

Some recommendations that impose rigour and reduce errors are:

Formal representation of space and time data - Survey data is inherently spatiotemporal and should be fundamentally treated as such. It is recommended the data be treated as per GIS, such that there is no ambiguity about time and location of observations and surveyed areas. This imposes a basic level of rigour in the data storage and makes subsequent analysis easier and more robust. For example, combining with other spatiotemporal data (e.g. OWF polygon boundaries or raster covariate information) where spatial projections and time-zones/date formats must be correctly accounted for.

Adherence to coding conventions and limit free form data - Species coding should follow established conventions (ESAS or BTO) and free-form data collection/entry (e.g. spreadsheets) should be minimised to avoid entry errors. Additionally free-form data collection permits data to be represented as formatting (e.g. colours) which are not platform independent and likely lost in analysis.

Data in files, not names - Information ought not be solely recorded in filenames e.g. survey dates – these should be integral to the dataset itself. The lack of audit trails on filename changes, and the ambiguity and/or errors from manipulating filename strings to access these data, are compelling reasons to avoid this.

2.2. Initial data treatment

The following are steps *a priori* necessary to have data in a form suitable for modelling. The previous section 2.1 indicates some basic desirable data formats, however the analyst may be drawing on a range of data sources and not be integral to their collection. Visual observation data will be subject to additional analysis, as per section 2.2.4.

Data checks ought to be conducted throughout, consisting of extensive plotting and summary statistics to ensure the data has no obvious errors. A fully transparent, reproducible, record of data treatments ought to be maintained in all instances, as per section 4.

2.2.1. Consistency of format and general QA

Data needs to be broadly checked for errors and placed into a common format. For these types of data (effort and observations data), checks and treatments will include:

- Ingestion of all data in its various formats to an analysis package[4] (spreadsheets, csv, shapefiles)
- Formal spatial representations for coordinates, with projections defined
- Formal time/date representations for observations

[4] R is recommended, refer section 0

- Alignment of all factor-coding e.g. species codes
- Ensuring areas surveyed, but without animals, are represented in the data

2.2.2. Combining effort and observations data

The data required for modelling is a single flat-file, in "tidy" format – meaning each row is defined by a single response value (number of animals at a surveyed position). Additional values within the row are all associated variables that might be used to functionally explain this response e.g. time, location, bathymetry, construction phase etc.

Areas surveyed, even without observed animals, must be represented, meaning a merging of observations and effort data may be necessary. In the case of continuous surveying such as digital video, this can be obtained by discretising survey paths (e.g. 1 km^2 cells) and allocating counts with from the observations data. Effort information for any such discretisation must be calculated i.e. area covered as per realised swath, which may be a function of the number of cameras in operation. Digital stills taken at planned periods along transects are already discretised, but zero count sampling points and coverage/effort must be similarly represented in the modelling dataset.

2.2.3. Derived variables and additional covariates

As the modelling is to be based on the BAG approach, potential confounding factors need to be accounted for to allow statistical separation of development effects, and better associated power. The models to be fitted are descriptive/interpretative (as opposed to predictive) meaning the fitted functions are of interest themselves. There are also a range of variables that will require calculation (derived variables) for the model. An initial list follows, which may not be exhaustive:

- Date information to reflect construction e.g. date of construction/completion, or at least factors for their phases. Construction phases will be highly variable across developments, encapsulating periods of inactivity and a range of development activities. Detailed site-specific modelling could be attempted, but most simply needs encompassing with a simple construction category. The essential aspect is that it be distinct from baseline/unperturbed data for the estimation of redistribution effects.
- Distances from relevant parts of the development(s) e.g. the realized footprint after construction (as opposed to planned).
- Influential covariates (section 2.3.2).

Data at this point needs to be subject to a range of fundamental checks to detect and amend obvious errors. Data joins in particular (e.g. combining covariate information with observations data) are operations that can introduce serious errors.

2.2.4. Adjustments for visual observations

All data progressed to analysis are based on designed surveys, where the platform and methodology are either visual boat, visual aerial or digital/photographic aerial. Any visual method, where the sighting of animals is over varying distances, will be subject to some level of detection bias. The consequences of this can be viewed in several ways (e.g. effective effort), but primarily animals far from the observer will be less likely to be observed, leading to an under-estimate of the animals within the purported area surveyed. The standard adjustment for this is through distance analysis (Buckland et al. 2001).

This analysis will be required for each combination of species and visual survey. The distance analysis should follow standard distance analysis guidance, for example including recorded factors likely to have affected detectability, such as sea-state.

A properly conducted distance analysis will adjust for detection bias, making the data reflective of true abundances – whereas they would be considered only as relative prior to this. It is possible to analyse relative abundance data, but when made absolute, the data from different collection types will be more compatible. Some surveyed regions may be a mix of survey types, and such adjustment will reduce platform effects in the modelling phase.

The R package **Distance** (Miller *et al.*, 2019) is recommended for any such analysis, as opposed to point-and-click variants, to ensure reproducibility – a full audit trail from data to results can only be based on code.

2.3. Modelling

Assessing animal redistribution from survey data, involves estimating relationships between animal distributions and their environment, and how these may have changed with the introduction of an OWF. Modelling needs to provide estimates of utility, be appropriate for these data, and be specified and fitted correctly. There is substantive natural variability in animal distribution data, and this uncertainty needs to be appropriately captured in the models for inference to be believed.

The requirements of the models are outlined below, and by extension the most suitable statistical models identified. These are described such that the specific tool for fitting the models isn't fully prescriptive – the statistical modelling of redistribution effects is complex, and the specifics of a particular case requires a considered, iterative approach. The models should allow:

- complex relationships between the animals and their environment
- count responses
- flexibility in modelling errors, which may not be independent
- estimation of functional relationships between animal distributions and OWF developments
- statistical separation of effects

Approached as a regression, these requirements imply variants of Generalised Additive Models (GAMs), with account for correlated errors. GAMs can model drivers of animal distribution as separable functions and permit a range of error distributions. Mixed effect variants (GAMMs) accommodate forms of correlated data, or relatedly by fitting using Generalised Estimating Equations (GEEs). In this context, the analyses in Peterson (2011, 2014), Trinder *et al.* (2019) and Garthe (2023) serve as exemplars, with general guidance in Mackenzie *et al.* (2013).

Viewed from a spatial point process perspective, models based on Log-Gaussian Cox-Process (LGCP) might also be used, as fitted using INLA – refer section 7.2.2 for discussion and caveats on this approach. Grundlehner *et al.* (2025) serves as an exemplar in the context of seabird OWF redistribution analysis.

Modelling is an iterative process, with fitted models examined and modified in light of diagnostics and various tests. Given the maturity of GAMs and their well-developed tools[5], the following guidance assumes these to be the general modelling approach. Inference can be acceptably approached from a frequentist or Bayesian perspective, noting the former is more commonplace for prosaic reasons[6].

2.3.1. Model structure

Count values[7] (i.e., the number of individuals) will be used as the response variable to be modelled. A log-link, Poisson-errors model is most appropriate for count data as an initial specification. Data preparation as previously described means including effort as an additive offset term (i.e., log(effort)) for modelling, which latterly allows density predictions. Note the units of effort define the units of density, with km^2 being common in the OWF context.

This (log) response will be modelled as an additive set of covariate functions, initially as smooth terms for those real-valued, or as factor terms where appropriate e.g. survey month often suits this representation. Interactions are similarly specified where logically required e.g. a spatial smooth, being an interaction of Northing and Easting, further interacting with factor month to model month-level changes in distribution.

The complexity of individual smooth terms requires estimation, which should be integral to the fitting process e.g. smoothing parameter selection, or knot optimisation, depending on the software used.

The details of the specification are subject to change after model diagnostics - in particular the assumed error distribution. There is a common misconception that if the response data is rich in zeros, then some type of zero-inflated model is required – whereas this depends on the full distribution of counts, mean-variance relationships etc. A preponderance of zeroes is fully expected when densities are low, and the Poisson may be suitable if non-zero counts are small. Model diagnostics examining the error distributions will instruct which distributions are appropriate e.g. zero-rich with a high variance relative to mean, might suggest zero-inflated models or quasi-Poisson.

2.3.2. Covariates

We seek to model animal distributions over the OWF development site and near surrounds. The model will seek to separate/estimate additional redistribution components that potentially form over the course of development. The greater the amount of variability in the animal's distributions that can be explained in the models, the better the ability to characterise changes both coincident and related to the OWF development.

At a minimum, the covariates would initially consist of time (e.g. factors to capture seasonality), a spatial smooth, their interaction, and terms to capture the progression of the OWF development (section 2.3.3). Other variables might include bathymetry (influence via prey or benthic feeder's limits), distance to coast or colony (influence via breeding season constraints), current flows (influence via prey influences), habitat

[5] These were popularised in 1990 (Hastie and Tibshirani, 1990), and there has been extensive tool development in R, particularly since 2000 with the genesis of mgcv.

[6] Most statistics education is frequentist, and tools similarly reflect this dominance.

[7] Adjustments for detection probabilities may make these real-valued, non-negative.

classifications (influence via foraging preferences), and the distance to/presence of other developments animals may respond to. The exact utility of these will be very case-specific, being heavily influenced by data availability/resolution/quality and the various potential confounding with other model components.

For an effective estimation of redistribution effects, other potential predictors of animal distribution deemed important should be included in the model. This will be case specific, but predictor variables that may change coincident with OWF developments over time are of particular import.

2.3.3. Redistribution effects

The model requires terms to estimate potential redistribution over the pre- to post-construction phases. This requires key development stages for the OWF to be encoded for modelling – at the simplest level consisting of pre- and post-construction. Other distinct phases can be included if the data support these, but power considerations favour simplicity. There are decisions required about time-periods should be contrasted (section 2.3.4), but the following assumes this contrasting is established.

Two types of model specification for redistribution are proposed in decreasing order of complexity, noting the more complex variant can be used to calculate the simpler:

- Pre- post-development spatial smooths
- Defined spatial blocks

Contrasting spatial smooths This estimates redistribution within the survey region at its most general and is exemplified in several previous studies (Peterson *et al.*, 2011, 2014, Garthe *et al.* 2023, and Trinder *et al.* 2019). Spatial smooths are fitted with an interaction with the development phase. It is assumed significant differences in these surfaces before/after development are potentially due to the OWF.

Focussed contrasts are created with post-hoc calculations from the model. Following Mackenzie *et al.*, (2013), repeated pairs of bootstrapped surfaces from the pre-/post-smooths can be coupled to give difference surfaces. Spatially explicit significant differences are inferable from these distributions i.e. if zero is outside the central 95% at a specific location. Changes in pre-/post-construction density, as a function of distance from the OWF, can be similarly calculated from these surfaces, or for polygon sub-regions of interest e.g. footprint and buffer.

Spatial block estimates Predefined regions of interest are encoded into the data and model – a common example being the development footprint of the OWF and buffers around these. These enter the model as factor variables, which coupled with an interaction with development phase give impact contrasts. For example, was the change in abundance within the footprint significant with the introduction of the development, with other factors accounted for – noting a BACI design makes simple comparisons like this markedly more powerful.

When the analysis is performed post-construction, then the locations of turbines are knowable in detail. Calculations involving distance to the development (e.g. buffer regions and post-hoc estimates) should use this detail where possible i.e. distance to nearest structure.

It is recommended that the more complex model be attempted in the first instance, as this offers a more general perspective on potential redistribution. However, there will be site-specific considerations, where complicated spatiotemporal models may be obfuscatory. Assessment in some cases may benefit from a simpler, targeted estimates for a region of interest.

2.3.4. Temporal contrasts

Substantial care is needed when contrasting pre-/post-construction, that these be temporally comparable – in effect to avoid confounding. For example, pre-construction summer distributions cannot be simply compared to post-construction winter to estimate impacts as there is clear confounding. While obvious in this case, similar, more subtle effects may be present and addressed.

Relatedly, some level of pooling may be advisable to provide sufficient observations for modelling, or more robust and meaningful comparisons e.g. seasonal contrasts to avoid the vagaries of monthly changes.

2.3.5. Model examination and adaptation

Standard good modelling practice applies, with the assumptions of the models examined in detail. In this regression context these are primarily the adequacy of systematic component capture the underlying signal, and whether the stochastic component/model for the noise is approximately correct. A range of diagnostics should be examined to ensure model adequacy. These include, but are not limited to:

- Partial plots for residuals and fitted additive components to explore under/over-fitting and distributionally inconsistent data
- Residual plots to compare assumed, with observed, error distributions
- Residual plots and tests to explore dependencies in the errors e.g. runs tests

Note, approximate conformity to assumptions is sought. In the case of substantial data, formal tests of distributional assumptions are often powerful, and failure is commonplace even in the case of good approximation. Emphasis should be on approximate adequacy in practice.

It is expected that a level of model selection will be conducted, particularly in the case where there are large numbers of covariates or additive terms. Model selection can consist of several processes and serve different objectives. Generally, it implies modifying the model to obtain a justifiable level of complexity. This can be:

- The removal of fitted terms that are not distinguishable from noise e.g. tests of significance or measures of parsimony such as AIC and its variants
- Determining the level of complexity of additive terms e.g. knots in an adaptive spline method like MRSea (Scott-Harward, *et al.* 2014), or penalty terms via mgcv (Wood, 2017) – noting that these are usually automatically determined in the fitting process

It is necessary to consider this to: avoid under/overfitting (with the concomitant lack of model generality), increase power for estimating other model components, avoid interpreting model elements that are unimportant, and generally answer questions about the relative importance of model components.

The approach to model selection should be justifiable and adhere to general good practice advice for the model being fitted. For example, shrinkage smoothers and penalty approaches for mgcv optimise the smoothing and effectively remove irrelevant terms (Mara & Wood, 2011), whereas in MRSea, one of the various information criteria appropriate to the model would be used.

2.3.6. Results and utility

The previously described modelling will:

a) inform whether such redistribution is detectable, and

b) provide estimates of the level, extent and nature of any redistribution.

The consequences of any detectable redistribution, or effect of mitigations, are likely determined by secondary modelling or examinations. A general view of the patterns of redistribution might have utility, but the translation of these to population-level effects will be of particular interest.

Predictions of redistributions will have particular use when speculating on their population consequences via a mortality displacement matrix, or simulations via seaBORD (Searle *et al.*, 2018) or other IBMs (refer ORJIP DisNBS project).

In these cases, the estimated redistribution outputs of section 2.3.3, with uncertainty, are directly useful. They will provide:

- Simple estimates of the proportion/probability and/or numbers of animals displaced outside a specified region. These underpin additional mortality calculations at the population level, which can inform PVAs or other uses like IBMs.
- Redistribution as a function of distance from an OWF development. These can be used to calculate simple estimates as above, or more detailed projections for IBMs
- Redistribution maps as a function of an OWF development. These similarly can be used to calculate simple effects or provide complex redistributions for use in IBMs. Note, if this type of model is favoured over the simpler direction-invariant model previous, it is unlikely to be transferable to other locales – it indicates a significantly site-specific redistribution.

Note, where avoidance (/attraction) is understood to be macro influences on flying birds, the models described would be applied to only flying bird data. This would have particular relevance when considering downstream analyses focussing on collision impacts – via adjustments to the predicted numbers of birds within a development, and hence at-risk.

2.3.7. Reproducibility

The finalised modelling approach should be documented concisely in a reproducible manner. As indicated generally in section 4, an unambiguous record from data to results such as provided by markdown and version control. There will be substantial prototyping that need not be recorded in full, but a concise path to the final model must be fully described from unambiguous starting data.

2.3.8. Limitations

There are a range of issues that may afflict estimation of redistribution with these data and models. These include, but are not limited to:

- **Low power to detect effects**. Transect survey guidance has been based on power calculations to detect simple abundance changes over the survey region, or sub-regions within this. The power to detect small changes is typically low (albeit species and site dependent), and this would translate to low power to detect subtle redistributions. In short, false negatives may be likely –

where the failure to detect redistribution could be a function of low power, rather than no effect. Additional survey effort can increase power but may be infeasible given the relatively intensive surveying effort already recommended (noting the presence of unprocessed data section 2.1.1). Higher power can also be achieved by attempting to estimate simpler, larger effects.

- **Confounding factors**. The drivers of animal distributions are complex and there and is substantial natural variability surrounding our observation of these. Even in the best-case scenario of a well measured BACI design, there is the potential for confounding factors i.e. an observed redistribution may be in fully, or in part, due to drivers coincident with the OWF development. This is more likely for the more common BAG study structure. For example, changes in prey distribution unrelated to, but coincident with, development phases. These cannot be fully guarded against, but efforts to model and/or identity such possibilities are advised.

Relatedly, when combining different types of survey data, these may also be coincident with development phases. Steps are indicated previously to mitigate these (e.g. adjustments to visual surveys) but confounding effects may remain.

2.4. Post-hoc adjustments

Where there are established biases in the data, these ought to be adjusted for as far as possible. There are two common cases in survey data, whose importance is both species and platform dependent e.g. only affects diving animals, and classification precision varies by survey type:

- **Availability**. Species that spend an appreciable amount of time below the water surface (unavailable to detection) will have biased estimates from survey counts if not accounted for. Without adjustment, model predictions are considered *relative* i.e. high and low values are relatively correct, but the *absolute* number is not known. Where estimates exist for the proportion of time below surface, adjustments to the model predictions can be made proportionally.

  For example, if a species is unavailable 20% of the time and N animals observed, the adjusted count $N_{adj} = N$ / (1-0.2) i.e. an additional 25% are expected as only 80% of the animals are being observed. Note the N being adjusted for may depend on behaviour, for example only applicable to animals on the surface. Care is required how adjustments are applied when there are multiple behaviours and overall estimates are being calculated.

  There is a strong assumption that availability is spatiotemporally invariant, whereas it is likely not, due to seasonality, time-of-day influences, and location with regards foraging areas. More granular estimates may be available and justifiable, but even basic informed adjustment is preferable to known underestimation.

- **Uncertain species classification**. The level of precision in species classification varies across survey data, primarily by broad survey type e.g. boat visual vs aerial digital video. Results however are generally needed at species-level for consenting purposes. Where there are substantive numbers of imprecise observations, account ought to be taken of these.

  In simple cases, the treatment is clear – for example where the observation is classified as ambiguous between of two morphologically similar species. The ambiguous observations are allocated to a species proportionally, based on the species-level counts for that survey. This is a multiplicative adjustment for the model predictions similar to the previous availability correction. For example, if there are N_{AB} ambiguously identified animals (species A or B), and the confirmed species-level counts are N_A and N_B, then the adjusted count for species A is: $N_{\text{A-adj}} = N_A + N_{AB} (N_A / (N_A + N_B))$.

This is simply the unambiguous species-level count combined with an appropriate proportion of the ambiguous animals. This also provides a simple multiplier for any spatially explicit models (e.g. DSMs) with N_{adj}/N_A, giving the multiplicative increase required. Extension to larger groups of ambiguous species is direct.

This is subject to many assumptions but primarily: species in the ambiguous class are equally confusable at an individual level (hence proportional allocation $N_A / (N_A + N_B)$ is justified), and that the proportional allocation is spatiotemporally correct. Making this adjustment spatially varying is fraught with complexity, but calculation at the individual survey-level is recommended to address temporal changes in species composition.

3. Tracking data

While redistribution studies were found to be largely based on to transect survey data, tracking data studies (radar, GPS tags) comprised a significant minority group (Murrell *et al.* 2025). These data are discussed together here, as they provide repeated fine-scale spatiotemporal fixes of individual animals (or flocks in some radar instances).

In comparison to transect survey data, the published tracking data studies had little consistency in terms of field methods, study design, and particularly analysis, even if sharing similar research questions. Research also tended to focus on the collision risk implications of avoidance, with macro-scale redistribution being secondary.

This lack of firm precedence for estimating redistribution means formal guidance here is not comprehensive. Nonetheless, tracking data has clear information about animal's distributions around OWF – some recommendations can be made to improve utility for consenting on this basis.

3.1. Initial method contrasts

In contrast to transect surveys, radar has limited spatial range – studies typically offer a few kms of coverage focussed on one side of an OWF. With this design, redistribution cannot be estimated generally for a development, being limited to a portion of it. Further, the radar data is not species-specific without supplementary information (visual observations) or assumptions about the composition of birds in flight. There are emergent technologies combining visual sensors and radar which give both radar tracking information and species identification. However, there is a complex interplay of visual uncertainty (detection and identification probabilities with distance) and extent of effective overlap with the wider-ranging radar sensors, which are active research questions[8]. Data is also limited to birds in flight, may be at flock/group-level, and not equally effective for small birds (Nilsson and Green, 2011). Radar does however capture large amounts of track data on large numbers of objects, in contrast to tags which are on captured animals.

Tagging naturally requires animal capture. The labour-/equipment-intensive nature of this, and welfare issues, means sample sizes are typically small although the level of information about a specific individual however is very detailed – being fine-scale spatiotemporal (metre and minute level) information. This individual-level sampling introduces issues about representativeness, where bias might enter through the selection of animals for tracking, which is without analogue in transect surveys, or possible behavioural changes due to attachment of tracking devices (Clairbaux et al., 2025).

Given the above, radar will be excluded for in discussion of direct estimation of redistribution. While it offers information of utility particularly for collision risk, redistribution requires species-level information on OWF scales, including pre-construction periods of open ocean without a natural survey structure.

[8] 8th Conference on Wind energy and Wildlife Impacts (CWW 2025)

3.2. Study design

Some regulatory guidance exists for tagging studies in support of OWF, although not specifically for the purposes of estimating redistribution (Cook *et al.,* 2023). Animal welfare is a dominant factor and should be carefully considered with due scrutiny and permissions from regulator bodies.

Some common gaps in published studies are presented below, for improving prospective estimation of redistribution.

Collect pre-construction baseline data – the reviewed studies are predominantly post-construction. Questions about redistribution in response to OWF implies, and benefits from, the collection of data that explicitly covers pre-/post-construction phases. There are analytical methods that attempt to overcome this (e.g. simulated Null distributions – Skov *et al.,* 2018, Johnston *et al.*, 2022) but will be inferior to measuring pre-construction distributions. Degaer *et al.* (2021) notably includes a complete BACI design, allowing direct estimation of changes in space use under impacts.

Sample size/power analysis – the amount of sampling effort (here the number of tagged animals) ought to be determined by calculating statistical power. Some guidance for this is given in Cook *et al.* (2023) in the context of estimating species home ranges. If the tagging study is explicitly being conducted to estimate redistribution, then the calculations should be made against this goal. This will require a well-defined statistical analysis plan, as power depends intimately on the statistics/models to be estimated from the data. Bespoke simulations of the type underpinning MRSeaPower (Scott-Hayward & Mackenzie, 2017) is suggested.

3.3. Modelling

More than twenty tracking studies were considered in the preceding work-package, as being relevant to estimating redistribution (Murrell *et al.,* 2025). With the exception authors repeating their analysis methods (e.g. Peschko *et al.*2020a, 2020b, Peschko *et al.*2021), a different bespoke analysis was effectively conducted in each case. In addition, focus was typically on collision risk and frequently only conducted post-construction.

This lack of consensus simultaneously argues strongly for guidance on methods but without offering a firm basis to provide it[9]. A single analysis approach is correspondingly not firmly advocated here for the estimation of redistribution effects, as it would be largely unproven. Instead, general desirable properties are presented with candidates, noting a future consensus should be sought.

Note, Hidden Markov Models are frequently applied to tracking data but are not considered further here (e.g. McClintock *et al.*, 2020). These provide very fine-scale spatiotemporal modelling of movement decisions, are theoretically dense, and operate on fundamental animal behaviours. Their use in answering the redistribution questions here can be envisaged (e.g. parameterising a simulation) but is sufficiently speculative that it will not form general guidance.

[9] Masden *et al.*, (2009) noted a lack of standard methodology (in evaluating barriers to movement), with Peschko et al. 2020a more recently labelling analysis as challenging.

3.3.1. Properties and candidates

The outputs of utility for consenting given in section 2.3.6 apply equally here. Reiterating the key redistribution outputs sought, with their uncertainty:

- Simple estimates of the proportion/probability and/or numbers of animals displaced outside a specified region. These underpin additional mortality calculations at the population level, which can inform PVAs or other uses like IBMs.
- Redistribution as a function of distance from an OWF development. These can be used to calculate simple estimates as above, or more detailed projections for IBMs
- Redistribution maps as a function of an OWF development. These similarly can be used to calculate simple effects or provide complex redistributions for use in IBMs.

Generalised Additive Mixed Models (GAMMs) – GPS tracking data can be modelled in a broadly similar fashion to section 2.3 (survey data), based on a GAMM, as per Vanermen *et al.* (2020). A clear inferential difference between the two types of data are the repeated measures taken on individuals, which is accounted for using a mixed model variant of the GAM.

In Vanermen *et al.* (2020), the study is post-construction meaning a direct contrast with unimpacted measurements is not estimated, but relationships with the distance to OWF boundaries and presence of a turbine within a grid-cell. In this regard the model is focussing on meso-scale influences but is still informative for an analysis approach.

Guidance in section 2.3 broadly applies here, with two notable modifications. The response variable must represent space utilisation, and repeated measures on individuals becomes a clear and dominant source of correlation in the errors. Vanermen *et al.* address these by a) thinning the data to 20-minute fixes and summarising to counts within a spatial grid, and b) inclusion of random effects. The response is now a count variable of cell occupation (over a period of time), noting it is also interpretable as an amount or proportion of time given the thinning rate. The sensitivity of the results to thinning choices should be checked, but there will be substantial redundant information in the raw GPS that can be reasonably discarded.

If the study consists of pre- and post-construction data as recommended, then section 2.3 elements generally apply:

- influential covariates should be included as additive terms, smooths or factors as befits, along with variables to quantify OWF influences
- model assessment, selection and modification
- post-hoc inference to estimate OWF influences

Kernel Density Estimation (KDE) – several studies characterise individual animal's utilisation distributions using KDEs (e.g. Thaxter *et al.,* 2015, 2018 following Worton, 1989), noting that autocorrelation should be addressed when these are adopted (Fleming *et al.,* 2015). These offer some basis for estimating redistribution maps and outputs as previously described, subject to some calculation to provide combined density maps that would provide population level estimation and inference.

While this approach was not represented within the literature review (i.e. OWF redistribution studies), there is substantial general research in this area. If utilisation distributions are used, the approach given in Watson *et al*. (2021) is recommended, which is based on the same tools outlined in section 7.2.2 for transect survey data. Coupled with a pre- and post- construction study design and inclusion of OWF related variables, useful redistribution estimates should be possible. There is currently little precedent in the context of OWF redistribution for these analyses, so is considered suitable but not fully proven.

3.3.2. Initial limitations

There are several issues immediately apparent in tagging studies:

- Sample sizes are typically small, which is expected to be generally true given the difficulty and invasiveness of tagging animals.
- These is wide individual variability in animal's use of space. This is of note given these low sample sizes – concomitant precision is expected to be low.
- For long term studies, the same individuals cannot be reliably tracked throughout – which is a source of variability that might be avoided in other types of longitudinal studies (i.e. would allow comparisons within individuals pre- to post-impact).
- There is great potential for biases in sampling of animals for tagging. A random and representative sample of animals is difficult to obtain logistically, and there is the potential of effects from the tagging process itself.

Large sample sizes may not be possible, but if analysed correctly the lack of data should be simply reflected in the precision of estimates. The possibility of sampling biases would be addressed at the design phase, and researchers ought to already be cognizant of this.

4. Software and reproducibility

Data treatment and analysis is recommended to be conducted in R (R Core Team, 2024). R is the preeminent open-source statistical analysis tool and offers both the general and very specialized methods needed for this redistribution analysis. Some analyses are best supported in R – advanced GAMs being case-in-point.

The data for analysis is fundamentally spatiotemporal. For consistency and quality assurance, all spatial data should be treated explicitly as such – in particular using a GIS approach with due consideration to projections and scales. The **sf** (Pebesma, 2018, Pebesma & Bivand, 2023) package is recommended.

Transparency and reproducibility are important for confidence and quality assurance for this modelling. All analysis should be documented such that the link from data to results is fully established. Markdown is recommended as this interweaves code, explanations/documentation and results into a common file. Subject to some qualification (version control), the results will be fully reproducible by another analyst.

Further, given these analyses are complex, likely collaborative, and requiring high-levels of quality assurance, the bulk of the analysis should be version-controlled. **git** is a good choice, and github is a good cloud platform to support this, however there are many suitable variants to these. Due to the size of the data used in these modelling exercises, versioning can be challenging. However, systems such as git-lfs (large file size) can be utilized as well as other frameworks such as Microsoft Sharepoint/OneDrive which can track file changes.

To further ensure reproducibility the analysis environment, such as versions of packages used, should be recorded e.g. the package **renv** (Ushey & Wickham, 2025) can ensure consistency.

4.1. Alternative approaches

The guidance is not fully prescriptive on software and solutions for quality assurance and reproducibility. The recommendations above are proven, but there are other approaches that would be suitable alternatives, for example:

- Elements of the workflows may use python
- Markdown/analysis documents may be based on quarto, r-markdown, jupyter, etc
- Version control might be based on other tools e.g. subversion
- Git repositories may be hosted on gitlab, bitbucket, etc

5. Outputs and reporting of results

The following outlines the types of outputs expected from the displacement modelling, and broadly how they are presented for consenting utility and general consistency. A distinction is drawn here between the presentation of results, and outputs required for future calculations – although these may overlap markedly for simple cases. For example, a complex spatiotemporal model might be summarised graphically with confidence bounds, but detailed future re-use would necessitate model objects or reproducible workflow (section 4). Here we present general requirements, followed by specifics.

5.1. General requirements

The fundamental outputs are the retrospective estimates of spatial redistribution of animals, and/or their estimated propensity of redistribution, for prospective uses. Although these are arrived at through the same modelling process, a distinction is drawn between retrospective estimation and prospective/predictive uses. In the former, the absolute numbers of affected animals are sought, in the latter, relative measures that are provided by probabilities or proportions of displacement.

Different levels of complexity are considered here, but key requirements in every case are:

- Mean estimates – proportions, probabilities or absolute values
- Precision of these estimates – details follow
- Spatiotemporal applicability – proximity to developments

The overarching requirement is that the results be transparent, reproducible and by extension reusable. This is fully ensured via the recommendations in section 4, however the analysis endpoints should be standardised for reporting and direct use in calculations. The exact representation of these depends on the level of model complexity but are broadly described here.

5.2. Expressing uncertainty

It is commonplace to present estimates with a simple measure of precision e.g. mean and standard error. This is generally the minimum requirement, however will not completely specify the error distribution and limits the reusability of the results. Here we recommend the presentation/reporting of uncertainty be as informative as possible (possibly fully), and where this is can only serve as a summary, there be the means to generate or retrieve full information.

It is recommended that estimates be reported with 95% confidence intervals and sufficient information to generate the distribution in its entirety where possible. For simple analytic estimates these can be completely defined in reported figures e.g. a beta distribution with given shape parameters, or link-scale parameters for a described generalised linear model, say binomial errors, logit-link.

For more complex cases, such as bootstrapping or spatial functions, presentation should still consist of mean estimates and 95% confidence intervals (single figures, or 1- or 2-dimensional functions), but external representations of the uncertainty need to be stored e.g. a series of bootstraps with full context (meta-data of structure, units, scales).

5.3. Reporting by broad model complexity

Three redistribution models of broadly increasing complexity are discussed, with the recommended level of reporting and storage required for future calculations ("prediction" below). A fully reproducible workflow as per section 4 allows this, but here we focus on analysis endpoints in isolation.

5.3.1. Simple rates and distance bands

The simplest redistribution estimates are for defined regions e.g. development footprint polygons, and extension to adjacent buffer regions of fixed width. Where these are characterised by established statistical distributions, they can be fully reported through tables.

Reporting should consist of tabulated mean estimates, standard errors, 95% confidence intervals, named distributions and their associated parameter estimates. Plots of mean estimates and 95% confidence intervals are beneficial, particularly when several regions are being expressed. General reporting and plotting for the data support and surveyed region would be needed to provide context.

Prediction For simple cases, the described distributions previously provide a full predictive tool. Where the models are not simple distributions (e.g. bootstrapping), reporting remains the same, but the full distributional information must be retrievable externally. For example, an R list object, stored in RDS format, consisting of bootstrap replicates and meta-data fully describing the contents.

5.3.2. Simple distance functions

Redistribution may be modelled as a simple function of distance from development – the previous section being a discrete version of this. The model fitted may take on many forms, but the marginal function for redistribution is isolated in any case.

Reporting The fitted redistribution function should be reported graphically, with mean estimate as a function of distance to development, with associated 95% confidence envelope. A high-level model description should accompany this, with general reporting and plotting for the data support and surveyed region.

Prediction Where the function can be characterised by a fitted model, with inference, this should be stored as a model object with associated meta-data – e.g. applicable distance units. Where the model inference is not simple (e.g. bootstrapping), the full distributional information must be retrievable. As before, an R list object, stored in RDS format, consisting of bootstrap replicates and meta-data fully describing the contents.

5.3.3. General spatial functions

Redistribution may be modelled as a 2-dimensional function of proximity to development, the previous section 5.3.2 being a directionally invariant version of this. Such a model will be location specific and not directly transferable to other locales.

Reporting The fitted marginal function should be reported graphically, with mean surfaces, and associated upper and lower 95% confidence surfaces. A high-level model description should accompany the function, along with general reporting and plotting for the data support and surveyed region.

Prediction Where the function can be characterised by a fitted model, with inference, this should be stored as a model object with associated meta-data e.g. units of distance. Where the model inference is not simple (e.g. bootstrapping), the full distributional information must be retrievable externally. As before, an R list object, stored in RDS format, consisting of bootstrap surfaces and meta-data fully describing the contents.

6. Post analysis data treatments and archiving

Datasets underpinning the analyses ought to be arranged in a clear and consistent fashion. If it is survey data, consistency with the data model of ESAS is recommended, whether they are to be stored with ESAS or not. This benefits from being particularly prescriptive, making the data predicable and easily reusable. The full description is accessible here: https://esas-docs.ices.dk/ - comprising 5 basic data tables, and formats required for validation in uploading. The data should pass through basic quality assurance but not be adulterated by modelling decisions e.g. without adjustment for detection probabilities.

For GPS tracking data, consistency with the data model of the seabird tracking database is recommended, whether they are to be stored with seabirdtracking.org or not. As for survey data, the requirements are prescriptive, and there is a quality control and vetting process, which can see data that does not conform to standards be declined.

There will be a series of intermediate datasets from raw, to final modelling data, which if not stored must be derivable from their markdown documentation. The totality of analysis information should be stored in a version-controlled repository. This should contain at least:

- Analysis vignettes provided by compiled markdown documents
- The means to create modelling datasets, which incorporate all adjustments, data derivations and cleaning prior to model fitting
- Links to raw datasets, which are completely unadulterated. These may vary widely in content, so there is no prescription beyond being stored in a secure and unambiguous fashion
- Information on the analysis environment e.g. package versions via renv

7. Emergent and excluded methods

This guidance necessarily focusses on data and methods that are proven, practically feasible, and will support consenting requirements of OWF development. However, there are some emergent methods that may meet these criteria in the near future, that are described here for completeness. We have also excluded micro-scale "redistribution" as being fine-scale turbine-level interactions more related to avoidance and collision risk. Recent work relating to this scale is discussed here also for completeness.

7.1. Data collection

Only data from visual surveys (boat/aerial), digital surveys (aerial), GPS tagging and radar are considered in this guidance. There is increasing use of Unmanned Aerial Vehicles (UAVs) for data collection in contexts of, or similar to, OWF developments with clear affordability benefits. From an analysis point of view, most of these data will be simply DAS.

However, an emergent approach is the use of airships or blimps which offer the advantage of near-continuous coverage of a survey location. These are currently used relatively rarely but are noted here for their potential as an effective method for quantifying redistribution in future (Amerson et al., 2023). Logistical considerations aside, survey design, data treatment and modelling would have to be fundamentally reconsidered, given the data are no longer snapshots of animal abundance.

7.2. Modelling

7.2.1. Data integration

Very recently published work by Blackwell and Matthiopoulos (2024) seeks to combine both tagging and survey data to provide a joint statistical analysis. It was found that there are inferential advantages to the joint analysis, offering greater precision. No recommendation is made here for the use of this approach for several reasons:

- there is no practical track-record, only theoretical development and supporting simulation studies
- the models would require bespoke construction and fitting
- the examples are only adjacent to OWF redistribution questions and would require substantial reworking to provide estimates of regulatory utility
- The two types of data would ideally be collected coincidently

The method is highlighted here, as future work combining different sources of data in redistribution questions around OWF may show benefits.

7.2.2. Log-Gaussian Cox Process models using INLA

The bulk of analysis discussed in this guidance are variants of regression, with spatial components. Spatial statistics in the traditional statistical sense is specifically for spatial data and encompasses things like spatial point processes and random fields, with some overlap with regression methods, particularly in geostatistics[10].

There have been recent advances in software tools that have seen these models more widely used for the analysis of ecological data – specifically, Bayesian models fitted with Integrated Laplace Approximation (INLA) which has wide applicability. Fitting models with INLA for these types of problems is technically challenging in contrast to the regression models presented here, as evidenced by the development of the inlabru R package (Bachl *et al.*, 2019) to facilitate fitting models to ecological survey data.

These models can be used to address redistribution questions from the types of survey data described in section 2, and do so more naturally in some respects – for example, spatial point-process models use the animal locations directly without the need to aggregate their counts to a grid, although gridded data can be used. Simple related examples can be found at the inlabru webpages.

These models are not described in the body of the guidance for several reasons, although their use is not precluded:

- There is comparatively little published track-record for their use in the context of OWF survey data, or similar situations – see Vilela *et al.* 2021 for one such example, focussed estimating abundance changes in diver species in response to developments. Grundlehner *et al.* (2025) notably provides analysis and outputs that match those described for the frequentist models of Section 2.3.
- The statistical expertise required to build and assess these models is advanced, and less widespread, including at the regulatory level.

Countering this there are reasons for this approach to be adopted: well-developed theory and Bayesian[11] in nature, an active INLA and inlabru community, ongoing R software development, and increasing use in analysing aerial survey data. Future guidance might include this approach as generally recommended, but at this point would only be advised for domain experts, noting also that regulatory experience with such models may be limited.

7.2.3. Meso/micro-scale randomisation tests

Trinder *et al.* (2024) conducts an analysis of redistribution in keeping with the methods in Section 2 for the Beatrice OWF. In addition, they propose a new method exploring the distribution of animals within a windfarm footprint. This is in essence a randomisation test, with simulations under a null hypothesis of "no influence" with regards distance from animals to turbine.

This method is not promoted in this guidance not through simple omission, but because:

- This is a meso-scale, turbine-level effect, for animals within the windfarm. This is below the scale of redistribution considered here.
- The estimates/calculations are performed on animals already within the OWF, so does not speak to any broader redistribution of animals that might have avoided the area completely. In effect, it

[10] For example co-kriging and thin-plate spline regression.

[11] A statistical paradigm for inference that is strongly preferred by some statisticians

answers questions about animal distribution, conditioned on their lack of macro-scale avoidance behaviour.

The method does not have particular track-record at this point, and it isn't clear what direct utility it will have in the consenting process e.g. how the estimates provide figures for downstream analyses for population impacts and/or mitigation.

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