Scottish Waters East Region Regional Sectoral Marine Plan Strategic Ornithology Study: final report

Searle, K. R., A. Butler, D. C. Mobbs, Trinder, M., Waggitt, J., Evans. P. & F. Daunt

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CEH contact	Dr Francis Daunt
details	Centre for Ecology & Hydrology, Bush Estate, Penucuik, Midlothian, EH26 0QB t: 0131 445 8526 e: frada@ceh.ac.uk

Author	Dr Francis Daunt
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Executive Summary

- The Scottish Government has set a target for 100% of Scottish demand for electricity to be met by renewable sources by 2020, and the marine environment offers considerable potential for delivering this. However, the Scottish Government must ensure that offshore renewable developments (ORDs) are achieved in a sustainable manner, by protecting the natural environment from adverse impacts.

- ORDs may affect seabird populations that are protected by the EU Birds Directive, notably from collisions and through displacement. A number of research projects have addressed and attempted to estimate these different impacts, often in isolation, or in a single season or breeding colony. However, there is a desire to develop a framework for assessing ORD impacts on seabirds over all seasons, and at multiple population scales.

- Increasing recognition of the importance of assessing potential ORD impacts on seabirds and other ecosystem components throughout the year and over different geographic regions in a coherent and repeatable manner has led to the European Commission funded 'Strategic Environmental Assessment North Seas Energy initiative' (SEANSE). In line with this, Marine Scotland (MS) undertakes Sectoral marine planning underpinned by Strategic Environmental Assessment (SEA), whereby they must consider how to apply strategic assessment for seabird impacts that may result from cumulative ORD developments.

- In this project, we developed and implemented a framework for performing strategic assessments either cumulatively or for a single development, and illustrated the application of this framework to a set of hypothetical wind farm developments in the Forth and Tay region for five key seabird species (black-legged kittiwake, common guillemot, razorbill, Atlantic puffin and Northern gannet). This framework leveraged the best currently available data and tools to underpin baseline understanding of seabird populations and habitat use, their potential interactions with ORDs and subsequent demographic consequences and population forecasts.

- We combined a series of data sets and tools/models in an overarching assessment framework, producing population level estimates for impacts of different hypothetical offshore renewable energy development scenarios. Estimated baseline spatial distributions of birds were derived from at-sea survey data and GPS tracking data. These bird distribution maps were used to estimate bird densities within, and interacting with, the relevant offshore wind farm (OWF) footprints in the scenarios used in the project. They were therefore the primary inputs for the tools and models for estimating collision and displacement. Collision effects were assessed using stochastic collision risk models at monthly scales, and these monthly estimates were aggregated to produce overall estimates of collision effects during both the breeding and non-breeding seasons, using the BDMPS breeding season definitions. We estimated displacement effects in the chick-rearing period for four species (all except northern gannet) using two currently available approaches; the SeabORD simulation model and the matrix method. However, for northern gannet, this was only assessed using the matrix method, because there is no currently available parameterisation of the SeabORD model for this species. For black-legged kittiwake, common guillemot, razorbill and Atlantic puffin, displacement during chick-rearing scaled up to year-round impacts on demography was estimated using SeabORD, and displacement during the non-breeding season was also assessed using the matrix method.

- Three hypothetical scenarios were considered within this project: Scenario (1), in which there were no ORDs; Scenario (2), in which hypothetical ORDs with a capacity equal to that of currently consented developments (1.2 GW of inshore OWDs and 1 GW of offshore OWDs reflecting the combined GW of NNG, Inch Cape, and Seagreen Phase 1 - Alpha-Bravo) and potential new developments from Round 3

(Seagreen Phase 2 – Charlie-Delta-Echo-Foxtrot-Golf) were assumed to exist; Scenario (3), in which hypothetical ORDs with a capacity equal to Scenario 2 plus approximately 2.8 GW of offshore OWDs (reflecting OWDs in scenario 2, plus one large hypothetical offshore development) were assumed to exist. The impact of each scenario upon annual survival and productivity were assessed in terms of four separate components: a) collision effects during the breeding season; b) collision effects during the non-breeding season; c) displacement effects during the breeding season; d) displacement effects during the non-breeding season.

- Population Viability Analysis (PVA) is used to translate annual effects on demographic rates into longer-term projections of population size. Here, semi-integrated population models (SIPMs) were used because they allow the rates that are least well supported by empirical data – typically immature survival – to be estimated based upon the match of the PVA outputs to historical time series data on abundance. The SIPMs were fitted within a Bayesian framework, allowing the uncertainty associated with the estimation of these rates to be fully accounted for when generating the PVAs. The following PVA metrics were calculated: a) M1: median ratio of impacted to unimpacted population size; b) M2: median ratio of impacted to unimpacted growth rate; c) M3: quantile for unimpacted population size that equals the median impacted population size.

- We present a qualitative assessment of sources of uncertainty within the Discussion, outlining the caveats, limitations and sources of types of uncertainty associated with each method, and the likely consequences of these uncertainties. Three of the methods used in producing the impact assessments use stochastic models that automatically account for variability over time and/or between individuals, and, to some extent, uncertainty, within their calculation of risk. These are: a) SeabORD; b) stochastic Collision Risk Models; c) Leslie matrix models used in producing PVAs.

- We present the results of each stage within the assessment framework. We present maps of overall estimated distribution of birds separately from data from at-sea surveys and from GPS tracking, for all populations and for each SPA separately. We present breeding and non-breeding season apportioning to SPAs. We present the percentage time that birds from each SPA spend in each footprint. We then present the estimated effects of collision on survival and displacement on survival and on productivity, the latter only in cases where SeabORD was used. We present effects of collision and displacement separately and combined. Finally, we present estimated impacts from the PVA models using a range of metrics.

- Estimates of effects of collisions varied between species and SPAs. There were marked differences in effects between Scenario (1) and Scenarios (2) and (3). However, Scenario (3) did not differ markedly from Scenario (2) for most species at most SPAs because the footprint of the additional wind farm within Scenario (3) was located outside their breeding season foraging range. Effects also depended on methods used, in particular whether distributions were derived from at-sea survey or GPS data and whether the SeabORD or the displacement matrix was used to estimate displacement effects. We discuss the criteria that need to be accounted for in the choice of methods and the uncertainty estimates obtained.

- This project successfully delivered the core objective of a general framework for regional assessment that brings together a series of modelled data sets and tools/models to combine within an overarching assessment framework, producing population level estimates for impacts of different offshore renewable development scenarios. The framework has very broad applicability, and we outline how the framework could be applied more broadly to regions other than the Forth/Tay. We also provide recommendations on future work including empirical data collection and modelling advancements.

1. Introduction

The Scottish Government has set a target for 100% of Scottish demand for electricity to be met by renewable sources by 2020. The marine environment offers considerable potential with respect to harvesting renewable energy, through wind, wave and tidal stream energy generators. However, the Scottish Government has a duty to ensure that offshore renewable developments (ORDs) are achieved in a sustainable manner, by protecting the natural environment from adverse impacts in accordance with the requirements of the Marine Strategy Framework Directive (EC/2008/56), the Habitats Directive (EC/92/43) and the Birds Directive (EC/79/409).

Offshore renewable developments have the potential to impact on seabird populations that are protected by the EU Birds Directive, notably from collisions with turbine blades and through displacement from important habitat (Drewitt & Langston 2006; Larsen & Guillemette 2007; Masden et al. 2010; Grecian et al. 2010, Langton et al. 2011, Scottish Government 2011). Other factors of concern are barrier effects to the movement of migrating or commuting birds, noise and visual disturbance, direct habitat loss during survey and installation, toxic and non-toxic contamination and negative effects of developments on the distribution and abundance of prey. These potential effects are predicted to be particularly important for breeding seabirds that, as central place foragers, are constrained to obtain food within a certain distance from the breeding colony (Daunt et al. 2002; Enstipp et al 2006). Significant gaps in knowledge on the potential for ORD developments to impact seabirds have been identified (e.g., Searle et al. 2014, Furness & Trinder 2016, Green et al. 2016, Cook & Robinson 2017, Searle et al. 2017). A range of research projects have addressed and attempted to estimate these different impacts, often in isolation, or in a single season or breeding colony. Accordingly, there is a strong need to develop a framework for assessing ORD impacts on seabirds over all seasons, and at multiple population scales which utilises currently available tools and data products.

Increasing recognition of the importance of assessing potential ORD impacts on seabirds and other ecosystem components throughout the year and over different geographic regions in a coherent and repeatable manner has led to the European Commission funded 'Strategic Environmental Assessment North Seas Energy initiative' (SEANSE). This initiative aims to develop a coherent approach to Strategic Environmental Assessments (SEAs), with a focus on renewable energy in the North Sea. In line with this, in Scottish Waters, Marine Scotland (MS) undertakes Sectoral marine planning to advise Scottish Ministers on the spatial policy for commercial scale development, which are underpinned by legally required Sustainability Appraisal (SA). In Scotland, SA is defined as Strategic Environmental Assessment (SEA), strategic Habitats Regulation Assessment (sHRA), Socio-economic Assessment (Soc-EA), and consultation to meet public participation requirements. As such, in order to fulfil its duties under the SEA process, Marine Scotland must consider how to apply strategic assessment for seabird impacts that may result from cumulative ORD developments for the Forth and Tay area.

In this project, we developed and implemented an over-arching framework for performing strategic assessments either cumulatively or for a single development. This framework leveraged best currently available data products and tools to underpin baseline understanding of seabird populations and habitat use, their potential interactions with ORDs and subsequent demographic consequences and population forecasts. We illustrated the application of this framework to a set of hypothetical wind farm developments in the Forth and Tay region for five key seabird species (black-legged kittiwake, common guillemot, razorbill, Atlantic puffin and Northern gannet). However, the framework has very broad applicability, and we outline how it can be applied in other regions, and provide recommendations on future research priorities.

2. Methodology

The spatial focus is on the East Region of Scotland Waters, which corresponds approximately to the Forth and Tay and North East areas (Figure 1). We are focusing upon the four key Special Protection Areas (SPAs) within this region – Forth Islands SPA, Fowlsheugh SPA, St Abbs to Fast Castle SPA and Buchan Ness to Collieston Coast SPA, hereafter 'Buchan Ness' (Table 1). Where relevant, however, our approach accounts for birds that arise from breeding colonies outside these SPAs. For instance, when quantifying the effects of competition, we include effects of neighbouring large colonies such as the Farne Islands, and when apportioning birds to SPAs we account for all other breeding colonies.

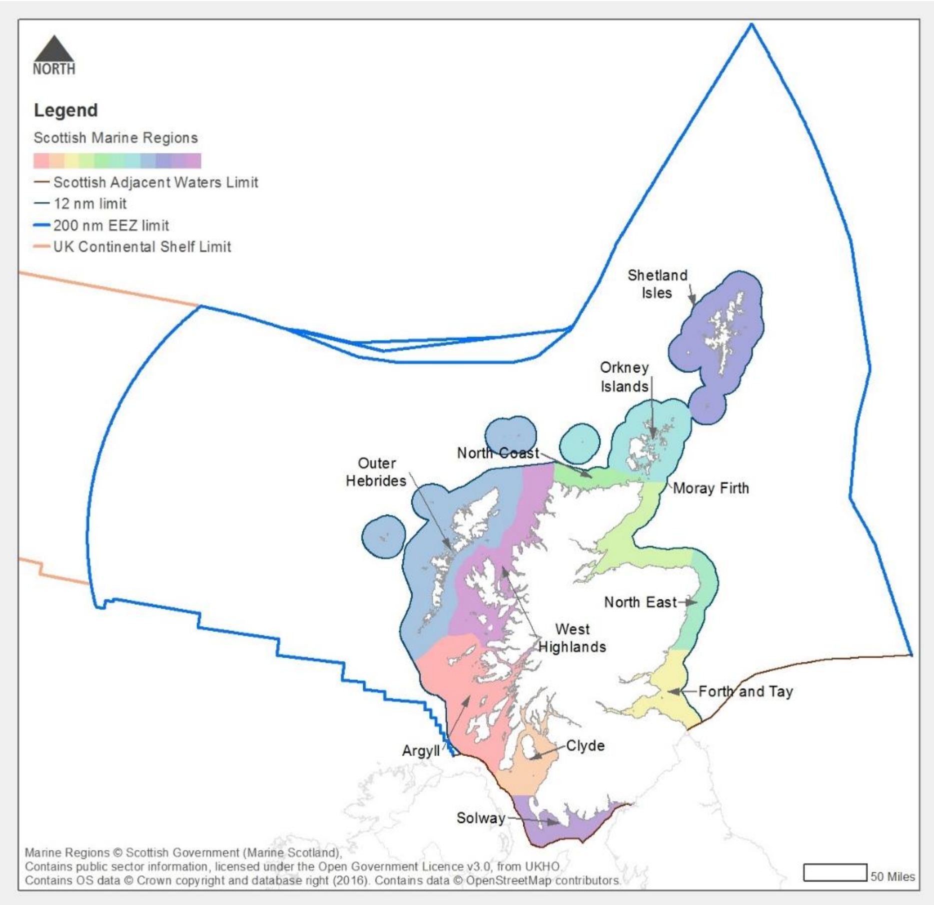


Figure 1. Marine planning areas for Scotland.

Table 1. List of Special Protection Areas (SPAs) included in assessment for each of the five seabird species.

	Forth Islands SPA	St. Abbs to Fast Castle SPA	Fowlsheugh SPA	Buchan Ness to Collieston Coast SPA
Kittiwake	Yes	Yes	Yes	Yes
Guillemot	Yes	Yes	Yes	Yes
Razorbill	Yes	Yes	Yes	No
Puffin	Yes	No	No	No
Gannet	Yes	No	No	No

The general framework for the regional assessment brings together a series of modelled data sets and tools/models to combine within an overarching assessment framework, producing population level estimates for impacts of different offshore renewable energy development scenarios (Figure 2):

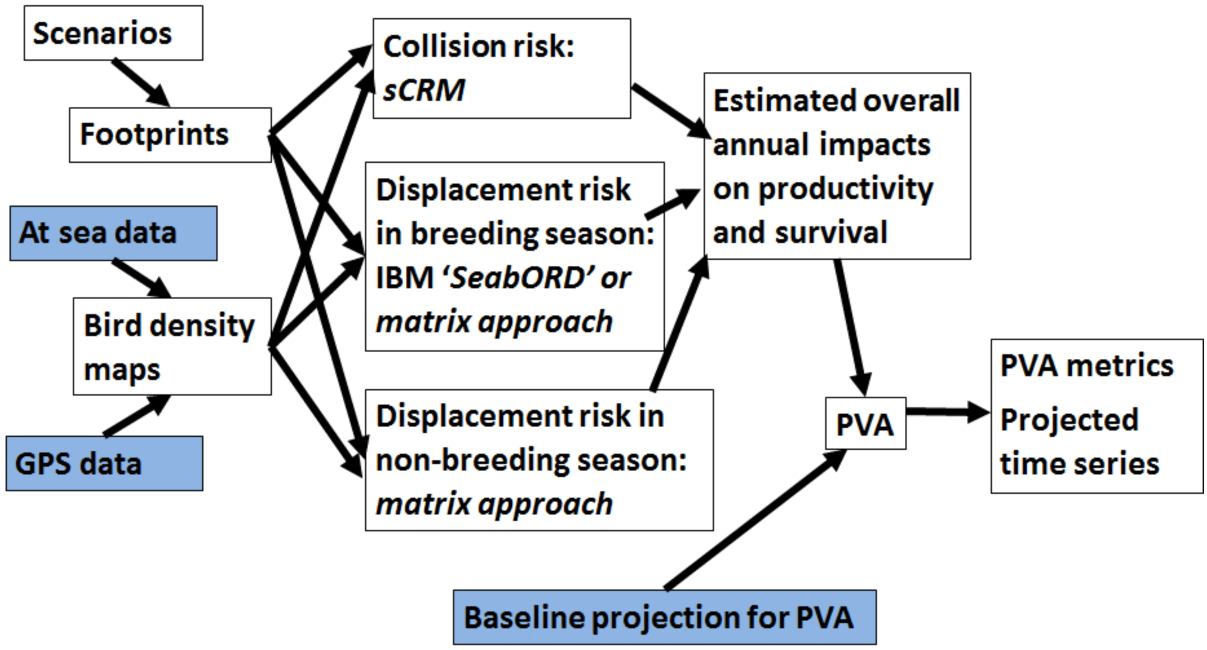


Figure 2. General framework for the regional assessment of offshore renewable energy developments and their potential impacts upon seabirds in the breeding and non-breeding seasons.

2.1. Baseline maps

Estimated baseline spatial distributions of birds can be derived from two main data sources: at-sea survey data, or GPS tracking data. At-sea survey data have extensive coverage – they survey large areas of sea and large numbers of birds, and cover the non-breeding as well as the breeding season. GPS tracking data, on the other hand, provide detailed data on individual-level movements unavailable from at-sea survey data – in particular, these data provide direct information on the spatial distribution of birds of known status and colony origin. However, GPS tracking data are not currently available during the non-breeding season.

The ORJIP Seabird Sensitivity Mapping tool provides a user-friendly interface for accessing recently developed spatial maps of bird distributions derived using both GPS tracking and at-sea data approaches (Wakefield et al. 2017, Waggitt et al. 2019). For three of the species under consideration in this project (black-legged kittiwake, common guillemot, razorbill), this tool provides GPS-based estimates of spatial distributions for the breeding season, and for all five species under consideration it provides estimates for both the breeding and non-breeding season based upon at-sea data. The baseline maps of spatial distributions that we use in this project were either taken directly from the ORJIP tool, or, where appropriate, derived using methods similar to those used in producing the maps within that tool.

For comparison, in this project we ran the risk calculations using maps derived from at-sea survey data for all species, as well as deriving risk calculations using maps derived from GPS tracking for the three species for which data are available (GPS tracking data for gannets in the Forth-Tay area are not available within this project). Running both sets of analyses is good practice, because each of the data sources has different advantages and limitations, and can be regarded as a form of sensitivity analysis.

Maps derived from at-sea survey data

As part of the ORJIP Sensitivity Mapping Project (Development of a 'Seabird Sensitivity Mapping Tool for Scotland') a variety of different at-sea survey datasets – both vessel and aerial surveys, covering the period from 1985 to 2017 – were used to create estimated monthly spatial maps of bird densities for cells on a regular 2.5 x 2.5km grid that covers the entire exclusive economic zone of Scotland (for full details see Waggitt et al. 2019).

Species Distribution Models (SDMs, Elith and Leathwick, 2009) were used in deriving the estimated maps from the raw data; in order to account properly for the large number of zero values in the observed data these models used hurdle count distributions (Zuur et al., 2009b). Generalized Linear Models (GLM) in combination with General Estimating Equations (GEE) were used throughout the analysis (Koper and Manseau, 2009), and implemented using the 'geepack' package (Højsgaard et al., 2006) within the R statistical programming environment (R Core Team, 2014). Throughout the analysis, forwards-model selection based on AIC was used to select the optimal model (Zuur et al., 2009a). Estimated maps of predicted bird abundance were produced separately for both "flying" and "on water" behaviours.

The at-sea maps relate to the entire spatial distribution, including birds of unknown origin (breeders from colonies within the study region, breeders from colonies outside the region, and non-breeders). The proportion of birds that arise from each breeding colony within the breeding season is derived within the ORJIP Seabird Sensitivity Mapping tool and in current practice, using the SNH Apportioning Tool (https://www.nature.scot/interim-guidance-apportioning-impacts-marine-renewable-developments-breeding-seabird-populations). The current version of this tool assumes that, at a particular location, the proportion of birds that originate from each breeding colony is proportional to

$$\frac{\text{Colony size}}{(\text{Distance to colony by sea})^2 * \text{Prsea}}$$

if the distance to colony by sea is less than the foraging range, and is equal to zero otherwise. “Prsea” refers to the proportion of sea within the foraging range RR of the colony, and is equal to:

$$\frac{(\text{Number of grid cells whose distance to colony is less than } R) * \text{Area of a grid cell}}{\pi R^2}$$

The spatial distribution of birds originating from a particular colony is derived within the ORJIP tool by multiplying the predicted maps of abundance derived from at-sea data by the map of apportioning proportions associated with the colony of interest, as produced by the SNH apportioning tool. We derived the spatial distribution of birds from each SPA in the same way for this project.

To apportion impacts to SPA populations in the nonbreeding season, the SPA population was divided by the relevant seasonal BDMPS (Biologically Defined Minimum Population Scale; Furness 2015) for that species, to obtain the percentage of the BDMPS population expected to originate from the SPA.

Foraging ranges during breeding season

The Project Steering Group (PSG) provided the foraging ranges to use when using the SNH apportioning method (Table 2). These foraging ranges represent the ‘mean-max’ foraging range for each species (i.e. the maximum observed foraging range for each colony, averaged across colonies), following current SNH guidance (last updated November 2018, see: https://www.nature.scot/interim-guidance-apportioning-impacts-marine-renewable-developments-breeding-seabird-populations), and derived from Thaxter et al. (2012).

The sizes of the standard deviations in Table 2 show that the inter-colony variation in foraging ranges is substantial. Within our uncertainty quantification we account for this variation by simulating the foraging range for each colony repeatedly from a gamma distribution whose mean is equal to the “mean-max” foraging range of Thaxter et al. (2012), and whose 99% quantile is equal to the “max-max” foraging range of Thaxter et al. (2012).

Table 2. Mean, standard deviations and maximum of the colony-specific maximum foraging ranges for each of the five species considered in this project (Thaxter et al., 2012); the first of these is usually called the “mean-max foraging range” and the last the “max-max foraging range”.

Species	“Mean-max” foraging range (i.e. mean of colony-specific max foraging ranges)	Standard deviation of colony-specific max foraging ranges	“Max-max” foraging range (i.e. maximum of colony specific max foraging ranges)
Common Guillemot	84.2km	50.1km	135km
Razorbill	48.5km	35.0km	95km
Atlantic Puffin	105.4km	46.0km	200km
Northern Gannet	229.4km	124.3km	590km
Black-legged kittiwake	60.0km	23.3km	120km

For modelling of the GPS-based maps we use a different definition of the foraging range for each species. In those models (see below), we use 1.1 * max-max foraging range (as in Wakefield et al., 2017), where the max-max foraging range has been derived from the local GPS data for the Forth-Tay. We propose to use these two different methods for defining foraging ranges for at-sea versus GPS tracking data because:

- it matches current practice for both at-sea and GPS tracking data
- it seems inconsistent to use regional or local GPS-derived foraging range in situations where the assessment is otherwise based entirely on at-sea data
- this approach reflects the fact that foraging ranges are used rather differently in the statistical models for GPS-based and at-sea-based maps
- using both approaches enables the uncertainty associated with calculation of foraging ranges to be partly quantified within our comparison of methods

In consultation with the PSG, the SNH breeding season definitions were used to define the set of months to be aggregated to form inputs in to the individual based simulation model, SeabORD (Table 4). For aggregating across months in estimating collision risk impacts and non-breeding season displacement impacts using the Displacement Matrix, the BDMPS breeding season definitions were used.

Table 3. Months used to define breeding season under the 'SNH_breeding_season' definition for each species (based on SNH guidance).

Species	start of association with colony	end of association with colony
Northern Gannet	March	September
Common guillemot	April	August
Black-legged Kittiwake	April	August
Razorbill	April	August
Atlantic puffin	April	August

Within this project, we used both the aggregated maps (breeding season) and underlying monthly maps. The aggregated 'breeding season' and 'non-breeding' season maps were used to assess displacement risk in each season (see details below), and the monthly maps were used to assess collision risk in each month.

Maps derived from GPS tracking data

The SNH apportioning tool makes some crude assumptions regarding the spatial distribution of birds – in particular, it does not account for the effects of competition and environmental heterogeneity – and this reduces the defensibility of colony-specific maps derived from at-sea survey data. Colony-specific distributions of birds can be estimated more directly using GPS tracking data, for species and sites where this is available.

The ORJIP tool allows users to access maps derived from GPS tracking data. These maps are based upon modelling by Wakefield et al. (2017), which produced predicted maps of distributions for four seabird species (guillemot, razorbill, kittiwake and shag) for breeding colonies throughout the British Isles, by fitting habitat association models to a large multi-colony GPS tracking dataset collected within the FAME and STAR projects.

For the current project, we modelled GPS tracking data for the Forth-Tay, rather than using the GPS-derived maps within the ORJIP tool. We took this approach because:

- The Forth-Tay is a region with very good coverage for GPS tracking data, so it is possible to create maps using fewer assumptions than those required for a national-scale analysis (Table 4);
- There are more recent GPS tracking data for this region than those used in Wakefield et al. (2017);
- This approach also allows us to bring in GPS maps for an additional species – Atlantic puffin;
- The use of maps based on local GPS data is consistent with the way that inputs to the SeabORD displacement modelling tool have previously been specified when running this tool in the Forth-Tay region (https://www2.gov.scot/Topics/marine/marineenergy/mre/current/SeabORD) – this is not essential for running SeabORD (any estimated map of the utilisation distribution of birds arising from the colony of interest can be used as an input), but means that the approach used in this work is consistent with that used previously;
- Using these maps allows us to use a higher spatial resolution (1x1km) than that used in Wakefield et al. (2017) (2x2km for the species of interest).

Table 4. Summary of GPS tracking data used within the study to generate bird utilisation distributions for the four species at each SPA.

Species	Common guillemot	Black-legged kittiwake	Razorbill	Atlantic puffin
Number of individuals	Fowlsheugh = 9 Isle of May = 90 St Abbs Head = 8	Fowlsheugh = 35 Isle of May = 87 St Abbs Head = 25	Isle of May = 50	Isle of May = 30
Number of years	Fowlsheugh = 1 Isle of May = 5 St Abbs Head = 1	Fowlsheugh = 1 Isle of May = 5 St Abbs Head = 1	Isle of May = 5	Isle of May = 2
Total number of days	Fowlsheugh = 3 Isle of May = 43 St Abbs Head = 4	Fowlsheugh = 12 Isle of May = 56 St Abbs Head = 8	Isle of May = 41	Isle of May = 38

The maps are created using GPS tracking data collected at the study SPAs from 2010 to 2018 (Table 4). We created the GPS-derived maps using a similar approach to that used in Wakefield et al. (2017), but modified to the needs of providing local scale, rather than national scale, maps. The key difference is that because we focus on a small number of colonies and a small spatial area, and the majority of these have colony-specific GPS tracking data, so we can model the "environmental suitability" map non-parametrically, rather than building a habitat association model for this. This is desirable, as it means that the results will rely upon weaker assumptions about the form of any environmental relationships, but is only feasible in situations where, as here, GPS data are available for all or most of the populations of interest. The "nonparametric" approach assumes that the maps vary smoothly with location, but imposes no other constraints upon the form (shape) of the relationship between bird density and environmental variables, and hence provides a very flexible approach.

Wakefield et al. (2017) used a Binomial Generalized Linear Model (GLM) to model "cases" (GPS tracking point) versus "controls" (points on a regular grid), using data for multiple colonies simultaneously, in relation to a range of explanatory variables. We use a similar approach:

Stage 1. Fit a GLM, with the following as potential explanatory variables (possibly transformed): distance to colony by sea; cumulative area of sea within this distance of the colony; predicted density of birds from other colonies. This step is essentially the same as in Wakefield et al. (2017).

Stage 2. Fit a Generalized Additive Model, which contains the explanatory variables from Stage 1 and a smooth spatial term for "location". Wakefield et al. (2017) attempted to explain the environmental heterogeneity in terms of explanatory variables (sea surface temperature), but, because we are only interested in a specific area with good coverage, we focus instead solely upon providing an empirical map of environmental heterogeneity. However, there are potential limitations with GPS data associated with the limited sample of years and span of dates within years.

Due to differences in data availability for the different species and SPAs, we used the following covariates in the GPS models for each species:

Species	SPA	Smooth term	Cumulative area	Distance to colony	Competition term
Black-legged kittiwake	All	Yes	Yes	Yes	Yes
Common guillemot	All	Yes	Yes	Yes	Yes
Razorbill	Forth Islands	Yes			
	Other		Yes	Yes	
Atlantic puffin	Forth Islands	Yes			

Full details of this approach are given in Appendix A.

Adjusting GPS maps to relate to separate months and behaviours

Some of the tools that were used for assessing risks (e.g. the Stochastic Collision Risk Model [sCRM] and the Displacement Matrix Approach) require monthly estimates of absolute abundance, and the sCRM requires inputs to be provided that relate to a single behaviour (flying).

GPS tracking data relate to a combination of all behaviours, relate to the entire breeding season, and solely quantify relative (rather than absolute) abundance. GPS tracking data do not directly record separate behaviours. Analyses of GPS data allow behaviour to be inferred indirectly, based on the idea that different behaviours will exhibit different statistical characteristics in relation to movement (speed and turning angle). However, this is relatively involved, in particular for certain distinctions such as foraging vs commuting flight in surface feeders and active foraging vs resting on the sea surface in diving species. We therefore considered it beyond the scope of this project. Variations in temporal coverage of the GPS tracking data also make it difficult to produce defensible monthly maps solely using these data. This is a particularly challenge with species that show variation in distribution among months or breeding stages during the breeding season.

We address the first two of these issues by exploiting the fact that the at-sea data do allow monthly maps to be produced, as well as producing maps separately for each behaviour. We propose to use this information to adjust the maps derived from the GPS data. Specifically, we use the at-sea data to derive two maps:

- **Map 1**. Map of overall bird distributions (including birds from all colonies) derived from at sea data, for the month and behaviour of interest;
- **Map 2**. Map of overall bird distributions (including birds from all colonies) derived from at sea data, for the entire breeding season (based on the SNH definition for each species) and for all behaviours combined;

The ratio of Map 2 to Map 1 provides an "adjustment factor" associated with the month and behaviour of interest. The GPS data allow us to derive a map of bird distributions from each colony; we can convert these into maps for specific seasons/months and/or behaviours by multiplying these maps by the adjustment factor, and rescaling the resulting map so that the values sum to one. This allowed us to produce monthly maps from GPS tracking data, for birds in flight and birds on the water, derived using information from the at-sea survey maps. Note that this method is only used to rescale GPS data for different behaviours in individual months within the breeding season. In the non-breeding season, only at sea maps are used in the assessment methods because it is not appropriate to use summer GPS data to inform non-breeding season distribution of adult birds not generally acting as central placed foragers.

In order to deal with the fact that the GPS data only provide relative estimates of abundance, we multiply the resulting estimates by the colony sizes derived from Seabird 2000. It was necessary to use Seabird 2000 abundance estimates for this, because this is the most recent data source with abundance counts for all breeding colonies.

Summary of baseline maps

The at-sea data (after apportioning) and GPS data (after applying the adjustments described above) can each be used to provide monthly maps of abundance for each cell on a regular spatial grid, for each behaviour (flying, non-flying) for each species and SPA.

Both data sources can also be used to provide estimates of the relative abundance of non-flying birds within the chick-rearing period.

2.2. Scenarios and footprints

Three scenarios are considered within this project:

- **Scenario (1)**, in which there are no ORD impacts;

- **Scenario (2)**, in which ORDs with a capacity equal to that of currently consented developments (1.2 GW of inshore OWDs and 1 GW of offshore OWDs reflecting the combined GW of NNG, Inch Cape, and Seagreen Phase 1 - Alpha-Bravo) are assumed to exist, along with potential new developments from Round 3 (Seagreen Phase 2 – Charlie-Delta-Echo-Foxtrot-Golf);

- **Scenario (3)**, in which ORDs with a capacity equal to Scenario 2 plus approximately 2.8 GW of offshore OWDs (reflecting OWDs in scenario 2, plus one large offshore development) are assumed to exist.

In consultation with Marine Scotland, we have generated footprints for the OWFs in each of the scenarios as follows:

- Found the centroid of any existing footprints (NNG, Inch Cape, Seagreen Phase 1 alpha+bravo, Seagreen Phase 2 charlie+delta+echo+foxtrot+golf)
- Randomly moved each centroid to a new location within 8-10km of the old location, whilst maintaining the same distance to the coast as the original centroid location
- Generated a square footprint centred on the new centroid using the area of the original footprint
- Created shapefiles for each new footprint after checking for overlap issues

This process resulted in a final set of fictional footprints (Table 5, Figure 3).

Table 5. Old and new locations (Lat Long WGS84) for each of the five footprints to be used in the SEANSE project, along with areas for each (note that 2km borders were added to all footprints when considering displacement risk, based upon advice from SNH and MS; these are not included in the areas listed below).

Footprint Name and shapefile	Original centroid	New centroid	Area (m^2)
OWF_1	-2.250622, 56.26386	-2.270239, 56.33586	82765832
OWF_2	-2.195601, 56.49461	-2.140301, 56.56971	150028676
OWF_3	-1.742699, 56.59183	-1.670363, 56.65757	391003406
OWF_4	-1.646558, 56.32079	-1.532046, 56.27096	1441201928
OWF_5	-0.649653, 57.0035019	-0.6077966, 57.03962	3988261065

Figure 3. Final layout and size of OWF footprints to be used in Scenarios 2 and 3 in the SEANSE project. SCENARIO 2 = Pink: OWF_1, Yellow: OWF_2, Red: OWF_3, Grey: OWF_4; and SCENARIO 3 = Brown: OWF_5.

2.3. Summarising interactions between birds and footprints

Each scenario involves a set of footprints (represented by GIS shapefiles, Figure 3). For a given map and scenario it is straightforward to derive monthly estimates of the density of birds (per km^2) within each footprint, for flying and non-flying behaviours, using (total predicted abundance summed across the footprint / footprint area). The effect calculations either use these predicted footprint-level densities, or, in the case of the SeabORD model, take the underlying predicted maps (for non-flight behaviour in the entire chick-rearing period) and footprints as inputs for running the model.

2.4. Quantifying annual impacts

The effect of each scenario upon annual survival and productivity were assessed in terms of four separate components:

a) collision effects during the breeding season;
b) collision effects during the non-breeding season;
c) displacement effects during the breeding season;
d) displacement effects during the non-breeding season

For all species, monthly collision effects were assessed using a stochastic Collision Risk Model(CRM), and these monthly estimates were aggregated to produce overall estimates of collision effects during both the breeding and non-breeding seasons, using the BDMPS breeding season definitions.

We estimated displacement effects in the chick-rearing period for four species (all except northern gannet) using both available approaches; the SeabORD simulation model and the matrix method (Table 6). However, for northern gannet, this was only assessed using the matrix method, because there is no currently available parameterisation of the SeabORD model for this species. For black-legged kittiwake, common guillemot, razorbill and Atlantic puffin, displacement during chick-rearing scaled up to year-round effects on demography was estimated using the individual based simulation model, SeabORD, and displacement during the breeding and the non-breeding season was also assessed using the matrix method.

Table 6. Summary of methods used within three alternative approaches to assessing demographic impacts of OWFs on seabirds ("BS" = breeding season, "NBS" = non-breeding season, "SCRM" = Stochastic Collision Risk Model).

Type of impact				Approach 1	Approach 2	Approach 3
Impact on annual survival rates	Displacement	During BS	Adults	Matrix	SeabORD	SeabORD
			Juveniles		Matrix	
		During NBS	(All ages)	Matrix	Matrix	Matrix
	Collision	During BS	(All ages)	SCRM	SCRM	SCRM
		During NBS	(All ages)	SCRM	SCRM	SCRM
Impact on productivity rate	Displacement	During BS		Matrix (= no impact)	SeabORD	SeabORD

Approaches 1 and 3 differ in whether SeabORD or the Displacement Matrix approach were used to estimate the effects of displacement during the breeding season. SeabORD is only designed to estimate effects on adult survival and productivity, so it is unclear if it is also defensible to use it for estimating effects on juvenile survival rates: Approach 2 therefore bases effects on juvenile survival rates on the Matrix method, rather than SeabORD. All three approaches use the same methods for assessing effects of displacement during the non-breeding season (the Displacement Matrix is used as SeabORD is only designed to consider the breeding season), and use the same methods for assessing effects of collision (Table 6).

We also used GPS- and at-sea-derived bird density maps to provide inputs for each method (stochastic collision risk models, SeabORD, and matrix method) to compare estimates arising from the different data and modelling approaches. This was done for all species except northern gannet, meaning a total of six approaches were considered (three methodological approaches to estimating annual displacement risk, and two data sources for constructing baseline maps).

2.5. Estimating collision effects

It was intended that collision predictions would be calculated using the stochastic version of the Band (2012) collision risk model (sCRM). However, repeated attempts to do this using the bootstrapped density data (generated as discussed above) failed for unknown reasons. As an alternative, an independently developed stochastic implantation of the Band (2012) model was utilised, hereafter 'stochastic collision risk model', or 'CRM'). This model was scripted by MacArthur Green and contains identical calculations as those in the Band (2012) spreadsheet, but written using R so that it can accept either single values (as the original spreadsheet) or multiple randomly generated input parameters when run as a stochastic simulation. The model has been extensively tested in its deterministic format against the Band (2012) outputs and produces identical results. When run as a stochastic simulation it is not possible to compare the outputs with the deterministic Band model, although checks of the mean simulated results were made against Band outputs obtained using the mean values. While it is acknowledged that it would have been preferable to use the official stochastic model for the current project, it is also important to note that the framework which has been developed for this project was able to accommodate this method revision with minimal adaptation, highlighting the flexible approach adopted.

The simulations were not fully stochastic (i.e. only a subset of parameters were entered as random values), with only seabird density (bootstrapped samples as described above), the collision avoidance rate (using a beta distribution) and the proportion at rotor height (subsampled from the bootstrapped height distributions produced by Johnston et al. 2014a,b) included as stochastic elements. The values for the collision model input parameters followed industry standards (e.g. mean species biometric data were taken from recent offshore wind farm impact assessments) and avoidance rates were those recommended by statutory nature conservation agencies (means and standard deviations). The Band (2012) model can produce collision estimates using one of two model structures that differ in how the proportion of birds at rotor height is calculated. For the current exercise only the basic model was used in conjunction with a bootstrapped sample of seabird flight heights (Johnston et al. 2014a,b), referred to as option 2. Apart from the explicitly stochastic nature of this model, the method is identical to that used for wind farm impact assessments. Outputs were obtained for 1,000 simulations for each month, which have been summarised by season (breeding, migration, nonbreeding etc.) and assigned to SPA populations using the methods discussed above.

2.6. Estimating displacement effects

Displacement effects can be defined to be

Displacement effects = Baseline exposure * Displacement rate * Mortality rate for displaced birds (**Equation 1**)

"Baseline exposure" represents the number of birds that are estimated to use the wind farm footprint (plus buffer) using data on the baseline spatial distribution of birds - which may either be at-sea survey data or GPS tracking data. The "displacement rate" represents the proportion of birds that are susceptible to displacement – i.e. the proportion of birds that will undertake displacement behaviour if they encounter a wind farm. The "mortality rate for displaced birds" represents the proportion of displaced birds that die as a result of being displaced – note that this represents the mortality rate for birds that are both exposed and susceptible to displacement.

Two approaches are currently used in practice for the estimation of displacement effects within Scottish waters. The "Displacement Matrix" approach involves calculating baseline exposure, and then calculating effects for pre-specified values of the "displacement rate" and "mortality rate for displaced birds". The "Displacement Matrix" often involves calculating displacement risk for a range of values of the latter two inputs, but we focus here upon running it for a single, "best estimate", of each rate.

Displacement rates and mortality rates for displaced birds were used within the Displacement Matrix approach were selected in consultation with the Project Steering Group (Table 7). The rates are based on expert judgement, largely originating from a workshop held in 2015 (JNCC, 2015) and summarised in a Joint SNCB Advice Note (SNCB, 2017).

Table 7. Displacement and displacement-associated mortality rates for all species used within the project.

Species	Displacement rate	Mortality rate of displaced birds	Season for assessments
Atlantic puffin	60%	2%	Breeding
Common guillemot	60%	1%	Breeding and non-breeding
Razorbill	60%	1%	Breeding and non-breeding
Black-legged kittiwake	30%	2%	Breeding
Gannet	80%	0.5% (B) 0.25% (NB)	Breeding and non-breeding

SeabORD is a mechanistic model of seabirds foraging, energetics, demographics and ORD interactions, which provides an alternative to the Displacement Matrix approach. SeabORD takes a map of baseline spatial distribution of birds from the breeding colony of interest, and the footprint(s) for the ORDs of interest, and produces an estimate of displacement effects – the increase in mortality (as a percentage of population size) associated with displacement caused by the ORDs.

SeabORD does not directly use Equation 1 in calculating displacement risk, but because it does require users to specify both baseline exposure (via a bird utilisation distribution map) and the displacement rate it is straightforward to express SeabORD using Equation 1. Specifically, Equation 1 can be rearranged to give

Mortality rate for displaced birds = Displacement effect / (Baseline exposure * Displacement rate)

which is directly comparable to the "mortality rate for displaced birds" used within the Displacement Matrix approach.

Expressing it in this way illustrates that the fundamental difference between SeabORD and the Displacement Matrix lies in the way that the mortality rate for displaced birds is calculated: SeabORD calculates this using a mechanistic model, whereas the Displacement Matrix approach currently derived these rates from expert judgement. Within this project we use the same baseline maps, and the same displacement rates (from Table 7) when running both SeabORD and the Displacement Matrix approach, which means that the "mortality rate for displaced birds" is the *only* difference between the two approaches. The Displacement Matrix approach also uses a particular way of visualising and summarising uncertainty (via the "Matrix"), which is not currently used when applying SeabORD, but the connection between the approaches described here shows that this could also potentially be used in conjunction with SeabORD.

Note that when calculating the effects of displacement using either the SeabORD model or matrix method, a 2km border was added to all OWF footprints. This 2km border was removed when estimating the density of birds required as input for the collision risk modelling.

2.7. Estimating displacement effects using SeabORD

The SeabORD tool was used to estimate the effects of displacement during chick rearing for four of the species in this project: black-legged kittiwake, common guillemot, razorbill and Atlantic puffin. The model estimates impacts on productivity and year-round adult survival for breeding birds. This tool simulates individual behaviour and energetics in 'baseline' scenarios with no OWF present, and compares resulting population demographic estimates to model runs with OWFs present. The model simulates changes in seabird behaviour and energetics arising from displacement and barrier effects. Final model metrics are produced for additional adult and chick mortality (percentage points, %) arising as a result of the OWFs assuming moderate environmental conditions. For a full description of the tool and underlying methodology see Searle et al. 2018, Mobbs et al. 2018a & Mobbs et al. 2018b.

For each species, ten matched paired model runs are used to calculate a single metric assessing additional adult and chick mortality as a result of the OWFs in each of the scenarios. Initial model baseline runs are first used to identify the range of median prey values within the model that result in 'moderate' conditions (based on empirical data for adult mass loss over the chick-rearing period and chick productivity). Once the lower and upper bound for moderate conditions have been established, the model executes ten paired runs over this range using stratified random sampling to produce ten estimates for each model metric capturing the variation over the 'moderate' prey range. These estimates are them combined to produce a single metric for additional adult and chick mortality for each breeding colony of interest, with associated 95% confidence interval (P1; for full details see Searle et al. 2018 and Mobbs et al. 2018a,b).

Metric P1 calculates the population-level impact of the ORD:

(mortality with ORD present - mortality in baseline) / (population size)

More specifically:

$$P1 = 100 * \frac{\begin{array}{c}(\text{Total number of birds simulated to die when the ORD is present} - \\ \text{Total number of birds simulated to die when the ORD is absent})\end{array}}{\text{Total population size}}$$

This metric represents the overall impact of the ORD. This is the additional mortality that occurs as a result of the wind farm.
Outputs are generated for each model run; for any particular output – e.g. the change in adult mortality that results from including the ORD. For each metric we then calculate:

1. the mean of this value across runs, m (to provide our "best estimate" for this quantity); and
2. the standard deviation across runs, s, to capture the uncertainty associated with natural stochastic variation.

Quantifying uncertainty within SeabORD outputs

In order to present the uncertainty associated with the SeabORD output in a format that is of practical use, we constructed the 95% prediction interval associated with using these R simulated populations to predict the output that we would have obtained for the true but unobserved "real" population. We assume that the outputs from the model runs follow a normal distribution; by standard formulae the prediction interval is then equal to $(m - ws, m + ws)$, where

$$w = T_{R-1}\sqrt{1+\frac{1}{R}}$$

and T_{R-1} represents the 97.5% quantile of t-distribution with $R - 1$ degrees of freedom.

2.8. Estimating displacement effects using the matrix approach

Non-breeding season

Displacement effects outside the breeding season were estimated using the current methods advised for offshore wind farm assessments. This involves input of an appropriate seasonal estimate (e.g. the peak monthly value within that season) into a matrix specifying a range of percentage values for displacement and mortality rates. Typically, offshore wind farm impact assessments present these over very wide ranges (e.g. from 0-100% for both measures), with the recommended species-specific values highlighted (e.g. for auks 30-70% displacement and 1-10% mortality). In this project, to reduce the otherwise large number of tabulated outputs that would be produced for each species, SPA, wind farm and season combination, we used the single value rates provided by the PSG (Table 7). Bird density inputs for each footprint using at-sea survey data were derived from monthly maps averaged across the relevant months, using the 'SNH' breeding season definitions, as advised by Marine Scotland and the PSG.

Breeding season

We also used the matrix method to estimate displacement effects during the breeding season, to provide an alternative method to the SeabORD model for four of the study species, and as the only available method in this project for northern gannet. The same approach (peak monthly value for at-sea maps) was used as described above for the non-breeding season. Bird density inputs for each footprint were derived from monthly maps averaged across the relevant months, using the BDMPS breeding season definitions, to align with the methodology used in the non-breeding season. We used inputs for bird density derived from both at-sea survey data and GPS tracking data for the breeding season months. Bird density inputs for each footprint using GPS data were derived on a monthly basis, only within the breeding season, using the adjustment described above exploiting information in the at-sea survey behaviour by month maps.

2.9. Estimating combined annual impacts

The final stage in assessing annual impact involves combining the estimates of the three individual risk sources together. There are two elements to this:

1. converting the estimated effects so that they are expressed in a common currency; and
2. combining the individual effects together in order to derive an overall estimate of impact using a PVA.

The easiest "common currency" to work with is the change in each demographic rate that results from the scenario, because this is the currency used in the PVA calculations that form the final part of the risk assessment. In other words, for each demographic rate (productivity, adult survival, and the immature survival rates for each immature age class) we derived the annual effect of each scenario upon the demographic rate associated with each of the three risk components ($k = 1$ is collision effect, $k = 2$ is displacement effect in the breeding season, $k = 3$ is displacement effect in the non-breeding season). SeabORD outputs the effect directly in this format. The collision risk model and displacement matrix approach output the estimated absolute number of birds killed as a result of the risk, but assume that the number killed was proportional to the population size. These numbers can therefore be converted into the estimated change in demographic rates simply by dividing by the current total population size, which we took to be the most recent SPA-level count for each population.

The total annual effect of each scenario upon each demographic rate is assumed, in the absence of other information, to be equal to the sum of the four individual components of impact. This calculation assumes that the three sources of effect (collision in the breeding season, collision in the non-breeding season, displacement in the breeding season, displacement in the non-breeding season) operate independently of each other.

2.10. Population Viability Assessment

Population Viability Analysis (PVA) is used to translate annual effects on demographic rates into longer-term projections of population size. PVAs are typically produced by projecting/simulating forwards within a Leslie matrix model, which assumes that the population size in year t depends upon the population size in year $t - 1$ and upon relevant demographic rates (productivity, adult survival and immature survival).

PVAs involve running projections forward under a range of different scenarios, and comparing these against a "baseline" projection that assumes current demographic rates will be maintained into the future.

A very broad range of models for PVAs are available: in particular, the methods can incorporate demographic and environmental stochasticity, and density dependence. Natural England have produced a user-friendly Shiny tool (Natural England: 'A population viability analysis modelling tool for seabird species' ITT 4555) that implements a broad range of PVA methods.

PVAs rely upon baseline demographic rates being specified. PVAs may produce results that are inconsistent with observed abundance data, when run for the historical period; this will typically occur because one or more of the demographic rates has been poorly estimated. Semi-integrated population models (SIPMs; Freeman et al 2014, and Jitlal et al 2017) allow the rates that are least well supported by empirical data – typically immature survival – to be estimated based upon the match of the PVA outputs to historical time series data on abundance (colony size). The SIPMs are fitted within a Bayesian framework, allowing the uncertainty associated with the estimation of these rates to be fully accounted for when generating the PVAs. CEH, under contract to MSS, have already produced SIPMs for the Forth-Tay for kittiwake, guillemot, razorbill and puffin (Freeman et al 2014, and Jitlal et al 2017).

PVA model structure

Freeman et al (2014) and Jitlal et al (2017) generated PVA projections for the Forth-Tay region for black-legged kittiwake, common guillemot, razorbill and Atlantic puffin using a Leslie matrix model that contained environmental and demographic stochasticity, but assumed density independence (a detailed technical specification is given in Appendix B). Specifically, the model used assumed that:

- annual productivity rates arose from a log-normal distribution (kittiwake) or logit-normal distribution (guillemot, razorbill, puffin) – the parameters of this distribution were determined by moment matching against the mean and standard deviation of productivity derived from nest monitoring data

- adult survival rates arose from a logit-normal distribution – the parameters of this distribution were determined by moment matching against the mean and standard deviation of productivity derived from ring-recovery data

- immature survival rates were fixed over time, and constant across all ages up to age at first breeding, but uncertain

The immature survival rate was estimated by matching the output from the PVA to the observed abundance data for each population, within a Bayesian framework – a "semi-integrated population modelling" (SIPM) approach.

We generated PVAs for these four species using the PVA models developed by Freeman et al (2014) and Jitlal et al (2017). Specifically, the PVAs that we generated for these species:

1. use the same model structure as in Freeman et al (2014) and Jitlal et al (2017) (i.e., assume density independence, and make the same distributional assumptions regarding environmental and demographic stochasticity);
2. use the same empirical demographic rates as in Freeman et al (2014) and Jitlal et al (2017) – productivity (mean and SD), adult survival (mean and SD), age at first breeding, and maximum brood size
3. use the immature survival rates derived by Freeman et al (2014) and Jitlal et al (2017)
4. use the most recent available population sizes to initialise the PVA

The PVAs were generated using R code developed to work with output from the SIPM. The results were, however, checked against values generated using the NE PVA tool – the latter is capable of generating PVAs from this model, but we base our final results upon the code rather than NE PVA tool, because:

1. the code accounts for the uncertainty involved in estimating immature survival rates from abundance data; the NE PVA tool is not currently capable of doing this;

2. the SIPM model uses Poisson distributions to describe demographic stochasticity, whilst the NE PVA model uses Binomial distributions

Both approaches involve generating the PVAs using a simulation-based approach.

For northern gannets, no SIPM has been developed for the Forth-Tay region, and it is not feasible to develop such a model within the constraints of this project. For this species, we generated PVAs using a model that has the same structure as the SIPM (for consistency with the methodology used for the other species). We derived means and SDs of baseline adult survival and productivity rates from ring-recovery and nest monitoring data, as for the other four species, and determine age at first breeding from the literature. We assumed logit-normal distributions for inter-annual variations in adult survival and productivity, and assumed density independency, for consistency with the approach used for the other four species. We estimated immature survival in a way that is similar to that used in the SIPM, but more straightforward (Appendix C); note, however, that this approach does not allow a defensible quantification of uncertainty in the juvenile survival rate.

A summary of the PVA input rates used are shown below (Table 8).

Table 8. Baseline demographic rates and initial population sizes used in running the Population Viability Analysis (PVA) for each population (combination of species and SPA).

Species	Age at first breeding	Max brood size	Adult survival (mean,SD)	SPA	Breeding success (mean,SD)	Immature survival (mean, SE)	Initial population size (year)
Kittiwake	4	2	0.857 (0.067)	Forth Islands	0.55 (0.35)	0.697 (0.054)	4206 (2019)
				St Abbs	0.63 (0.33)	0.605 (0.045)	4651 (2019)
				Fowlsheugh	0.78 (0.33)	0.637 (0.036)	9444 (2018)
				Buchan Ness	0.61 (0.34)	0.738 (0.050)	12542 (2007)
Guillemot	6	1	0.926 (0.044)	Forth Islands	0.725 (0.108)	0.796 (0.012)	21812 (2019)
				St Abbs		0.803 (0.013)	34182 (2018)
				Fowlsheugh		0.757 (0.013)	48929 (2018)
				Buchan Ness		0.823 (0.015)	22077 (2016)
Razorbill	5	1	0.909 (0.057)	Forth Islands	0.63 (0.078)	0.838 (0.021)	4855 (2019))
				St Abbs		0.764 (0.027)	2061 (2018)
				Fowlsheugh		0.821 (0.022)	9024 (2018)
Puffin	5	1	0.906 (0.059)	Forth Islands	0.691 (0.133)	0.921 (0.019)	49210 (2017)
Gannet	5	1	0.916 (0.019)	Forth Islands	0.6971 (0.0858)	0.859 (N/A)	75259 (2014)

The period of impact for each OWF in the two scenarios, used within the PVA modelling was as follows:

- The impacts of the first four wind farms (those included within both Scenarios 2 and 3) was assumed to operate for a 25 year period, starting in 2020 and finishing in 2045
- The impacts of the remaining wind farm (that within Scenario 3 only) was also assumed to operate for a 25 year period, starting in 2020 and finishing in 2045
- The PVAs for the two scenarios were matched against a common baseline, and against each other, to enable direct comparisons between scenarios, as well as comparison against the baseline
- The PVAs were run from the present day (the latest year with available counts) through until 2055
- Metrics were produced for the years 2045, 2050 and 2055 under each scenario (outputs were actually also produced for all years through from 2020 until 2055, but focussed on these three years when presenting the outputs).
- Growth rates (used in Metric M2) were calculated relative to the year that the first wind farm begins operating (2020)

PVA outputs

The PVA produces a set of **simulated future time series** for the size of each population. It does this for each **scenario**, including the baseline. The scenarios are **matched**: i.e., the stochastic decisions within the simulations that are unrelated to the ORD are assumed to be identical. A range of PVA metrics can be used in summarising the impact of each scenario; we propose to focus upon a selection of the metrics used in the NE PVA tool (Searle et al. 2019b):

M1. Median ratio of impacted to unimpacted population size
M2. Median ratio of impacted to unimpacted growth rate
M3. Quantile for unimpacted population size that equals the median impacted population size

2.11. Quantification of variability and uncertainty

Qualitative assessment

We provide a qualitative assessment of sources of uncertainty within the Discussion section, outlining the caveats, limitations and sources of types of uncertainty associated with each method, and the likely consequences of these uncertainties.

Quantitative assessment of uncertainty

Three of the methods used in producing the impact assessments used stochastic models that automatically account for variability over time and/or between individuals, and, to some extent, uncertainty, within their calculation of risk. These are:

- SeabORD
- The stochastic collision risk model
- Leslie matrix models used in producing PVAs

Each of these models produced both "average" outputs that ignore uncertainty, and some assessment of the uncertainty associated with these average outputs. In the case of the PVA models, metrics M1-M2 quantify "average" outputs, whilst M3 is a "probabilistic" metrics that are designed to account for the effects of uncertainty. Other probabilistic metrics, such as the probability of quasi-extinction or the probability of reaching a conservation-related threshold, can also be produced using a PVA, but these depend upon the specification of thresholds, and as we are considering a range of different populations we have not attempted to apply these here.

We included estimates of uncertainty when presenting the outputs from each individual modelling stage.

It is also possible to quantify "overall" uncertainty in the final PVA outputs by propagating uncertainty through from SeabORD and the stochastic collision risk model into the PVAs, using a simulation-based approach. We did propagate uncertainty within some aspects of our assessments, to demonstrate how this can be achieved within the framework, but we note that resulting estimates of uncertainty should be interpreted with great caution, given that uncertainty can only defensibly be quantified within certain components of the assessment, and using certain methods. Unless all individual sources of uncertainty have been accounted for, there is a risk that the final uncertainty estimates will not be defensible.

In the context of this project, there are various sources of uncertainty that are difficult or impossible to quantify.

Baseline maps

The uncertainties associated with the baseline maps are particularly hard to quantify. It is possible to quantify confidence intervals around the overall maps derived from at-sea survey data, but not with the SNH apportioning tool – and structural errors (e.g., missing processes) in the equations used by the SNH apportioning tool are likely to be a key source of uncertainty in the estimated colony-specific distributions. Standard errors for the models fitted to GPS tracking data can easily be calculated, but are likely to be severe underestimates because they ignore the effects of residual autocorrelation (Wakefield et al., 2017) – there are potential ways to resolve this underestimation, but they are beyond the scope of this project.

Within this project we calculated estimates of uncertainty using the at-sea maps, but not using the GPS maps, as we think the former can be done in a way that has some degree of defensibility, whereas the latter, using current methods, cannot (Wakefield et al. 2017). Within the uncertainty quantification for the at-sea based maps, we used the bootstrap samples produced as part of the modelling of the at-sea data. We also attempted to account for one key component of the uncertainty associated with the SNH apportioning tool by accounting for inter-colony variability in foraging range, which is substantial (Thaxter et al., 2012). We did this by simulating the foraging range of each colony repeatedly from a gamma distribution whose mean was equal to the "mean-max" foraging range of Thaxter et al. (2012), and whose 99% quantile was equal to the "max-max" foraging range of Thaxter et al. (2012).

Displacement in the non-breeding season

The non-breeding season displacement method (application of the matrix of displacement and mortality rates) is based on a wide range of displacement and mortality rates as a simple means of presenting uncertainty in these parameters. It is also possible to use upper and lower population size estimates to indicate the boundaries of potential impacts. Consideration was given to how these can be presented to reflect the inherent uncertainty in this aspect of impact assessment.

SeabORD

The SeabORD prediction intervals represent the uncertainty that arises from trying to predict what will occur within a finite population in a system that is subject to inherent stochastic variability, together with the uncertainty associated with determining the overall level of prey. The latter tends, in practice, to be a much larger source of uncertainty than the former. It is crucial to note that the intervals do *not* account for any other sources of uncertainty: e.g., for the uncertainty associated with estimating model parameters, for the uncertainty associated with the underlying structure of the model, for the uncertainty associated with the spatial distribution of birds, or for the uncertainty in the translation of end of season masses into subsequent overwinter adult survival. Because a number of these other sources of uncertainty – particular the uncertainty in the adult mass-survival relationship – are likely to be large, the prediction intervals associated with SeabORD output should be treated with caution, and regarded as *lower* bounds on the actual level of uncertainty.

PVA

The PVA outputs account for the effects of natural variability in demographic rates (and hence abundance) between years. PVA metrics based on SIPMs also account for uncertainty in estimation of immature survival rates, and uncertainty in initial population size. The PVA outputs do not account for uncertainty in adult survival or productivity rates (even when SIPMs are used), and they do not account for structural error in the formulation of the PVA models – for example, all of the PVA models used here assume density independence, and the uncertainty estimates do not account for the potential failure of this assumption.

3. Results

3.1. Bird utilisation and density maps derived from GPS tracking data and at-sea survey data

Overall spatial distribution of birds

The maps derived from at-sea survey data relate to the overall distribution of birds, including birds from all populations. We show the estimated maps for each species within the East of Scotland region, for both behaviours, averaged across both the breeding and non-breeding seasons (Figure 4 - Figure 8).

For all species, there is spatial variation in the density of birds, with the highest densities tending to occur close to SPAs, as we might expect, but the spatial variation in densities appears relatively modest. Note, however, that the colour scheme is presented on a log scale (for comparability with subsequent maps), so that even modest differences on this scale can still correspond to reasonably large differences in absolute abundance). The spatial distribution of birds within both the breeding and non-breeding seasons is relatively similar between different species.

Figure 4. Estimated spatial distribution of birds within the East of Scotland region, as derived from at-sea survey data, for black-legged kittiwake. Distributions are shown separately for birds in flight (top) and on the water (bottom), and for birds in the breeding season (left) and non-breeding season (right); locations of SPAs for this species are shown as black dots, and locations of ORD footprints (including a 2km buffer) are shown as black rectangles.

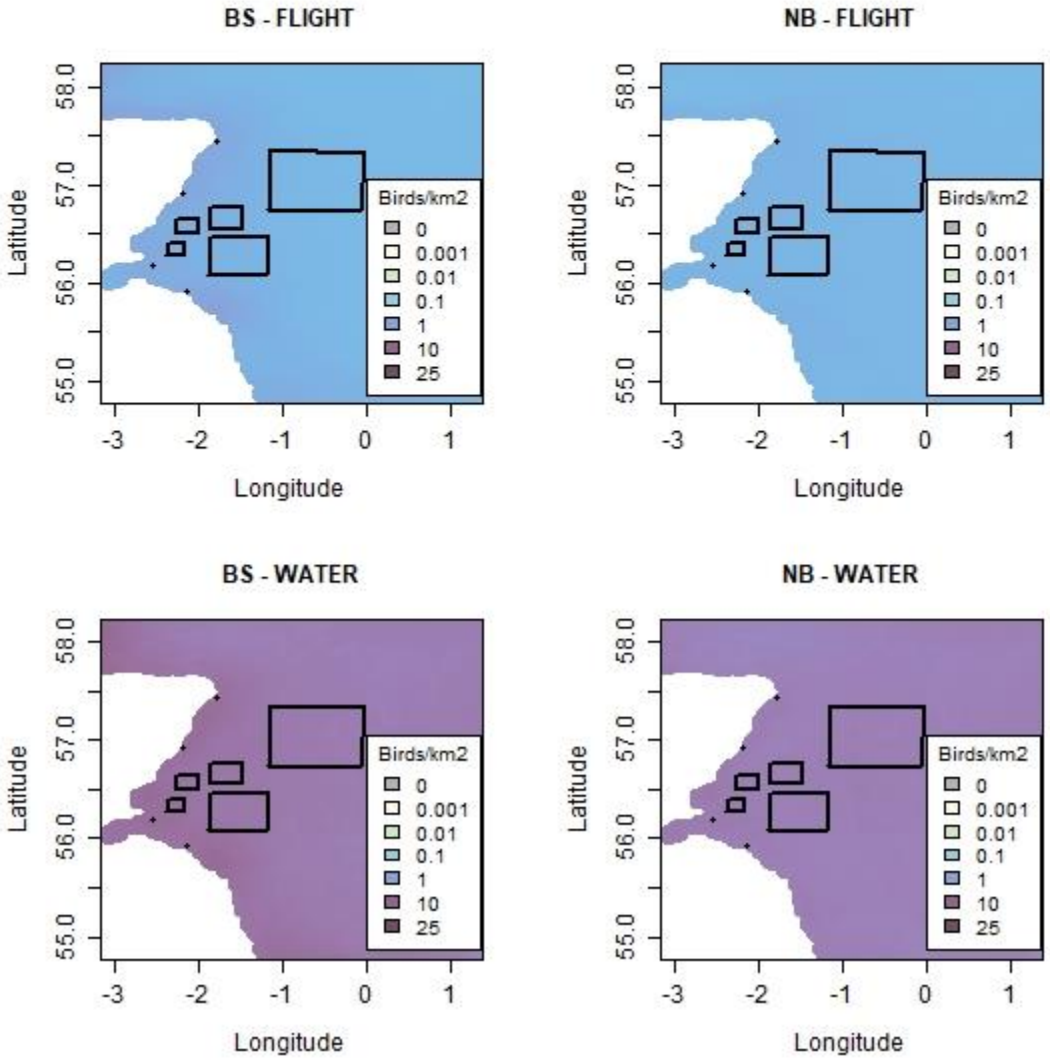


Figure 5. As Figure 4 but for common guillemot.

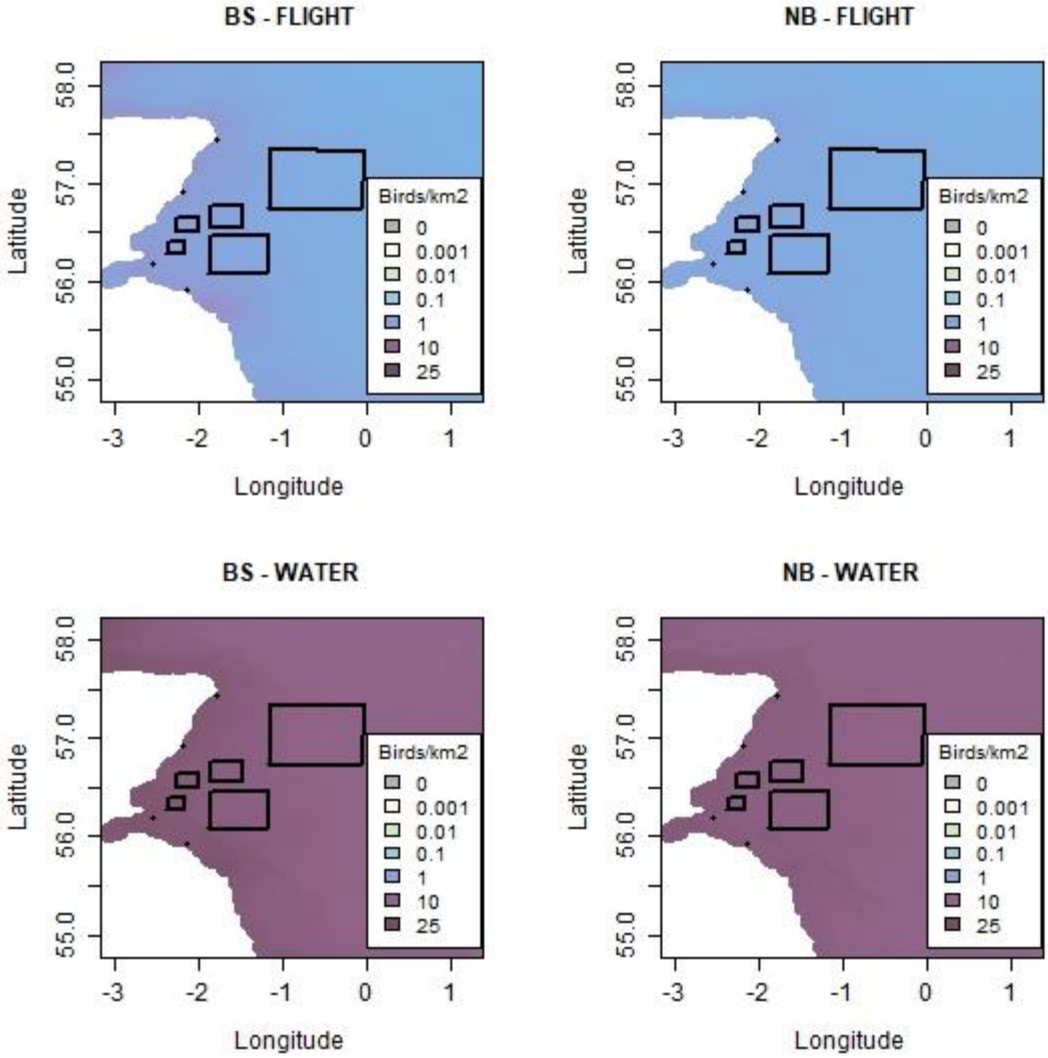


Figure 6. As Figure 4 but for razorbill.

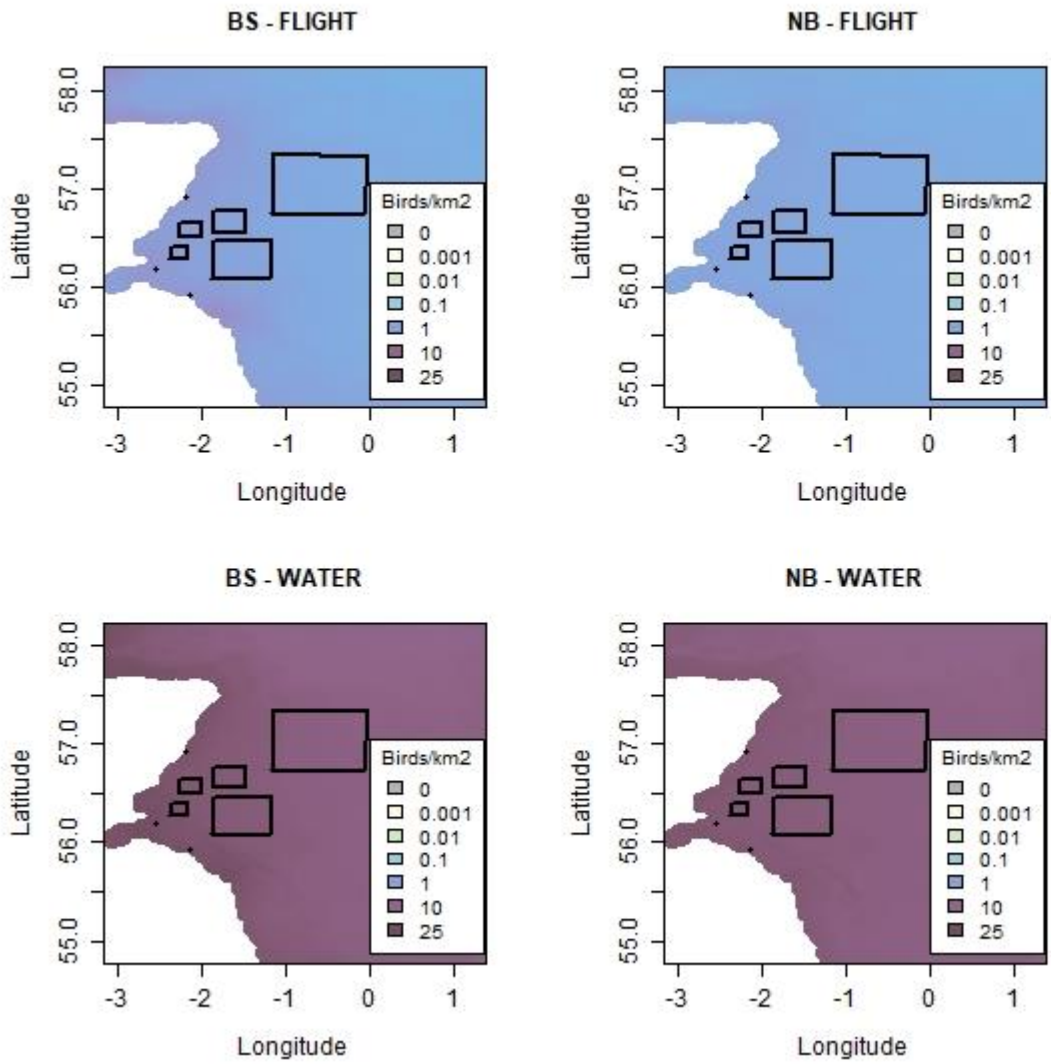


Figure 7. As Figure 4, but for Atlantic puffin.

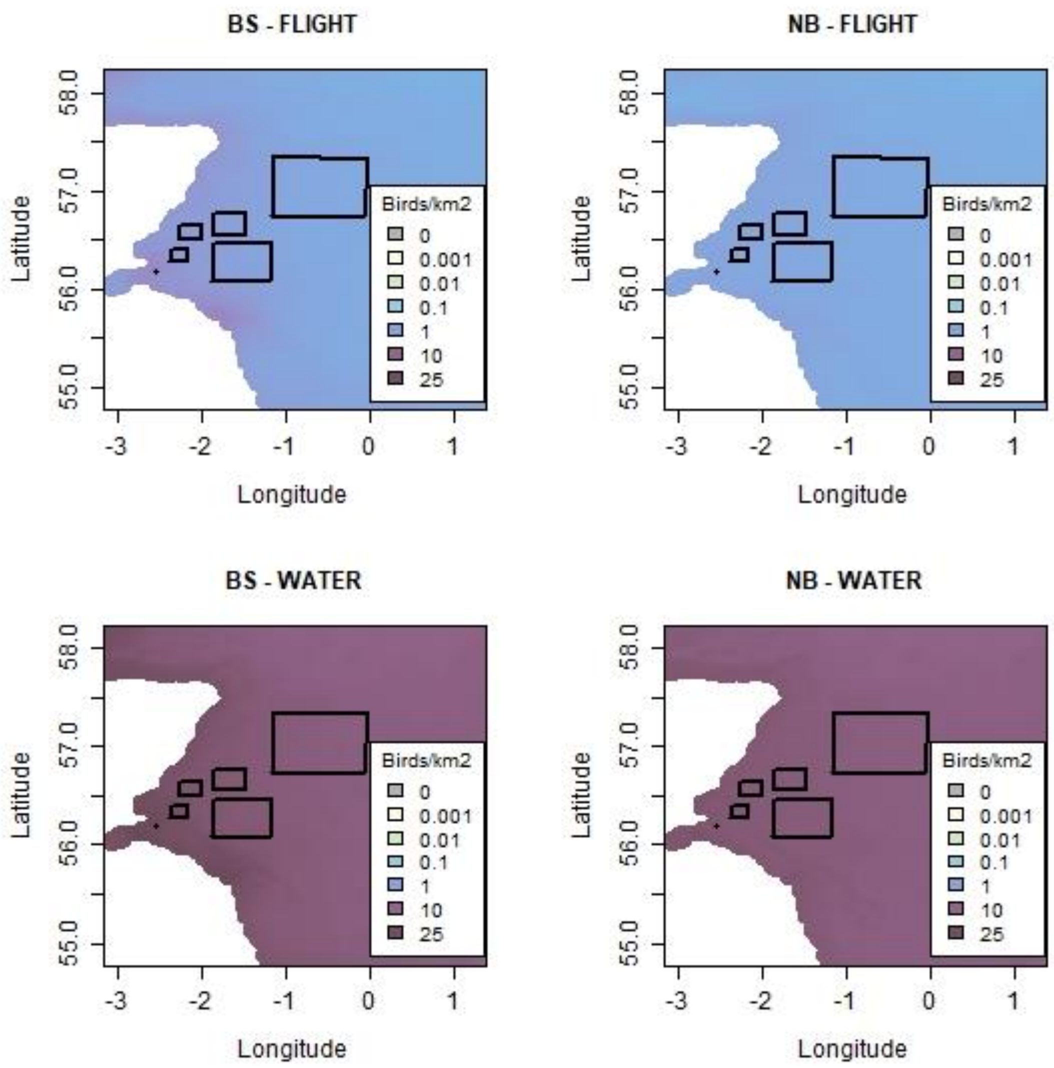
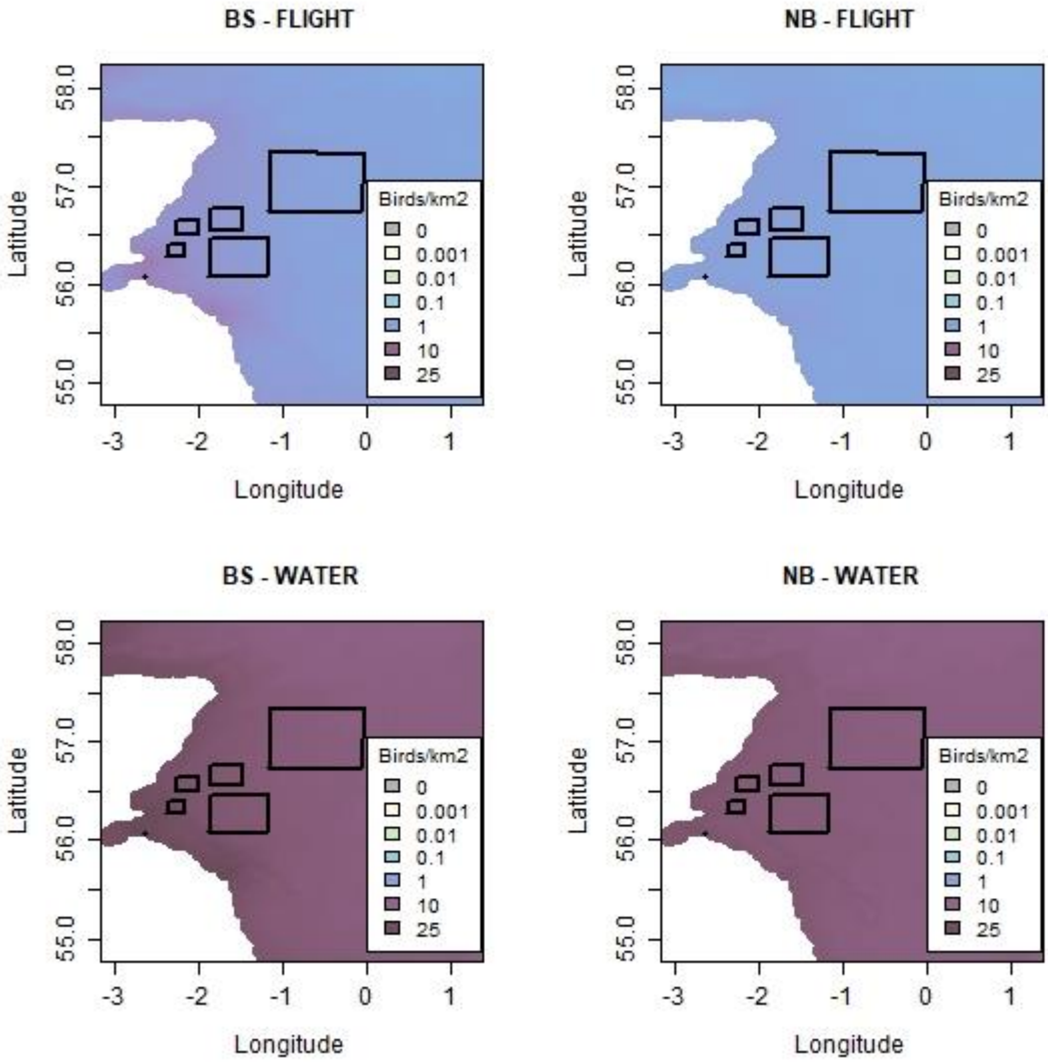


Figure 8. As Figure 4, but for northern gannet.



Non-breeding season BDMPS apportioning

During the non-breeding season, it is necessary to apportion birds seen at sea to their respective breeding colonies, in order to attribute impacts to the relevant SPAs. This was done using the BDMPS regions (Furness 2015), and results in an estimate of the proportion of the source population (across all ages) attributable to each SPA for each species, across all at-sea locations (Table 9).

The percentage of birds that can be attributed to the individual SPAs of interest is substantial for the Forth Islands SPA for both gannet (42-46%) and puffin (28%), but for kittiwake, guillemot and razorbill is always lower than 5% for each of the SPAs of interest.

The total percentage of birds that can be attributed to any of the SPAs of interest (summed across the SPAs, and averaged across the months of the non-breeding season) is: 44.3% gannet, 27.9% puffin, 13.8% guillemot, 6.9% kittiwake and 3.2% razorbill.

Table 9. Proportion of the population in the non-breeding season that is assigned to each SPA using BDMPS, for each period within the non-breeding season.

Species	SPA	Season	Month		Population size		Proportion of population attributable to SPA (all ages)	Source: BDMPS table number
			Start	end	BDMPS	SPA (all ages)		
Gannet	Forth Islands	post-breeding	10	11	456298	191857	0.4205	14
		pre-breeding	12	2	248385	113627	0.4575	16
Kittiwake	St. Abbs	post-breeding	9	12	829937	6479	0.0078	47
		pre-breeding	1	2	627816	5880	0.0094	49
	Forth Islands	post-breeding	9	12	829937	5902	0.0071	47
		pre-breeding	1	2	627816	5357	0.0085	49
	Buchan Ness	post-breeding	9	12	829937	23880	0.0288	47
		pre-breeding	1	2	627816	21673	0.0345	49
	Fowlsheugh	post-breeding	9	12	829937	17778	0.0214	47
		pre-breeding	1	2	627816	16134	0.0257	49
Guillemot	St. Abbs	nonbreeding	8	2	1617306	65955	0.0408	62
	Forth Islands	nonbreeding	8	2	1617306	43787	0.0271	62
	Buchan Ness	nonbreeding	8	2	1617306	34078	0.0211	62
	Fowlsheugh	nonbreeding	8	2	1617306	79344	0.0491	62
Razorbill	St. Abbs	post-breeding	8	10	591874	4084	0.0069	64
		nonbreeding	11	12	2189622	914	0.0004	66
		pre-breeding	1	3	591874	4084	0.0069	64
	Forth Islands	post-breeding	8	10	591874	8794	0.0149	64
		nonbreeding	11	12	2189622	1969	0.0009	66
		pre-breeding	1	3	591874	8794	0.0149	64
	Fowlsheugh	post-breeding	8	10	591874	11805	0.0199	64
		nonbreeding	11	12	2189622	2643	0.0012	66
		pre-breeding	1	3	591874	11805	0.0199	64
Puffin	Firth of Forth	nonbreeding	9	3	231957	64820	0.2794	68

Population-specific maps

The assessments of effects are derived separately for each SPA. GPS-based maps relate directly to individual SPAs, and the maps derived from at-sea survey data can be apportioned to colonies using either the SNH Apportioning Tool (in the breeding season) or BDMPS (in the non-breeding season). In Figure 9 - Figure 21 we present the SPA-specific spatial distributions for each species within the breeding season, for each behaviour, as derived from both at-sea survey data and GPS tracking data.

The SPA-specific maps show much larger spatial variations than the maps of overall distribution, whether derived from at-sea survey data or GPS tracking data. The SPA-specific maps, unsurprisingly, focus the density around the SPA being considered, with the density of birds decaying rapidly as the distance to the SPA increases. The most obvious differences between the SPA-specific maps produced using the two data sources relate to the choice of foraging range – the foraging ranges used in apportioning at-sea survey data to SPAs were typically much smaller than those used in modelling the GPS data. The densities within the foraging range are typically estimated to be higher for at-sea survey data, but this makes sense as the lower foraging ranges mean that the birds are assumed to be constrained to feed within a smaller area around the breeding colony. For some specific species and SPAs there are additional differences between the maps produced using the two data sources – in particular, for kittiwake and guillemot at Buchan Ness the distributions derived from GPS data show strong directional effects, which are not present in the maps derived from at-sea survey data. This directionality may reflect the availability of profitable food for central-place foraging breeders, though it is also possible that this is because data were limited to a narrow time window in a single season.

We do not present maps for the non-breeding season. These can only be derived using at-sea survey data (as the GPS-based maps only relate to the breeding season), and because the at-sea survey maps are apportioned to SPAs using BDMPS, and the entire region of interest lies within a single BDMPS region, the relative spatial distributions associated with each SPA are always identical to the overall relative spatial distribution for the species (i.e. to the spatial distributions shown in Figure 4 - Figure 8).

Figure 9. Estimated spatial distribution of birds within the East of Scotland region, as derived from at-sea survey data, for black-legged kittiwake at Buchan Ness. Distributions related to the breeding season. They are shown separately for birds in flight (top) and on the water (bottom), and for maps derived from at-sea survey data that have been apportioned using the SNH tool (left) and using GPS tracking data (right). The location of the SPA is shown as a black dot, and locations of ORD footprints (including a 2km buffer) are shown as black rectangles.

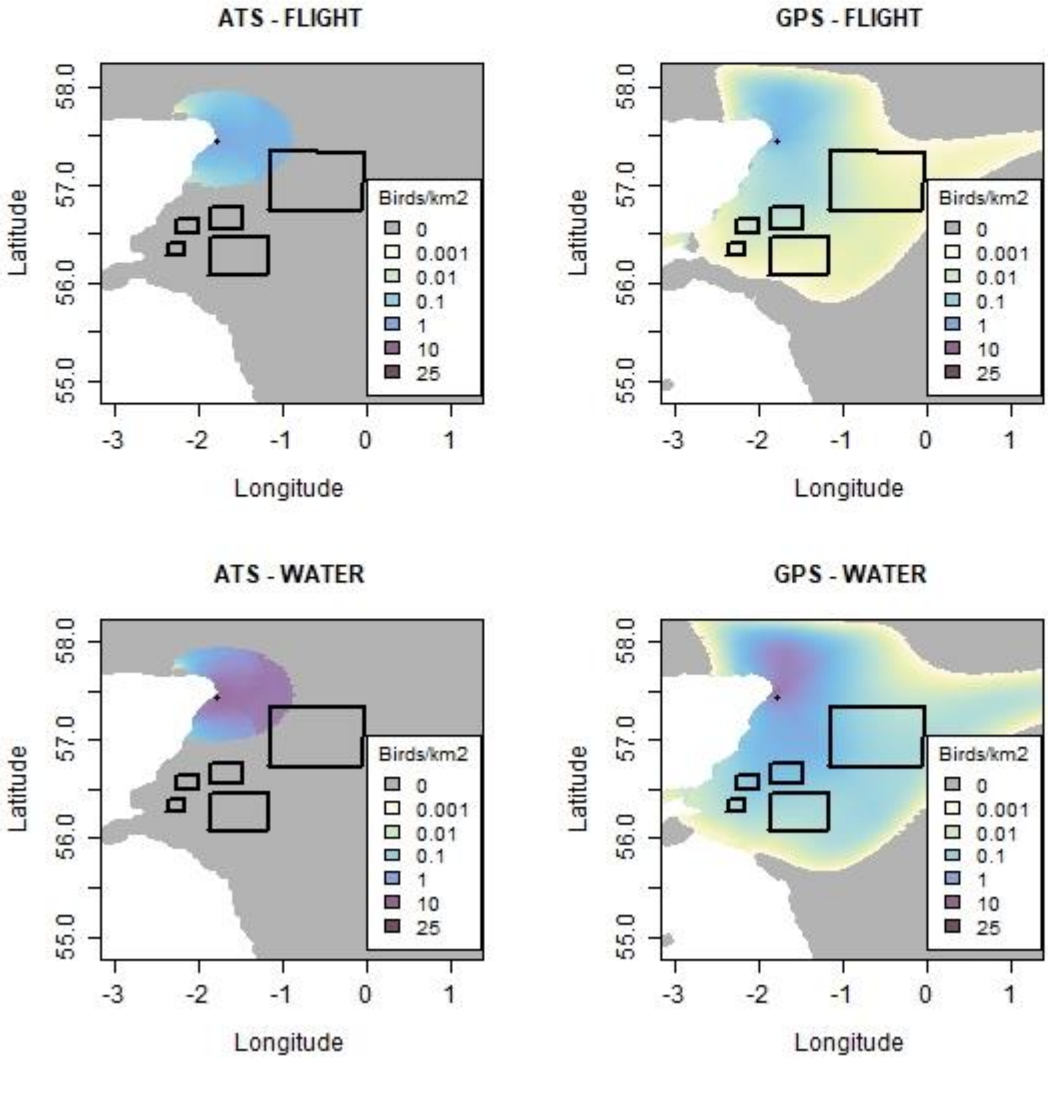


Figure 10. As Figure 9 but for Kittiwake at Forth Islands.

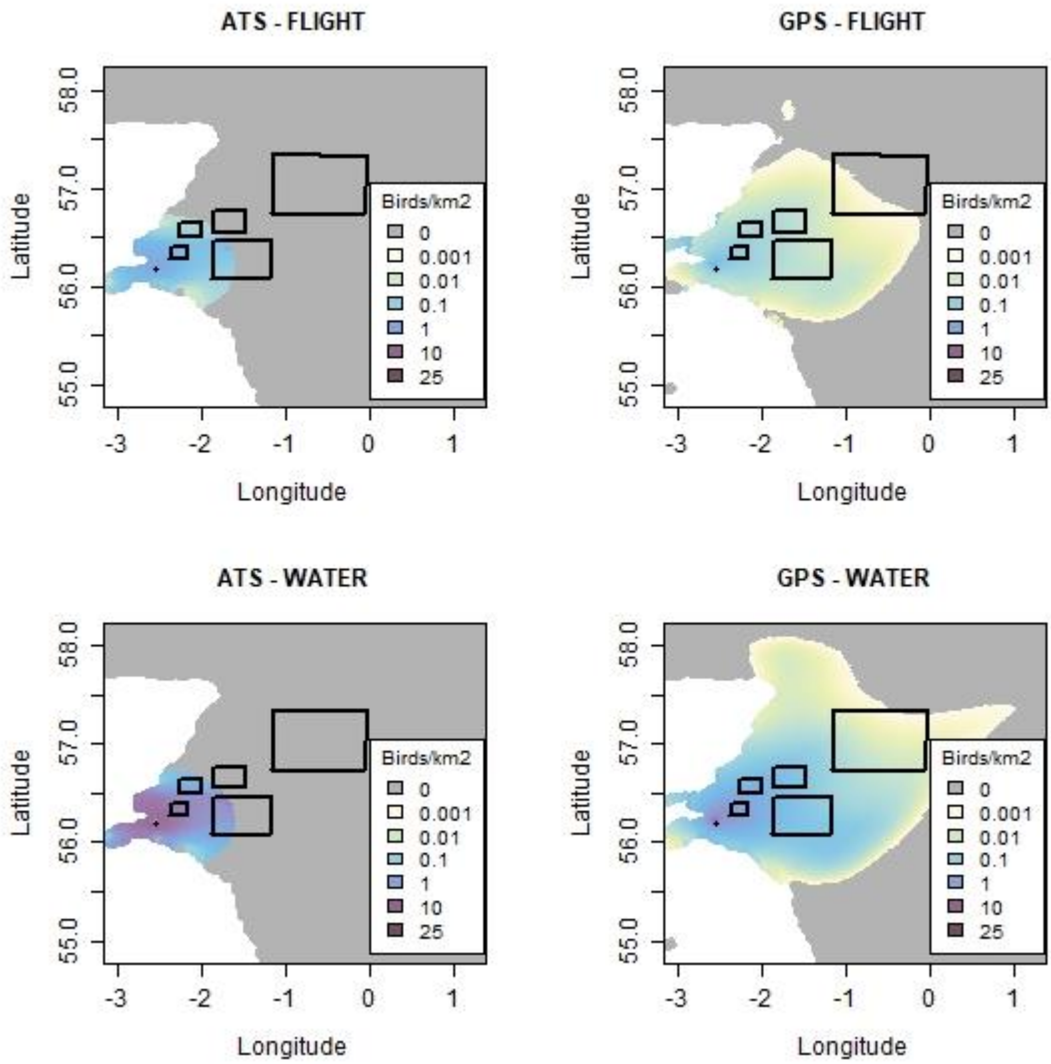


Figure 11. As Figure 9 but for Kittiwake at Fowlsheugh

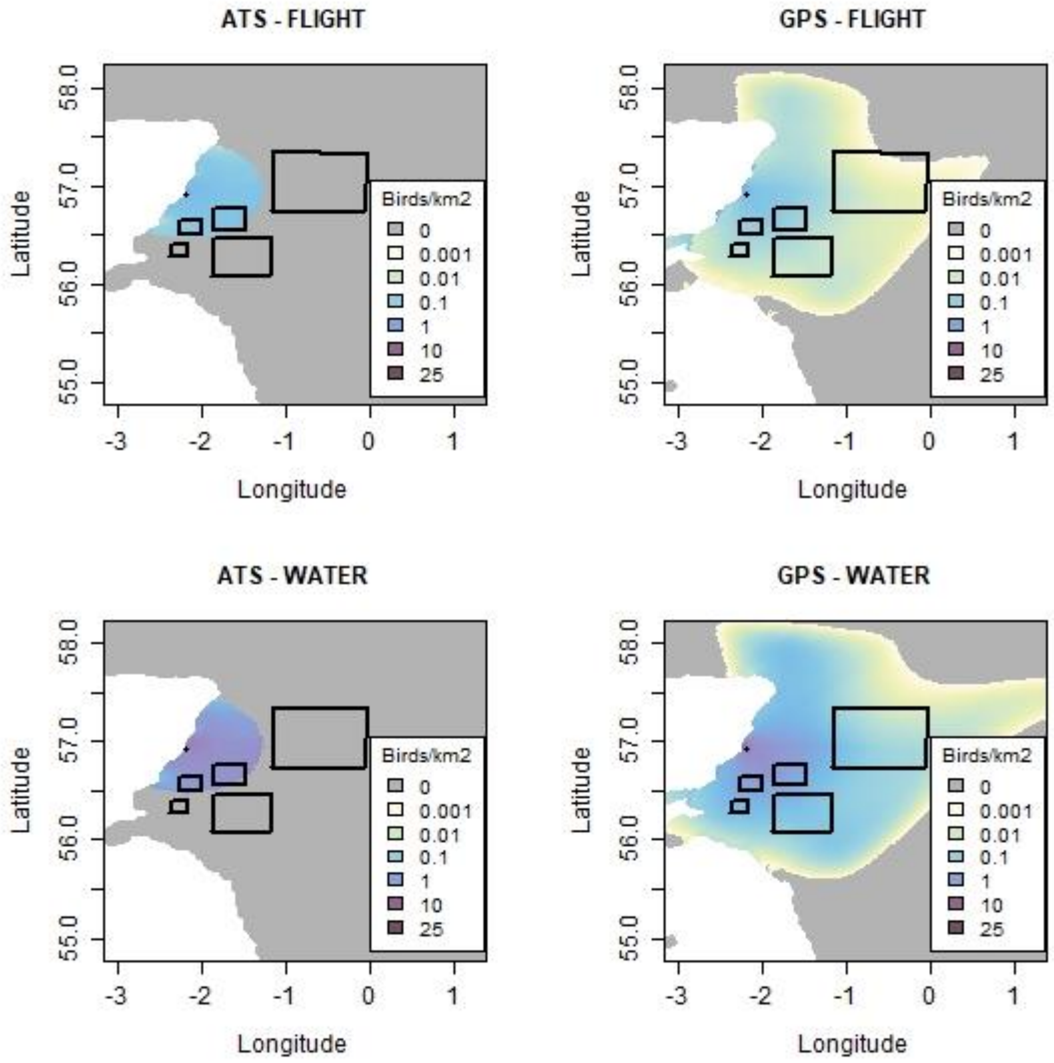


Figure 12. As Figure 9 but for Kittiwake at St Abbs

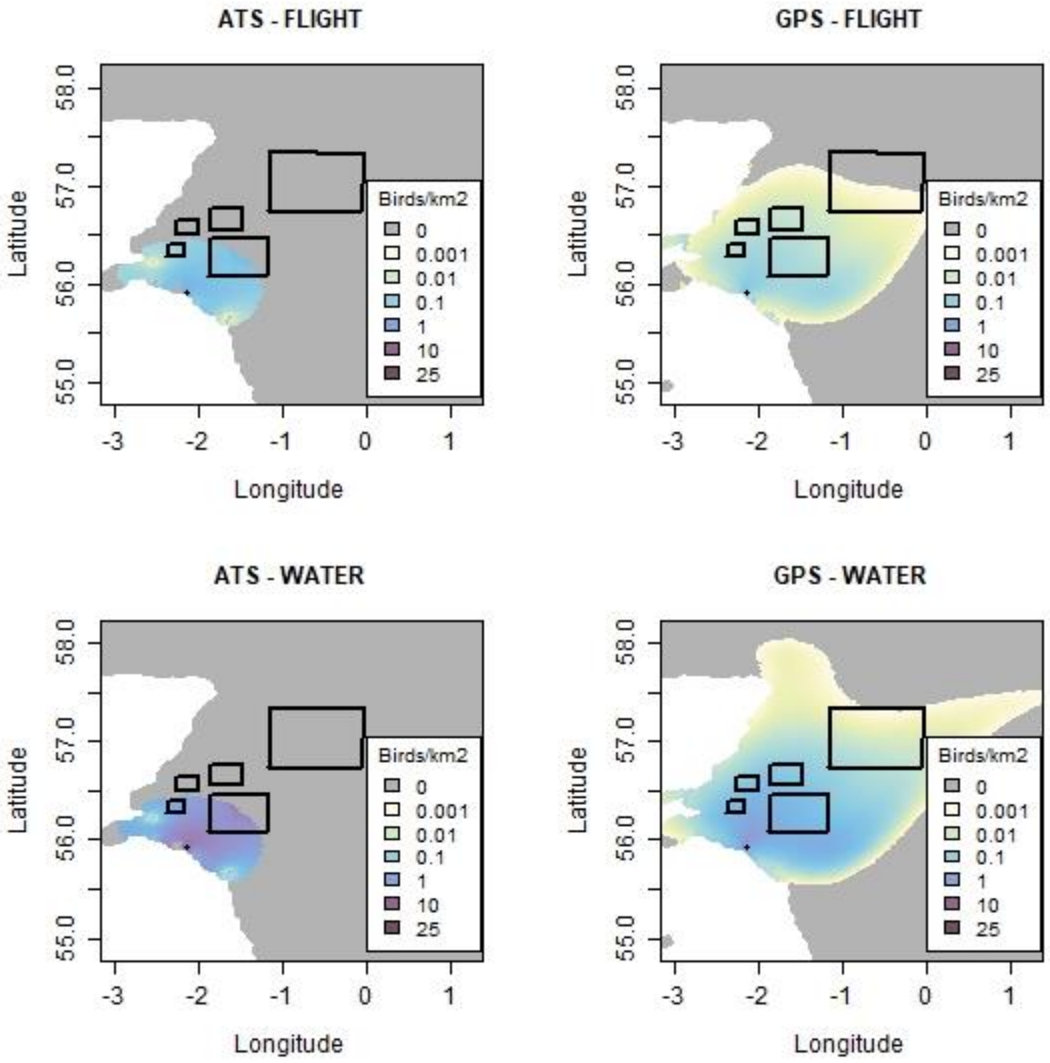


Figure 13. As Figure 9 but for Guillemot at Buchan Ness

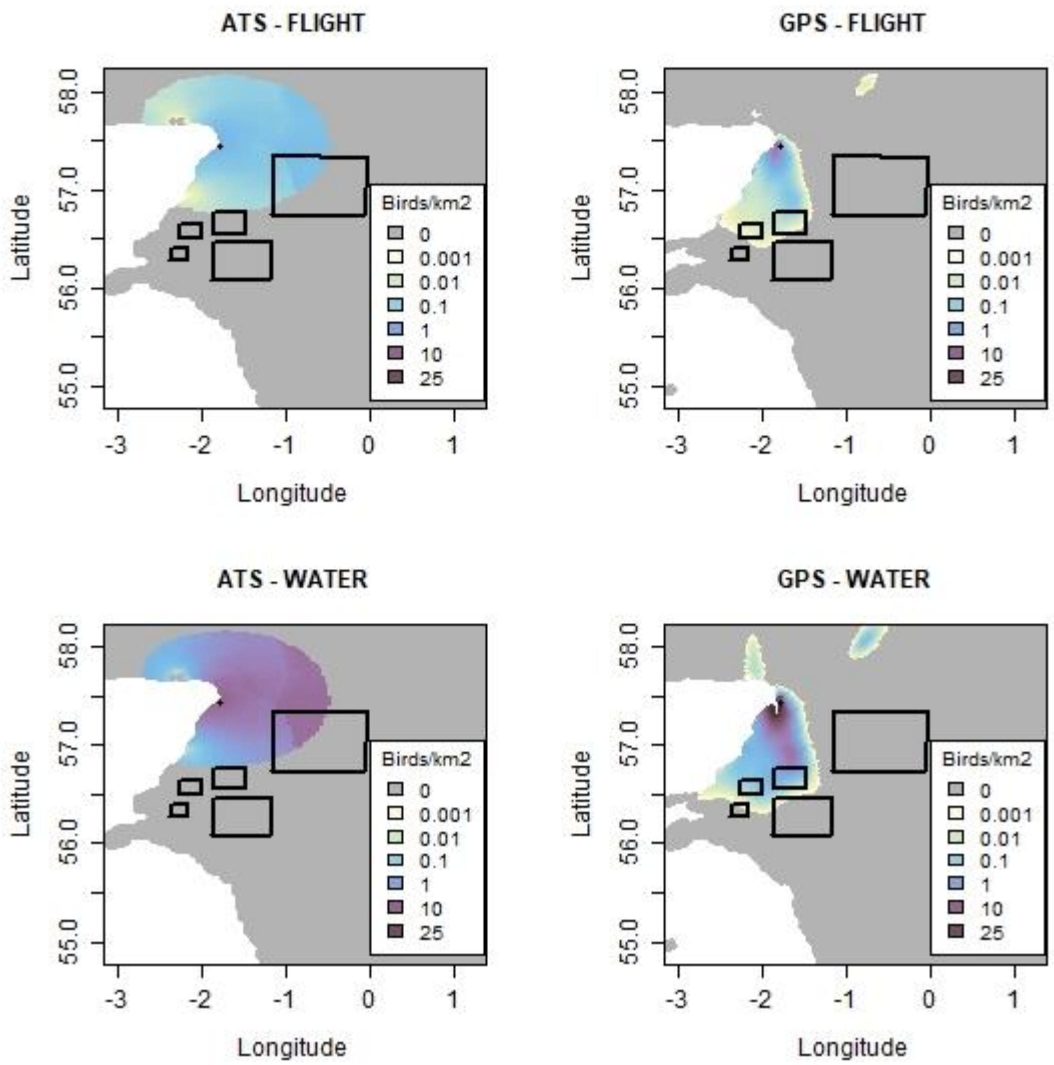


Figure 14 As Figure 9 but for Guillemot at Forth Islands

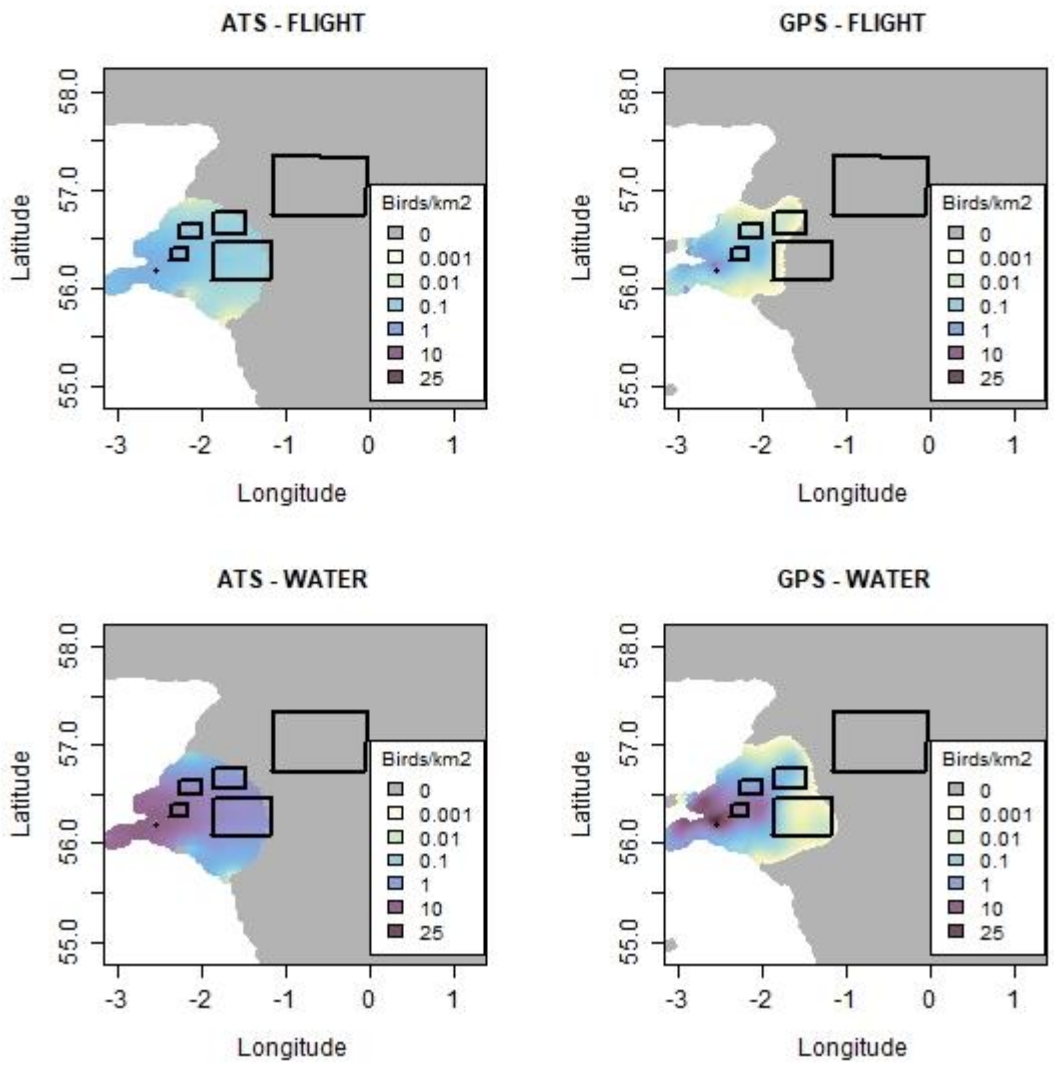


Figure 15. As Figure 9 but for Guillemot at Fowlsheugh

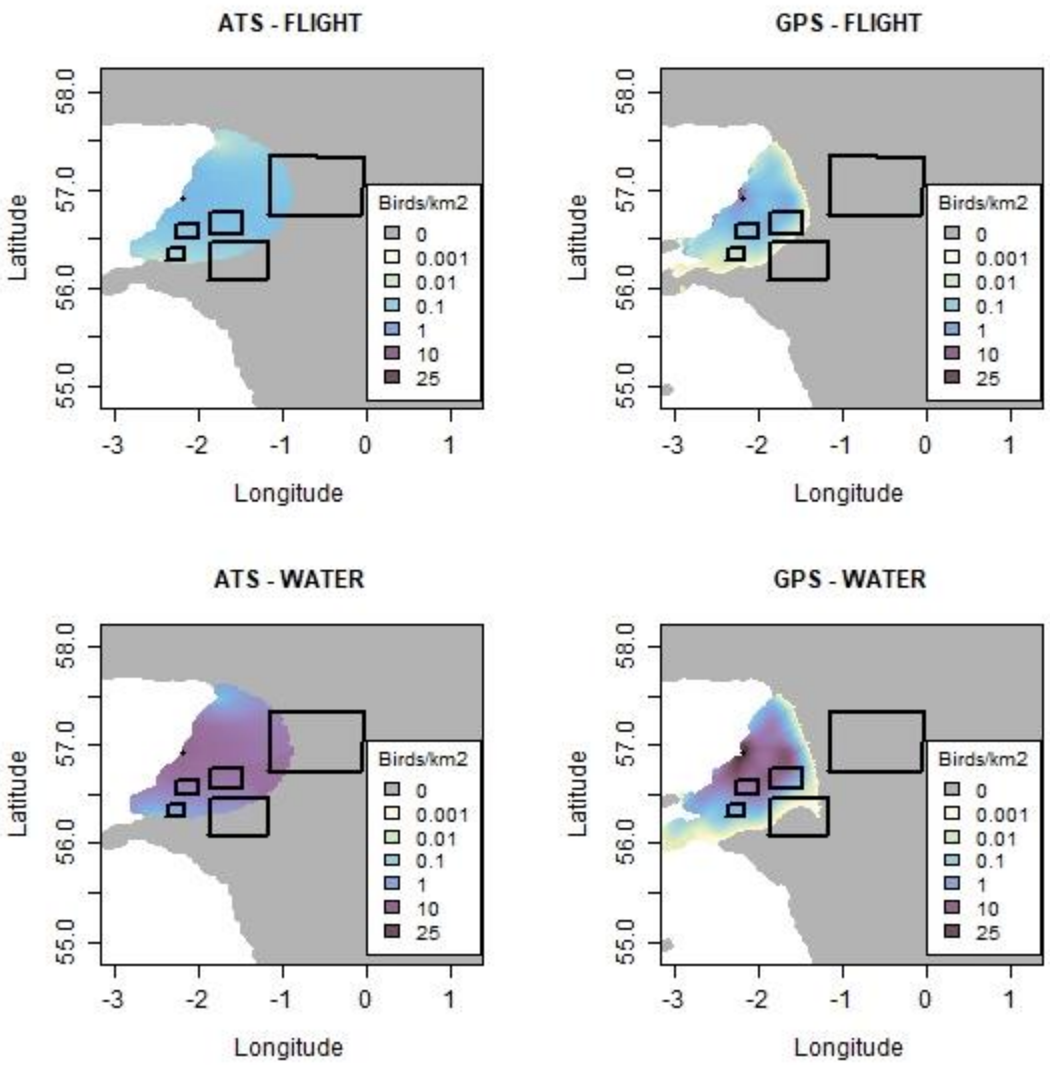


Figure 16. As Figure 9 but for Guillemot at St Abbs

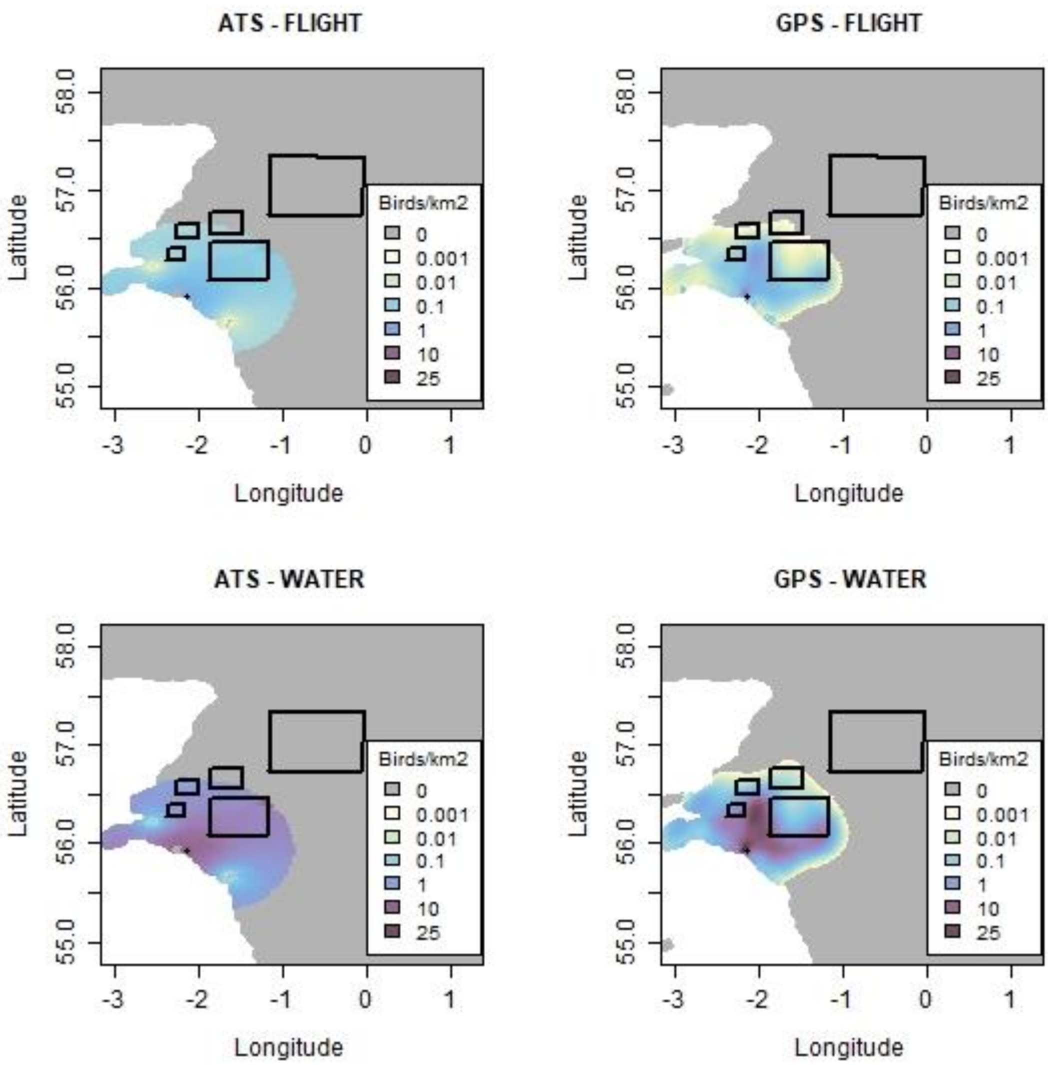


Figure 17. As Figure 9 but for Razorbill at Forth Islands

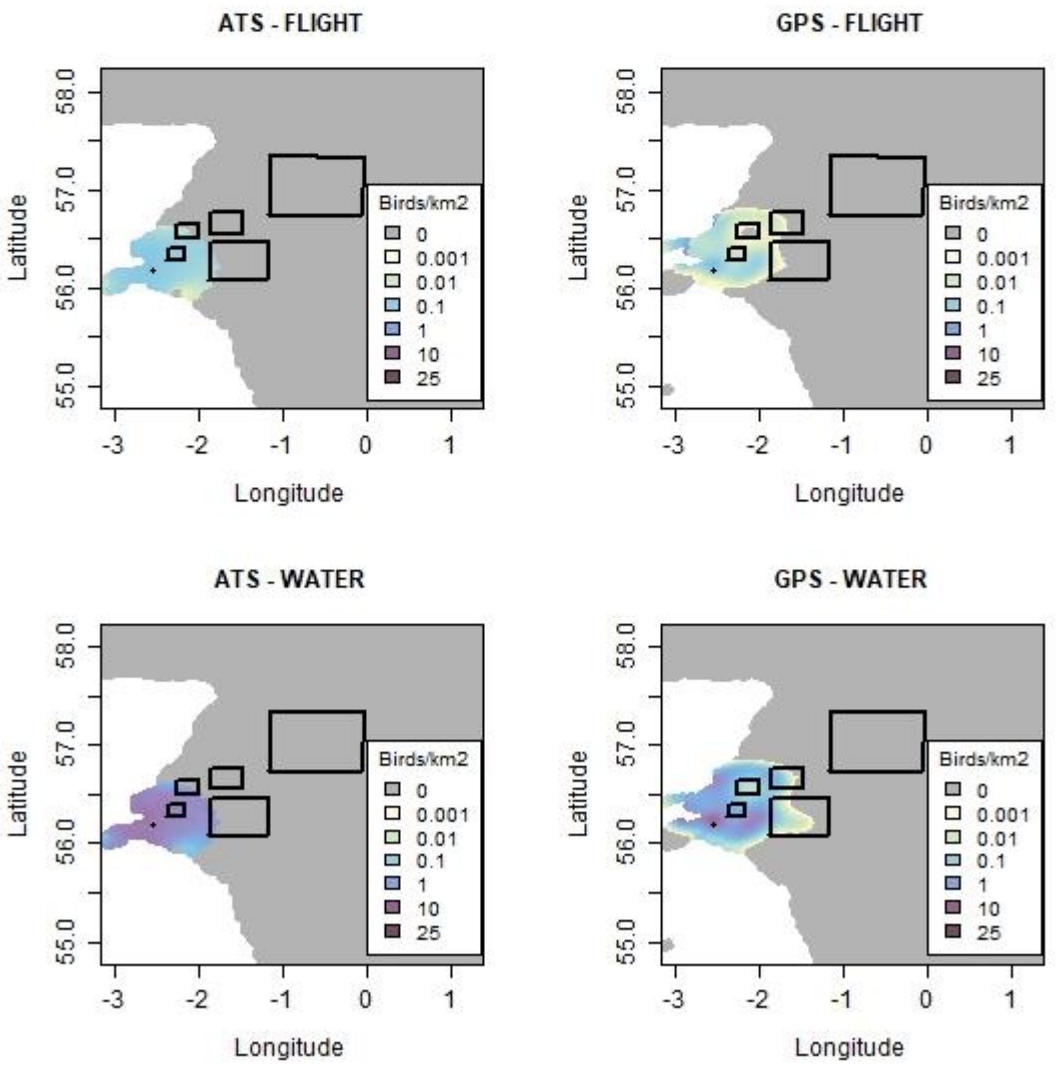


Figure 18. As Figure 9 but for Razorbill at Fowlsheugh

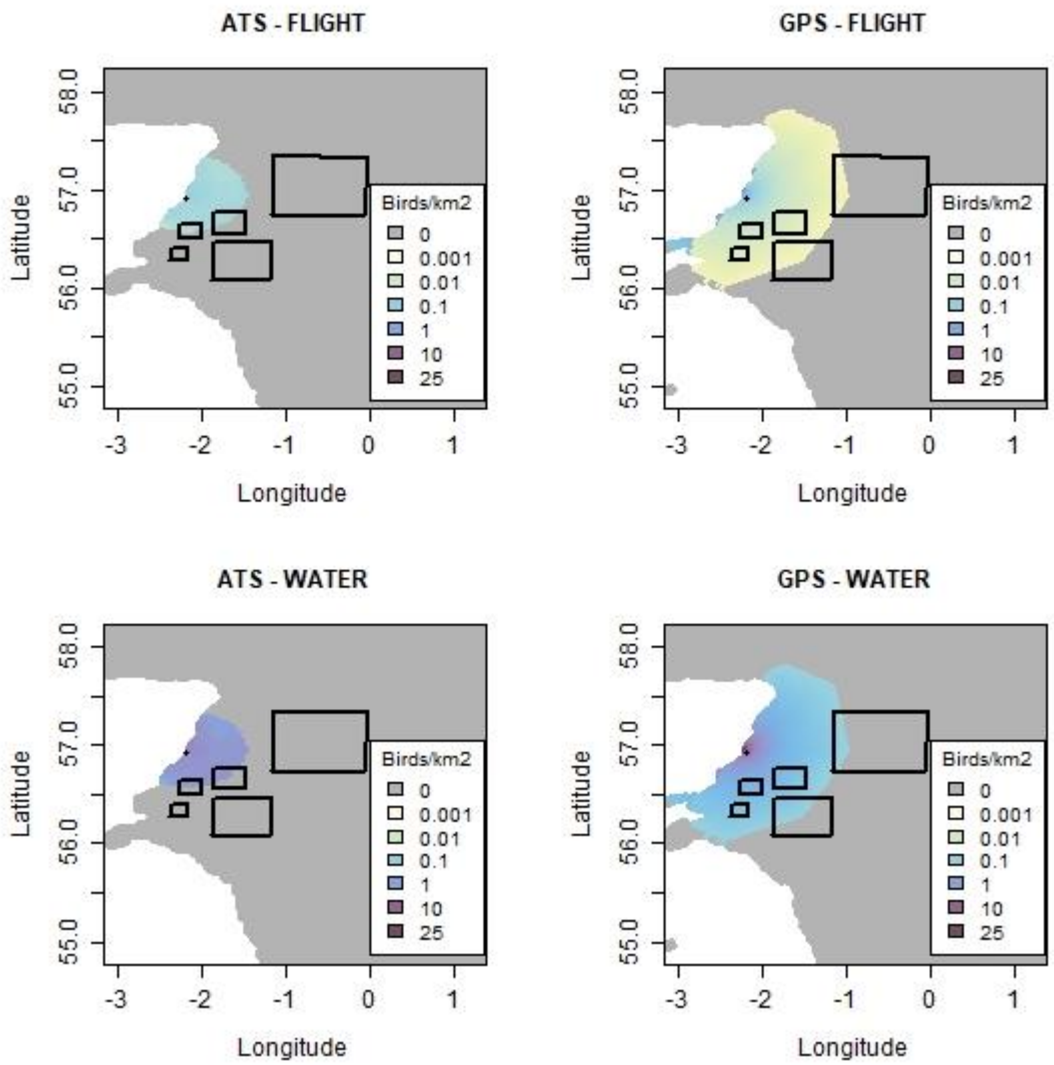


Figure 19. As Figure 9 but for Razorbill at St Abbs

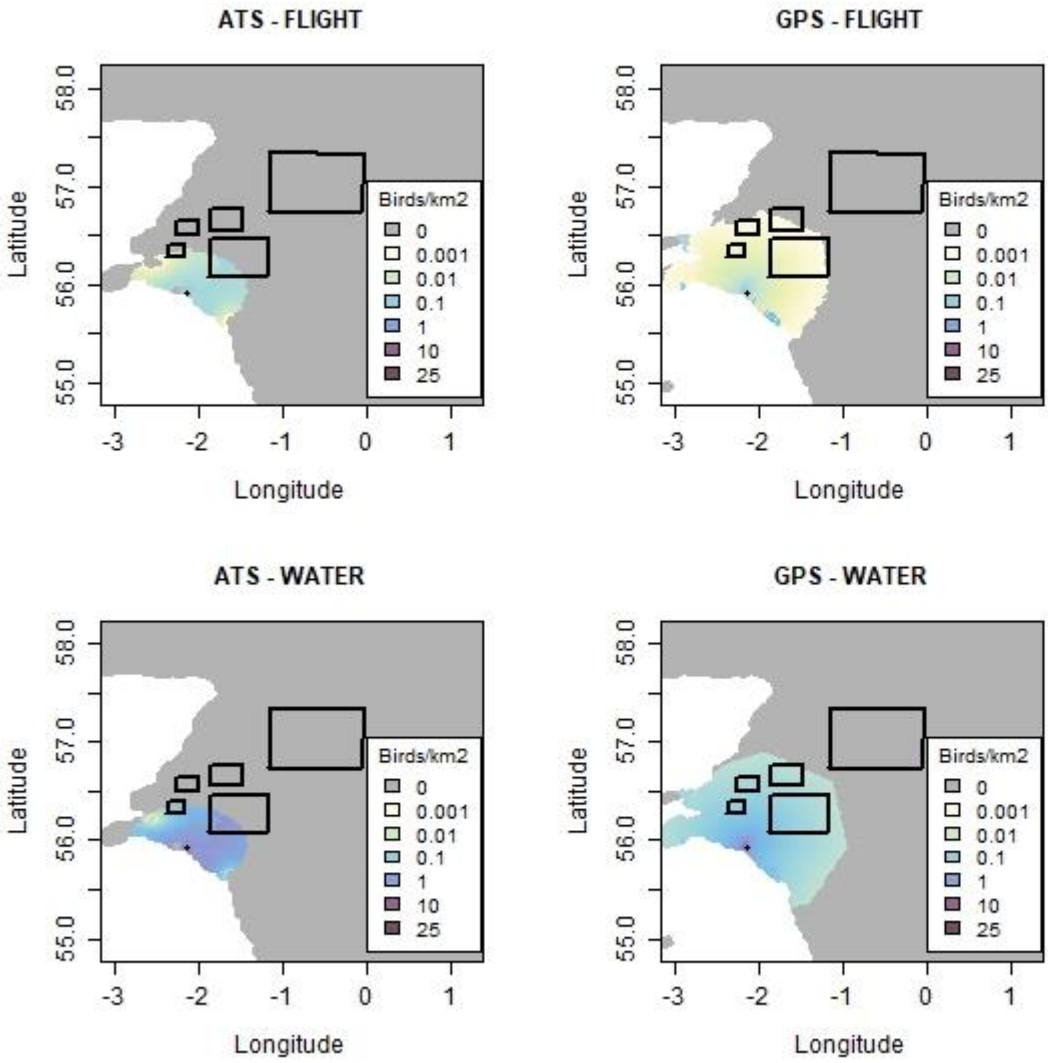


Figure 20. As Figure 9 but for Puffin at Forth Islands

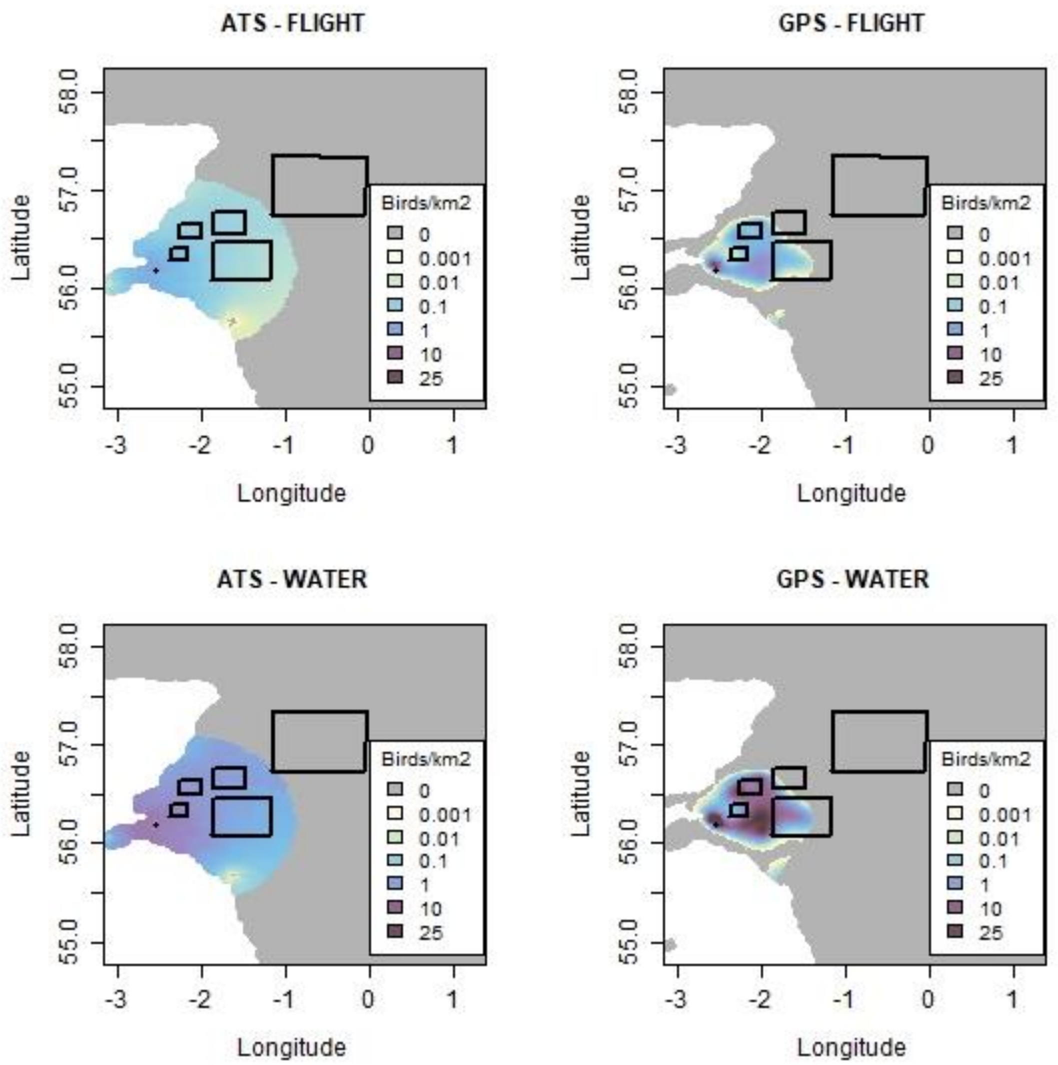
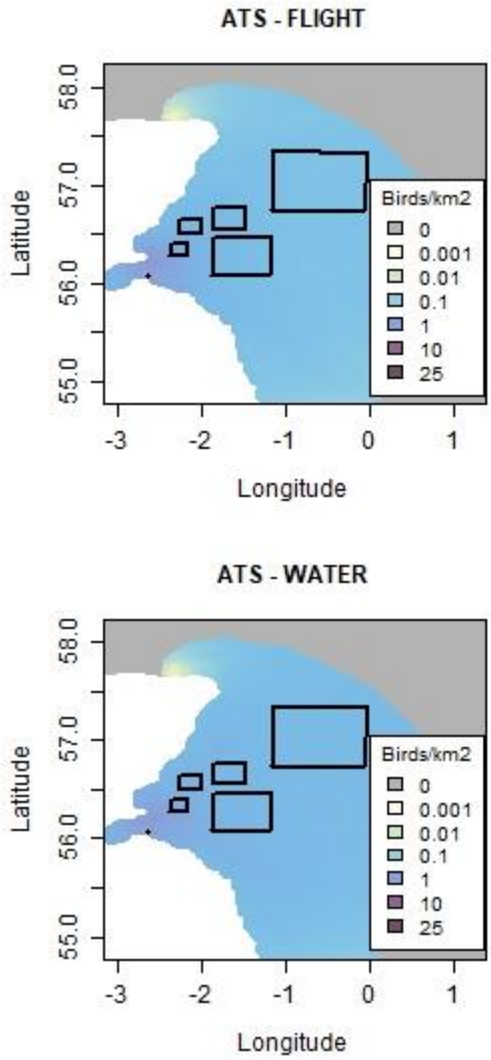


Figure 21. As Figure 9 but for Gannet at Forth Islands



Estimated exposure to footprint

In Table 10 we show the percentage of time on the water that is estimated to be within the footprint of an ORD (including a 2km buffer) for each population under each scenario. It can be seen that there is estimated to be considerable interaction with the ORDs for birds from a number of populations under both scenarios, but much less interaction in the non-breeding season in all cases.

For some populations the level of interaction is substantially higher when using at sea maps than when using GPS maps (e.g. guillemot and razorbill at St. Abbs) and for others substantially lower (e.g. razorbill at Forth Islands).

The level of interaction under Scenario 3 is broadly similar to that under Scenario 2, suggesting that there is minimal interaction with ORD5 (the only difference between the two scenarios). However, there are some important exceptions - kittiwake at Buchan Ness, guillemot at Buchan Ness (but only when using maps derived from at-sea data) and gannet at Forth Islands – which suggest that for these populations there is a potentially substantial interaction with ORD5.

Table 10. Total percentage of time on the water spent within ORD footprints under each scenario, for birds originating from each population, as derived using maps derived from either at-sea survey data or GPS tracking data.

Species	SPA	Percentage of time spent in footprint in the baseline maps (i.e. prior to displacement)					
		At sea data, breeding season		At sea data, non-breeding season		GPS data, chick-rearing period	
		Scen2	Scen3	Scen2	Scen3	Scen2	Scen3
Kittiwake	St Abbs	21.9	21.9	0.9	2.5	19.3	20.4
	Forth Islands	15	15	0.9	2.5	19.4	20.5
	Buchan Ness	0	7.7	0.9	2.5	3.1	7.1
	Fowlsheugh	16.7	16.7	0.9	2.5	16.5	20.3
Guillemot	St Abbs	21.6	21.6	1	2.4	7.2	7.2
	Forth Islands	19.6	19.6	1	2.4	6	6
	Buchan Ness	0.1	18.2	1	2.4	2.2	2.2
	Fowlsheugh	14.1	23.6	1	2.4	14.6	14.6
Razorbill	St Abbs	14	14	1.5	3.3	5.3	5.3
	Forth Islands	9.1	9.1	1.5	3.3	13.6	13.6
	Fowlsheugh	15.6	15.6	1.5	3.3	9.7	11
Puffin	Forth Islands	18.1	18.1	0.5	1.3	14.4	14.4
Gannet	Forth Islands	5.9	13.4	0.4	1.2	---	---

The results when looking at time spent in flight, rather than time spent on the water, are qualitatively similar (Table 11).

Table 11. As Table 10, but for time spent in flight rather than time spent on the water.

Species	SPA	Percentage of time spent in footprint in the baseline maps (i.e. prior to displacement)					
		At sea data, breeding season		At sea data, non-breeding season		GPS data, chick-rearing period	
		Scen2	Scen3	Scen2	Scen3	Scen2	Scen3
Kittiwake	St Abbs	21.5	21.5	0.7	1.9	19.1	20.1
	Forth Islands	15.3	15.3	0.7	1.9	19	20
	Buchan Ness	0	7.2	0.7	1.9	2.6	5.9
	Fowlsheugh	16.3	16.3	0.7	1.9	15.5	18.9
Guillemot	St Abbs	20.5	20.5	1	2.4	6.9	6.9
	Forth Islands	18.3	18.3	1	2.4	5.1	5.1
	Buchan Ness	0.1	17.5	1	2.4	1.9	1.9
	Fowlsheugh	14.5	23	1	2.4	13.8	13.8
Razorbill	St Abbs	13.5	13.5	1.2	2.9	3.9	3.9
	Forth Islands	8.5	8.5	1.2	2.9	11.2	11.2
	Fowlsheugh	15.4	15.4	1.2	2.9	7.3	8.4
Puffin	Forth Islands	14.2	14.2	0.4	1	9.7	9.7
Gannet	Forth Islands	6.7	13.8	0.5	1.2	---	---

3.2. Estimated effects - displacement in the breeding season

Estimated effects of displacement during the breeding season can be estimated using two different methods (SeabORD and the Displacement Matrix Approach), and can be based upon maps derived using two different data sources (at-sea survey data or GPS tracking data).

Estimated using the individual based simulation model (SeabORD)

The individual based simulation model, SeabORD, calculates population level changes in demography caused by OWFs by comparing baseline simulations to simulations with one or more OWFs present. The results are expressed in terms of additional adult mortality (percentage point from 0 to 100%) and the reduction in productivity (percentage point from 0 to 100%). All estimates have as associated standard deviation and 95% confidence intervals, derived from the multiple model simulations across a range of moderate prey levels. Positive impacts may occur within the SeabORD model (positive values for additional adult mortality or reduction productivity imply that demographic rates of adult survival and productivity increased when OWFs were included in simulations). The primary reason for this is a displacement of birds closer to the breeding colony, resulting in reduced travel costs. For this same reason, effects from Scenario 3 are occasionally slightly lower than effects for Scenario 2; because the addition of the large offshore OWF in Scenario 3 caused some birds to be displaced closer to their breeding colonies, therefore lowering their travel costs and resulting in improved survival estimates over the subsequent winter for this subset of birds, in comparison to Scenario 2.

Variation in effects of OWFs upon demography vary predictably in line with the variation in bird densities and foraging ranges from the two bird distribution input methods – GPS and at-sea (Tables 8-11).

Table 12. Estimates for changes in demographic rates (additional adult mortality and reduction on chick productivity) for common guillemots, as estimated by the individual based simulation model, SeabORD. Focus SPAs are: Buchan Ness (bod), Fowlsheugh (fow), Forth Islands (iom), and St Abbs Head (sta).

ORD used	Bird density map	Focus colony	Additional mortality %, mean	Additional mortality %, sdev	Additional mortality % lower confidence interval	Additional mortality % upper confidence interval	Productivity reduction mean	Productivity reduction SD	Productivity reduction LCI	Productivity reduction UCI
Scenario 2	GPS	bod	0.0021	0.0453	-0.1053	0.1095	0.0297	0.1202	-0.2554	0.3149
Scenario 2	At-sea	bod	0.0234	0.0667	-0.1350	0.1817	0.0764	0.1990	-0.3956	0.5485
Scenario 2	GPS	fow	0.3404	0.0516	0.2180	0.4628	0.7491	0.4864	-0.4049	1.9032
Scenario 2	At-sea	fow	0.3868	0.0555	0.2551	0.5184	0.6686	0.6574	-0.8912	2.2284
Scenario 2	GPS	iom	0.2750	0.0884	0.0652	0.4848	0.7146	0.3631	-0.1468	1.5760
Scenario 2	At-sea	iom	0.1039	0.1167	-0.1730	0.3809	0.3551	0.2936	-0.3414	1.0517
Scenario 2	GPS	sta	-0.1304	0.0691	-0.2944	0.0336	-0.0373	0.2016	-0.5156	0.4411
Scenario 2	At-sea	sta	0.3943	0.0743	0.2179	0.5707	9.4412	0.4054	8.4792	10.4031
Scenario 3	GPS	bod	0.0021	0.0453	-0.1053	0.1095	0.0297	0.1202	-0.2554	0.3149
Scenario 3	At-sea	bod	0.0892	0.2379	-0.4752	0.6535	8.1699	0.6327	6.6686	9.6711
Scenario 3	GPS	fow	0.3392	0.0530	0.2135	0.4649	0.7467	0.4826	-0.3983	1.8917
Scenario 3	At-sea	fow	0.3197	0.0533	0.1933	0.4461	0.3197	0.3900	-0.6056	1.2450
Scenario 3	GPS	iom	0.2750	0.0884	0.0652	0.4848	0.7146	0.3631	-0.1468	1.5760
Scenario 3	At-sea	iom	0.1667	0.1081	-0.0896	0.4231	0.3854	0.3597	-0.4680	1.2389
Scenario 3	GPS	sta	-0.1304	0.0691	-0.2944	0.0336	-0.0373	0.2016	-0.5156	0.4411
Scenario 3	At-sea	sta	0.5293	0.1439	0.1880	0.8706	9.0189	0.2715	8.3747	9.6632

Table 13: Estimates for changes in demographic rates (additional adult mortality and reduction on chick productivity) for black-legged kittiwake, as estimated by the individual based simulation model, SeabORD. Focus SPAs are: Buchan Ness (bod), Fowlsheugh (fow), Forth Islands (iom), and St Abbs Head (sta). Note that the reduction in productivity is percentage point change in nest level productivity.

Bird density map	ORD used	Focus colony	Additional mortality %, mean	Additional mortality %, sdev	Additional mortality % lower confidence interval	Additional mortality % upper confidence interval	Productivity reduction mean	Productivity reduction SD	Productivity reduction LCI	Productivity reduction UCI
GPS	Scenario 2	bod	0.1480	0.1128	-0.1196	0.4157	0.4731	0.2398	-0.0957	1.0420
At-sea	Scenario 2	bod	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
GPS	Scenario 2	fow	0.4505	0.1987	-0.0210	0.9219	3.1308	1.4893	-0.4027	6.6644
At-sea	Scenario 2	fow	0.3659	0.2324	-0.1855	0.9172	2.0642	0.9726	-0.2434	4.3718
GPS	Scenario 2	iom	0.8327	0.3263	0.0586	1.6069	5.4182	2.1337	0.3558	10.4806
At-sea	Scenario 2	iom	0.1644	0.1381	-0.1633	0.4921	0.8935	0.5992	-0.5282	2.3152
GPS	Scenario 2	sta	0.6654	0.3161	-0.0845	1.4153	3.9306	1.5749	0.1940	7.6672
At-sea	Scenario 2	sta	-0.4824	0.2035	-0.9653	0.0005	-1.8964	1.3218	-5.0325	1.2397
GPS	Scenario 3	bod	0.2990	0.1389	-0.0306	0.6286	0.9985	0.4144	0.0153	1.9818
At-sea	Scenario 3	bod	-0.1597	0.1165	-0.4361	0.1168	-0.4819	0.3045	-1.2043	0.2406
GPS	Scenario 3	fow	0.4781	0.1730	0.0677	0.8885	3.4173	1.3645	0.1799	6.6548
At-sea	Scenario 3	fow	0.3763	0.2178	-0.1406	0.8931	2.0918	0.9373	-0.1321	4.3157
GPS	Scenario 3	iom	0.8613	0.2666	0.2287	1.4939	5.3538	2.1025	0.3654	10.3422
At-sea	Scenario 3	iom	0.1608	0.1069	-0.0928	0.4144	1.0007	0.6831	-0.6200	2.6215
GPS	Scenario 3	sta	0.6583	0.3268	-0.1171	1.4337	4.1683	1.7309	0.0616	8.2749
At-sea	Scenario 3	sta	-0.4444	0.2087	-0.9395	0.0508	-1.9629	1.3415	-5.1458	1.2199

Table 14. . Estimates for changes in demographic rates (additional adult mortality and reduction on chick productivity) for Atlantic puffins, as estimated by the individual based simulation model, SeabORD. Focus SPAs are: Forth Islands (iom).

Forage data file	ORD used	Focus colony	Additional mortality %, mean	Additional mortality %, sdev	Additional mortality % lower confidence interval	Additional mortality % upper confidence interval	Productivity mean	Productivity SD	Productivity LCI	Productivity UCI
GPS	Scenario 2	iom	0.4548	0.1640	0.0656	0.8440	0.2291	0.4958	-0.9473	1.4055
GPS	Scenario 3	iom	0.4548	0.1640	0.0656	0.8440	0.2291	0.4958	-0.9473	1.4055
At-sea	Scenario 2	iom	1.7698	0.7521	-0.0145	3.5541	1.3665	2.4385	-4.4191	7.1521
At-sea	3	iom	1.7698	0.7521	-0.0145	3.5541	1.3665	2.4385	-4.4191	7.1521

Table 15. Estimates for changes in demographic rates (additional adult mortality and reduction on chick productivity) for razorbill, as estimated by the individual based simulation model, SeabORD. Focus SPAs are: Fowlsheugh (fow), Forth Islands (iom), and St Abbs Head (sta).

Forage data file	ORD Scenario	Focus colony	Additional mortality %, mean	Additional mortality %, sdev	Additional mortality % lower confidence interval	Additional mortality % upper confidence interval	Productivity mean	Productivity SD	Productivity LCI	Productivity UCI
At-sea	Scenario 2	fow	-0.2384	0.1398	-0.5701	0.0933	-0.1120	0.1913	-0.5658	0.3419
GPS	Scenario 2	fow	0.8012	0.2044	0.3162	1.2861	0.9710	0.7334	-0.7689	2.7110
At-sea	Scenario 3	fow	-0.2384	0.1398	-0.5701	0.0933	-0.1120	0.1913	-0.5658	0.3419
GPS	Scenario 3	fow	0.7519	0.2417	0.1786	1.3253	0.9344	0.7027	-0.7328	2.6016
At-sea	Scenario 2	iom	0.5563	0.1304	0.2469	0.8658	1.1149	1.0061	-1.2722	3.5020
GPS	Scenario 2	iom	0.4596	0.1069	0.2060	0.7132	1.4630	0.7637	-0.3488	3.2749
At-sea	Scenario 3	iom	0.5563	0.1304	0.2469	0.8658	1.1149	1.0061	-1.2722	3.5020
GPS	Scenario 3	iom	0.4744	0.0783	0.2887	0.6601	1.4243	0.7300	-0.3077	3.1563
At-sea	Scenario 2	sta	-0.1708	0.1121	-0.4367	0.0951	-0.2733	0.3399	-1.0798	0.5332
GPS	Scenario 2	sta	0.5038	0.1200	0.2191	0.7886	0.5551	0.4401	-0.4890	1.5992
At-sea	Scenario 3	sta	-0.1708	0.1121	-0.4367	0.0951	-0.2733	0.3399	-1.0798	0.5332
GPS	Scenario 3	sta	0.4782	0.1524	0.1167	0.8397	0.6191	0.5081	-0.5864	1.8247

The estimated effects upon productivity and adult survival for each species and SPA are summarised in Figure 22 and Figure 23.

There are substantial differences between the results obtained for effects on productivity and effects for adult survival, and between effects obtained using maps derived from GPS data and maps derived from at-sea survey data. These differences are qualitative, as well as quantitative. When using at sea maps, there are very large estimated effects on guillemots as St. Abbs, for example, but correspondingly large effects on adult survival are not seen, and the effects on productivity are not seen when using GPS-based maps. In general, the results obtained under the two scenarios are very similar, but for guillemots at Buchan Ness, a substantial effect on productivity is estimated under Scenario 3 but not under Scenario 2.

Figure 22. Estimated impacts of scenarios 2 (black) and 3 (gray) upon productivity via displacement effects, represented as a percentage point change, for each population. Estimates (circles) are generated by applying SeabORD to maps derived from either at-sea survey data (top) or GPS tracking data (bottom), and associated 95% confidence intervals are also shown (as lines).

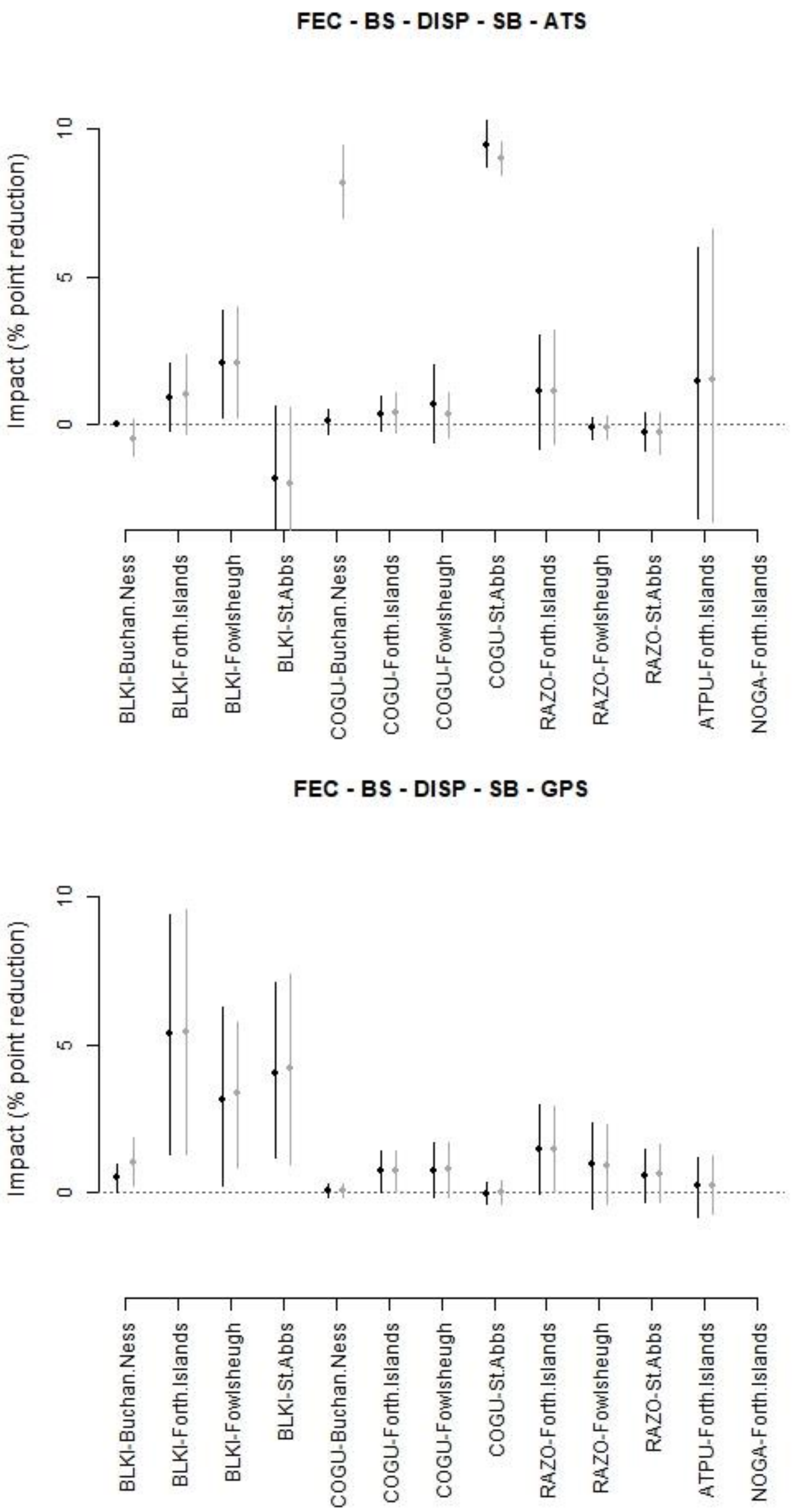
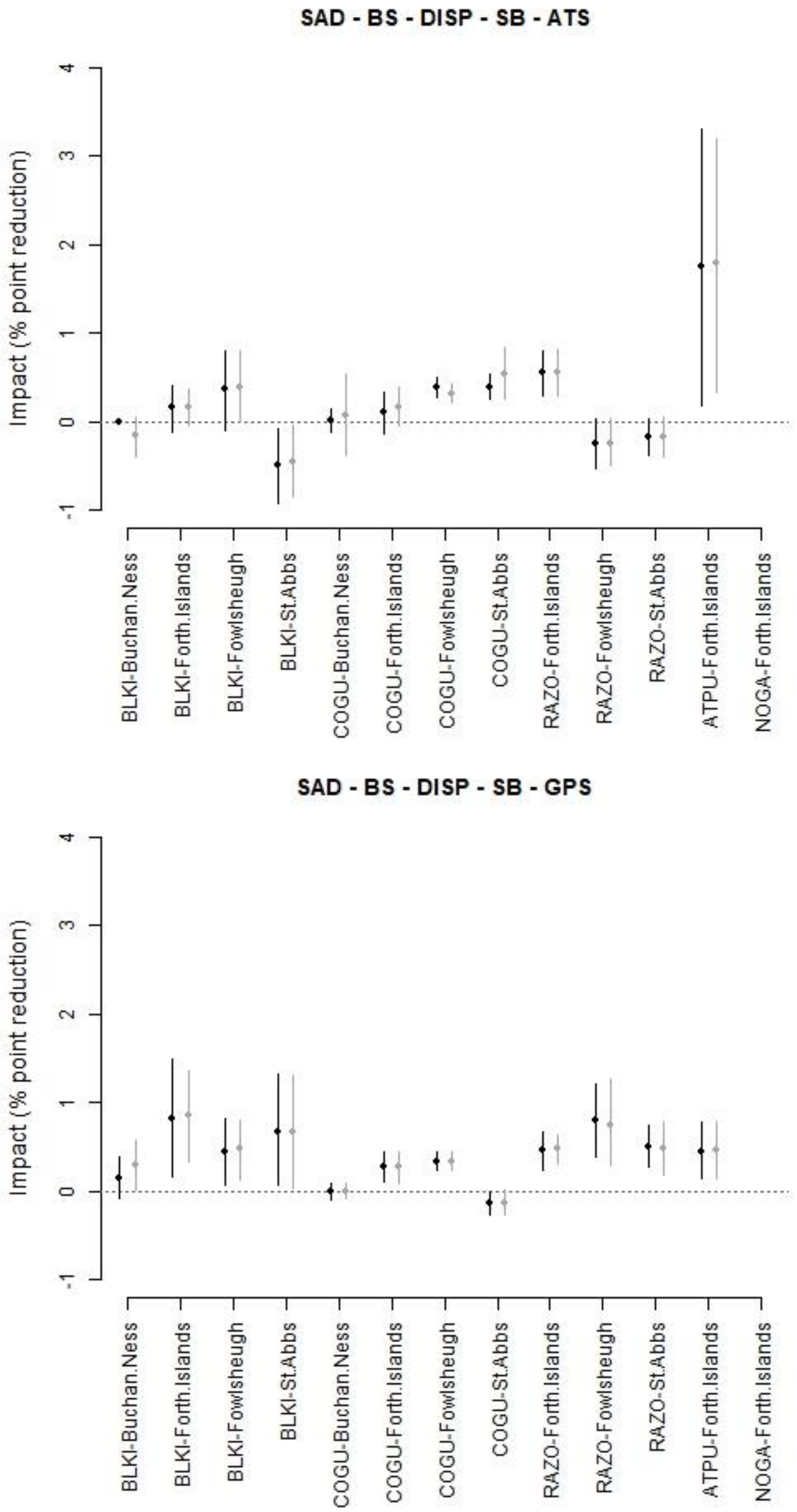


Figure 23. Estimated impacts of scenarios 2 (black) and 3 (ray) upon adult survival within the breeding success via displacement, represented as a percentage point change, for each population. Estimates (circles) are generated by applying SeabORD to maps derived from either at-sea survey data (top) or GPS tracking data (bottom), and associated 95% confidence intervals are also shown (as lines).

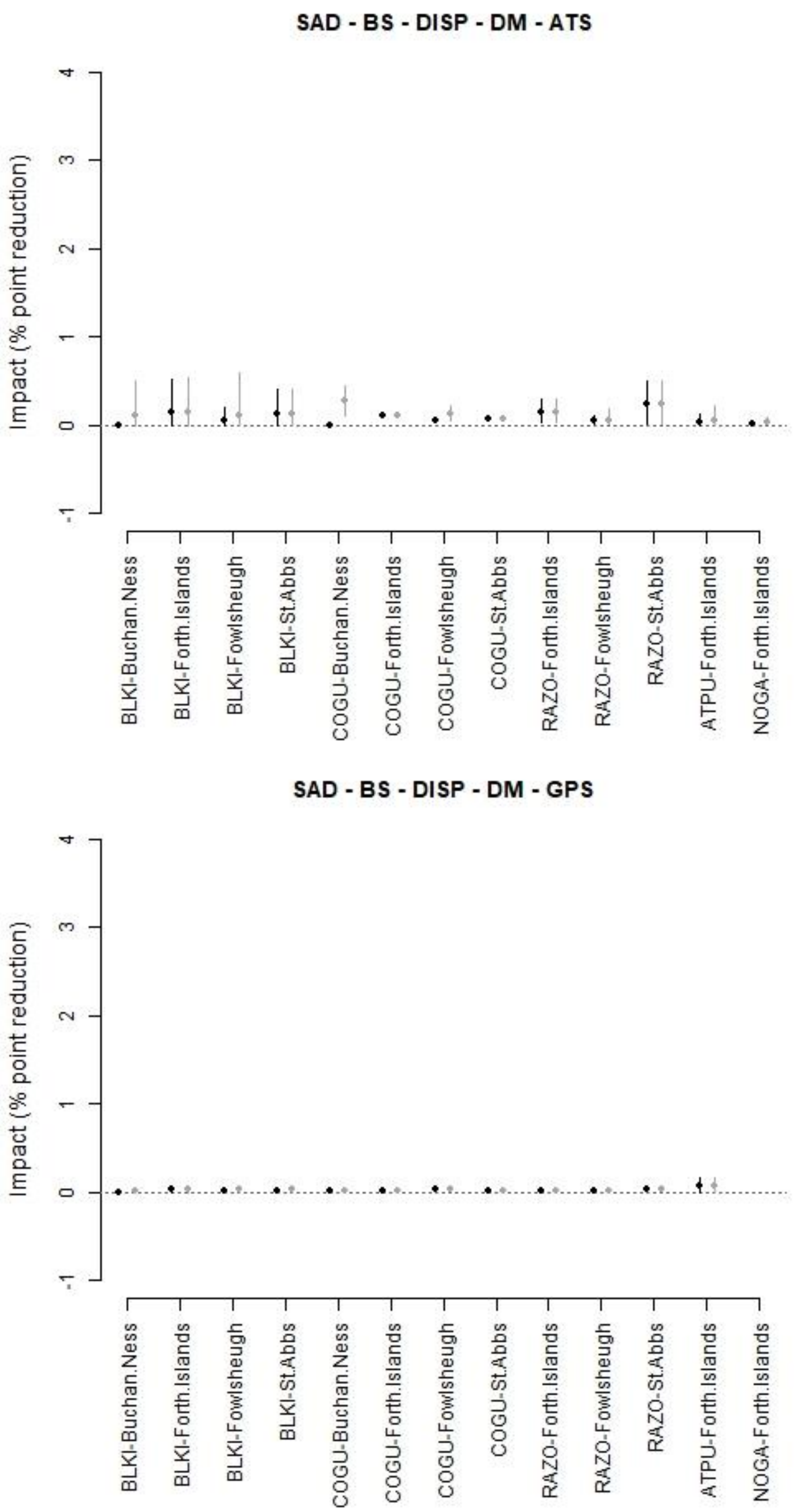


Effects estimated using the Displacement Matrix Approach

Figure 24 shows the corresponding effects upon adult survival that are using the Displacement Matrix approach; the Displacement Matrix approach does not estimate effects upon productivity, and so effectively assumes that these are zero.

There are considerable differences between the results obtained using SeabORD and the Displacement Matrix approach, in terms of both the populations that are associated with the largest estimated effects, and with the magnitude of effects. Overall, however, the effects estimated using SeabORD tend to be substantially larger than those estimated using the Displacement Matrix.

Figure 24. Estimated impacts of scenarios 2 (black) and 3 (grey) upon adult survival within the breeding season via displacement, represented as a percentage point change, for each population. Estimates (circles) are generated by applying the displacement matrix approach to maps derived from either at-sea survey data (top) or GPS tracking data (bottom), and associated 95% confidence intervals are also shown (as lines).

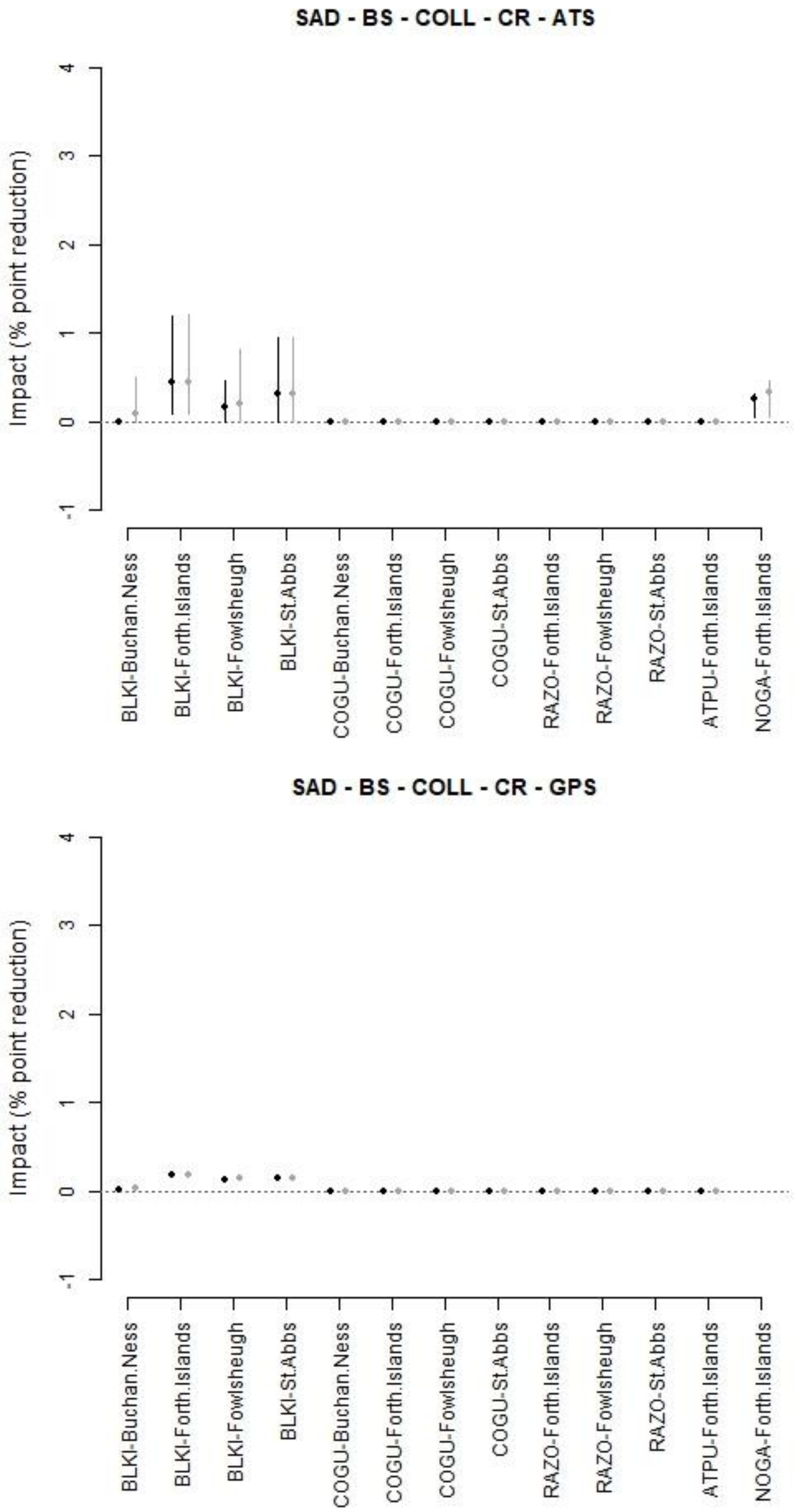


3.3. Estimated effects – collision in the breeding season

Figure 25 shows estimated collision effects during the breeding season, obtained using a stochastic collision risk model.

Collision risk estimates are assumed to be zero for guillemot, razorbill and puffin, and so are not estimated for these species (these zero values are nonetheless included in the graphs, in order to ensure easy comparability with previous and subsequent results). When using at-sea maps the largest estimates of collision effects are for kittiwakes at Forth Islands, and the smallest are for kittiwake at Buchan Ness, with intermediate estimates for kittiwakes at St. Abbs and Fowlsheugh and for gannets at Forth Islands. Qualitatively similar results for kittiwake are obtained using GPS-based maps, but with lower overall estimated effects. GPS-based maps for gannet were not considered within this project.

Figure 25. Estimated impacts of scenarios 2 (black) and 3 (grey) upon adult survival within the breeding success via collision, represented as a percentage point change, for each population. Estimates (circles) are generated by applying the collision risk model to maps derived from either at-sea survey data (top) or GPS tracking data (bottom), and associated 95% confidence intervals are also shown (as lines).



3.4. Estimated effects – displacement & collision in the non-breeding season

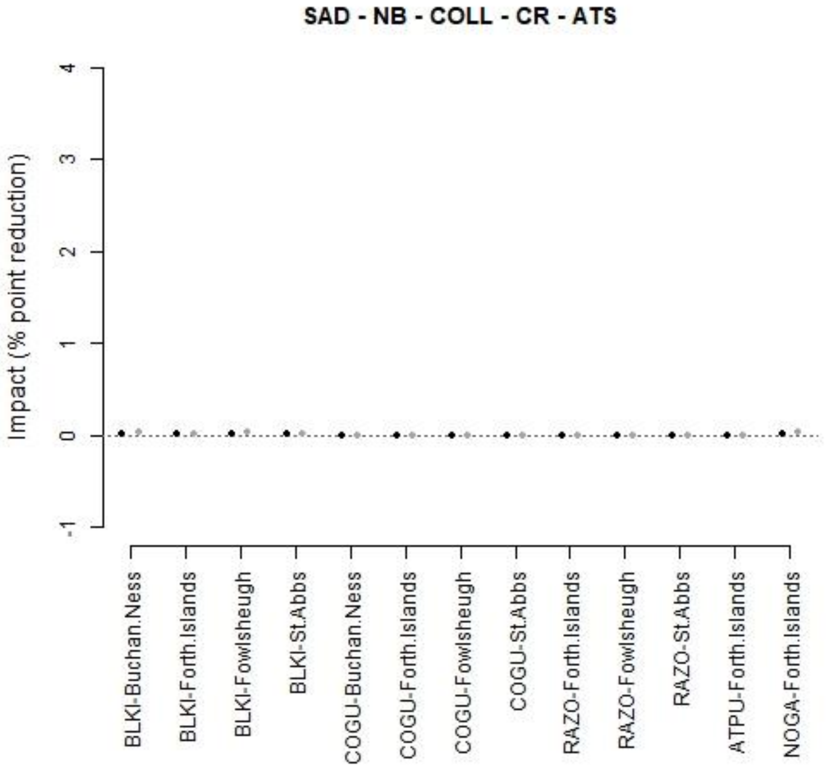
Figure 26 shows estimated effects of both displacement and collision during the non-breeding season. In this case all estimates are based on a single method (the displacement matrix approach or collision risk model, as relevant), and are always applied to maps derived from at-sea survey data.

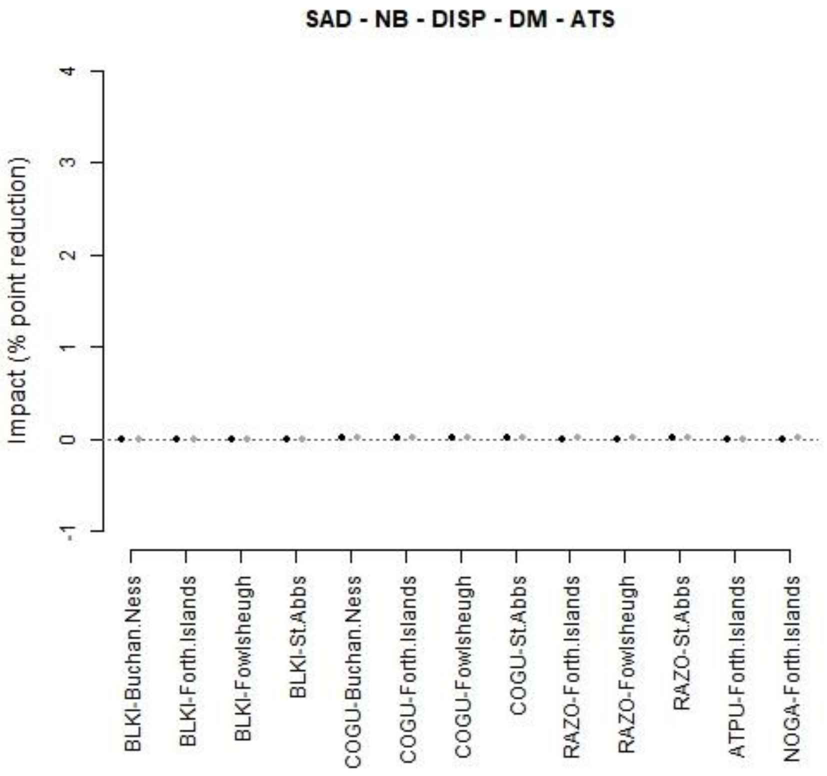
The estimated effects of both displacement and collision in the non-breeding season are small, for all species and SPAs, under both scenarios, even in situations where the corresponding effects for the breeding season are reasonably large.

In terms of displacement-related effects, the small effects in the non-breeding season probably arise because the effects of puffin and gannet are always estimated to be small using the displacement matrix approach, even in the breeding season, and because the BDMPS apportions relatively few birds to the SPAs of interest for the remaining three species (kittiwake, guillemot, razorbill).

In terms of collision effects, for guillemot, razorbill and puffin the effect of collision is assumed to be zero, and the effect for kittiwake is estimated to be small in both the breeding and non-breeding season. The estimated effect on gannet is relatively large in the breeding season, however, and the BDMPS attributes a substantial percentage of the population to the Forth Islands SPA in the non-breeding season, so the low estimate for collision risk in the non-breeding season is more surprising in this case. Further investigation revealed that this arises from the mean abundance within the footprints in the unapportioned at-sea maps being substantially lower in the non-breeding season than in the breeding season (Appendix D). This can also be seen in Figure 8, but the log scale used in that plot makes it difficult to appreciate the magnitude of the difference.

Figure 26. Estimated impacts of scenarios 2 (black) and 3 (grey) upon adult survival within the non-breeding season, represented as a percentage point change, for each population. Estimates (circles) relate to collision impacts (top) and displacement impacts (bottom), and are produced by applying the collision risk model or displacement matrix approach, respectively, to maps derived from at-sea survey data. Associated 95% confidence intervals are also shown (as lines).





3.5. Annual impact estimates – combined

In Figure 29 and Figure 30 we summarise the overall annual estimated magnitudes and directions of effects for each population, under each scenario: this involves summing displacement and collision effects together, and summing across both breeding and non-breeding seasons.

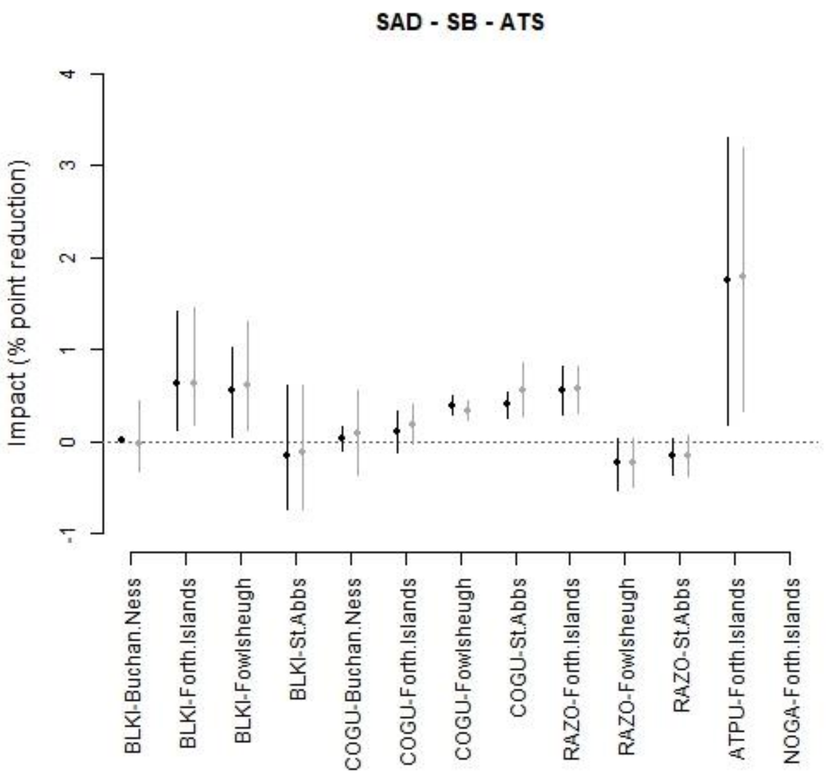
Figure 30 shows the results obtained when the displacement matrix is used to estimate displacement-related effects within the breeding season, whereas Figure 29 shows the results obtained when SeabORD is used for this purpose. In both cases, results are shown when quantifying effects within the breeding season using maps derived from either at-sea survey data (top) or GPS data (bottom). Note that in the non-breeding season, effects are always assessed using at-sea survey data, and displacement-related effects are always assessed using the displacement matrix.

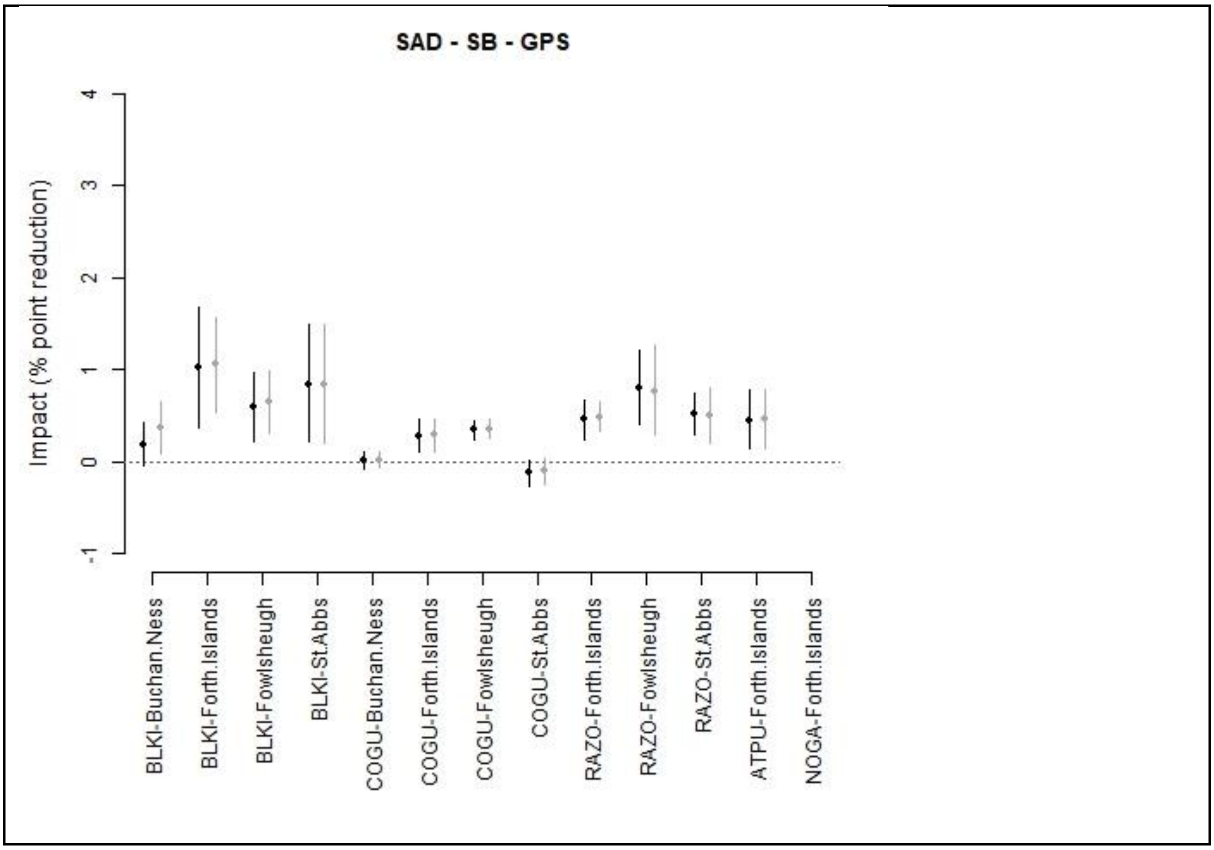
There are considerable differences between the four approaches, reflecting the fact that the largest estimated effects for most populations are for displacement effects in the breeding season, and the four approach differ substantially in the estimates of these effects.

In general, estimated effects obtained using the Displacement Matrix approach tend to be lower than those obtained using SeabORD. When using the Displacement Matrix approach the estimated effects are consistently lower when using GPS-based maps, relative to using at-sea survey based maps, but when using SeabORD this is not always the case – in some cases, the GPS-based maps lead to estimated effects that are larger than those obtained using at-sea maps.

Figure 27. As Figure 24, but with displacement-related impacts in the breeding season estimated using SeabORD rather than the displacement matrix approach.

Estimated impacts of scenarios 2 (black) and 3 (grey) upon adult survival within the breeding season, represented as a percentage point change, for each population. Estimates (circles) relate to displacement impact, and are produced by applying the SeabORD model to maps derived from at-sea survey data (top) or GPS tracking data (bottom). Associated 95% confidence intervals are also shown (as lines).





3.6. PVA results

In Figure 28 - Figure 36 we show the values of PVA metrics M1, M2 and M3 for each population, as estimated using each data type and method.

M1. Median ratio of impacted to unimpacted population size
M2. Median ratio of impacted to unimpacted growth rate
M3. Quantile for unimpacted population size that equals the median impacted population size

The absolute magnitudes of impacts differ between metrics, as each is on a different scale, but the relative variations between populations in the values of the counterfactual metrics (metrics M1 and M2) are similar to the variations in the estimates of combined annual impacts, as we would expect.

The results for metric M3 should be interpreted with considerable caution, as this is a probabilistic metric, and the ability to quantify uncertainty varies substantially between the different approaches being considered.

Figure 28. Values of PVA metric 1 (the ratio of the annual growth rate under impacted to baseline scenarios) for each population under each scenario (black = Scenario 2, red = Scenario 3), for years 2045 (left hand value for each population), 2050 (centre) and 2055 (right). This is for values obtained by using SeabORD to quantify displacement impacts on both adult and juvenile survival in the breeding season using maps derived from at-sea survey data (top) or GPS tracking data (bottom)..

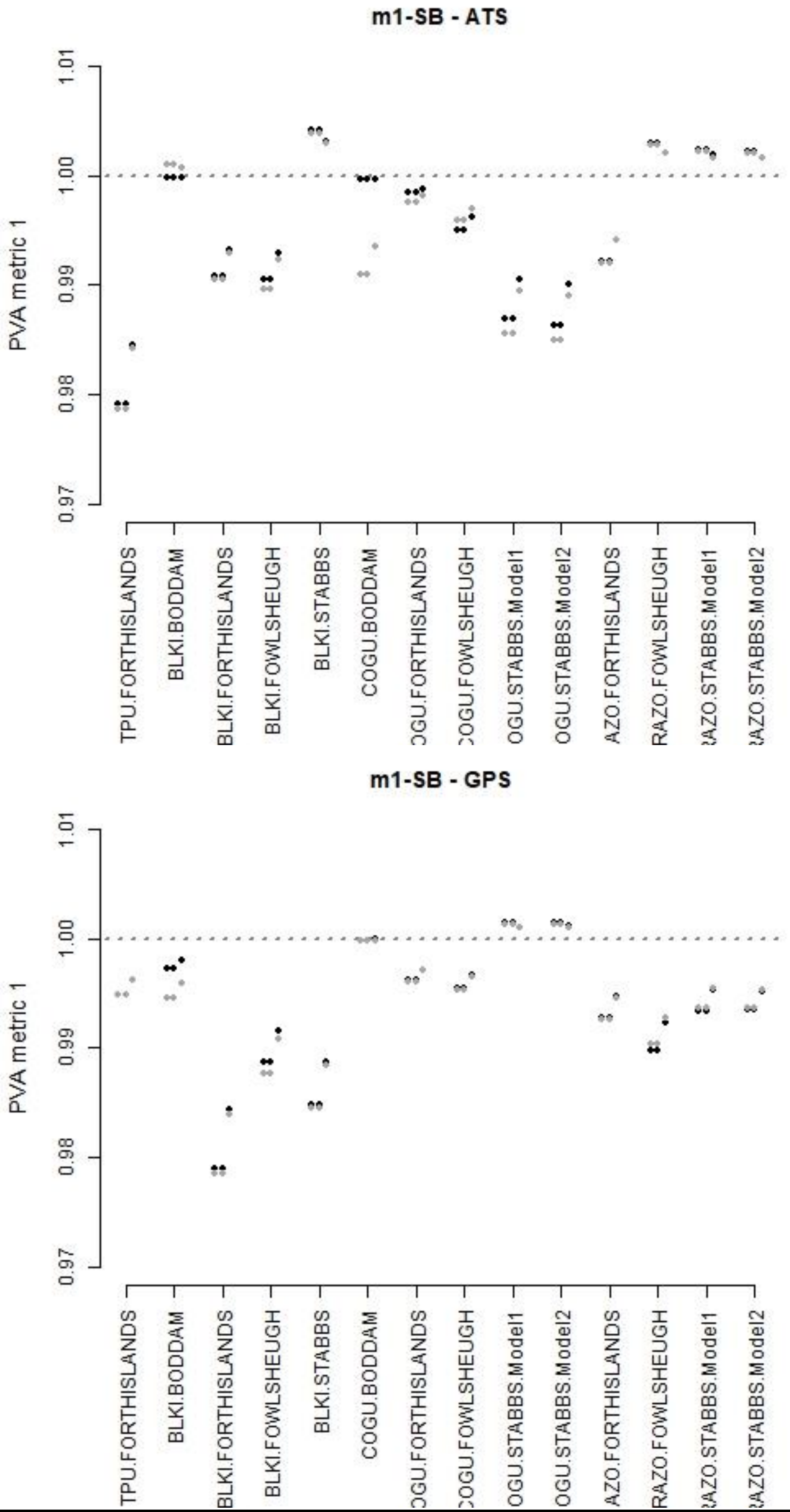
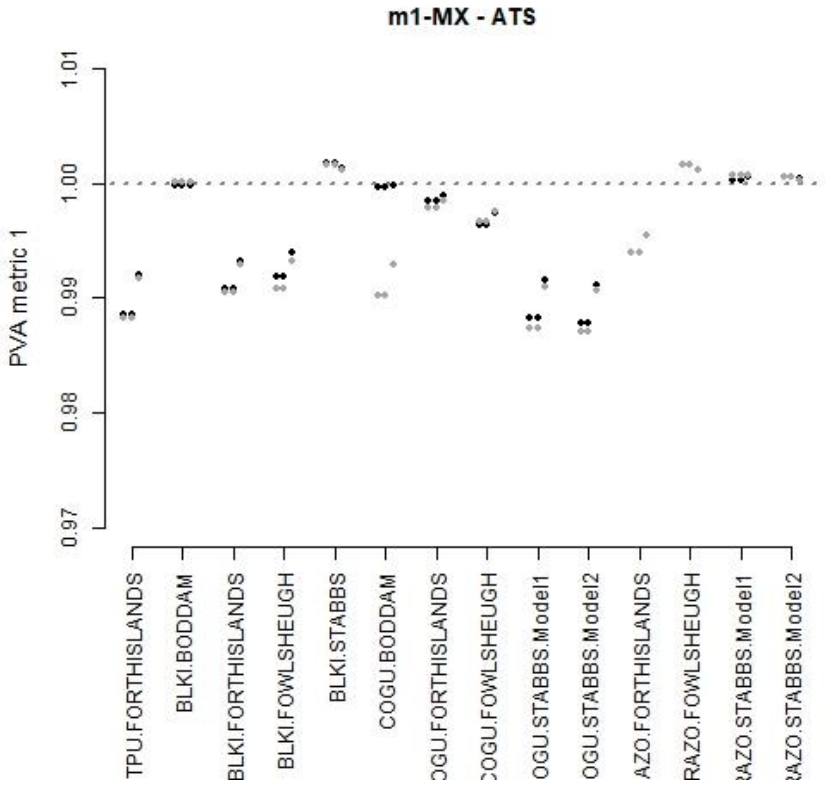


Figure 29. As Figure 28, but with displacement impacts in the breeding season estimated using SeabORD only for adult survival – impacts on juvenile survival are estimated using the displacement matrix. Results are shown for estimates derived from at-sea survey data (top) or GPS tracking data (bottom).



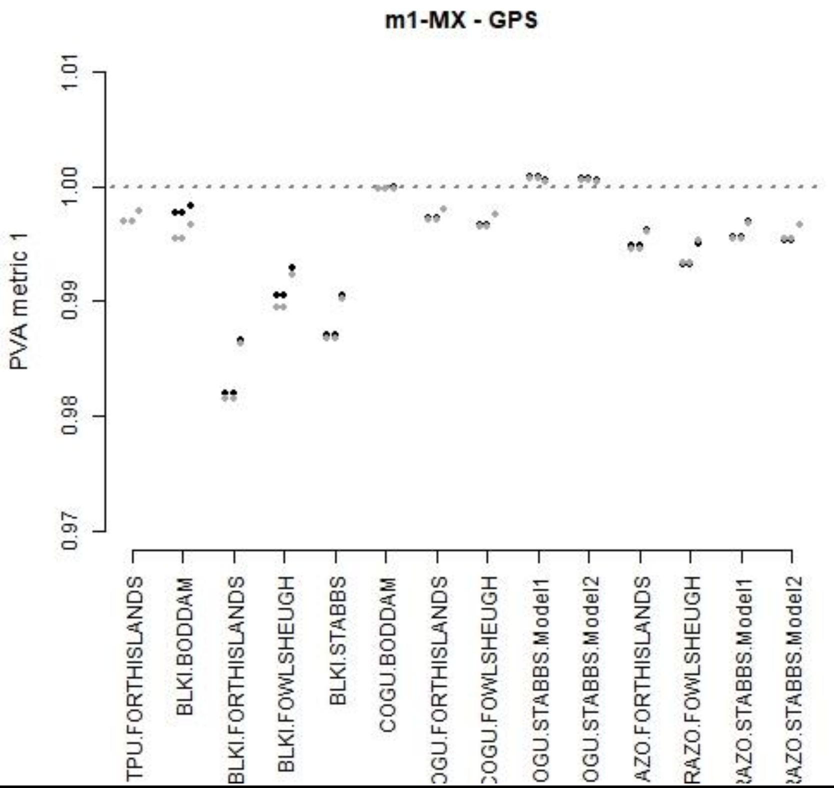
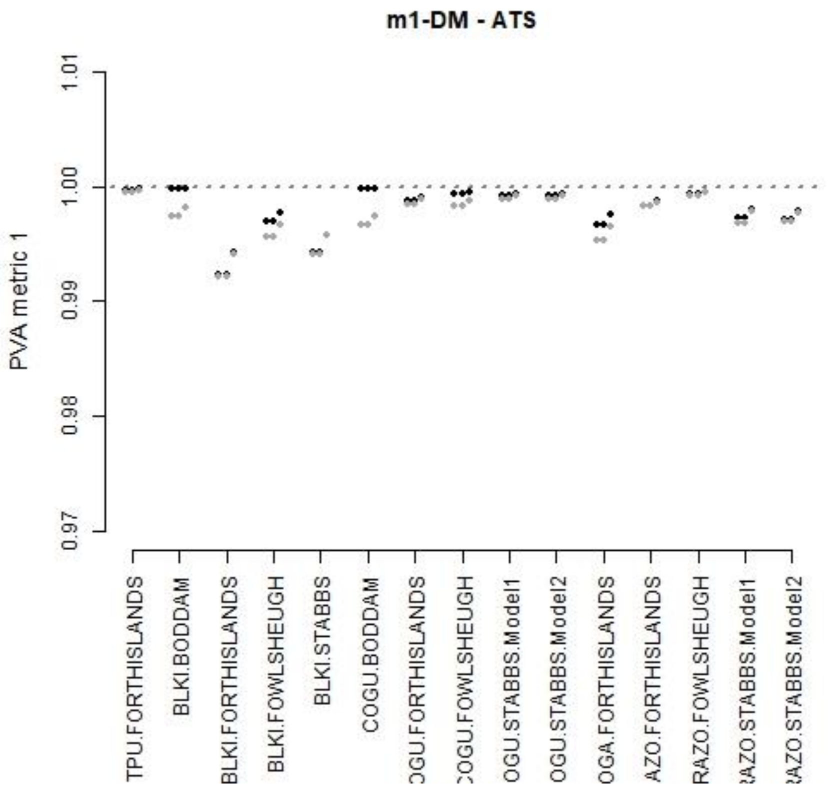


Figure 30. As Figure 28, but with displacement impacts in the breeding and non-breeding season estimated using the displacement matrix. Results are shown for estimates derived from at-sea survey data (top) or GPS tracking data (bottom).



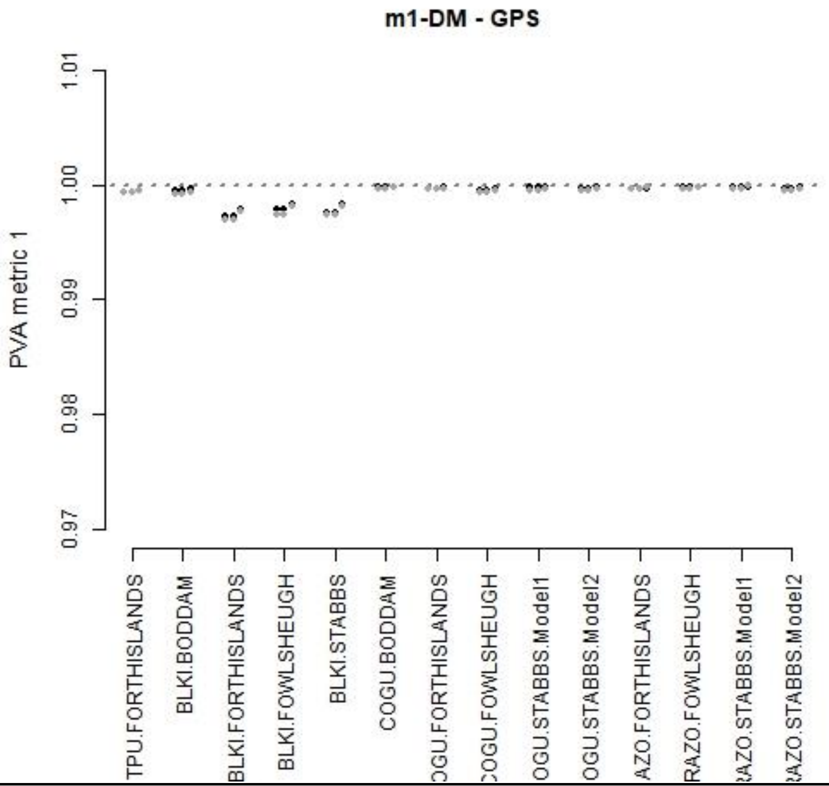


Figure 31. Values of PVA metric 2 (the ratio of the final population size under impacted to baseline scenarios) for each population under each scenario (black = Scenario 2, red = Scenario 3), for years 2045 (left hand value for each population), 2050 (centre) and 2055 (right). This is for values obtained by using SeabORD to quantify displacement impacts on both adult and juvenile survival in the breeding season. Results are shown for estimates derived from at-sea survey data (top) or GPS tracking data (bottom).

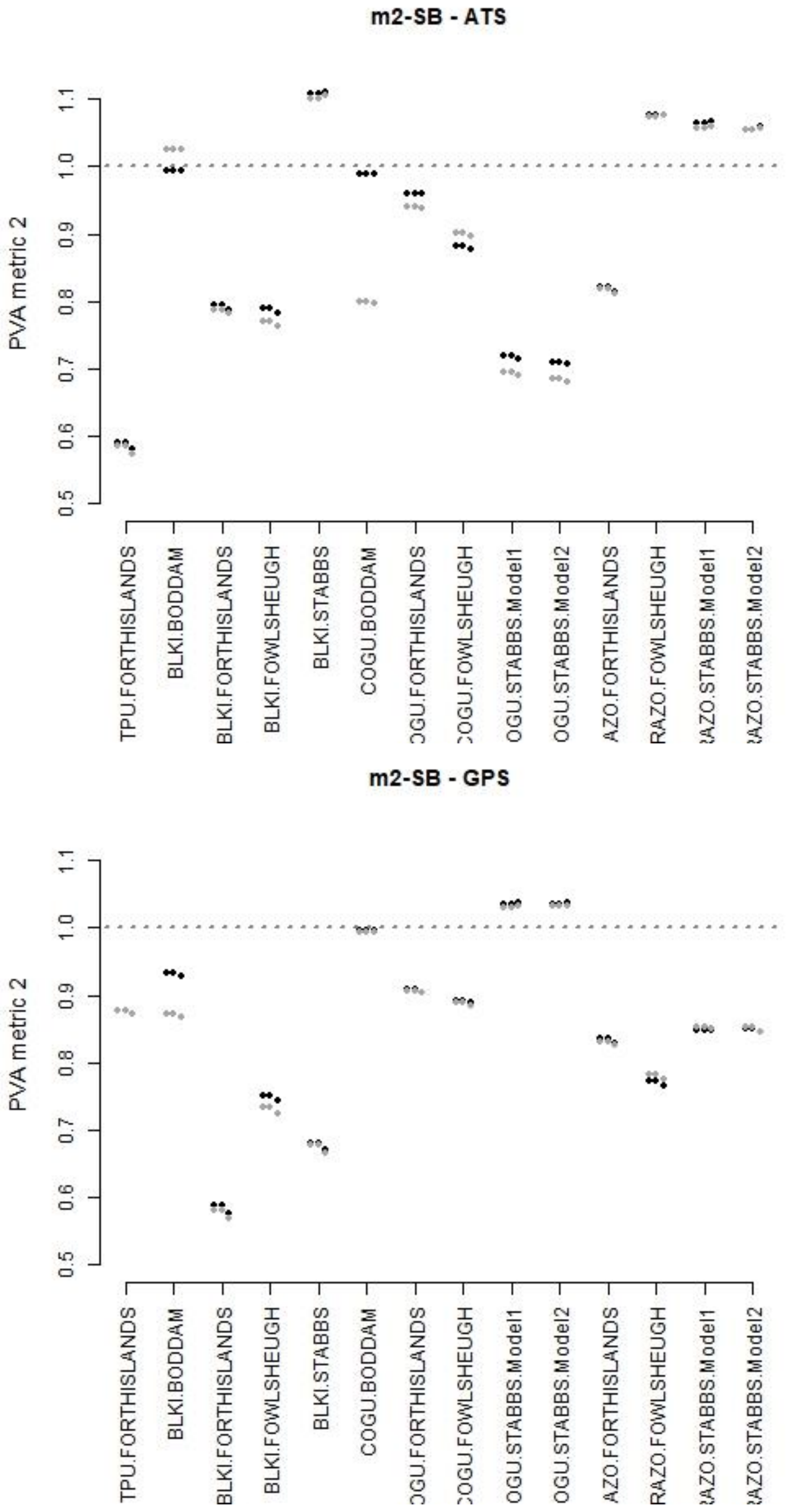


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Figure 32. As Figure 31, but with displacement impacts in the breeding season estimated using SeabORD only for adult survival – impacts on juvenile survival are estimated using the displacement matrix. Results are shown for estimates derived from at-sea survey data (top) or GPS tracking data (bottom).

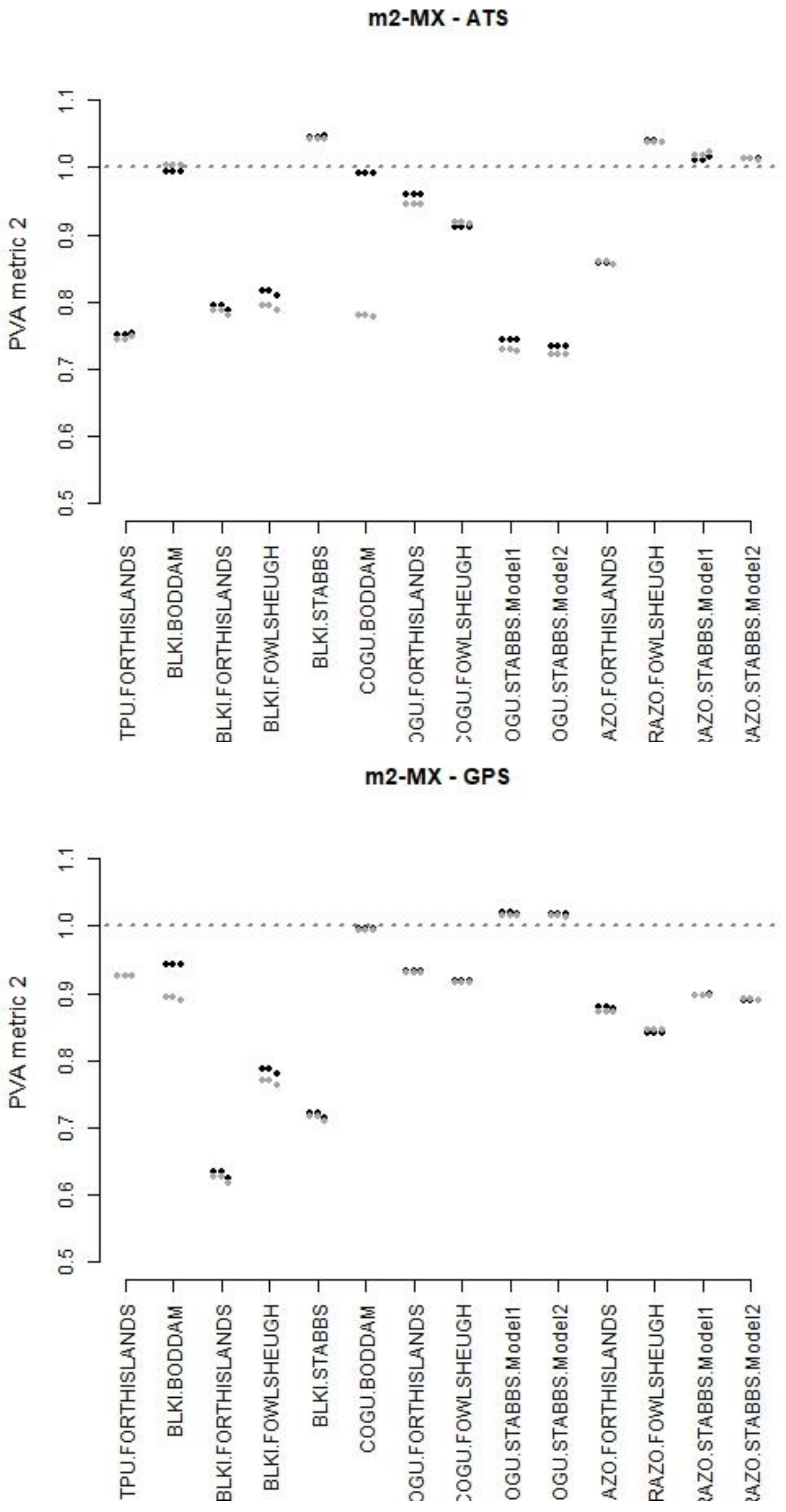


Figure 33. As Figure 31, but with displacement impacts in the breeding and non-breeding season estimated using the displacement matrix. Results are shown for estimates derived from at-sea survey data (top) or GPS tracking data (bottom).

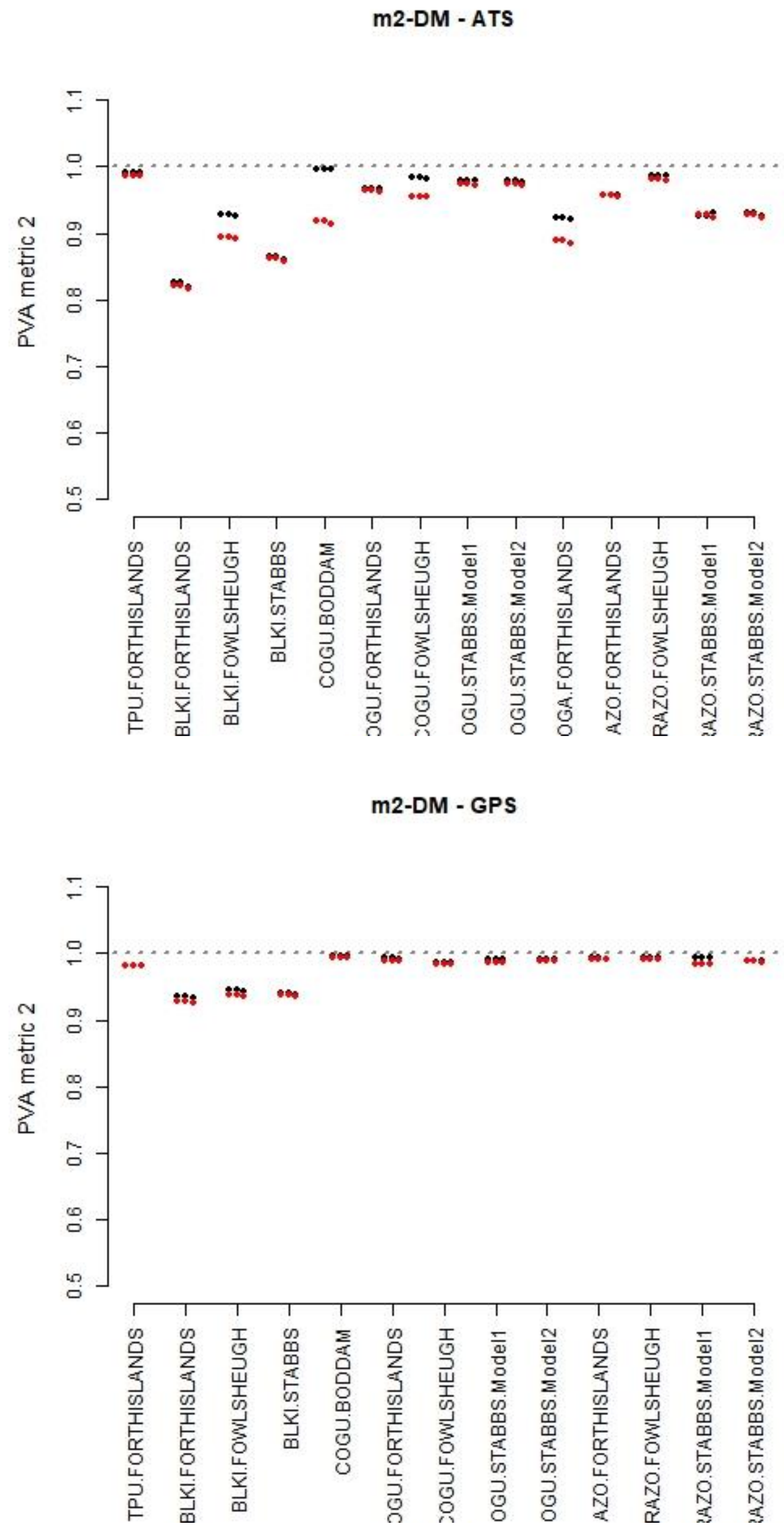
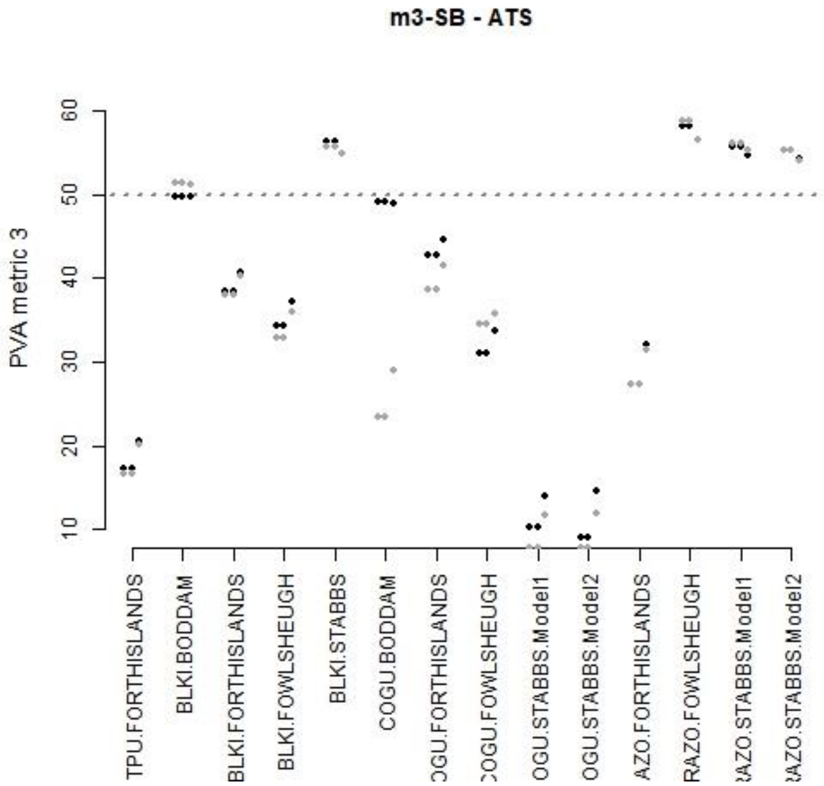


Figure 34. Values of PVA metric 3 (the centile of the baseline associated with the median impacted population size) for each population under each scenario (black = Scenario 2, red = Scenario 3), for years 2045 (left hand value for each population), 2050 (centre) and 2055 (right). This is for values obtained by using SeabORD to quantify displacement impacts on both adult and juvenile survival in the breeding season. Results are shown for estimates derived from at-sea survey data (top) or GPS tracking data (bottom).



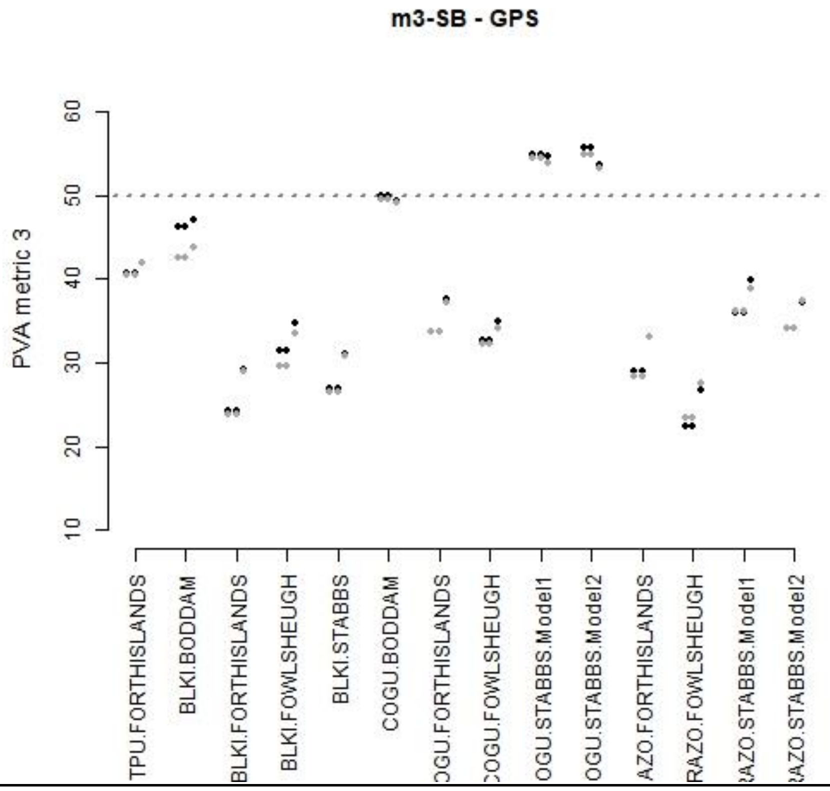
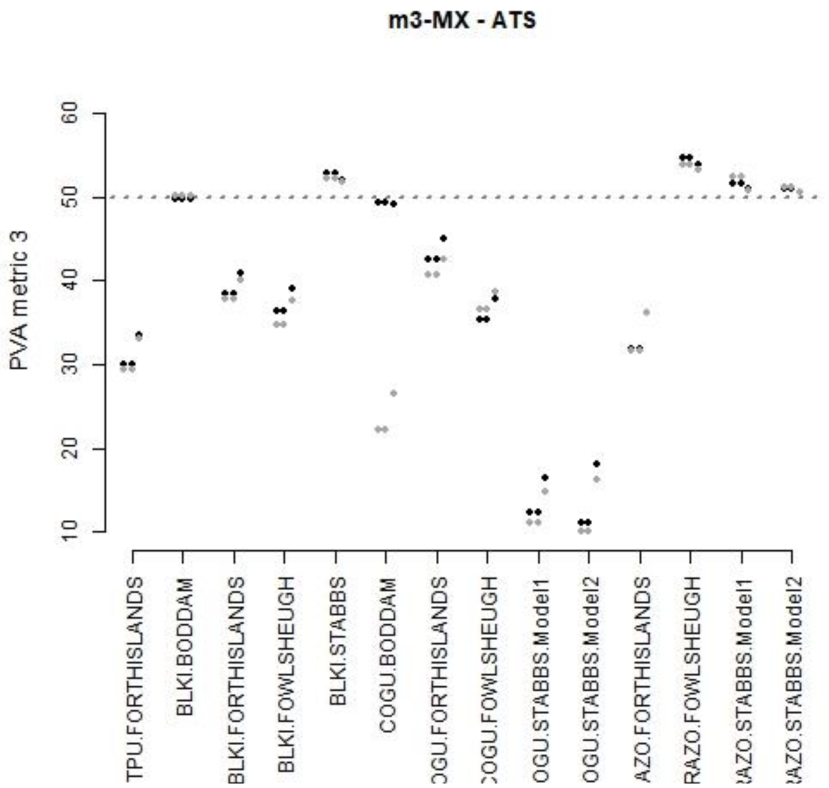


Figure 35. As Figure 34 but with displacement impacts in the breeding season estimated using SeabORD only for adult survival – impacts on juvenile survival are estimated using the displacement matrix



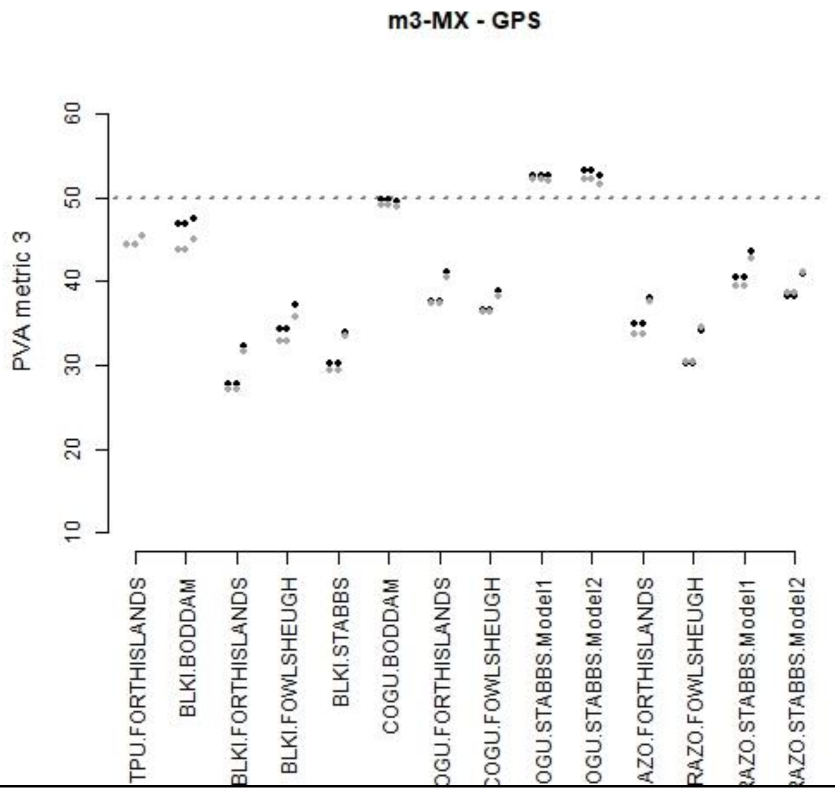
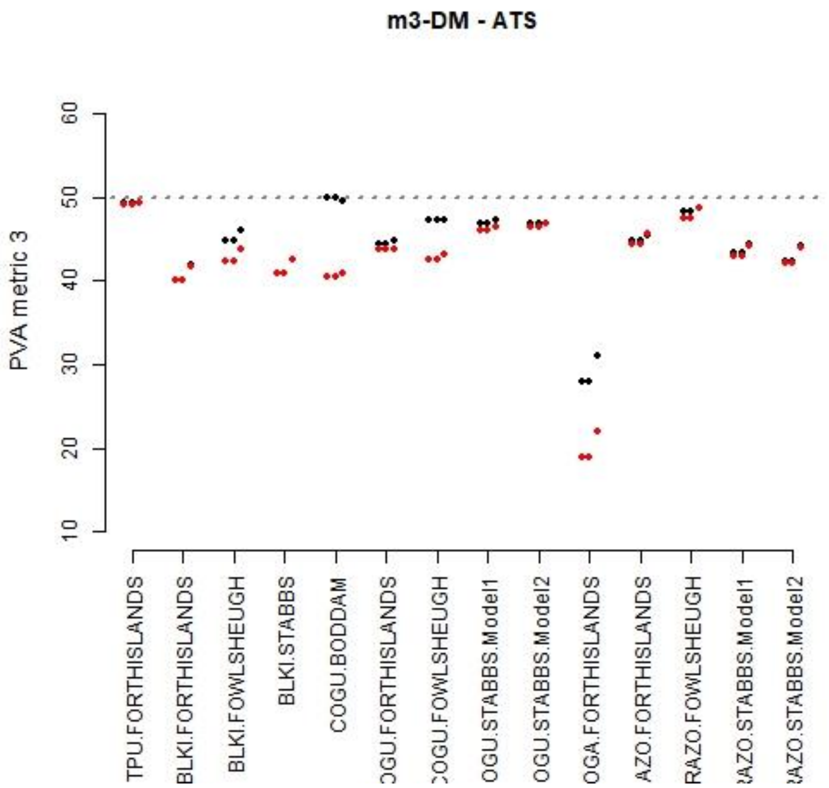
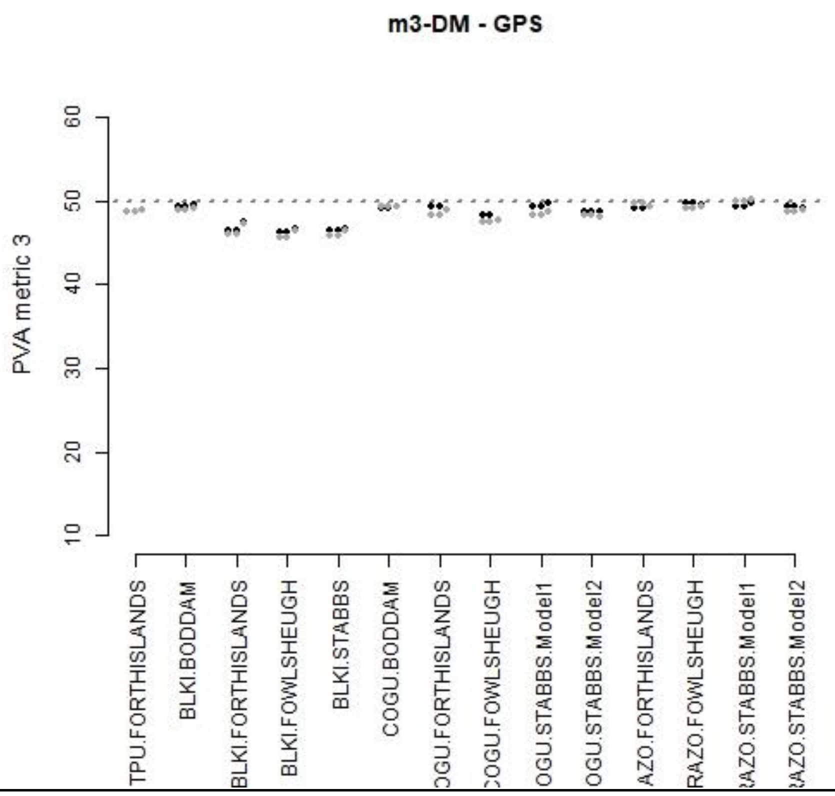


Figure 36. As Figure 34 but with displacement impacts in the breeding and non-breeding season estimated using the displacement matrix





4. Discussion

4.1. Summary of overall framework

The general framework for the regional assessment brings together a series of modelled data sets and tools/models to combine within an overarching assessment framework, producing population level estimates for impacts of different offshore renewable energy development scenarios (37:

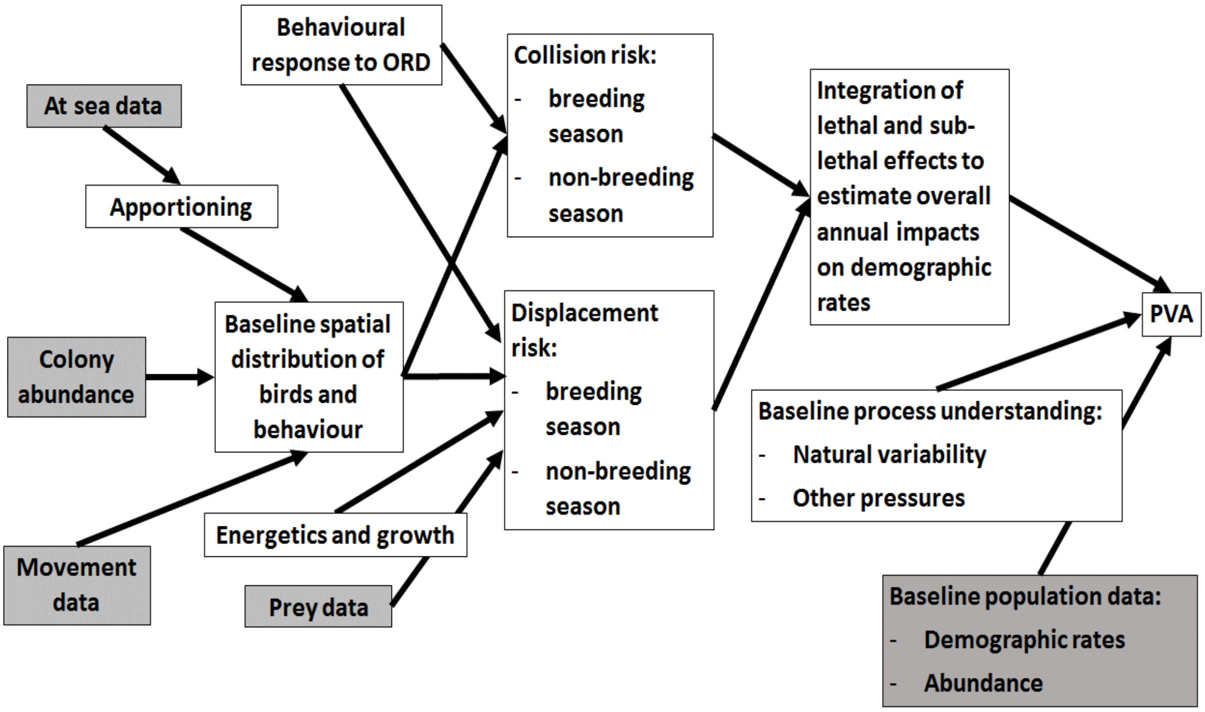


Figure 37. Framework for assessing impacts of ORDs on seabirds.

The primary data driving the outputs from the framework were bird utilisation distributions derived from GPS tracking data, and bird density distributions derived from at-sea survey data. These bird distribution maps were used to estimate bird densities within, and interacting with, the relevant OWF footprints in the two scenarios used in this project. They were the primary inputs for both the displacement (SeabORD and matrix method) and collision (sCRM) effect assessments. In the case of bird density maps from at-sea survey data, this required the use of apportioning methods – SNH apportioning in the breeding season, and BDMPS apportioning in the non-breeding season.

The use of different datasets (GPS tracking versus at-sea) and different assessment methods (SeabORD, displacement matrix, sCRM) with different assumptions regarding effects on demography of different life-stages, allowed us to examine the impacts of these decisions upon final combined impact assessments, manifested within PVA models.

4.2. Summary of results from the Forth-Tay case study

We applied this framework to thirteen seabird populations in the Forth-Tay region, relating to five species and four SPAs, using two scenarios for the construction of hypothetical sets of offshore wind farms.

Estimated effects from both collision and displacement in the non-breeding season were consistently small. This appears to largely be because the BDMPS apportioning method assigns a small proportion of the birds within the footprints to arise from the populations of interest.

Estimated effects for both collision and displacement (for those species where these mechanisms are relevant) in the breeding season were typically larger. The magnitude of effects varied between populations, but also varied depending upon the methods used – the estimated effects derived using maps based on GPS tracking data differed from those derived using at-sea survey data, and the estimated effects using SeabORD were different from (and typically large than) those derived using the "displacement matrix" approach.

The results showed relatively very similar estimated impacts under the two scenarios for most populations, because the two scenarios differed only in the inclusion of a single additional wind farm and birds from these populations were not estimated, using either at-sea survey data or GPS tracking data, to interact with the footprint of this wind farm (Table 10). In situations where birds were estimated to have a substantial interaction with this footprint (e.g. kittiwake and guillemot at Buchan Ness) the differences between scenarios were also substantial.

4.3. Interpretation of results in light of different methods used

Comparison of SeabORD and the displacement matrix

The results show that the annual adult mortality levels from displacement that were estimated by SeabORD often differed substantially from those produced by the Displacement Matrix approach, with estimated effects from the Displacement Matrix Approach often being substantially lower than those obtained using SeabORD.

As outlined in Section 2.6, the key difference between SeabORD and the Displacement Matrix approach lies in the way that the mortality rate for displaced birds in selected. SeabORD calculates this by simulating from a mechanistic model, whereas the Displacement Matrix approach uses values that are based on expert judgement. Within the context of the current project, the choice of this rate is, in effect, the only difference between the two methods (aside from differences in the way uncertainty is treated). We can therefore understand the differences between the two approaches by calculating the "mortality rate for displaced birds" associated with SeabORD, for each species, SPA and scenario, using the formulae given in Section 2.6. In Table 16 we do this, using the outputs from SeabORD derived using GPS-based maps. Note that the "mortality rate for displaced birds" differs from the overall effect on mortality simulated by SeabORD, and is equivalent to the mortality rate used in the displacement matrix for the Matrix approach - as such, it only applies to individuals that are vulnerable to displacement. As the baseline distribution maps, and displacement rates, were taken to be the same within this project for both SeabORD and the Matrix approach, differences between the two approaches arise solely from differences in the value of "mortality rate for displaced birds" that they use.

We see from Table 16 that "mortality rates for displaced birds" calculated using SeabORD are typically much higher than the corresponding mortality rates for displaced birds within the Displacement Matrix approach. The rates estimated by SeabORD are based on the latest available data and understanding of the ecology of seabirds, whereas the values used in the Displacement Matrix are based on expert judgement, largely originating from a workshop held in 2015 (JNCC, 2015) and summarised in a Joint SNCB Advice Note (SNCB, 2017). As such, the rates from SeabORD are more readily defensible. Accordingly, a key priority for future work is to use the SeabORD-derived rates to revise the mortality rates for displaced birds used in future use of the Displacement Matrix (so that SeabORD would be used to quantify the effect of displacement; the probability of displacement occurring – i.e. the displacement rate – would still be calculated as at present).

Table 16. Mortality rates for displaced birds (percentage point additional mortality for birds that are in the footprint and are displacement-susceptible) for each population under each scenario, as derived using SeabORD and expert judgement (Table 7).

Species	SPA	Mortality rate of displaced birds (as %point impact)						
		SeabORD						Expert judgement (JNCC, 2015; SNCB, 2017)
		Scenario 2 (mean, lower 95% CI, upper 95% CI)			Scenario 3 (mean, lower 95% CI, upper 95% CI)			
Kittiwake	Forth Islands	13.0	2.7	23.3	12.6	5	20.2	2.0
	Fowlsheugh	8.7	1.3	16.2	7.3	2.1	12.3	
	St. Abbs	10.9	1.0	21.2	10.0	0.4	19.8	
Guillemot	Buchan Ness	0.2	-6.7	7.0	0.1	-6.3	6.5	1.0
	Forth Islands	7.2	2.7	11.9	7.1	2.4	11.7	
	Fowlsheugh	3.8	2.7	4.9	3.8	2.6	5.0	
	St. Abbs	-2.7	-5.6	0.1	-2.7	-5.6	0.1	
Razorbill	Forth Islands	13.9	7.3	20.1	14.5	9.8	19.4	1.0
	Fowlsheugh	13.6	6.8	20.5	11.2	4.3	18.8	
	St. Abbs	6.2	3.4	9.1	5.9	2.3	9.5	
Puffin	Forth Islands	4.8	1.5	8.3	4.8	1.5	8.3	2.0

GPS vs at-sea survey data

We found marked differences in the effect sizes dependent on whether the underlying distributions were based on GPS or at-sea survey data. In general, we would expect bird utilisation distributions estimated from GPS tracking data (Wakefield et al. 2017) and from at-sea survey data (Waggitt et al. *2019*) to differ from one another for a number of reasons.

Biological reasons include differences between the breeding status of individuals in the different datasets; at-sea surveys contain counts of all birds (breeding and non-breeding), whilst GPS tracking is restricted to breeding adults in most cases. The distribution of all birds may at some locations differ markedly from those of breeding birds. In particular, the less marked decline with distance from colonies and higher densities at some locations further offshore in the at-sea survey maps that are not apparent in the GPS maps may occur if non-breeding birds are less strongly associated with colonies and accessing resources that are too distant from colonies to be profitable to breeding birds. This process in large parts explains why we typically found larger effects from at-sea survey than GPS-based data – when foraging ranges were sufficiently large as to overlap with ORD footprints, at-sea survey density estimates tended to be higher resulting in more birds interacting with the ORD. Within SeabORD, this could lead to a potential overestimate of the effect on demographic rates, because SeabORD is designed to model only breeding birds, not non-breeding birds whose behaviour may differ in important ways, such as a relaxation of central place foraging due to not needing to provision for offspring.

Differences in distribution from the two methods may also arise because the habitat utilisation models underlying the two types of data use different environmental covariates. Data collection methods may also explain differences between the two distributions. At-sea survey data typically encompass a much longer time period (set of years, and span of dates within years) than GPS tracking data, thereby potentially capturing more year to year variation in bird densities. However, at-sea survey data are subject to weather and diurnal bias, with data typically only collected under good weather conditions and in daylight, compared to GPS tracking data that are collected in a broader range of weather conditions and across all hours of day.

4.4. Uncertainty

Spatial distribution of birds

The key inputs to the impact calculations were spatial maps that quantified the relative spatial distributions of birds, and separated these distributions by different periods of the year and by different modes of behaviour. These maps were derived from two distinct sources: at-sea survey data, and GPS tracking data. The spatial distributions derived from GPS tracking data already related to specific SPAs; those derived from at-sea survey data are apportioned to SPAs using either the SNH apportioning tool (in the breeding season) or BDMPS apportioning (in the non-breeding season).

Within this project, we have not attempted to quantify the uncertainty associated with the maps derived from GPS tracking data, because the methods that we have used for modelling these data (GAMs) do not readily allow uncertainty to be quantified in a defensible way. The models do produce estimates of uncertainty, but these models ignore the strong temporal correlation within the data, and ignore variation between individuals, and so are liable to yield substantial underestimates of the true uncertainty – we therefore do not regard them as reliable. It would be possible in future to produce reliable estimates of uncertainty – the most obvious way to do this would be by using alternative, more sophisticated, methods to model the GPS tracking data. The methods we would envisage using for such a purpose are movement models, which automatically account for the spatial and temporal structure of the data and account for variation between individuals. There are a number of computational and statistical challenges in applying biologically plausible movement models to large-scale seabird GPS tracking data, however, so this would be a substantive piece of work. Another possibility would be to try to calculate more defensible estimates of uncertainty within the existing maps using some form of bootstrap procedure – the approach used to deal with correlation within MRSEApower could be a starting point, but it is unclear without further work whether this approach could defensibly be applied to GPS tracking data.

We have, by contrast, attempted to quantify the uncertainty associated with the maps derived from at-sea survey data, although these uncertainty estimates should still be treated with considerable caution. Uncertainties within the underlying maps were quantified using a bootstrap procedure (Waggitt et al. 2019). The SPA-specific maps derived from at-sea survey data was uncertain not only because the underlying maps are uncertain, however, but also because the proportions of birds that can be attributed to each colony, at each point in space, are unknown. A second stage of bootstrapping was used to partially quantify the uncertainty associated with apportioning: this only focused on the breeding season, however (since we could not see a way to quantify uncertainty within the BDMPS apportioning proportions, which are used to apportion in the non-breeding season). Even within the breeding season, this second stage of bootstrapping only deals with one aspect of uncertainty – the value of the foraging range for each colony – and does not account for uncertainty in the form of decay of bird density with distance, or for the impacts of environmental heterogeneity upon the apportioning proportions. Despite these caveats we feel that the uncertainty estimates associated the at-sea survey maps have value, because they have captured two important, and typically large, sources of uncertainty.

Impacts upon annual demographic rates

The individual based simulation model, SeabORD, only partially accounts for uncertainty in parameters and inputs. The majority of the parameters within SeabORD use empirically estimated mean values, and although multiple simulations are run to estimate impacts, the primary source of uncertainty that these multiple simulations account for is uncertainty in the levels of prey in the system, not uncertainty in individual model parameters, such as bird growth rates or the mass-survival relationship.

Where possible, model parameters have both a mean and standard deviation derived from empirical data, and for each individual simulated bird, the value of these parameters used within calculations are drawn from a distribution derived from these quantities. Therefore, some of the uncertainty in these model parameters is accounted for through variation in processes across individuals.

The SeabORD prediction intervals represent the uncertainty that arises from trying to predict what will occur within a finite population in a system that is subject to inherent stochastic variability, together with the uncertainty associated with determining the overall level of prey and what constitutes moderate conditions in terms of prey availability. The latter tends, in practice, to be a much larger source of uncertainty than the former. It is crucial to note that the intervals do *not* account for any other sources of uncertainty: e.g., for the uncertainty associated with estimating model parameters, for the uncertainty associated with the underlying structure of the model, for the uncertainty associated with the spatial distribution of birds, or for the uncertainty in the translation of end of season masses into subsequent overwinter adult survival. Because a number of these other sources of uncertainty – in particular the uncertainty in the adult mass-survival relationship – are likely to be large, the prediction intervals associated with SeabORD output should be treated with caution, and regarded as *lower* bounds on the actual level of uncertainty.

Population Viability Analysis

Aside from the uncertainties that we have already discussed, the production of a PVA also involves quantifying uncertainty and variability in baseline demographic rates. The approach that we use for producing the PVAs follows that of Freeman et al. (2014) and Jitlal et al. (2017): this essentially accounts for uncertainty (but not variability) in juvenile survival, and for variability (but not uncertainty) in adult survival and productivity. The estimation of variability in the latter rates assumes independence between years, which is likely to be a biologically implausible assumption, which is liable to lead to underestimation of overall uncertainty in projections of future population sizes (Searle et al. 2019). This underestimation is likely to be considerably offset, however, by the fact that the PVAs account for uncertainty in juvenile survival, which will usually be the demographic rate that has least empirical support. This is likely to explain why the PVAs produced by Freeman et al. (2014) and Jitlal et al. (2017) led to considerably higher levels of uncertainty than those produced by stochastic Leslie matrix models (which account for variability, but do not account for uncertainty in any demographic rate estimates).

4.5. Broader application of the framework

We have developed a conceptual framework for undertaking assessments, and have applied this framework to a specific case study involving two scenarios for the construction of hypothetical wind farms within the Forth-Tay region. The results, and some of the specific choices made in relation to data selection and model fitting, are specific to the case study, but the underlying framework has very broad applicability. In this section, we outline how the framework could be applied more generally. In particular, the Forth-Tay is a very data-rich region, so the key focus here is upon how the framework could also be applied in other regions, where less local data are available.

There are four basic components to the framework: the specification of baseline spatial distributions; the calculation of annual effects on demography; the conversion of these into longer-term impacts; and the quantification and visualisation of the uncertainty associated with this process.

Baseline spatial distributions

Baseline spatial distributions can either be estimated using maps derived from at-sea survey data or maps derived from GPS tracking data. In either case, these maps can be derived from local data, relating to the region of interest, or from data products that have been constructed using data from a much wider spatial area (e.g. the ORJIP Seabird Sensitivity Mapping Tool). The key advantage of the latter products is that they can be applied to any population, regardless of local data availability, but maps derived from local data will typically be more data-driven and hence rely upon fewer biological assumptions. Therefore, in situations where extensive local data are available these will typically be more defensible than the use of products such as the ORJIP Seabird Sensitivity Mapping Tool.

In general, local GPS tracking data provide the most defensible basis for running assessments, in situations where extensive local GPS data are available, but will have less applicability as it is only a proportion of populations for which this is the case. In contrast, local at sea survey data and general tools based upon data for a broad spatial scale (e.g. the ORJIP Seabird Sensitivity Mapping Tool) all have limitations, in terms of defensibility, but are broadly applicable. The key issues in using local at sea survey data are (a) that they need to be apportioned to SPAs, and the current methods for doing this in both the breeding season (the SNH Apportioning Tool) and non-breeding season (BDMPS) have relatively low levels of defensibility and (b) they cannot be used in conjunction with SeabORD. The at-sea maps within the ORJIP Sensitivity Mapping tool do not have the latter limitation (as they cover a sufficiently broad spatial area that they can be used to estimate the entire utilisation distribution for each breeding colony, as required by SeabORD), but do still have the former limitation. In contrast, the GPS-based maps within the ORJIP Sensitivity Mapping Tool apportion birds to colonies in a relatively defensible way (as they derive this empirically), but lack the ability to separate flying and non-flying behaviours, a feature that is of key importance in determining collision risk.

Estimating displacement and collision effects

The second component of the framework involves calculating annual effects associated with collision and displacement. In the UK the Band (2012) collision risk model has been adopted as the standard for collision risk assessments. This model is deterministic in its original incarnation, but can be made stochastic with randomly generated input values. An official stochastic version of the model which performs this has recently been developed (MacGregor et al. 2018) and it was planned to use this to estimate collision risk for this project. As noted above, this did not prove possible due to technical errors identified during the project (which are being addressed) and hence a stochastic implementation of Band, developed by MacArthur Green, was utilised instead. It is important to note, however, that irrespective of the programme used (e.g. Excel or R) the results were derived using the Band model equations, albeit for this project they were not calculated using the original spreadsheet. Displacement effects in the breeding season can either be calculated either using a mechanistic model (SeabORD) or by specifying an impact rate based upon expert judgement (as in the current version of the “Displacement Matrix” approach). Both approaches require a “displacement rate” – i.e. the proportion of birds that are susceptible to displacement – to be specified, and allow uncertainty in this rate to be accounted for. SeabORD should provide more defensible estimates of effects on demographic rates than those based on expert judgement, as the latter were based on extremely limited empirical data, but SeabORD is currently only parameterized for four species (kittiwake, razorbill, puffin and guillemot). SeabORD has previously only been run using baseline maps derived from GPS tracking data, but we have demonstrated in this project that it can also be run using maps derived from at-sea survey data. Because it requires a map of the entire utilisation distribution associated with a breeding colony it cannot, however, be run using maps derived from the at-sea survey data that are typically collected prior to construction of a wind farm, as these typically only cover a relatively limited spatial area (e.g. the area around the ORD footprint). SeabORD is currently only available for the breeding season, so effects on rates in the non-breeding season can only currently be based on expert judgement.

Population Viability Analysis

The third component of the framework involves translating annual effects into longer-term impacts via Population Viability Analysis (PVA). PVA methods are based upon Leslie matrix models; the PVA models that we have used here are based upon baseline demographic rates that have been tuned to local abundance data in a way that accounts for the uncertainty involved in tuning, using Bayesian state space models (Freeman et al., 2014; Jitlal et al., 2017). In situations where a reasonable time series of local abundance data exist we recommend this as the preferred approach for running PVAs (Searle et al. 2019a); in other situations (e.g. where local abundance data are very limited) we recommend using stochastic Leslie matrix models (Searle et al. 2019b), but interpreting the results carefully, given their apparent tendency to underestimate uncertainty (Searle et al. 2019a).

Quantification of Uncertainty

The final component of the framework involves the quantification of uncertainty, and the visualisation and use of the resulting uncertainty estimates. We have quantified uncertainty within the components where defensible uncertainty estimation is currently possible (e.g. not within the GPS-based maps).

We quantify uncertainty within the entire process by propagating uncertainty between the different components using a simulation-based approach. This simulation-based approach has been implemented within a free, open source programming environment, and the approach can be used regardless of the specific data sources and models used within each component of the assessment process, although the defensibility of the resulting uncertainty estimates will depend upon the defensibility of the uncertainty estimation within each individual component.

We have focused upon developing a framework for quantifying effects, and the uncertainty associated with these effect estimates. The use of the outputs, and uncertainty estimates, within decision-making is beyond the scope of this project, and additional work is needed to develop visualisation tools that can be used to present the results of the assessment in a way that provides the maximum utility for decision making.

4.6. Future work/recommendations for research and data collection

This project has identified a number of important priorities for future research:

- A future framework should account for birds seen at sea that are from colonies outside the UK that admix with UK seabirds and overlap with UK wind farms, particularly outside the breeding season. A useful source of data are the current projects funded by SEATRACK, Vattenfall and Equinor that have collected year-round tracking data on hundreds of individuals from multiple colonies and species from the UK to Russia based on geolocation technology.

- The individual based simulation model, SeabORD, should be used to revise mortality rates used in the displacement matrix, and to quantify the uncertainty associated with these rates. This would require running SeabORD across a comprehensive range of species, populations and footprint characteristics in order to provide a representative set of estimates to use within the displacement matrix. We envisage that a statistical model could then be built to link the estimated mortality rates for displaced birds to the characteristics of the footprint and population, in order to produce a straightforward basis for predicting the mortality rate for displaced birds for a new population and footprint(s) without needing to re-run SeabORD, This means that SeabORD could be used to support the estimation of rates even in contexts where it is challenging (e.g. due to a lack of available data) to directly run SeabORD.

- There are several components within the individual based simulation model, SeabORD, that could be improved to provide more precise estimates of impacts, with more full quantification of uncertainty:
    - Better quantification of uncertainty in model parameters, for instance using Bayesian calibration methods for large process-based models
    - Incorporation of recent estimates of uncertainty in the mass-survival relationship for 4 species, derived from the recent MSS research project (Daunt et al. 2019).
    - An adaptation to allow foraging birds to increase their foraging range when encountering barrier or displacement effects from OWFs at the edge of their foraging range
    - Improvement of model simulation for flight paths and foraging trips
    - Temporal expansion to include periods of the breeding season other than chick-rearing (e.g. incubation), and to include the non-breeding season.

- Improvements to the calculation of apportioning proportions within both the breeding and non-breeding season would be valuable. Within the breeding season, improvements to the SNH apportioning method to try to ensure that the decay with distance reflects the relation seen in real data would be beneficial. There would also be value in more widespread use of the MSS Apportioning Tool (which is based on GPS tracking data), and in extending this tool to include more species (it is currently only available for four species – guillemot, kittiwake, razorbill and shag). Within the non-breeding season it would be beneficial to improve upon the current BDMPS approach for relevant species. Again, the GLS tracking projects would be provide useful input data on distribution outside the breeding season of individuals of known colony origin across north-western Europe.

- Use of novel statistical methodologies could better estimate uncertainty in bird distributions and densities. The approach to the analysis of GPS tracking data that we have used here follows that of Wakefield et al. (2017) and other recent work in applying static statistical models to tracking data. A more conceptually appealing approach, which would readily allow a proper assessment of uncertainty, would be to construct movement models (i.e. spatio-temporal models) that describe the trajectories of birds in time as well as space. Such models have already been developed, but their application to large multi-colony datasets has not been undertaken and would still be a substantial challenge.

- The reasonably large differences between the maps produced by GPS tracking data and at-sea survey data are rather difficult to interpret, and further work is needed to better understand and model these differences, and to develop methods that integrate both sources of data to estimate the underlying map of the behaviour-specific spatial distribution of birds. Integrated Population Models provide a general framework for estimating a common underlying process using multiple different data types, and there is potential to apply these methods to this problem.

- We recommend research into better quantification of some of the key processes used within PVA models, such as correlation in demographic rates (adult survival, juvenile survival and productivity), the presence and strength of density dependence within populations, and exchange of individuals among populations and its implications on meta-population dynamics. We also recommend that research be undertaken to facilitate assessments of climate effects and other pressures on population demography to allow for inclusion of multiple pressures within PVA projections.

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Appendix A - Methodology for deriving maps from GPS tracking data

The methodology used is a simplified and modified version of that used in Wakefield et al. (2017), and an updated and modified version of that used in Searle et al. (2014). The basic approach involves, as in Wakefield et al. (2017):

a) pre-processing the GPS tracking data;
b) generating a set of "control" points; and
c) using logistic regression (Binomial) models to compare "cases" (GPS tracking data locations) against "controls" in relation to a range of potential explanatory variables;
d) using the final model for each species to generate predicted maps of spatial distributions for each colonies (rescaled so that the maps sum to one), including both colonies with GPS tracking data and those without

Within this framework, we follow Wakefield *et al.* (2017) in using a two-stage approach, but modify and simplify the second stage of this approach:
Stage 1: fit a "null model" - a Poisson GLM which contains the following explanatory variables: "colony" (a categorical variable), "biological distance to colony" (a numeric variable), "cumulative area of sea" (a numeric variable), and the interaction between "colony" and "cumulative area of sea". The predictions generated by this model are used to calculate an index of parapatric competition (Wakefield *et al.*, 2017).
Stage 2: fit a Poisson GAM which contains the same explanatory variables as the GLM in Stage 1, plus, additionally:

- log(index of parapatric competition), as calculated in Stage 1
- a non-parametric geographical smoother

This model is fitted in R using the **mgcv** package, with the **bam** function.
A technical description of the steps involved in preprocessing and applying this method, and how these differ from those in Wakefield et al. (2017), is given in Table A1.

Comparison to previous work
This approach is similar to that used by Searle et al. (2014) in assessing displacement risk from ORDs to SPAs in the Forth-Tay using an early version of the SeabORD model. The essential features of our approach to estimating bird distributions are unchanged from that work:

(a) it is based on a generalized additive model (GAM);
(b) birds from all target colonies are modelled simultaneously within a single statistical model;
(c) the model accounts for accessibility (distance to colony) and parapatric (inter-colony) competition effects by including specific variables relating to these mechanisms as explanatory variables in the model;
(d) the model assumes that environmental, colony-independent, effects, can be captured using a spatial smoother in geographical location, where the degree of smoothing is determined automatically via a form of cross-validation;
(e) the model uses a fixed effect for "colony" to adjust for overall differences in abundance between colonies;
(f) the models are fitted in R, using the **bam** function within the **mgcv** package.

Statistical methods for analysing spatial ecological data have progressed considerably in recent years, however, and we have updated our methodology to reflect recent technical developments. More specifically, we have updated the methodology to reflect, where appropriate, the approach used in the landmark paper of Wakefield *et al*. (2017), which produced a predictive model for the spatial distribution of four seabird species (kittiwake, guillemot, razorbill and shag) within UK waters using state-of-the-art statistical methods. We have revised our approach in the following ways, to improve defensibility and link more close to the work of Wakefield et al. (2017):

(1) we have moved from a binomial case-control model to a Poisson approximation to a point process model, as recent literature (Warton & Shepherd, 2010) suggests that there are conceptual reasons to prefer the latter approach, and because this is the approach adopted by Wakefield *et al*. (2017). The two modelling approaches are asymptotically equivalent (up to a constant of proportionality), and so will hopefully yield similar results in practice.

(2) we have changed from calculating "distance to colony" as the distance by air, to being the distance by sea, given that the seabird species being considered here do not typically fly over land (Wakefield *et al*., 2017).

(3) we include "cumulative area of sea" as an additional explanatory variable in our models, and include the interaction between this and "colony", since Wakefield *et al*. (2017) found both the variable itself and the interaction to be important (i.e. to improve predictive performance) for all four of the species they modelled;

(4) we use the index of parapatric competition developed by Wakefield *et al*. (2017), rather than the simpler and cruder variable ("distance to nearest other colony") that we considered as an index of parapatric competition in our earlier work;

(5) the geographical smoother is applied to coordinates in an equal-area projection, rather than longitude and latitude, since there are technical reasons to prefer smoothing simultaneously across variables that have the same units.

The differences from Wakefield et al. (2017) lie in the explanatory variables that are considered, and in how model selection is performed. The key difference is that Wakefield et al. (2017) attempted to relate the spatial distribution to a range of potential explanatory variables relating to environmental conditions – i.e., they perform habitat association modelling. We focus upon a much smaller spatial area and set of colonies, and so there is both less rationale for using habitat association modelling (as the environmental gradients will be less pronounced within this much smaller spatial area) and less need to do so (within the national scale analysis of Wakefield et al., 2017, only a small proportion of breeding colonies have GPS tracking data; within the Forth-Tay region, by contrast, most breeding colonies have GPS tracking data). We therefore replace the environmental variables within the model by a nonparametric, smooth, function of spatial location – this means that we fit our final model as a Generalized Additive Model (GAM) rather than as a GLM. We construct the model in a hierarchical way, as in Wakefield et al. (2017), but our approach is much simpler, and involves far fewer models, because we do not attempt to separate out the effect of specific environmental variables.

Table A1. A detailed description of the steps involved in deriving SPA-specific maps of spatial distribution from at sea tracking data, via: (a) the approach used in this project, and (b) the predictive modelling approach of Wakefield et al. (2017).

Stage		**Description**	**This project**	**Predictive models e.g. Wakefield et al. (2017)**
Stage 1: Data pre-processing	Stage 1.1	Clean GPS data	Yes	Yes
	Stage 1.2	Calculate foraging range	Yes	Yes
	Stage 1.3	Pre-process GPS data (interpolate, filter)	Yes	Yes
	Stage 1.4	Re-project coordinates to target projection system	Yes	Yes
Stage 2: Data assembly	Stage 2.1	Calculate biological distance and cumulative area	Yes	Yes
	Stage 2.2	Create basic dataset to use for modelling	Yes	Yes
Stage 3: Add auxiliary data	Stage 3.1	Create nest density variables	No	Yes
	Stage 3.2	Create environmental grid	No	Yes
	Stage 3.3	Append environmental variables to modelling data	No	Yes
Stage 4: Use null model to derive parapatric competition	Stage 4.1	Model selection for "null" model	No	Yes
	Stage 4.2	Fit final "null" model and generate local predictions	Yes	Yes
	Stage 4.3	Calculate competition variable	Yes	Yes
	Stage 4.4	Append competition variable to datasets	Yes	Yes
Stage 5: Main modelling	Stage 5.1	Model selection for "final" model	No	Yes
	Stage 5.2	Fit final "final" model and generate local predictions	Yes	Yes
	Stage 5.3	Generate global predictions	No	Yes
	Stage 5.4	Parametric bootstrap	No	Yes
	Stage 5.5	Plot cross validation results	No	Yes

Appendix B - Technical definition of PVA models used in the IPM

The PVA model associated with the SIPM developed by Freeman et al (2014) and Jitlal et al (2017) is of the form:

$$N_t bN_t = n_t + m_t$$
$$n_t \sim \text{Poisson}\,(N_{t-1} bN_{t-1} s_{t-1})$$
$$m_t \sim \text{Poisson}\left(\frac{N_{t-a}}{2} f_t \prod_{k=1}^{a} m_{t-k}\right)\left(\frac{Nb_{t-a}}{2} f_t \prod_{k=1}^{a} jm_{t-k}\right)$$

where

$N_t bN_t$: number of breeding adults in year t
a : age at first breeding
s_t : adult survival rate for year t
f_t : productivity rate for year t
$m_t mj_t$: immature survival rate for year t

Appendix C - Estimating the parameters of the PVA model for gannets

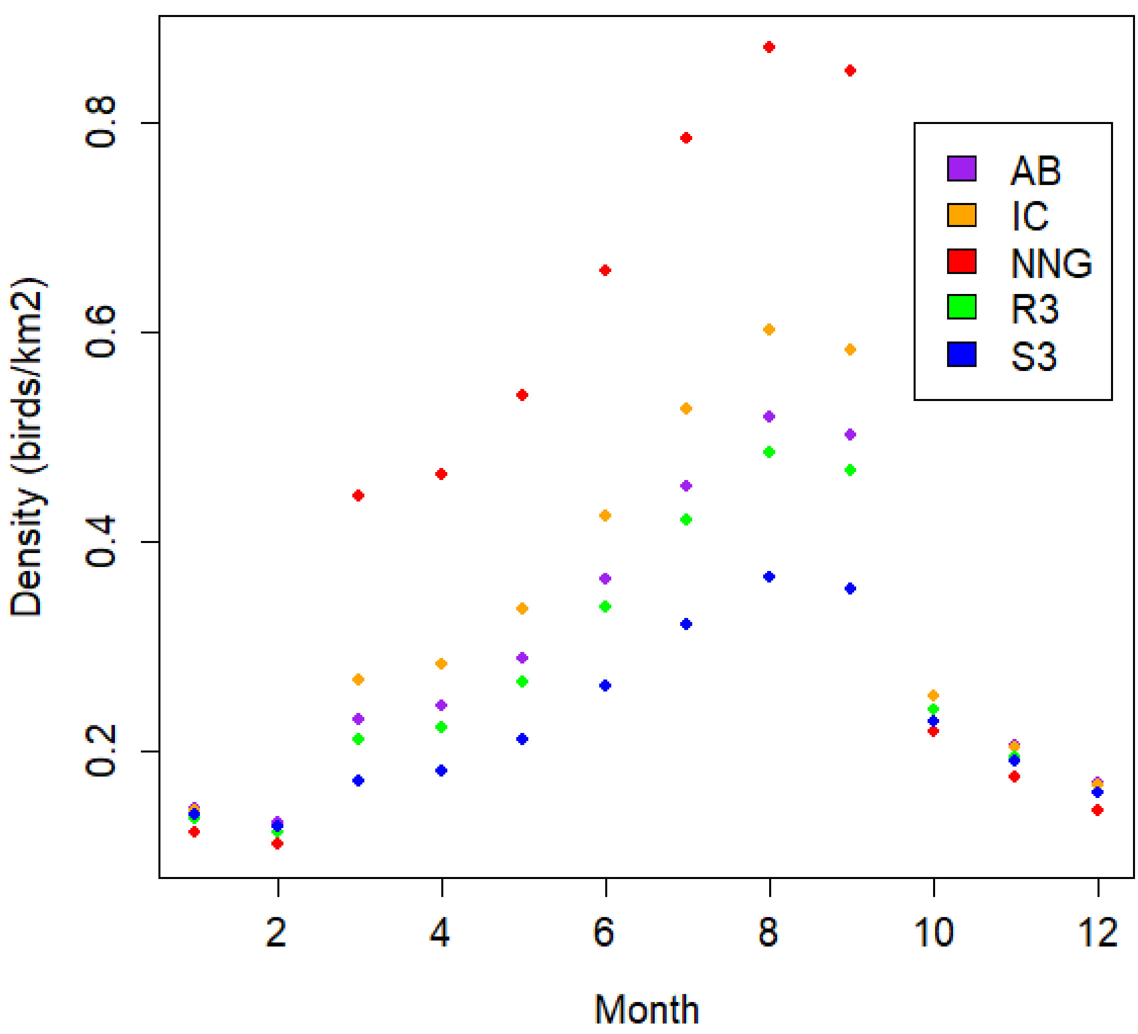
For most of the populations of interest the parameters of the model described in Appendix B have already been estimated from data within previous projects (Freeman et al (2014), Jitlal et al (2017)), and we make use of these estimates here.

For gannets, that is not the case. It was not feasible to apply the Bayesian approach of Freeman et al. (2014) within this project, so we instead use a simpler maximum likelihood approach. This involves:

a) For each of a range of possible values of the juvenile survival rate, simulating multiple time series from the stochastic PVA associated with this juvenile survival rate, for the period for which observed counts are available
b) Calculating the Poisson log-likelihood for each simulation, for each possible rate, and averaging across simulations
c) Selecting the juvenile survival rate that gives the maximum value of the Poisson log-likelihood

Appendix D – monthly densities for gannet

Figure D1. Monthly estimated mean densities of gannets in flight within each of the footprints, based on at-sea survey data.



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BANGOR
Centre for Ecology & Hydrology
Environment Centre Wales
Deiniol Road
Bangor
Gwynedd
LL57 2UW
United Kingdom
T: +44 (0)1248 374500
F: +44 (0)1248 362133

EDINBURGH
Centre for Ecology & Hydrology
Bush Estate
Penicuik
Midlothian
EH26 0QB
United Kingdom
T: +44 (0)131 4454343
F: +44 (0)131 4453943

LANCASTER
Centre for Ecology & Hydrology
Lancaster Environment Centre
Library Avenue
Bailrigg
Lancaster
LA1 4AP
United Kingdom
T: +44 (0)1524 595800
F: +44 (0)1524 61536

WALLINGFORD - Headquarters
Centre for Ecology & Hydrology
Maclean Building
Benson Lane
Crowmarsh Gifford
Wallingford
Oxfordshire
OX10 8BB
United Kingdom
T: +44 (0)1491 838800
F: +44 (0)1491 692424

enquiries@ceh.ac.uk
www.ceh.ac.uk