AppSaS – Apportioning seabirds seen-at-sea

WP2 – Data acquisition

February 2024

Contents

ORJIP Offshore Wind

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

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

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

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

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

Acknowledgements

Who we are

Our mission is to accelerate the move to a decarbonised future.

We have been climate pioneers for more than 20 years, partnering with leading businesses, governments and financial institutions globally. From strategic planning and target setting to activation and communication - we are your expert guide to turn your climate ambition into impact.

We are one global network of 400 experts with offices in the UK, the Netherlands, South Africa, China, Singapore and Mexico. To date, we have helped set 200+ science-based targets and guided 3,000+ organisations in 70 countries on their route to Net Zero.

1. Introduction

In this report, we identify what information is required to support the improvement of existing apportioning tools or the development of new apportioning tools. Such information may be found either in published sources (e.g. peer- reviewed literature) or extracted from databases or other data stores. Here, we list the key information requirements needed to improve, or develop new approaches for, apportioning. Based on this review, we produce a detailed list of data sources that could be used to improve methods for apportioning. We carefully consider the utility of each of these data sources to addressing the key information needs in order to support improvements to the methodologies for apportioning. We assess the strengths and biases associated with each of these data sources. Following this process, we propose which data sources are the most promising and should be taken forward into WP3 for methods evaluation.

2. Potential data sources

GPS Tracking Data

Data from the GPS tracking of seabirds has been a key part of previous methods of apportioning during the breeding season (Butler et al., 2020; NatureScot, 2018). Initially, these approaches were based on summarised data on species foraging ranges (e.g. Thaxter et al., 2012; Woodward et al., 2019). These data were then used to apportion impacts to breeding colonies using weightings based on the size and location of those colonies. Subsequent approaches to apportioning have used habitat modelling to identify areas used by birds from different colonies (Wakefield et al., 2017), the outputs from these models were then used to determine the likely origins of birds in any given area (Butler et al., 2020).

It is important to consider how representative any GPS tracking data are. The potential for tag effects (e.g. Bodey et al., 2018; Geen et al., 2019) means that there may be a bias toward tracking larger birds, particularly with older, heavier devices. Further, the need to recapture birds has usually meant that tagging has been restricted to breeding adults, though the availability of remote download technology (e.g. Bouten et al., 2013) has opened up the potential to track juvenile and immature birds (e.g. Borrmann et al., 2021). However, even with remote download technology, biases are likely to persist towards birds in easy to access parts of the colony, which may not be representative of the colony as a whole (Calladine, 1997). Analytical approaches are available to assess how representative GPS tracking data may be (e.g. Soanes et al., 2013; Thaxter et al., 2017), and these should be considered.

To extend the approach of Butler et al., (2020) beyond the four existing species, long-term GPS tracking data are available for Lesser Black-backed Gulls from a number of UK colonies (Figure 1).
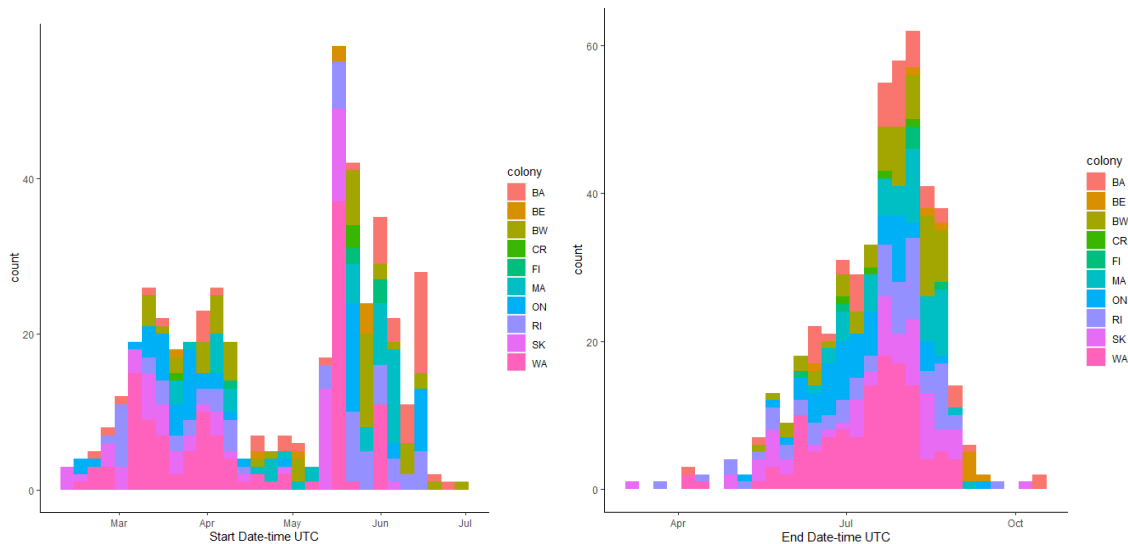
Figure 1. Tracking data start and end dates for all colonies to give an indication of within season temporal spread of data

In contrast to the data used in the Wakefield et al. (2017) analysis that underpinned the apportioning approach set out in Butler et al. (2020), the tags deployed on Lesser Black-backed Gulls (University of Amsterdam, 'UvA' or Movetech, 'MT') were long-life solar-powered storage devices that record spatial and temporal data that can be downloaded remotely, removing the need to recapture birds. Tags were deployed using permanent or weak-link harnesses, meaning data covered the full breeding season, and for some individuals, multiple years. As tags were solar-powered, data may include incomplete trips as a consequence of loss of battery life in dark or overcast conditions. How best to incorporate these incomplete trips in any analysis will need careful consideration.

For the purposes of this summary, we are defining the breeding season as c. March – September, loosely defined as associated with the colony i.e. containing data pre-breeding through to post-breeding inclusive. Examining data from all birds, we can see a bimodal distribution in relation to the start dates, reflecting first deployment of devices in May and June, and first arrivals back from tags deployed in previous years, in ca Mar-Apr. In contrast, the end dates, reflecting when birds leave their breeding colonies, all peak towards the end of September (Figure 1). For the purposes of this work, these dates can be refined further to ensure the underpinning approaches to apportioning are based on data that accurately reflect the breeding season.

At the time of writing, data are available from 238 birds across 10 years, and 10 sites, reflecting a range of different habitats (Figure 2, Table 1). Tags were set with sample rates ranging from 3 seconds – 60 minutes during the core breeding season, with faster rates reserved for time periods when birds were likely to be within offshore wind farms. In order to conserve battery power, the sampling rate of Movetech tags was reduced to 180 minutes overnight.
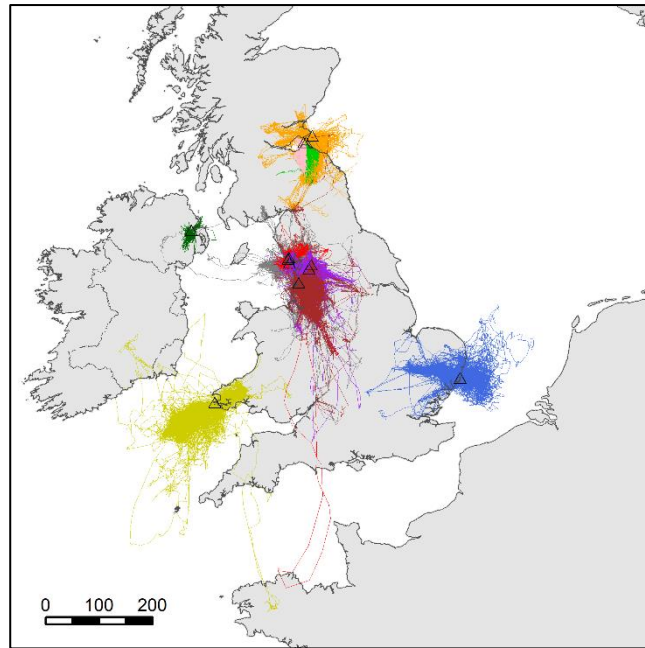
Figure 2. Tracking data available for Lesser Black-backed Gulls (2010-2020) from ten colonies in the UK (England, Wales, Scotland and Northern Ireland). Colony locations are depicted by triangles for: Isle of May (2019-2020, orange), Craigleith (2019-2020, green), Fidra (2019-2020, pink), Belfast (2018-2020, dark green), Walney (2014-2020, grey), Barrow (2016-2019, red), Bowland (2015-2019, purple), Ribble (2016-2020, brown), Skokholm (2014-2017, yellow) and Orford Ness (2010-2015, blue).

Table 1. Numbers of tags providing initial GPS data in each year for LBBGU studied between 2010 and 2020. Individuals often contributed data across multiple years; the total number providing data across years for each colony is also shown, further broken down by the tag type used. Tag types are given as: MT= Movetech, UvA =University of Amsterdam.

Colony	Colony type	Individual GPS tracking data by year											Total N	Tag type	
		2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020		MT	UvA
Walney	Coastal	0	0	0	0	24	16	38	24	14	7	0	49	5	44
Skokholm	Island	0	0	0	0	25	20	14	3	0	0	0	25	0	25
Orford Ness	Coastal	11	19	15	11	4	2	0	0	0	0	0	24	0	24
Isle of May	Island	0	0	0	0	0	0	0	0	0	28	20	28	3	25
Craigleith	Island	0	0	0	0	0	0	0	0	0	3	1	3	3	0
Fidra	Island	0	0	0	0	0	0	0	0	0	5	1	5	5	0
Barrow	Urban	0	0	0	0	0	0	9	19	13	6	0	31	31	0
Belfast	Urban	0	0	0	0	0	0	0	0	4	5	1	6	6	0
Ribble	Coastal	0	0	0	0	0	0	9	17	16	18	6	38	30	8
Bowland	Inland	0	0	0	0	0	6	21	16	9	4	0	29	29	0
TOTAL		**11**	**19**	**15**	**11**	**53**	**44**	**91**	**79**	**56**	**76**	**29**	**238**	**112**	**126**

The number of birds and colonies covered across these studies is similar to that for the species covered in Wakefield et al. (2017), although the tracks cover a much longer time period. Given the uneven sampling rates across tags, and potential for incomplete trips, there will be a need to standardize these data. As with Wakefield et al. (2017), there may also be a need to subsample from the data in order to ensure even coverage in the data from each individual.

In attempting to apply the methodology of Wakefield et al. (2017) to lesser black-backed gulls, it is important to note that, in addition to the data themselves, there are some important ecological differences between the species concerned that must be overcome. Substantial numbers of lesser black-backed gulls breed away from traditional colonies, often in urban areas (Mitchell et al., 2004), meaning colonies for these species are likely to be less tightly defined than is the case for those covered by Wakefield et al. (2017). Additionally, as generalist foragers, lesser black-backed gulls forage within both the marine and terrestrial environments (Langley et al., 2021; Spelt et al., 2019). In modelling GPS data for lesser black-backed gulls, and using these models to make predictions about offshore habitat use by birds from new regions, it will be important to consider how onshore and offshore habitat use varies between colonies.

The Lesser Black-backed Gull GPS tracking data are suitable for use with the breeding season apportioning methods of NatureScot (2018) or Butler et al. (2020). As data have been collected on a year-round basis, they are also suitable for informing apportioning outside the breeding season. Permission to use these data as part of this project has been obtained.

Focal follow data

Focal follow is an approach that was first developed in order to track terns species in order to identify key foraging areas (Perrow et al., 2011). The approach is of particular value for species, such as terns, which have been too small to track with GPS tags until recently. Using this approach, an individual bird is identified as it leaves its breeding colony. The bird is then followed in a Rigid-hull Inflatable Boat (RIB) equipped with an onboard GPS to record the boat's track as a proxy for the track of the target bird. The RIB is kept around 50-200m from the focal bird, with two observers on board; the first to maintain contact with the bird, and the second to record any changes in behaviour and note the timing of these. As such, the data are akin to that collected using GPS tracking. However, given the size of tern colonies from which these data have been collected, it should be noted that it is unlikely that any individual bird will have been followed on more than one occasion.

Initially, these data were collected with a view to informing the EIAs of offshore wind farms close to the North Norfolk Coast SPA (Perrow et al., 2011; PERROW et al., 2006), with analyses focussing on the flight heights of the birds concerned, and the potential overlap of their flights with proposed wind farms. However, there was interest in the potential of this approach to identify foraging areas for birds from SPAs, with a view to identifying marine SPAs and marine extensions to existing SPAs (Wilson et al., 2014).

Data were collected from 10 SPAs (Wilson et al., 2014), in addition to the data available from two colonies within the North Norfolk Coast SPA collected by Perrow et al. (2011) (Figure 3). A key aim of this project was to produce models of foraging distributions of terns around SPAs, with a view to applying these to new sites in order to inform marine SPAs and marine extensions to existing SPAs. In total, 1276 tracks were obtained from four species (Arctic, Common, Roseate and Sandwich Terns) from 10 SPAs, though this was reduced to 801 tracks once trips with no foraging activity recorded were removed from the analysis (Table 2, Wilson et al., 2014).

Figure 3. Tern colonies from which focal follow data are available

Table 2. Sample sizes of Common, Arctic, Roseate and Sandwich Terns tracked from colonies and included in the analysis presented in Wilson et al. (2014)

Species	SPA	Tracks included in analysis (total number of tracks)
Arctic Tern	Farne Islands	32 (42)
	Coquet Island	91 (104)
	Outer Ards & Copeland Islands	24 (24)
Common Tern	Coquet Island	75 (90)
	North Norfolk Coast	20 (24)
	Ynys Feurig, Cemlyn Bay and the Skerries	19 (32
	Larne Lough	32 (49)
	Imperial Dock Lock	118 (137)
	Glas Eileanan	49 (63)
Roseate Tern	Coquet Island	40 (53)
Sandwich Tern	Coquet Island	90 (127)
	North Norfolk Coast	88 (108)
	Ynys Feurig, Cemlyn Bay and the Skerries	72 (248)
	Ythan Estuary, Sands of Forvie and Meikle Loch	51 (51)

The resulting data were analysed using a case-control approach with logistic regression. Cases were locations at which birds were observed (all locations where foraging was recorded, and a thinned dataset for commuting flight), and controls were randomly sampled points within the area available to

the birds. In these models, cases take a value of 1 and controls a value of 0, meaning they model the probability of a point being used by the terns in relation to environmental parameters including distance to colony, distance to shore, bathymetry, salinity and chlorophyll concentration (Wilson et al., 2014). Following final model selection, the models were then used to predict the distribution of terns around colonies from which no data were collected. The resulting models offered moderate to good predictions of tern foraging areas.

A substantial proportion of trips were incomplete (63%). This could occur as a result of challenges in maintaining visual contact with the birds if they joined a flock, or flew faster than a rib could follow. It could also occur if tracking had to cease due to safety issues, such as encountering shallow reef habitat. This is likely to pose challenges in analysing and interpreting the resulting data for the purposes of apportioning as data may underestimate usage of areas further offshore and in habitats that could not be accessed safely by the boat (e.g. shallow reefs).

As the data were collected for a similar purpose to that of Wakefield et al. (2017), i.e. applying models of habitat usage to novel colonies, they may be suitable to support approaches to apportioning such as that of Butler et al. (2020). However, given potential biases in the data, caution would be needed in relation to the interpretation of the resulting data. The data necessary for this are held by JNCC, and permission to use these data for the purposes of this project has been obtained.

Geolocation Data

Geolocation devices have been widely used in order to identify the wintering locations of a range of seabird species from different colonies (e.g. Amélineau et al., 2021; Fort et al., 2012; Frederiksen et al., 2012a; Glew et al., 2018; Leat et al., 2013). Geolocation loggers record ambient light levels with day length being used to estimate latitude and the timing of midday relative to GMT being used to estimate longitude (Phillips et al., 2004). The loggers have the advantage of being considerably smaller and lighter than GPS tags meaning that they can be deployed on a wider range of species for longer time periods. However, the reliance on light levels to estimate location in combination with a limited number of fixes per day means that there can be considerable uncertainties surrounding the inferred locations, in the range of 100-200 km (Merkel et al., 2016). Despite these uncertainties, geolocation data can offer valuable insights into the movement and distribution of seabirds during the non-breeding season(s) that could not be obtained using other methods.

In order to develop data-driven methods for apportioning birds for birds outside the breeding season, geolocation data are available for guillemots and razorbills tagged at 11 colonies in northern UK over three years (2017-20) (Buckingham et al., 2021, Figure 4). Across these colonies, data are available for 280 guillemots and 131 razorbills from winters 2017/18 and 2018/19.

Figure 4. Colonies from which geolocation data were collected from guillemots and razorbills between 2017 and 2020

As geolocation data lack the spatial and temporal resolution of GPS data, habitat modelling approaches, such as that of Wakefield et al. (2017) are not generally used. However, these data could be used to estimate colony-specific Utilization Distributions (UDs) (e.g. Léandri-Breton et al., 2019) which, in combination with estimates of colony size, could be used to apportion birds back to their breeding colonies in the non-breeding season(s). It is important that these models account for observation error in the geolocation data, which is likely to be heterogeneous. As the observation error is likely to vary in relation to known factors, for example time of year, this variability can be modelled.

It would be possible to use a four-stage approach to analysing geolocation data from the guillemots and razorbills in order to produce estimates of apportioning during the moulting and wintering seasons:

1. To visualise the data in space and time with uncertainty, it is possible to map the tracks from each colony using space-time cubes (Demšar et al., 2015; Fig. 9), which visualise spatio-temporal data. Little is known of the key drivers of seabird distributions in the non-breeding season. An advantage of more advanced visualisation methods, such as space-time cubes, is that insights can be gained about pathways to their non-breeding sites including whether all birds from a colony use the same transition corridors or whether their tracks vary greatly by individual.
2. Utilisation kernels including location uncertainty can be calculated by colony/species/season to produce a set of utilisation distributions.
3. A set of metrics characterising overlap between the UDs can be developed to allow apportioning to be carried out with a measure of uncertainty. New regions to aggregate colonies can be defined. For colonies without tagging data, apportioning can be carried out according to the region they are placed in and uncertainty will be defined as the upper confidence limit, calculated by data-driven colonies. Apportioning can be scaled up to

population size using colony counts.

4. Species will vary with how consistent their distribution is by colony and over time. We can develop a RAG visual to label how confident we are in our apportioning metrics for each species/area.

Permission to use the geolocation data reported in Buckingham et al. (2021) for the purposes of this project has been obtained.

Data from Local Bird Reports

Many local bird groups produce annual reports at either a local, or regional level. Such reports typically include records of all species observed within the area over the course of the year. The types of information reported in relation to different species typically varies between area, and in relation to how unusual a record may be. Phenological data are commonly recorded, for example the first and last date on which a migrant species was recorded or, the dates on which the first eggs or chicks were recorded. Where an area includes colonial species, more detail may be provided about these, such as peak counts and more detailed breeding information.

Local bird reports from coastal areas may contain useful data in relation to phenology, particularly in relation to the timing of migration. However, extracting such data is likely to be time-consuming, and a similar level of information is likely to be available through resources such as BirdTrack. **Should these data be deemed of value for this project, the BTO Library holds a comprehensive collection of local bird reports which could be reviewed in order to extract the necessary data.**

Literature on the Timing of Migration

Several studies have sought to review and describe the annual cycles of seabirds, including defining migratory periods (e.g. Phillips et al., 2017). Whilst migration is often thought of as a single event within an annual cycle, recent analysis has highlighted that the non-breeding seasons are better thought of as a series of periods defined by either active migration or stationary segments (Amélineau et al., 2021).

Assessments of the timing of the breeding season and migration have traditionally been made with reference to parameters such as the arrival and departure dates of birds at breeding colonies or the date on which the first chicks or eggs were observed (e.g. Huffeldt & Merkel, 2013; WANLESS et al., 2009). However, such studies limit our understanding of seabird migration to the periods in which birds arrive at, and depart from, their breeding colonies. We lack information on the timing and location of life-history events such as moult periods, when an inability to fly may make birds particularly vulnerable to the impacts of offshore wind farms, increasing the importance of being able to robustly apportion impacts back to breeding populations. The rapid expansion in tracking technology, combined with technological innovation to reduce the size of these devices has meant that recently published literature offers a more detailed understanding of the timing of migratory movements and key parts of species' annual cycles. High resolution GPS tracking has been used to explore migration patterns in the lesser black-backed gull (Borrmann et al., 2021; Brown et al., 2021). These data can be used to precisely define the timing of key events such as arrival on breeding and wintering grounds (Borrmann et al., 2021) and the overall duration of migration (Brown et al., 2021). Data are of sufficient resolution, and cover a sufficient time period, that they can be used to explore differences in the timing of these events between individuals, colonies, and years.

For species such as northern gannets, common guillemots and black-legged kittiwakes, it is not currently possible to deploy GPS loggers over winter due to a combination of body size, morphology and behaviour. However, the use of GLS tags offers a means to explore the timing of migration in these species (e.g. Bogdanova et al., 2017; Dunn et al., 2020; Fort et al., 2012; Frederiksen et al., 2012; Kubetzki et al., 2009; Merkel et al., 2019). Whilst these data typically have low spatial and temporal resolution, inferences can be made in relation to monthly changes in distribution, for example by looking at median monthly locations of birds (e.g. Dunn et al., 2020; Frederiksen et al., 2012). Whilst the low resolution of the data can mean making inferences about finer scale timings, such as the return to the colony at the start of the breeding season, challenging, this information can be inferred through combining data from multiple individuals (Merkel et al., 2019).

Data from the studies highlighted above may be available on request from the authors. Through a more detailed review of the literature, it may be possible to clearly define the start and end of migration periods for some key species. However, the most robust estimates of the timing of migration in the peer-reviewed literature relate to data from tracking studies using either GPS or GLS loggers. Consequently, robust estimates are likely to be available from analyses of the datasets described above.

Trektellen, BirdTrack and eBird

Trektellen[1], BirdTrack[2] and eBird[3] are tools for facilitating the collection and collation of unstructured observations of birds. Whilst BirdTrack and eBird accept data from birdwatchers across the wider environment, Trektellen focuses on observations at coastal sites, particularly during migration periods. However, data from Trektellen are uploaded to BirdTrack meaning that there is some overlap between these datasets. Where data relate to widespread species, population trends derived from these datasets may be reflective of the population status of the species concerned (Boersch-Supan et al., 2019). However, for rarer and/or less widespread species, population trends generated using these data are less robust.

Data are typically summarised as the proportion of complete lists in which a given species was recorded. As such, it would be challenging to use these data to estimate population sizes of species of concern to the offshore wind industry, or to link the birds present in any given area back to an SPA population or breeding colony. However, there is the potential for these data to be used to investigate phenology, and the timing of the breeding and non-breeding seasons, identified as being of importance in relation to BDMPS.

As an unstructured survey, data are likely to be noisy, and subject to biases. Below, we consider the example of Northern Gannets by summarising the proportion of weekly complete lists collected within 20km of the coast in which the species was recorded (Figure 5). We can consider this at either a national or a regional level. At a national level, interpreting these data can be challenging. Whilst the timing of post-breeding movements is clear, as illustrated by a marked drop in the reporting rates starting around weeks 35-40, the timing of the return migration and breeding season are less clear. However, there are clear biases to the data at a national level, with trends driven by regions with high

[1] https://www.trektellen.org/
[2] https://www.bto.org/our-science/projects/birdtrack
[3] https://ebird.org/home

numbers of observers, like the Forth and Tay region in Scotland. At a regional level, increases and decreases in the reporting rate for gannets can be used to identify key migration periods, with more stable numbers recorded over the course of the breeding season.

The resolution of these data is relatively coarse. However, they may have some value for species where the timing of migration cannot be inferred from GPS or other tracking data. Should data be required, they could be obtained via data request to BTO.
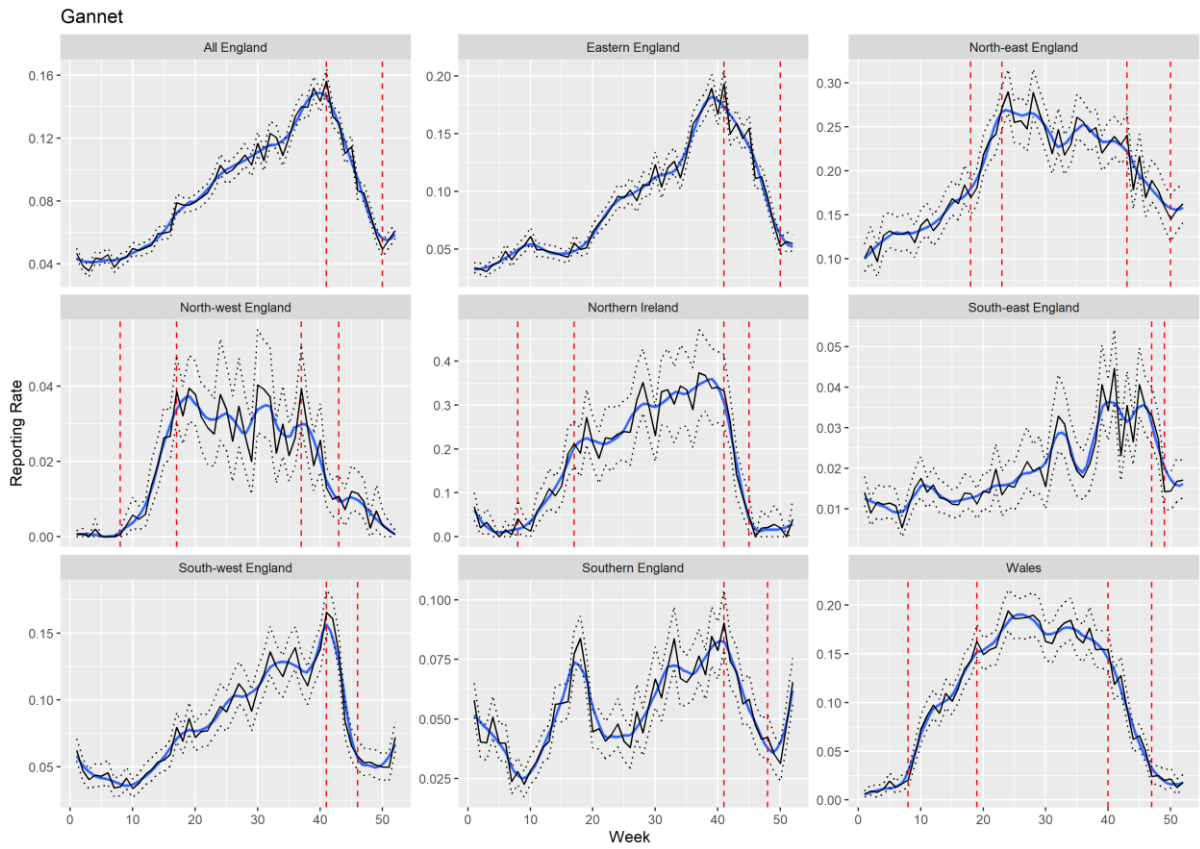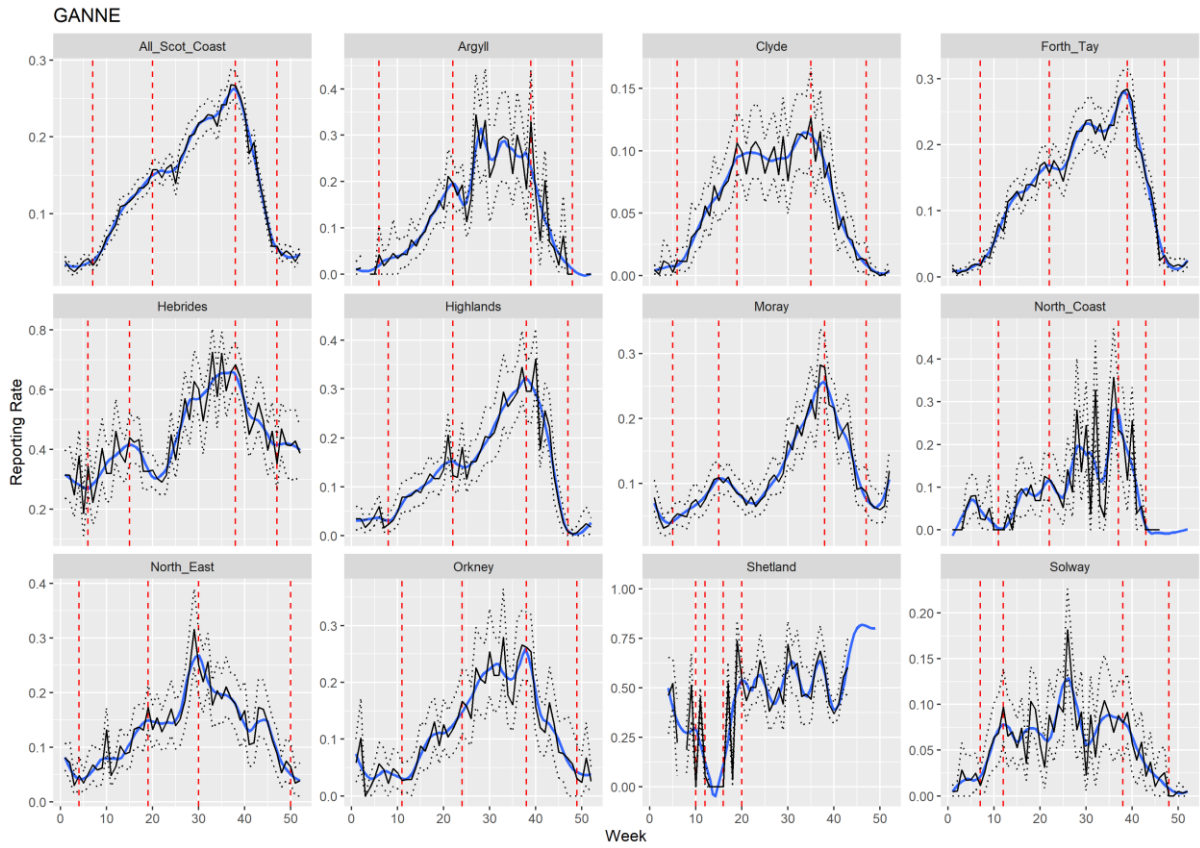
Figure 5. Weekly reporting rates for Northern Gannets at a regional scale in the UK.

Colony Specific Data on Phenology

The Seabird Monitoring Programme[4] collects data on the abundance and breeding success of seabirds across the UK. On their own, these data are of limited value in relation to assessing phenology. However, in addition to this, more detailed data are collected at four key sites – Fair Isle, the Isle of May, Skomer and Canna (Figure 6). Furthermore, detailed data on breeding seabirds may also be collected at the 19 sites covered by the UK Bird Observatories Council[5] (Fair Isle and the Isle of May are both SMP Key Sites and Bird Observatories).

At sites covered by the UK Bird Observatories Council, and some of the SMP Key Sites, regular counts of some species are recorded. These data could give an indication of fluctuations in numbers over the course of the year and can be used to identify when birds return to colonies for the breeding season and leave at the end of the breeding season. In addition to these data, information on the dates for the first egg, first chick and first fledging may be reported, given valuable information on colony phenology, and different stages of the breeding season. Data are collected from sites around the UK and Ireland (Figure 6), meaning they are likely to give a good overview of regional patterns in phenology for a range of species. In some cases, reports may extend back decades, potentially offering useful insights into temporal trends in phenology. However, in many cases, data have not been digitised (particularly in the case of older data) and it is likely to be a significant undertaking to review and extract the necessary data from reports. Consequently, it is important to consider the value of such information relative to what can be obtained from other sources (e.g. GPS tracking, BirdTrack etc.).

Should the data on phenology that may be available from Bird Observatory Annual Reports, and the reports from SMP Key Sites be deemed valuable for this work, the reports are held in the BTO library and the necessary data could be extracted from them.
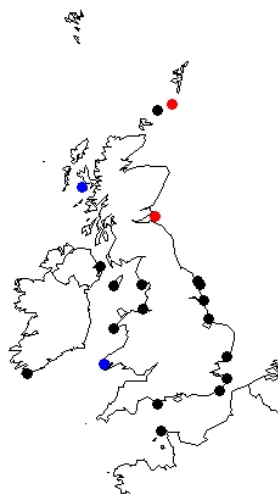
Figure 6. Sites which are part of the UK Bird Observatories Council (black), Seabird Monitoring Programme Key Sites (blue), or both (red)

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[4] https://jncc.gov.uk/our-work/seabird-monitoring-programme/

[5] https://www.birdobscouncil.org.uk/

Ring Recovery Data

Ringing recovery data have been widely used in the terrestrial environment to make inferences about intra-specific movements and distributions of populations of different species (e.g. Hewson et al., 2016). Recently, this approach has been used to assess the potential connectivity of Shelduck *Tadorna tadorna* from SPAs and offshore wind farms during the migration periods (Green et al., 2019). These data may be obtained from birds which have (i) been recaptured alive; (ii) been resighted alive (e.g. through colour-ringing), or; (iii) recovered dead. Whilst there have been some very successful studies considering the distribution of colour-ringed seabirds outside the breeding season (e.g. Grist et al., 2014), these have focussed on species that primarily use the near-shore environment and are readily alive detected by colour-ring observers. These species may be less sensitive to offshore wind farms (Furness et al., 2013), and are therefore of less interest in terms of apportioning.

The majority of ringing recovery data relating to seabirds outside the breeding season is derived from dead birds. Such data may be obtained through records submitted by members of the public or, through structured Beached Bird Surveys. In the past, Beached bird surveys have been used to assess the incidence of anthropogenic impacts such as oil pollution, fisheries bycatch and marine plastic pollution on seabirds (Acampora et al., 2016; Camphuysen & Heubeck, 2001; ZYDELIS et al., 2006). Such studies have also identified birds which are likely to have collided with offshore wind turbines (Newton & Little, 2009). Where birds have been ringed, it is possible to establish a link between the ringing location and the recovery location (Figures 7-12).

Sample sizes of ringed birds recovered following mass mortality events are often limited, making inferences about the geographic origins of affected birds challenging (Table 3; Grantham, 2004). These challenges may be exacerbated by age (Grantham, 2004; Laurenson et al., 2021) and sex (Deakin et al., 2019; Leat et al., 2013) linked differences in wintering area.

We extracted ringing recovery data that had been submitted to the British Ringing Scheme for five seabird species – Northern Gannet, Black-legged Kittiwake, Lesser Black-backed Gull, Razorbill and Common Guillemot – over the past 10 years (Table 3). For each species, we plotted the distribution of recoveries during the winter (October – March) and linked those to the breeding colonies at which they were ringed. For Lesser Black-backed Gulls, we also considered the breeding season (April-August) recovery locations of birds which had been ringed in the UK over winter (October – March) (Figures 7-12). Given the sample sizes, it is difficult to distinguish clear patterns in distribution for any species other than Lesser Black-backed Gull. However, it is important to note that for Lesser Black-backed Gull recovered in the UK during the breeding season, there appears to be a bias towards being recovered in the South West of the UK (Figure 8). This does not fully reflect the distribution of the species in the UK during the breeding season (Mitchell et al., 2004), suggesting that there is likely to be a bias in the distribution of observers. It seems reasonable to assume that similar biases may exist in relation to the recoveries of other species, and at other times of year. Furthermore, it is important to recognise that the location at which the ring was reported reflects that location at which the bird was recovered, which, if the bird died at sea, may be driven local currents rather than the location the bird was when it died.

In some cases, ringing recovery data may give a general indication of overall distribution patterns outside the breeding season, limited sample sizes and biases linked to the distribution of ringers and

observers mean that these data should be treated with caution. Should ringing recovery data be required for this project, they can be obtained through data request to the BTO.

Table 3. Number of individual seabirds recovered during the winter (October – March) that were ringed in the UK during the breeding season (April – August) between 2010 and 2020. Also shown are the number of Lesser Black-backed Gulls ringed in the UK over winter and recovered during the breeding season.

| Species	Number of Recoveries
Northern Gannet	0
Black-legged Kittiwake	123
Lesser Black-backed Gull (Breeding Birds)	9983
Lesser Black-backed Gull (Wintering Birds)	4252
Common Guillemot	461
Razorbill	267
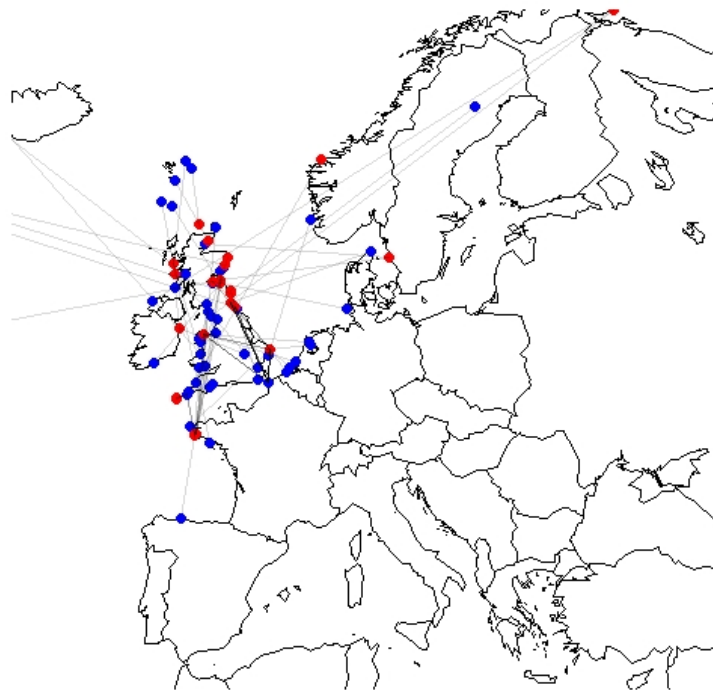
Figure 7. Ringing (red) and recovery (blue) locations of black-legged kittiwakes recovered over winter and reported to the UK ringing scheme.
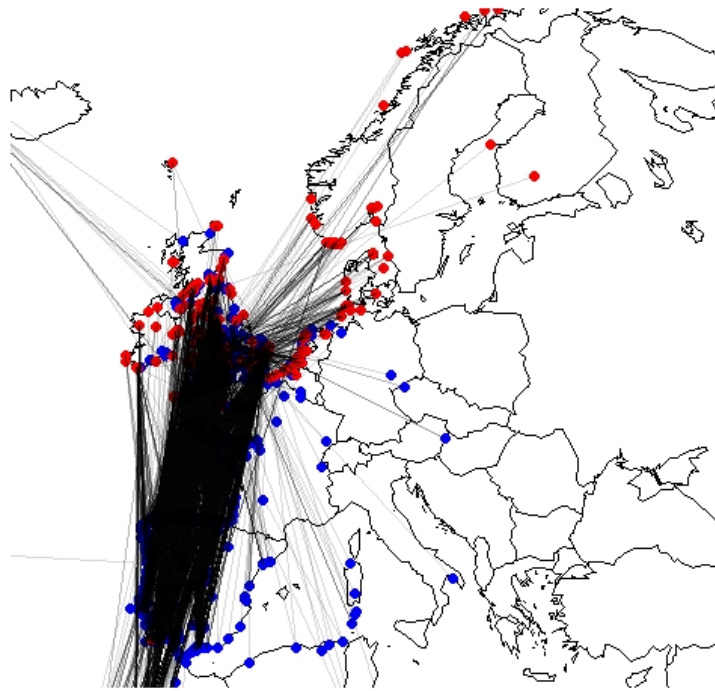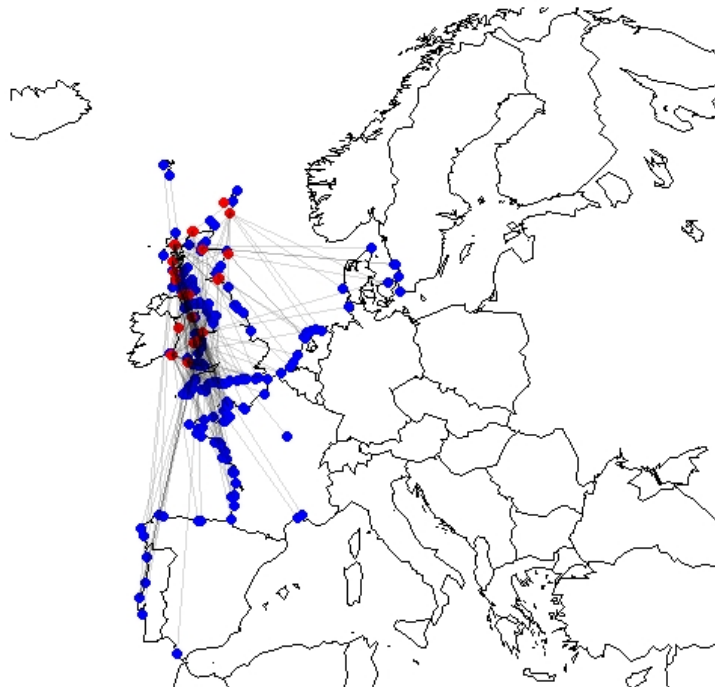
Figure 8. Ringing (red) and recovery (blue) locations of lesser black-backed gulls recovered over winter and reported to the UK ringing scheme.
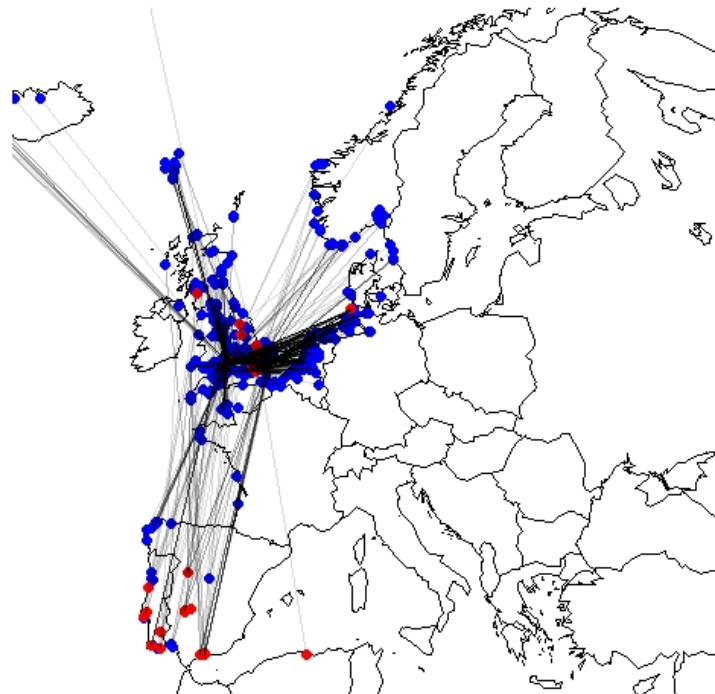
Figure 9. Ringing (red) and recovery (blue) locations of lesser black-backed gulls recovered over the breeding season and reported to the UK ringing scheme.
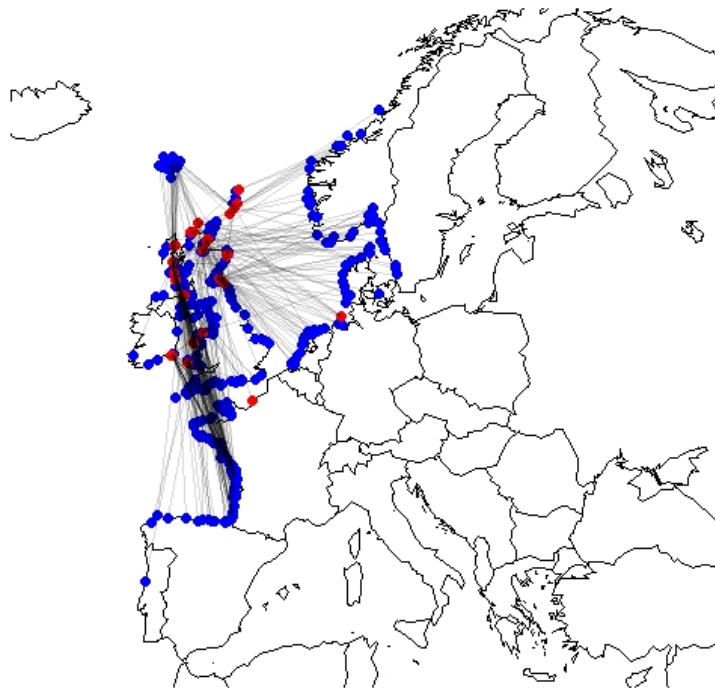
Figure 10. Ringing (red) and recovery (blue) locations of guillemots recovered over winter and reported to the UK ringing scheme.

Figure 11. Ringing (red) and recovery (blue) locations of razorbills recovered over winter and reported to the UK ringing scheme.

Figure 12. Ringing (red) and recovery (blue) locations of puffins recovered over winter and reported to the UK ringing scheme.

Biometric Data
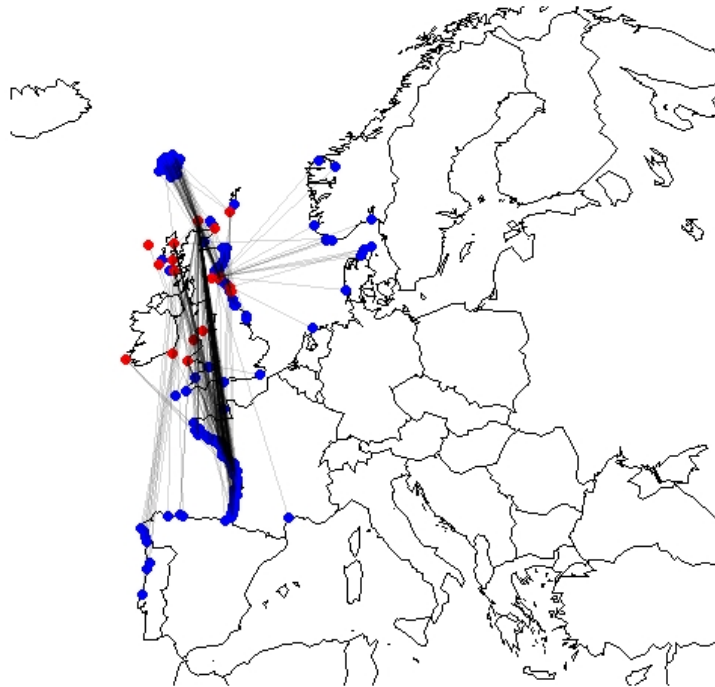
Bergmann's rule suggests that body size should increase with latitude. Whilst the exact mechanisms for this are unclear, possible explanations include more efficient thermoregulation and resource availability (Blackburn et al., 1999). This phenomenon has been investigated in seabirds, with a particular focus on the wing lengths of puffins and kittiwakes (Barrett et al., 1985; Harris, 1979; Pennington et al., 2011). Established patterns in seabird body size and latitude has led to interest in using biometrics as a basis for identifying the origins of birds outside the breeding season, particularly in response to mass mortality events such as oil spills and seabird wrecks (e.g. Anker-Nilssen et al., 2017; Hope Jones et al., 1980).

We briefly review published estimates of wing length in puffins and kittiwakes (Anker-Nilssen et al., 2018; Barrett et al., 1985; Corkhill, 1972; Harris, 1979; Helfenstein et al., 2004; Pennington et al., 2011; Porter & Coulson, 1987; Smith, 1988) and investigate the relationship between wing length in both species and breeding colony latitude. In both cases, there was a clear positive relationship between the two (Figures 13 and 14; Kittiwake coef 0.55 ± 0.02, P <0.0001; Puffin coef 1.00 ± 0.01, P < 0.0001). However, there was also substantial variation in wing length within a colony, leading to an overlap in distribution of wing lengths at different latitudes. There may be several factors driving this overlap. Firstly, wing lengths may vary with age, with first year birds having shorter wings than those in their second year, or older (Smith, 1988). Furthermore, the wing length of adult birds may vary through time, potentially reflecting changes in food availability (Porter & Coulson, 1987). However, of greater

importance is likely to be pronounced sex-related differences in biometrics. For example, female kittiwakes are likely to have substantially shorter wings than males (Smith, 1988), creating an additional layer of complexity in attempts to assign birds to breeding locations on the basis of their body size. Given the variation in wing length for birds from any given breeding colony, using biometric data as the basis for assigning birds to their breeding locations is not recommended due to a high probability of mis-classification (BARRETT et al., 1997).

Whilst biometric data are not seen as an optimal tool for apportioning birds back to their breeding colonies, data to facilitate such assessments would be available via data request to the UK ringing scheme.
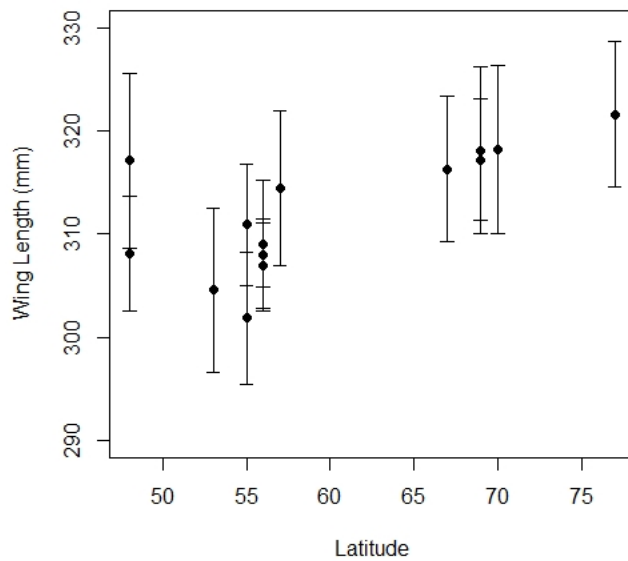
Figure 13. Variation in kittiwake wing length with latitude based on data presented in (Barrett et al., 1985; Helfenstein et al., 2004; Pennington et al., 2011; Porter & Coulson, 1987; Smith, 1988)
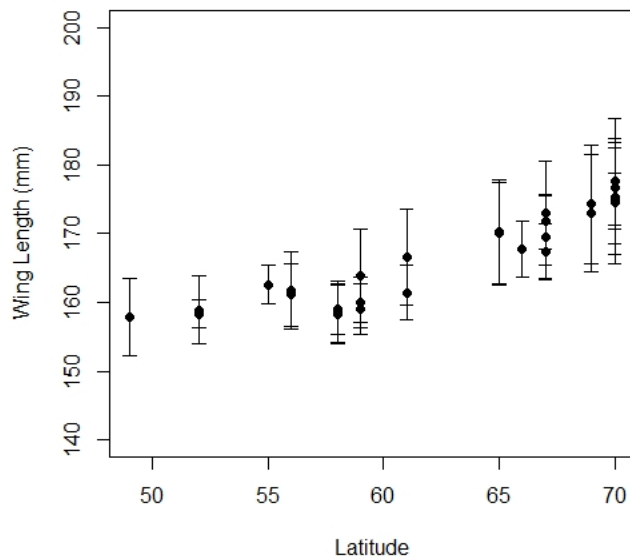
Figure 14. Variation in puffin wing length with latitude based on data presented in (Anker-Nilssen et al., 2018; Barrett et al., 1985; Corkhill, 1972; Harris, 1979)

Genetic Marker Data

Genetic markers such as micro-satellites or mitochondrial DNA can be used to identify the breeding origins of seabirds (e.g. Barlow et al., 2011; Burg et al., 2003; Sauve et al., 2019). However, this depends on the level of structure between different populations. Where populations are weakly structured, genetic markers are likely to be a less powerful tool for determining the breeding origins of birds. The degree of population structure is likely to vary between species.

At a broad spatial scale, genetic markers have been used to determine whether populations of species such as black-legged kittiwake and Leach's petrel, which breed in both the Atlantic and Pacific Oceans may be isolated from one another (Bicknell et al., 2012; Sauve et al., 2019). Genetic analysis confirmed that there was isolation between populations in each ocean. Whilst further analysis identified a structured population in the Atlantic population of black-legged kittiwakes (Sauve et al., 2019), this was not the case for the Atlantic population of Leach's petrel (A. W.J. Bicknell et al., 2012). Furthermore, whilst there was evidence of a structured population in black-legged kittiwake, there were genetic similarities between birds from Brittany, the Isle of May and Shetland, meaning that differentiating between birds from these populations is likely to be challenging (Sauve et al., 2019).

A high degree of population structuring may be expected in species like European shags, which exhibit a high degree of philopatry and limited dispersal. However, as with black-legged kittiwakes, population structuring did not appear to occur at a scale relevant to apportioning for offshore wind farms. There is evidence of three distinct populations of European shags, relating to the North Atlantic, Spain and Corsica, and the Eastern Mediterranean (Thanou et al., 2017). However, at a finer scale, within the North Atlantic region, there was little evidence of population structure, making attributing birds to breeding populations on the basis of genetic markers challenging (Barlow et al., 2011).

Attempts have been made previously to link birds back to their breeding colonies using genetic markers. Following oil spills in the Bay of Biscay, analysis of six microsatellites in guillemots was used in an attempt to link affected birds back to their breeding populations (Riffaut et al., 2005). However, weak population structure meant that there was little genetic differentiation between colonies, even at broad spatial scales. Instead, identifying the geographic origin of birds relied on the recovery of ringed individuals (Cadiou et al., 2004).

The value of genetic markers for apportioning birds to their breeding populations is likely to vary by species, and may not be effective in the case of species of relevance to the offshore wind industry. Data from the above studies may be available through contacting the authors. However, it is likely to require supplementing this through additional data collection, e.g. the collection of corpses from beached birds and subsequent DNA sequencing, to be of significant value for apportioning.

Stable Isotope Data

The stable isotope composition of body tissue reflects the conditions in which that tissue was grown. Consequently, if you have data to describe an isoscape, e.g. for the North Sea, you can make inferences about where a bird was at the point at which any given body tissue was grown. Of particular relevance to seabirds in the North Sea are $\delta 13C$ and $\delta 15N$. Through knowledge of moult timing in seabirds, we can make inferences about when different feathers are likely to have been grown, and by referring to the isotopic composition of these feathers, may make inferences about where birds are likely to have been at the point at which the feathers were grown (Bicknell et al., 2014; Glew et al., 2018; González-Solís et al., 2011; Grecian et al., 2019; St. John Glew, Graham, et al., 2019; St. John Glew, Wanless, et al., 2019).

By examining primary feathers from kittiwakes found dead at breeding colonies in Norway, González-Solís et al. (2011) were able to identify three areas used by the birds during their moulting periods, based on the order birds are known to moult their primary feathers. For these birds, the inner-most primaries showed isotopic signatures consistent with the breeding ground in Norway, middle feathers showed signatures consistent with staging areas in the Barents Sea and the outermore feathers showed signatures consistent with wintering areas in the Labrador Sea and Newfoundland. Similarly, Grecian et al. (2019) used outer primaries in northern gannets to link birds to wintering areas off the coast of West Africa.

Recent work has resulted in the development of an isoscape map for the North Sea covering $\delta 34S$, $\delta 13C$ and $\delta 15N$ (K. St. John Glew, Graham, et al., 2019). This information has been used to investigate the wintering distribution of auk species based on isotopic signatures in feather samples (Glew et al., 2018; K. St. John Glew, Wanless, et al., 2019). Whilst these data can be used to make inferences about species' wintering areas, they have typically been used in conjunction with other approaches, such as GLS loggers. By combining data from two, or more, imprecise methods in this way, it is possible to make more refined assessments of species wintering locations.

Data from the above studies may be available on request to authors. However, to make robust inferences about apportioning based on stable isotope data, additional data collection and analysis is likely to be required, from a broader range of colonies than has been considered to date.

Ectoparasite data

As with the birds themselves, there may be genetic structure in populations of the parasites carried by those birds. Populations of the tick *Ixodes uriae* carried by black-legged kittiwakes and Atlantic puffins from multiple sites across the Atlantic (McCoy et al., 2003). Potentially reflecting the patterns seen in the seabirds themselves, there were differences in the extent of any structure in the populations of the ticks. Whilst there was evidence of population structure in the ticks hosted by black-legged kittiwakes, the population structure of those hosted by Atlantic puffins was much weaker. Consequently, attempts to use information from ectoparasites to inform apportioning is likely to be less effective than using genetic markers, or other approaches.

Should these data be considered of value in relation to apportioning, they may be available through request to authors.

3. Model covariates

Approaches to apportioning such as that of Butler et al. (2020) are underpinned by habitat use models informed by tracking data. For the breeding season, these models are available for shag, kittiwake, common guillemot and razorbill (Wakefield et al., 2017). This approach could also be used in relation to lesser black-backed gulls, which have been tracked at multiple colonies across the UK, and potentially also common, Arctic, Sandwich and roseate terns, drawing from the focal follow data described above. Below, we summarise the covariates used by the Wakefield et al., (2017) models, and highlight additional variables that may be of relevance to the additional species, particularly lesser black-backed gulls.

Colony Size

Colony size data are included within the modelling process of Wakefield et al. (2017); in particular, this tests the assumption of prey depletion and Ashmole's Halo as well as sympatric and conspecific (parapatric) competition effects (e.g. Wakefield et al. 2013), using further derived covariates; for sympatric competition Wakefield et al. (2017) examined the effect of inverse-distance weighted distance to number of breeding conspecifics (Apparently Occupied Nests, AONs) including alternative square-root transformation. For parapatric competition, Wakefield et al. (2017) tested the hypothesis that birds would avoid locations where the null density of conspecifics from other colonies is high and in doing so tested the ratio of expected intensity of locations from the breeding site in relation to the sum of those from all other colonies in the region. These steps of modelling population-level information were carried out prior to further environmental covariates being tested.

The Seabird Monitoring Database portal was used for this purpose and Wakefield et al. (2017) used the data from the last main census of Seabird 2000 – see Fig 15; however, there were a number of complexities. As noted by Wakefield et al. (2017), objective definition of colonies is challenging because the magnitude of clustering depends on spatial scale. Survey segments of coastline although nominally divided into 1 km segments were not always surveyed as such thus Wakefield et al. (2017) further split data into stricter 1 km segments splitting those larger and dividing counts equally.

Further improvements can therefore be applied for Lesser Black-backed Gulls using the methods in Butler et al. (2020) that uses an extrapolation approach to quantify the probable population change, including uncertainty. This method uses most recent population estimates where available, but then relies on simulation of the log-ratio of change, following Butler et al. (2020) simulating the value of:

$$c_{jk}^* = c_j \exp(l_{jk}^*)$$

where c_j is the abundance of colony j in Seabird 2000 and:

$$l_{jk}^* \sim N(m_j, s_j)$$

gives the simulated log-ratio of change between Seabird 2000 and the tracking period, although this will vary for individual tracking datasets per colony, requiring a further decision on the precise period. Mean mj and standard deviation sj for the log-ratio of change are calculated through a multiple imputation – see Butler et al. (2020).

However, Lesser Black-backed Gulls present further unique challenges beyond the four marine species that were examined by Wakefield et al. (2017). Firstly, as gulls utilise both terrestrial and marine environments, the interplay between how terrestrial sites may tie into the competition effects as stated by Wakefield et al. (2017) are not straightforward to capture. Therefore, decisions must be made on whether marine or terrestrial systems are modelled separately. Should that be the case, the extent of marine usage by Lesser Black-backed Gull populations that are not breeding directly on the coast may need to be considered, for example perhaps including a decreasing likelihood of marine usage with increasing distance inland.

Among gull species, those considered in sympatry likely include populations of herring gull and great blacked-backed gull and indeed at the sites tracked, populations of colonies were a mix of these species. The wide variation in diets of these species, but still with overlapping niches, makes it is less clear as to the strength of such patterns, but when faced with variable anthropogenic resources, such as fisher discards or land fill closures, resource partitioning between species may decline and increase competition (Matos et al. 2018).

Finally, a key consideration for gulls is the issue of urban and natural nesters. Urban sites were covered in the Seabird 2000 3rd census, using traditional survey methods using predominantly vantage points (78% counts in S2K, others being aerial and ground-based surveys). The SMP ongoing annual surveys for both natural and urban nesters is uncertain for production of trends (JNCC 2021) and consequently census data should be relied on for this task. However, although a greater effort was made in S2K to cover urban nesters than previous censuses i.e. high coverage, it has since been realised those methods likely underestimated counts, e.g. those more obscured sites – see Ross et al. (2016), necessitating a move to further stratified random sample-based approaches using different survey methodologies within a model-based approach. This work is currently ongoing (Burnell et al. 2021a, b), with recent trials in counting approaches conducted for urban sites in England and Wales for Herring and Lesser Black-backed Gull (Woodward et al. 2020, Burnell et al. 2021b). Refined model-based estimates of urban populations may become available as time progresses, but not yet UK-wide, and not within the timescale of this project; as such a caveat may be needed to take the previous datasets within Seabird 2000. This issue is also magnified by the switch in breeding habitat use of Lesser Black-backed and Herring Gulls in the UK from natural to urban sites (Ross-Smith et al. 2014). Again, decisions of proximity between urban and natural nesters in the competition variables will need further scrutiny, although simplification of potential hypotheses able to be tested may also be required.
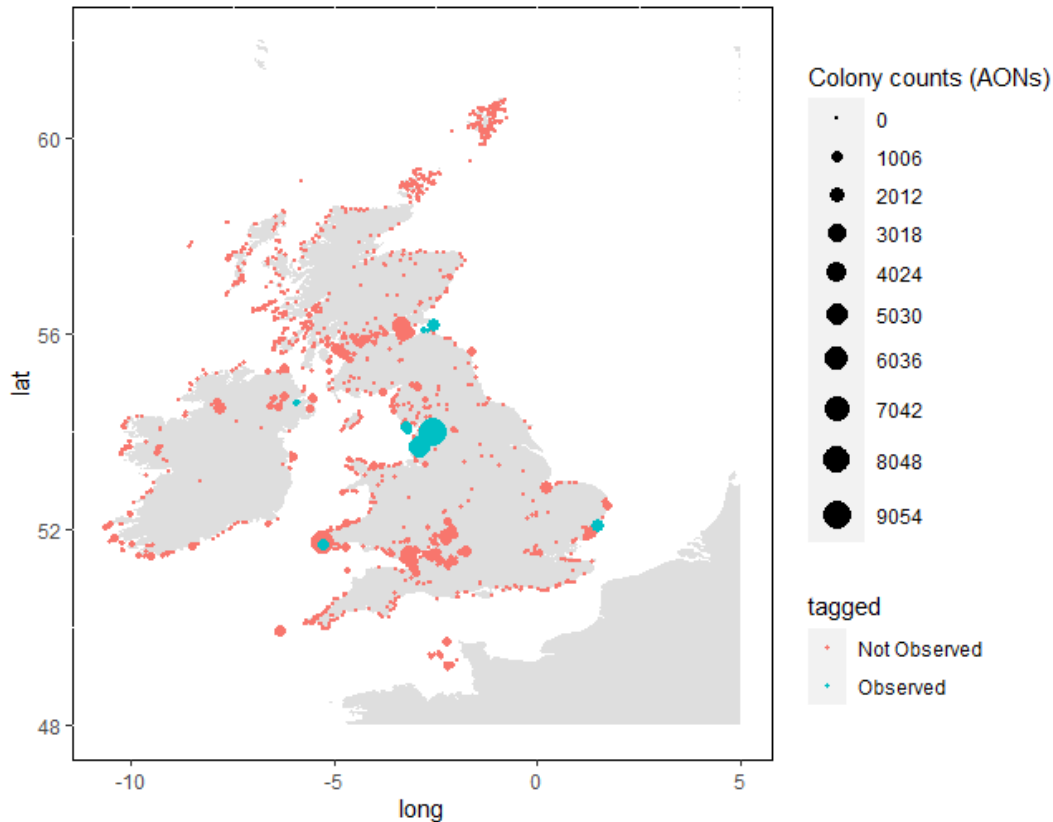
Figure 15. Example of the Seabird 2000 Lesser Black-backed Gull data, with most recent counts taken for sites supplemented by the Seabird Monitoring Programme, i.e. not necessarily the counts at the time of tagging. Observed colonies are highlighted in blue and unobserved in red; note population counts here have not been adjusted for 1 km boundary issues identified by Wakefield, nor have counts been imputed through time (e.g. Butler et al. 2020).

Environmental covariates

A total of 11 environmental covariates were included for Wakefield et al. (2017). These were (1) depth, (2) seabed slope, (3) minimum distance to coast, (4) proportion of gravel, (5) sand:mud ratio, (6) potential energy anomaly (PEA), (7) proportion of time water column stratified, (8) sea surface temperature, (9) standardised sea surface temperature, (10) thermal front gradient density (TFGD), and (11) net primary production (alpha-chlorophyll). These data are mostly publically available, and available to scientific research institutions and so can be acquired and updated for new datasets. Further, new data are available that supersedes the previous versions used in Wakefield et al. (2017). The above 11 variables are obtained from four separate data sources:

(a) ETOPO2 Global Relief 2v2, originally provided by the U.S. Department of Commerce, National Oceanic and Atmospheric Administration, National Geophysical Data Center (2006) is now deprecated and has been replaced by a higher resolution 1v1 dataset https://www.ngdc.noaa.gov/mgg/global/; this is used for depth and seabed slope (variables 1, and 2) (NOAA 2021);

(b) The British Geological Survey 1:250,000 scale sediment map (Edina digimap http://digimap.edina.ac.uk), for estimating variables 4 and 5; further Wakefield et al. (2017)

translated the raw information from the shapefiles into a numerical categorical scale for each of proportion of gravel and the sand:mud ratio.

(c) The UK Met Office FOAM AMM reanalysis dataset (http://marine.copernicus.eu/) (EU Copernicus Marine Service Information, 2021) was used by Wakefield et al. (2017) to estimate the next variables: (6) potential energy anomaly (PEA), and (7) proportion of time water column stratified (following Carroll et al. 2016). The same portal is available but the dataset originally used has also been superseded by a single dataset "NWSHELF_MULTIYEAR_PHY_004_009"; there are details and complexities with this dataset outlined below, but this dataset package contains the necessary key variables of potential salinity and temperature through the water column (3D netcdf dataset) that can be used to derive PEA and the time water column stratified.

(d) Finally, the remaining four variables are available from the Natural Environment Research Council Earth Observation Data Acquisition and Analysis Service (NEODAAS), https://data.neodaas.ac.uk. In particular, the Advanced Very-high-resolution radiometer (AVHRR) space-borne sensor, used by Wakefield et al. (2017), and other sensors such as MODIS Aqua, OLCI Ocean and Land Colour Instrument (OLCI), Visible Infrared Imaging Radiometer Suite (VIIRS) and are available online through the NEODAAS web portal; for fronts, the AVHRR 11 µm processed by the Plymouth Marine Laboratory Remote Sensing Group (Peter Miller Pers. Com.). Together, this data source satisfies the variables of SST, and further standardised SST following Wakefield et al. (2015), thermal front gradient density (TFGD), following Scales et al. (2014) and Miller and Christodoulou (2014), and net primary production (NPP), variables, 8-11. It is noted that there are often many sensors available for SST and net primary production; here it was assumed a multi-sensor approach was best.

Further environmental dataset details

Seabed relief (depth)

The new ETOP01 model is described as follows in the associated NOAA (2021) documentation: *"ETOPO1 is a 1 arc-minute global relief model of Earth's surface that integrates land topography and ocean bathymetry. Built from global and regional data sets, it is available in "Ice Surface" (top of Antarctic and Greenland ice sheets) and "Bedrock" (base of the ice sheets). ETOPO1 Global Relief Model is used to calculate the Volumes of the World's Oceans and to derive a Hypsographic Curve of Earth's Surface. ETOPO1 was built using GMT 4.3.1 (http://gmt.soest.hawaii.edu/), development version/CVS."*. This dataset is presented below in Fig 16.
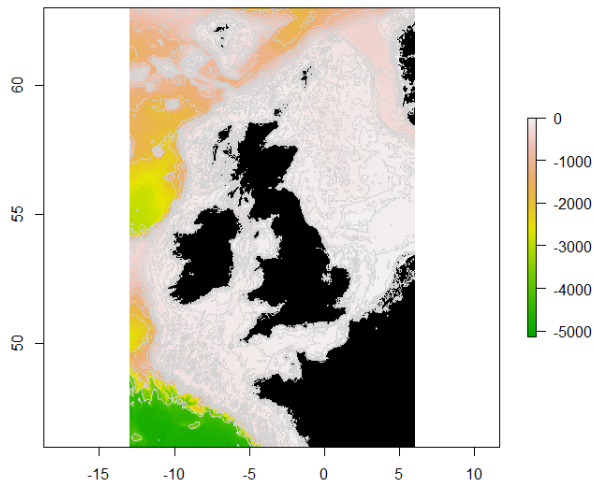
Figure 16. Seabed topography (depth)

This dataset can be extracted as a global sea relief dataset (i.e. sea depth) and read into R as a netcdf file to be further cropped and processed. The further derivation of the change in relief can then also be calculated to estimate "seabed slope" from this dataset.

Seabed substrate

The seabed sediment dataset can also be read into R as a shapefile and rasterized, and further following the instructions in Wakefield et al. (2017) the sediment triangle of gravel vs sediment:mud to ratios can be translated into a categorical scale. For example, the gravel proportional index is shown below on a new categorical scale from 1:4. As with Wakefield et al. (2017), we converted the shapefiles to 1 km LAEA rasters and then applied the equivalent 5 x 5 mean filter:

```
raster::focal (rp,w=matrix(1/25,nrow=5,ncol=5)).
```

We used the "LEX_ROCK" attribute of the shapefile data layer, as stated by Digimap as being the two-part code used to label each polygon of the Geology Digimap data and creating map keys and legends. The LEX_ROCK codes matched perfectly with those listed in Wakefield et al. 2017 Supplementary; see Fig 17 and 18.
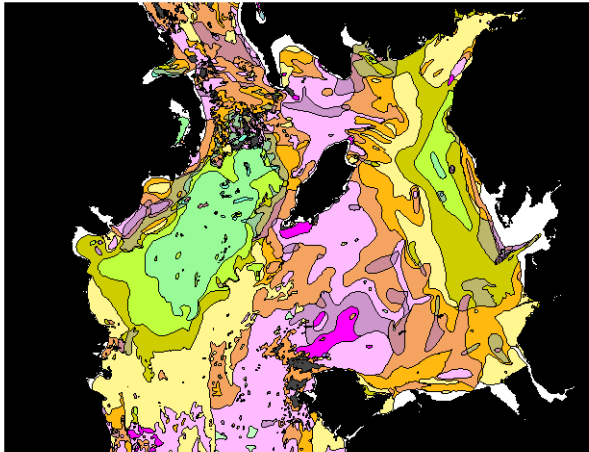
Figure 17. Original sediment shapes with local view in the Irish Sea from the Digimap BGS service

(a) Gravel   (b) Sand:mud ratio
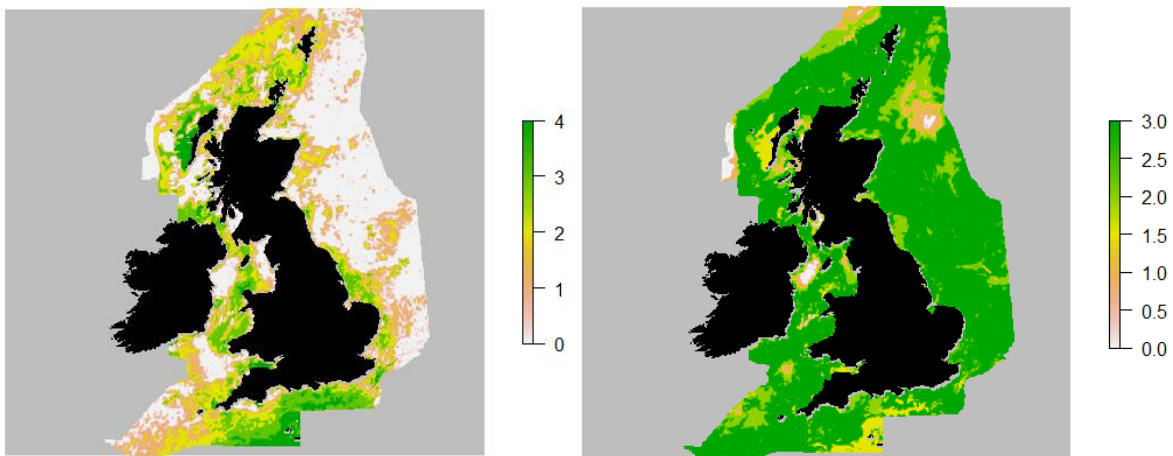

Figure 18. Rescaled and rasterised seabed sediment maps for (a) gravel proportion and (b) sand:mud ratio, using the methods and scaling approach as described in Wakefield et al. (2017)

Potential Energy Anomaly and mixed layer depth

The data source used for these covariates were the UK Met Office Forecasting Ocean Assimilation Model Atlantic Margin model via the MyOcean website (https://resources.marine.copernicus.eu/). Wakefield et al. (2017) accessed daily multi depth layer temperature and salinity data using the products: "NORTHWESTSHELF_REANALYSIS_PHYS_004_009" and "NORTHWESTSHELF_ANALYSIS_ FORECAST_PHYS_004_001_b". These datasets are now collected under a single catalogue called: "NWSHELF_MULTIYEAR_PHY_004_009" and carry the same grid resolution (ca 7 km) as in Wakefield et al. (2017). Given the accessibility, multiple products were downloaded, restricted to long: -13 to 6 lat: 46 to 63 to reduce memory download and storage. The availability was suitable across the study period, although for 2020, the data span only up to 2020-06-30 12:00:00. Some of these datasets are three-dimensional, for potential temperature and salinity at 24 binned at depths of 0 to 5000 m, required for

the potential energy anomaly equations. Further, separate datasets of mixed layer depth as a single 2D dataset: "ocean_mixed_layer_thickness_defined_by_sigma_theta" as defined in Kara, 2000 (reference depth at 3 m instead of 10 m). Sea water salinity (sea_water_salinity, *S*) was stored as annual files given this was a 3D dataset, as was potential temperature having substantial memory storage size of files.

For estimating the PEA, we trialled the method outlined in Carroll et al. (2016), defined as the energy per unit depth to mix the water column, i.e. the intensity of thermohaline stratification (Holt et al. 2010). The formula for estimating PEA (φ) is defined in Carroll et al. (2016) as:

$$\varphi = -\frac{g}{h} \int_{z=-h}^{0} z \left(\rho(T(z), S(z)) - \rho(\bar{T}, \bar{S}) \right) \, dz$$

numerically equivalent to equations in Hofmeister (2010), where, g = gravitational acceleration, h = water depth (or 400 m if h exceeds this, Carrol et al. 2016), z = the vertical coordinate (0 indicating the surface, negative values indicating deeper water), ρ = density (calculated using a polynomial function - Jackett et al. 2006, Feistel 2003), T = temperature, S = salinity; here the overbar indicates that the quantity is averaged from h to the surface. Further, as data were available for discrete depths, the integral was evaluated numerically using Simpson's rule as per Carroll et al. (2016). Note also, this equation follows others e.g. Hofmeister (2010) as originally defined by Simpson et al. (1977), and further in Holt et al. (2010). This PEA formula gives units of mechanical energy (J) per m^3, and is zero for a fully mixed water column, positive for stable stratification and negative for unstable stratification. In other studies, Carrol et al. (2016), Hol et al. (2010) and Wakefield et al. (2017), for convenience φ is defined to be positive only, for stable stratification. Higher values indicate stronger stratification. 400 m was chosen to represent a consistent comparison between conditions on and off-shelf while also revealing potential deep water mixing and subsequent changes (Holt et al. 2010). Wakefield et al. (2017) also represent the PEA variable in the appendices raised to the power of 0.5, i.e. sqrt-transformed.

Further, Wakefield et al. (2017) defined a mixed layer depth following Monterey and Levitus (1997), which expresses a threshold choice in terms of density change in relation to thermal expansion and thus assigns a threshold of 0.5 °C; this is stated in Kara et al. (2003) However, Kara et al. (2003) use a slightly different definition, where MLD is where density has changed by a fixed amount, i.e. not directly through temperature. The consequence is that the MLD field is deeper with the Kara approach, with a larger temperature difference criterion of 0.8°C, and also allows for convective mixing to remove instability from density profiles. Importantly, the dataset acquired through myOcean in "NWSHELF_MULTIYEAR_PHY_004_009" already contains a specific (time, x, y) netcdf file of MLD ("cmems_mod_nws_phy-mld_my_7km-2D_P1D-m"); however, this is based upon the method of Kara et al. (2003) not Monterey & Levitus (1997), and further, the equations as presented in the Plymouth-lab Python resources also follow a density threshold of 0.03 kg/m³, again as with PEA based on the Jackett et al. (2005) temperature~salinity density estimator. Further, the grid cells in Wakefield et al. (2017) were flagged as stratified if the mixed layer depth was < water depth, and then the mean proportion of days during which stratification occurred was calculated, which results in a proportional variable bounded 0 to 1 (Fig 19). The netcdf datasets are available daily and can be amalgamated (e.g. averaged) over any given period, if as in Wakefield et al. (2017) dynamic raster datasets need to be combined to static ones for the modelling. The PEA formula was available via a collection of Python functions and scripts allowing processing for more recent data (Fig 20).
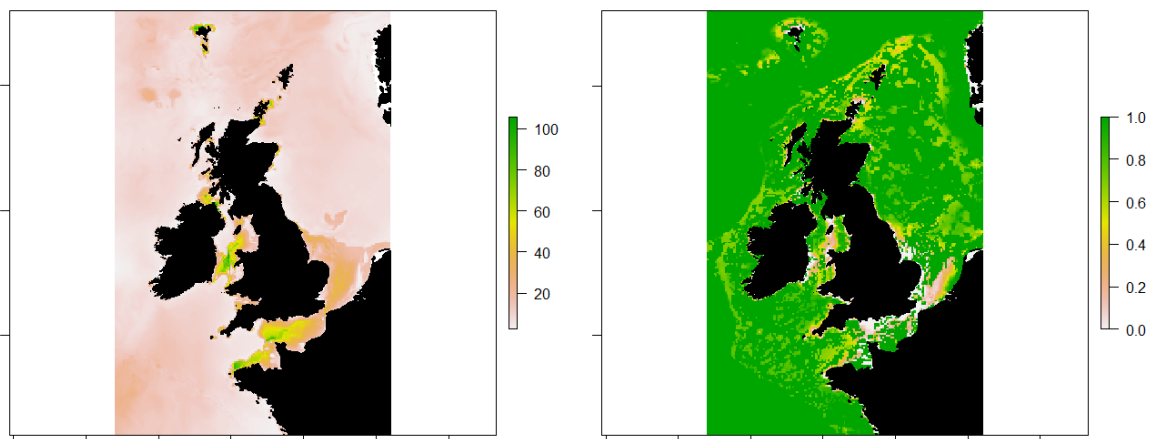
(a) 23rd June 2020 example one day   PEA   (b) Composite PEA J/m^3^0.5 for Mar-June 2020
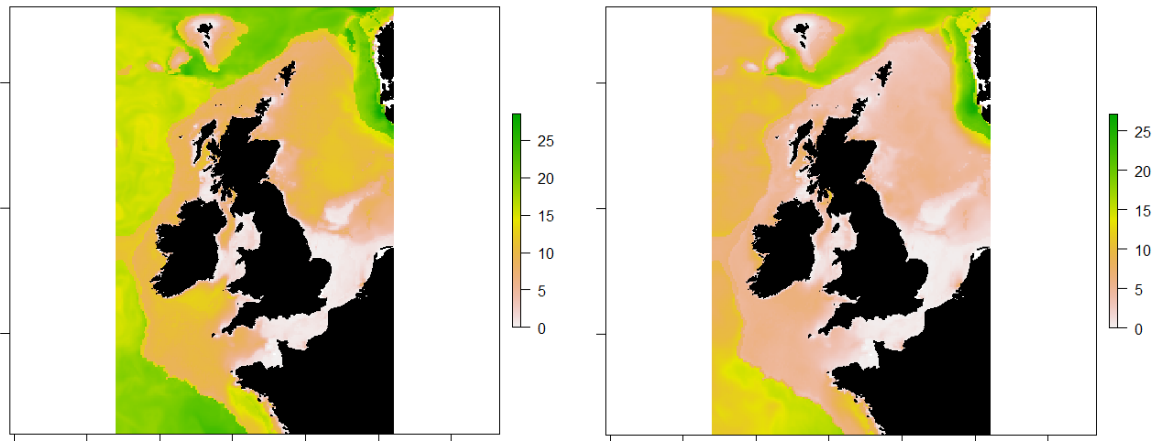
Figure 19. Example of one day slice in 2020, and a further composite for the March-June 2020 period, depending on how the rasters will be amalgamated for analysis

(a) 23rd June 2020 example one day   (m)   (b) Composite proportional time stratified

Figure 20. Example of the stratification layer, showing a single day slice of the raster for 23rd June 2020 and then a composite as per Wakefield et al. (2017) for a March-June 2020 proportional of days stratified (MLD < max water depth); for the latter the sea relief dataset was used.

Sea surface temperature

The NEODAAS SST data can be accessed through an online visualisation tool (https://data.neodaas.ac.uk/visualisation/); a variety of sensors can also be specified to create a composite image, but including the AVHRR. Here the following source was trialled: Indicator type: ocean temp, Data provider: NASA JPL, Interval: Daily, Version: NRT and Refined, Sensor: Multi sensor, Resolution: 1 km, Bound box: 89.99N, 180E, -89.99S, -179.99W, Data range: 2002-06-01 2021-08-22, from which subsetted areas and date-selections can be specified. This data source is a version 4 (L4 analysis); see Fig 21.
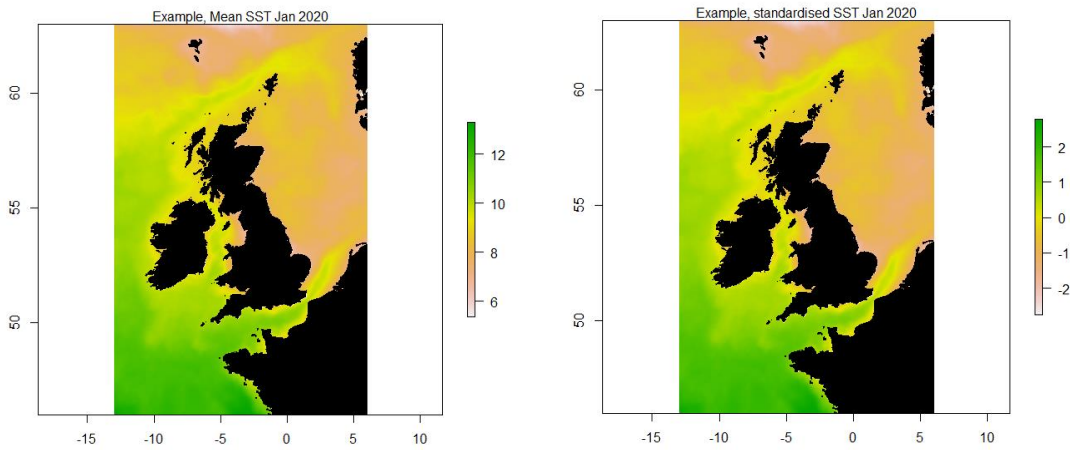
Figure 21. Example SST datasets for 2020, here plotted for January 2020 as a composite image across daily datasets

Alpha Chlorophyll

The alpha-chlorophyll net primary productivity dataset was also accessed through the above NEODAAS visualisation tool, for the following source: Indicator type: Ocean Colour, Data provider: ESA CCI, Region: Global, Interval: Daily, Version: Refined-OC-CCI-v5, Sensor: Multi-sensor, Resolution: 1km, Sub-region: Global, Bound box: 89.99N, 180E, -89.99S, -179.99W, Data range: 1997-09-04 2020-12-31. Given the tracking data timespan, this dataset includes the long-running European Space Agency Ocean Colour Climate Change Initiative (OC-CCI) product (Sentinal 3A and 3B). The scale of the accessed data is mg/m^3 for daily maps, although Wakefield present this as "gC/m^3/day". Example Chlorophyll data for August 2020 daily average on the original milligram scale is shown below (Fig 22).
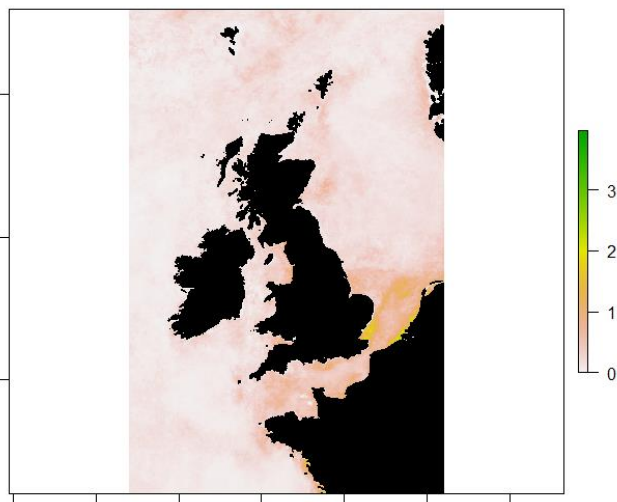

Figure 22. Example plot for August 2020 alpha-chlorophyll as a composite image across daily datasets

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Thermal fronts

Strong front maps were obtained from the NEODAAS Multiview tool (https://data.neodaas.ac.uk/multiview/). These front maps are available as seven-day composite images generated as per methods developed by Peter Miller (Plymouth Marine Laboratory); however, the thermal front gradient index requires processing of individual seven-day composite Mercator-projected .png images that can be sourced, compiled to a raster stack (mosaic) and amalgamated with prior knowledge of mathematical transformation of the Mercator to WGS84 conversion. Seven-day time slices can then be aligned to work out seasonally persistent fronts (Scales et al. 2014), e.g. in Fig 23 below for five raster for June 2020, from which clearer patterns can be revealed using a Gaussian smooth (Scales et al. 2014, Wakefield et al. 2017). Note that both Scales et al. (2014) and Miller and Christodoulou (2014) consider the same dataset and result in a percentage of time (per grid cell) that a strong front occurs (greater than 0.015 F_{comp}); however, Wakefield present the frontal map as degC/1.2 km (i.e. the resolution of the raster cell), representing, if interpreted correctly, the provided units of the raster images for Fcomp that scale between ca. 0 and 0.3.

The raster layers included are a mix of dynamic and static; however, again due to computational costs, the dynamic variables were reduced down (monthly composites). Thus although the method is a suitable robust framework, there may be analytical alternatives or improvements in future methods that circumvent the current drawbacks.
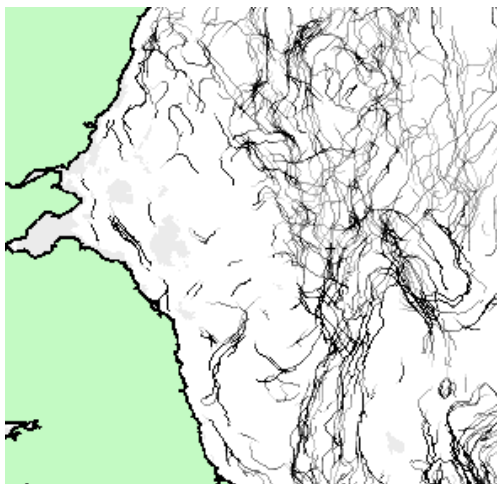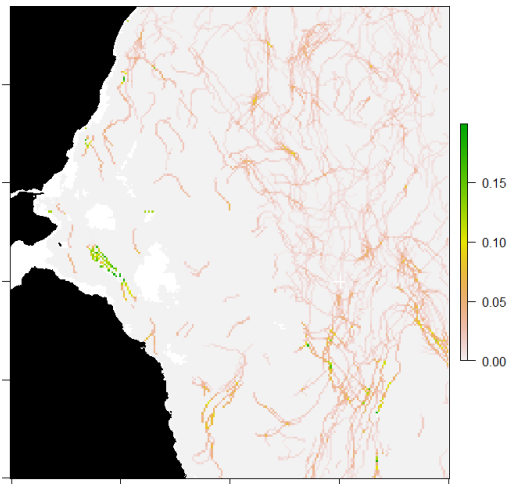
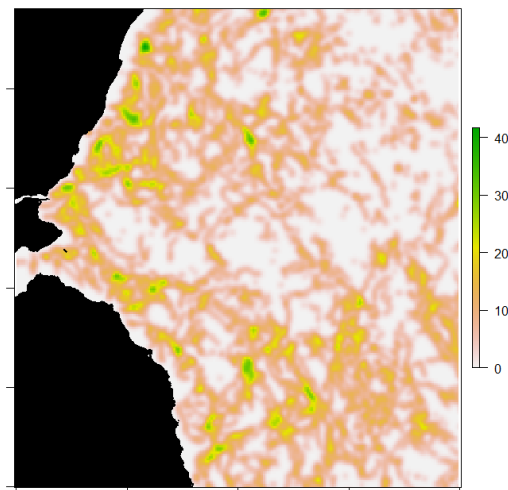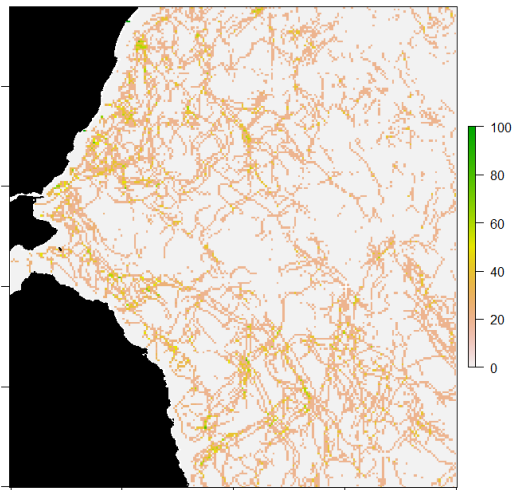(a) Original png
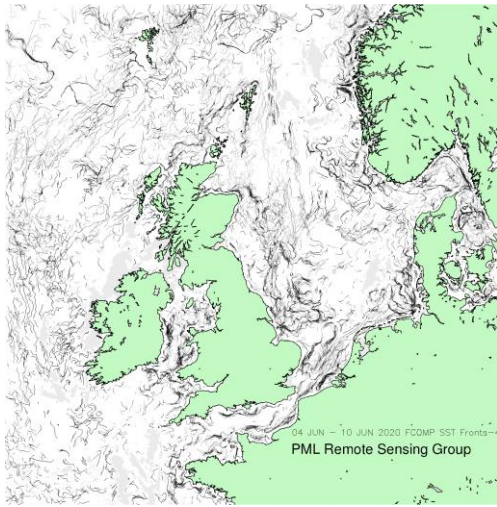
(b) Georeferenced unbalanced raster
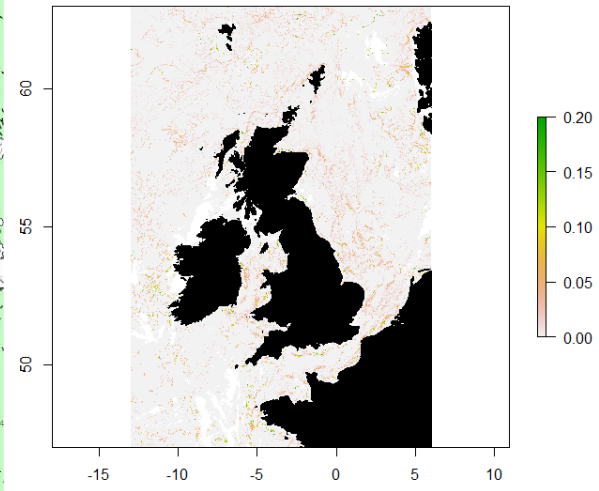
(c) Zoomed in view of png around Isle of May

(d) Scale here if Fcomp in Miller and C et al.

(e) June composite % days / month front observed

(f) June composite as in 'e' using Gaussian filter

Figure 24. Example front data processing png front data; (a) example single front map for 2020-06-04 to 2020-06-10 (b) further georeferenced raster for that single 7-day period; (c) zoomed in front view around Isle of May and (d) translated scale (Fcomp) following Miller and Christodoulou (2014); (e) using a threshold of 0.15 (Scales et al. 2014) for front yes or no, the proportion of 7-day maps with a front observed, here for the month of June, and (f) application of a further Gaussian filter [focalWeight(r,sqrt(2), "Gauss")]; maps at 1.2 km; alternatively it is possible to take a mean of the Fcomp scale, as likely done in Wakefield et al. (2017).

Distance to coast

Minimum distance to the coast can be calculated in R or ArcGIS. These covariates have been scrutinised and have clear mechanistic links to aspects of seabird ecology (reviews by Hunt (1997), Mann and Lazier (2006), and Wakefield et al. (2009) as stated in Wakefield et al. (2017).

Further available data layers specific to gulls

Vessel movement data

For a general use of a layer to determine fishing effort, the resource of the Global Fishing Watch (GFW) Initiative may be useful (Kroodsma et al. 2018). These data will need careful scrutinising as it may be the vessels target the habitat for fish, which are also targeted separately for birds, and thus direct connection between boat and bird is potentially not therefore established through coarser measures. Further covariate variance inflation within modelling may also arise. It is also not possible to get detailed VMS data from the UK without further specific requests, nor at the level of individual tracks for seabirds, again without further requests.

However, for a general value of daily activity the GFW portal may be a sensible dataset to consider in keeping with the level of the analysis. Data csv files were here obtained on a daily basis giving fishing effort per grid cell, available 2012 to 2020; this may mean it is not fully possible to model the Orford Ness data (2010-2015). Data were extracted for the 2012-2020 period using the latest AIS algorithms, neural network models, and vessel registry database (v2 of data provisions). Two resolutions are available, 0.01 degree (1.11 km) or 0.1 degree (11.1 km), daily, here selecting the 1 km dataset in keeping with the previous Wakefield et al. (2017) datasets – see Fig 25. As in Wakefield, the provided daily data were rasterised as a raster stack and then averages taken to represent potential aggregations that could be fed into the modelling procedure. This dataset includes options to select gear types and all hours of fishing hours; below plots are of all hours and all gear types.

(a) Walney, July 2014, bird 4032   (b) Skokholm July 2014, bird 5017
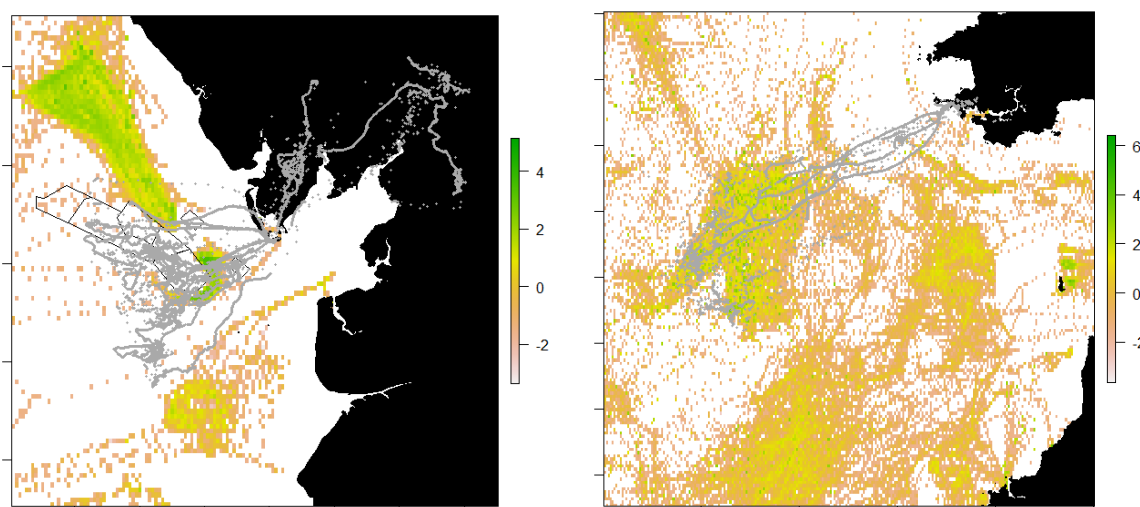
Figure 25. Example of July 2020 amalgamated daily data for fishing effort overlain with single tracks of two birds over the same time period; the scale is log(hours / day) of fishing activity, including all fishing related activity, but excluding wider vessel movements such as servicing offshore structures.

Further similar vessel density data are available from the Emodnet data portals (https://www.emodnet-humanactivities.eu/view-data.php), but only from 2017-2020, and would therefore not span most of the tracking data available. This however, does include the information on vessel density of all vessels i.e. beyond just fishing.

4. Discussion

The datasets available to inform apportioning are given in Table 4, below. Permission has been obtained to make use of the Lesser Black-backed Gull GPS tracking datasets, the tern focal follow datasets and the Guillemot and Razorbill geolocation data. These data have been obtained by the project team and are in a suitable format for analysis.

In relation to the breeding season data, the GPS tracking data and the tern focal follow data are comparable to the data analysed in Wakefield et al. (2017), meaning that the approach of Butler et al., (2020) is likely to be suitable, following modelling of these data. We have identified the necessary data sources for the covariates to run these models, and ensured their availability. Both the tracking data and the covariate data are readily available in a format suitable for the modelling. In relation to the non-breeding season data, we have determined that the geolocation data available for Guillemots and Razorbills is likely to be suitable for the bespoke approach described above, based on kernel density estimation. As such, we concluded that the two highest priority situations in which new or extended methods were likely to rapidly provide added value, and therefore formed the focus of methods evaluation in WP3, were those associated with LBBG GPS and auk GLS data.

While we have identified other data sources that may be available to inform apportioning, we feel that the spatial and temporal resolution of these data is coarser than that available from either the GPS or the geolocation data. Biases in the distribution of effort for ringers and observers means that data from ring recoveries is unlikely to give a clear picture in relation to the origins of ringed birds. Similarly, using genetic markers to identify the origins of birds is likely to be challenging due to a lack of population structure. Related to this, while there are clear trends in biometric data with latitude, variation in body size between birds from the same breeding colony mean using these data to apportion wintering birds back to their breeding colonies is unlikely to be practical. Consequently, while there may be some value in using sources such as ringing or biometric data to identify colonies which contribute to non-breeding populations, the challenges of working with these data mean that they are unlikely to be suitable for apportioning at present.

For species, or regions, from which tagging data are not available, colony-level data on phenology and/or from resources such as Trektellen or BirdTrack may be useful in relation to defining the timing of migration. For other species, tracking data is likely to be more valuable.

Table 4. Summary of potential datasets to inform apportioning

Type of Data	Potential Use in Apportioning	Data	Permissions	Permissions secured
GPS Tracking Data	Temporal variability in space use during the breeding season; Wintering location of breeding birds; timing of breeding and non-breeding seasons.	Lesser Black-backed Gull (Walney)	BTO	✓
		Lesser Black-backed Gull (Skokholm)	BTO	✓
		Lesser Black-backed Gull (Orfordness)	BTO	✓
		Lesser Black-backed Gull (Isle of May)	BTO	✓
		Lesser Black-backed Gull (Craigleith)	BTO	✓
		Lesser Black-backed Gull (Fidra)	BTO	✓
		Lesser Black-backed Gull (Barrow)	BTO	✓
		Lesser Black-backed Gull (Belfast)	BTO	✓

		Lesser Black-backed Gull (Ribble)	BTO	✓
		Lesser Black-backed Gull (Bowland)	BTO	✓
Focal follow data	Temporal variability in space use during the breeding season (terns only)	Blakeney Point	JNCC	✓
		Cemlyn Bay	JNCC	✓
		Outer Ards	JNCC	✓
		Copeland Islands	JNCC	✓
		Coquet Island	JNCC	✓
		Farne Islands	JNCC	✓
		Glas Eileanan	JNCC	✓
		Imperial Dock Leith	JNCC	✓
		Sands of Forvie	JNCC	✓
		Scolt Head	JNCC	✓
		South Shian	JNCC	✓
Geolocation Data	Wintering location of breeding birds; start and end of breeding season	Colonsay - Guillemot	UKCEH	✓
		Treshnish Isles – Guillemot	UKCEH	✓
		Canna – Guillemot	UKCEH	✓
		Shiant Islands – Guillemot	UKCEH	✓
		Foula – Guillemot	UKCEH	✓
		Fair Isle – Guillemot	UKCEH	✓
		Orkney – Guillemot	UKCEH	✓
		East Caithness – Guillemot	UKCEH	✓

		Whinnyfold – Guillemot	UKCEH	✓
		Isle of May – Guillemot	UKCEH	✓
		Farne Islands – Guillemot	UKCEH	✓
		Colonsay - Razorbill	UKCEH	✓
		Treshnish Isles- Razorbill	UKCEH	✓
		Canna – Razorbill	UKCEH	✓
		Shiant Islands – Razorbill	UKCEH	✓
		Foula – Razorbill	UKCEH	✓
		Fair Isle – Razorbill	UKCEH	✓
		Orkney – Razorbill	UKCEH	✓
		East Caithness- Razorbill	UKCEH	✓
		Whinnyfold- Razorbill	UKCEH	✓
		Isle of May- Razorbill	UKCEH	✓
		Farne Islands- Razorbill	UKCEH	✓
Data from Local Bird Reports	Timing of migratory movements; Annual reports from Bird Observatories may also offer data on the timing of the breeding season	Local bird reports	Available from BTO Library	Data available to be extracted if appropriate
Colony Specific Data on Phenology	Start and end of breeding season	Bird Observatory Annual Reports	Available from BTO Library	Data available to be extracted if appropriate
Literature on the Timing of Migration	Timing of migratory movements	Buckingham et al. in press – Guillemot & Razorbill		Data available to be extracted if appropriate
		Merkel et al. 2019 - Guillemot		Data available to be extracted if appropriate

			Dunn et al. 2020 Guillemot		Data available to be extracted if appropriate
			Bormann et al. 2021 Lesser Black-backed Gull		Data available to be extracted if appropriate
			Brown et al. 2021 – Lesser Black-backed gull		Data available to be extracted if appropriate
			Frederiksen et al. 2012 - Kittiwake		Data available to be extracted if appropriate
			Bogdanova et al. 2017 - Kittiwake		Data available to be extracted if appropriate
			Fort et al. 2012 – Gannet		Data available to be extracted if appropriate
			Lane et al. 2021 - Gannet		Data available to be extracted if appropriate
			Kubetzki et al. 2021 - Gannet		Data available to be extracted if appropriate
			Laurenson et al. 2021 – Gannet		Data available to be extracted if appropriate
			Amelieanu et al. 2021 – multi-species		Data available to be extracted if appropriate
			Davies et al. 2021 – multi-species		Data available to be extracted if appropriate

		Keogan et al. 2018 – multi-species		Data available to be extracted if appropriate
Trektellen/BirdTrack data	Timing of migratory movements	BirdTrack	BTO	Subject to data request ~2 weeks
Ring Recovery Data	Breeding origin of wintering birds	UK Ringing Scheme	BTO	Subject to data request ~2 weeks
Biometric Data	Breeding origin of wintering birds	UK Ringing Scheme	BTO	Subject to data request ~2 weeks
Genetic Marker Data	Breeding origin of wintering birds	Bicknell et al. 2012 – Leach's Storm Petrel	Authors	
		Barlow et al. 2011 – Shag	Authors	
		Thanou et al. 2017 – Shag	Authors	
		Sauve et al. 2019 – Kittiwake	Authors	
		Burg et al. 2003 – Fulmar	Authors	
		Cadiou et al. 2004 - Guillemot	Authors	
Stable Isotope Data	Wintering location of breeding birds; breeding origin of wintering birds; Foraging areas of breeding & immature birds	Glew et al. 2019 – auks	Authors	
		Glew et al. 2018 – auks	Authors	
		Gonzalez-Solis et al. 2011 – Kittiwake	Authors	
		Leat et al. 2013 Great Skua	Authors	
		Bourgeon et al. 2014 Great Skua	Authors	
		Kakela et al. 2007 – Gannet, Great Skua, Shag, Guillemot	Authors	
		Grecian et al. 2019 - Gannet	Authors	
		Votier et al. 2011 - Gannet	Authors	

		Votier et al. 2010 - Gannet	Authors	
		Bicknell et al. 2014 – Leach's Storm Petrel	Authors	
Ectoparasites	Origin of wintering birds	McCoy et al. 2007 – Puffin & Kittiwake	Authors	

5. References

Acampora, H., Lyashevska, O., Van Franeker, J. A., & O'Connor, I. (2016). The use of beached bird surveys for marine plastic litter monitoring in Ireland. Marine Environmental Research, 120, 122–129. https://doi.org/10.1016/J.MARENVRES.2016.08.002

Amélineau, F., Merkel, B., Tarroux, A., Descamps, S., Anker-Nilssen, T., Bjørnstad, O., … Strøm, H. (2021). Six pelagic seabird species of the North Atlantic engage in a fly-and-forage strategy during their migratory movements. *Marine Ecology Progress Series*, *676*, 127–144. https://doi.org/10.3354/MEPS13872

Anker-Nilssen, T., Harris, M. P., Kleven, O., & Langset, M. (2017). Status, origin, and population level impacts of Atlantic Puffins killed in a mass mortality event in southwest Norway early 2016. *SEABIRD*, *30*, 1–14. Retrieved from www.met.no

Anker-Nilssen, T., Jensen, J. K., & Harris, M. P. (2018). Fit is fat: winter body mass of Atlantic Puffins Fratercula arctica. *Bird Study*, *65*(4), 451–457. https://doi.org/10.1080/00063657.2018.1524452

Barlow, E. J., Daunt, F., Wanless, S., Álvarez, D., Reid, J. M., & Cavers, S. (2011). Weak large-scale population genetic structure in a philopatric seabird, the European Shag Phalacrocorax aristotelis. *Ibis*, *153*(4), 768–778. https://doi.org/10.1111/J.1474-919X.2011.01159.X

BARRETT, R. T., ANKER-NILSSEN, T., & KRASNOV, Y. V. (1997). CAN NORWEGIAN AND RUSSIAN RAZORBILLS ALCA TORDA BE IDENTIFIED BY THEIR MEASUREMENTS? *Marine Ornithology*, *25*, 5–8. Retrieved from http://www.marineornithology.org/content/get.cgi?ident=25_2

Barrett, R. T., Fieler, R., Anker-Nilssen, T., & Rikardsen, F. (1985). Measurements and weight changes of Norwegian adult puffins Fratercula arctica and kittiwakes Rissa tridactyla during the breeding season. *Ringing & Migration*, *6*, 102–112.

Bicknell, A. W.J., Knight, M. E., Bilton, D., Reid, J. B., Burke, T., & Votier, S. C. (2012). Population genetic structure and long-distance dispersal among seabird populations: Implications for colony persistence. *Molecular Ecology*, *21*(12), 2863–2876. https://doi.org/10.1111/J.1365-294X.2012.05558.X

Bicknell, Anthony W.J., Knight, M. E., Bilton, D. T., Campbell, M., Reid, J. B., Newton, J., & Votier, S. C. (2014). Intercolony movement of pre-breeding seabirds over oceanic scales: implications of cryptic age-classes for conservation and metapopulation dynamics. *Diversity and Distributions*, *20*(2), 160–168. https://doi.org/10.1111/DDI.12137

Blackburn, T. M., Gaston, K. J., & Loder, N. (1999). Geographic gradients in body size: a clarification of Bergmann's rule. *Diversity and Distributions*, *5*(4), 165–174. https://doi.org/10.1046/J.1472-4642.1999.00046.X

Bodey, T. W., Cleasby, I. R., Bell, F., Parr, N., Schultz, A., Votier, S. C., & Bearhop, S. (2018). A phylogenetically controlled meta-analysis of biologging device effects on birds: Deleterious effects and a call for more standardized reporting of study data. *Methods in Ecology and Evolution*, *9*(4), 946–955. https://doi.org/10.1111/2041-210X.12934

Boersch-Supan, P. H., Trask, A. E., & Baillie, S. R. (2019). Robustness of simple avian population trend models for semi-structured citizen science data is species-dependent. *Biological Conservation*, *240*, 108286. https://doi.org/10.1016/J.BIOCON.2019.108286

Bogdanova, M. I., Butler, A., Wanless, S., Moe, B., Anker-Nilssen, T., Frederiksen, M., … Daunt, F. (2017). Multi-colony tracking reveals spatio-temporal variation in carry-over effects between breeding success and winter movements in a pelagic seabird. *Marine Ecology Progress Series*, *578*, 167–181. https://doi.org/10.3354/MEPS12096

Borrmann, R. M., Phillips, R. A., Clay, T. A., & Garthe, S. (2021). Post-fledging migration and wintering strategies of individual juvenile Lesser Black-backed Gulls (Larus fuscus). *Ibis*, *163*(3), 1017–1031. https://doi.org/10.1111/IBI.12917

Bouten, W., Baaij, E. W., Shamoun-Baranes, J., & Camphuysen, K. C. J. (2013). A flexible GPS tracking system for studying bird behaviour at multiple scales. *Journal of Ornithology*, *154*(2), 571–580. https://doi.org/10.1007/s10336-012-0908-1

Brown, J. M., van Loon, E. E., Bouten, W., Camphuysen, K. C. J., Lens, L., Müller, W., … Shamoun-Baranes, J. (2021). Long-distance migrants vary migratory behaviour as much as short-distance migrants: An individual-level comparison from a seabird species with diverse migration strategies. *Journal of Animal Ecology*, *90*(5), 1058–1070. https://doi.org/10.1111/1365-2656.13431

Buckingham, L., Bogdanova, M., Green, J., Dunn, R., Wanless, S., Bennett, S., … Daunt, F. (2021). Interspecific variation in non-breeding aggregation: a multi-colony tracking study of two sympatric seabirds. *Marine Ecology Progress Series*. https://doi.org/10.3354/MEPS13960

Burg, T. M., Lomax, J., Almond, R., Brooke, M. D. L., & Amos, W. (2003). Unravelling dispersal patterns in an expanding population of a highly mobile seabird, the northern fulmar (Fulmarus glacialis). *Proceedings of the Royal Society of London. Series B: Biological Sciences*, *270*(1518), 979–984. https://doi.org/10.1098/RSPB.2002.2322

Butler, A., Carroll, M., Searle, K., Bolton, M., Waggitt, J., Evans, P., … Daunt, F. (2020). Attributing seabirds at sea to appropriate breeding colonies and populations. *Scottish Marine and Freshwater Science*, *11*(8).

Cadiou, B., Riffaut, L., McCoy, K. D., Cabelguen, J., Fortin, M., Gélinaud, G., … Boulinier, T. (2004). Ecological impact of the "Erika" oil spill: Determination of the geographic origin of the affected common guillemots. *Aquatic Living Resources*, *17*(3), 369–377. https://doi.org/10.1051/ALR:2004036

Calladine, J. (1997). A comparison of Herring Gull Larus argentatus and Lesser Black-backed Gull Larus fuscus nest sites: their characteristics and relationships with breeding success. *Bird Study*, *44*(3), 318–326. https://doi.org/10.1080/00063659709461067

Camphuysen, C. J., & Heubeck, M. (2001). Marine oil pollution and beached bird surveys: the development of a sensitive monitoring instrument. *Environmental Pollution*, *112*(3), 443–461. https://doi.org/10.1016/S0269-7491(00)00138-X

Corkhill, P. (1972). Measurements of Puffins as criteria of Sex and Age. *Bird Study*, *19*, 193–202.

Deakin, Z., Hamer, K. C., Sherley, R. B., Bearhop, S., Bodey, T. W., Clark, B. L., … Votier, S. C. (2019). Sex differences in migration and demography of a wide-ranging seabird, the northern gannet. *Marine Ecology Progress Series*, *622*, 191–201. https://doi.org/10.3354/MEPS12986

Dunn, R. E., Wanless, S., Daunt, F., Harris, M. P., & Green, J. A. (2020). A year in the life of a North Atlantic seabird: behavioural and energetic adjustments during the annual cycle. *Scientific Reports 2020 10:1*, *10*(1), 1–11. https://doi.org/10.1038/s41598-020-62842-x

Fort, J., Pettex, E., Tremblay, Y., Lorentsen, S.-H., Garthe, S., Votier, S., … Gremillet, D. (2012). Meta-population evidence of oriented chain migration in northern gannets (*Morus bassanus*). *Frontiers in Ecology and Environment*, *10*(5), 237–242. https://doi.org/10.1890/110194

Frederiksen, M., Moe, B., Daunt, F., Phillips, R. A., Barrett, R. T., Bogdanova, M. I., … Anker-Nilssen, T. (2012a). Multicolony tracking reveals the winter distribution of a pelagic seabird on an ocean basin scale. *Diversity and Distributions*, *18*(6), 530–542. https://doi.org/10.1111/J.1472-4642.2011.00864.X

Frederiksen, M., Moe, B., Daunt, F., Phillips, R. A., Barrett, R. T., Bogdanova, M. I., … Anker-Nilssen, T. (2012b). Multicolony tracking reveals the winter distribution of a pelagic seabird on an ocean basin scale. *Diversity and Distributions*, *18*(6), 530–542. https://doi.org/10.1111/j.1472-4642.2011.00864.x

Furness, R. W., Wade, H. M., & Masden, E. A. (2013). Assessing vulnerability of marine bird populations to offshore wind farms. *JOURNAL OF ENVIRONMENTAL MANAGEMENT*, *119*, 56–66. https://doi.org/10.1016/j.jenvman.2013.01.025

Geen, G. R., Robinson, R. A., & Baillie, S. R. (2019, February 1). Effects of tracking devices on individual birds – a review of the evidence. *Journal of Avian Biology*. Blackwell Publishing Ltd. https://doi.org/10.1111/jav.01823

Glew, K. S. J., Wanless, S., Harris, M. P., Daunt, F., Erikstad, K. E., Strøm, H., & Trueman, C. N. (2018). Moult location and diet of auks in the North Sea inferred from coupled light-based and isotope-based geolocation. *Marine Ecology Progress Series*, *599*, 239–251. https://doi.org/10.3354/MEPS12624

González-Solís, J., Smyrli, M., Militão, T., Gremillet, D., Tveraa, T., Phillips, R. A., & Boulinier, T. (2011). Combining stable isotope analyses and geolocation to reveal kittiwake migration. *Marine Ecology Progress Series*, *435*, 251–261. https://doi.org/10.3354/MEPS09233

Grantham Grantham, M. M. (2004). Age structure and origins of British & Irish Guillemots Uria aalge recovered in recent European oil spills. *Atlantic Seabirds*, *6*(3), 95–108.

Grecian, W. J., Williams, H. J., Votier, S. C., Bearhop, S., Cleasby, I. R., Grémillet, D., … Bodey, T. W. (2019). Individual spatial consistency and dietary flexibility in the migratory behavior of northern gannets wintering in the northeast Atlantic. *Frontiers in Ecology and Evolution*, *7*(JUN), 214. https://doi.org/10.3389/FEVO.2019.00214/BIBTEX

Green, R. M. W., Burton, N. H. K., & Cook, A. S. C. P. (2019). Review of the migratory movements of Shelduck to inform understanding of potential interactions with offshore wind farms in the southern North Sea.

Grist, H., Daunt, F., Wanless, S., Nelson, E. J., Harris, M. P., Newell, M., … Reid, J. M. (2014). Site Fidelity and Individual Variation in Winter Location in Partially Migratory European Shags. *PLOS ONE*, *9*(6), e98562. https://doi.org/10.1371/JOURNAL.PONE.0098562

Harris, M. P. (1979). Measurements and weights of British Puffins. *Bird Study*, *26*, 179–186.

Helfenstein, F., Danchin, E., & Wagner, R. H. (2004). Assortative Mating and Sexual Size Dimorphism in Black-legged Kittiwakes. *Https://Doi.Org/10.1675/1524-4695(2004)027[0350:AMASSD]2.0.CO;2*, *27*(3), 350–354. https://doi.org/10.1675/1524-4695(2004)027

Hewson, C. M., Thorup, K., Pearce-Higgins, J. W., & Atkinson, P. W. (2016). Population decline is linked to migration route in the Common Cuckoo. *Nature Communications 2016 7:1*, *7*(1), 1–8. https://doi.org/10.1038/ncomms12296

Hope Jones, P., Monnat, J., & Harris, M. P. (1980). Origins, age and sex of auks (Alcidae) killed in the "Amoco Cadiz" oiling incident in Brittany, March 1978. *Seabird*, *6*(122–131).

Huffeldt, N. P., & Merkel, F. R. (2013). Remote Time-lapse Photography as a Monitoring Tool for Colonial Breeding Seabirds: A Case Study Using Thick-billed Murres (Uria lomvia). *Https://Doi.Org/10.1675/063.036.0310*, *36*(3), 330–341. https://doi.org/10.1675/063.036.0310

John Glew, K. S., Wanless, S., Harris, M. P., Daunt, F., Erikstad, K. E., Strøm, H., & Trueman, C. N. (2018). Moult location and diet of auks in the North Sea inferred from coupled light-based and isotope-based geolocation. *Marine Ecology Progress Series*, *599*, 239–251. https://doi.org/10.3354/MEPS12624

Kubetzki, U., Garthe, S., Fifield, D., Mendel, B., & Furness, R. (2009). Individual migratory schedules and wintering areas of northern gannets. *Marine Ecology Progress Series*, *391*, 257–265. https://doi.org/10.3354/meps08254

Langley, L. P., Bearhop, S., Burton, N. H. K., Banks, A. N., Frayling, T., Thaxter, C. B., … Votier, S. C. (2021). GPS tracking reveals landfill closures induce higher foraging effort and habitat switching in gulls. *Movement Ecology*, *9*(1), 1–13. https://doi.org/10.1186/S40462-021-00278-2/FIGURES/6

Laurenson, K., Atkins, K., Clark, B., Morgan, G., Morgan, L., & Votier, S. (2021). Gannet Morus Bassanus ring recoveries suggest shorter migrations than geolocator tracking, but indicate no long-term change in migration distances. *Bird Study*, *68*(1), 1–8. https://doi.org/10.1080/00063657.2021.1960270/SUPPL_FILE/TBIS_A_1960270_SM4880.DOCX

Léandri-Breton, D.-J., Lamarre, J.-F., & Bêty, J. (2019). Seasonal variation in migration strategies used to cross ecological barriers in a nearctic migrant wintering in Africa. *Journal of Avian Biology*, *50*(6). https://doi.org/10.1111/JAV.02101

Leat, E. H. K., Bourgeon, S., Magnusdottir, E., Gabrielsen, G. W., Grecian, W. J., Hanssen, S. A., … Borgå, K. (2013). Influence of wintering area on persistent organic pollutants in a breeding migratory seabird. *Marine Ecology Progress Series*, *491*, 277–293. https://doi.org/10.3354/MEPS10455

McCoy, K. D., Boulinier, T., Tirard, C., & Michalakis, Y. (2003). HOST-DEPENDENT GENETIC STRUCTURE OF PARASITE POPULATIONS: DIFFERENTIAL DISPERSAL OF SEABIRD TICK HOST RACES. *Evolution*, *57*(2), 288–296. https://doi.org/10.1111/J.0014-3820.2003.TB00263.X

Merkel, B., Descamps, S., Yoccoz, N. G., Danielsen, J., Daunt, F., Erikstad, K. E., … Strøm, H. (2019). Earlier colony arrival but no trend in hatching timing in two congeneric seabirds (Uria spp.) across the North Atlantic. *Biology Letters*, *15*(10). https://doi.org/10.1098/RSBL.2019.0634

Merkel, B., Phillips, R. A., Descamps, S., Yoccoz, N. G., Moe, B., & Strøm, H. (2016). A probabilistic algorithm to process geolocation data. *Movement Ecology*, *4*(1), 1–11. https://doi.org/10.1186/S40462-016-0091-8/FIGURES/3

Mitchell, P. I., Newton, S. F., Ratcliffe, N., & Dunn, T. E. (2004). *Seabird Populations of Britain and Ireland*. Poyser.

NatureScot. (2018). Interim Guidance on apportioning impacts from marine renewable developments to breeding seabird populations in SPAs | NatureScot. Retrieved December 2, 2021, from https://www.nature.scot/doc/interim-guidance-apportioning-impacts-marine-renewable-developments-breeding-seabird-populations#Data+led+empirical+approaches

Newton, I., & Little, B. (2009). Assessment of wind-farm and other bird casualties from carcasses found on a Northumbrian beach over an 11-year period. *Bird Study*, *56*(2), 158–167. https://doi.org/10.1080/00063650902787767

Pennington, M. G., Bainbridge, I. P., & Fearon, P. (2011). Biometrics and primary moult of non-breeding Kittiwakes Rissa tridactyla in Liverpool Bay, England. *Http://Dx.Doi.Org/10.1080/03078698.1994.9674069*, *15*(1), 33–39. https://doi.org/10.1080/03078698.1994.9674069

Perrow, M. R., Skeate, E. R., & Gilroy, J. J. (2011). Visual tracking from a rigid-hulled inflatable boat to determine foraging movements of breeding terns. *Journal of Field Ornithology*, *82*(1), 68–79. https://doi.org/10.1111/J.1557-9263.2010.00309.X

PERROW, M. R., SKEATE, E. R., LINES, P., BROWN, D., & TOMLINSON, M. L. (2006). Radio telemetry as a tool for impact assessment of wind farms: the case of Little Terns Sterna albifrons at Scroby Sands, Norfolk, UK. *Ibis*, *148*, 57–75. https://doi.org/10.1111/j.1474-919X.2006.00508.x

Phillips, R. A., Silk, J. R. D., Croxall, J. P., Afanasyev, V., & Briggs, D. R. (2004). Accuracy of geolocation estimates for flying seabirds. *Marine Ecology Progress Series*, *266*, 265–272. https://doi.org/10.3354/MEPS266265

Phillips, Richard A., Lewis, S., González-Solís, J., & Daunt, F. (2017). Causes and consequences of individual variability and specialization in foraging and migration strategies of seabirds. *Marine Ecology Progress Series*, *578*, 117–150. https://doi.org/10.3354/MEPS12217

Porter, J. M., & Coulson, J. C. (1987). Long-term Changes in Recruitment to the Breeding Group, and the Quality of Recruits at a Kittiwake Rissa tridactyla Colony. *The Journal of Animal Ecology*, *56*(2), 675. https://doi.org/10.2307/5076

Riffaut, L., McCoy, K. D., Tirard, C., Friesen, V. L., & Boulinier, T. (2005). Population genetics of the common guillemot Uria aalge in the North Atlantic: geographic impact of oil spills. *Marine Ecology Progress Series*, *291*, 263–273. https://doi.org/10.3354/MEPS291263

Sauve, D., Patirana, A., Chardine, J. W., & Friesen, V. L. (2019). Mitochondrial DNA reveals genetic structure within the Atlantic but not Pacific populations of a holarctic seabird, the Black-legged Kittiwake Rissa tridactyla. *Marine Ornithology*, *47*, 199–208. https://doi.org/10.1675/063.039.0302

Smith, R. D. (1988). Age and sex-related differences in biometrics and moult of Kittiwakes Age and sex-related differences in biometrics and moult of Kittiwakes. *Ringing and Migration*, *9*, 44–48. https://doi.org/10.1080/03078698.1988.9673921

Soanes, L. M., Arnould, J. P. Y., Dodd, S. G., Sumner, M. D., & Green, J. A. (2013). How many seabirds do we need to track to define home-range area? *Journal of Applied Ecology*, *50*(3), 671–679. https://doi.org/10.1111/1365-2664.12069

Spelt, A., Williamson, C., Shamoun-Baranes, J., Shepard, E., Rock, P., & Windsor, S. (2019). Habitat use of urban-nesting lesser black-backed gulls during the breeding season. *Scientific Reports 2019 9:1*, *9*(1), 1–11. https://doi.org/10.1038/s41598-019-46890-6

St. John Glew, K., Graham, L. J., McGill, R. A. R., & Trueman, C. N. (2019). Spatial models of carbon, nitrogen and sulphur stable isotope distributions (isoscapes) across a shelf sea: An INLA approach. Methods in Ecology and Evolution, 10(4), 518–531. https://doi.org/10.1111/2041-210X.13138

St. John Glew, K., Wanless, S., Harris, M. P., Daunt, F., Erikstad, K. E., Strøm, H., … Trueman, C. N. (2019). Sympatric Atlantic puffins and razorbills show contrasting responses to adverse marine conditions during winter foraging within the North Sea. *Movement Ecology 2019 7:1*, *7*(1), 1–14. https://doi.org/10.1186/S40462-019-0174-4

Thanou, E., Sponza, S., Nelson, E. J., Perry, A., Wanless, S., Daunt, F., & Cavers, S. (2017). Genetic structure in the European endemic seabird, Phalacrocorax aristotelis, shaped by a complex interaction of historical and contemporary, physical and nonphysical drivers. *Molecular Ecology*, *26*(10), 2796–2811. https://doi.org/10.1111/MEC.13996

Thaxter, C. B., Clark, N. A., Ross-Smith, V. H., Conway, G. J., Bouten, W., & Burton, N. H. K. (2017). Sample size required to characterize area use of tracked seabirds. *The Journal of Wildlife Management*, *81*(6), 1098–1109. https://doi.org/10.1002/jwmg.21283

Thaxter, C. B., Lascelles, B., Sugar, K., Cook, A. S. C. P., Roos, S., Bolton, M., … Burton, N. H. K. (2012). Seabird foraging ranges as a preliminary tool for identifying candidate Marine Protected Areas. *Biological Conservation*, *156*, 53–61. https://doi.org/10.1016/j.biocon.2011.12.009

Wakefield, E. D., Owen, E., Baer, J., Carroll, M. J., Daunt, F., Dodd, S. G., … Bolton, M. (2017). Breeding density, fine-scale tracking, and large-scale modeling reveal the regional distribution of four seabird species. *Ecological Applications*, *27*(7), 2074–2091. https://doi.org/10.1002/eap.1591

WANLESS, S., FREDERIKSEN, M., WALTON, J., & HARRIS, M. P. (2009). Long-term changes in breeding phenology at two seabird colonies in the western North Sea. *Ibis*, *151*(2), 274–285. https://doi.org/10.1111/J.1474-919X.2008.00906.X

Wilson, L. J., Black, J., Brewer, M. J., Potts, J. M., Kuepfer, A., Win, I., … Webb, A. (2014). *Quantifying usage of the marine environment by terns Sterna sp. around their breeding colony SPAs*. Retrieved from www.jncc.defra.gov.uk

Woodward, I., Thaxter, C. B., Owen, E., & Cook, A. S. C. P. (2019). *Desk-based revision of seabird foraging ranges used for HRA screening*.

ZYDELIS, R., DAGYS, M., & VAITKUS, G. (2006). Beached bird surveys in Lithuania reflect oil pollution and bird mortality in fishing nets. *Marine Ornithology*, *34*, 161–166. Retrieved from http://www.marineornithology.org/content/get.cgi?ident=34_2_161-166

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