OFFSHORE RENEWABLES JOINT INDUSTRY PROGRAMME (ORJIP) FOR OFFSHORE WIND

Integration of tracking and at-sea survey data: WP1. Data collation and review

InTAS

June 2025

working to accelerate offshore consenting

ORJIP Offshore Wind

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

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

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

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

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

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- Joint Nature Conservation Committee (JNCC)
- Natural England
- Natural Resources Wales
- NatureScot
- Scottish Government's Marine Directorate

This report was sponsored by the ORJIP Offshore Wind programme. For the avoidance of doubt, this report expresses the independent views of the authors.

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, Germany, South Africa, 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.

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Summary

Work under this package critically reviews the suitability of different seabird species as exemplars for the type of integrated analysis developed in the project. Considerations of conservation priority and data availability, as well as statistical challenge are combined into a shortlist of proposed species submitted to the ORJIP Steering Group and the Project Expert Panel (PEP) for final decision, at the midpoint of the project. Based on our assessment of the available data, we suggest that the analysis focus on seabird populations on the east coast of Scotland during the 2010-2017 period. The key species for analysis would be black-legged kittiwake, common guillemot and razorbill, with GPS tracking data available for all three species from multiple sites within the region. Of secondary interest is northern gannet. Whilst GPS data are only available from a single site for this species, data are available for both adult and immature birds, which can also be distinguished from digital aerial imagery, enabling us to consider differences in distributions between age classes. All four species are well represented in digital aerial survey data collected from this region.

Objectives of WP1

The specific deliverables from this WP are:

- A detailed summary report outlining the review findings.
- Presentation of results to the ORJIP SG and PEP.

The review serves the broader objective of informing about the state of the art in data availability and species prioritisation. Within the project, the review will identify suitable exemplar species and rank them in order of suitability for data integration. We propose that this is done according to a set of hierarchical objective criteria, outlined in the following section. For coherence, it makes sense to structure the review according to these three criteria.

Selection criteria

Suitability of seabird species will be evaluated via four selection filters, applied in the following order:

Filter 1. Vulnerability to offshore wind farm development: The set of species of interest is already determined by the ITT, placing the emphasis on 15 species of high concern. No priority ranking is applied within this set, so the review will attempt to outline gradations in vulnerability to offshore wind farm development.

Filter 2. Availability and quality of data: The analysis will prioritise species that have spatially expansive survey data sets, preferably at similar periods of time and with concurrent and proximate GPS tracking data. There are very few examples of tracking data from immature, or non-breeding individuals, but these will be considered where available.

Filter 3. Level of analytical challenge: For the framework to be sufficiently validated it will be necessary to use species where colonies are sufficiently close together for their ranges to (potentially) overlap. These regions of interest will also need to overlap with regions where surveys have been conducted and close to areas of interest for current or planned leasing rounds (e.g., England and Wales Round 4, ScotWind).

Vulnerability to offshore wind farm development

The UK hosts internationally important numbers of breeding seabirds (Mitchell et al., 2004), many of which are declining (JNCC, 2015). These species are vulnerable to a range of pressures including climate change, fisheries and renewable energy developments (Burthe et al., 2014; Furness and Tasker, 2000; Furness et al., 2012; Furness et al., 2013; Garthe and Hüppop, 2004).

An initial attempt to assess the sensitivity of vulnerable seabird populations to offshore wind farms was made by Garthe and Hüppop (2004), accounting for species behaviour, demography and population status (Table 1). As the industry developed, this assessment was updated by Furness et al. (2013), reflecting an improved understanding of species behaviour and how they may respond to offshore wind farms. A key difference between Garthe and Hüppop (2004) and Furness et al. (2013) was the distinction between vulnerability to collision risk and vulnerability to displacement, and the recognition that most species were more vulnerable to one than the other (Table 1), with the possible exception of black-legged kittiwake and northern gannet which fly at altitudes where they may be at risk of collision and evidence from post-construction monitoring suggests may also be vulnerable to displacement (Dierschke et al., 2016; Johnston et al., 2014).

Table 1. Offshore wind farm sensitivity scores from Garthe and Hüppop (2004) and Furness et al., (2013) for species considered as part of this project (a higher score indicates greater sensitivity to offshore wind farms).

	Garthe and Huppop (2004) (range 5.8 -44)	**Furness et al. (2013)**	
		Collision (range 0 – 1306)	**Displacement** (range 1-32)
Red-throated diver	44	213	32
Sandwich tern	25	245	9
Great black-backed gull	18.3	1225	6
Northern gannet	16.5	725	3
Razorbill	15.8	32	14
Atlantic puffin	15	27	10
Lesser black-backed gull	13.8	960	3
Great skua	12.4	320	3
Common guillemot	12	37	14
Herring gull	11	1306	3
Arctic skua	10	327	3
Black-legged kittiwake	7.5	523	6
European storm-petrel	-	91	2
Leach's storm-petrel	-	85	2
Manx shearwater	-	0	2

There are some similarities between the rankings in Garthe and Hüppop (2004) and Furness et al. (2013), with species like red-throated diver identified as being particularly vulnerable to displacement. This sensitivity, and that of other species such as guillemot and razorbill, is supported by evidence from post-construction studies at operational wind farms, which confirm that large numbers of individuals may be displaced by the developments (Dierschke et al., 2016; Mendel et al., 2019; Peschko, Mercker, et al., 2020). Whilst northern gannets may also exhibit a strong avoidance response to offshore wind farms (Peschko, Mendel, et al., 2020; Welcker and Nehls, 2016), this is believed to be mitigated by the large foraging areas of the species, enabling it to access a broader area of habitat (Furness et al., 2013).

In contrast to Garthe and Hüppop (2004), who consider them to be at moderate sensitivity, Furness et al. (2013) highlight the vulnerability of black-legged kittiwake and large gulls to the impact of collision. This is likely to reflect an improved understanding of their collision vulnerability as a result of data available to describe their flight heights (Borkenhagen et al., 2018; Johnston et al., 2014; Ross-Smith et al., 2016) and increasing concerns in relation to potential cumulative impacts associated with multiple wind farms (Brabant et al., 2015; Busch and Garthe, 2017).

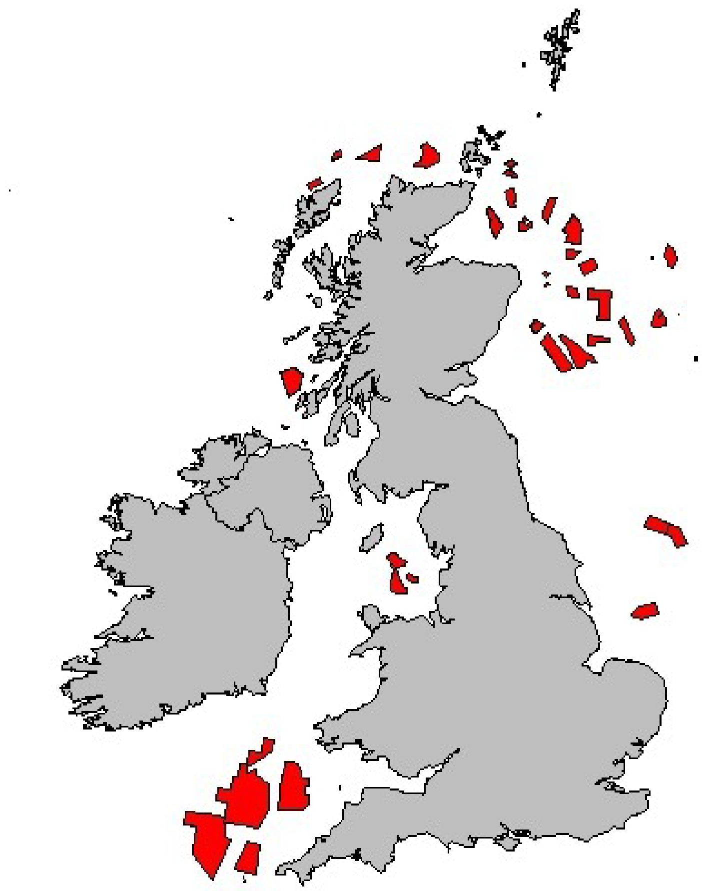


Figure 1. Wind farms currently under consideration as part of the UK Round 4, ScotWind, Innovation and Targeted Oil and Gas and Celtic Seas Floating Offshore Wind Leasing Rounds.

As the number of offshore wind farms increases, so too does the potential for species to be exposed to the risks associated with them. At present, there are 41 proposed new wind farms in the UK as part of the Round 4, ScotWind, Innovation and Targeted Oil and Gas and Celtic Seas Floating Offshore Wind

Leasing Rounds (Figure 1). Drawing from the estimates of species foraging range presented in (Woodward et al., 2019), we can assess the potential for birds from different SPAs to be exposed and interact with these wind farms (e.g. see Figure 2 as an example for black-legged kittiwake). Of the species considered as part of this project, and for which robust foraging range data are available, SPA populations of northern gannet, black-legged kittiwake, lesser-black-backed gull, common guillemot, razorbill and Atlantic puffin all have the potential to interact with these proposed new offshore wind farms (Figure 3). These species are believed to be amongst the most vulnerable to collision and displacement by Furness et al. (2013) (Table 1).

Based on previous assessments of species vulnerability to offshore wind farm development and exposure to potential new projects, the key species of concern are northern gannet, red-throated diver, black-legged kittiwake, lesser black-backed gull, great black-backed gull, common guillemot, razorbill and Atlantic puffin.

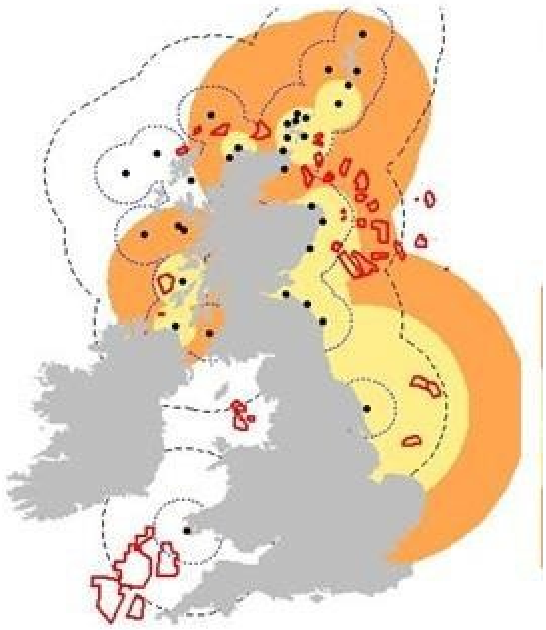


Figure 2. Generic mean maximum (dotted line) and maximum (broken line) and site specific mean (yellow) and maximum (orange) foraging ranges for SPA populations of black-legged kittiwakes (dots), and the potential for birds from each population to interact with new, proposed offshore wind farms (red outlines).

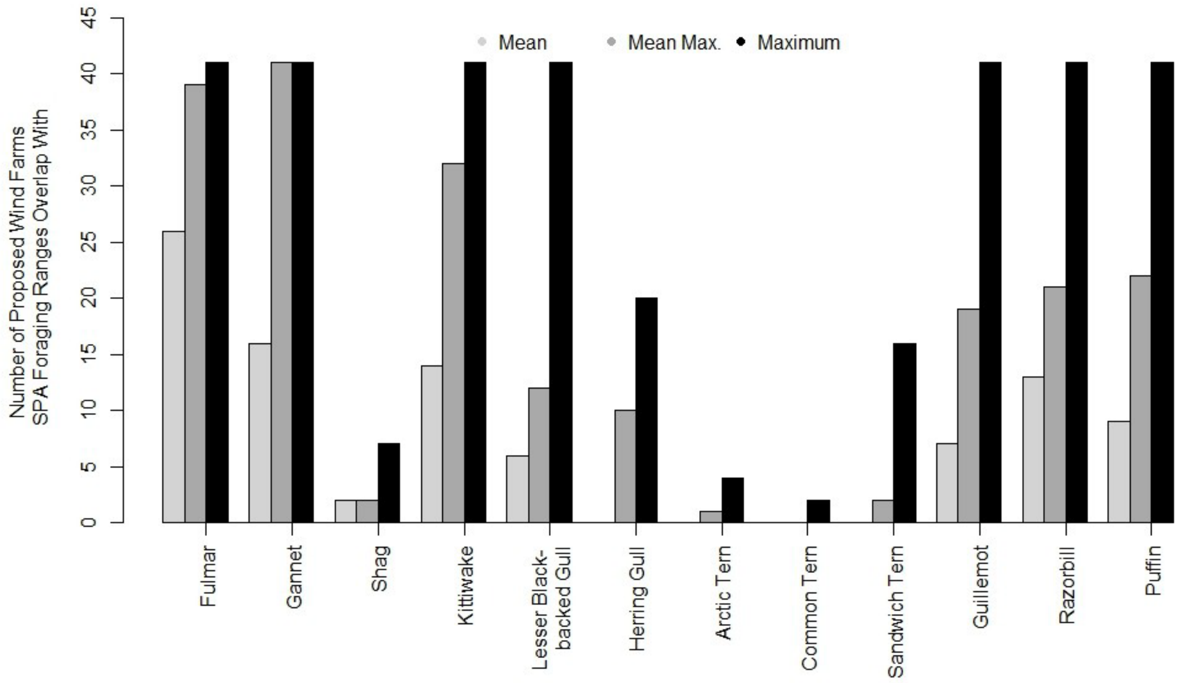


Figure 3. Number of wind farms currently under consideration as part of the UK Round 4, ScotWind, Innovation and Targeted Oil and Gas and Celtic Seas Floating Offshore Wind Leasing Rounds which overlap with the mean, mean maximum or maximum foraging ranges from at least one SPA where the above species are a designated feature, based on the data reviewed in (Woodward et al., 2019).

Data availability

Breeding colony locations and sizes

Information on the number of individuals or Apparently Occupied Nests (AONs) through time is useful for two purposes: The relative weighting of the contributions of different colonies to the amount of at-sea usage by breeders, and the approximate estimation of the number of non-breeders that were produced at these colonies.

Information on colony location and size will be obtained through a data request to the Seabird Monitoring Programme (SMP). Previous analyses (Wakefield et al., 2017) made use of the data from the last main census, Seabird 2000 (Mitchell et al., 2004). However, there were a number of complexities in this. How colonies are defined objectively presents an issue as the magnitude of any 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. In the Marine Scotland Apportioning Tool (Butler et al., 2020) these counts are then aggregated up to the SPA level.

The approach used here will be consistent with that used by the Marine Scotland Apportioning Tool (Butler et al., 2020), the Cumulative Effects Framework and the ORJIP AppSaS project.

Strength of natal site fidelity for exemplar species

This will come in the form of expert opinions, possibly summarised in section 3 of the main report. This is necessary information for the construction of colony-specific numbers of non-breeders that are likely to be using any given colony as a temporary focal point at any given time. The questionnaire will be drafted and distributed once the format of priors is known.

Survey data

For the purposes of this project, we will focus on survey data which have been collected using Digital Aerial Surveys (DAS). DAS have increasingly become industry standard in recent years. The ability to survey offshore and reduce or eliminate disturbance is one of the key advantages of DAS over other survey methods, such as boat survey or visual aerial survey, that has led to it becoming the industry standard in offshore ornithology. Additionally, DAS results in more birds being detected from footage compared to visual aerial surveys with more of those being identified down to species level (Žydelis et al., 2019) aided by birds occurring in in serval video frames making identification easier (Connelly et al., 2015). Further, DAS provides a permanent record of survey data which can allow resampling and the independent audit of any data.

The DAS data are typically used to generate population, and density estimates for the entire survey area. The standard deviation, the 95% confidence intervals (CIs) and coefficient of variance (CV) are estimated using a non-parametric block bootstrap method. For diving species such as auks, in addition the relative abundance, absolute abundance is calculated following Barlow et al. (1988) to account for the proportion of animals that are submerged at the time of survey (availability bias). As much of the contemporary offshore survey data have been collected using digital aerial survey, and there can be challenges in integrating data from different survey platforms (Waggitt et al., 2019), it is considered that the data collected during these digital aerial surveys are the most appropriate for use in this project. Furthermore, as DAS is the recommended standard and quality assured survey method for offshore surveys, it facilitates combining existing data with that from future DAS surveys, allowing easier comparisons.

Digital aerial survey data available for this project have been collected by HiDef Aerial Surveying Ltd. ("HiDef"). HiDef were commissioned by developers to collect data through digital aerial surveys. The collected datasets are privately owned by each developer, therefore HiDef cannot freely provide survey outputs. Release of the privately owned data is not standard practice as it may have implications during project application stages. In order to use data in this project, permission has been granted by individual companies. However, at this stage discussions are still underway as to how these data can be presented. In addition to the HiDef datasets, we will also be seeking permission to use the data collected by APEM from the Scottish East Coast as part of surveys funded by the Scottish Government[1].

HiDef aircraft are equipped with four HiDef Gen II cameras set to a resolution of 2cm Ground Sample Distance (GSD) which provide a combined sampled width of 500m within a 575m overall strip. Strip transects are flown over the survey area, ensuring a minimum site coverage target is met (usually 12.5%) and a Garmin GPS Map 296 receiver provides aircraft positioning to 1m accuracy. Surveys are flown at

[1] https://www.gov.scot/publications/digital-aerial-seabird-cetacean-surveys-east-coast-scotland/

a height of 550m above sea level to ensure there is no risk of flushing species that are easily disturbed by aircrafts (Buckland et al., 2012; Thaxter and Burton, 2009).

HiDef footage is viewed by trained reviewers and the ID team of ornithologists and marine mammal specialists, with an additional blind review as part of the quality assurance process. All objects are identified to the lowest possible taxonomic level. Individual sex, behavioural traits and approximate age are also recorded where they can be determined. A summary of the total number of individuals from each species recorded in the datasets for which permission has been obtained to use in this project is presented in Table 2.

Table 2. Summary of the total number of individuals from each recorded in datasets for which permission has been obtained for use in this project.

Northern Gannet	Blacklegged Kittiwake	Common Guillemot	Razorbill	Lesser blackbacked gull	Atlantic puffin
12343 (including 4183 adults and 615 immatures)	57602	235719	20707	528	7494

Based on the occurrence of species in DAS data, the most suitable species for further analysis are likely to be northern gannet, black-legged kittiwake, common guillemot, razorbill and Atlantic puffin.

Tracking data

For the purposes of this project, we will focus on GPS data, rather than data obtained from geolocators or ARGOS devices, reflecting the spatial and temporal resolution of data which can be obtained from the different tag types. GPS tags can be programmed to collect data at a temporal resolution ranging from a few seconds to a few hours, depending on the tag type and environmental conditions (Bouten et al., 2013). These fixes typically have an error in the region of 1-2 m (Bouten et al., 2013), in comparison to geolocators where the error can be in the range of ~40 km or more (Rakhimberdiev et al., 2016). Whilst it may be feasible to build observation models that account for the coarser resolution of data obtained from geolocators or ARGOS data, this would be beyond the scope of the current project.

There has been substantial effort in relation to the GPS tracking of UK seabird species. Since 2010, GPS data have been collected from over 3,500 individuals from the 15 species under consideration as part of this project (Table 3). The total number of individuals and colonies from which data have been collected varies between species, with only red-throated diver lacking any GPS data from the UK. These differences relate to the size of the species concerned and the potential for device effects (Bodey et al., 2018; Geen et al., 2019). In particular, significant device effects have been reported for Atlantic puffin (Harris et al., 2012), great skua (Thaxter et al., 2016) and great black-backed gull (Maynard et al., 2022). Similarly, it is only recently that GPS devices have been developed which are small enough to deploy on species such as European storm-petrel (Bolton, 2021).

The most extensively tracked species have been northern gannet, Manx shearwater, lesser blackbacked gull, herring gull, black-legged kittiwake, common guillemot and razorbill, with data collected from multiple colonies across multiple years (Table 3). Much of the research into the movements of large gulls and northern gannets has been funded by the offshore wind industry with a view to better understanding the potential impacts of offshore wind farms (e.g. Cleasby et al., 2015; Johnston et al., 2021; Lane et al., 2020; Thaxter et al., 2015).

There has also been industry interest in the collection of GPS data for black-legged kittiwake, common guillemot and razorbill, particularly around the Firth of Forth (Table 3). However, much of the available data for these species was collected as part of the RSPB Future of the Marine Environment (FAME) and Seabird Tracking And Research (STAR) programmes. These data have previously been analysed to model the distribution of birds around breeding colonies (Wakefield et al., 2017), with the outputs from these models subsequently used to apportion the impacts of offshore wind farms back to breeding populations (Butler et al., 2020).

Table 3. Number of seabirds from each breeding colony from which GPS data have been collected since 2010.

Species	Colony	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	TOTAL
Arctic skua	Fair Isle									6				6
	TOTAL									**6**				**6**
Atlantic puffin	Isle of May	10												10
	Skomer									2				2
	TOTAL	**10**								**2**				**12**
Black-legged kittiwake	Fair Isle	2	1	2		2								7
	Sule Skerry		4											4
	Copinsay	11	7	8	3									29
	Muckle Skerry	9	9	12	8	12								50
	Cape Wrath					5								5
	Bullers of Buchan			5										5
	Whinnyfold			20									21	41
	Fowlsheugh			15										15
	Isle of May			17	22	11				16	25	23	50	164
	Colonsay	9	26	24	13	12								84
	St Abbs			15									39	54
	Coquet		13	23										36
	Rathlin			1	8				17					26
	Filey				18	16								34
	Bempton	23	17	9	20	17								86
	Lambay	10	4											14
	Puffin Island	15	30	24	4		9	10						92
	Bardsey			8										8
	St Martins		18	14	3									35
	Skomer							11	6					17
	St Agnes			2	2									4
	TOTAL	**79**	**129**	**199**	**101**	**75**	**9**	**21**	**23**	**16**	**25**	**23**	**110**	**810**
Common guillemot	Fair Isle		3	6	1	4								14
	Copinsay			4		5								9
	Shiants					1								1
	Bullers of Buchan			2										2
	Whinnyfold			5										5
	Fowlsheugh			10										10
	Lunga					3								3

	Isle of May			20	20	11				24	24	25	23	147
	Colonsay	3	24	15	13	22								77
	St Abbs			1										1
	Lambay	3	1											4
	Puffin Island			5	10									15
	TOTAL	**6**	**28**	**68**	**44**	**46**				**24**	**24**	**25**	**23**	**288**
European stormpetrel	Lunga												19	19
	Mousa					42								42
	TOTAL					**42**							**19**	**61**
Great black-backed gull	East Caithness Cliffs					11								11
	TOTAL					**11**								**11**
Great skua	Foula	4	10											14
	Hoy		10											10
	TOTAL	**4**	**20**											**24**
Herring gull	Walney					24	5	10						39
	Isle of May										1	2	13	16
	Craigleith										1	1	1	3
	Fidra										2	1		3
	Bangor								2	1				3
	Belfast										3	1		4
	Copeland					5	20	6	1	1	2	1		36
	East Caithness Cliffs					7								7
	TOTAL					**24**	**16**	**38**	**24**	**14**	**7**			**111**
Leach's storm-petrel	St Kilda												14	14
	TOTAL												**14**	**14**
Lesser black-backed gull	Walney					24	16	38	24	14	7			123
	Skokholm					25	20	14	3					62
	Orford Ness	11	19	15	11	4	2							62
	Isle of May										28	20		48
	Craigleith										3	1		4
	Fidra										5	1		6
	Barrow							9	19	13	6			47
	Belfast									4	5	1		10
	Ribble							9	17	16	18	6		66
	Bowland						6	21	16	9	4			56
	TOTAL	**11**	**19**	**15**	**11**	**53**	**44**	**91**	**79**	**56**	**76**	**29**		**484**

Manx shearwater	Rum	9	16											25
	Skomer	48	62	16	74	59	43	82						384
	Skokholm						10	8						18
	Copeland	31	37											68
	Lundy	29	29	2										60
	Lighthouse Island	36	25	37	26	37	25	8						194
	TOTAL	**153**	**169**	**55**	**100**	**96**	**78**	**98**						**749**
Northern gannet	Les Etacs and Ortac		17		16	13	17							63
	Lambay		3											3
	Grassholm	26	54	43	54	41	27	38	22					305
	Bempton	14	9											23
	Ailsa Craig		16											16
	St Kilda	21												21
	Sule Skerry		2											2
	Bass Rock	41	28				188 adults + 21 immature							278
	TOTAL	**102**	**129**	**43**	**70**	**54**	**213**							**711**
Razorbill	Fair Isle	2	20	22	8	17	7							76
	Copinsay	1	1	6	3	3								14
	Swona	3	8	9	7	2								29
	Muckle Skerry	8	4	9	7	5								33
	Flannans					4								4
	Shiants					4								4
	Lunga					7								7
	Isle of May			15	7	5				14	14	15	11	81
	Colonsay	5	10	10	11	6								42
	Rathlin			1										1
	Lambay		5											5
	Puffin Island		12	10	12									34
	Bardsey		19											19
	Skomer		7	4										11
	TOTAL	**19**	**86**	**86**	**55**	**53**	**7**			**14**	**14**	**15**	**11**	**360**
Red-throated diver	-													
Sandwich tern	Scolt Head							10	4	20	9			43
	TOTAL							**10**	**4**	**20**	**9**			**43**

Based on the availability of GPS tracking data, the most suitable species for analysis as part of this project are likely to include northern gannet, Manx shearwater, black-legged kittiwake, lesser black-backed gull, herring gull, common guillemot and razorbill.

Covariate data

Previous analyses (Wakefield et al., 2017) considered a total of 11 environmental covariates: (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 publicly 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:

1. 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).

2. 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.

3. 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.

4. 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.

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 figure 4.

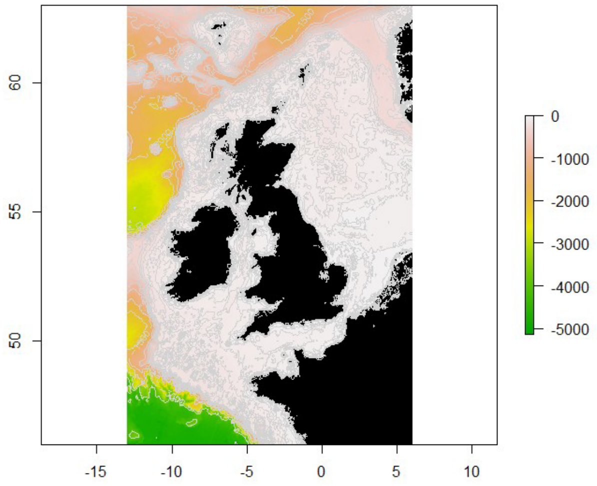


Figure 4. Seabed topography (depth).

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 figures 5 and 6.

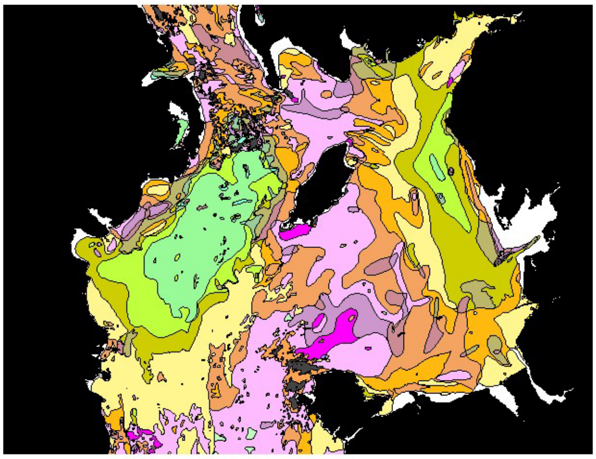


Figure 5. Original sediment shapes with local view in the Irish Sea from the Digimap BGS service.

(a) Gravel (b) Sand:mud ratio

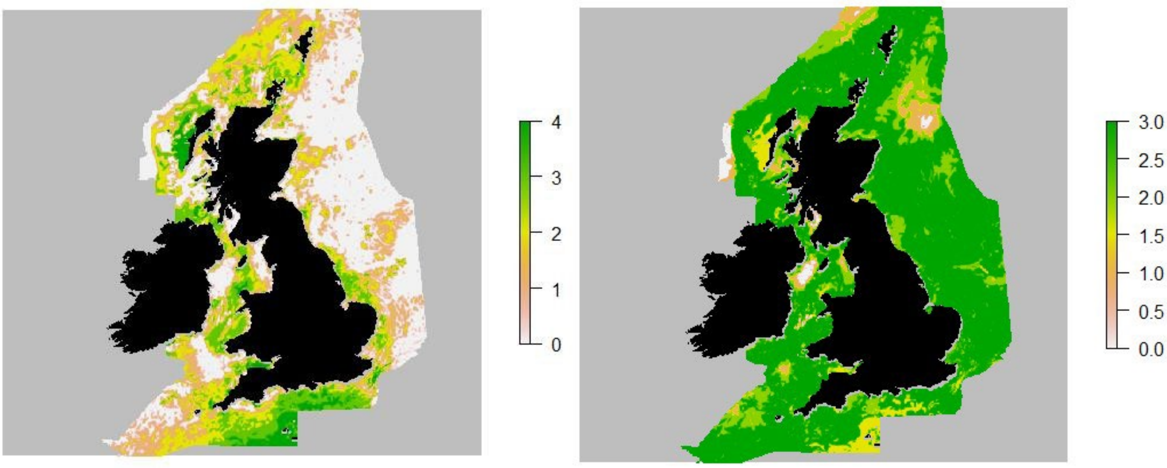


Figure 6. Rescaled and rasterised seabed sediment maps for (a) gravel proportion and (b) sand:mud ratio, using the methods and scaling approach as described in Wakefield et al. (2017).

Potential Energy Anomaly (PEA) 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 2020-0630 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:

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

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 also represents 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 and Levitus (1997), and further, the equations as presented in the Plymouthlab Python resources also follow a density threshold of 0.03 kg/m^3, 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 (Figure 7). 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 (Figure 8).

(a) 23rd June 2020 example one day PEA (b) Composite PEA J/m^3^0.5 for Mar-June 2020

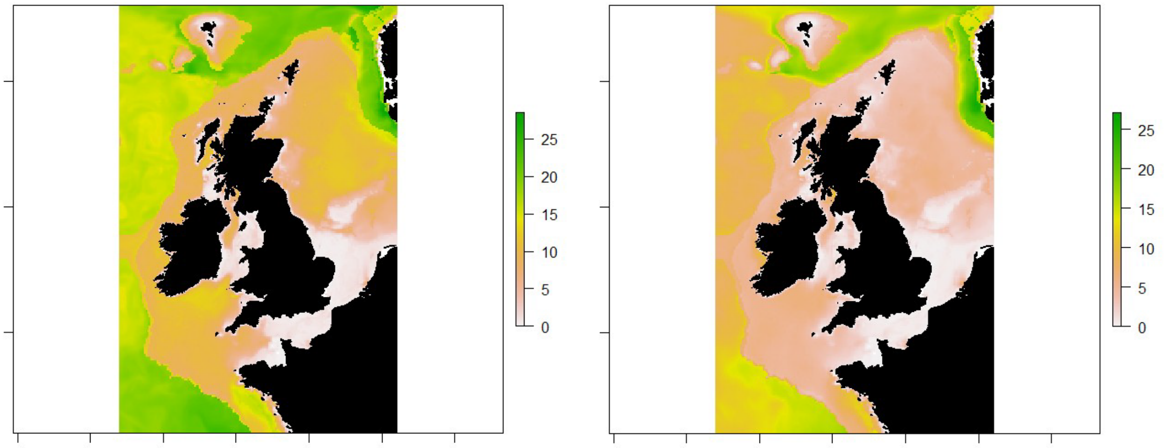


Figure 7. Example of one day slice in 2020, and a further composite for the March-June 2020 period, depending on how the rasters will be amalgamated for analysis.

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

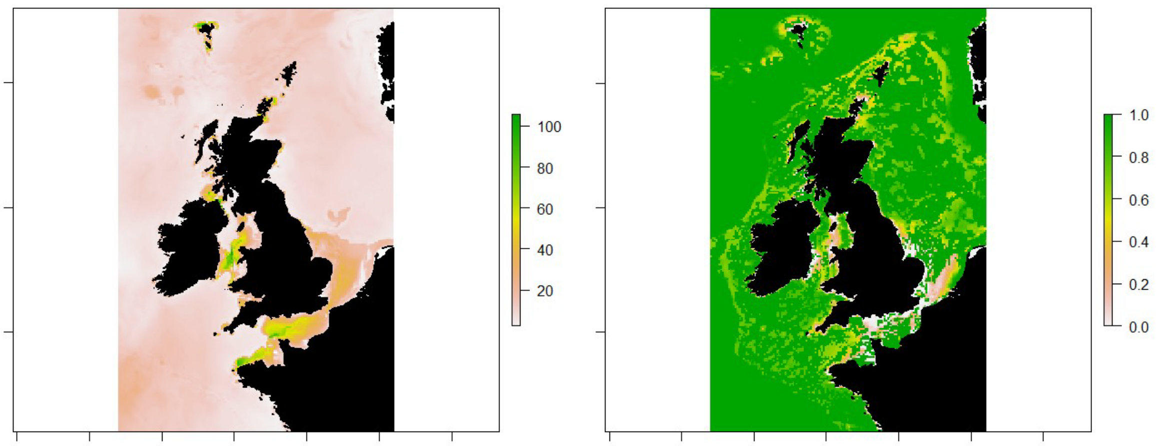


Figure 8. Example of the stratification layer, showing a single day slice of the raster for 23rd June 2020 and then a composite as per Wakefield et al. (2017) for a March-June 2020 proportional of days stratified (MLD < max water depth); for the latter the sea relief dataset was used.

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 Figure 9.

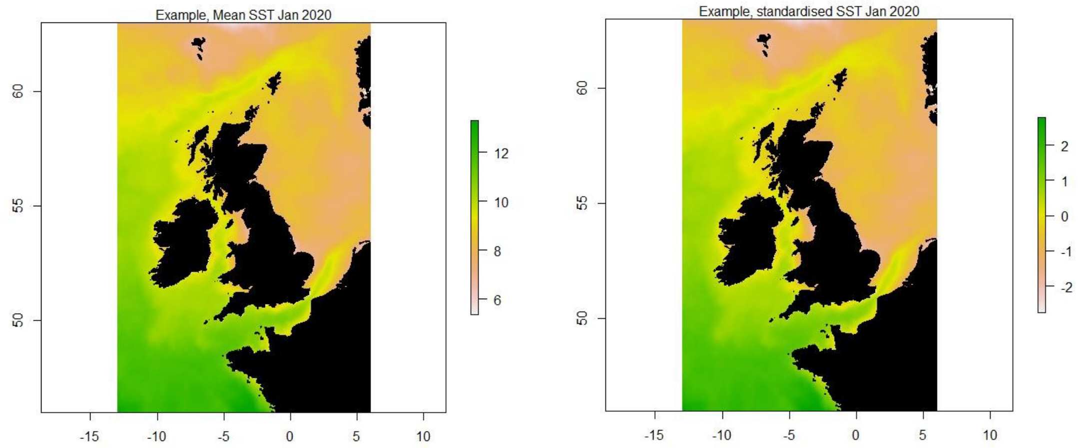


Figure 9. Example SST datasets for 2020, here plotted for January 2020 as a composite image across daily datasets.

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, Subregion: 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 presents this as "gC/m^3/day". Example Chlorophyll data for August 2020 daily average on the original milligram scale is shown below (Figure 10).

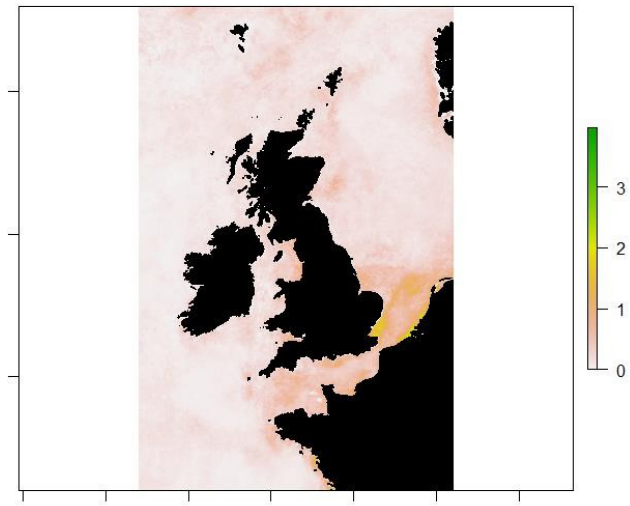


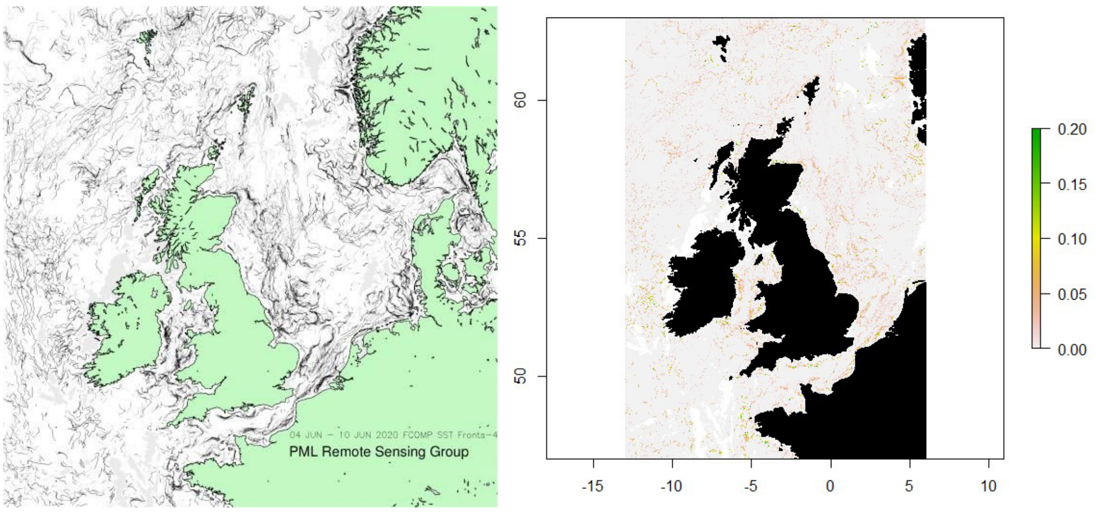
Figure 10. Example plot for August 2020 alpha-chlorophyll as a composite image across daily datasets.

Thermal fronts

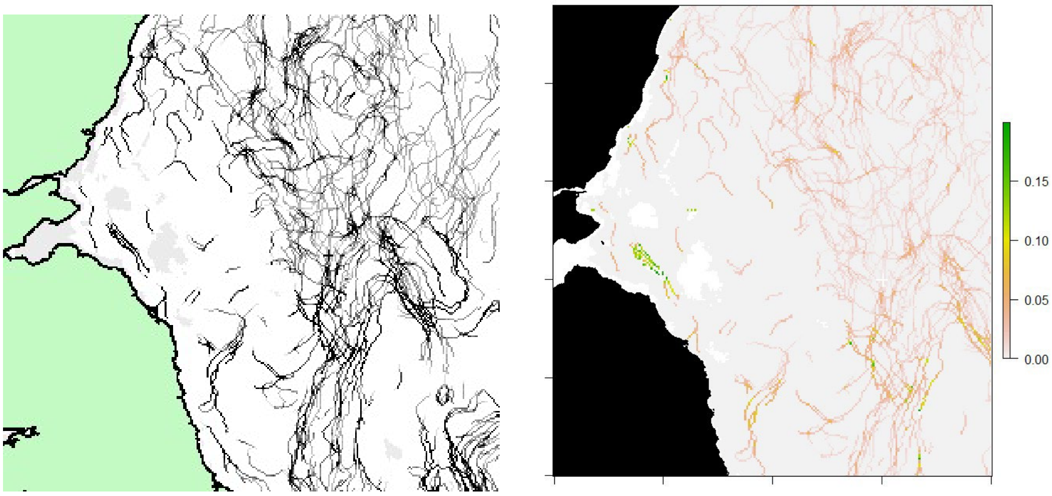
Strong front maps were obtained from the NEODAAS Multiview tool (https://data.neodaas.ac.uk/multiview/). These front maps are available as seven-day composite images generated as per methods developed by Peter Miller, however, the thermal front gradient index requires processing of individual seven-day 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 Figure 11 below for five rasters 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

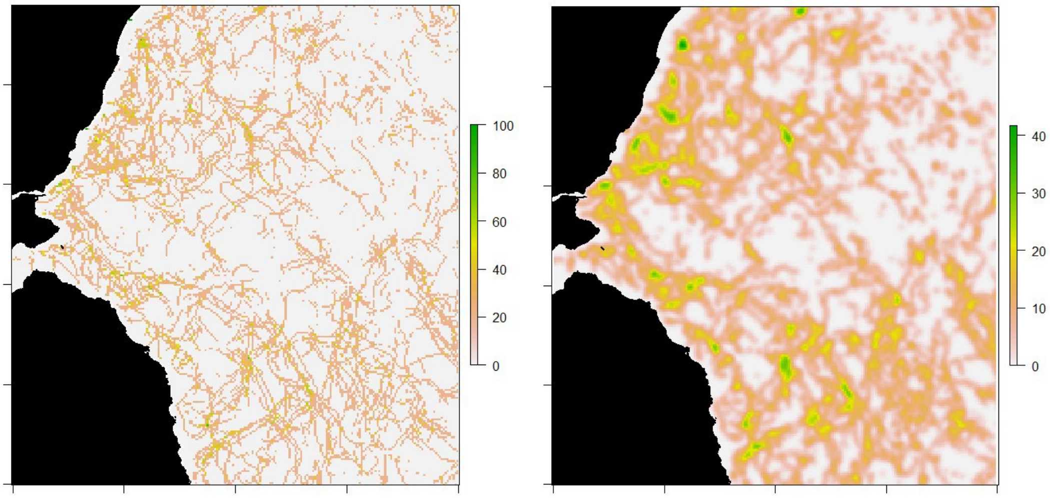


Figure 11. Example front data processing png front data; (a) example single front map for 2020-06-04 to 2020-06-10 (b) further georeferenced raster for that single 7-day period; (c) zoomed in front view around Isle of May and (d) translated scale (F_{comp}) following Miller and Christodoulou (2014); (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 F_{comp} 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).

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.

Spatiotemporal extent of data

Ideally, the analysis will focus on a region with multiple species present, and where there are several colonies with overlapping home-ranges for each of these species. For the species with the greatest quantity of GPS data available, an obvious choice is the east coast of Scotland (Figure 12). A number of SPAs are present within this region, for which several of the key species are designated features.

Further, GPS data are available for a number of these species at multiple sites, following the RSPB FAME and STAR tracking programmes (Wakefield et al., 2017), and GPS tracking of gannets carried out by Leeds University (Lane et al., 2020) (Figures 12 and 13). Previous analyses of species foraging ranges (Woodward et al., 2019) also suggests that this region is likely to include birds from colonies at which home ranges are likely to overlap (Figure 12).

In addition to the GPS data available from the east coast of Scotland, there has been substantial survey effort within this region, including strategic DAS carried out on behalf of the Scottish Government (Figure 13). For reasons of commercial confidentiality, it is not possible to present all survey transects at this stage. However, there appears to be a reasonable spatial overlap between the FAME, STAR and Leeds University gannet data and the Scottish Government strategic DAS (Figure 13). Furthermore, the covariate data necessary for modelling should also cover the full extent of this region (Figures 4-11). In terms of temporal coverage, the FAME and STAR data cover the period from 2010 – 2014, and the Leeds University gannet data were collected in 2015. The period covered by the DAS data for which permission has been received to use is from 2012-2017, indicating a reasonable degree of temporal overlap in the data. However, it should be noted that, due to seasonal changes in species foraging distribution throughout the breeding cycle (e.g. Thaxter et al., 2015), ideally any DAS data should be restricted to the June-July period, to reflect the period in which the GPS data were collected.

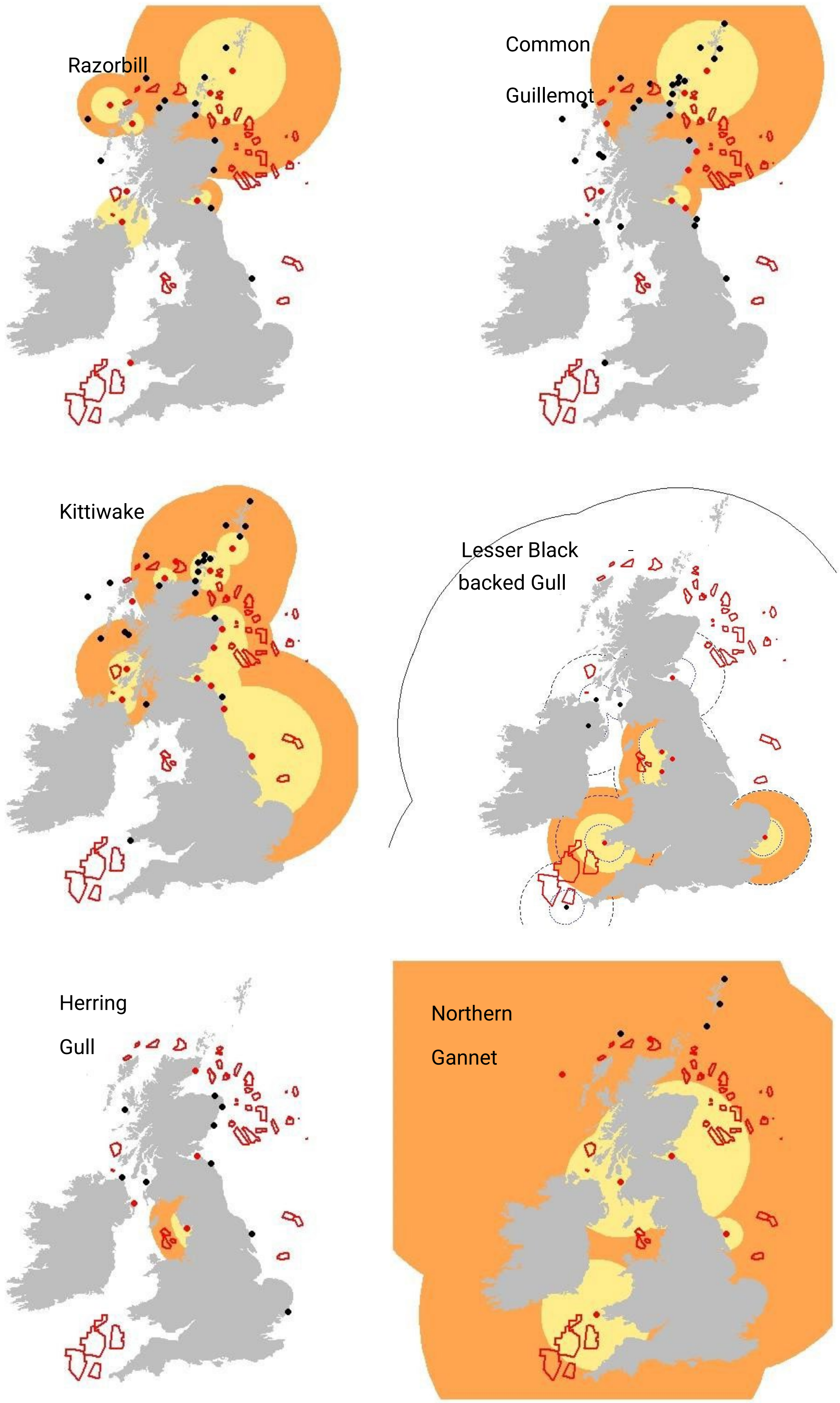

Razorbill
Common
Guillemot
Kittiwake
Lesser Black
backed Gull
Herring
Gull
Northern
Gannet

Figure 12. Designated SPAs for key species (black dots), including sites for which GPS data are available (red dots). With site specific mean (yellow) and maximum (orange) foraging ranges shown where available.

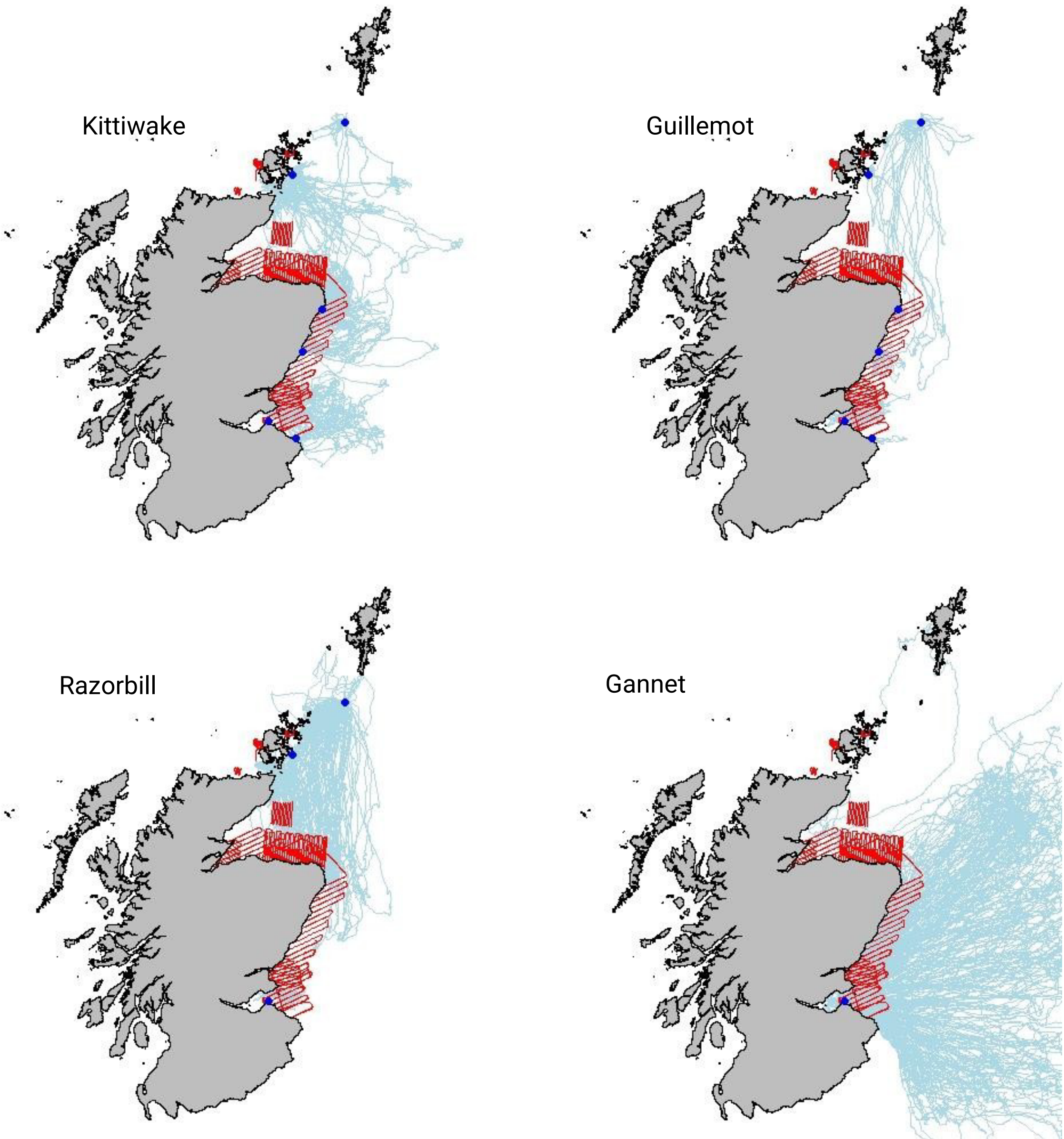


Figure 13. Comparison between strategic DAS carried out on behalf of the Scottish Government and GPS data for Kittiwake, Guillemot and Razorbill collected as part of FAME and STAR and GPS data for adult and immature gannets collected by the Leeds University. Blue dots indicate colonies from which GPS tracking data were collected.

Level of analytical challenge

In order to properly test the proposed analytical framework, ideally the final species selected should pose a technical challenge through presence of multiple colonies with overlapping home ranges in the proposed study region. For the species which are both abundant in DAS data, and for which GPS data are available from multiple sites, this is true for black-legged kittiwake, common guillemot and razorbill. However, the availability of GPS data for immature northern gannets and, the presence of both adult and immature northern gannets in the DAS datasets, mean there may be value in considering these data further.

Proposed species for further analysis

Based on the information presented above, and in Table 4, the species most suitable for analysis as part of this project are black-legged kittiwake, common guillemot and razorbill. In addition to being of policy concern due to the risk of collision and/or displacement (Furness et al., 2013), these species reflect those for which the highest quality of GPS and DAS data are available and present a challenge to the framework in relation to the potential overlap in foraging ranges for individuals from multiple colonies within the proposed study region. As a secondary consideration, the potential to model differences in the distribution of adult and immature northern gannets, also of policy relevance in relation to collision and displacement risk, could be considered as this is the only species for which such an approach is currently possible.

Table 4. Summary of information used to determine priority species for further analysis (dark red indicates highest priority, light red indicates secondary consideration).

Species	Furness et al. (2013) Vulnerability to Collision (range 0 – 1306)	Furness et al. (2013) Vulnerability to Displacement (range 1-32)	Tracking data (Y/N)	Number of Colonies with Tracking data (number of birds tracked)	Number of Observations in Survey data
Redthroated diver	213	32	N	-	-
Sandwich tern	245	9	Y	1 (43)	-
Great blackbacked gull	1225	6	Y	1 (11)	-
Northern gannet	725	3	Y	8 (711)	12343 (inc. 4183 aged as adults and 615 aged as immature)
Razorbill	32	14	Y	14 (360)	20707
Atlantic puffin	27	10	Y	2 (12)	7494
Lesser blackbacked gull	960	3	Y	10 (484)	528
Great skua	320	3	Y	2 (24)	-
Common guillemot	37	14	Y	12 (288)	235719
Herring gull	1306	3	Y	8 (111)	-
Arctic skua	327	3	Y	1 (6)	-

Black-legged kittiwake	523	6	Y	21 (810)	57602
European stormpetrel	91	2	Y	2 (61)	-
Leach's stormpetrel	85	2	Y	1 (14)	-
Manx shearwater	0	2	Y	6 (749)	-

Data collation and pre-processing steps

Project partners tasked with collating data will enact these activities during the month that follows the workshop in WP3. For each study species, we will prepare data sheets comprising survey data, population data and telemetry data. A level of pre-processing will be required for these. All spatial data will be mapped to the same projection. Survey data will be given as counts with accompanying strip width (depending on survey platform and observation covariates). Population data will be given as individual or AON counts, depending on species. Tracking data will be assigned to colony of origin and may require some filtering for error.

Substantial progress has been made in relation to obtaining permission to use data for analysis (Table 5).

Table 5. Datasets required for modelling framework and progress in relation to obtaining permission for the use of these data.

Data type	Data Set	Data Owner	Permission
Breeding colony sizes and locations	SMP Database	Seabird Monitoring Programme Partnership	Subject to data request
Survey Data	Digital Aerial Survey datasets (5 sites)	HiDef Aerial Survey Ltd. and their clients	✓
Tracking Data	Black-legged Kittiwake - Fair Isle	RSPB	✓
	Black-legged Kittiwake – Copinsay	RSPB	✓
	Black-legged Kittiwake - Muckle Skerry	RSPB	✓
	Black-legged Kittiwake - Bullers of Buchan	RSPB	✓
	Black-legged Kittiwake – Whinnyfold	RSPB	✓
	Black-legged Kittiwake – Fowlsheugh	RSPB	✓
	Black-legged Kittiwake - Isle of May	UKCEH	✓

	Black-legged Kittiwake - St Abbs	RSPB	✓
	Black-legged Kittiwake – Coquet	RSPB	✓
	Black-legged Kittiwake – Filey	RSPB	✓
	Black-legged Kittiwake – Bempton	RSPB	✓
	Common guillemot - Fair Isle	RSPB	✓
	Common guillemot – Copinsay	RSPB	✓
	Common guillemot - Bullers of Buchan	RSPB	✓
	Common guillemot – Whinnyfold	RSPB	✓
	Common guillemot – Fowlsheugh	RSPB	✓
	Common guillemot - Isle of May	UKCEH	✓
	Common guillemot – Colonsay	RSPB	✓
	Common guillemot - St Abbs	RSPB	✓
	Razorbill - Fair Isle	RSPB	✓
	Razorbill – Copinsay	RSPB	✓
	Razorbill – Swona	RSPB	✓
	Razorbill - Muckle Skerry	RSPB	✓
	Razorbill - Isle of May	UKCEH	✓
	Northern Gannet – Bass Rock	University of Leeds	✓
Covariate Data	Depth		✓
	Seabed slope		✓
	Minimum distance to coast		✓
	Proportion of gravel		✓
	Sand:mud ratio		✓
	Potential Energy Anomaly (PEA)		✓
	Proportion of water column stratified		✓
	Sea surface temperature		✓
	Standardised sea surface temperature		✓
	Thermal front gradient density	Plymouth Marine Laboratory	Subject to data request
	Net primary productivity		✓

	Vessel movement data	Global fishing watch	Subject to data request
	Anthropogenic activities	EmodNET	✓

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