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**Quantifying Similarity of Correlations between Seabird and Cetacean Distributions and Environment in the Northeast Atlantic** 

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# Quantifying Similarity of Correlations between Seabird and Cetacean Distributions and Environment in the Northeast Atlantic



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Supervised by Dr James Waggitt

### Abstract

Understanding the role of mechanistic processes in species distributions is a key aspect of understanding the species spatial ecology, particularly interspecific interactions between species with overlapping resource requirements. However, comprehensive understanding is often hindered by spatial and temporal coverage of abundance data and lack of established statistical methodology to derive this from abundance data. This study aims to address these challenges by quantifying similarity among distributions of seabird and cetacean species. Intra-guild or taxa separation could indicate potential habitat partitioning, and equally, similarity between sympatric species could indicate potential coexistence. This study used zero-inflated generalised linear models to model a large-collation of seabird and cetacean abundance data across the northeast Atlantic, so that relationships within their likely ranges can be identified. Clustering and principal component analysis of the conditional model regression coefficients were used to quantitatively identify similarity between seabird and cetacean distributions and their environment within each species likely range. There was dissimilarity within guilds, and similarity between some sympatric species from different guilds. Furthermore, the scale of the relationship between abundance and their environment was distinct between taxa, as non-delphinid cetaceans had much stronger correlations than delphinids and seabirds. Explainers of dissimilarity can be simplified into species' spatial, behavioural and prey differences. These outcomes align with coexistence and competition theories, indicate that products of mechanistic processes are observable on a large scale, and that interspecific interactions are potentially involved. Future research includes identifying if interspecific interactions are the responsible mechanisms driving this similarity structure, then how to appropriately integrate this in species distribution modelling processes to improve ecological realism.

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'>75 <sup>th</sup> ' means that the species absolute value is greater than the 75 <sup>th</sup> percentile of all species
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When the value contains '+', the abundance of that species increases linearly with an
increase in the value of the corresponding predictor. When the value contains '-', the

# Table of abbreviations

 ${\it Table~1.1~Table~of~species~abbreviations~and~environmental~parameter~codes.}$ 

Туре	Abbr.	Definition
	ATPF	Atlantic Puffin
	BLKW	Black-legged Kittiwake
	BTND	Bottlenose Dolphin
	CMGM	Common Guillemot
	COMD	Common Dolphin
	EPSH	European Shag
	EPSP	European Storm Petrel
	FINW	Fin Whale
	HRBP	Harbour Porpoise
	HRGL	Herring Gull
es	KILW	Orca
Species	LBGL	Lesser Black-backed Gull
Sp	MINW	Minke Whale
	MXSH	Manx Shearwater
	NTFU	Northern Fulmar
	NTGA	Northern Gannet
	PILW	Pilot Whale
	RAZB	Razorbill
	RISD	Risso's Dolphin
	SPRW	Sperm Whale
	STRD	Striped Dolphin
	WHBD	White-beaked Dolphin
	WHSD	White-sided Dolphin
	BAT	Depth (m)
	CHS	Total Chlorophyll (mg) in surface layer (satellite imagery)
er	CHT	Total Chlorophyll (mg) depth summed between 0 and 150m from surface (modelled)
net	CON	Distance to 300m isobath (m)
arar	FEA	Depth gradient (m), calculated using terrain ruggedness index
l Pe	LND	Distance to Land (m)
ınta	SPM	Mean surface current speed (ms-1), including tidal influence
Environmental Parameter	TPF	Thermal stratification gradient, where higher values indicate greater frontal activity
Envii	TPM	Mean potential temperature (Celsius) between 0 and 150m from surface (modelled)
	TPR	Range of potential temperature (Celsius) between 0 and 150m from surface (modelled)
	TPS	Potential temperature (Celsius) in surface layer (satellite imagery)

### 1.Introduction

Seabirds and cetaceans have an ecologically important role in top-down mediation of species assemblages (Heithaus *et al.*, 2008; Townsend *et al.*, 2008; Baum & Worm, 2009; Certain *et al.*, 2011; Mann & Karniski, 2017), therefore, population size and dynamics of predators in the highest trophic levels are often considered to be indicators of ecosystem health (Moore & Kuletz, 2019). As seabirds and cetaceans are highly mobile, they can fill functional roles in multiple ecosystems, for example transporting and cycling nutrients. Seabird and cetacean populations are susceptible to a wide variety of pressures, such as overfishing on prey resources (DeMaster *et al.*, 2001; Bearzi *et al.*, 2006; Herr *et al.*, 2009; Grémillet *et al.*, 2016), noise disturbance (Bailey *et al.*, 2010, 2014; Baltzer *et al.*, 2020), bycatch mortality from fisheries (Reeves *et al.*, 2013) and climate change impacts (C. D. Macleod *et al.*, 2005; Burthe *et al.*, 2014).

To mitigate these issues, a comprehensive understanding of seabird and cetacean spatial ecology is necessary (Grémillet & Boulinier, 2009). One of the fundamental aspects in ecological theory is species interactions, such as habitat partitioning or coexistence (Kneitel & Chase, 2004). Understanding these processes on a large scale could be particularly relevant for seabirds and cetaceans due to their highly mobile nature (Ritchie, 2002), however, there is a lack of understanding of how these processes operate on a large scale, potentially in part due to a lack of adequate large-scale data.

Environmental conditions are widely used as proxies for prevalence of suitable prey resources in seabird and cetacean distribution or habitat models, which is widely considered to be one of the main drivers of marine top predator distribution (Cox *et al.*, 2018; Waggitt *et al.*, 2020). The key components of a prey type being suitable include abundance or prey patch density (Friedlaender *et al.*, 2020), nutritional quality (Wanless *et al.*, 2005; Paredes *et al.*, 2012; Spitz *et al.*, 2012, 2018), size (Burke & Montevecchi, 2009), and accessibility, such as position in the water column (Anderwald *et al.*, 2012; Embling *et al.*, 2012; Lambert *et al.*, 2014; Baptist *et al.*, 2019), which can vary by season, to month and even at a diurnal scale (van der Kooij *et al.*, 2008; Romero-Romero *et al.*, 2019) related to their behaviours, ontogeny and quality and accessibility of their prey (Røjbek *et al.*, 2014). The distribution of

the top predators can change throughout the year often related to seasonal variation in availability of suitable prey resources within the predators range (Nichol, 1990; Couperus, 1997; K. Macleod et al., 2004; Visser et al., 2011; Sveegaard et al., 2012; Esteban et al., 2014; Berrow et al., 2015). The physical and biological oceanographic characteristics or environmental conditions of a habitat can influence how suitable the prey is as a resource for the top predators, as certain conditions can influence the nutritional value (Røjbek et al., 2014), behaviour (Embling et al., 2013), distribution (Pacariz et al., 2016), and abundance of the prey (Maravelias et al., 2000), which can influence the distribution of the top predators (Hastie et al., 2004; Teloni et al., 2008; Paredes et al., 2014; Shoji et al., 2015). Environmental parameters commonly used have been found to correlate with seabird and cetacean distribution and abundance, for example, sea surface temperature (MacLeod et al., 2007; Nøttestad et al., 2015; Víkingsson et al., 2015; Rogan et al., 2017; Wakefield et al., 2017; Mannocci et al., 2020), water depth (K. Macleod et al., 2003, 2009; Wall et al., 2006; Ingram et al., 2007; Teloni et al., 2008; Pirotta et al., 2011; Nøttestad et al., 2015; Laran, Pettex, Authier et al., 2017), seabed gradient (Cañadas et al., 2002; Weir et al., 2007; Canning et al., 2008; Skov & Thomsen, 2008; Booth et al., 2013; Jones et al., 2014; Wakefield et al., 2017), chlorophyll concentration as a proxy for primary productivity (MacLeod et al., 2007; de Stephanis et al., 2008; Cotté et al., 2010; Gilles et al., 2011; Wong & Whitehead, 2014; Griffiths, 2015) and fronts (Doniol-Valcroze et al., 2007; Scales et al., 2014).

Seabird and cetacean distributions relative to oceanographic parameters over a large spatiotemporal scale is also an amplification or reflection of their varying modern morphologies and life strategy, driven by convergent evolution (analogous and homologous) and radial expansion, between and within the seabirds and cetaceans (Woodward *et al.*, 2006; Sato *et al.*, 2007; Mccurry *et al.*, 2017), since the divergence of their lineages around 310 million years ago (Hedges *et al.*, 1996). In the current stage of the seabird and cetacean evolutionary history, simplified as aquatic (shared ancestor) to terrestrial (diverged from shared ancestor), then back to aquatic dependency (independent lineages) (Carroll, 2001), there is overlap in resource use and varying degrees of plasticity of resource use between modern seabirds and cetaceans (Camphuysen *et al.*, 2006). Therefore, there are convergent evolutionary traits, for example, related to energy-efficient locomotion underwater,

breathe-holding, coping with low oxygen, carbon dioxide build-up and changes in pressure between cetaceans and seabirds that forage below the sea surface (Davis & Guderley, 1990; Kooyman & Ponganis, 1998; Sato *et al.*, 2007; Mirceta *et al.*, 2013). There is great dietary overlap between the seabirds and cetaceans in this study, within and across taxonomic and foraging guilds (Pierce *et al.*, 2004; Santos *et al.*, 2004; Jansen *et al.*, 2010; Fayet *et al.*, 2021), even seabirds and cetaceans with no obvious convergent evolutionary traits, for example surface feeding seabirds such as gulls that feed on the same forage fish as cetaceans such as minke whales and are commonly observed in multi-species feeding aggregations (Anderwald *et al.*, 2011).

The foraging behaviour and strategy of the seabirds and cetaceans can lead to interspecific differences and similarities in their distribution, through influencing what prey types are accessible to them, and allowing them to occupy a niche (Woodward *et al.*, 2006; Garthe *et al.*, 2014; Lambert *et al.*, 2014; Petalas *et al.*, 2021). Furthermore, the energetic demands related to morphology (i.e., influences of body size on thermoregulatory constraints) and life history/strategy (all of which can vary by gender and ontogeny), can influence what prey types, densities, abundances and behaviours are required to maintain healthy body condition by consumption rate and quality of prey (Spitz *et al.*, 2012; Kahane-Rapport *et al.*, 2020). In turn, this can have a confounding effect on the fluctuations of distribution and abundance of the top predators within their ranges, if they are to match these resources spatially and temporally (Anderwald *et al.*, 2012; Nøttestad *et al.*, 2015).

Other studies have used overlap (often distance-based calculations) of species distribution model (SDM) predictions (using individual species occurrence data) as a metric of potential for species interactions (Godsoe, 2014). An alternative is to compare species environmental niches to infer interspecific interactions (related to how this influences species distribution) (Broennimann *et al.*, 2012). It has been considered that the niche of a species can be described by the environmental conditions where a species is present (Godsoe, 2014), and species occurrence and environmental data is suitable for describing a species' environmental niche (Broennimann *et al.*, 2012). Whilst species niche differences defined by biological data relating success and resource use are commonly used in species comparisons, (Broennimann *et al.*, 2012) suggest that comparing species based on how

species distribution relates to environmental conditions is more relevant to answering questions about changes in species distribution and consider this method of defining environmental niche to align with Grinellian niche theory.

Based on the logic of (Broennimann *et al.*, 2012) and (Godsoe, 2014), identifying how similar or dissimilar relationships with environmental parameters are between species, could potentially provide insight into influences of interspecific dynamics on species distribution within a community (Broennimann *et al.*, 2012). Exploring the structure of similarity or dissimilarity of relationships between seabird and cetacean distribution and environmental parameters could provide context to anecdotal observations, investigate validity of assumptions of similarities between guilds and closely related taxa. It could also be useful to understand how similar data-poor species are to other species, especially where multiple species' distribution data are sometimes amalgamated (Baines *et al.*, 2017; Lambert, Pettex *et al.*, 2017; Wong *et al.*, 2018; Leonard & Øien, 2020).

Based on Wilson's theory (Wilson, 1999) that species within intrinsic guilds would not cooccur, it could be expected that species in the same intrinsic guild should be most abundant
in dissimilar environmental conditions. The theory of Phylogenetic Niche Conservatism
(Pyron et al., 2015) would expect there to be partitioning (dissimilarity) between seabirds
and cetaceans in the similarity structure. For count data of closely related species to be
amalgamated in species abundance models with an assemble first, predict later approach,
these species should be similar in the similarity structure. The aim of this study is to quantify
the similarity structure of correlations between large-scale seabird and cetacean
distributions and their environment, and the objective is to identify if there are patterns of
similarity or dissimilarity between species that share guilds and/or are closely related taxa,
as this could indicate potential habitat partitioning or coexistence.

### 2.Methods

Sightings data of 23 species were used in this study, 11 species representing three seabird orders, with two families each, and 12 species representing two cetacean orders, with one family in one order, and three families in the other order (table 2.1). These species were chosen to maximise use of available abundance data, which was collated from a variety of sources, described by (Waggitt *et al.*, 2020). The temporal extent of the data was between the years 1985 and 2015, and the temporal resolution was on a monthly scale and the spatial resolution of the data was 10 km<sup>2</sup>.

Table 2.1 Table of study species. Taxa (from Order to Species) and common name.

Order and Family	Genus and species	Common name
<u>Charadriiformes</u>		
Alcidae	Fratercula arctica	Atlantic Puffin
	Uria aalge	Common Guillemot
	Alca torda	Razorbill
Laridae	Rissa tridactyla	Black-legged Kittiwake
	Larus argentatus	Herring Gull
	Larus fuscus	Lesser Black-backed Gull
<u>Pelecaniformes</u>		
Phalacrocoracidae	Phalacrocorax aristotelis	European Shag
Sulidae	Morus bassanus	Northern Gannet
<u>Procellariiformes</u>		
Hydrobatidae	Hydrobates pelagicus	European Storm Petrel
Procellariidae	Puffinus puffinus	Manx Shearwater
	Fulmarus glacialis	Northern Fulmar
Mysticete		
Balaenopteridae	Balaenoptera acutorostrata	Minke Whale
	Balaenoptera physalus	Fin Whale
<u>Odontocete</u>		
Delphinidae	Tursiops truncatus	Bottlenose Dolphin
	Delphinus delphis	Common Dolphin
	Globicephala melas	Pilot Whale
	Stenella coeruleoalba	Striped Dolphin
	Lagenorhynchus albirostris	White-beaked Dolphin
	Lagenorhynchus acutus	White-sided Dolphin
	Orcinus orca	Orca
	Grampus griseus	Risso's Dolphin
Physeteridae	Physeter macrocephalus	Sperm Whale
Phocoenidae	Phocoena phocoena	Harbour Porpoise

The study area covers the northeast Atlantic (figure 2.1), which has a varied and complex biogeography, including shelf seas and oceanic waters, with a variety of topographic features such as islands, seamounts, ridges, canyons and shallow banks and complex coastlines (figure 2.1). The study area is influenced by multiple oceanographic processes, such as large-scale oceanic currents with varying properties, large tidal ranges on the continental shelf, producing features such as fronts, and regions of freshwater influence. The study area has high primary productivity, particularly in areas of upwelling of nutrient rich water, which peaks in spring, and again in autumn. The study area has a temperate climate, which is highly influenced by the north Atlantic oscillation of the jet stream and the Atlantic meridional overturning circulation.

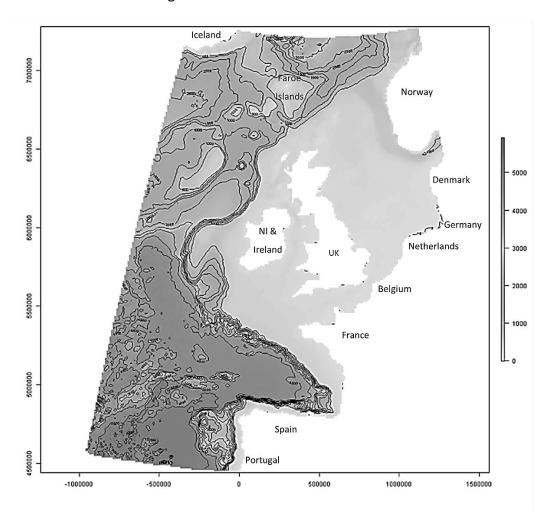


Figure 2.1 Map of study area

To model the effects of different environmental factors listed in Table 2.2 on the distribution of 12 cetacean and 11 seabird species (table 2.1), Zero-inflated generalised linear models were used, as frequency graphs showed that the data was zero-inflated. these models are also referred to as ZIGLM throughout this thesis. The package "glmmTMB" (Brooks et al., 2017) was used for the zero-inflated generalised linear models. To compare model coefficients between all of the species, the parameters of the ZIGLM conditional model were chosen to be consistent, and the parameters for the logistic model were unique to each species, to improve model parsimony. Model covariates for the logistic component of the ZIGLMs (table 2.3) were selected from the pool of ecologically relevant environmental parameters (table 2.2) if they improved model fit. To reduce overparameterisation of the ZIGLM, a maximum of five variables were chosen for the conditional model. The variables for the conditional model (Table 2.2; highlighted grey) were chosen to represent sea temperature, primary productivity, fronts, and static landscape features, due to their ecological relevance to the species, and more comparable to other studies because these environmental . Maps of these environmental parameters are displayed in appendix 1.

**Table 2.2 Details of environmental parameters and parameter codes.** The sources of these data are described by (Waggitt *et al.*, 2020).

Parameter	Explanation				
codes					
BAT	Depth (m)				
CHS	Total Chlorophyll (mg) in surface layer (satellite imagery)				
CHT	Total Chlorophyll (mg) depth summed between 0 and 150m from surface (modelled)				
CON	Distance to 300m isobath (m)				
FEA	Depth gradient (m), calculated using terrain ruggedness index				
LND	Distance to Land (m)				
SPM	Mean surface current speed (ms-1), including tidal influence				
TPF	Thermal stratification gradient, where higher values indicate greater frontal activity				
TPM	Mean potential temperature (Celsius) between 0 and 150m from surface (modelled)				
TPR	Range of potential temperature (Celsius) between 0 and 150m from surface (modelled)				
TPS	Potential temperature (Celsius) in surface layer (satellite imagery)				

**Table 2.3 Details of chosen models.** The species column details the common name of each species. The logistic parameter column lists the environmental parameter codes used in the logistic models and a colon between two parameters denotes interaction term between the two parameters. The environmental parameters corresponding to the codes are detailed in table 2.2. The offset column, 'Km': kilometres travelled per observation, 'Hr': survey time (in hours) per observation. Distribution column, 'NB 1': negative binomial distribution where the variance increases linearly with the predicted mean, 'NB 2': negative binomial distribution where the variance increases quadratically with the predicted mean, 'P': poisson distribution.

Species	Logistic parameter	Offset	Distribution
Puffin	CHT, TPS, BAT, TPF	Km	NB 1
black-legged kittiwake	TPM, TPF	Km	NB 1
bottlenose dolphin	CHT:BAT, TPS	Km	Р
	TPM, SPM, CHS,		
common guillemot	TPF	Km	NB 1
	TPM:CON, CHT,		
Common Dolphin	TPR	-	NB 1
European shag	SPM, TPF, CHS, TPR	-	Р
European Storm petrel	TPM, TPF, TPR	-	NB2
Fin whale	CHT:BAT	Km	NB 1
	TPM:BAT, CHT,		
harbour porpoise	SPM	Km	NB 1
herring gull	CHT, TPM, SPM	Km	Р
Lesser Black Backed Gull	CHT, TPM, SPM	Km	NB 1
Manx Shearwater	CHT, SPM	Km	Р
Minke Whale	TPF, SPM	Km	NB 1
Northern Fulmar	CHT, FEA	Hr	Р
Northern Gannet	TPM, TPF	Km	NB 1
Orca	TPR:TPS, CON:BAT	-	Р
Pilot Whale	CON:TPM, FEA	-	NB 1
	LND, TPF, TPM,		
Razorbill	TPR	Km	NB 1
Risso's Dolphin	BAT:TPM, CON	-	Р
Sperm Whale	BAT:FEA, CON	Km	NB 2
Striped Dolphin	BAT:TPM	Km	Р
White-beaked Dolphin	BAT:TPM	-	Р
White-sided Dolphin	SPM:TPM	-	NB 1

As pod size of cetaceans can vary greatly (from pods of 2, to superpods from 200 to 1,000), a qualitative decision was made that it is reasonable to consider the maximum count values (for cetacean abundance in the dataset used for this study), non-anomalous, as it is probable that the values were accurate and not a produce of error. For many species, extremely high-count values were identified from visual inspection of Cleveland Dotplots. Since these high values are extreme (although not necessarily anomalous), there was not

enough observations to model the abundance and distribution of superpods with high accuracy. Furthermore, these values could have a large and disproportionate, influential effect on the model, skewing the fit, and so the rest of the observations would not have a close fit with the model, and little predictive power. When there are extreme values within a dataset, an option is to apply a transformation to the response data, however, transformations affect the relationship between the response and explanatory variables, so should be used with caution (Zuur et al., 2009). Consequently, the extreme observations were discarded, and no transformation used. Influential observations are usually identified by visually inspecting a Cook's distance plot, however, published R functions did not have the capability to use zero-inflated models. It was not within the scope of this project to write a custom function that would not be ignorant of the zero-inflated nature of the data. Consequently, Cook's distance was calculated using the fit of a generalised linear model (GLM) of the count data only, and interpreted with caution, as it did not represent the full dataset. To assess for collinearity among explanatory variables, pair plots were generated and analysed, and Variance Inflation Factor (VIF) analysis was also conducted.

Overdispersion arises when the mean is smaller than the variance (Zuur *et al.*, 2009), which is common in heteroskedastic data. When a model is overdispersed, an option is to include overdispersion parameters, however this uses parameter space. Too many parameters can lead to overfitting, which lowers the predictive power of a model. The distribution families tested were poisson distribution and two functions of negative binomial. Poisson distribution is often used for count data (Zuur *et al.*, 2009), as it doesn't predict negative values.

**Negative binomial function 1** is where the variance increases linearly with the predicted mean (Hardin & Hilbe, 2007):

$$variance = \mu * (1 + \varphi)$$

Where  $\mu$  (mu) is the predicted mean, and  $\phi$  (phi) is the dispersion parameter:

$$\varphi = \exp(\eta)$$

Where  $\eta$  (eta) is the linear predictor from the dispersion model.

**Negative binomial function 2** is where the variance increases quadratically with predicted mean

$$variance = \mu * (1 + \frac{\mu}{\varphi})$$

The link is the relationship between the expected value of the response variable and the systematic part (Zuur *et al.*, 2009), (put more simply, it is the type of relationship between the mean and the variance). As the link specifies the expected relationship, it affects the coefficient values. Within the nested models, the log link function was used in the conditional regression model, and the logit link was used in the logistic model; this remained consistent among all models for comparability. The R function glmmTMB has capabilities of using Matern, Gaussian and Exponential covariance structures, to model the correlation between decay and distance and autoregressive order-1 functionality. When there is likely a bias in the data from collection, an option is to include an offset parameter, if, however, the effort bias does not influence the response variable, then parameter space should be saved, so the model does not become overparameterised.

Because the logistic part of the model refines the range of the conditional model to only the areas where they are likely to be present, the estimates for the slope values are only based on the relationship between their abundance and the environment within their likely range rather than the whole study area and represents the conditions where they are most likely to be abundant allowing us to see the nuance of their relationships with environment and facilitating more detailed comparisons between species that occur sympatrically.

### 2.1. Model validation and Selection

The use of both k-fold cross validation and Random-Walk Metropolis Sampling provides information on how parsimonious the models are. The k-fold cross validation assesses the predictive power of the model, and the Random-Walk Metropolis Sampling assesses the reproducibility of the regression coefficients on new data. The models were validated using the k-fold cross validation technique, where k is equal to 5. To understand how well the coefficients of the last parameters represent the model, posterior distribution samples of the coefficients were simulated using a random walk Metropolis sampling algorithm, using MCMCpack::MCMCmetrop1R (Martin  $et\ al.$ , 2011), which is a frequently used Markov Chain Monte Carlo algorithm. Trace and density plots from the random walk Metropolis sampling are displayed in appendix 2. Mean squared error for the predicted values of training data as a function of the test dataset for each iteration of the k-fold cross validation are reported in

appendix 2, along with other fit statistics of the ZIGLM, and maps of ZIGLM predictions of species distributions.

Histograms and density plots of the model residuals were used to assess normality. Pearson residuals were plotted against fitted values to assess whether the model was heteroskedastic. Residuals were plotted against explanatory variables to assess for non-independence. Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) were considered when selecting the best model for each species. The log-likelihood values were compared when selecting the best model for each species.

# 2.2. Quantifying Similarity

As guilds and taxa groups are used to describe ecological or morphological similarity, it could be relevant to identify if their similarities are reflected in relationships between their distribution and environment. The results of this study identified where species sharing guilds/ taxa groups (table 2.4) are in the similarity structure in relation to each other and other species. Guilds/taxa groups (table 2.4) will be highlighted in the results section figures that represent the similarity structure, to assist visualisation of patterns. The guilds/ taxa groups defined in table 2.4 that are highlighted in the results section have been subset from guilds/ taxa groups and species with amalgamated data as they are commonly used groups. Furthermore, the groups provide simplification to interpretation of similarities between guilds/ taxa groups and are at a similar level of shared trait uniqueness compared to other species in the study and include more than two species within groups. Additionally, crossover between guild and closely related taxa are represented in some of these groups, for example auks are deep pursuit diving seabirds, gulls are surface feeders, rorquals (balaenopterids) are lunge filter-feeding cetaceans and deep diving odontocetes also represent teuthophageous cetaceans. The harbour porpoise, orca, European shag, and gannet were not highlighted in guilds/ taxa groups but were included for context, as they have similarities with other species in guilds/ taxa groups such as shared diet (although only the piscivorous orca ecotype share diet with the other species) and occur sympatrically in large parts of their ranges, and the European shag forages at similar depths to the auks.

Moreover, this maximised use of available data of many species in the marine top predator community in the northeast Atlantic.

Table 2.4 Guilds/taxa groups to investigate.

Guilds/ taxa groups	Species common names	References
Auks	Razorbill, common guillemot, Atlantic puffin	(Anderwald <i>et al.</i> , 2011; McClellan <i>et al.</i> , 2014; Le Rest <i>et al.</i> , 2016; Wong <i>et al.</i> , 2018)
Deep diving odontocetes	Sperm whale, pilot whale, Risso's dolphin	(Praca & Gannier, 2008; Spitz et al., 2011; Giorli et al., 2016)
Small-sized delphinids	Common dolphin, striped dolphin, white-sided dolphin, white-beaked dolphin, bottlenose dolphin	(Sigurjónsson <i>et al.,</i> 1991; Lambert, Laran <i>et al.,</i> 2017; Lambert, Pettex <i>et al.,</i> 2017)
Gulls	Lesser black-backed gull, herring gull, black-legged kittiwake	(Anderwald <i>et al.</i> , 2011; Wong <i>et al.</i> , 2018)
Procellariiformes	Manx shearwater, European storm petrel, northern fulmar	
Rorquals	Fin whale, minke whale	(Kot <i>et al.,</i> 2014; Baines <i>et al.,</i> 2017; Kahane-Rapport <i>et al.,</i> 2020)

# 2.2.1. Slope value scaling

Because  $m=\frac{dy}{dx}$ , the response variables (y) need to be scaled if they are to be compared with slope values of other models with different response variables. However, models struggle to converge when a response variable is scaled 0-1, resulting in Standard Errors of around 4-5 orders of magnitude larger than the slope value. Therefore, the response variable was not scaled. To allow slope values of models with different response variables to be comparable, the slope values were scaled using the following equation:

$$m_{sc} = \frac{m(x_2 - x_1) - Y_{min}}{Y_{max} - Y_{min}} \cdot (s_{max} - s_{min}) + s_{min}$$

Where:

 $m_{sc}$  = scaled slope value

Y = response variable (vector)

 $x_1$  = sample value of x

 $x_2$  = sample value of x , where  $x_2 > x_1$ 

 $S_{max}$  = maximum value to scale slope values to (0.8) (arbitrary positive value)

 $S_{min}$  = minimum value to scale slope values to (-0.8) (negative value with equal proximity to 0 as  $S_{max}$ )

This equation was derived from  $y = (\sum m_i x_i) + c$ , the Straight-Line Equation.

Percentage change in population with a 20% increase in the value of the predictor was calculated using the following equation, where  $x_1 = 0.1$  and  $x_2 = 0.3$ :

$$\frac{m(x_2-x_1)}{y_{max}}\cdot 100$$

# 2.2.2. Dissimilarity

A distance matrix was calculated, using stats::dist (R Core Team, 2018), as a proxy for dissimilarity. The Euclidean distance measure was used.

$$S_{au}\sqrt{{S_{tu}}^{-2}+{S_{cu}}^{-2}+{S_{tfu}}^{-2}+{S_{du}}^{-2}+{S_{dgu}}^{-2}}$$

**Table 2.5 Table of distance matrix equation terms.** Term description and non-standardised parameter the term represents (ZiGLM parameter code).

Equation Term	Term Description	ZiGLM parameter code
Sau	Standardised Abundance Units	-
$S_{tu}$	Standardised Temperature Units	TPM
$S_{cu}$	Standardised Chlorophyll Units	CHT
$S_{tfu}$	Standardised Thermal Front Units	TPF
$S_{du}$	Standardised Depth Units	BAT
$S_{dgu}$	Standardised Depth Gradient Units	FEA

### 2.2.3. Clustering

Using stats::kmeans (R Core Team, 2018). To select the *k* value, an elbow method was used. The apex of the curve was six, which was therefore selected to represent *k*. Agglomerative hierarchical clustering was also used, an unsupervised machine learning technique was used to group the species by similarity in how their abundance varies with variation in environmental parameters. Agglomerative clustering starts off with all observations in individual clusters, (whereas divisive clustering starts with all observations in one cluster). Clusters most proximate to one another are merged with each time-step. The point where the clusters are joined is the node, the height of which shows the extent to which the leaves are similar. Various linkage criteria for agglomerative hierarchical clustering exist, which is the function used to compute pairwise distances. The function used determines the way in

which the clusters are considered distant. There are four main linkage criterions for agglomerative clustering; single, average, complete and ward's link and a distance matrix (Euclidean or Manhattan are commonly used metrics) as a measure of dissimilarity between observations. The clustering algorithm used Ward's 1963 linkage criterion (Murtagh & Legendre, 2014), which minimizes the total within-cluster variance. Clusters with minimum between-cluster distance are agglomerated. Using stats::hclust (R Core Team, 2018). Code used, including project package "MScResPACK" available at:

https://github.com/RGreensmith/MScResPACK The use of these methods allowed 2,645 comparisons (number of species squared, multiplied by the number of parameters) to be evaluated and quantitatively simplified into latent similarity structures.

# 2.2.4 Cross-validation of similarity structure

To cross-validate the similarity structure, Pearson product-moment correlation coefficients were calculated between distance metrics representing structure of the different analyses (listed in table 2.6), to identify how well the latent structure identified by the analyses was mirrored throughout the different analyses.

**Table 2.6 Table of inputs for Pearson product-moment correlation coefficient used in latent similarity structure cross validation.** Distance metrics detail how the structure identified in the analysis type is represented as an input in the Pearson product-moment correlation coefficient to cross-validate the latent similarity structure.

Analysis type	Distance metrics
Hierarchical	Cophenetic distances derived from the
clustering	agglomerative hierarchical clustering analysis
Principle Component Analysis	Euclidean distances between the observation scores from principal components 1 and 2 from principal component analysis
ZIGLM conditional model coefficients	Euclidean distances between the conditional coefficients of the zero-inflated generalised models for each species
Classical multi- dimensional scaling	Euclidean distances between coordinates derived from classical multi-dimensional scaling

# 3.Results

Figures 3.1, 3.3 and 3.4 show that the guilds/taxa groups were dispersed throughout the similarity structure. The within guild/ taxa group dissimilarity was particularly stark between the rorquals (blue rectangle; figures 3.1 and 3.4a) and deep-diving odontocetes (green rectangle; figures 3.1 and 3.4a).

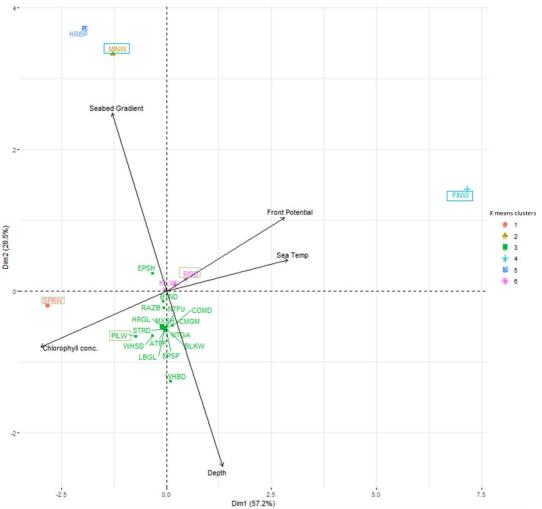
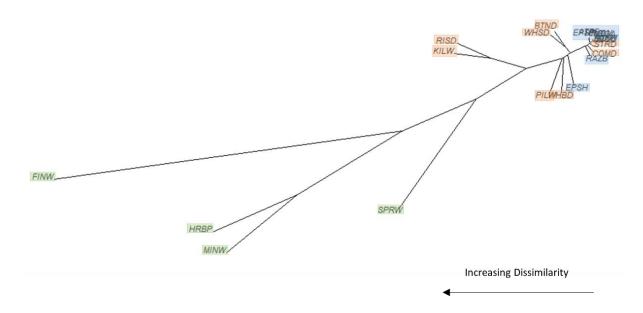


Figure 3.1 Biplot of principle components 1 and 2, of coefficients from the conditional models. Colour coded by the cluster to which the k means cluster algorithm assigned each species. Eigen vectors (direction of the variable plane through the matrix) of the variables are represented by the direction of the black arrows (each labelled with variable name in black) and the Eigen values (loading, or weighting of the variable) of the variables are represented by the length of the black arrows (each labelled with variable name in black). The scores of species are represented by positioning of the points (labelled with species abbreviation). Blue rectangles highlight rorquals, green rectangles highlight deep-diving odontocetes.

Figures 3.1 and 3.4a show that the minke whale (MINW) and harbour porpoise (HRBP) are close together within the similarity structure, and the combination of relationships with

environmental variables that explain their uniqueness to the other species, are also the combinations that make the minke whale and harbour porpoise similar to one another. The K-means clustering analysis identified a large cluster of 17 species and other than a cluster containing the Rissos dolphin and the Orca, the remainder of the clusters only contained one species. This was because the scale of the slope estimates for the 6 species not in this cluster were so much larger than the other species such that comparitively, the species with smaller slope estimates appeared to be similar. Because of this, the large group was taken as a subset and re-analysed to investigate if there were any other patterns present at the scale of those species. A taxa-based dissimilarity gradient can be observed in figure 3.2, where highly similar species were mostly seabirds, and progressing along the gradient of increasing dissimilarity, delphinids overlapped with seabirds, then the non-delphinid cetaceans had the greatest dissimilarity.



**Figure 3.2 Unrooted dendrogram of hierarchical clustering.** Unrooted dendrogram quantitatively derived from agglomerative hierarchical clustering of species ZIGLM conditional coefficients. Black arrow denotes increasing dissimilarity between species from right to left (length of arrow is arbitrary). Green shading highlights non-delphinid cetaceans, orange shading highlights delphinids and blue shading highlights seabirds.

Within the subset analysis, there was greatest dispersion throughout the similarity structure between the small-sized delphinids (green highlight; figures 3.3 and 3.4b) and auks (orange highlight; figures 3.3 and 3.4b). Within the gulls (yellow highlight; figures 3.3 and 3.4b), there was high similarity between the herring gull (HRGL) and black-legged kittiwake

(BLKW), but the lesser black-backed gull (LBGL) was dissimilar to the other gulls. Within the procellariiformes (purple highlight; figures 3.3 and 3.4b), there was high similarity between the manx shearwater (MXSH) and northern fulmar (NTFU), and the European storm petrel (EPSP) was more distant. The guillemot (CMGM), kittiwake (BLKW) and herring gull (HRGL) were highly similar to eachother, as were the gannet (NTGA), northern fulmar (NTFU) and manx shearwater (MXSH) to one another (figures 3.3 and 3.4b).

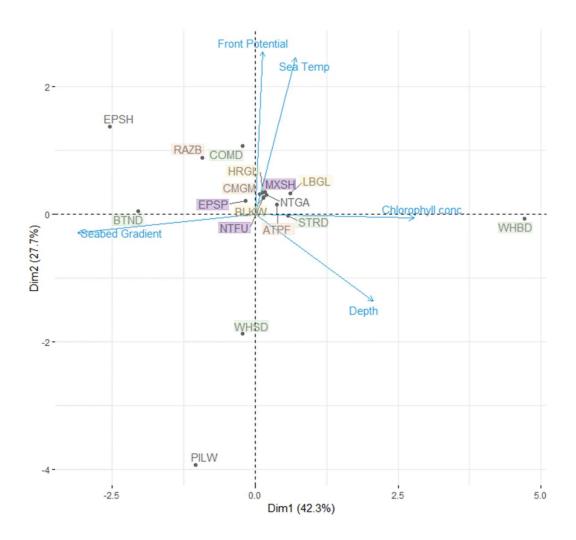
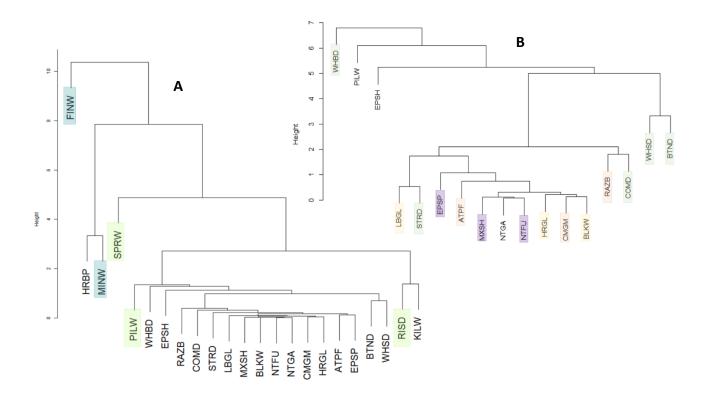


Figure 3.3 Biplot of principle components 1 and 2, of coefficients from the conditional models from the subset analysis of k means cluster 3. Eigen vectors (direction of the variable plane through the matrix) of the variables are represented by the direction of the black arrows (each labelled with variable name in black) and the Eigen values (loading, or weighting of the variable) of the variables are represented by the length of the blue arrows (each labelled with variable name in blue). The scores of species are represented by the grey points (labelled with species abbreviation). The scores of species are represented by positioning of the points (labelled with species abbreviation). Shaded rectangles highlight species groups, orange: auks, green: small-sized delphinids, yellow: gulls, purple: procellariiformes.



**Figure 3.4 Dendrograms of hierarchical clustering of species ZIGLM conditional coefficients.** Figure A is clustering of all species and figure B is the subset clustering. Shaded rectangles highlight species groups; in figure A, blue: rorquals and green: deep-diving odontocete, in figure B, orange: auks, green: small-sized delphinids, yellow: gulls, purple: procellariiformes.

The majority of seabirds and cetaceans abundance had the same direction of correlation with the dynamic variables: positive correlation with fronts and negative correlation with sea temperature and chlorophyll (table 3.1). However, the majority of seabirds and cetaceans' abundances were oppositely correlated with the static parameters: majority of seabirds were negatively correlated with seabed gradient and depth, whereas the majority of cetaceans were positively correlated (table 3.1). Depth was the only parameter with seabird coefficients over the 75<sup>th</sup> percentile (razorbill and European shag) and the most cetaceans below the 25<sup>th</sup> percentile (common, Risso's and striped dolphins) (table 3.1). Sea temperature was the only parameter where no cetacean coefficients were below the 25<sup>th</sup> percentile (table 3.1). For the seabirds, the order of the most important variables was: (i) depth, (ii) sea temperature, (iii) fronts, then (iv) both chlorophyll and seabed gradient equally, the order was opposite for the least important variables of seabirds (table 3.1). For cetaceans, the order of the most important variables was (i) fronts, (ii) depth, (iii) both sea

temperature and chlorophyll equally, then (iv) seabed gradient (table 3.1). The order of the least important variables for cetaceans was (i) depth, (ii) both chlorophyll and seabed gradient equally, then (iii) both fronts and sea temperature equally (table 3.1).

Fronts was the most important variable to the cetaceans that are predominantly found on the shelf edge and oceanic waters: two of the deep diving odontocetes (pilot whale and sperm whale), striped dolphin (all negatively correlated with fronts) and fin whale (positively correlated) (table 3.1). The most important variable for the predominantly neritic cetaceans (minke whale, white-beaked dolphin and harbour porpoise) was water depth, with which the white-beaked dolphin was negatively correlated (table 3.1). The only cetaceans with chlorophyll as the most important variable (Risso's and bottlenose dolphin) were negatively correlated (table 3.1). The most important variable for 3 of the deep diving seabirds was depth (guillemot, razorbill and shag), whereas sea temperature was most important to the puffin (table 3.1).

**Table 3.1 Summary of conditional model slope estimates.** Bold text highlights where species are above the 75<sup>th</sup> percentile. '<25<sup>th</sup>' identifies that the species absolute value is lower than the 25<sup>th</sup> percentile of all species absolute values for the corresponding predictor. '>75<sup>th</sup>' means that the species absolute value is greater than the 75<sup>th</sup> percentile of all species absolute values for the corresponding predictor, 'IQR' denotes the interquartile range. When the value contains '+', the abundance of that species increases linearly with an increase in the value of the corresponding predictor. When the value contains '-', the abundance of that species decreases linearly with an increase in the value of the corresponding predictor. Dark grey shading highlights the parameter with the steepest slope estimate compared to the other parameters for the species, light grey shading highlights the parameter with the shallowest slope estimate for the species.

	Species	Guild/taxa group	Sea Temp.	Thermal fronts	Chlorophyll	Seabed Gradient	Depth
	Atlantic puffin	Auk	IQR -	IQR +	IQR +	IQR -	IQR -
	Common guillemot	Auk	IQR -	IQR +	IQR -	IQR -	IQR -
	Razorbill	Auk	<25 <sup>th</sup> +	IQR +	IQR -	IQR +	>75 <sup>th</sup> -
	Black-legged kittiwake	Gull	<25 <sup>th</sup> -	<25 <sup>th</sup> +	IQR -	<25 <sup>th</sup> -	<25 <sup>th</sup> -
Seabirds	Herring gull	Gull	<25 <sup>th</sup> -	<25 <sup>th</sup> +	<25 <sup>th</sup> -	IQR -	IQR -
ab	Lesser black-backed gull	Gull	IQR +	IQR -	IQR +	<25 <sup>th</sup> -	IQR -
Š	European storm petrel	Procellariiform	IQR -	IQR -	IQR -	IQR -	IQR -
	Manx shearwater	Procellariiform	<25 <sup>th</sup> +	<25 <sup>th</sup> +	<25 <sup>th</sup> +	<25 <sup>th</sup> +	IQR -
	Northern Fulmar	Procellariiform	<25 <sup>th</sup> -	<25 <sup>th</sup> +	<25 <sup>th</sup> -	<25 <sup>th</sup> +	<25 <sup>th</sup> -
	European shag		IQR -	IQR +	<25 <sup>th</sup> +	IQR +	>75 <sup>th</sup> -
	Northern Gannet		<25 <sup>th</sup> -	<25 <sup>th</sup> +	<25 <sup>th</sup> +	<25 <sup>th</sup> -	<25 <sup>th</sup> -
	Pilot whale	Deep diving odontocete	>75 <sup>th</sup> -	>75 <sup>th</sup> -	IQR -	>75 <sup>th</sup> +	IQR +
	Risso's dolphin	Deep diving odontocete	IQR -	>75 <sup>th</sup> +	>75 <sup>th</sup> -	IQR +	<25 <sup>th</sup> +
	Sperm whale	Deep diving odontocete	>75 <sup>th</sup> -	>75 <sup>th</sup> -	>75 <sup>th</sup> +	>75 <sup>th</sup> +	>75 <sup>th</sup> +
	Fin whale	Rorqual	>75 <sup>th</sup> +	>75 <sup>th</sup> +	> 75 <sup>th</sup> -	IQR+	>75 <sup>th</sup> +
S	Minke whale	Rorqual	>75 <sup>th</sup> -	>75 <sup>th</sup> +	IQR -	>75 <sup>th</sup> +	>75 <sup>th</sup> -
Cetaceans	Bottlenose dolphin	Small-sized delphinid	IQR -	IQR +	IQR -	IQR+	IQR +
etac	Common dolphin	Small-sized delphinid	IQR+	IQR +	IQR -	<25 <sup>th</sup> -	<25 <sup>th</sup> +
Ö	Striped dolphin	Small-sized delphinid	IQR+	IQR -	IQR +	IQR +	<25 <sup>th</sup> +
	White-beaked dolphin	Small-sized delphinid	IQR -	<25 <sup>th</sup> +	>75 <sup>th</sup> +	>75 <sup>th</sup> -	IQR +
	White-sided dolphin	Small-sized delphinid	>75 <sup>th</sup> -	IQR+	<25 <sup>th</sup> -	IQR -	IQR +
	Harbour porpoise		IQR -	IQR +	>75 <sup>th</sup> +	>75 <sup>th</sup> +	> 75 <sup>th</sup> -
	Orca		>75 <sup>th</sup> -	>75 <sup>th</sup> +	>75 <sup>th</sup> -	>75 <sup>th</sup> +	IQR +

The strong positive correlations between the analyses and the dissimilarity matrix of species based on the ZIGLM conditional coefficients (table 3.2) validates the latent similarity structure persistent in the different analysis.

**Table 3.2 Pearson product-moment correlation coefficient matrix** of cophenetic distances derived from the agglomerative hierarchical clustering analysis (HClust. cophenetic dist.), Euclidean distances between the observation (species) scores from principle dimensions 1 and 2 from principle component analysis (Euclid dist. between pc1 and pc2 scores) and the Euclidean distances between the conditional coefficients of the zero-inflated generalised mixed models for each species (Euclid dist. between ZIGLM coefficients (conditional) for each species) and the Euclidean distances between coordinates derived from classical multi-dimensional scaling (Euclid dist. between coordinates from classical MDS).

HClust. cophenetic dist.	-			
Euclid dist. between pc1 and pc2 scores	0.963	-		
Euclid dist. between ZIGLM coefficients (conditional) for each species	0.976	0.984	-	
Euclid dist. between coordinates from classical MDS	0.963	1	0.984	-
	HClust. cophenetic dist.	Euclid dist. between pc1 and pc2 scores	Euclid dist. between ZIGLM coefficients (conditional) for each species	Euclid dist. between coordinates from classical MDS

# 4. Discussion

This study has identified a similarity structure amongst some of the seabird and cetacean community in the northeast Atlantic. On a coarse scale, the identified similarity structure followed a taxa-based dissimilarity gradient, where highly similar species were mostly seabirds, and progressing along the gradient of increasing dissimilarity, delphinids overlapped with seabirds, then the non-delphinid cetaceans had the greatest dissimilarity. The scale at which the non-delphinid cetaceans were dissimilar resulted in the dissimilarity of the seabirds and delphinids being negligible, resulting in a nested similarity structure that is observable when the non-delphinid cetaceans and the orca and Risso's dolphin are removed. Across both structures, there is a common theme of dissimilarity between species in the same guild, and similarity between sympatric species from separate guilds, and not closely related taxa.

The dissimilarity gradient largely reflected steepness of gradient of correlation with the environmental parameters, which could be expected to occur if species at one end of the gradient had a relatively low abundance in the study area and the other end of the gradient had a relatively high abundance. However, there was a mixture of species across this gradient with varying abundance in the study area, for example, species at the dissimilar end of the gradient includes the harbour porpoise, the most abundant cetacean in the study area (Hammond et al., 2013), and the sperm whale and fin whale, which have a relatively low abundance in the study area (K. Macleod et al., 2009; Rogan et al., 2017). Furthermore, at the other end of the gradient are species with relatively high abundance such as the guillemot (Mitchell et al., 2004), and species with relatively low abundance, such as the European storm petrel (Mitchell et al., 2004). Another potential explanation could be annual variation in the presence of the species and similarity of the distribution across the seasons. However, this was also mixed across the dissimilarity gradient, for example, species that have a consistent year-round presence and have comparatively low variation in range across the seasons, such as the harbour porpoise (Laran, Pettex, David et al., 2017) and European shag (Acker et al., 2020) were spread across the dissimilarity gradient, and migratory species with low abundance in the study area at some parts of the year, such as the fin whales

(Laran, Pettex, David *et al.*, 2017; Gauffier *et al.*, 2020) and Manx shearwater (Guilford *et al.*, 2009), were at either end of the dissimilarity gradient.

A weak correlation between species distribution and the environmental parameters could occur if multiple environmental gradients were crossed, which could be more common amongst central place foragers, for example, seabirds during the breeding season (Patrick et al., 2014). Another instance where this might also apply is when intraspecific habitat partitioning occurs within a range that encompasses multiple populations of a species. Intraspecific habitat partitioning has been found in many of the species in this study, particularly between male and female (Edwards et al., 2016; Clark et al., 2021), which, could result in more environmental gradients being crossed by that species if both genders were encompassed in the spatial range of the study. Within this study area, both genders of the seabirds are present, but relationships between foraging behaviours and habitat can be different between the genders for some species such as gannets (Cox et al., 2016), which could result in more environmental gradients being represented by the species. Another example is the use of a dual foraging strategy by Manx shearwaters at the Skomer Island colony during the breeding season, where short foraging trips to the Celtic Sea front were used for chick provisioning, and longer foraging trips to the north and west of the Irish Sea front for maintaining personal body condition (Shoji et al., 2015). Whilst both types of foraging trip were to fronts, there is potential for other environmental gradients to be crossed with this dual foraging strategy. Furthermore, high abundances of some seabirds in different habitats can occur where species such as Manx shearwaters raft in the sea nearby their breeding colony, often in large numbers (Richards et al., 2019), which is a different type of habitat to areas where most intense foraging activity occurs. Furthermore, densitydependent competition results in foraging habitat partitioning between neighbouring colonies of conspecifics for a variety of seabirds, such as gannets (Wakefield et al., 2013), lesser black-backed gulls (Corman et al., 2016), kittiwakes and guillemots (Wakefield et al., 2017), which could also result in more environmental gradients being crossed. At the other end of the taxa-based dissimilarity gradient, latitudinal partitioning can occur between genders of many of the non-delphinid cetaceans (Born et al., 2003; Teloni et al., 2008; Laidre et al., 2009), so counts of these species within the northeast Atlantic could be more composed of one of the genders, which could result in less environmental gradients being

represented by the species. For example, mature male sperm whales mainly occur at higher latitudes than their conspecifics (Teloni *et al.*, 2008).

There was dissimilarity within guilds, which was particularly pronounced among auks, smallsized delphinids, rorquals, Larus gulls and deep-diving odontocetes. Niche partitioning has been found to occur within these guilds in numerous fine-scale studies, for example spatial partitioning of foraging areas between sympatric auks (Linnebjerg et al., 2013; Symons, 2018; Gulka et al., 2019; Delord et al., 2020) and Larus gulls (Kubetzki & Garthe, 2003). Habitat partitioning within the small-sized delphinid guild has also been observed, for example, between white-sided and common dolphins (Gowans & Whitehead, 1995), common and striped dolphins (Giménez et al., 2017), white-beaked and white-sided dolphins (MacLeod et al., 2007), and trophic niche partitioning between the white-beaked and white-sided dolphins (Das et al., 2003). Fine-scale spatial partitioning and trophic niche partitioning between the rorquals has also been found (Ingram et al., 2007; Ryan et al., 2013; Gavrilchuk et al., 2014). The dissimilarity between the deep-diving odontocetes in the current study reflects observations of habitat and trophic niche partitioning between these species in literature (Azzellino et al., 2008; Spitz et al., 2011; Giorli et al., 2016). Policy makers, planning authorities and conservationists frequently use species distribution models (SDMs) in planning and decision-making processes to predict the current and/or future distribution of a species (Mannocci et al., 2017). However, ecological processes such as those observed in this study are rarely incorporated, potentially due to lack of data, reliable quantification of the processes and a lack of clarity on how relevant the processes are to the scenario. The results found here indicate that these processes, that are also observed in fine scale studies, could potentially be occurring on a larger scale.

There was a similarity pattern of species that share similar diets and occur sympatrically throughout parts of their range, but were from different guilds. For example, the northern fulmar is a surface feeder, the Manx shearwater is a pursuit plunger, and northern gannet a plunge diver (Furness & Tasker, 2000), yet they showed similarity. Despite sharing prey resources, aspects of the ecology of species showing similarity could result in comparatively low competitive pressure, potentially explaining how their relationships between distribution and environmental parameters could be relatively similar. The high similarity

between the gannet, fulmar and shearwater is largely due to their particularly weak relationships with environmental parameters in this study, which could be related to potentially being observed crossing many environmental gradients, as they are less constrained by central place foraging than the other seabirds in the study, frequently travelling over 50 km from their nests with maximum ranges over 330 km (Furness & Tasker, 2000; Thaxter *et al.*, 2012). The similarity could also be because of lack of competition, of the species in the current study, (Furness & Tasker, 2000) considered the gannet and fulmar (along with the herring gull and storm petrel) to have the greatest plasticity in diet and/or foraging methods, and the shearwater slightly less varied methods of foraging and/or prey types.

The guillemot, kittiwake and herring gull are the only species in this study with matching direction and similar magnitude of correlation between distribution and the parameters. The guillemot and kittiwake were more similar to each other than the herring gull. The guillemot and kittiwake are similar in that they share the same diet, as their main prey type is sandeels and other forage fish. They are both heavily dependent on sandeels, such that their breeding productivity has been linked to population dynamics of sandeels (Frederiksen et al., 2006). They are also similar in that they have similar foraging ranges from the colony (Furness & Tasker, 2000; Thaxter et al., 2012), their at-sea distribution overlaps (Waggitt et al., 2020), their colonies can be adjacent to one-another (Newell et al., 2015), and they are both present in the study area during the non-breeding season (Lambert, Pettex et al., 2017). However, whilst they target the same prey and have similar ranges, their foraging behaviours are vastly different, as the kittiwake is a surface feeder, and the guillemot is a pursuit diver (Camphuysen & Webb, 1999). As their methods of catching prey greatly differ, it could be expected that they would need different physical environments for optimising efficiency of prey capture, specific to their behaviours. However, they are frequently observed in the same multi-species feeding aggregations, as the guillemots facilitate kittiwakes in capturing prey (Skov et al., 2000; Camphuysen et al., 2006). Camphuysen and Webb (Camphuysen & Webb, 1999) suggested that facilitation by guillemots could be a driver of kittiwake distribution, that auks could determine kittiwake foraging range extent, and that this mechanism influencing kittiwake distribution is greatly underestimated. The expected result from this theory would be that the guillemot and kittiwake have similar

relationships between their distribution and environment, which is present in the results of this study.

The kittiwake facilitates herring gulls in locating prey patches, described as 'catalysts' in multi-species feeding aggregations due to their high visibility (Camphuysen & Webb, 1999; Anderwald *et al.*, 2011). The behaviours of herring gulls can break up the multi-species feeding aggregations, by sitting in the centre of the prey patch, blocking the other surface feeders, where they often remain until another aggregation is visible (Camphuysen & Webb, 1999). Since many kittiwake populations are declining (Frederiksen, 2010), it is important to have a clear understanding of the processes influencing their distribution. Future research must be undertaken to identify if facilitation by feeding guillemots influences kittiwake distribution, and if this is the case, then it is important to understand the extent of this effect.

The minke whale and harbour porpoise were found to be similar in this study however, unlike the possible explanation for similarity between the guillemot and kittiwake, it is highly unlikely that facilitation occurs between the minke whale and harbour porpoise. Despite their range and dietary overlap, the similarity between the minke whale and harbour porpoise could be explained by lack of competitive exclusion due to their different foraging strategies (Johnston & Berta, 2011; Kot *et al.*, 2014). Furthermore, their solitary nature (Sigurjónsson *et al.*, 1991) could be less exclusionary to each other at prey patches.

### 4.1 Critical appraisal of the methods

Using linear models to model non-linear data results in information loss, however, it was outside of the scope of the project to develop statistical methods to enable a quantifiable comparison of the species relationships of non-linear models, which is why generalised linear models were chosen. Further improvement to the models would be incorporating spatial and temporal autocorrelation structures, however there was not enough time to run these models. Slope estimates used in the similarity analysis were scaled to allow comparison of slope estimates amongst models, however, this did not account for skewness of the different species abundance data.

This could be problematic, for instance, scaling slope estimates to the maximum value of right-skewed data will result in a shallower slope estimate than that of similarly correlated data with a more normal distribution. Whilst a square root transformation of the count data would reduce right-skewedness, this can be problematic as transformations alter the relationship between the response and explanatory variables (Zuur *et al.*, 2009). A more robust approach would be to account for right skewedness of the response variable in scaling the slope estimates, by using the 75<sup>th</sup> percentile of the response variable rather than the maximum value when scaling.

To test this theory, this and the original scaling methods were applied to a conditional coefficient of two species, (one heavily skewed, and the other more normally distributed), the outcome was that the relative difference between slope estimate scaled using 75<sup>th</sup> percentile of *y* was slightly smaller than when the slope estimate was scaled using maximum *y*, however the extent that it could affect interpretability of the similarity structure was sufficiently negligible. Furthermore, count data for most of the species are right skewed, therefore the effect of skewedness on coefficient scaling is relatively consistent and patterns of similarity are still interpretable.

### 4.2 Conclusion

The scale of the relationship between species abundance and their environment was distinct between taxa, as non-delphinid cetaceans had much stronger correlations than delphinids and seabirds. Furthermore, species with resource overlap that were not closely related or from the same guilds, showed similarity and there was a pattern of dissimilarity between species that were closely related or sharing guilds, which reflected patterns expected from species interactions such as habitat partitioning and coexistence. The relationships between distribution and environmental parameters of many marine top predators cannot be grouped together purely based on them being closely related or sharing guilds. Future research directions arisen from this study includes identifying underlying mechanisms driving this similarity structure and exploring whether interspecific interactions have a role.

# 5.References

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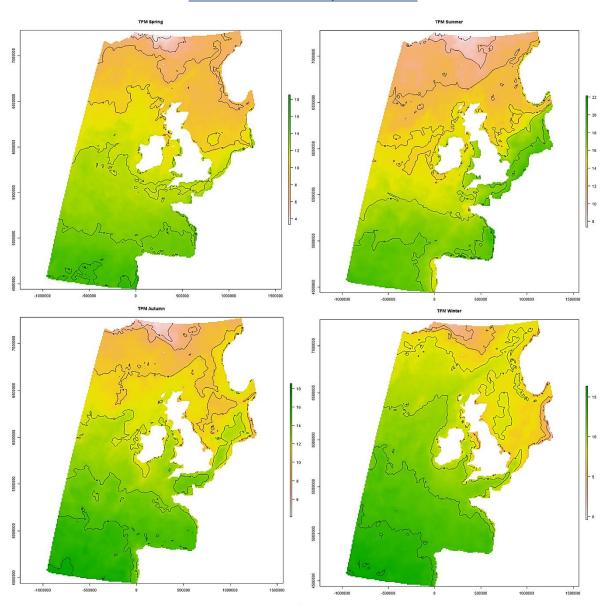
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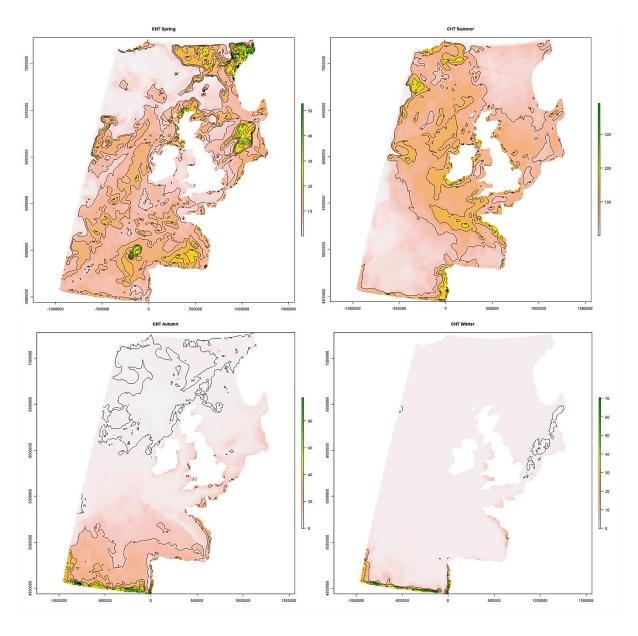
# 6.Appendices

### Appendix 1: Methodology

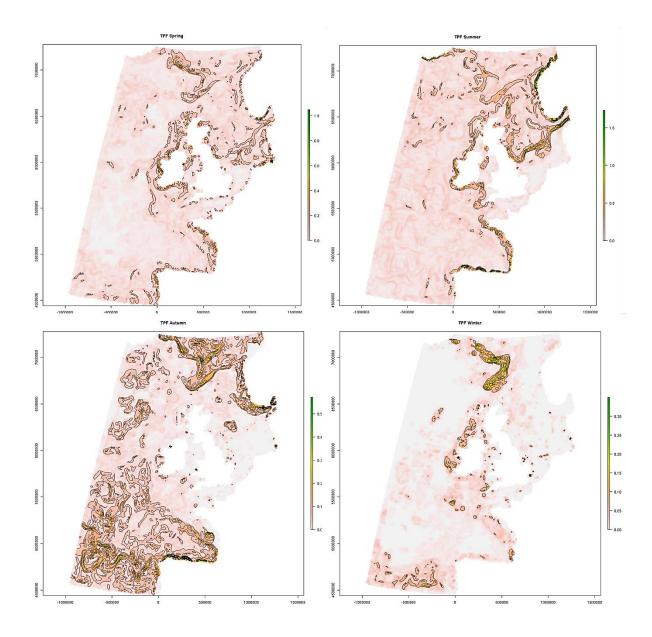
# 1.1 Environmental parameters



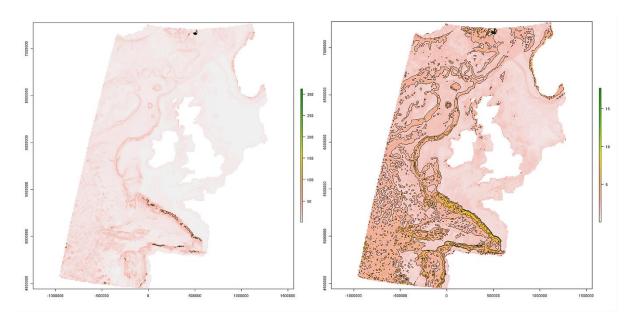
**Figure 6.1.1.** Mean potential temperature (Celsius) between 0 and 150m from surface (modelled) per season (parameter code: TPM). Top left: spring, top right: summer, bottom left: autumn, bottom right: winter.



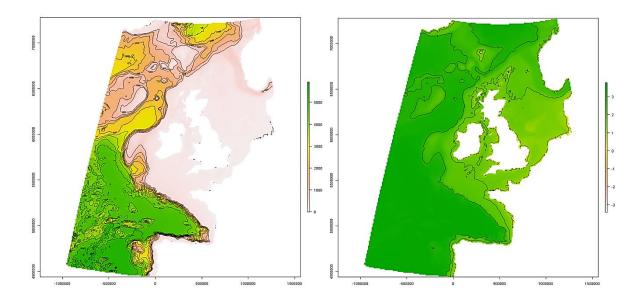
**Figure 6.1.2.** Total Chlorophyll (mg) depth summed between 0 and 150m from surface (modelled) (parameter code: CHT). Top left: spring, top right: summer, bottom left: autumn, bottom right: winter.



**Figure 6.1.3.** Thermal stratification gradient (unitless) (parameter code: TPF). Higher values indicate greater frontal activity Top left: spring, top right: summer, bottom left: autumn, bottom right: winter.



**Figure 6.1.4.** Seabed gradient, and square root transformed seabed gradient (parameter code: FEA). Depth gradient (m) calculated using terrain ruggedness index. Seabed gradient (left), square root transformed seabed gradient (right).

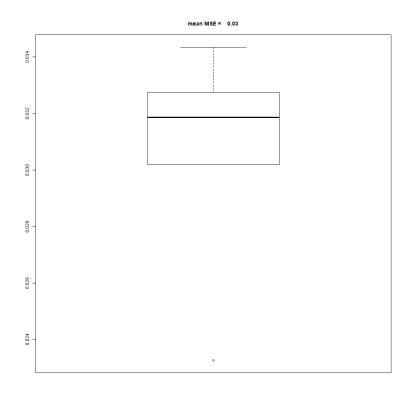


*Figure 6.1.5.* Depth (m), and log10 transformed depth (m) (parameter code: BAT). Depth (m) (left), log10 transformed water depth (right).

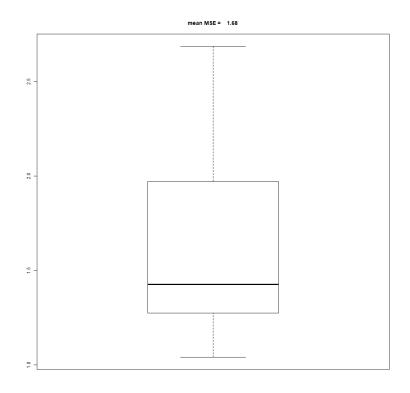
# Appendix 2: Results

**Table 6.2.1.** Table of k fold cross validation mean squared errors and Durbin-Watson residuals statistic.

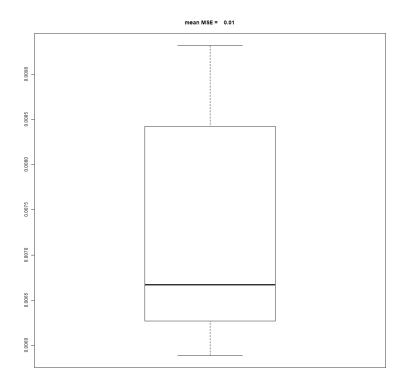
Species	k 1 (MSE)	k 2 (MSE)	<i>k</i> 3 (MSE)	k 4 (MSE)	<i>k</i> 5 (MSE)	mean of k 1-5 MSEs	Durbin- Watson (residuals)
Puffin	257.61	37.88	75.33	99.2	16.16	97.24	1.64
black-legged kittiwake	3974.56	1055.15	900.41	1757.98	140.73	1565.77	1.97
bottlenose dolphin	2.47	1.58	1.47	1.34	0.8	1.53	1.8
common guillemot	3178.47	915.93	1097.99	1230.71	248.27	1334.27	1.76
Common Dolphin	142.78	65.12	47.92	79.16	27.74	72.54	1.94
European shag	11.03	2.58	2	5.36	0.66	4.33	1.8
European Storm petrel	32	7.15	10.52	13.95	2.57	13.24	1.95
Fin whale						0.03	1.8
harbour porpoise						1.68	1.86
herring gull	999.68	201.22	262.96	404.53	56.45	384.97	1.92
Lesser Black Backed Gull	638	195	183	278	52	269	1.93
Manx Shearwater	2951	1203	781	1111	56	1220	1.88
Minke Whale							1.93
Northern Fulmar	23678	5829	3994	11484	433	9083	1.89
Northern Gannet	1429.14	430.93	270.02	714.29	106.26	590.13	1.85
Orca	0.05	0.02	0.01	0.03	0.02	0.03	2.002
Pilot Whale	2.34	0.7	0.87	1.51	0.59	1.2	1.97
Razorbill	146.67	39.52	48.79	60.73	16.07	62.35	1.86
Risso's Dolphin	0.23	0.08	0.09	0.12	0.05	0.11	1.95
Sperm Whale						0.01	2
Striped Dolphin	5.53	1.9	1.96	3	1.06	2.69	1.98
White-beaked Dolphin	0.94	0.37	0.44	0.59	0.31	0.53	1.9
White-sided Dolphin	18.56	3.49	1.81	9.66	1.39	6.98	2



**Figure 6.2.1.** Boxplots of averages of fin whale model K fold cross validation mean squared errors



**Figure 6.2.2.** Boxplots of averages of harbour porpoise model K fold cross validation mean squared errors



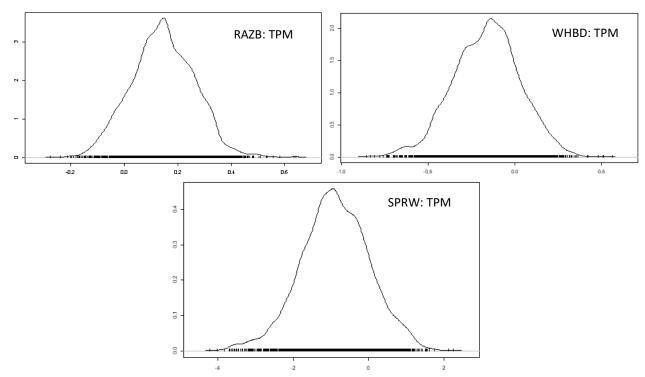
**Figure 6.2.3.** Boxplots of averages of sperm whale model K fold cross validation mean squared errors

#### 2.1 Coefficient Validation

**Table 6.2.2.** Table of conditional model parameters where coefficients p value were greater than 0.05, wide standard error of slope estimate, or predicted coefficients from RW Metropolis sampling overlapping zero.

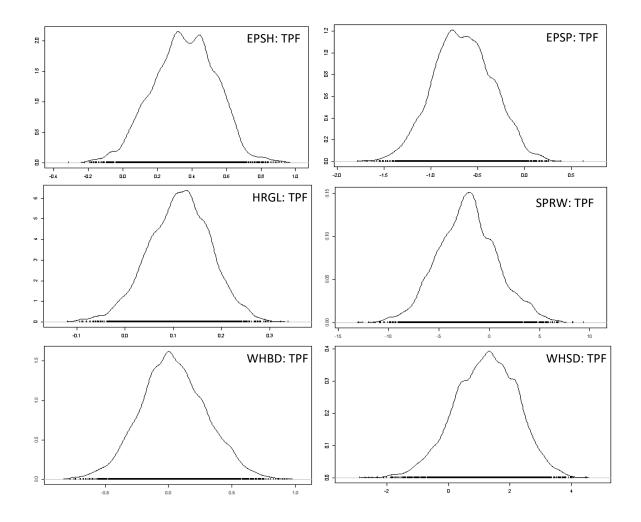
Species	Variable	р	m% of SE
Razorbill	TPM	0.19	73
Sperm whale	TPM		
White-beaked dolphin	TPM		
European shag	TPF	0.047	51
Storm petrel	TPF	0.038	48
Herring gull	TPF	0.08	55
Sperm whale	TPF		
White-beaked dolphin	TPF		
White-sided dolphin	TPF		
European shag	CHT	4.33	13
Orca	CHT	0.278	91
Pilot whale	CHT	0.78	27
Sperm whale	CHT		
White-sided dolphin	CHT		
Common dolphin	FEA	0.9	14
Fin whale	FEA	0.92	10
Lesser black-backed gull	FEA	0.263	89
Northern gannet	FEA	0.0214	41
Orca	FEA	0.634	48
Sperm whale	FEA		
White-sided dolphin	FEA		
Orca	BAT	0.312	100
Risso's dolphin	BAT	0.998	
Sperm whale	BAT		

Razorbill, TPM, proposal distribution = 0.15 (smallest absolute m value of all variables), the coefficient values range from around -0.3 to 0.69, and the majority of coefficients have values between -0.05 and 0.35. The density of coefficient values are roughly normally distributed where the peak density is around 0.15. There is a high density of coefficients with values around 0, providing support for the p values probability score that the null hypothesis cannot be rejected. There is also a high density of coefficients with values around 0.25. the density of coefficients with positive values was still much greater than those with negative values (proposal is positive).



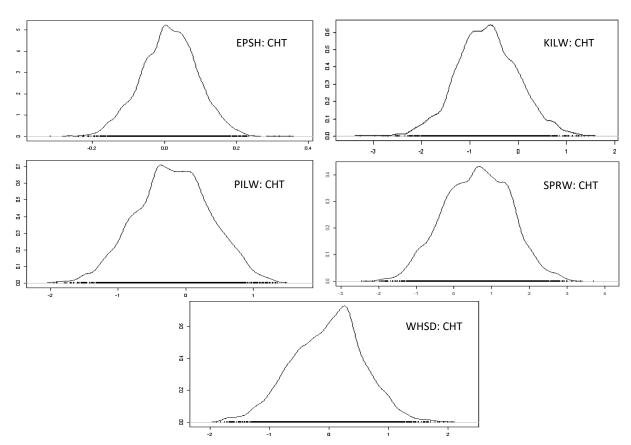
**Figure 6.2.3.** density plot (bottom) of random-walk metropolis sampling of the conditional model mean sea temperature coefficients.

Herring gull, TPF, the proposal distribution was centred at 0.11, there was greater density of predicted coefficients over 0.2, than the density of coefficients below 0, and the greatest density of coefficients had values between 0.025 and 0.21. The density of values not equal to zero was much larger than the density of values equal to zero. European shag, TPF, tail of metropolis sampling overlaps zero, but density is extremely low. Storm petrel, TPF, tail of metropolis sampling overlaps zero, but density is extremely low. Orca, CHT, tail overlaps 0, but greatest density of coefficients had values between around -1.25 and 0, and proposal distribution was -0.67. Pilot whale, CHT, proposal distribution -0.15, similar density of coefficients with positive and negative values, greatest density between around -1 and 0.75, slightly greater density of negative values than positive (proposal is negative). European shag, CHT, normal distribution around 0, base range < all other variables. Northern gannet, FEA, proposal distribution was centred at -0.17. The range of coefficient values was from around -0.4 to around 0.1. The majority of values were between -0.3 and -0.05.

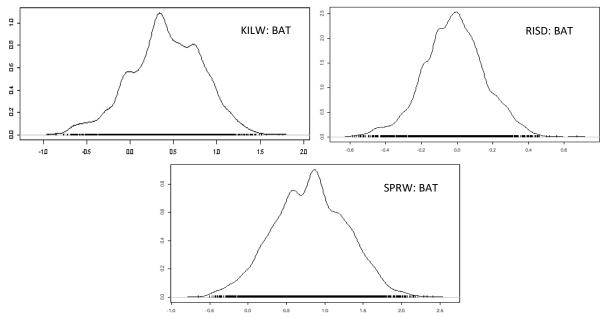


**Figure 6.2.4.** density plot (bottom) of random-walk metropolis sampling of the conditional model thermal front potential coefficients.

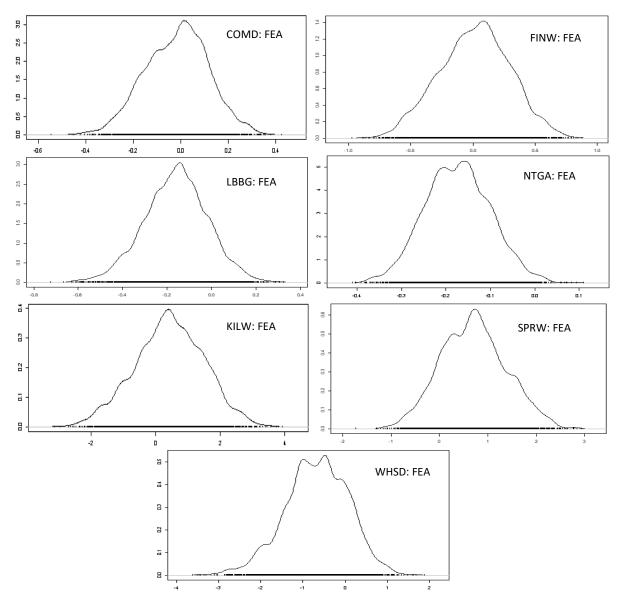
There was a high-density coefficients with values around -0.14 and another peak in density of values around -0.225. There was also a high density of coefficients with values around -0.1. The density of coefficients with a value of zero was much less than the density of coefficients with a value not equal to zero. Orca, FEA, proposal distribution was 0.51, and greatest density of coefficients was between around -1 and 1.75, close to a normal distribution centred around 0, with similar density of coefficients being positive and negative, although a slightly greater density of positive values than negative. Lesser black-backed gull, FEA, high density of coefficients overlapping 0, although greatest density of coefficients is between 0 and  $\sim$ -0.3 (proposal distribution -0.154). Common dolphin, FEA, normal distribution around 0, base range < all other variables. Fin whale, FEA, normal distribution around 0, base range < all other variables.



**Figure 6.2.5.** density plot (bottom) of random-walk metropolis sampling of the conditional model chlorophyll concentration coefficients.



**Figure 6.2.6.** density plot (bottom) of random-walk metropolis sampling of the conditional model water depth coefficients.



**Figure 6.2.7.** density plot (bottom) of random-walk metropolis sampling of the conditional model seabed gradient coefficients.

Orca, BAT, proposal distribution was 0.4, and the greatest density of coefficients had values between around -0.15 and 0.75, and the majority of coefficients were positive rather than negative (proposal was positive). Risso's dolphin, BAT, similar density of coefficients with positive and negative values, greatest density of coefficients have values between -0.2 and 0.2 (both still smallest absolute slope value of all variables), normal density distribution of predicted coefficients centred around 0.

#### 2.2 Model Outputs

**Table 6.2.3.1. Atlantic puffin** ZIGLM model outputs. Slope estimate, standard error, z-value, and p-value for each parameter within both nested models (conditional and logistic). Parameter details are the full names of each parameter, corresponding to the parameter code.

Model	Parameter Code	Slope Estimate	Standard Error	z-Value	<i>p</i> -Value
	(Intercept)	3.16	0.07	44.14	0
<u>la</u>	TPM_s	-6.44	0.13	-51.38	0
tior	TPF_s	3.96	0.17	22.67	9.37E-114
Conditional	CHT_s	1.35	0.08	15.9	6.65E-57
8	FEA_s	-2.11	0.24	-8.68	3.79E-18
	BAT_s	-2.56	0.15	-17.37	1.36E-67
	(Intercept)	3.88	0.17	22.82	2.63E-115
<u>::</u>	CHT_s	3.32	0.28	11.93	8.66E-33
Logistic	TPS_s	-2.87	0.35	-8.15	3.65E-16
2	BAT_s	-149.17	9.07	-16.45	8.86E-61
	TPF_s	-65.28	2.58	-25.34	1.25E-141

**Table 6.2.3.2.** Black-legged kittiwake ZIGLM model outputs. Slope estimate, standard error, z-value, and p-value for each parameter within both nested models (conditional and logistic). Parameter details are the full names of each parameter, corresponding to the parameter code.

Model	Parameter Code	Slope Estimate	Standard Error	z-Value	<i>p</i> -Value
	(Intercept)	2.77	0.03	102.80	0
la	TPM_s	-2.81	0.05	-55.30	0
tior	TPF_s	1.69	0.10	16.30	1.16E-59
Conditional	FEA_s	-1.41	0.12	-11.90	8.18E-33
S	BAT_s	-1.07	0.06	-17.60	1.83E-69
	CHT_s	-0.97	0.04	-24.40	2.29E-131
tic	(Intercept)	4.48	0.26	17.26	9.34E-67
Logistic	TPM_s	-21.70	1.03	-20.97	1.14E-97
2	TPF_s	-44.89	10.82	-4.15	3.33E-05

**Table 6.2.3.3.** Bottlenose dolphin ZIGLM model outputs. Slope estimate, standard error, z-value, and p-value for each parameter within both nested models (conditional and logistic). Parameter details are the full names of each parameter, corresponding to the parameter code.

Model	Parameter Code	Slope Estimate	Standard Error	z-Value	<i>p</i> -Value
	(Intercept)	2.73	0.05	51.91	0
la	TPM_s	-1.93	0.08	-22.78	7.90E-115
conditional	TPF_s	2.55	0.17	15.27	1.26E-52
ipu	FEA_s	1.85	0.05	34.13	2.78E-255
8	BAT_s	0.34	0.06	5.71	1.14E-08
	CHT_s	-0.71	0.13	-5.29	1.20E-07
	(Intercept)	7.53	0.12	61.15	0
. <u>::</u>	CHT_s	-3.39	0.30	-11.40	4.35E-30
logistic	BAT_s	-0.18	0.20	-0.89	0.38
<u>0</u>	TPS_s	-4.32	0.19	-22.81	3.34E-115
	CHT_s:BAT_s	5.16	2.02	2.56	0.01

**Table 6.2.3.4.** Common guillemot ZIGLM model outputs. Slope estimate, standard error, z-value, and p-value for each parameter within both nested models (conditional and logistic). Parameter details are the full names of each parameter, corresponding to the parameter code.

Model	Parameter Code	Slope Estimate	Standard Error	z-Value	<i>p</i> -Value
	(Intercept)	3.52	0.03	138.34	0
lal	TPM_s	-3.30	0.05	-67.54	0
conditional	TPF_s	4.02	0.12	33.46	2.11E-245
ndi	FEA_s	-1.51	0.19	-7.98	1.49E-15
03	BAT_s	-7.41	0.18	-41.09	0
	CHT_s	-1.28	0.04	-28.50	1.08E-178
	(Intercept)	5.32	0.27	20.07	1.32E-89
<u>:2</u>	TPM_s	-18.78	0.96	-19.64	7.14E-86
logistic	SPM_s	-9.42	0.69	-13.61	3.53E-42
<u>o</u>	CHS_s	-2.67	0.73	-3.65	0.0003
	TPF_s	16	0.88	18.23	3.01E-74

**Table 6.2.3.5.** Common dolphin ZIGLM model outputs. Slope estimate, standard error, z-value, and p-value for each parameter within both nested models (conditional and logistic). Parameter details are the full names of each parameter, corresponding to the parameter code.

Model	Parameter Code	Slope Estimate	Standard Error	z-Value	<i>p</i> -Value
	(Intercept)	-5.21	0.18	-28.65	1.67E-180
la	TPM_s	10.26	0.37	28.02	9.51E-173
conditional	TPF_s	1.68	0.27	6.33	2.48E-10
ndi	FEA_s	-0.02	0.14	-0.12	0.9
8	BAT_s	0.71	0.08	8.76	2.03E-18
	CHT_s	-3.05	0.27	-11.09	1.45E-28
	(Intercept)	-20.96	1.11	-18.85	3.17E-79
	TPM_s	32.18	1.57	20.52	1.51E-93
logistic	CON_s	34.85	2.55	13.66	1.65E-42
ogi	CHT_s	-2.66	0.69	-3.86	0.0001
_	TPR_s	-0.78	0.20	-3.89	9.92E-05
	TPM_s:CON_s	-42.53	3.59	-11.84	2.52E-32

**Table 6.2.3.6.** European shag ZIGLM model outputs. Slope estimate, standard error, z-value, and p-value for each parameter within both nested models (conditional and logistic). Parameter details are the full names of each parameter, corresponding to the parameter code.

Model	Parameter Code	Slope Estimate	Standard Error	z-Value	<i>p</i> -Value
	(Intercept)	2.11	0.04	47.01	0
<u>la</u>	TPM_s	-0.99	0.09	-10.85	1.94E-27
conditional	TPF_s	0.35	0.18	1.99	0.047
ndï	FEA_s	3.13	0.34	9.32	1.13E-20
8	BAT_s	-26.43	1.90	-13.92	4.66E-44
	CHT_s	0.01	0.08	0.17	0.862
	(Intercept)	3.09	0.06	55.73	0
<u>:</u>	SPM_s	2.95	0.19	15.59	8.94E-55
logistic	TPF_s	-7.21	0.37	-19.51	9.18E-85
<u>o</u>	CHS_s	-1.54	0.23	-6.75	1.47E-11
	TPR_s	9.41	0.42	22.46	9.13E-112

**Table 6.2.3.7.** European storm petrel ZIGLM model outputs. Slope estimate, standard error, z-value, and p-value for each parameter within both nested models (conditional and logistic). Parameter details are the full names of each parameter, corresponding to the parameter code.

Model	Parameter Code	Slope Estimate	Standard Error	z-Value	<i>p</i> -Value
	(Intercept)	0.39	0.19	2.08	0.04
<u>la</u>	TPM_s	-1.03	0.30	-3.43	0.001
tior	TPF_s	-0.65	0.31	-2.08	0.038
conditional	FEA_s	-1.18	0.28	-4.14	3.51E-05
8	BAT_s	-3.06	0.18	-17.08	1.97E-65
	CHT_s	-1.06	0.20	-5.30	1.15E-07
	(Intercept)	4.67	0.22	21.70	1.85E-104
logistic	TPM_s	-3.25	0.38	-8.51	1.68E-17
logi	TPF_s	-12.48	2.27	-5.49	3.93E-08
	TPR_s	-48.63	2.33	-20.92	3.44E-97

**Table 6.2.3.8.** Fin whale ZIGLM model outputs. Slope estimate, standard error, z-value, and p-value for each parameter within both nested models (conditional and logistic). Parameter details are the full names of each parameter, corresponding to the parameter code.

Model	Parameter	Slope	Standard	z-Value	<i>p</i> -Value
wiodei	Code	Estimate	Error	z-value	<i>p</i> -value
	(Intercept)	-6.25	0.29	-21.73	1.06E-104
lal	TPM_s	4.45	0.46	9.68	3.55E-22
tior	TPF_s	5.36	0.88	6.08	1.22E-09
conditiona	FEA_s	0.03	0.29	0.10	0.92
00	BAT_s	2.08	0.25	8.31	9.71E-17
	CHT_s	-4.40	0.75	-5.90	3.58E-09
()	(Intercept)	1.90	0.26	7.30	2.99E-13
stic	CHT_s	17.00	2.48	6.86	6.80E-12
logistic	BAT_s	4.39	1.37	3.21	0.001
_	CHT_s:BAT_s	-690.83	89.05	-7.76	8.66E-15

**Table 6.2.3.9.** Harbour porpoise ZIGLM model outputs. Slope estimate, standard error, z-value, and p-value for each parameter within both nested models (conditional and logistic). Parameter details are the full names of each parameter, corresponding to the parameter code.

Model	Parameter	Slope	Standard	7 \/aluo	<i>p</i> -Value
wiodei	Code	Estimate	Error	z-Value  -31.50 -7.00 6.60 21.20 -40.80 26.40  -17.17 4.92 4.76 7.79 19.76 -4.58	<i>p</i> -value
	(Intercept)	-1.19	0.04	-31.50	4.23E-218
la	TPM_s	-0.50	0.07	-7.00	2.64E-12
tior	TPF_s	0.95	0.14	6.60	4.01E-11
conditional	FEA_s	6.43	0.30	21.20	6.35E-100
8	BAT_s	-55.37	1.36	-40.80	0
	CHT_s	3.16	0.12	26.40	5.29E-154
	(Intercept)	-10.60	0.62	-17.17	4.56E-66
	TPM_s	7.11	1.45	4.92	8.85E-07
Logistic	BAT_s	414.17	87.01	4.76	1.93E-06
Logi	CHT_s	7.42	0.95	7.79	6.60E-15
_	SPM_s	13.46	0.68	19.76	6.22E-87
	TPM_s:BAT_s	-1204.43	262.92	-4.58	4.63E-06

**Table 6.2.3.10.** Herring gull ZIGLM model outputs. Slope estimate, standard error, z-value, and p-value for each parameter within both nested models (conditional and logistic). Parameter details are the full names of each parameter, corresponding to the parameter code.

Model	Parameter Code	Slope Estimate	Standard Error	z-Value	<i>p</i> -Value
	(Intercept)	2.81	0.01	306.47	0
a	TPM_s	-1.02	0.02	-52.38	0
conditional	TPF_s	0.11	0.06	1.74	0.08
ndi	FEA_s	-2.03	0.13	-15.36	3.25E-53
8	BAT_s	-10.28	0.23	-44.79	0
	CHT_s	-0.33	0.02	-16.23	3.19E-59
	(Intercept)	0.05	0.04	1.42	0.155
stic	CHT_s	0.19	0.06	3.03	0.00242
logistic	TPM_s	3.37	0.07	49.31	0
_	SPM_s	-0.46	0.06	-7.58	3.56E-14

**Table 6.2.3.11.** Lesser black-backed gull ZIGLM model outputs. Slope estimate, standard error, z-value, and p-value for each parameter within both nested models (conditional and logistic). Parameter details are the full names of each parameter, corresponding to the parameter code.

Model	Parameter Code	Slope Estimate	Standard Error	z-Value	<i>p</i> -Value
	(Intercept)	-1.02	0.0377	-27.04	4.97E-161
lal	TPM_s	1.171	0.0642	18.24	2.33E-74
tior	TPF_s	-0.891	0.1544	-5.77	8.07E-09
conditional	FEA_s	-0.154	0.1376	-1.12	0.263
8	BAT_s	-2.78	0.1248	-22.28	5.84E-110
	CHT_s	3.471	0.0753	46.09	0
	(Intercept)	-3.85	0.386	-9.96	2.23E-23
istic	CHT_s	10.01	0.53	18.88	1.71E-79
logistic	TPM_s	-3.57	0.558	-6.39	1.68E-10
	SPM_s	-3.46	0.943	-3.67	0.000243

**Table 6.2.3.12.** Manx shearwater ZIGLM model outputs. Slope estimate, standard error, z-value, and p-value for each parameter within both nested models (conditional and logistic). Parameter details are the full names of each parameter, corresponding to the parameter code.

Model	Parameter Code	Slope Estimate	Standard Error	z-Value	<i>p</i> -Value
	(Intercept)	0.91	0.02	49.80	0
lal	TPM_s	3.19	0.03	113.10	0
conditional	TPF_s	2.48	0.02	108.60	0
ndi	FEA_s	1.10	0.07	15.00	1.52E-50
3	BAT_s	-5.93	0.07	-85.50	0
-	CHT_s	0.88	0.02	40.00	0
Ë	(Intercept)	3.48	0.03	115.46	0
logistic	CHT_s	-3.77	0.08	-49.52	0
	SPM_s	-0.68	0.08	-8.19	2.65E-16

**Table 6.2.3.13.** Minke whale ZIGLM model outputs. Slope estimate, standard error, z-value, and p-value for each parameter within both nested models (conditional and logistic). Parameter details are the full names of each parameter, corresponding to the parameter code.

Model	Parameter Code	Slope Estimate	Standard Error	z-Value	<i>p</i> -Value
	(Intercept)	-2.70	0.13	-21.14	3.58E-99
<u>Ja</u>	TPM_s	-1.45	0.21	-6.88	5.86E-12
conditional	TPF_s	1.19	0.42	2.85	0.004
ndi	FEA_s	3.26	0.35	9.38	6.70E-21
8	BAT_s	-6.45	0.60	-10.71	9.35E-27
	CHT_s	-0.80	0.30	-2.66	0.008
ic	(Intercept)	0.76	0.17	4.57	4.84E-06
logistic	TPF_s	-95.03	8.18	-11.62	3.32E-31
<u>o</u>	SPM_s	6.76	0.62	10.89	1.24E-27

**Table 6.2.3.14.** Northern gannet ZIGLM model outputs. Slope estimate, standard error, z-value, and p-value for each parameter within both nested models (conditional and logistic). Parameter details are the full names of each parameter, corresponding to the parameter code.

Model	Parameter Code	Slope Estimate	Standard Error	z-Value	<i>p</i> -Value
	(Intercept)	4.17	0.005	880.6	0
lal	TPM_s	-2.43	0.010	-240.4	0
conditional	TPF_s	1.81	0.020	91.5	0
ndi	FEA_s	1.69	0.021	79.6	0
8	BAT_s	-0.64	0.014	-46.4	0
	CHT_s	-0.53	0.008	-69	0
.i.	(Intercept)	0.25	0.010	25.61	1.21E-144
logistic	CHT_s	0.27	0.043	6.33	2.53E-10
	FEA_s	3.47	0.109	31.9	2.86E-223

**Table 6.2.3.15.** Northern gannet ZIGLM model outputs. Slope estimate, standard error, z-value, and p-value for each parameter within both nested models (conditional and logistic). Parameter details are the full names of each parameter, corresponding to the parameter code.

Model	Parameter	Slope	Standard	7 \/aluo	<i>p</i> -Value
wiodei	Code	Estimate	Error	z-Value 46.12 -8.96 24.33 -2.30 -30.90 13.92 40.18 -41.77 -3.67	p-value
	(Intercept)	1.40	0.03	46.12	0
lal	TPM_s	-0.46	0.05	-8.96	3.30E-19
tior	TPF_s	1.90	0.08	24.33	9.41E-131
conditional	FEA_s	-0.17	0.07	-2.30	0.0214
8	BAT_s	-1.59	0.05	-30.90	1.06E-209
	CHT_s	0.47	0.03	13.92	4.81E-44
ij	(Intercept)	5.57	0.14	40.18	0
logistic	TPM_s	-18.09	0.43	-41.77	0
	TPF_s	-7.42	2.02	-3.67	0.0002

**Table 6.2.3.16.** Orca ZIGLM model outputs. Slope estimate, standard error, z-value, and p-value for each parameter within both nested models (conditional and logistic). Parameter details are the full names of each parameter, corresponding to the parameter code.

Model	Parameter Code	Slope Estimate	Standard Error	z-Value	<i>p</i> -Value
	(Intercept)	2.47	0.28	8.91	5.19E-19
<u>la</u>	TPM_s	-2.73	0.60	-4.57	4.83E-06
tior	TPF_s	3.02	0.78	3.86	0.0001
conditional	FEA_s	0.51	1.07	0.48	0.634
8	BAT_s	0.40	0.40	1.01	0.312
	CHT_s	-0.67	0.61	-1.09	0.278
	(Intercept)	5.33	0.53	10.13	4.04E-24
	TPR_s	-4.69	1.90	-2.48	0.01
. <u>:</u> :	TPS_s	1.92	1.06	1.80	0.07
logistic	CON_s	5.43	0.78	6.93	4.09E-12
<u>o</u>	BAT_s	0.84	0.88	0.96	0.34
	TPR_s:TPS_s	5.70	3.25	1.75	0.08
	CON_s:BAT_s	-5.04	7.82	-0.64	0.519

**Table 6.2.3.17.** Pilot whale ZIGLM model outputs. Slope estimate, standard error, z-value, and p-value for each parameter within both nested models (conditional and logistic). Parameter details are the full names of each parameter, corresponding to the parameter code.

Model	Parameter code	Slope Estimate	Standard Error	z-Value	<i>p</i> -Value
	(Intercept)	3.13	0.38	8.35	6.84E-17
nal	TPM	-3.27	0.76	-4.29	1.78E-05
Conditional	TPF	-9.31	1.76	-5.29	1.20E-07
nd.	CHL	-0.15	0.56	-0.28	0.78
S	FEA	1.33	0.36	3.75	0.0002
-	BAT	1.52	0.26	5.91	3.53E-09
	(Intercept)	4.36	0.33	13.33	1.56E-40
tic	CON	22.55	3.51	6.43	1.32E-10
Logistic	TPM	-1.85	0.66	-2.79	0.005
2	FEA	-1.53	0.31	-4.98	6.24E-07
	CON: TPM	-16.77	6.27	-2.67	0.0075

**Table 6.2.3.18.** Razorbill ZIGLM model outputs. Slope estimate, standard error, z-value, and p-value for each parameter within both nested models (conditional and logistic). Parameter details are the full names of each parameter, corresponding to the parameter code.

Model	Parameter Code	Slope Estimate	Standard Error	<i>z</i> -Value	<i>p</i> -Value
	(Intercept)	0.61	0.05	12.32	6.76E-35
اع	TPM_s	0.15	0.11	1.31	0.19
conditional	TPF_s	5.01	0.25	20.20	1.05E-90
ndi	FEA_s	4.33	0.35	12.19	3.66E-34
8	BAT_s	-30.36	0.96	-31.58	6.77E-219
	CHT_s	-1.28	0.07	-18.85	2.93E-79
	(Intercept)	-10.78	0.34	-32.11	3.46E-226
<u>::</u>	LND_s	16.28	0.57	28.49	1.53E-178
logistic	TPF_s	3.47	0.47	7.37	1.67E-13
<u>o</u>	TPM_s	15.19	0.47	32.46	3.51E-231
	TPR_s	3.07	0.20	15.05	3.56E-51

**Table 6.2.3.19.** Risso's dolphin ZIGLM model outputs. Slope estimate, standard error, z-value, and p-value for each parameter within both nested models (conditional and logistic). Parameter details are the full names of each parameter, corresponding to the parameter code.

Model	Parameter Code	Slope Estimate	Standard Error	<i>z</i> -Value	<i>p</i> -Value
	(Intercept)	1.94	0.18	10.90	1.21E-27
lal	TPM_s	-0.86	0.34	-2.57	0.0101
conditional	TPF_s	2.22	0.41	5.41	6.37E-08
ipu	FEA_s	0.90	0.23	3.93	8.47E-05
8	BAT_s	0.00	0.17	0.00	0.998
	CHT_s	-2.33	0.46	-5.08	3.76E-07
	(Intercept)	6.36	0.30	21.53	7.4E-103
. <u>::</u>	BAT_s	7.95	2.35	3.38	0.000715
logistic	TPM_s	-2.34	0.51	-4.56	5.11E-06
<u>0</u>	CON_s	3.92	0.33	11.93	8.13E-33
	BAT_s:TPM_s	-10.05	3.51	-2.87	0.00414

**Table 6.2.3.20.** Sperm whale ZIGLM model outputs. Slope estimate, standard error, z-value, and p-value for each parameter within both nested models (conditional and logistic). Parameter details are the full names of each parameter, corresponding to the parameter code.

Model	Parameter Code	Slope Estimate	Standard Error	z-Value	<i>p</i> -Value
	(Intercept)	-3.93	0.43	-9.23	2.65E-20
la	TPM_s	-0.91	0.94	-0.97	0.33
tior	TPF_s	-2.26	2.99	-0.76	0.45
Conditional	FEA_s	0.89	0.66	1.37	0.17
ပိ	BAT_s	0.75	0.48	1.55	0.12
	CHT_s	0.64	0.89	0.72	0.47
	(Intercept)	4.28	0.96	4.46	8.06E-06
<u>.2</u>	BAT_s	-50.72	9.41	-5.39	7.06E-08
logistic	FEA_s	-6.45	3.54	-1.82	0.07
<u>0</u>	CON_s	28.05	14.53	1.93	0.05
	BAT_s:FEA_s	80.08	18.75	4.27	1.94E-05

**Table 6.2.3.21.** Striped dolphin ZIGLM model outputs. Slope estimate, standard error, z-value, and p-value for each parameter within both nested models (conditional and logistic). Parameter details are the full names of each parameter, corresponding to the parameter code.

Model	Parameter Code	Slope Estimate	Standard Error	z-Value	<i>p</i> -Value
	(Intercept)	2.28	0.132	17.25	1.10E-66
la	TPM_s	0.43	0.193	2.21	0.0272
conditional	TPF_s	-2.01	0.609	-3.3	0.000966
ndi	FEA_s	0.39	0.070	5.55	2.81E-08
8	BAT_s	0.40	0.062	6.38	1.82E-10
	CHT_s	0.75	0.176	4.27	1.99E-05
	(Intercept)	13.07	0.540	24.2	2.15E-129
logistic	BAT_s	-11.23	1.064	-10.56	4.71E-26
lgo	TPM_s	-9.77	0.806	-12.13	7.52E-34
	BAT_s:TPM_s	10.02	1.581	6.34	2.34E-10

**Table 6.2.3.22.** White-beaked dolphin ZIGLM model outputs. Slope estimate, standard error, z-value, and p-value for each parameter within both nested models (conditional and logistic). Parameter details are the full names of each parameter, corresponding to the parameter code.

Model	Parameter Code	Slope Estimate	Standard Error	z-Value	<i>p</i> -Value
	(Intercept)	1.55	0.09	16.90	4.26E-64
la	TPM_s	-0.16	0.19	-0.82	0.41
conditional	TPF_s	0.03	0.27	0.11	0.91
ndi	FEA_s	-1.91	0.91	-2.09	0.04
8	BAT_s	2.49	0.49	5.08	3.83E-07
	CHT_s	1.03	0.22	4.68	2.81E-06
	(Intercept)	3.93	0.10	38.22	0
stic	BAT_s	8.18	3.79	2.16	0.0307
logistic	TPM_s	1.48	0.21	7.15	8.45E-13
	BAT_s:TPM_s	-0.47	7.52	-0.06	0.95

**Table 6.2.3.23.** White-sided dolphin ZIGLM model outputs. Slope estimate, standard error, z-value, and p-value for each parameter within both nested models (conditional and logistic). Parameter details are the full names of each parameter, corresponding to the parameter code.

Model	Parameters	Slope	Standard	z-Value	<i>p</i> -Value
		Estimate	Error		
conditional	(Intercept)	7.52	0.85	8.85	8.51E-19
	TPM_s	-18.77	1.48	-12.73	3.99E-37
	TPF_s	1.36	1.01	1.34	0.18
	CHT_s	-0.05	0.61	-0.09	0.93
	FEA_s	-0.59	0.75	-0.78	0.43
	BAT_s	1.18	0.32	3.69	2.26E-04
logistic	(Intercept)	12.19	1.00	12.19	3.76E-34
	SPM_s	9.54	6.08	1.57	0.12
	TPM_s	-28.10	2.39	-11.74	8.47E-32
	SPM_s: TPM_s	8.58	13.89	0.62	0.54

#### **Atlantic Puffin**

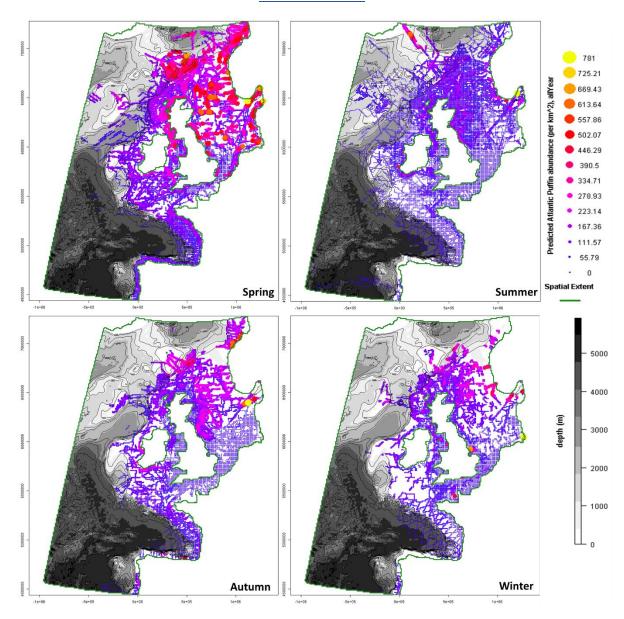


Figure 6.2.8.1. Maps of predicted abundance of Atlantic puffin, overlaying bathymetry. Maximum predicted abundance (per 10 km²) subset by season, from the same model, expressed as the expected value (mean of the conditional distribution multiplied by 1 minus the zero-inflation probability) scaled to the maximum observed abundance value in the Atlantic puffin dataset; represented by colour and size (blue-red-yellow scalebar). Each season covers 3 months, with spring starting in March. Water depth (m) represented by greyscale contours. Green line represents coastline or spatial extent.

### **Black-legged Kittiwake**

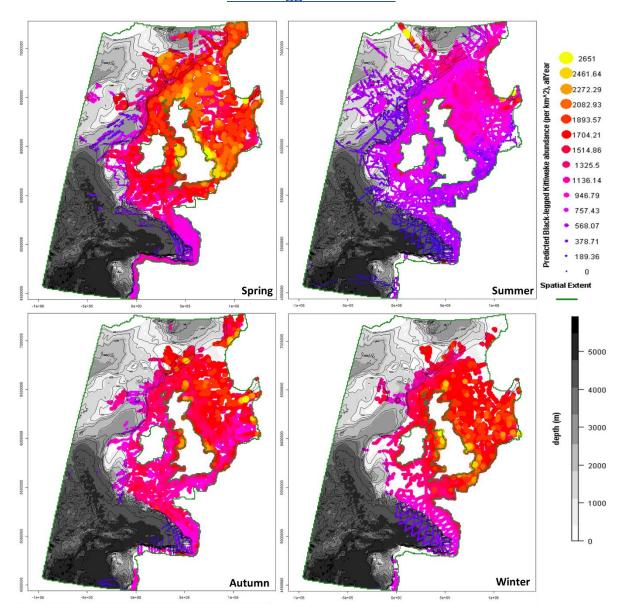


Figure 6.2.8.2. Maps of predicted abundance of black-legged kittiwakes, overlaying bathymetry. Maximum predicted abundance (per 10 km²) subset by season, from the same model, expressed as the expected value (mean of the conditional distribution multiplied by 1 minus the zero-inflation probability) scaled to the maximum observed abundance value in the black-legged kittiwake dataset; represented by colour and size (blue-red-yellow scalebar). Each season covers 3 months, with spring starting in March. Water depth (m) represented by greyscale contours. Green line represents coastline or spatial extent.

## **Bottlenose Dolphin**

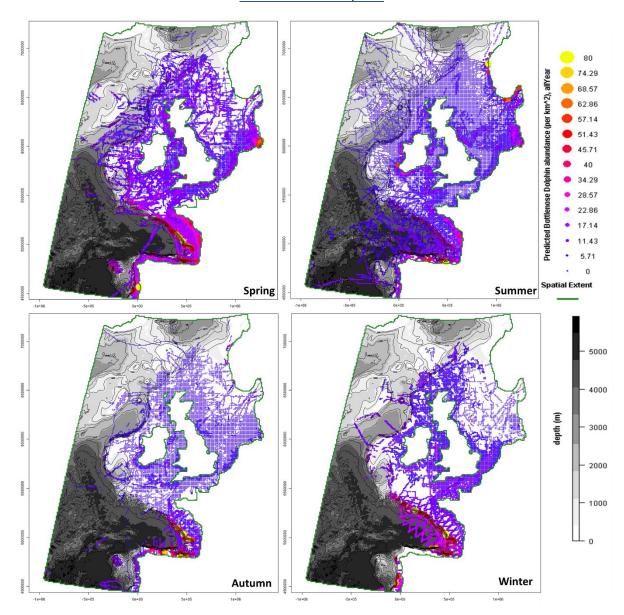


Figure 6.2.8.3. Maps of predicted abundance of bottlenose dolphins, overlaying bathymetry. Maximum predicted abundance (per 10 km²) subset by season, from the same model, expressed as the expected value (mean of the conditional distribution multiplied by 1 minus the zero-inflation probability) scaled to the maximum observed abundance value in the bottlenose dolphin dataset; represented by colour and size (blue-red-yellow scalebar). Each season covers 3 months, with spring starting in March. Water depth (m) represented by greyscale contours. Green line represents coastline or spatial extent.

#### **Common Guillemot**

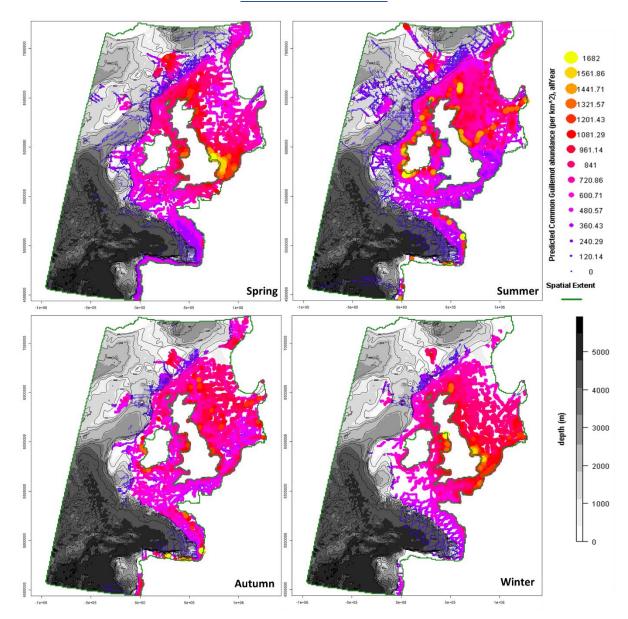


Figure 6.2.8.4. Maps of predicted abundance of common guillemots, overlaying bathymetry. Maximum predicted abundance (per 10 km²) subset by season, from the same model, expressed as the expected value (mean of the conditional distribution multiplied by 1 minus the zero-inflation probability) scaled to the maximum observed abundance value in the common guillemot dataset; represented by colour and size (blue-red-yellow scalebar). Each season covers 3 months, with spring starting in March. Water depth (m) represented by greyscale contours. Green line represents coastline or spatial extent.

#### **Common Dolphin**

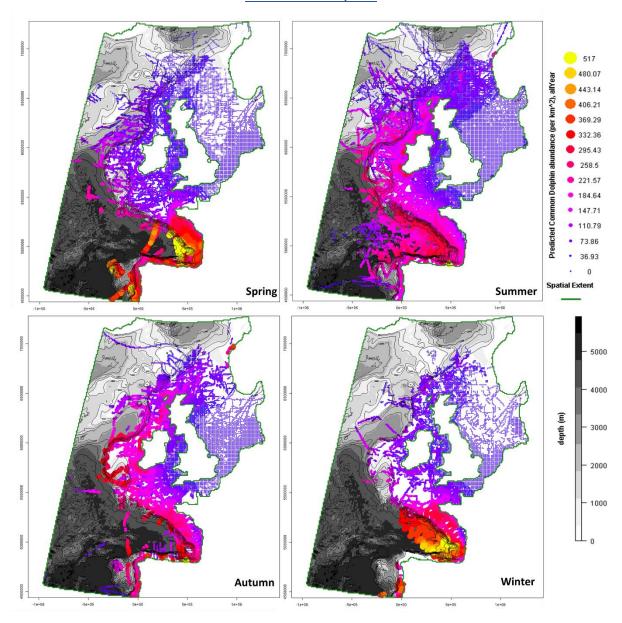


Figure 6.2.8.5. Maps of predicted abundance of common dolphins, overlaying bathymetry. Maximum predicted abundance (per 10 km²) subset by season, from the same model, expressed as the expected value (mean of the conditional distribution multiplied by 1 minus the zero-inflation probability) scaled to the maximum observed abundance value in the common dolphin dataset; represented by colour and size (blue-red-yellow scalebar). Each season covers 3 months, with spring starting in March. Water depth (m) represented by greyscale contours. Green line represents coastline or spatial extent.

### **European Shag**

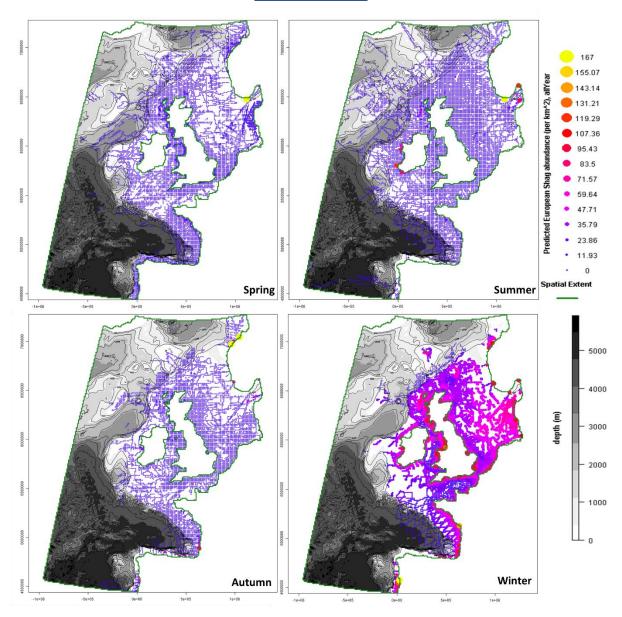


Figure 6.2.8.6. Maps of predicted abundance of European shags, overlaying bathymetry. Maximum predicted abundance (per 10 km²) subset by season, from the same model, expressed as the expected value (mean of the conditional distribution multiplied by 1 minus the zero-inflation probability) scaled to the maximum observed abundance value in the European shag dataset; represented by colour and size (blue-red-yellow scalebar). Each season covers 3 months, with spring starting in March. Water depth (m) represented by greyscale contours. Green line represents coastline or spatial extent.

#### **European Storm Petrel**

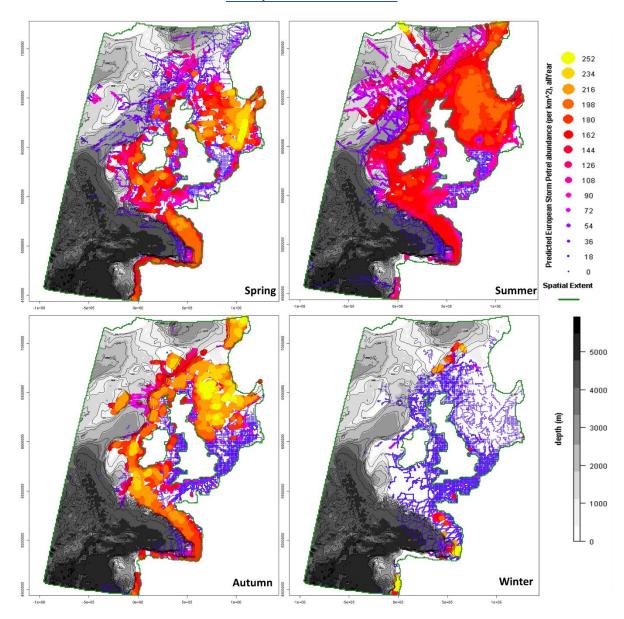


Figure 6.2.8.7. Maps of predicted abundance of European storm petrel, overlaying bathymetry. Maximum predicted abundance (per 10 km²) subset by season, from the same model, expressed as the expected value (mean of the conditional distribution multiplied by 1 minus the zero-inflation probability) scaled to the maximum observed abundance value in the European storm petrel dataset; represented by colour and size (blue-red-yellow scalebar). Each season covers 3 months, with spring starting in March. Water depth (m) represented by greyscale contours. Green line represents coastline or spatial extent.

# Fin Whale

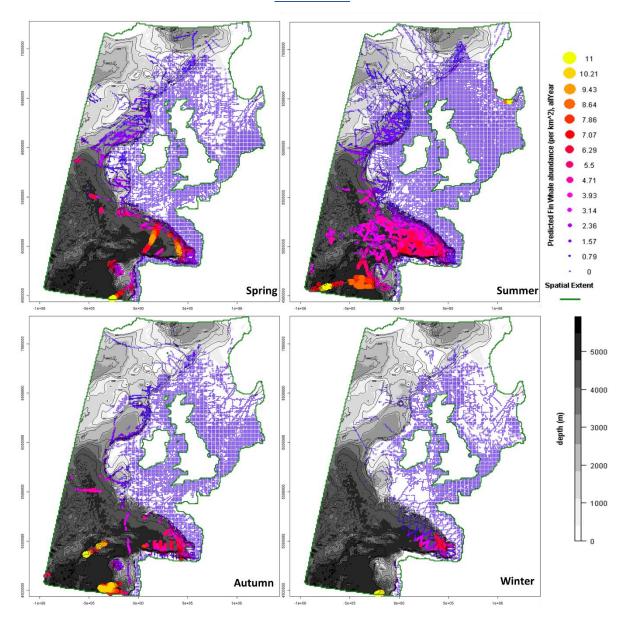


Figure 6.2.8.8. Maps of predicted abundance of fin whales, overlaying bathymetry. Maximum predicted abundance (per 10 km²) subset by season, from the same model, expressed as the expected value (mean of the conditional distribution multiplied by 1 minus the zero-inflation probability) scaled to the maximum observed abundance value in the fin whale dataset; represented by colour and size (blue-red-yellow scalebar). Each season covers 3 months, with spring starting in March. Water depth (m) represented by greyscale contours. Green line represents coastline or spatial extent.

### **Harbour Porpoise**

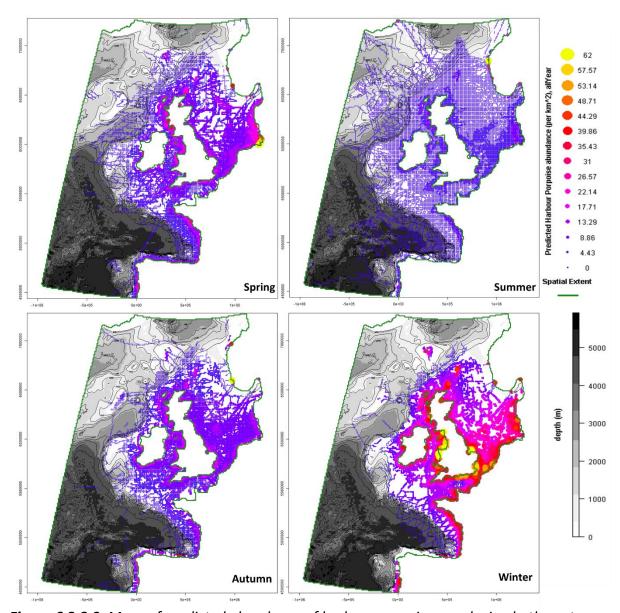


Figure 6.2.8.9. Maps of predicted abundance of harbour porpoise, overlaying bathymetry. Maximum predicted abundance (per 10 km²) subset by season, from the same model, expressed as the expected value (mean of the conditional distribution multiplied by 1 minus the zero-inflation probability) scaled to the maximum observed abundance value in the harbour porpoise dataset; represented by colour and size (blue-red-yellow scalebar). Each season covers 3 months, with spring starting in March. Water depth (m) represented by greyscale contours. Green line represents coastline or spatial extent.

### **Herring Gull**

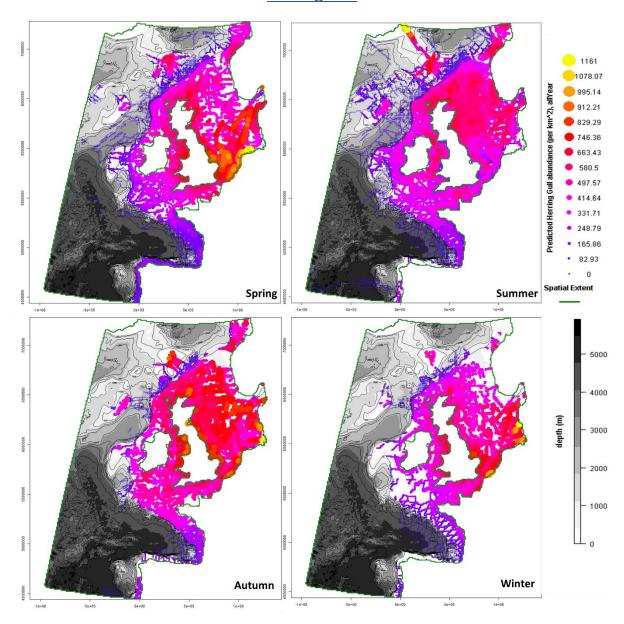


Figure 6.2.8.10. Maps of predicted abundance of herring gulls, overlaying bathymetry. Maximum predicted abundance (per 10 km²) subset by season, from the same model, expressed as the expected value (mean of the conditional distribution multiplied by 1 minus the zero-inflation probability) scaled to the maximum observed abundance value in the herring gull dataset; represented by colour and size (blue-red-yellow scalebar). Each season covers 3 months, with spring starting in March. Water depth (m) represented by greyscale contours. Green line represents coastline or spatial extent.

### Lesser Black Backed Gull

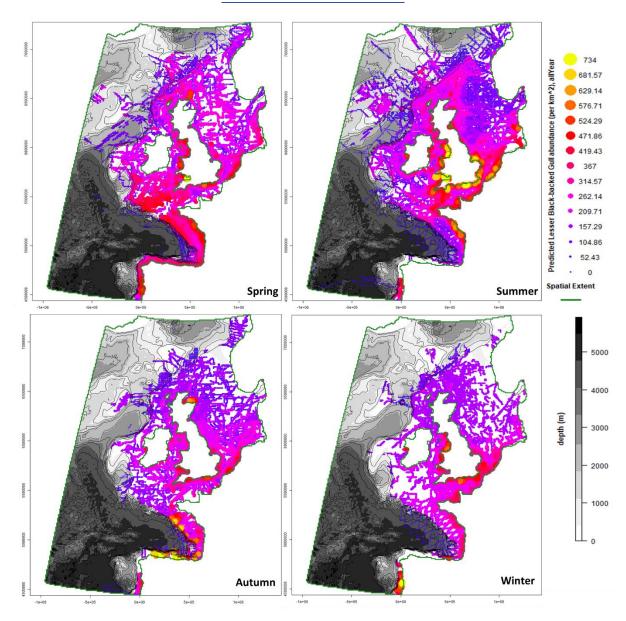


Figure 6.2.8.11. Maps of predicted abundance of lesser black-backed gulls, overlaying bathymetry. Maximum predicted abundance (per 10 km²) subset by season, from the same model, expressed as the expected value (mean of the conditional distribution multiplied by 1 minus the zero-inflation probability) scaled to the maximum observed abundance value in the lesser black-backed gull dataset; represented by colour and size (blue-red-yellow scalebar). Each season covers 3 months, with spring starting in March. Water depth (m) represented by greyscale contours. Green line represents coastline or spatial extent.

#### Manx Shearwater

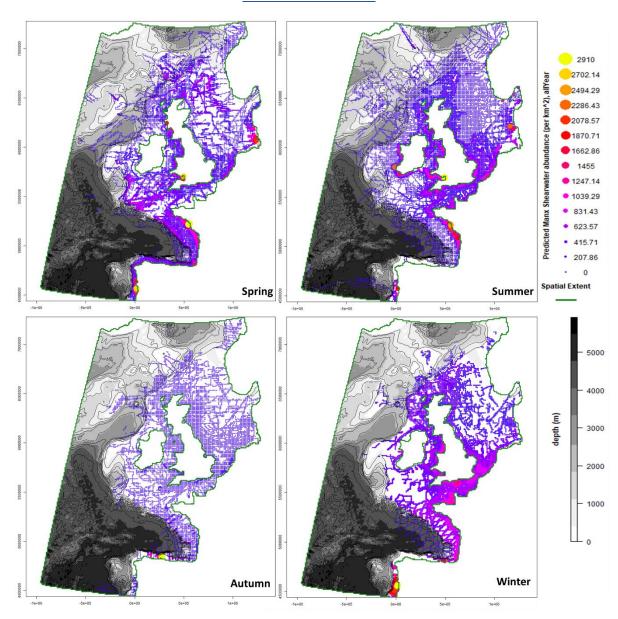


Figure 6.2.8.12. Maps of predicted abundance of Manx shearwaters, overlaying bathymetry. Maximum predicted abundance (per 10 km²) subset by season, from the same model, expressed as the expected value (mean of the conditional distribution multiplied by 1 minus the zero-inflation probability) scaled to the maximum observed abundance value in the Manx shearwater dataset; represented by colour and size (blue-red-yellow scalebar). Each season covers 3 months, with spring starting in March. Water depth (m) represented by greyscale contours. Green line represents coastline or spatial extent.

# Minke Whale

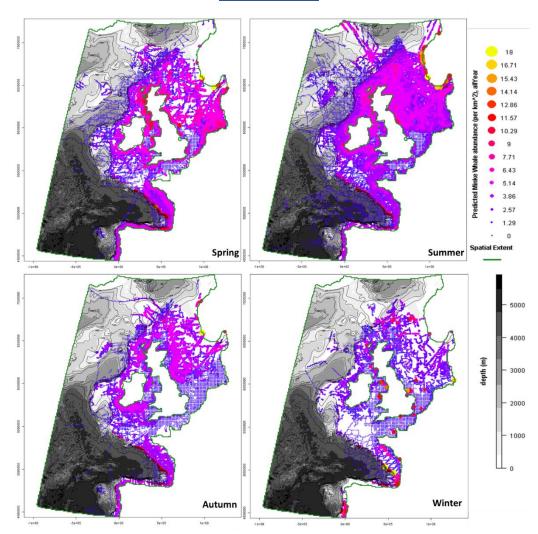


Figure 6.2.8.13. Maps of predicted abundance of minke whales, overlaying bathymetry. Maximum predicted abundance (per 10 km²) subset by season, from the same model, expressed as the expected value (mean of the conditional distribution multiplied by 1 minus the zero-inflation probability) scaled to the maximum observed abundance value in the minke whale dataset; represented by colour and size (blue-red-yellow scalebar). Each season covers 3 months, with spring starting in March. Water depth (m) represented by greyscale contours. Green line represents coastline or spatial extent.

### Northern Fulmar

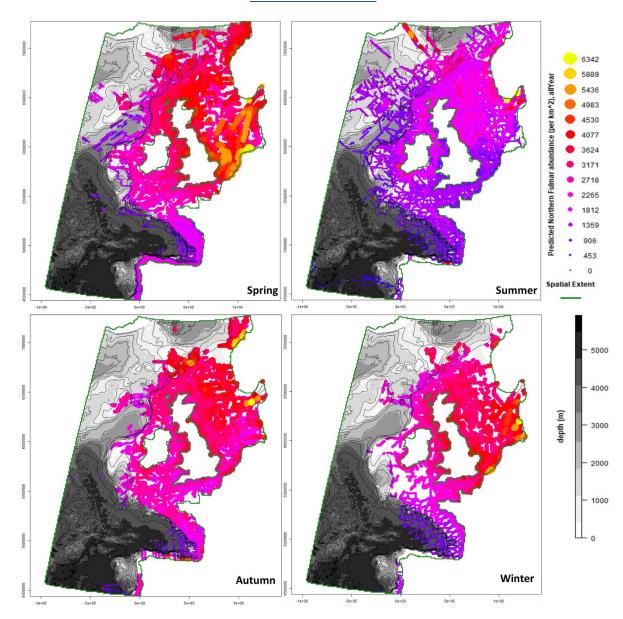


Figure 6.2.8.14. Maps of predicted abundance of northern fulmars, overlaying bathymetry. Maximum predicted abundance (per 10 km²) subset by season, from the same model, expressed as the expected value (mean of the conditional distribution multiplied by 1 minus the zero-inflation probability) scaled to the maximum observed abundance value in the northern fulmar dataset; represented by colour and size (blue-red-yellow scalebar). Each season covers 3 months, with spring starting in March. Water depth (m) represented by greyscale contours. Green line represents coastline or spatial extent.

### **Northern Gannet**

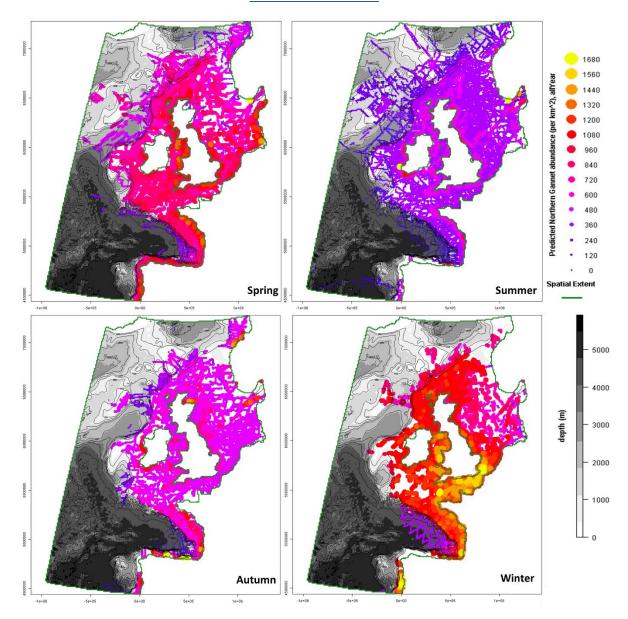
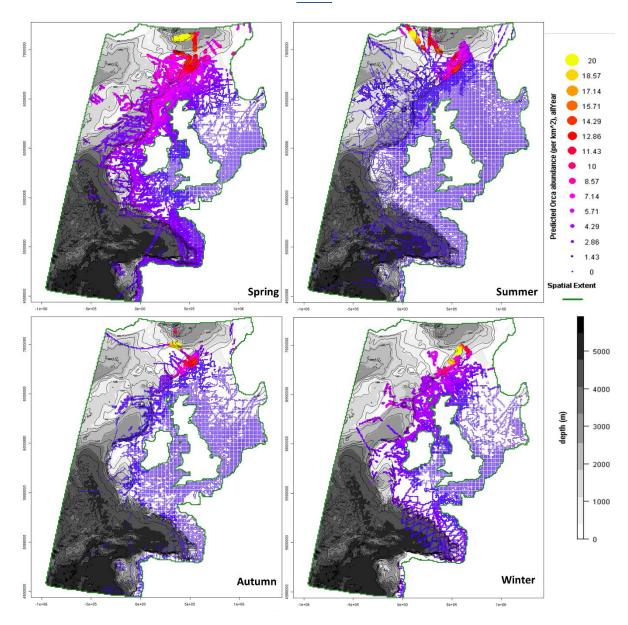


Figure 6.2.8.15. Maps of predicted abundance of northern gannets, overlaying bathymetry. Maximum predicted abundance (per 10 km²) subset by season, from the same model, expressed as the expected value (mean of the conditional distribution multiplied by 1 minus the zero-inflation probability) scaled to the maximum observed abundance value in the northern gannet dataset; represented by colour and size (blue-red-yellow scalebar). Each season covers 3 months, with spring starting in March. Water depth (m) represented by greyscale contours. Green line represents coastline or spatial extent.

### Orca



**Figure 6.2.8.16.** Maps of predicted abundance of orcas, overlaying bathymetry. Maximum predicted abundance (per 10 km²) subset by season, from the same model, expressed as the expected value (mean of the conditional distribution multiplied by 1 minus the zero-inflation probability) scaled to the maximum observed abundance value in the orca dataset; represented by colour and size (blue-red-yellow scalebar). Each season covers 3 months, with spring starting in March. Water depth (m) represented by greyscale contours. Green line represents coastline or spatial extent.

### **Pilot Whale**

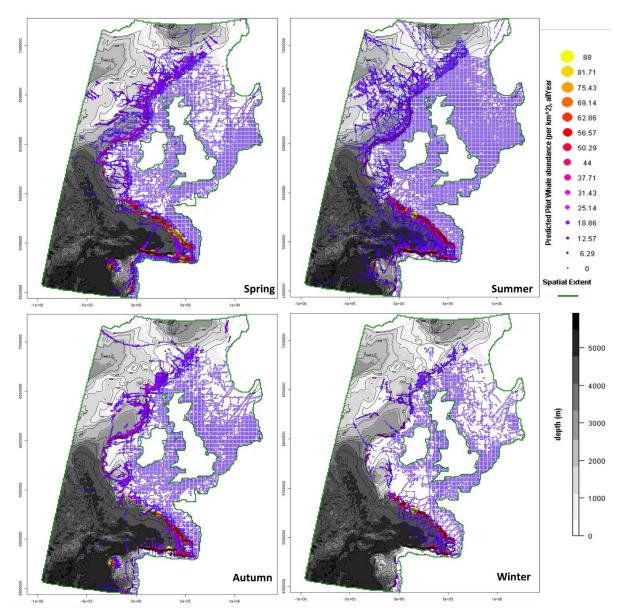


Figure 6.2.8.17. Maps of predicted abundance of pilot whales, overlaying bathymetry. Maximum predicted abundance (per 10 km²) subset by season, from the same model, expressed as the expected value (mean of the conditional distribution multiplied by 1 minus the zero-inflation probability) scaled to the maximum observed abundance value in the pilot whale dataset; represented by colour and size (blue-red-yellow scalebar). Each season covers 3 months, with spring starting in March. Water depth (m) represented by greyscale contours. Green line represents coastline or spatial extent.

### Razorbill

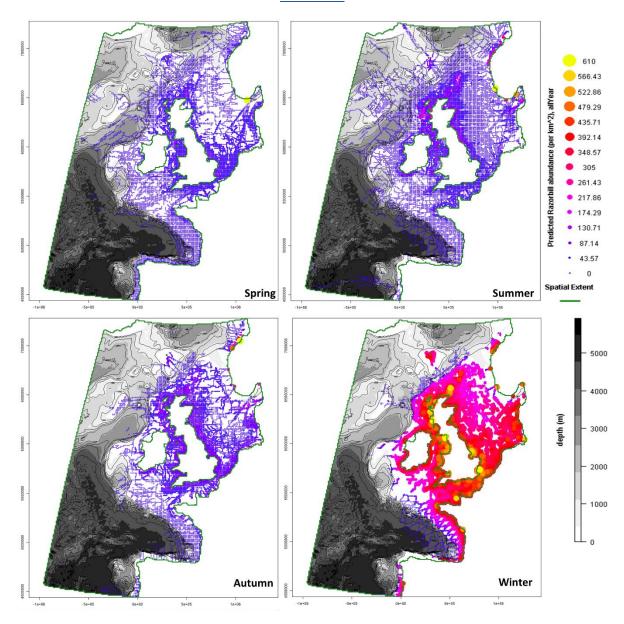


Figure 6.2.8.18. Maps of predicted abundance of razorbills, overlaying bathymetry. Maximum predicted abundance (per 10 km²) subset by season, from the same model, expressed as the expected value (mean of the conditional distribution multiplied by 1 minus the zero-inflation probability) scaled to the maximum observed abundance value in the razorbill dataset; represented by colour and size (blue-red-yellow scalebar). Each season covers 3 months, with spring starting in March. Water depth (m) represented by greyscale contours. Green line represents coastline or spatial extent.

# Risso's Dolphin

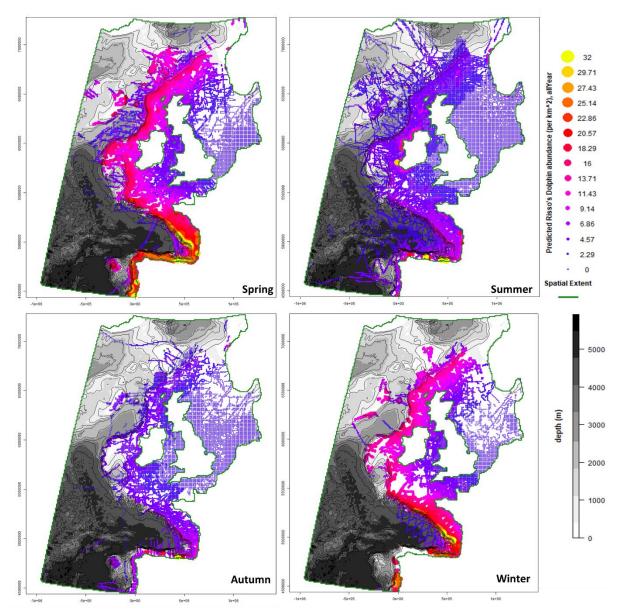


Figure 6.2.8.19. Maps of predicted abundance of Risso's dolphins, overlaying bathymetry. Maximum predicted abundance (per 10 km²) subset by season, from the same model, expressed as the expected value (mean of the conditional distribution multiplied by 1 minus the zero-inflation probability) scaled to the maximum observed abundance value in the Risso's dolphin dataset; represented by colour and size (blue-red-yellow scalebar). Each season covers 3 months, with spring starting in March. Water depth (m) represented by greyscale contours. Green line represents coastline or spatial extent.

### **Sperm Whale**

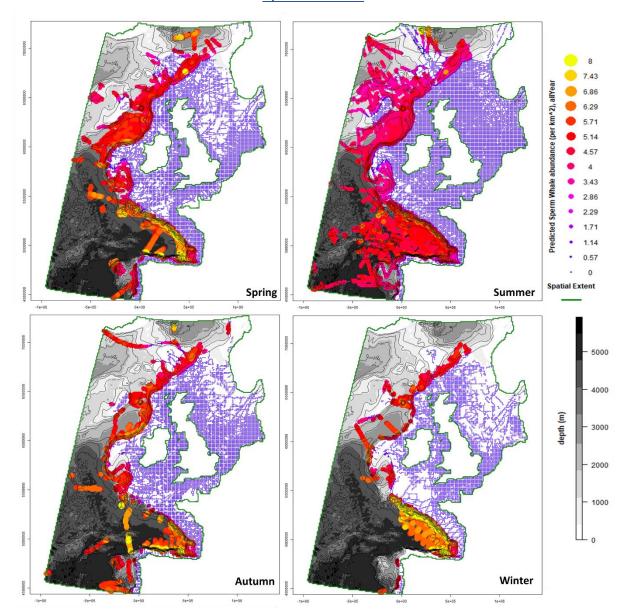


Figure 6.2.8.20. Maps of predicted abundance of sperm whales, overlaying bathymetry. Maximum predicted abundance (per 10 km²) subset by season, from the same model, expressed as the expected value (mean of the conditional distribution multiplied by 1 minus the zero-inflation probability) scaled to the maximum observed abundance value in the sperm whale dataset; represented by colour and size (blue-red-yellow scalebar). Each season covers 3 months, with spring starting in March. Water depth (m) represented by greyscale contours. Green line represents coastline or spatial extent.

# **Striped Dolphin**

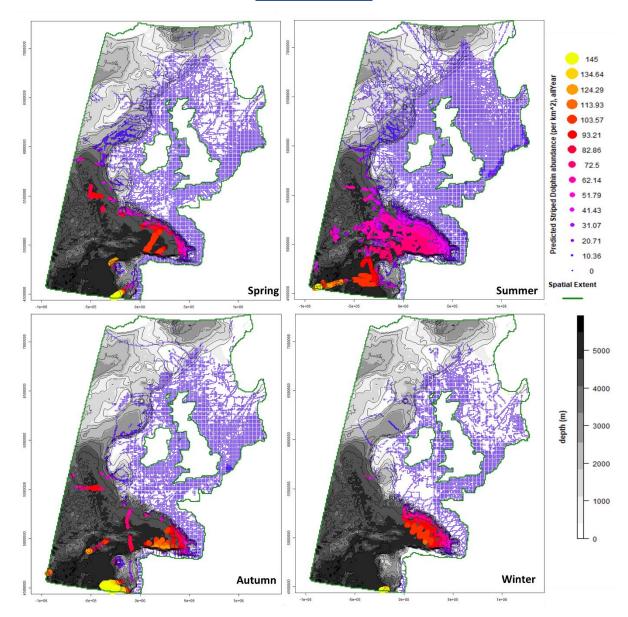


Figure 6.2.8.21. Maps of predicted abundance of striped dolphins, overlaying bathymetry. Maximum predicted abundance (per 10 km²) subset by season, from the same model, expressed as the expected value (mean of the conditional distribution multiplied by 1 minus the zero-inflation probability) scaled to the maximum observed abundance value in the striped dolphin dataset; represented by colour and size (blue-red-yellow scalebar). Each season covers 3 months, with spring starting in March. Water depth (m) represented by greyscale contours. Green line represents coastline or spatial extent.

### White-beaked Dolphin

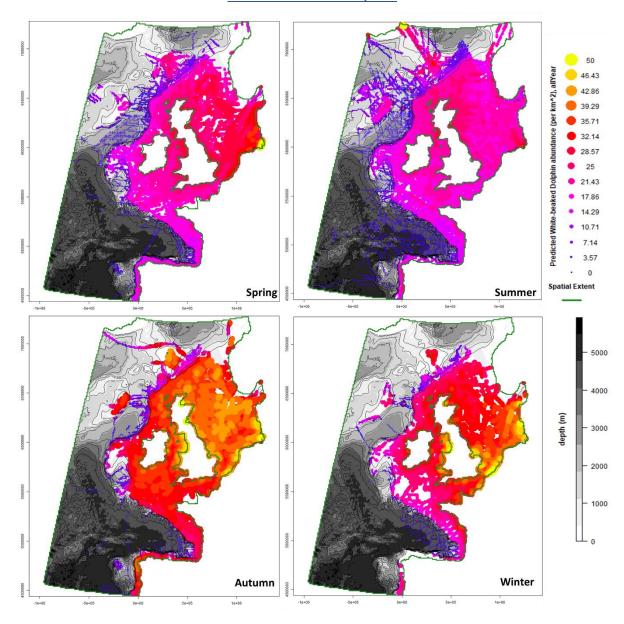


Figure 6.2.8.22. Maps of predicted abundance of white-beaked dolphins, overlaying bathymetry. Maximum predicted abundance (per 10 km²) subset by season, from the same model, expressed as the expected value (mean of the conditional distribution multiplied by 1 minus the zero-inflation probability) scaled to the maximum observed abundance value in the white-beaked dolphin dataset; represented by colour and size (blue-red-yellow scalebar). Each season covers 3 months, with spring starting in March. Water depth (m) represented by greyscale contours. Green line represents coastline or spatial extent.

### White-sided Dolphin

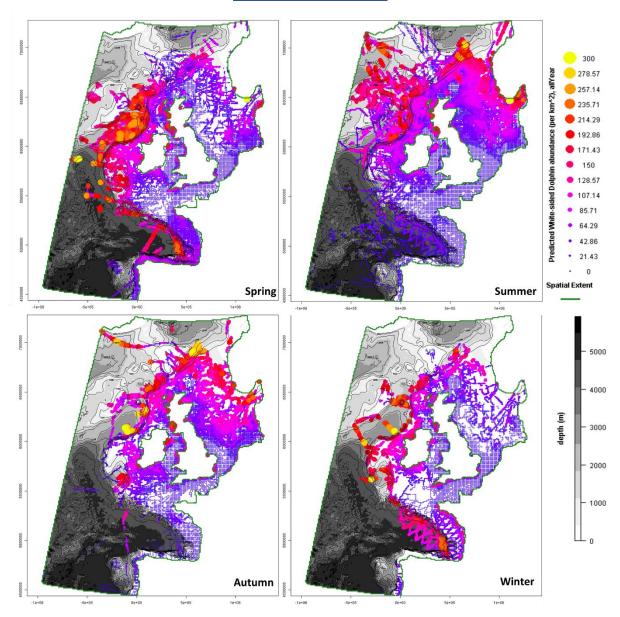


Figure 6.2.8.23. Maps of predicted abundance of white-sided dolphins, overlaying bathymetry. Maximum predicted abundance (per 10 km²) subset by season, from the same model, expressed as the expected value (mean of the conditional distribution multiplied by 1 minus the zero-inflation probability) scaled to the maximum observed abundance value in the white-sided dolphin dataset; represented by colour and size (blue-red-yellow scalebar). Each season covers 3 months, with spring starting in March. Water depth (m) represented by greyscale contours. Green line represents coastline or spatial extent.

### 2.3 Additional results

**Table 6.2.4**. Table of  $75^{th}$  and  $25^{th}$  percentile of absolute values of percentage change in species abundance with a 20% increase in the value of each predictor.

Parameter			7	75 <sup>th</sup>	perc	enti	le (%	6/20	%)	25	5 <sup>th</sup> p	erce	ntile	e (%,	/20%	6)							
	Sea temperature				(	0.30	6						014										
	Fronts				C	).29 <sup>-</sup>	7					0.	011										
	Chlorophyll				C	).27						0.	003	3									
				•	, radi	ent		).24							007								
	Depth					0.76							017										
	υεριπ				,,,,							<u> </u>											
	RAZB	ATPF	CMGM	HRGL	LBGL	BLKW	EPSH	NTGA	EPSP	NTFU	MXSH	MINW	FINW	COMD	PILW	RISD	WHSD	WHBD	KILW	STRD	BTND	HRBP	SPRW
	0.00		1000	1000		1	0.50	1	1000	1		1.00	7.00				0.70			0.00	0.50	4.50	0.57
RAZB					0.29														1.91				3.57
ATPF					0.13									_		1.19						4.86	
CMGM										_		4.30							1.94				3.60
HRGL					0.07	_	_	_	_	_	_					_							
LBGL								_				4.30 4.30										4.83 4.86	
BLKW												3.67							1.95			4.00	
EPSH NTGA												4.30										4.85	
EPSP				_	_	_		_	_	_	_	4.35		_									
NTFU												4.29										4.85	
MXSH												4.29										4.84	
MINW												0.00							3.83				
FINW	7.30	7.36			7.35							8.54							_			9.47	
COMD												4.33		_					2.08				3.68
PILW					0.98														2.31				2.76
RISD						_		_	_			3.69						_	1.38				3.84
WHSD												4.26											3.47
WHBD												5.12										5.43	
KILW	1.91	1.89	1.94	1.96	1.99	1.95	2.02	1.95	1.96	1.95	1.96	3.83	7.49	2.08	2.31	1.38	1.55	2.33	0.00	2.04	1.52	5.08	4.10
STRD	-0.33	0.22	0.17	0.17	0.12	0.15	0.86	0.15	0.23	0.14	0.14	4.28	7.39	0.26	0.88	1.26	0.70	0.91	2.04	0.00	0.64	4.84	3.47
BTND	0.53	0.61	0.61	0.63	0.63	0.61	0.85	0.60	0.68	0.60	0.60	3.81	7.28	0.70	1.11	0.79	0.70	1.38	1.52	0.64	0.00	4.69	3.41
HRBP	4.58	4.86	4.84	4.83	4.83	4.86	4.00	4.85	4.85	4.85	4.84	3.34	9.47	4.87	4.90	4.82	4.92	5.43	5.08	4.84	4.69	0.00	5.42
SPRW	3.57	3.61	3.60	3.60	3.57	3.58	3.51	3.58	3.63	3.57	3.58	4.06	10.02	3.68	2.76	3.84	3.47	4.07	4.10	3.47	3.41	5.42	0.00
	0					10																	

**Figure 6.2.9.** Matrix of dissimilarity between species ZIGLM conditional coefficients. Dissimilarity matrix calculated using Euclidean distances between species ZIGLM conditional coefficients, detailed in dissimilarity section of methodology.

**Table 6.2.5.** Eigen values of each principle component, representing percentage of variance explained by components 1 to 5, and the standard deviations of each component.

Component	Variance explained (%)	Standard Deviation
1	57.2	1.7
2	28.5	1.2
3	9.5	0.7
4	4.6	0.5
5	0.3	0.1

 Table 6.2.6.
 Variable loadings in components 1 to 5.

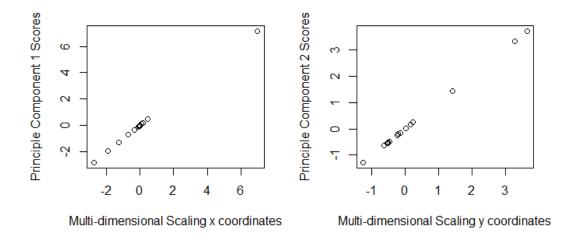
	Component	Component	Component	Component	Component
Variable	1	2	3	4	5
Sea Temp	0.54	0.12	0.20	0.74	0.32
Front Potential	0.52	0.27	0.11	-0.66	0.45
Seabed Gradient	-0.24	0.66	-0.65	0.14	0.24
Depth	0.25	-0.65	-0.67	-0.01	0.26
Chlorophyll conc.	-0.56	-0.21	0.28	0.04	0.75

**Table 6.2.7.** Scores of each species for principle components 1 to 5.

Species	Component 1	Component 2	Component 3	Component 4	Component 5
ATPF	-0.039	-0.557	0.214	-0.023	0.041
BLKW	-0.011	-0.531	0.178	0.062	0.045
BTND	-0.070	-0.150	-0.214	-0.215	0.135
CMGM	-0.009	-0.520	0.195	0.045	0.038
EPSH	-0.329	0.246	0.422	0.083	-0.061
EPSP	-0.010	-0.554	0.252	0.042	-0.046
FINW	7.160	1.444	-0.495	0.474	-0.016
HRBP	-1.958	3.717	1.833	0.311	-0.061
HRGL	-0.017	-0.522	0.223	0.063	0.028
LBGL	-0.042	-0.529	0.205	0.096	0.089
MXSH	-0.009	-0.512	0.178	0.081	0.062
NTFU	-0.014	-0.522	0.168	0.071	0.053
NTGA	-0.011	-0.523	0.178	0.067	0.057
PILW	-0.715	-0.642	-0.275	0.388	-0.377
RAZB	-0.060	-0.242	0.239	0.057	0.040
RISD	0.456	0.168	-0.448	-0.448	-0.274
SPRW	-2.831	-0.203	-1.919	1.047	0.022
STRD	-0.098	-0.536	0.137	0.181	0.075
WHBD	0.096	-1.278	0.599	-0.060	0.090
WHSD	-0.332	-0.633	0.059	-0.442	-0.150
COMD	0.155	-0.485	0.194	0.210	0.083
KILW	-0.039	0.016	-0.505	-1.727	0.009
MINW	-1.275	3.346	-1.416	-0.362	0.119

**Table 6.2.8.** Table of k means cluster centroids for each explanatory variable (ZIGLM conditional coefficients) in each cluster, and within-cluster sum of squares.

		Within-cluster						
Cluster Nº	TPM	TPF	FEA	BAT	CHT	sum of - squares by		
		Clus	ter centro	ids		cluster		
1	-0.205	-0.509	0.201	0.168	0.144	0		
2	-0.145	0.119	0.326	-0.645	-0.080	0		
3	-0.013	-0.007	0.002	-0.017	0.001	0.162		
4	0.728	0.878	0.004	0.340	-0.719	0		
5	-0.014	0.028	0.187	-1.607	0.092	0		
6	-0.147	0.199	0.048	0.018	-0.095	0.034		



**Figure 6.2.10**. Principle components scores as a function of multi-dimensional scaling coordinates.

#### Appendix 3: Discussion

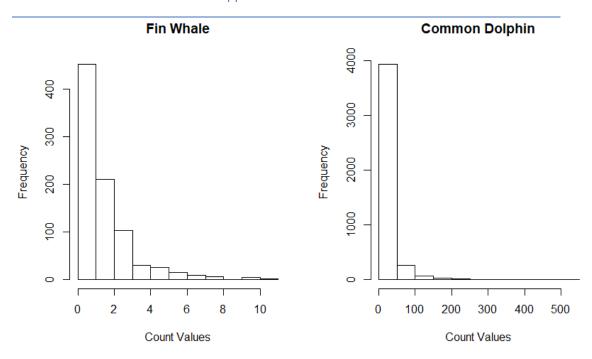
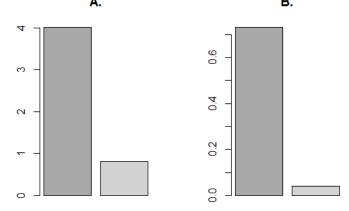


Figure 6.3.1. Frequency of observation count values for fin whale and common dolphin.



**Figure 6.3.2.** Fin whale slope estimate is dark grey (left bar) common dolphin slope estimates are light grey (right bar). A = slope scaled with  $75^{th}$  percentile of y, B = slope scaled with maximum y.