Investigating effects of shipping on common scoter and red-throated diver distributions in Liverpool Bay SPA

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Foreword

Liverpool Bay/Bae Lerpwl SPA (referred to as Liverpool Bay SPA) is a large area in the Eastern Irish Sea extending from Anglesey in Wales to Blackpool in England and covers from low water to approximately 20 km offshore. It is classified to protect a number of bird species, including common scoter (*Melanitta nigra*) and red-throated diver (*Gavia stellata*) due to the large wintering populations in the area. This document reports the findings of a study to understand the effect of anthropogenic activities on the spatial distribution of the two waterbirds within the SPA.

Common scoter and red-throated diver are sensitive to disturbance from anthropogenic activities such as shipping and offshore wind farms. Liverpool Bay SPA is next to the port of Liverpool, one of the busiest in the UK and a large number of ships pass through the SPA daily. In addition, the arrays of four offshore wind farms are within the boundary of the SPA with the accompanying shipping traffic for servicing.

This report outlines the statistical analysis and modelling undertaken to understand how different aspects of shipping (i.e. ship size and distance to birds), offshore wind farms and environmental variables (i.e. depth and salinity) influences the spatial distribution of common scoter and red-throated diver within the Liverpool Bay SPA.

This report and accompanying appendices could be used to inform similar studies in Liverpool Bay and in offshore SPAs with similar levels of anthropogenic activities. The results will be used for evidence in relation to future plans and projects within the Liverpool Bay SPA.

Note: DONG Energy changed name to Ørsted in 2017.

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This report constitutes work carried out at the Centre for Research into Ecological and Environmental Modelling (CREEM), University of St Andrews, and WWT (Consulting) Limited under contract to Natural England.

Executive summary

Liverpool Bay SPA is classified for important wintering numbers of common scoter (*Melanitta nigra*) and red-throated diver (*Gavia stellata*). These species are known to be sensitive to disturbance from shipping traffic and Liverpool Bay is affected by such traffic. Ships regularly cross the SPA to enter or leave the port of Liverpool, one of the busiest ports in the UK, and to fish or service the wind farms and other marine industries within the area.

Digital aerial surveys of Liverpool Bay SPA were carried out in winter 2011 and 2015; JNCC and Dong Energy have made the data collected on common scoter and red-throated divers during these surveys available for this project. The aim of this project was to statistically model the numbers of each species in relation to shipping, other anthropogenic activities (such as fishing and presence/absence of wind farms) and habitat in order to determine the important factors in their distribution and assess possible impacts of shipping.

Ships fitted with Automatic Identification System (AIS) transceivers can be tracked, thus providing information on ship position as well as information about the ship such as length. These data are publicly available and information on ship traffic recorded on the day of the aerial surveys were collated as well as shipping data for longer time periods to provide a more general picture of shipping within the SPA.

Statistical models were fitted separately to the observed numbers of sitting and flying common scoters and sitting red-throated diver; there were too few flying red-throated observed to consider a separate analysis. The response variable for these models was the number of birds observed within small sections, or segments (approximately 1 km in length), of the strip transects covered during the aerial survey. Given the number (and diversity) of the candidate explanatory variables associated with each segment, special attention was given to model selection in this project and models were fitted using a Complex Region Spatial Smoother (CReSS) in a Generalized Estimating Equation (GEE) framework to account for residual correlation and provide reliable model selection. These models were implemented in R (R Core Team 2017) using the MRSea library (Scott-Hayward et al. 2017).

The high variance in the response data used as inputs for each model severely limited the utility of absolute fit measures for each model (since even a perfect data-model combination will naturally have large differences between individual values and the mean). However, more appropriate diagnostics assessed spatially and overall were reassuring and provide no cause for concern about how well the models represent the response data, for any of the models fitted here.

All three selected models included terms for presence/absence of a wind farm in a segment, depth (as a one-dimensional smooth function) and location (as a two-dimensional smooth function). In all cases, the presence of a wind farm decreased the estimated number of birds compared to the absence of a wind farm.

The shipping metrics selected for each model varied across species. For red-throated divers, the selected shipping metrics were the average length of ships, the length of the nearest ship and the distance to the nearest ship. A distance of 2 km to the nearest ship appeared to be an important distance with average

predicted numbers increasing as the distance increased from 0 to 2 km. The effect of the length of a ship was more ambiguous. Salinity and a variable indicating whether the segments were inside or outside the Liverpool Bay SPA were also selected for red-throated divers. Being inside the SPA had a positive effect on the estimated number of sitting red-throated divers compared to being outside.

The model for sitting common scoter included the presence/absence of ship traffic at two temporal scales, the length of the average ship plus a factor variable describing segments where ship traffic was: absent, sometimes present or present on the day of the aerial survey and, if so, classified by ship length. Generally, the larger the ship present on the day of the survey, the more negative the impact on the estimated number of birds.

This same factor variable was included in the model for flying common scoter but the impacts were less severe than for sitting common scoter.

The final models were used to estimate abundance throughout the Liverpool Bay SPA using values for the selected temporal variables in the model that had been observed on the day of the survey. By imposing a hypothesised change to the explanatory variables, the impact of different scenarios were investigated by estimating the difference in the number of birds before and after the imposed change. Further, these model results were used to investigate a wider range of shipping effects by adjusting the values for the explanatory variables in each model. There are naturally a large number of scenarios that could be envisioned and here only a few have been considered, for example, changing the distance to a ship and increasing the length of some ships. Although outside the scope of this project, these methods could also be used to assess the impact of a new shipping lane or extending the footprint of a wind farm. The MRSea package (Scott-Hayward *et al.* 2017) contains specialised routines for assessing such differences and thus provides a useful tool for such work.

Data and computer code generated as part of this project have been made available to Natural England such that when new data become available the analyses can be rerun.

Project steering group: Tim Frayling (Natural England), Sophy Allen (Natural England), Julie Black (JNCC), Alice Kimpton (Natural England), Allen Risby (DONG Energy).

1. Introduction

1.1 Context

Special Protection Areas (SPAs) are protected sites for rare and vulnerable species and regularly occurring migratory species of bird. The Liverpool Bay SPA is classified for important wintering numbers of common scoter (*Melanitta nigra*) and red-throated diver (*Gavia stellata*) and common scoter and red-throated diver are known to be sensitive to disturbance from shipping traffic (Garthe and Huppop, 2004; Kaiser *et al.* 2006; Schwemmer *et al.* 2011; Furness *et al.* 2013). An increasing amount of Natural England's work involves considering the impact from shipping on populations of these birds within SPAs. The aim of this project was to investigate the effects of shipping on common scoter and red-throated diver in the Liverpool Bay SPA, in particular to quantify the temporal and spatial scales of disturbance caused by different types of shipping.

The Joint Nature Conservation Committee (JNCC) commissioned digital aerial surveys of Liverpool Bay SPA in February and March 2011. Following consent of the Burbo Bank Extension Offshore wind farm, post-consent monitoring was undertaken as part of the requirements under the deemed Marine Licence and included digital aerial surveys in January and February, 2015. JNCC and DONG Energy have made these digital aerial survey data available to NE for the purposes of this project.

The Automatic Identification System (AIS) is an automatic tracking system used on ships to help prevent collisions. Vessels fitted with AIS transceivers can be tracked by AIS base stations along the coast, thus providing information on ship position as well as information about the ship, such as name and length. AIS data are publicly available and these data on shipping were combined with the data on common scoter and red-throated diver from the digital aerial surveys to model the distribution of each species within Liverpool Bay SPA.

In addition to shipping, the distribution of birds is also likely to be a function of the habitat (such as depth and salinity) and other anthropogenic effects (e.g. presence of a wind farm or fishing activity) and so this information was also included in the modelling. Indeed, there are many factors that could potentially influence the distribution of birds and the first stage of the project was to identify variables which had been found to be useful in previous studies of the species of interest. Having identified potentially useful variables, the next stage was to collate and process them into the required format for modelling. Subsequent to this, careful model selection was carried out and the details are included later in this report.

The selected models were used to estimate abundance for each species for each of the survey dates using values for the selected explanatory variables that were observed on the day of each survey. Finally, to assess potential impacts of shipping and also wind farms, different hypothetical scenarios were considered by imposing some change on the explanatory variables (compared with values observed), and estimating the difference in abundance before and after the induced change.

A glossary of statistical terms is provided at the end of the document to aid interpretation.

1.2 Objectives of the project

The objectives of the project were to:

- collate the common scoter and red-throated diver distributions from the digital aerial survey carried out in winter 2011 and 2015 and AIS data recorded on the day of the surveys
- undertake a literature review to determine a suite of environmental covariates that may be important in determining the at-sea wintering distribution for common scoter and red-throated divers
- process the shipping data to derive a suite of possible metrics to describe the levels of activity and the different types of shipping over different time periods
- develop computer code to fit statistical models to numbers of common scoter and red-throated diver distributions determining which candidate explanatory variables to include in models to describe the distributions

- using the final models, determine the spatial and temporal scales over which changes to different types, or levels, of shipping or wind farms which appear to affect the estimated bird distributions and abundance.

2. Literature review

A literature review was undertaken to identify which environmental covariates had been found to be useful for modelling common scoter and red-throated diver distribution and what metrics, as measures of shipping intensity, had been used in previous studies. Relevant projects known to the project team or steering group were reviewed first, followed by Google searches for keywords such as 'scoter', 'diver' or 'seaduck' with 'covariate', 'model', 'disturbance', etc.

2.1 Environmental Covariates

In the relevant references relating to environmental covariate data used in modelling sea ducks or divers, the majority of these references related to divers.

2.1.1 Common scoter

In modelling common scoters recorded during aerial surveys around the UK, Maclean *et al.* (2006) trialed six habitat covariates: bathymetry (mean water depth), distance to land, distance to shallow water (less than 10 m in depth), north slope aspect, east slope aspect and seabed complexity. These data were obtained at a resolution of 10 km x 10 km. Models with all combinations of covariates were tested and those with lowest Akaike's Information Criteria (AIC) were selected. Counts of common scoter were best explained by month, bathymetry, seabed complexity, eastward seabed aspect and northward slope aspect. Models with covariates included had a substantially lower variance to mean ratio than those without. The study suggested that incorporating hydrodynamic data would improve performance compared to including only static covariates.

In modelling the distribution of common scoter at Horns Rev wind farm off Denmark, Petersen (2007) used geographic location (as a two-dimensional function of location coordinates), water depth, distance to coast and mean distance to the ten closest wind turbines. Skov *et al.* (2008) compiled a long list of candidate covariates to model aerial survey data from Horns Rev II wind farm; current speed at surface, salinity gradient at surface, temperature gradient at surface, water depth, relief of sea floor, complexity of sea floor, distance to shipping lane, distance to coastline, distance to Horns Rev I wind farm, modelled distribution of the American razor clam (*Ensis americanus*) and the cut trough shell *Spisula subtruncata.* They used generalized additive models (GAMs) and found estimated habitat suitability for *S. subcontrata*, distance to Horns Rev I and distance to coastline to be significant. Petersen and Nielsen (2011), who weren't looking specifically at wind farm areas, used a two-dimensional term of geographical position in combination with water depth and distance to coast to model common scoter distributions in Danish waters.

For modelling and comparing pre- and post-construction distributions of long-tailed ducks, *Clangula hyemalis*, in and around the Nysted offshore wind farm, Denmark, Petersen *et al.* (2011) used geographic position and water depth.

2.1.2 Red-throated diver

Using the same candidate covariates as for common scoters above, Maclean *et al.* (2006) found red-throated diver counts were best explained by month, bathymetry, seabed complexity, distance from land and northern slope aspect.

Skov *et al.* (2008) (discussed for common scoter above) found that the significant covariates for red-throated divers were water depth, distance to coastline, distance to 32-33 psu (salinity) gradient and an interaction term between these.

O'Brien *et al.* (2012) reported that predictive habitat distribution models failed to successfully predict red-throated diver abundance, probably due to distribution data being strongly zero-inflated and possibly due to using only static, instead of dynamic, covariates. Thus, they used kernel density estimation to estimate bird density in order to delineate Marine Protected Areas.

In work for the Marine Environmental Monitoring Plan for EON's Robin Rigg Offshore Wind Farm in the Irish Sea, Natural Power (2014) examined the covariates water depth, distance to coast, distance to the wind farm, sediment type, geographic position (latitude and longitude), month (or season) and time of day. Of these, only the last three covariates were chosen in the final model.

In their identification of important marine areas in the UK for red-throated divers during the breeding season project, Black *et al.* (2015) collated more environmental data from various sources to include in a GAM than had been used in previous studies. The candidate covariates for modelling with boat survey bird data were; distance to coast, seabed depth, seabed slope, seabed aspect, maximum wave base (maximum depth at which wave passage causes significant water motion), maximum tidal bed stress (force exerted by the tide at the seabed), sea surface temperature, salinity, stratification (difference in temperature between surface and seabed), probability of fronts (probability that a front will form at given location during summer), seabed substratum and coastal physiography. Using forward selection of ranked predictors, the final model with the minimal significant deviance was: $P = s(Depth) + s(Dist) + s(Tidal) + s(Wave) + s(Front) + Seds : Coast$

where P was the probability of occurrence, s represents a spline smoothing function of covariates seabed depth (m; $Depth$), distance to coast (km; $Dist$), tidal bed stress (N m-2, $Tidal$), maximum wave base (m, $Wave$), probability of thermal fronts ($Front$) and $Seds : Coast$ was an interaction term combining seabed sediment classes and coastal physiography classes. Using an F test, the relationship between diver presence and each of the selected predictor variables was statistically significant (p-value<0.01). The model explained 33% of the variation in red-throated diver presence/absence for surveyed grid cells.

Hostetter *et al.* (2015) used environmental covariates as predictors in modelling the proportions of great northern divers to red-throated divers. Distance to shore was the strongest spatial predictor of species proportions, with proportions of great northern diver increasing with distance. Sea surface temperature was a significant predictor of species proportions and the relationship showed seasonal reversals. Similarly, distance to shore, grain size, salinity and chlorophyll-a were significant for some surveys. The 95% confidence intervals for each of estimated regression coefficients associated with each survey often overlapped zero indicating non significance and all the estimated coefficients for slope were not significant.

In their presentation at the red-throated diver conference, Hamburg, in 2016, Zydelis *et al.* (2016) used the candidate environmental covariates water depth, distance to wind farms, current U (east-west) velocity, current V (north-south) velocity, salinity and water temperature to model telemetry data. Current U velocity and current V velocity were unimportant in modelling and subsequently excluded. The remaining variables were significant (temperature only at 10% significance testing level, others at 5% level) indicating that red-throated divers aggregated on a distinct frontal area in the German Bight, most distinguishing by a salinity peak at 32 ppm. The frontal zone is created by Elbe outflow and tidal currents. The species showed preference towards shallower depths. Divers clearly avoided being in the proximity of offshore wind farms (the model showed avoidance up to 20 km), however, the authors urged when interpreting these results as the models were still in development.

Heinänen (2016), also presenting at the red-throated diver conference, used the DHI North Sea Hydrodynamic Model to produce the covariates U velocity, V velocity, density, salinity and temperature and from other sources added water depth, distance to wind turbine and Modis Chlorophyll-a 8 day mean for modelling data from digital aerial surveys. Salinity and temperature were important descriptors of fronts. A two-step, generalized additive mixed model (GAMM) approach was used, first modelling presence/absence and then density. Salinity and distance to wind farms were the most important covariates, with the frontal area apparently the driver of distribution during the time of the surveys and spatial extent studied.

APEM (2016) tested a wide suite of environmental covariates in modelling digital aerial survey data: chlorophyll-a concentration (from POL and JNCC), distance to shore (from OS high water polygon (open licence available online)), maximum tidal bed stress (POL and JNCC), maximum wave base (POL and

JNCC), sea surface temperature (POL and JNCC), seabed aspect (from bathymetry data set), seabed depth (1 arc second digital elevation model from Defra), seabed slope (derived from bathymetry), shear stress currents (POL, Defra), shear stress waves (POL, Defra), thermal front probability (POL, Defra). Shipping activity was considered as the number of ship tracks in each cell on the day of the survey (no source given) and also the number of tracks in each cell for the day prior to the survey (no source given). For red-throated divers, only construction period bathymetry and shipping activity on the day of the survey were retained in the final model due to collinearity or poor predictive effect through model selection.

Skov *et al.* (2016) also modelled digital aerial survey data of red-throated divers in the Thames estuary, using a two-step GAM approach, but using MIKE software to run real-time hydrodynamic models to produce a comprehensive range of covariates such as water level, vertical water velocity, current gradient and vorticity, which were combined with other covariates such as geographic position, seabed slope and ship densities. The use of simulated simultaneous environmental covariates was seen to increase performance of the GAM.

2.2 Shipping metrics

To assess the disturbance due to ships on common scoter, Kaiser et al. (2002) studied the flushing distance of common scoter due to an approaching vessel (35 m in length) and their observations suggested that flock size had an effect; small flocks would be disturbed at a distance of 1 km, whereas larger flocks would be disturbed at a distance 2 km.

As mentioned previously, APEM (2016) used shipping activity to model red-throated diver distribution; two shipping metrics were considered; the number of ship tracks recorded in each 1 km^2 grid cell on the day of the survey and also the number of tracks on the day before the survey. The number of tracks on the day of the survey was retained in the final model (together with bathymetry).

Although not considering common scoter and red-throated diver, Burger *et al.* (2016) used a variety of shipping metrics to model abundance of other seabird species. They used Automatic Identification System (AIS) shipping data within 1.5 km of digital aerial survey transects and within a time frame of 5 hours before surveys. They used a two-step approach using GAMM applied in R. They first tested all data for positive or negative effects of ship presence on bird abundance (Model 1). Second, for cells containing one or more ships, several parameters were tested: number of ships, time lag (since last ship), average speed, length and number of AIS signals (Model 2). Geographic coordinates were always included in the model and survey was included as a random parameter. For common Eiders, Model 1 (R^2=0.29) used smooths of number of ships and water depth; Model 2 (R^2=0.32) used smooths of number of AIS signals per cell, an interaction of vessel speed and length and a smooth of water depth. For Larus gulls, Model 1 (R^2=0.07) used smooths of number of ships and water depth and Model 2 (R^2=0.12) used smooths of time lag since last ship, an interaction of speed and length, type of vessel (fishing/non-fishing) and a smooth of water depth.

Common Eiders showed avoidance of areas where ships were present (36% cells with bird sightings vs. 50% cells when no ships are present). Number of AIS-signals was negatively related to bird densities. Least disturbance was by slow and medium-sized ships and fast and small (< 20 m) ships (e.g. pilot vessels).

Presence of Larus gulls was positively related to the presence of ships (32% cells with bird sightings vs. 22% cells when no ships are present). Larus gulls seemed to mainly associate with slow, small vessels that resembled fishing vessels. Larus gull densities soon declined after ships left the area.

2.3 Implications for this project

Table 2.3 summarises the explanatory variables that have been considered in previous studies to model the distribution of common scoter and red-throated diver and other sea bird species in the case of Burger *et al.* (2016). Depth, or bathymetry, has been considered most frequently in previous studies and in all but one study was used in the final model. Other habitat variables that have been considered as candidate explanatory variables are salinity, water temperature, seabed complexity, sediment and chlorophyll-a and of these salinity was selected in final models the most often. Geographic location (defined by x and y coordinates) was used in several of the studies. A variety of hydrodynamic variables have been considered but not always selected in final models. Distance to coast, or similar, and distance to wind farms were found to be important in several studies. Natural Power (2014) found that month and time of day were important in modelling abundance from surveys that were collected throughout the year for several years.

It seems clear that environmental, or habitat, variables are important, in particular depth and salinity and in this study both variables were considered. Geographical location was also included as a two-dimensional smooth function and incorporating it in this way negated the need for including distance to coast/wind farm as additional explanatory variables. Geographical location is a proxy summarising many potential explanatory variable and relationships between abundance and distance from some effect can be assessed by plotting estimated numbers obtained from a model by distance from the effect, such as a wind farm (see later). The wintering abundances of birds were of interest in this project and the aerial survey data were collected during the period end of January to early March and so season was not considered here. Sea surface temperature, chlorophyll-a, sediment and seabed complexity were also not considered here; an attempt was also made to obtain the suite of covariates used by Black *et al.* (2015), however, these data had been compiled/modelled commercially under contract for either that project or the previous UK SeaMap project and were not freely available for this study.

There is much less literature on shipping variables, likely due to AIS data being available relatively recently. Various shipping metrics were considered, similar to previous studies; the presence/absence of shipping and the number and length of vessels. In addition, shipping activity over different timescales were considered to incorporate shipping information both on the day of the survey (as in APEM 2016) and also over longer time periods, thus identifying regions of transient shipping and regions where ships were more persistent, for example along shipping lanes.

Table 2.3 Summary of the explanatory variables considered as candidate variables (0) and used in the final models (1) in previous studies; 1 APEM (2016); 2 Burger *et al.* (2016); 3 Black *et al.* (2015); 4 Heinänen (2016); 5 Hostetter *et al.* (2015); 6 Maclean *et al.* (2006); 7 Natural Power (2014); 8 Petersen (2007); 9 Petersen *et al.* (2011); 10 Petersen and Nielsen (2011); 11 Skov *et al.* (2008); 12 Skov *et al.* (2016); 13 Zydelis *et al.* (2016).

Explanatory_variable	1	2	3	4	5	6	7	8	9	10	11	12	13
Geographical location		1					1	1	1	1		1	
Depth	1	1	1	0		1	0	1	1	1	1		1
Distance to land/coast/shore	0		1		1	1	0	1		1	1		
Distance to shallow water						0							
Distance to wind farm				1			0	1			1		1
Seabed complexity (slope/aspect/relief)	0		0		0	1					0	1	
Sediment (type/substratum/grain size			1		1		0						
Salinity (gradient)			0	1	1						1		1
Sea temperature (surface/gradient)	0		0	0	1						0		1
Chlorophyll-a	0			0	1								
Mollusc distribution											1		
Shear stress waves	0												
Wave base	0		1										
Water level/tidal bed stress	0		1									1	
Vertical water velocity/vorticity												1	

Explanatory_variable	1	2	3	4	5	6	7	8	9	10	11	12	13
Currents (U/V velocity/speed/gradient/stress)	0			0							0	1	0
Water density				0									
Probability of fronts	0		1										
Coastal physiography			1										
Month/season						1	1						
Time of day							1						
Presence/absence of ships		0											
Number/density of ships/AIS signals	1	1											
Time lag		1											
Ship speed/length/type		1											
Distance to shipping lane											0		

3. Analysis methods

Data on the seabirds in Liverpool bay SPA were collected during a series of aerial surveys in 2011 and 2015. Data on shipping, other anthropogenic effects and habitat were collated from a variety of sources. All the data were then processed to generate the required format for modelling. These data were analysed to estimate the distribution of numbers of seabirds throughout the region of interest and determine if the numbers were dependent on shipping traffic or some aspect of shipping. Having a large suite of candidate explanatory variables required a robust model selection process. Each stage is described below.

3.1 Data collation

3.1.1 Aerial survey data

Digital aerial surveys were flown over the Liverpool Bay SPA on three days in 2011 and two days in 2015 (Table 3.1.1). The planes flew along predefined transect lines (Figure 3.1.1) and the spatial extent of the SPA covered by the surveys differed between surveys, the southern part of the region was surveyed on 12/02/2011, the northern part of the region on 18/03/2011 and the whole of the SPA was covered on three dates (07/03/2011, 24/01/2015 and 04/02/2015). Surveying started in the morning (between about 9:30am and 10:45am) and finishing in the afternoon (between about 1:30pm and 4:30pm).

Cameras were mounted on the airplane and recorded video footage along the transect lines. In 2011, three cameras each covered a 50 m wide strip and one camera covered a 25 m wide strip giving a total covered strip width of 175 m. In 2015, four cameras each covered a 125 m wide strip giving a total covered strip width of 500m.

Table 3.1.1 Summary of the aerial surveys; k is the number of transects flown and w is the total width of the covered strip (km).

Survey	Date	k	w
1	12/02/2011	58	0.175
2	07/03/2011	58	0.175
3	07/03/2011	38	0.175
4	18/03/2011	38	0.175
5	24/01/2015	44	0.5
6	04/02/2015	44	0.5
Total		280	

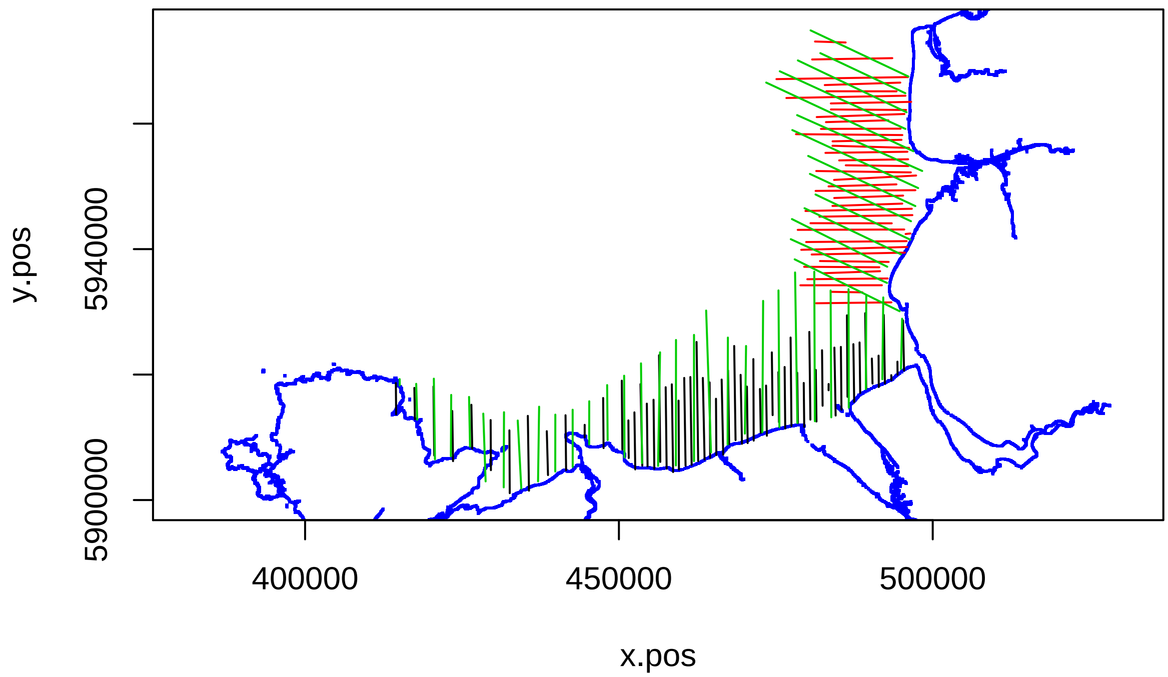

Figure 3.1.1 Transect lines for surveys 1 (black), 3 (red) and 5 (green). Surveys 2, 4 and 6 used similar transect lines to surveys 1, 3 and 5, respectively.

3.1.2 Shipping data

According to the Safety of Lives at Sea (SOLAS) Chapter V Regulation 19.2.4, the following ships are required to have AIS fitted:

- all ships over 300 gross tons engaged on international voyages,
- cargo ships over 500 gross tons not on international voyages and
- passenger ships irrespective of size.

All ships included in this regulation were required to have AIS installed by 1st July 2008, however, different classes of boat had different deadlines for AIS installation, ranging from 2002 - 2008. Nevertheless, all ships in these categories were legally obliged to by AIS installed by 2011 and 2015.

Fishing vessels were not legally required to install AIS until 2012 and there were different installation dates depending on length (https://www.gov.uk/government/publications/automatic-identification-system-ais-for-fishing-vessels):

- fishing boats of length 24m and over were required to carry AIS by 31st May 2012,
- fishing boats between 18 m and 24 m long were required by 31st May 2013 and
- fishing boats between 15 m and 18 m long were required to carry AIS by 31st May 2014.

This may mean that fishing vessels were under represented in the 2011 AIS data but fishing vessels over 15 m should be recorded in the 2015 data.

There is no requirement for small commercial vessels, private yachts or cruising vessels to carry AIS.

AIS data were collected in various forms from the website shipAIS.co.uk, the Marine Management Organisation (MMO) and the Royal Yachting Association (RYA).

The website shipAIS.co.uk was contacted and AIS data was requested and received for each of the five survey dates plus the previous day. Data fields included in these data were, latitude, longitude, date/time, ship name, Maritime Mobile Service Identity (MMSI) number, International Maritime Organisation (IMO) number, call sign, length, beam, tonnage, Dead Weight Tonnage (DWT), heading, bearing, speed and destination. Ship type was not immediately available, although an internet search of ship name, taking into account the destination, revealed that wind farm transit ships were recorded in this data set.

The MMO Anonymised AIS derived track lines 2011 data set was downloaded from the website data.gov.uk. Fields such as ship length, ship width, draught and ship type are available for some track lines but not others. Types of ship recorded in this data include tugs, carriers, tankers, barges, dredgers, fish factories, ice breakers and ferries. There were no data included on date, apart from the year. The 2015 data set was not available for this project.

Fishing activity data for commercial UK vessels 15m and over for 2011 were also downloaded. Details of the fields contained are given in Appendix B Table B1. The data were displayed per 3km cells. Data for 2015 were not available.

The RYA Coastal Atlas was a collection of data about recreational boats for May to September during 2011, 2012 and 2013. It was available as a relative density of AIS tracks within cells 1 square nautical mile, and provided by Natural England.

3.1.3 Other anthropogenic data

The Crown Estate provided data on the following features:

- pipeline location data
- gas storage location
- aggregate extraction areas
- meteorological mast location and
- offshore wind farms location

This information was freely available in shape file format from its website (https://www.thecrownestate.co.uk/energy-minerals-and-infrastructure/downloads/maps-and-gis-data/).

3.1.4 Environmental covariates

Following the literature review, the following environmental covariates were deemed potentially most useful and sourced/originated accordingly:

- water depth (from the UK Hydrographic Office six second bathymetry digital elevation model, used under licence to Natural England); and
- salinity data were also sourced for the study area (in parts per thousand) from Proudman Oceanographic Laboratories POLCOM 2004 data. More recent data, including those for 2011 and 2015 were unavailable for this study.

3.2 Data processing

3.2.1 Aerial survey data

The camera footage recorded during the aerial surveys was analysed to identify the location of any birds and their behaviour and species. Behaviour was recorded as sitting (which also included birds recorded as diving, taking off or flushing) or flying. The confidence of the species identification for each bird was categorised as either definite, probable or possible. All confidence categories were included. In addition, birds identified as 'diver sp.' were treated as red-throated diver.

The aerial survey global positioning system (GPS) tracks were split at transect start and end points using Esri ArcGIS 10 to produce the discreet survey transects flown. Added to these were fields for transect identification, length and the coordinates of the start and end points. Any parts of the transects which occurred on land (i.e. above the Ordnance Survey High Water poly line) were not included. The ET GeoWizard's 'split poly line by length' tool plugin was used to split the transects into 1 km sections, or segments (with shorter segments at ends). A segment length field was added and end segments shorter than 500 m were joined to neighbouring segments and the segment length field updated. Fields for segment identification, start, end and midpoint coordinates were added. The GPS track files were spatially joined to the segmented transects files to assign times back to the segments.

The aerial survey observation files were spatially joined to the associated segmented transect files and the fields from the latter added to the former and the number of birds per segment was enumerated. All of the segments (with and without bird observations on) were merged and sorted by time to produce segmented survey files for analysis. To these were appended fields for all the covariates, as detailed below.

3.2.2 Shipping data

The processing preparation required, after screening the shipping data sets, was to convert the point data provided from the shipais.co.uk website to line data and clip to the UK coastline using the ET GeoWizard 'erase' tool plugin. Some tracks and parts of tracks were deleted where intermittent signal collection gave the impression that ships travelled overland, or across islands. Appendix B Table B2 details the modified tracks.

Following the literature review and discussion with the project Steering Group, seven metrics of shipping activity were identified and described below. Details of how these were included as explanatory variables in the modelling are given in section 3.3.2.

- For the entire MMO and shipais.co.uk data sets (and the latter split into data from the day of each aerial survey and the day before each survey), the presence or absence of shipping tracks in each survey transect segment was assigned;
- For the shipais.co.uk data set from the day of each aerial survey, the number of shipping tracks in each segment was calculated;
- For the shipais.co.uk data set from the day of each aerial survey, the nearest distance of shipping tracks to the segment midpoint was calculated;
- For the shipais.co.uk data from the day of each aerial survey the average vessel length in each survey transect segment was extracted;
- For the shipais.co.uk data from the day of each aerial survey the maximum vessel length in each survey transect segment was extracted;
- For the shipais.co.uk data from the day of each aerial survey the length and name of the nearest vessel to the midpoint of each transect segment was extracted; and
- For the 2011 fishing activity data set the total time in hours in each survey transect segment was assigned.

To derive presence or absence, number of vessels, average and maximum length of vessels, polygons of the aerial survey segmented transect tracks were made by offsetting by half the total width of camera strip widths used on each survey (including inter-camera gaps) and intersecting these polygons by the different shipping activity layers. Nearest distance was measured to the segment midpoints and likewise total time of fishing activity was intersected with segment midpoints.

Records of vessels and fishing buoys recorded during the aerial surveys were also extracted from the survey data.

3.2.3 Other anthropogenic activity data

The anthropogenic activity data layers (gas pipelines, gas storage, aggregate extraction, wind farms and wind farm cable routes) were all intersected with the segmented survey transect polygons to populate respective presence/absence fields. An additional field was populated with presence/absence of any of these anthropogenic activities.

Wind farm presence/absence fields were made for those with foundation construction completed before the 2011 aerial surveys and those completed before the 2015 aerial surveys.

3.2.4 Environmental covariates

Depth in metres was assigned to the midpoint of each survey transect segment by extraction from the UK Hydrographic Office six second bathymetry digital elevation model. Segments with no associated depth data (over land) were assigned the value -9999.

Salinity in parts per thousand was assigned to the midpoint of each survey transect segment by extraction from Proudman Oceanographic Laboratories POLCOM 2004 data. Segments with no associated salinity (some inshore areas) were assigned the value '9999'.

3.2.5 Prediction grid

A 1km x 1km cell grid aligned to the Ordnance Survey Great Britain grid covering the Liverpool Bay SPA was originated in Esri ArcGIS 10 for the purpose of projecting model predictions. The resolution of model predictions depends on the resolution of the explanatory variables that are included in the model and although the covariates were naturally (mostly) available at a finer resolution, 1 km was chosen to match the length of the aerial survey segments (see later).

Each grid cell had fields for each of the anthropogenic and environmental covariates, produced in the same way as for the transect segments. Given that some of the variables were survey date specific, in order to make predictions for the different survey dates, a prediction grid was created for each survey date and populated with the appropriate values for the date specific variables.

3.3 Analysis methods

3.3.1 Statistical models

The counts of birds per segment along the transect lines were used to estimate bird abundance in the region of interest (Liverpool Bay SPA); this approach, as opposed to assuming a constant density, models trend in the spatial distribution and allows it to vary throughout the region of interest.

The number of birds in each segment (with known area) was enumerated, N_i where i indicates an individual segment and the numbers in each segment formed the response variable in the statistical model. Counts are often modelled using a Poisson distribution, however, these data were likely to be overdispersed (i.e. more variable than expected for Poisson distributed data), and so an overdispersed Poisson distribution was used with mean μ_i. For an overdispersed Poisson, the mean-variance relationship of the Poisson is relaxed so that the mean is proportional to the variance. This function contains a multiplicative factor (known as an overdispersion parameter) which was estimated from the data. The mean was modelled with location, habitat and shipping variables as candidate explanatory variables represented as follows.

$\mu_i = exp(log(a_i) + \ _0 + \sum_j^J \ _jF_{ij} + \sum_k^K s_k(D_{ik}) + s_l(X_i, Y_i))$

where

- $log(a_i)$ is an offset term (a term with known regression coefficient) that corresponds to the area of each segment ($a_i = w_i l_i$ where w_i and l_i are the total strip width and length for each segment i, respectively)
- $\ _0$ is an intercept

- $\ _jF_{ij}$ represent factor terms (e.g. indicating the presence/absence of shipping) with $\ _j$ representing the regression coefficients for factor variable F_j
- $s_k(D_{ik})$ represent one dimensional smooth terms (e.g. depth) implemented using quadratic B-splines with flexibility chosen using spatially adaptive smoothing (SALSA) methods (Walker *et al.* 2010)
- $s_l(X_i, Y_i)$ represents a two-dimensional smooth term of location (determined for each segment i by X_i and Y_i). This used radial Gaussian basis functions with flexibility also targeted using SALSA (Walker *et al.* 2010).

The models were fitted using the complex region spatial smoother (CReSS) in a Generalized Estimating Equations (GEE) framework with SALSA for model selection (Walker 2010) implemented in the R (R Core Team, 2017) library MRSea (Scott-Hayward *et al.* 2017). GEEs allowed for standard errors to be calculated taking account of any correlation in the residuals within a specified blocking structure (robust standard errors). In the presence of residual correlation it is important to use robust standard errors and corresponding p-values which are adjusted for this correlation when determining statistical significance. For this reason, robust standard errors were employed and since it was likely that counts of birds within segments along the transect lines would be correlated (and the model is unlikely to explain this correlation in full), transects were specified as the blocking structure.

The region of interest included headlands (e.g. Great Orme, Figure 3.1.1) which, it was felt, may prove barriers to the seabird species of interest and so they would fly around, rather than over them. Therefore, distances between segments were defined by geodesic distances rather than straight line distances to ensure that distances were more biologically reasonable and reflected distances around the coast.

The response variable was the number of birds per segment and separate models were fitted to common scoter and red-throated diver. The intention had been to include both sitting and flying birds in the same model with a term in the model indicating whether the number was for sitting or flying birds; specifically an interaction term between behaviour and location would allow the surface to vary by behaviour. However, in practice, fitting this model demonstrated some parameters were inestimable and so separate models were fitted to sitting and flying birds. Another benefit of fitting separate models to these groups also meant the covariates included in each model could vary and help us identify if the key drivers differed across activity state.

3.3.2 Candidate explanatory variables

The processed shipping data, other anthropogenic and environmental data provided a suite of candidate explanatory variables that were agreed during the project and are listed below (see Appendix C for further details). Birds could be located throughout the area of the segment and so (potentially) continuously varying covariates (e.g. depth, distance to a ship) may be different between birds within the segment and in these cases, a relevant summary statistic (e.g. mean) was used to obtain a single value to describe the segment. The names shown below in italics are the names that were used during the modelling process. The numbers in square brackets indicate that some variables could not be included in the same model because the coefficients associated with the factor levels could not all be estimated (see later). The numbers in parentheses indicate the coding used for each factor level.

- *LBspa* - inside (1) or outside (0) of the Liverpool Bay SPA
- *fish* - presence (1) or absence of fishing (0) within a segment derived from the number of hours of fishing in a segment (obtained from the total fishing activity data set for 2011). This was used as an indication of fishing locations.
- *windfarm* - the intersection (1) or no intersection (0) of the segment with wind farms where the foundations were constructed by the date of the survey
- *anthrop* - the intersection (1) or no intersection (0) of the segment with anthropogenic activities such as gas storage, aggregates extraction areas and wind export cables.
- *windcable* - the intersection (1) or no intersection (0) of the segment with wind export cables

- $shipAIS1$ [1] - presence (1) or absence (0) of a ship track within the segment based on ship tracks from the day of the survey
- $shipnumf$ [1] - the number of ships within the segment for the day of the survey. This was included as a factor variable with three levels, no ships (0), 1-4 ships (1) and >4 ships (2)
- *shiplenav* - the average length (metres) of the ships for shipping intersecting with the segments on the day of the survey. If there were no ships intersecting with the segment, the length was zero (also see below).
- *shiplenmax* - the maximum length of the ships intersecting with the segments on the day of the survey. If there were no ships intersecting with the segment, the value was zero.
- *shipnear* - nearest distance to ship (km) for the day of the survey included as a 1-dimensional smooth term. This would include ships that did not intersect with a segment but may have passed close by.
- *shiplennear* - the maximum length of the nearest ship on the day of the survey. If this differed between birds within a segment, the maximum length was used.
- $shipAIS5$ - presence (1) or absence (0) of a ship track intersecting with a segment using the combined ship tracks for all five days of the surveys
- $shipAIS10$ - presence (1) or absence (0) of ship track intersecting with a segment using the combined ship tracks for all 10 dates (i.e. the day before and the day of the survey for five dates)
- $shipMMO$ - presence (1) or absence (0) of all shipping tracks obtained from the MMO Anonymised AIS derived track lines data for 2011. This was used to describe the presence of shipping generally in the region.
- *depth* - depth (m) obtained from the UK Hydrographic Office six second elevation model. Depths for segments with no associated depth data (i.e. over land) were as missing were estimated (see below). Included as a 1-dimensional smooth term.
- *salinity* - salinity (parts per 1000) obtained from the Proudman Oceanographic Laboratories POLCOM 2004 data. Included as a 1-dimensional smooth term.
- location defined as a distance (m) from a reference point (*x.pos*, *y.pos*) included as a two-dimensional smooth term.

The shipping metrics provided information over various time scales, from the day of survey ($shipAIS1$, $shipnumf$ and *shipnear*, *shiplenav*, *shiplenmax*, *shiplennear*), a more general picture of the presence/absence of shipping ($shipAIS5$ and $shipAIS10$) and an overall picture of the presence/absence of shipping within a year ($shipMMO$). The latter three variables were included in order to determine if there were more persistent shipping effects and over what timescale these effects may last.

Many of the factors indicate the presence/absence of the shipping or installation within a segment. There may be a buffer region around a ship track, shipping lane or installation within which birds are still affected although not impacted directly. Fitting location as a two-dimensional smooth will allow the fitted surface to vary flexibly and thus allow for any differences around an installation or shipping lane. Fitting a two-dimensional smooth has the advantage over including the distance to the effect (e.g. distance to wind farm) as a one-dimensional smooth function, in that a two-dimensional smooth can model impacts which may not be symmetrical around the effect.

Two new variables were created that were a combination of shipping in general and the shipping on the day of the survey. The presence/absence data from the MMO AIS data for 2011 were combined with the lengths of ships present on the day of the survey to create a two new variables, one using the average length of ships present in a segment and the other using the maximum length of ships present in a segment. Using the quantiles of the length distributions to obtain approximately equal numbers in each length category, the variables were classified as follows:

- *shipcatAv* [1] - no ships present in segment (0), ships present sometimes but not on the day of the survey (1) and ships present in segment on the day of the survey and classified according to average length; ships with average length 10-15m (2), ships >15-20m (3), ships >20-36m (4), ships >36-89m (5) and ships >89m in length on average (6).
- *shipcatMax* [1] - no ships present in segment (0), ships present sometimes but not on the day of the survey (1) and ships present in segment on the day of the survey and classified according to maximum length; ships with maximum length 10-15m (2), ships >15-21m (3), ships >21-36m (4), ships >36-95m (5) and ships >95m in length on average (6).

Depth values were missing for some segments (3% of segments). Since depth was likely to be an important explanatory variable, rather than delete these segments, a GAM was used to model depth with salinity, distance to coast as smooth terms and location (x, pos, $y.pos$) as a two-dimensional smooth term. The model was used to estimate missing values in the survey segments and the prediction grid. A very few values of salinity were missing in the prediction grid - salinity was only available on a coarse resolution (see Appendix C) and so missing values were assigned the same value as adjacent segments.

3.3.3 Model selection

Separate models were fitted to each species (using the term 'species' to identify sitting and flying birds as different species) and with many candidate explanatory variables, some similar to, or derived from, other variables, selecting the variables (or combinations of variables) with the most predictive power to data unseen by the model (assessed using cross validation) was important. As mentioned above some variables could not be fitted together since they were essentially a subset of each other (see later for an example), therefore, these variables were grouped together and one variable from this group was selected based on its relative predictive power to data unseen by the model. This group (based on the explanatory variables) was the same for all species.

The model selection process for each species was done in several steps, firstly choosing the variable from those grouped together, identifying collinear variables, then using backward selection to select factor and one dimensional terms and finally including a two dimensional term for location and possible interaction. The details were as follows.

1. The predictive power of each term to data unseen by the model was assessed by fitting each term separately and, for each model, harvesting the k-fold cross validation (CV) score, a fit score (pseudo-R^2, measuring the squared correlation between the observed values and the fitted values) and the p-value associated with each term. This was done in order to assess all explanatory variables for their predictive power in explaining the response and to select the variable within each group which explained the most variation for the response variable. The variables were ranked based on the average CV score (100 replicates of the CV were generated to calculate a CV score for each covariate separately, the data are randomly divided into k subsets and the mean and percentile-based confidence intervals obtained).
2. A variable from those grouped together was chosen based on the lowest CV score. It was combined with all the other remaining variables and the multi-collinearity of these variables was checked. Generalized variance inflation factors (GVIFs) were used to quantify the severity of multi-collinearity in a generalized linear model. As a rule of thumb, values greater than 5 indicate that a variable is collinear with other variables and any collinear variables were excluded.
3. All remaining terms apart from spatial location, were included in a model - referred to as the 'Full model'. Backwards selection was used so that at the end of this stage all terms included were significant (i.e. the p-value, associated with the term was less than 0.05). The least significant term was removed from the model and a new average CV score and pseudo-R^2 value were obtained and the significance of remaining terms checked.
4. Having chosen the factor and one dimensional terms in step 3, a two-dimensional term for location was added. Thus, environmental and shipping metrics that were important in describing the response were selected before location was included since location may account for some of the variability due to

other variables. Having included location, some other terms may become non-significant and these were excluded, one at a time as before. Finally, an interaction term between location and any remaining shipping factor metric was included in order to determine if an interaction was required. If there was more than one candidate factor for the interaction, a pseudo-R^2 fit score and a cross validation (CV) score was calculated for each model and the model with the lowest average CV score was selected.

At the end of the process described above, the selected models were then checked to ensure that the assumptions of the model had not been violated and to assess the relationships between the variables and the response.

3.3.4 Diagnostics and model assessment

For each selected model, diagnostics were performed to ensure model assumptions were valid. To assess whether the residuals were correlated, an empirical runs test for randomness in the residuals was performed. Correlation in the residuals would indicate that a blocking structure was required. To assess whether the blocking structure chosen was appropriate, a plot of the lag between residuals within a block and the correlation at each lag was obtained (an Auto Correlation Function plot).

Predicted values for the survey data were obtained from the selected model and the residuals (observed values - predicted values) calculated. The residuals were plotted spatially and visually examined to determine if there were any patterns - ideally, there should not be any patterns discernible in residual plots and this is what was examined here.

Partial plots of each factor and one dimensional term in the selected model were visually examined to assess the relationships between the variables and the response (given the other variables in the model).

3.3.5 Estimating abundance and 95% confidence intervals

Using the final models, average predicted abundance for each species was calculated for a grid of points (the prediction grid), with associated area and known values for the explanatory variables, throughout the Liverpool Bay SPA. Total abundance for each survey date was estimated by summing predicted abundance over all grid points in the region using observed values for each survey date. The confidence intervals for total abundance were obtained from a parametric bootstrap procedure available in MRSea (Scott-Hayward *et al.* 2017) and implemented as follows. The selected model coefficients were re-sampled from a multivariate Normal distribution and new predictions obtained for every grid cell using these re-sampled coefficients. This process was repeated 500 times to build a distribution of abundance estimates. Percentile-based 95% confidence intervals of abundance were obtained from the distribution for each grid cell and as a collection.

Using the bootstrap predictions for each grid cell, the variation, or uncertainty, associated with these estimated surfaces was assessed by plotting the coefficient of variation for each grid cell.

3.3.6 Spatially explicit impact of shipping

The chosen models were used to investigate a series of hypothetical changes to shipping activity by determining differences between estimated numbers of birds using observed values for the explanatory variables in the prediction grid and estimated numbers of birds where some change had been applied to the shipping variables (based on the model and the estimated coefficients). The enforced change will necessarily depend on the selected explanatory variables in each model. Some scenarios that could potentially be simulated are as follows:

- an increase in the number of ships within existing shipping lanes; this could be implemented by using the variable $shipnumf$ and changing the records indicating 1-4 ships to indicate more than four ships.
- an increase in the disturbance to birds; this could be implemented by decreasing the distance to the nearest ship by changing the variable $shipnear$

- an increase (or decrease) in the length of the ships, within the existing shipping lanes.

For the combined category variables ($shipcatAv$ and $shipcatMax$), several scenarios could be considered, for example,

- the spreading of shipping activity into undisturbed regions by changing records never containing a ship (level 0) to contain a ship (i.e. level 1 or a ship of specified length)
- an increase in the length of ships.

If there was no impact in a grid cell due to changing relevant shipping variables compared to no change, then the differences in the estimated mean number of birds would be close to zero (and within the bounds of natural variability). An increase in the number of birds per grid cell would be a positive difference and a decrease in the number of birds would be a negative difference. The significance of the differences were assessed from the parametric bootstrap and assessed per grid cell.

These hypothetical scenarios were illustrated using the values of explanatory variables observed for the most recent survey (i.e. the survey on 04/02/2015) as the no change reference and then changing these observed values for relevant variables in order to reflect the scenario being considered. The possible scenarios were dependent on the final models for each species and so details of scenarios considered are provided in the results section.

3.3.7 Impact of wind farms and anthropogenic activity

The effect of a wind farm (or indeed any other anthropogenic effect) may not be limited to the footprint of the wind farm but extend to some region outwith the footprint. Plotting the relationship between estimated numbers of birds and the closest distance to the centre of a wind farm would indicate possible gradient effects, assuming these effects were symmetrical around the effect. A smooth function fitted to these data would allow any trends to be identified particularly in the presence of over plotting points.

The centres of the wind farms are shown in Appendix C Figure C5. In these data, the minimum closest distance to the centre of a wind farm for any of the prediction grid cells was 124 m. For the wind farms present in 2011, all prediction grid cell points within the footprint of a wind farm were within 3.1 km of the centre. A wind farm with a much larger footprint was constructed by 2015 and the maximum distance to the centre for a grid cell within this footprint was 7.5 km.

Similar to assessing hypothesised changes in shipping, the effects of extending, or removing, wind farms or other anthropogenic effects on the numbers of birds could also investigated, depending on the variables included in the final model. For example, if the variable $windfarm$ (i.e. the presence/absence of a wind farm) was retained in the final model, then the impact of removing the wind farm was investigated by estimating numbers using the observed values for the variable $windfarm$ and then comparing these with estimated numbers after changing all values in the prediction grid indicating presence of a wind farm to absence of a wind farm. To illustrate any differences, the prediction data for the most recent survey (February 2015) was used.

Location of wind farms has been included as presence/absence and so any differences will necessarily be limited to the footprint of the wind farm and thus may be underestimated if there is an effect of the wind farm beyond the boundary. Nevertheless, the differences in estimated numbers, with and without wind farms, can be plotted against the closest distance to the centre of a wind farm in order to assess how the differences change as distance from the centre of a wind farm increases.

Similarly (although outwith the scope of this project), the effects of extending a wind farm could be investigated where the impact is imposed by identifying the records in the prediction grid where the wind farm is to be extended and changing the values for $windfarm$ from absence to presence although any results on the basis of this would still be speculative.

4. Results

4.1 Aerial survey data

Liverpool Bay SPA covers an area of approximately 1,900 km^2. The total length of transects flown during all surveys was over 4,040 km and the surveys covered a total area of 1,182 km^2 (Table 4.1.1). The transects were divided into 4,039 segments.

Common scoter were recorded in large numbers and the numbers per segment were very variable. Common scoter were identified as sitting on the water in 955 segments (23.6% of segments; Figure 4.1.1) and the median number of birds per segment (in segments where they were identified) was 10 birds. A few, very large groups of sitting common scoter were observed; the maximum number observed within one segment was 6,277 birds (identified during the survey on 24/01/2015).

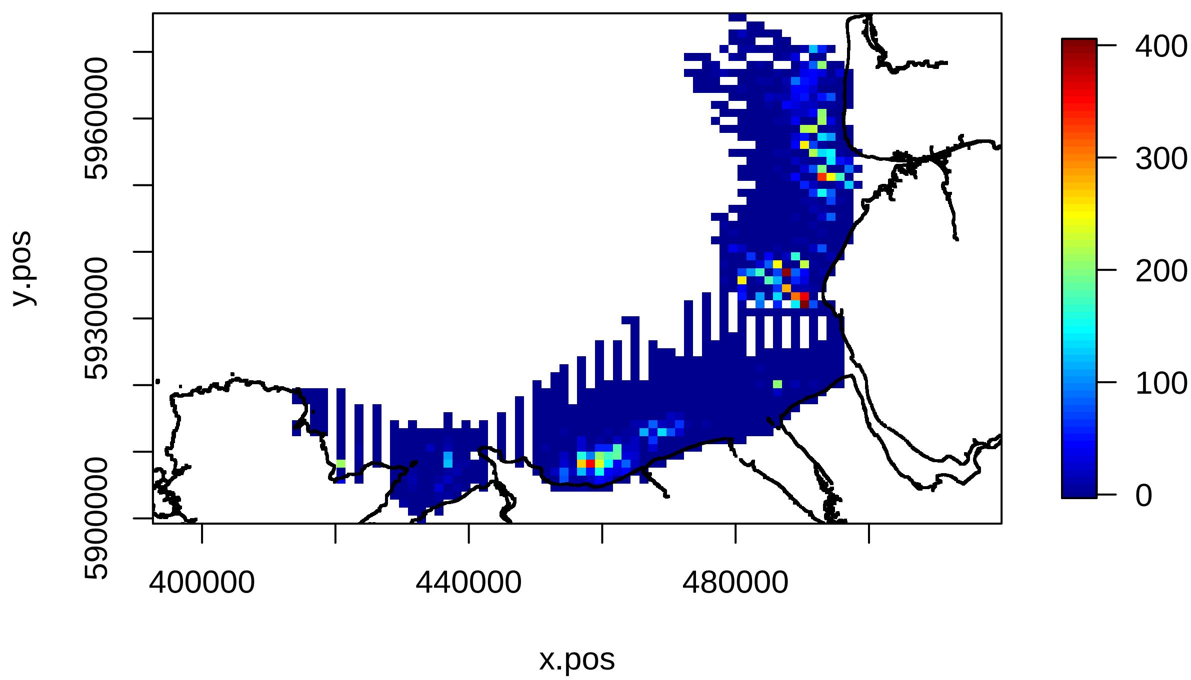

Figure 4.1.1 Numbers of sitting common scoter per segment averaged over all surveys. Since there were a few segments with very large numbers of birds, the numbers per individual segment have been capped at 1000 birds.

Flying common scoter were identified in only 214 segments (5.3% of segments; Figure 4.1.2) but as with sitting common scoter the number identified per segment was very variable. The median number per segment (where identified) was 3 birds and the maximum number identified per segment was 224 birds (seen on 07/03/2011).

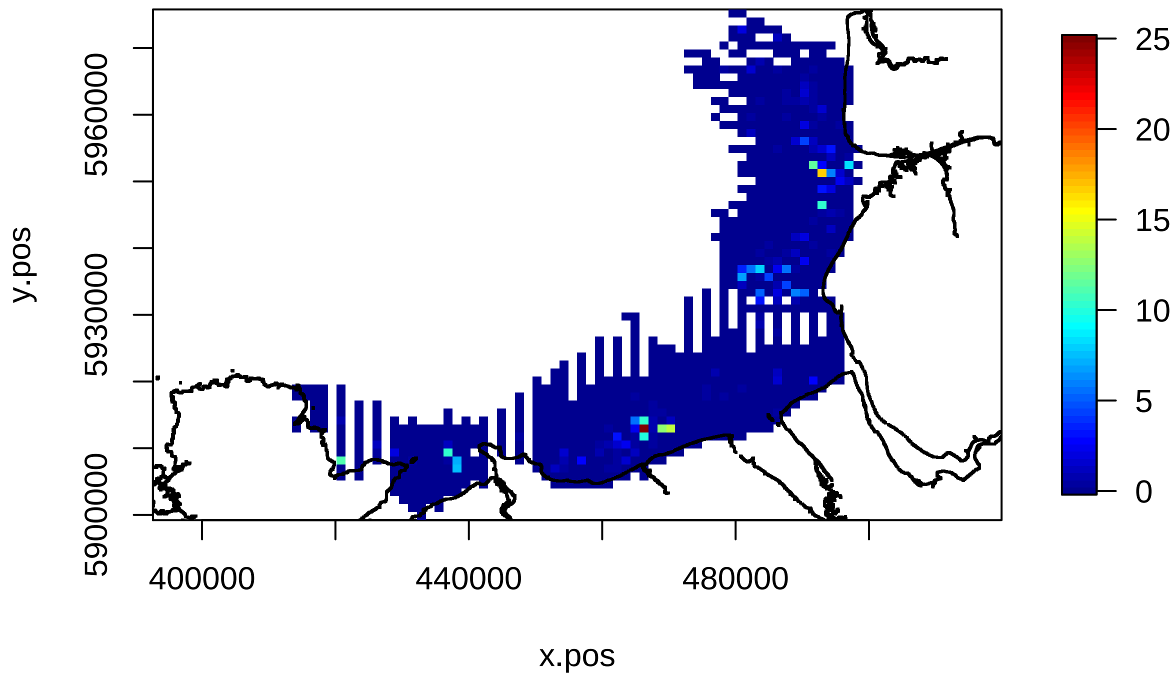

Figure 4.1.2 Numbers of flying common scoter per segment averaged over all surveys. The numbers per individual segment have been capped at 50 birds.

Red-throated diver were identified as sitting in 598 segments (14.8% of segments; Figure 4.1.3). The median number per segment (where identified) was one bird and the maximum number was 19 birds (recorded on 04/02/2015).

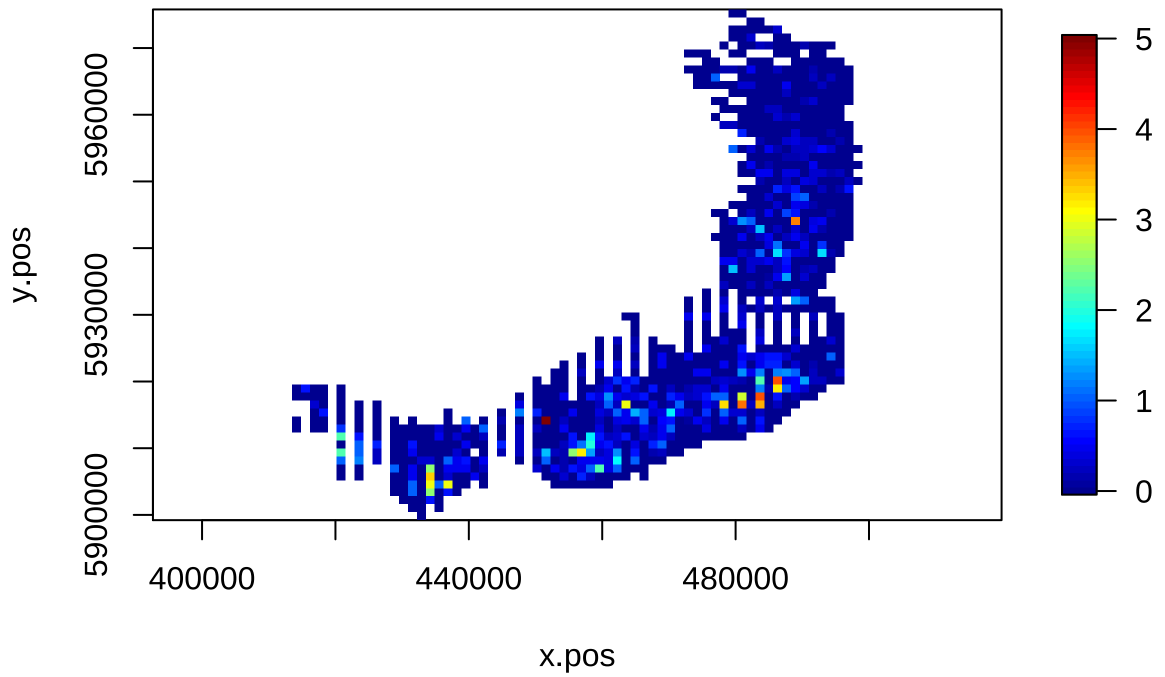

Figure 4.1.3 Numbers of sitting red-throated diver per segment averaged over all surveys.

Very few red-throated diver were identified as flying (22 birds recorded in total in 19 segments; Figure 4.4). This was too few to be able to analyse and so flying red-throated diver were not be considered further.

In general for all species, the majority of segments did not contain the species of interest and where birds were detected the numbers per segment were variable, particularly so for common scoter. The numbers of each species identified per segment for each survey are plotted in Appendix A.

Table 4.1.1 Summary of the aerial survey; L is the total length of transects covered during the survey (km), a is the total area of the strip covered (km^2) and the total numbers (N) of common scoter (CS) and red-throated diver (RTD) observed either sitting or flying.

Survey	Date	L	a	N CS sit	N CS fly	N RTD sit	N RTD fly
1	12/02/2011	708.4	124	6697	29	208	3
2	07/03/2011	697.8	122.1	4726	544	152	2
3	07/03/2011	585	102.4	2390	25	61	0
4	18/03/2011	591	103.4	4505	23	92	4
5	24/01/2015	742	371	34380	946	242	3
6	04/02/2015	717.3	358.6	41122	496	286	10
Total		4041	1182	93820	2063	1041	22

4.2 Identifying the 'group' of explanatory variables

The variables identifying ship traffic on the day of the survey were highly correlated for example, *shipAIS*1 (presence/absence of ship traffic on the day of the survey) and *shipnumf* (the number of ships intersecting the segment on the day of the survey) (Table 4.2.1). Hence, the regression coefficients associated with the factor levels could not all be estimated if they were included in the same model. The same was true with $shipAIS1$ and $shipcatAv$ (or $shipcatMax$) (Table 4.2.2). Thus, these four variables were grouped together and only one variable from this group was chosen.

Table 4.2.1 The number of segments in each level of $shipAIS1$ (rows) and $shipnumf$ (columns).

	0	1	2
0	3580	0	0
1	0	395	64

Table 4.2.2 The number of segments in each level of $shipAIS1$ (rows) and $shipcatAv$ (columns).

	0	1	2	3	4	5	6
0	1424	2156	0	0	0	0	0
1	0	0	128	65	89	86	91

The average length of ships in a segment was highly correlated to the maximum length of ships in a segment (Figure 4.2.1). Collinear relationships such as these were identified using the GVIF scores.

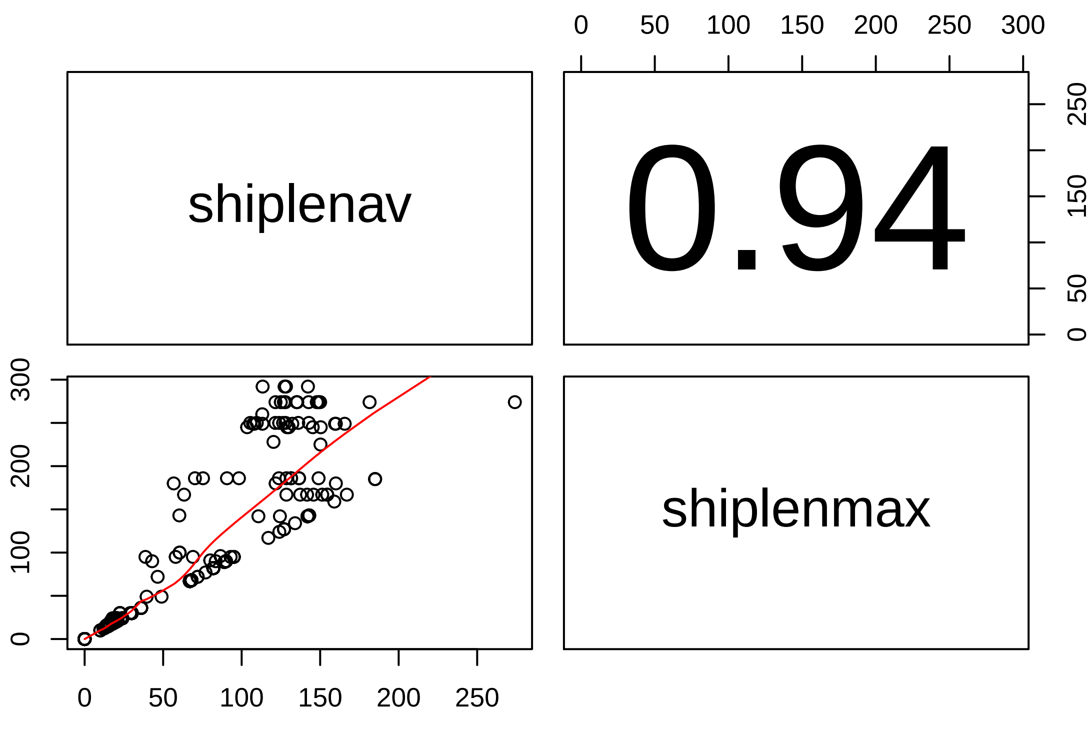

Figure 4.2.1 Scatter plot and (absolute) correlation between each pair of shipping length variables. The red line is a curve fitted to the pair of variables. The size of the text reflects the value of the correlation.

4.3 Red-throated divers sitting on the water

4.3.1 Selected model

Each candidate variable was assessed individually and although depth had the highest pseudo-R^2 fit score, each term fitted individually explained little of the variation observed in the response (Table 4.3.1). These very low scores are typical when overdispersion is high - even when we have a perfect data-model combination, values generated from this distribution can vary greatly from the mean when the mean is high giving rise to very large residuals and a low pseudo-R^2 score.The variable *shipcatAv* was selected from the variables grouped together because it had the lowest mean CV out of the four variables.

Table 4.3.1. Fit statistics for each term included separately to model red-throated diver counts ordered from best (according to average CV) to worst: average CV, and 2.5 and 97.5 percentile-based confidence limits, pseudo R^2 (R2, a measure of the squared correlation between the observed values and the fitted values from the model) and probability (p.value) associated with fitting each term separately. Numbers in the 'Group' column indicate variables which were grouped together and one variable from the group was chosen.

Variable	meanCV	lowCV	highCV	R2	p.value	Group
s(depth)	0.856	0.854	0.8584	0.02831	0	
shiplennear	0.8604	0.8597	0.8613	0.01884	1.412e-11	
as.factor(shipcatAv)	0.87	0.8691	0.8712	0.0118	0.02009	1
as.factor(shipMMO)	0.87	0.8692	0.8711	0.01035	0.01305	
as.factor(fish)	0.8702	0.8697	0.8712	0.01004	0.0002626	
as.factor(shipcatMax)	0.8704	0.8694	0.8718	0.01149	0.02385	1
as.factor(LBspa)	0.8707	0.8702	0.8712	0.01031	9.847e-07	
as.factor(windfarm)	0.8713	0.8709	0.872	0.0092	0.0003464	
s(shipnear)	0.8727	0.8705	0.8756	0.01242	4.687e-05	
as.factor(shipAIS1)	0.8732	0.8727	0.8738	0.007602	0.1262	1
as.factor(shipnumf)	0.8735	0.8729	0.8742	0.007577	0.2692	1
s(salinity)	0.8736	0.8718	0.8763	0.01269	9.292e-08	
s(shiplenmax)	0.8738	0.8723	0.8758	0.009091	0.0001043	
as.factor(shipAIS10)	0.874	0.8734	0.8748	0.007162	0.4525	
as.factor(shipAIS5)	0.8741	0.8736	0.8747	0.007171	0.4382	
as.factor(windcable)	0.8745	0.874	0.8752	0.007219	0.01743	
as.factor(anthrop)	0.8748	0.8743	0.8755	0.006726	0.1903	
s(shiplenav)	0.8776	0.872	0.901	0.009173	0	

Having chosen which term to include from those grouped together, the multi-collinearity of the remaining variables was assessed (Table 4.3.2). The term $shipMMO$ was likely collinear with *shipcatAv*; the CV scores for these two terms were very similar (Table 4.3.1) and since the *shipcatAv* included information on both transient shipping as well as more permanent shipping areas, *shipcatAv* was selected over $shipMMO$. Not surprisingly, *windcable* and *anthrop* were collinear (since one is a subset of the other) and *windcable* was selected because of potentially higher predictive power to unseen data as assessed by CV (Table 4.3.1). The adjusted GVIFs for *shiplenmax* and *shiplenav* were high but not above a threshold of 5 and so at this stage of the model selection process both these terms were included in the full model.

Table 4.3.2 Table of generalized variance inflation factors (GVIF) for red-throated divers, degrees of freedom (Df) and GVIFs adjusted for the degrees of freedom (GVIF^(1/2*Df)).

	GVIF	Df	GVIF^(1/(2*Df))
depth	1.845	1	1.358
shiplennear	1.719	1	1.311
as.factor(shipcatAv)	663.7	6	1.719
as.factor(shipMMO)	32.69	1	5.718

	GVIF	Df	GVIF^(1/(2*Df))
as.factor(fish)	1.179	1	1.086
as.factor(LBspa)	1.025	1	1.012
as.factor(windfarm)	1.038	1	1.019
shipnear	1.774	1	1.332
salinity	1.373	1	1.172
shiplenmax	15.85	1	3.981
as.factor(shipAIS10)	2.399	1	1.549
as.factor(shipAIS5)	2.425	1	1.557
as.factor(windcable)	5800155	1	2408
as.factor(anthrop)	5800155	1	2408
shiplenav	11.8	1	3.435

The variables *shiplennear* and *shiplenav* were included in the full model as linear terms was one because there were problems fitting them as flexible functions due to gaps in the covariate ranges providing little support for nonlinearities. The stages in the model selection process are summarised in Table 4.3.3. Not surprisingly, the fit score for the full model was improved compared to fitting terms individually and this score did not change substantially as non-significant factor and one-dimensional terms were removed. The addition of the two-dimensional term for location substantially improved the fit score to both the observed data (assessed by the pseudo-R^2) and to data unseen by the model (assessed by CV). .

Table 4.3.3. The iterations in model selection for red-throated divers; starting with the full model, the 'Model' column indicates terms that were dropped from ('-') or added to ('+') the model and shows the mean CV and percentile-based confidence limits associated with the model; the pseudo-R^2 fit score; the 'p.value' shows the probability associated with the term excluded/included from the model. 's(.)' indicates a smooth term.

NumIter	Model	meanCV	CI_2.5	CI_97.5	R2	p.value
1	Full model	0.8488	0.8327	0.8994	0.07248	NA
2	- as.factor(shipAIS5)	0.8478	0.8323	0.8971	0.07242	0.992
3	- shiplenmax	0.8745	0.8327	1.035	0.07303	0.9815
5	- as.factor(fish)	0.8779	0.8317	1.048	0.07355	0.597
5	- as.factor(fish)	0.8716	0.8316	1.014	0.07221	0.2684
6	- as.factor(shipAIS10)	0.8717	0.8316	1.019	0.07037	0.2309
7	- as.factor(shipcatAv)	0.8323	0.8281	0.8379	0.06849	0.1518
8	+ s(x.pos,y.pos)	0.7942	0.7875	0.8037	0.1317	5.045e-08

An interaction was considered between location and *shiplenav* and *shiplennear* (Table 4.3.4). Although the *p*-value associated with *shiplennear* was significant, the CV scores and pseudo-R^2 fit score did not indicate that an interaction term should be included, therefore, an interaction term was not included.

Table 4.3.4 Assessment of an interaction term in the model for red-throated divers; the top row provides the CV (mean and percentile-based confidence limits), pseudo-R^2 fit score and the p.value for the two-dimensional smooth for location with no interaction for comparison.

Term	meanCV	CI_2.5	CI_97.5	R2	p.value
s(x.pos,y.pos)	0.7942	0.7875	0.8037	0.1317	5.045e-08
s(x.pos,y.pos):shiplenav	0.8061	0.8011	0.8123	0.1094	0.2274
s(x.pos,y.pos):shiplennear	0.8004	0.795	0.8065	0.1179	0.0004607

The final model for red-throated diver included the following variables:

- factors, $LBspa$ and $windfarm$
- linear terms, *shiplennear* and *shiplenav*,
- one dimensional smooth terms $shipnear$, *depth* and *salinity* and
- location as a two-dimensional term between $x.pos$ and $y.pos$.

The fit score of the final model was 0.13 was an improvement over the other models fitted, whilst not capturing a substantial amount of the variation observed in the numbers of red-throated diver given the high overdispersion. The significance associated with each term is shown in Table 4.3.5.

Table 4.3.5 Analysis of variance table for the final model fitted to red-throated diver data; the number of degrees of freedom (Df), test statistic (X2) and *p*-value associated with each term in the model (P(>|Chi|)).

Table 10: Analysis of 'Wald statistic' Table

	Df	X2	P(>|Chi|)
as.factor(LBspa)	1	16.7	4.385e-05
as.factor(windfarm)	1	22.17	2.501e-06
shiplennear	1	11.9	0.0005607
shiplenav	1	4.955	0.02602
s(depth)	3	77.93	1.11e-16
s(shipnear)	4	23.25	0.0001131
s(salinity)	3	7.772	0.05097
s(x.pos, y.pos)	8	49.52	5.045e-08

In terms of assessment of the final model, the residuals did not cause any concerns regarding model fit (Figure 4.3.1). The predicted values are shown in the next section (Figure 4.3.4) and exhibited good agreement with the observed values (Figure 4.3.1). Further details of the model selection process and assessment for red-throated divers are included in Appendix D.

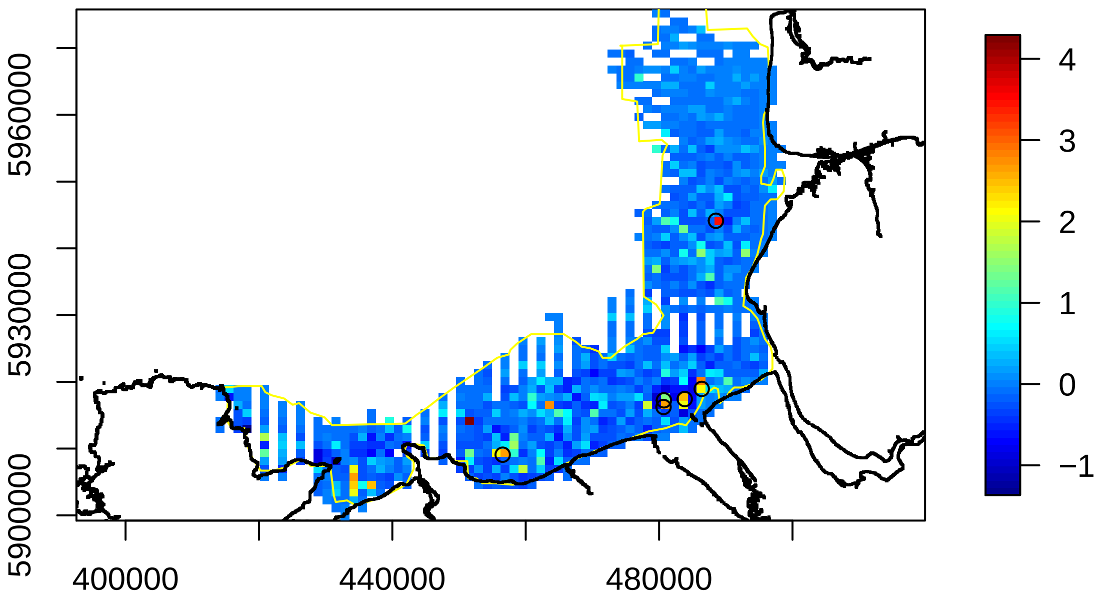

Figure 4.3.1 Residuals (difference between the observed number of birds and predicted number) averaged over all surveys. The yellow line indicates the approximate boundary of Liverpool Bay SPA. The black circles indicate the location of segments where large numbers of birds (>10 birds per segment) were observed.

The relationships of the variables (factors and one-dimensional terms) to the response (i.e. numbers of red-throated divers), given the other variables in the model, are shown in Figure 4.3.2. For red-throated divers, being inside Liverpool Bay SPA had a significant positive effect on the predicted numbers of birds compared to outside the SPA and the presence of a wind farm had a negative effect compared to the absence of a wind farm. The plot for *shiplennear* (length of the nearest ship) indicated a significant negative relationship so that the predicted average number of birds per segment decreased as the length of the nearest ship increased. For *shipnear* (distance to nearest ship), the important distance appeared to be about 2 km; within that range the predicted average numbers increased as the distance increased (i.e. the nearest ship was further away) and beyond that distance the relationship became considerably more uncertain and potentially the relationship was non-significant (i.e. no change in the response). There was also uncertainty associated with fitted function for *shiplenav* (average length of ships) and this positive relationship may be being driven by a few points at large values; the lower confidence interval was only just above, if not, zero.

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[1] "Making partial plots"
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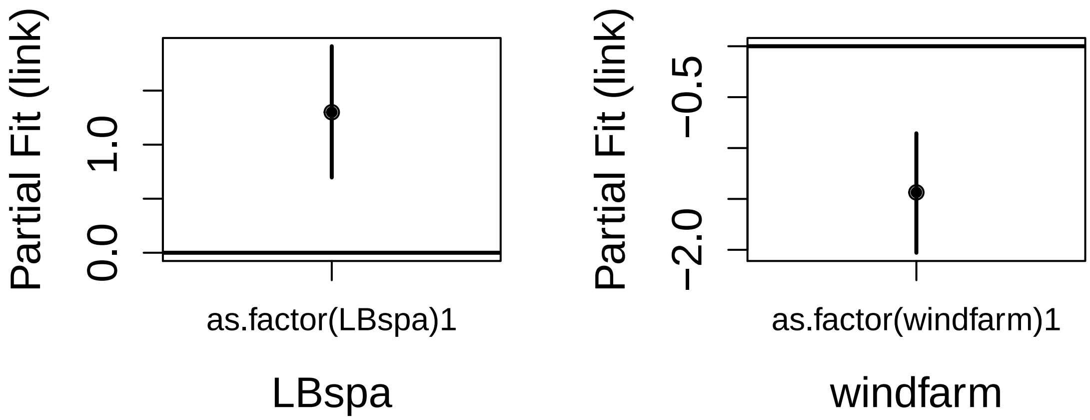

Figure 4.3.2a Relationship between the response and the factors in the final model for red-throated divers given the other variables in the model (on a logarithmic scale). For factors, the estimated coefficient (dot) and confidence interval (vertical line) are shown for each estimated factor coefficient with respect to factor level 0 which is used as a baseline, or reference, level. A positive value indicates an increase in the response, as for $LBspa$ factor level one (i.e. inside Liverpool Bay SPA), and a negative value indicates a decrease as for $windfarm$ factor level one (i.e. presence of a wind farm).

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[1] "Making partial plots"
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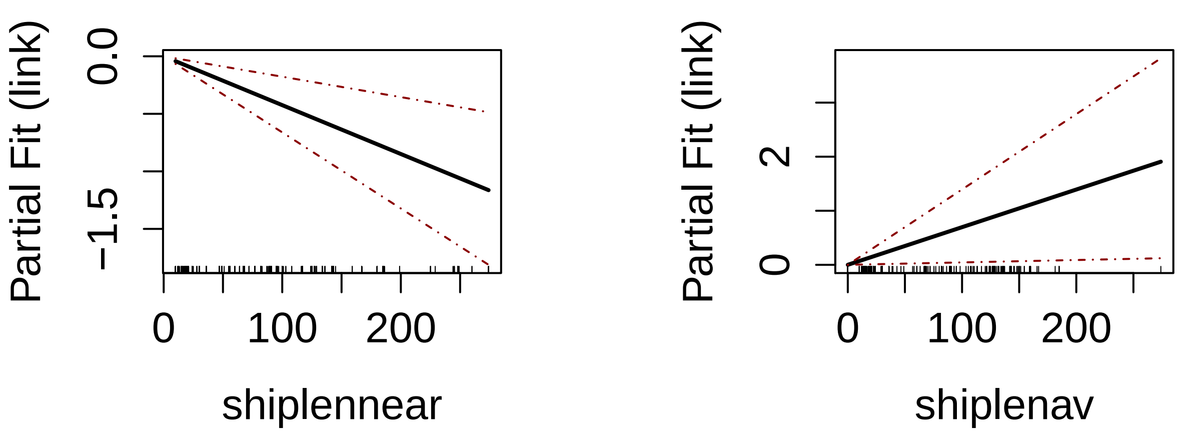


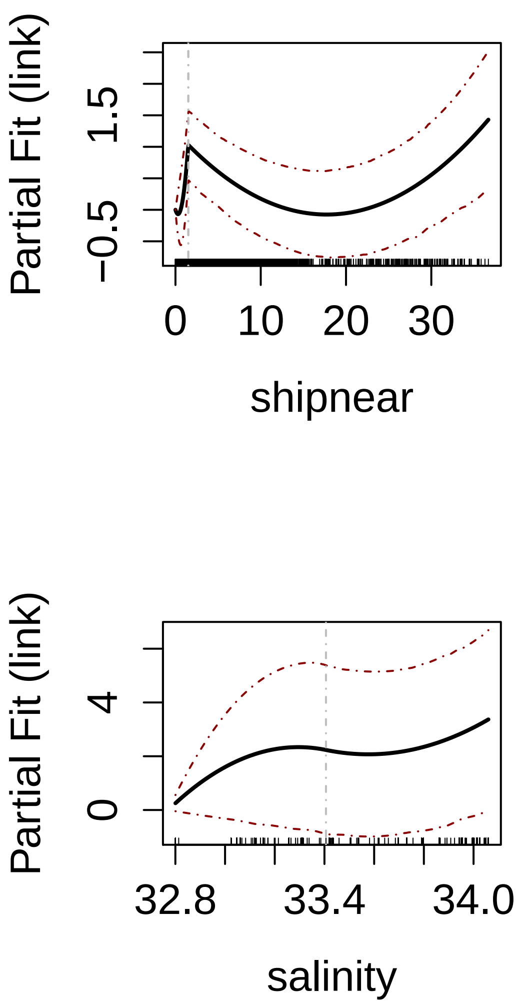


Figure 4.3.2b Relationship between the response and the one-dimensional terms in the final model for red-throated divers given the other variables in the model (on a logarithmic scale). The solid line indicates the relationship, the dashed lines show the confidence interval and the ticks along the x-axis indicate the observed values. A positive value indicates an increase in the response and a negative value indicates a decrease. The plot for *shiplennear* (length of the nearest ship; m) indicates that the number of birds decreases as the length of the nearest ship increases. For *shiplenav* (the average length of a ship in a segment; m) indicates the opposite, however, there is a gap in the distribution of observed values for this variable and this relationship may be being driven by a small number of observations with large values for *shiplenav* and so caution should be applied in interpreting this relationship. The increasing CI is due to the smaller numbers of observations as *shiplenav* increases. For *shipnear* (distance to nearest ship; km), as the distance increases (i.e. the ship is further away) to approximately 2 km, the number of birds increases, beyond 2 km the number decreases and then increases with high uncertainty. The plots for *depth* (m) and *salinity* (ppt) indicate a preference for a depth of approximately 5 m and salinity higher than 33 ppt, however, there is also considerable uncertainty about these fitted functions (shown by the wide confidence intervals). There is a gap in the distribution of observed values for salinity and so the first part of the curve is being driven by a few points with low values for salinity.

4.3.2 Estimated abundances

The shipping metrics and wind farm variable in the final model were survey specific and so prediction was made using the prediction data for each of the five survey dates (Figure 4.3.3) and then averaged over all surveys (Figure 4.3.4).

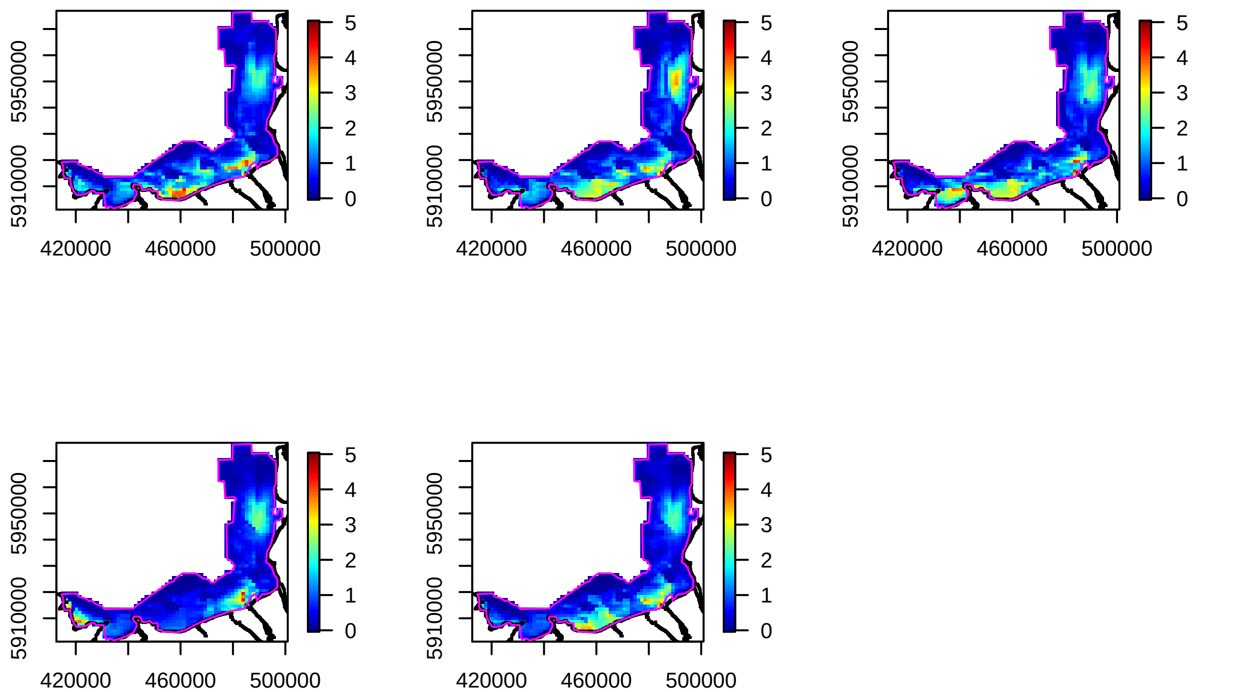


Figure 4.3.3 Estimated numbers of red-throated diver sitting per grid cell (1 km^2) based on the observed values for each survey date. The magenta line indicates the boundary of Liverpool Bay SPA.

The estimated total abundance of birds within Liverpool Bay SPA for each survey are shown in Table 4.3.6. Overall, the number of birds per grid cell (approximately 1 km^2) is low with highest numbers found towards the coast (Figure 4.3.4). The uncertainty associated with estimated abundance surface was low (Figure 4.3.5).

Table 4.3.6 Estimated abundances (N) and 95 percentile-based confidence intervals for red-throated divers sitting on the water for each survey date.

Date	Estimated.N	CI_2.5	CI_97.5
12/02/2011	1599.015	1413.918	1983.153
07/03/2011	1648.555	1458.337	2028.235
18/03/2011	1674.023	1476.951	2067.427
24/01/2015	1252.630	1106.238	1574.145
04/02/2015	1383.624	1265.284	1639.442
Mean	1511.569	1368.189	1816.919

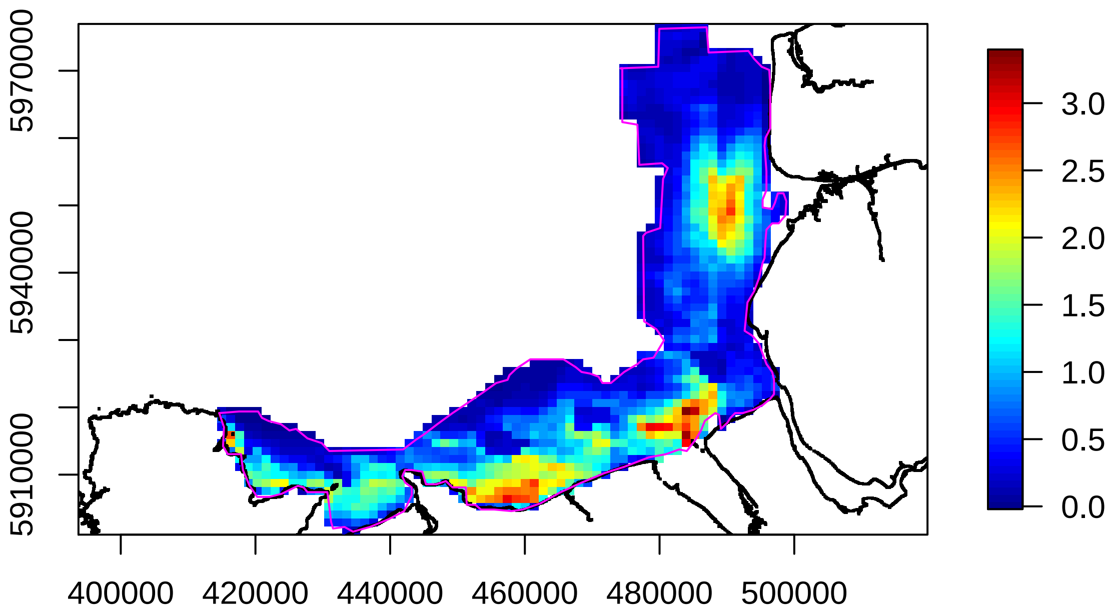


Figure 4.3.4 Estimated numbers per grid cell (1 km^2 approx.) of sitting red-throated divers averaged over all survey dates.

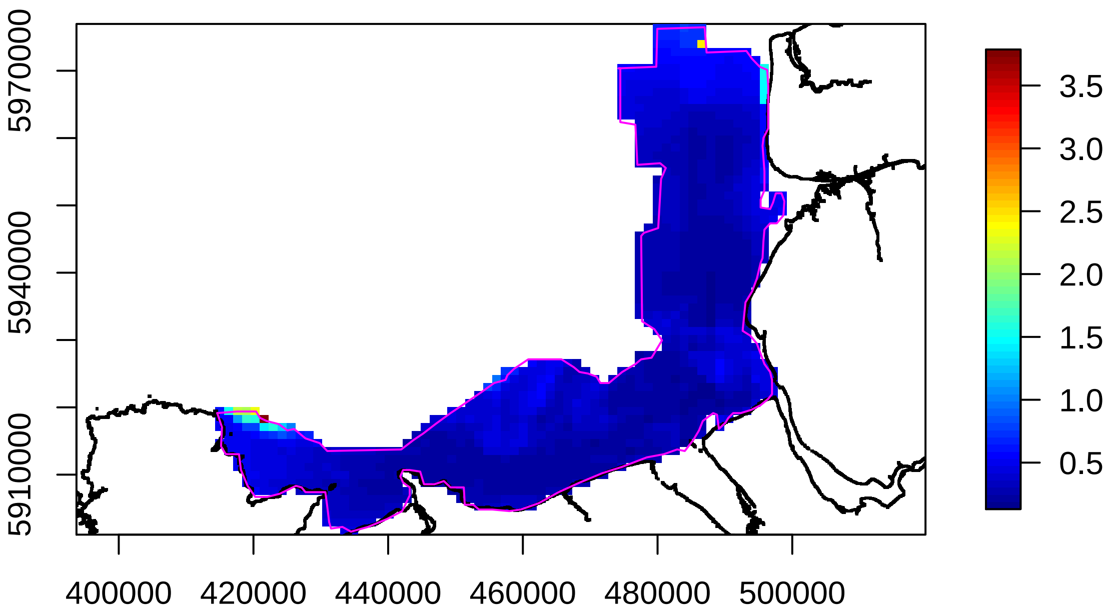


Figure 4.3.5 Coefficients of variation associated with the estimated numbers per grid cell for sitting red-throated diver averaged over all surveys. The magenta line indicates the approximate boundary of Liverpool Bay SPA.

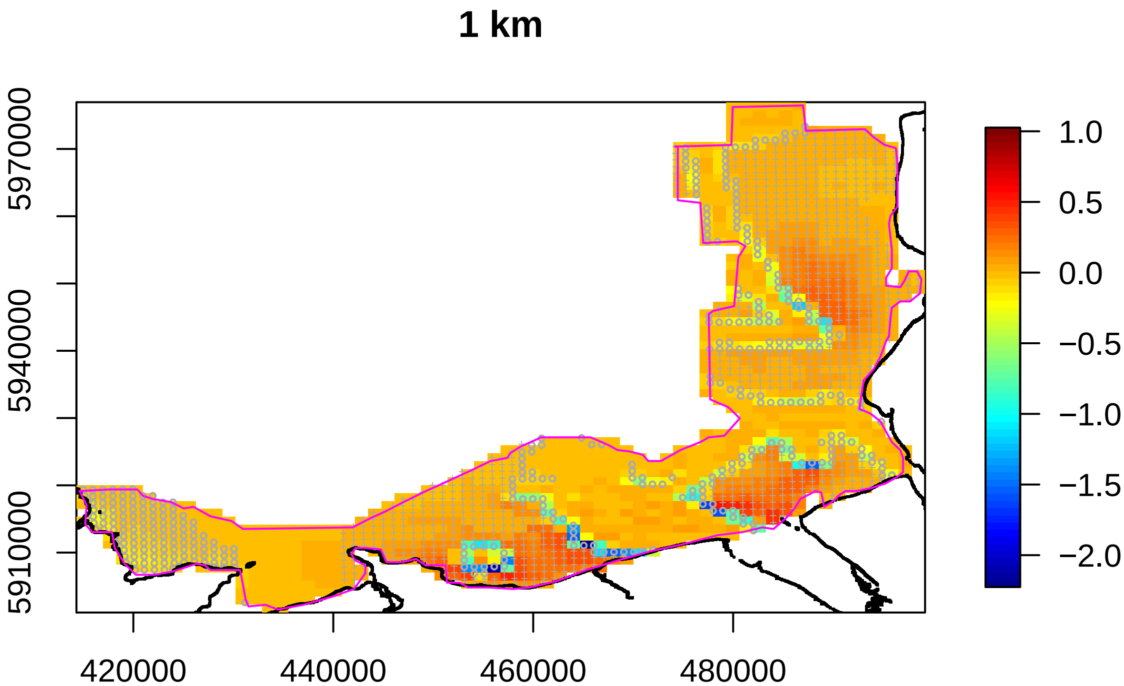
4.3.3 Impact of shipping

For red-throated divers, the shipping metrics chosen were the nearest distance to a ship (*shipnear*) and two metrics based on length (*shiplennear* and *shiplenav*). To illustrate the effect of the shipping using these metrics, two scenarios were considered:

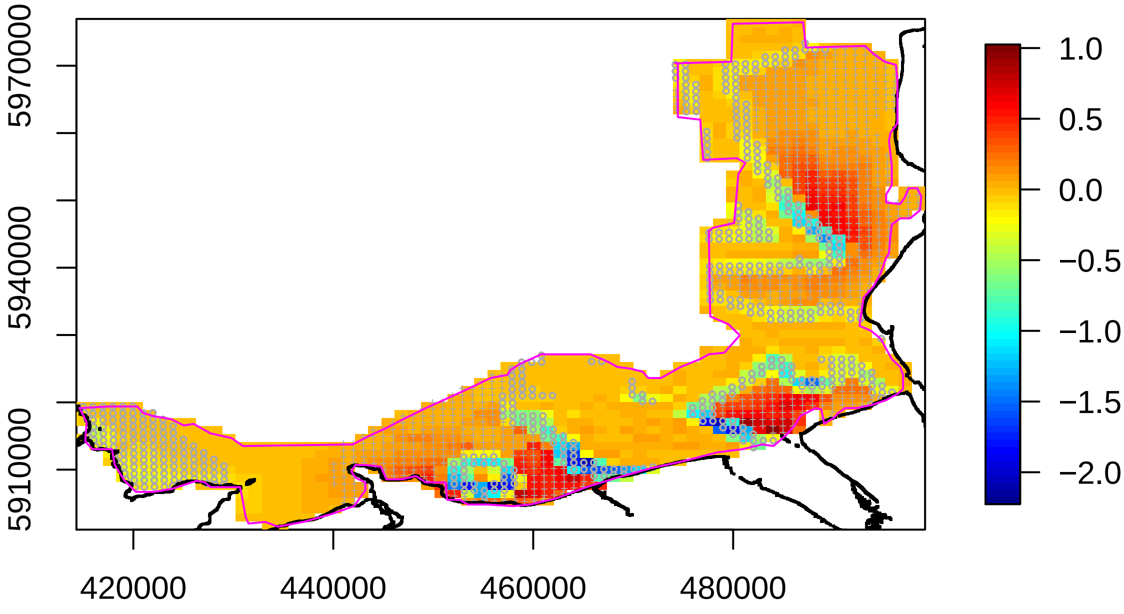
1. there are ships in more places throughout the region so that the nearest distance to a ship, compared to observed values, decreased by 1 km, 2 km and 3 km.
2. an increase of 20 m in the length of ships compared to observed values so that the length of the nearest ship was increased by 20 m and the average length of a ship (where present in a segment) was also increased by 20 m.

These scenarios were illustrated using the observed values of explanatory variables for the February 2015 survey.

The first scenario, impact of reducing the nearest distance to a ship involved the variable *shipnear* and reducing this by 1 km, 2 km and 3 km compared to observed values (up to the minimum distance observed in the data) (Figure 4.3.6). To help interpret these plots also see the observed values for *shipnear* shown in Appendix G and the estimated function for *shipnear* in Figure 4.3.2b. Figure 4.3.6 shows that where the distance to the nearest ship was already very short (i.e. a ship was recorded within the grid cell) there was little impact, however, around these cells (where the observed nearest distance to a ship was approximately 1 to 2 km) there was a negative impact on predicted numbers as the distance to the nearest ship decreased (i.e. the nearest ship moved closer). This region increased in width as the reduction in the nearest distance increased. Positive impacts occurred in regions where the nearest distance to ships were observed to be between about 2 km and 18 km (e.g. in the north of the region). Where observed distances to the nearest ship were long (i.e. in the south west of the region) a decrease in numbers was observed due to the estimated smooth function for *shipnear* increasing after approximately 18 km. There were small reductions in overall predicted abundance within the Liverpool Bay SPA (Table 4.3.7).



2 km


5970000
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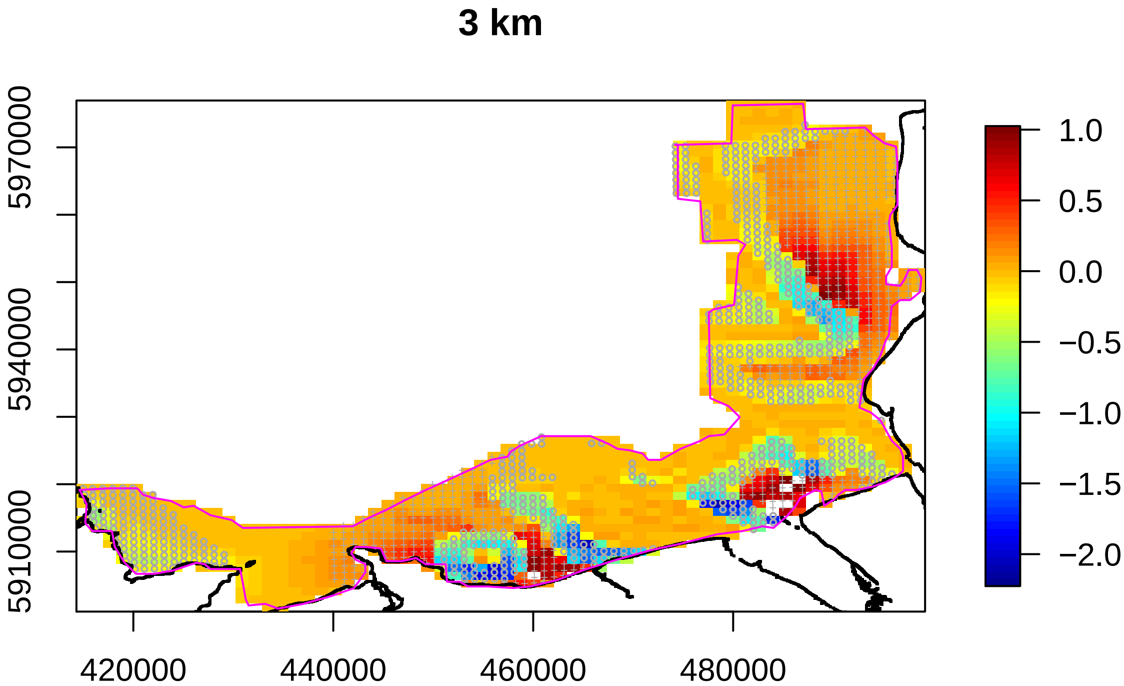

Figure 4.3.6 The differences in numbers of red-throated divers per grid cell when a decrease of 1 km, 2 km and 3km in the nearest distance to a ship is imposed on prediction data for February 2015. Symbols indicate significant differences, an increase in the number of birds (+) and a decrease in the number of birds (o).

For the second scenario, the imposed impact of increasing the length of the ships by 20 m is shown in Figure 4.3.7; this involved increasing the variables *shiplennear* and *shiplenav* (where ship were present) by 20 m compared to observed values. This shows that there was generally a significant decrease in the number of birds except where there were ships already present in a segment, in which case there was a small and non-significant increase (see Appendix G). Increasing the length of the nearest ship had a negative effect but where ships were already present this was offset somewhat by the positive effect due to *shiplenav* (see Figure 4.3.2b). The impacts on overall abundance within Liverpool Bay SPA are given in Table 4.3.7.

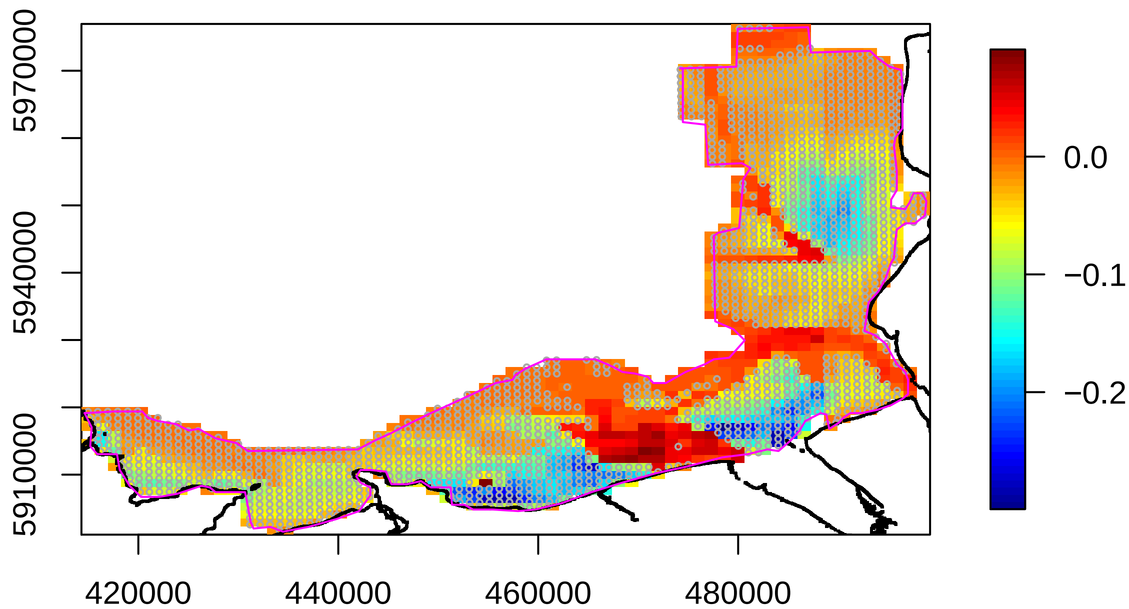

Figure 4.3.7 The differences in numbers of red-throated divers per grid cell when an increase of 20m is imposed on the length of the nearest ship and also on the length of a ship where present in a segment using the observed prediction data for 2015. Symbols indicate significant differences, an increase in the number of birds (+) and a decrease in the number of birds (o).

Table 4.3.7 Estimated abundances and 95 percentile-based confidence intervals for red-throated divers under hypothesised changes; scenario 1, decrease in the distance to the nearest ship and scenario 2, increase in the length of ships.

Date	Estimated.N	CI_2.5	CI_97.5	Scenario	Change
04/02/2015	1384	1265	1639	No change	
04/02/2015	1353	1208	1644	1	1 km
04/02/2015	1303	1140	1629	1	2 km
04/02/2015	1235	1053	1626	1	3 km
04/02/2015	1295	1154	1543	2	20 m

4.3.4 Impact of wind farms

Any buffering effect of a wind farm can be assessed by plotting the estimated number of birds per grid cell (given observed locations of wind farms) against closest distance from the centre of a wind farm. The estimated number of red-throated divers using all prediction data were plotted against the closest distance to the centre of a wind farm (Figure 4.3.8). There were few points very close to the centre of a wind farm and uncertainty of the fitted function was highest in this region. Moving away from the centre, numbers increased and, over all estimates, remained constant beyond about 3.8 km away the centre of a wind farm.

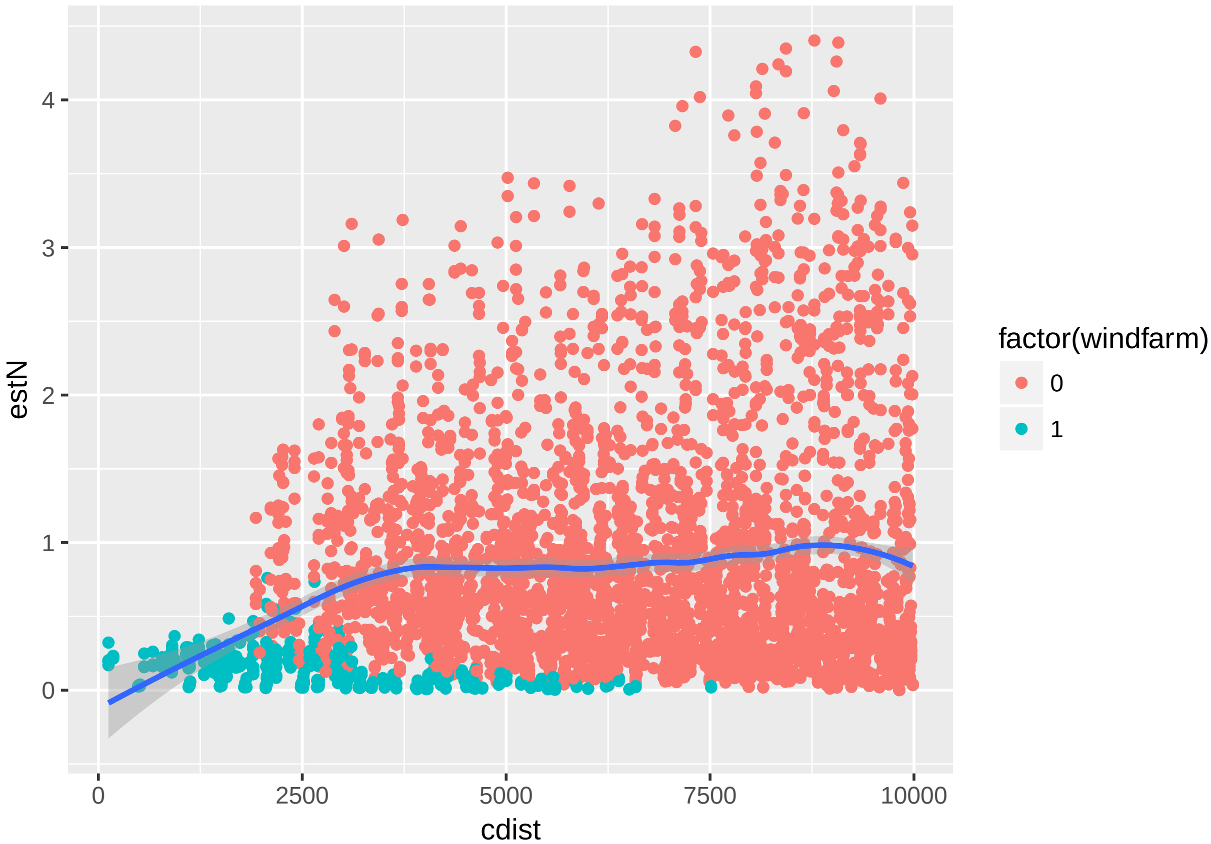

Figure 4.3.8 Estimated numbers of red-throated divers per grid cell (estN) against the closest distance to the centre of a wind farm (cdist, m) using all the prediction data (i.e. all survey dates). Values have been limited to a distance of 10 km from the centre of a wind farm and colour distinguishes points outside (0) or inside (1) the footprint of a wind farm. The grey region is a 95% confidence interval around the fitted function.

The impact of removing wind farms was illustrated using the prediction data for the February 2015 survey and changing the variable indicating the presence/absence of a wind farm ($windfarm$); the differences in numbers estimated with and without wind farms were calculated. Although the increase in the predicted abundance in the Liverpool Bay SPA was small (Table 4.3.8) there was a significance increase in numbers per grid cell within the footprint of the wind farms after imposing the hypothetical removal of the wind farms.

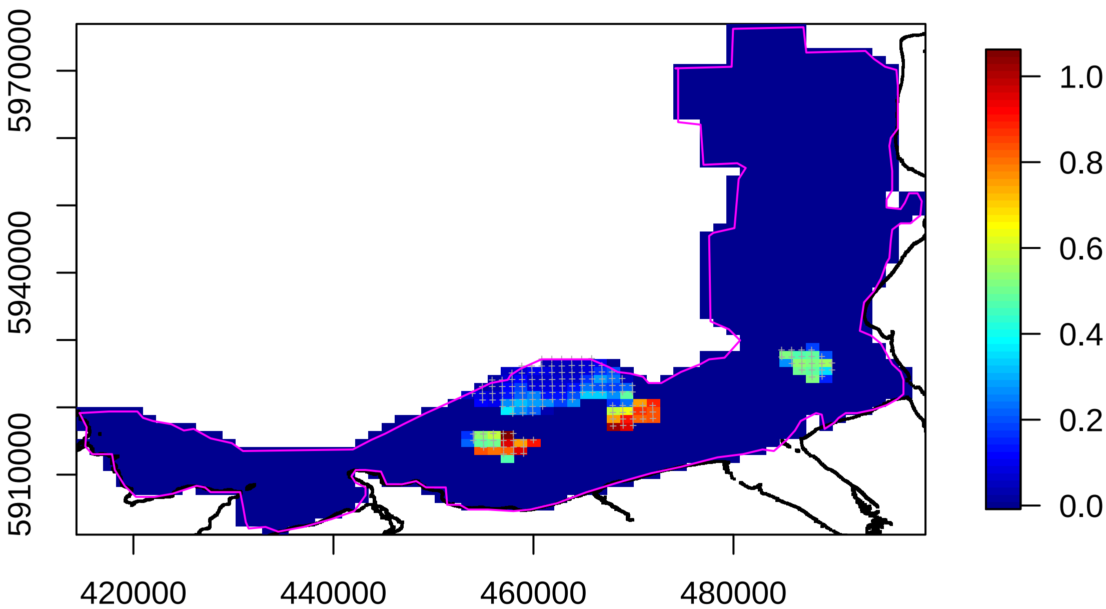

Figure 4.3.9 The differences in numbers of red-throated divers per grid cell after removing wind farms from the February 2015 prediction data. Symbols indicate significant differences, an increase in the number of birds (+) and a decrease in the number of birds (o).

Table 4.3.8 Estimated abundances of red-throated divers with and without wind farms for the February 2015 prediction data.

Date	Estimated.N	CI_2.5	CI_97.5	Scenario
04/02/2015	1384	1265	1639	No change
04/02/2015	1440	1318	1700	Wind farms removed

Figure 4.3.9 illustrates the locations of the differences in numbers with and without wind farms for one survey date. Table 4.3.8 shows the estimated abundance in red-throated divers for the Liverpool Bay SPA after removing the wind farms in the February 2015 prediction data.

Figure 4.3.10 looks at differences in numbers (within the wind farm footprints) over all prediction data against distance to the centre of the wind farm. The differences remained constant within about 2 km from the centre but declined further way from the centre; in 2011 all points within a wind farm footprint were within 3.1 km and in 2015 this distance increased to 7.5 km.

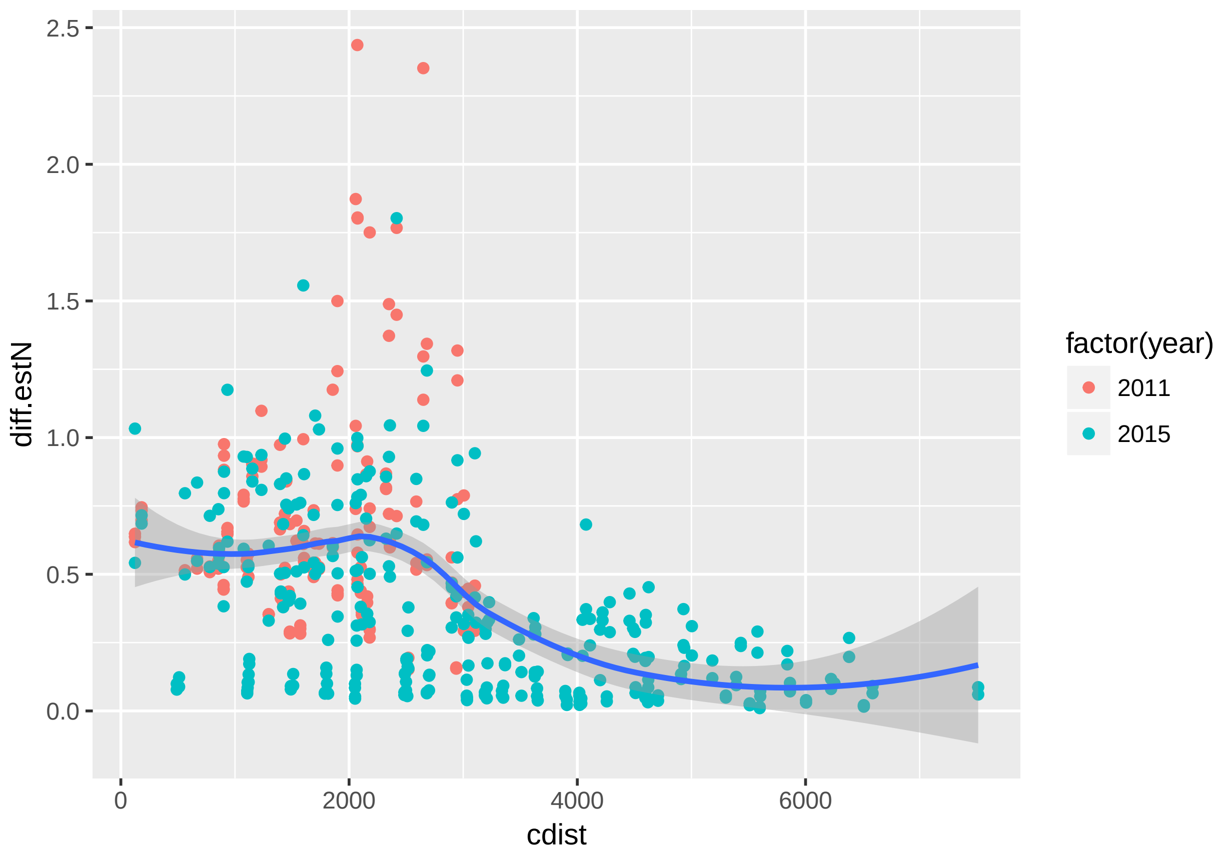

Figure 4.3.10 Difference in estimated numbers of red-throated divers per grid cell (diff.estN) with and without wind farms against the closest distance to the centre of a wind farm (cdist, m) using all prediction data. The grey region is a 95% confidence interval around a smooth function fitted to these data.

4.4 Common scoter sitting on the water

4.4.1 Selected model

Each candidate variable was assessed individually and although it was again depth which had the highest pseudo-R^2 fit score, each term fitted individually explained little of the variation observed in the response due to the overdispersion (Table 4.4.1). The variable *shipcatAv* was selected from the variables grouped together because it had the lowest mean CV out of the four variables.

Table 4.4.1. Fit statistics including each term separately to model sitting common scoter counts: average CV, and 2.5 and 97.5 percentile confidence limits, pseudo-R^2 (R2, a measure of the correlation between the observed values and the fitted values from the model) and probability (p.value) associated with fitting each term separately. Numbers in the 'Group' column indicate which variables were grouped together and one variable from the group was chosen.

Variable	meanCV	lowCV	highCV	R2	p.value	Group
s(depth)	15676	15618	15761	0.05513	0	
as.factor(shipcatAv)	15766	15747	15801	0.04842	1.592e-14	1
as.factor(shipcatMax)	15766	15750	15792	0.04841	1.794e-14	1
as.factor(shipMMO)	15795	15776	15820	0.04692	1.419e-13	
as.factor(shipAIS10)	15803	15790	15819	0.04253	5.094e-18	
s(salinity)	15956	15905	16027	0.04004	5.869e-07	
s(shipnear)	15995	15943	16050	0.03665	0.0004311	

Variable	meanCV	lowCV	highCV	R2	p.value	Group
as.factor(shipAIS5)	16013	16001	16037	0.02929	4.364e-08	
as.factor(shipnumf)	16047	16038	16059	0.02658	5.131e-07	1
as.factor(shipAIS1)	16048	16037	16066	0.02658	1.789e-07	1
shiplenav	16055	16045	16069	0.02652	0.009855	
s(shiplenmax)	16076	16047	16111	0.02658	1.11e-16	
as.factor(windfarm)	16087	16079	16100	0.02411	1.324e-05	
as.factor(LBspa)	16110	16101	16127	0.02249	0.001553	
as.factor(anthrop)	16139	16130	16150	0.02108	0.8328	
shiplennear	16140	16126	16160	0.02021	0.1393	
as.factor(windcable)	16140	16129	16154	0.02088	0.3196	
as.factor(fish)	16143	16130	16161	0.02178	0.2867	

Having chosen which term to include from those grouped together, the multi-collinearity of the remaining variables was assessed (Table 4.4.2). The term *shipMMO* was likely collinear with *shipcatAv* and as with red-throated divers, *shipcatAv* was selected over *shipMMO*. The terms *anthrop* and *windcable* were identified as being collinear and *anthrop* was selected because of potentially higher predictive power to data seen and unseen by the model (Table 4.4.1). Also, the adjusted GVIFs for *shiplenav* and *shiplenmax* indicated high correlation and *shiplenav* was selected over *shiplenmax* based on it's lower CV score.

Table 4.4.2 Table of generalized variance inflation factors (GVIF) for sitting common scoter, degrees of freedom (Df) and GVIFs adjusted for the degrees of freedom (GVIF^(1/2*Df)).

	GVIF	Df	GVIF^(1/(2*Df))
as.factor(shipcatAv)	2578	6	1.924
as.factor(shipMMO)	161.2	1	12.7
as.factor(shipAIS10)	4.24	1	2.059
as.factor(shipAIS5)	4.235	1	2.058
as.factor(windfarm)	1.002	1	1.001
as.factor(LBspa)	1.05	1	1.025
as.factor(anthrop)	3775264	1	1943
as.factor(windcable)	3775264	1	1943
as.factor(fish)	1.235	1	1.111
shiplennear	1.46	1	1.208
depth	1.674	1	1.294
salinity	1.292	1	1.137
shipnear	1.325	1	1.151
shiplenav	34.2	1	5.848
shiplenmax	42.49	1	6.518

The stages in the model selection process are summarised in Table 4.4.3. The variables *shiplennear* and *shiplenav* were included as linear terms, because there were problems fitting them as smooth functions. The pseudo-R^2 fit scores did not change substantially when non-significant terms were removed from the full model. After selecting factor and one-dimensional and including a two-dimensional term for location, there were four variables retained in the model that could potentially form an interaction with the two-dimensional smooth term of location. Each was tried in turn and the term selected for an interaction was $shipAIS5$ based on the mean CV score (Table 4.4.4).

Table 4.4.3. The iterations in model selection for common scoter sitting; starting with the full model, the 'Model' column indicates terms that were dropped from ('-') or added to ('+') the model and shows the mean CV and percentile-based confidence limits associated with the model, fit score pseudo-R^2 and the 'p.value' column shows the probability associated with the term excluded/included from the model. 's(.)' indicates a

smooth term.

NumIter	Model	meanCV	CI_2.5	CI_97.5	R2	p.value
1	Full model	15621	15465	15814	0.08573	NA
2	- salinity	15579	15441	15760	0.08609	0.7154
3	- as.factor(LBspa)	15575	15438	15757	0.08602	0.5052
4	- s(shipnear)	15585	15485	15750	0.0763	0.2896
5	- as.factor(fish)	15520	15417	15653	0.07534	0.6259
6	- shiplennear	15447	15343	15624	0.08041	0.1784
7	- as.factor(anthrop)	15438	15338	15583	0.0798	0.1522
8	+ s(x.pos,y.pos)	21019	15045	15444	0.1163	0.001876
9	+ s(x.pos,y.pos):shipAIS5	14791	14567	15123	0.1682	0.0003929

Table 4.4.4 CV scores for the candidate variables to include as a interaction term with location for sitting common scoter. The values for `s(x.pos, y.pos)` are included for comparison.

Term	meanCV	CI_2.5	CI_97.5	R2	p.value
s(x.pos,y.pos)	21019	15045	15444	0.1163	0.001876
s(x.pos,y.pos):as.factor(shipcatAv)	8.124e+16	14578	1.204e+10	0.1648	0
s(x.pos,y.pos):as.factor(shipAIS5)	14822	14584	15263	0.1682	0.0003929
s(x.pos,y.pos):as.factor(shipAIS10)	15194	14988	15509	0.1345	0.01796
s(x.pos,y.pos):shiplenav	15585	14794	15298	0.1343	0.0001553

The pseudo-R^2 fit score for the final model was 0.17 which while better than the other models assessed is low, however, these data in particular, were very variable and it will be difficult to capture this variability. The final model for sitting common scoter included the following variables:

- factors, $windfarm$, $shipcatAv$, $shipAIS5$ and $shipAIS10$,
- linear term $shiplenav$,
- one dimensional smooth term $depth$,
- location as two-dimensional term between $x.pos$ and $y.pos$ and
- an interaction term between location and $shipAIS5$.

The significance associated with each term is shown in Table 4.4.5.

Table 4.4.5 Analysis of variance table for the final model fitted to sitting common scoter data; the number of degrees of freedom (Df), test statistic (X2) and p-value associated with each term in the model (P(>|Chi|)).

Table 18: Analysis of ‘Wald statistic’ Table

	Df	X2	P(>|Chi|)
as.factor(windfarm)	1	64.3	1.11e-15
as.factor(shipcatAv)	6	57.1	1.747e-10
as.factor(shipAIS10)	1	36.55	1.489e-09
as.factor(shipAIS5)	1	5.533	0.01866
shiplenav	1	11.33	0.0007608
s(depth)	4	137.9	0
s(x.pos, y.pos)	5	21.26	0.000722
s(x.pos, y.pos):as.factor(shipAIS5)	5	22.65	0.0003929

In terms of model assessment, the residuals did not indicate any systematic departures from the model (indicated by clusters of extreme red or blue colours) but naturally gave large residuals where unusually large values were seen. This figure provided no cause for concern in this case (Figure 4.4.1) and the predicted values (Figure 4.4.4) showed agreement with the observed values (Figure 4.1.1). Further details of the model selection process and assessment for sitting common scoter are included in Appendix E.

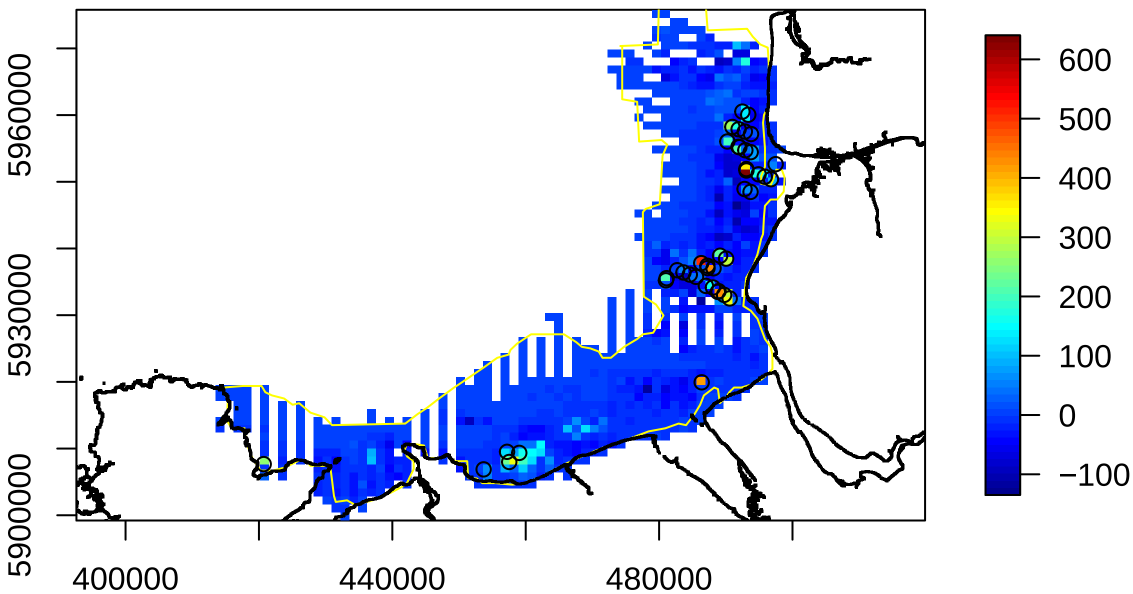

Figure 4.4.1 Plot of the residuals (difference between the observed number of birds and predicted number) averaged over all surveys. The large positive residuals (>150) occurred in segments where large numbers of birds (>500) were observed (black circles). The yellow line indicates the approximate boundary of Liverpool Bay SPA.

The relationships of the variables (factors and one-dimensional terms) to the response (i.e. numbers of birds) given the other variables in the model are shown in Figure 4.4.2. The presence of a wind farm compared to the the absence of a wind farm had a negative impact as does the presence of ship tracks in $shipAIS10$ (combined presence/absence of shipping on the day of the survey and the day before). Ships present on the day of the survey also had a negative impact and two levels (ships present but not on the day of the survey and ships 10-15m present on the day of the survey) both overlapped the baseline level (no ships present). Conversely, as the average length of ships increased, there was a positive effect although there was considerable uncertainty associated with the fitted function and this relationship may be being driven by a few large observations. There seems to be a slight preference for a depth of approximately 5 m but again there is considerable uncertainty associated with the fitted function.

```
[1] "Making partial plots"
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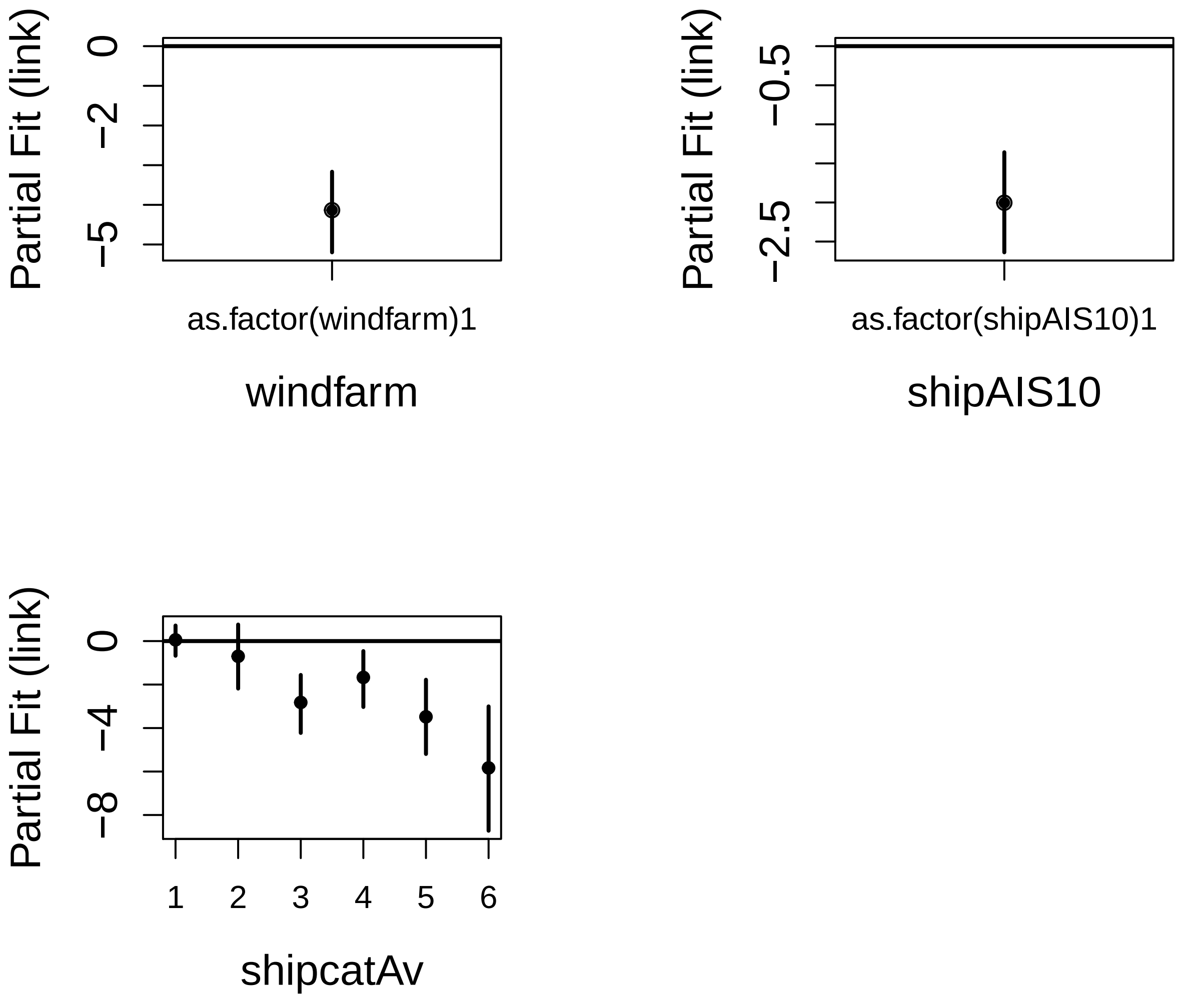

Figure 4.4.2a Relationship of the factors in the final model to the numbers of sitting common scoter (on a logarithmic scale) given the other variables in the model. For factors, the estimated coefficient (dot) and confidence interval (vertical line) are shown for each estimated factor coefficient; factor level 0 is used as a baseline, or reference, level. A positive value indicates an increase in the response and a negative value indicates a decrease. Both $windfarm$ factor level 1 (i.e. presence of a wind farm) and $shipAIS10$ factor level 1 (i.e. presence of a ship over a medium time scale) are associated with a decrease. For $shipcatAv$, factor level 1 (presence of a ship but not on the day of the survey) there is no change compared to factor level 0 (ships never present). For all other levels (i.e. ship present and categorised by length) there was a negative effect, however, for small ships (10-15 m) there was overlap with the reference level. The variable $shipAIS5$ is not shown because it was included in an interaction with location.

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[1] "Making partial plots"
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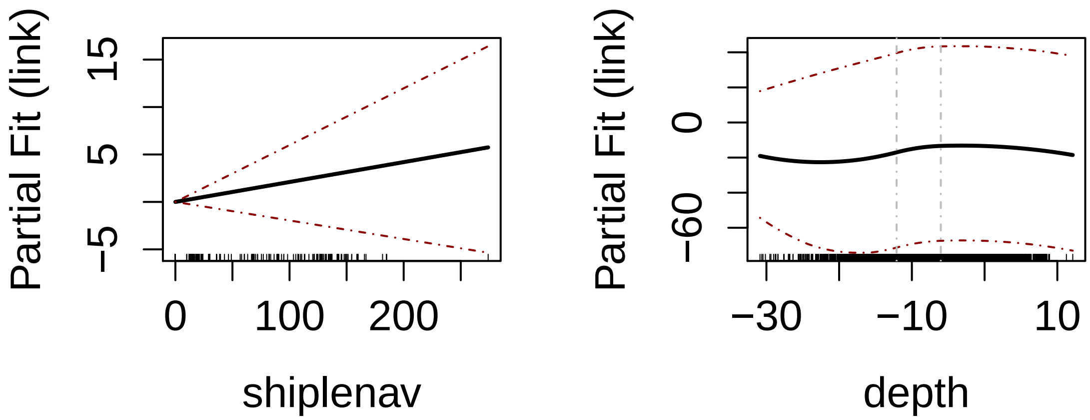

Figure 4.4.2b Relationship of the one-dimensional terms in the final model to the numbers of sitting common scoter (on a logarithmic scale) given the other variables in the model. The solid line indicates the relationship, the dashed lines show the confidence interval and the ticks along the x-axis indicate the observed values. A positive value indicates an increase in the response and a negative value indicates a decrease. The relationship with *shiplenav* (average length of a ship, m) should be interpreted with caution as the positive relationship may be being driven a large value for *shiplenav*. There is a slight preference for shallower depths (m) but again there is uncertainty associated with this relationship as evidenced by the wide confidence intervals.

4.4.2 Estimated abundances

The shipping metrics and the wind farm variable in the final model were survey specific and so prediction was made using the observed values for each of the five survey dates (Figure 4.4.3) and then averaged over all surveys (Figure 4.4.4).

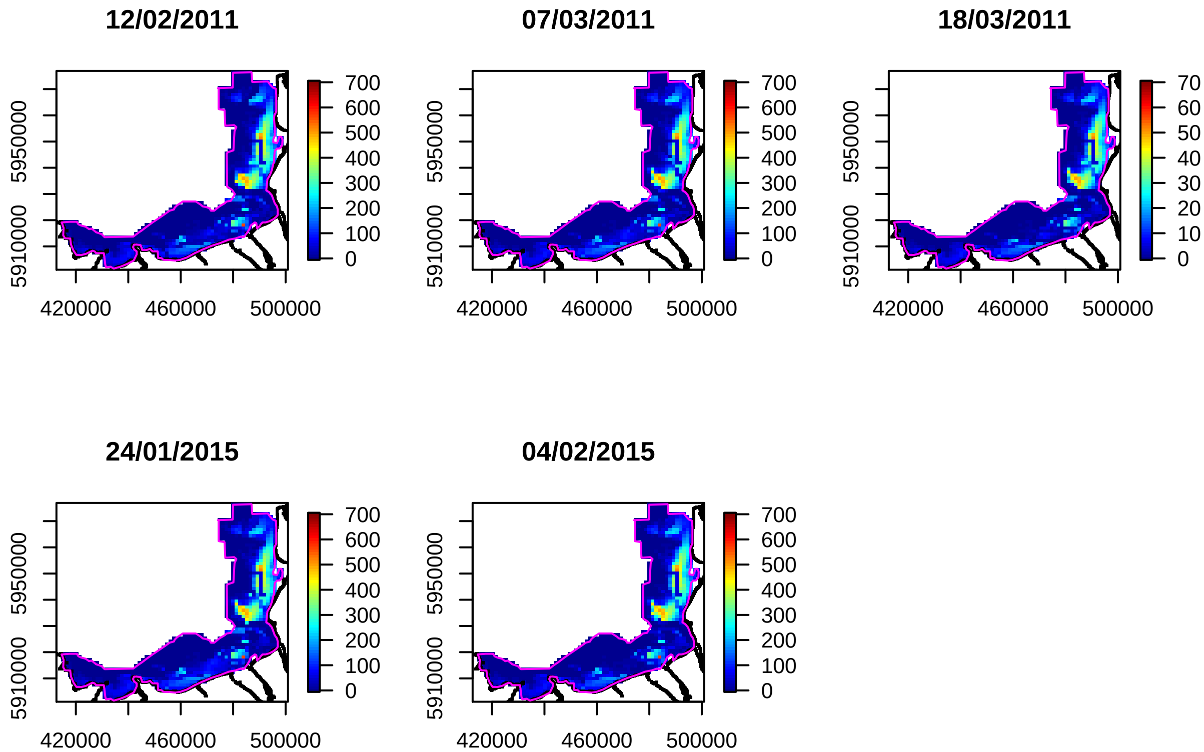

Figure 4.4.3 Estimated number of sitting common scoter per grid cell (~1 km^2) based on the observed values for each survey date. The magenta line indicates the boundary of Liverpool Bay SPA.

The estimated abundances (and 95 percentile-based confidence intervals) in the Liverpool Bay SPA using the observed values for each survey are shown in Table 4.4.5. The highest estimated numbers occurred closer to the coast and particularly in the north of the SPA (Figure 4.4.4). The uncertainty associated with the estimated surface (Figure 4.4.5) is low, except on the most northerly edge of the SPA where survey coverage was lower than in other parts of the region (Figure 4.1.1) however numbers estimated in this area were extremely close to zero and so any variability on these estimates returns a very high coefficient of variation. The estimated abundances are somewhat higher in 2011 than maybe anticipated from the observed numbers but note that average numbers are estimated based on functions fitted to data from all surveys.

Table 4.4.5 Estimated abundances (N) and percentile-based confidence intervals for common scoter sitting on the water for each survey date.

Date	Estimated.N	CI_2.5	CI_97.5
12/02/2011	117329	96496	170104
07/03/2011	119561	99150	171580
18/03/2011	117519	96839	170979
24/01/2015	121291	99862	175989
04/02/2015	117101	96539	168958
Mean	118560	97808	171898

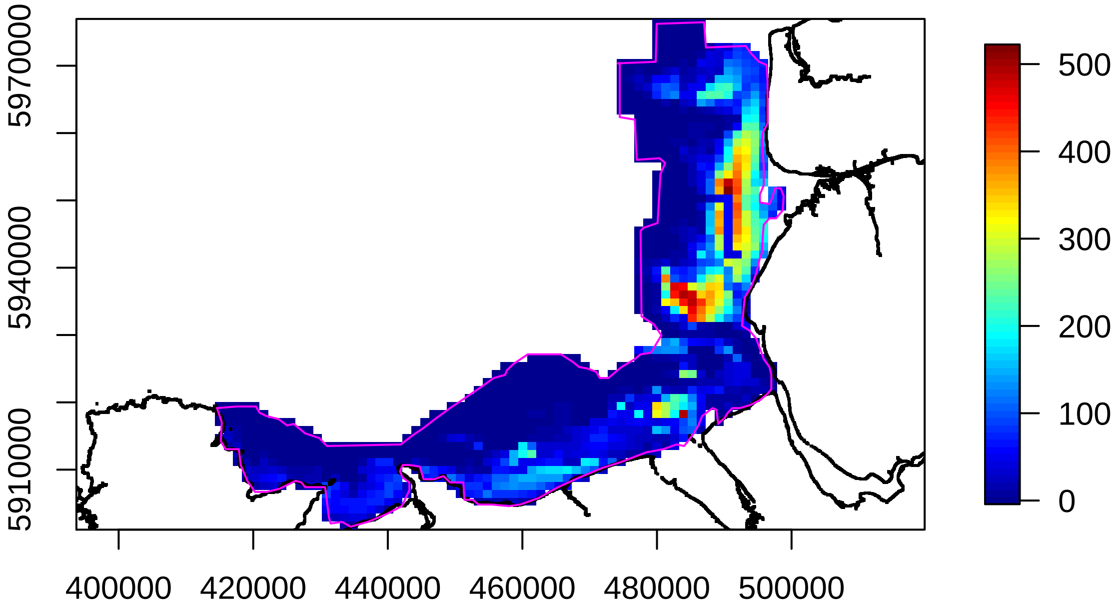

Figure 4.4.4 Estimated numbers of common scoter sitting per grid cell and averaged over all survey dates. The magenta line indicates the approximate boundary of Liverpool Bay SPA.

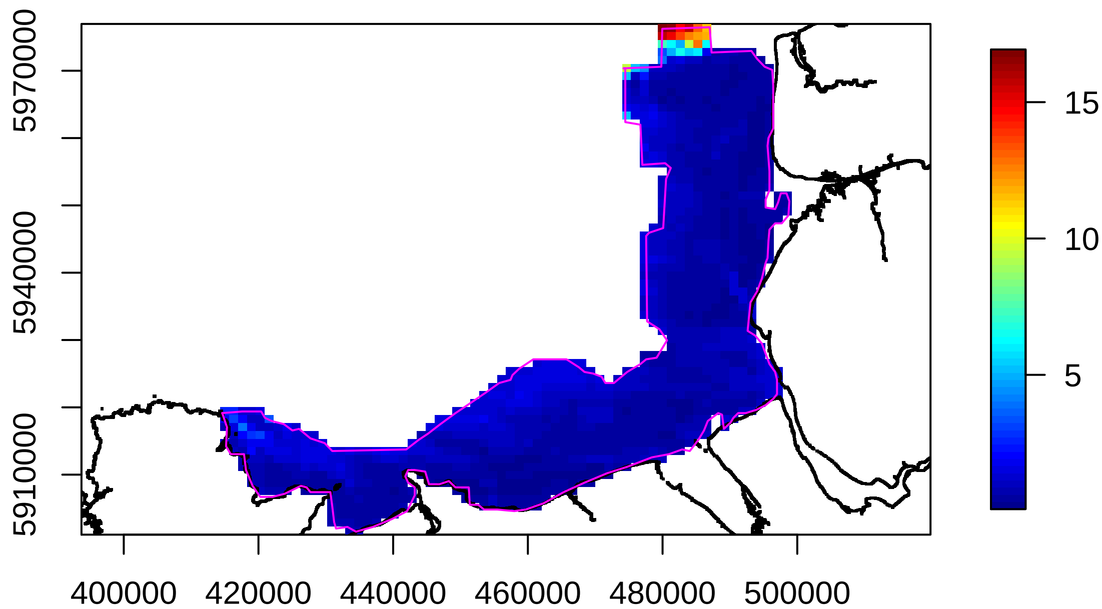

Figure 4.4.5 Coefficients of variation associated with the estimated numbers per grid cell for sitting common scoter and averaged over all surveys. The magenta line indicates the approximate boundary of Liverpool Bay SPA.

4.4.3 Impact of shipping

For sitting common scoter, several shipping metrics were included in the final model which incorporated information about the transient shipping on the day of the survey and metrics which incorporated information on the presence/absence of more general ship traffic. There are many scenarios that could be envisioned and the hypothetical scenario illustrated here was the impact of an increase in the length of ships using the existing shipping lanes.

Two variables in the final model incorporated information on ship length, *shipcatAv* and *shiplenav*. To impose a change in length, values for both variables were changed accordingly. In *shipcatAv*, average ship lengths were divided into five categories (see section 3.3.2) and to implement the hypothetical scenario (i.e. longer ships) the change imposed on observed values was that all ships would increase in length and move to a longer length category, except for the ships already in the longest category (i.e. >89m). The models were fitted with only five length categories and so obtaining a prediction for a new category (unobserved in the data) would not be possible. To ensure that *shiplenav* was consistent with the change specified in *shipcatAv*, the average lengths of ships per segment were replaced with a lengths chosen at random (and with replacement) from the observed lengths of ships in the new category. For example, ships of length 10-15 m were in category 2 and under the imposed change these moved to category 3 (i.e. ships >15-20 m in length) and new lengths (to populate values for *shiplenav*) were selected at random from the observed distribution of lengths in category 3.

The impact of the imposed change for one realisation is shown in Figure 4.4.6 (there are many realisations because of the random selection of new lengths). To help interpret this plot also see the observed values in

Appendix G and the fitted functions for the relevant variables (Figure 4.4.2). Figure 4.4.6 shows that there will be no change in large parts of the region but in lanes already used by large ships there will be a decrease in bird numbers of up to 30 birds per grid cell and some smaller increases likely due from ships moving from category 3 to 4. The effect on overall predicted abundance within the Liverpool Bay SPA as a whole was small (Table 4.4.6).

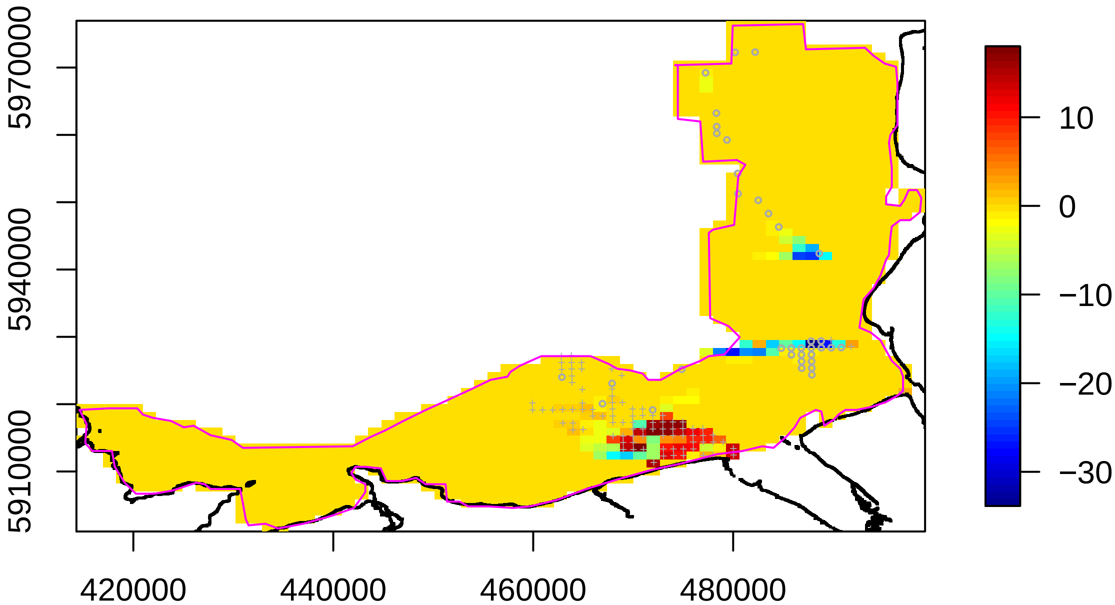

Figure 4.4.6 The differences in numbers of sitting common scoter per grid cell when the lengths of ships are increased using observed values for 2015. Symbols indicate significant differences, an increase in the number of birds (+) and a decrease in the number of birds (o).

Table 4.4.6 Estimated abundances and 95 percentile-based confidence intervals for sitting common scoter under hypothesised change of an increase in the length of ships.

Date	Estimated.N	CI_2.5	CI_97.5	Change
04/02/2015	117101	96539	168958	No change
04/02/2015	116726	96390	169324	Ship length increase

4.4.4 Impact of wind farms

Plotting estimated numbers of sitting common scoter per grid cell against the closest distance to a centre of a wind farm (using prediction data for all survey dates) indicated that numbers remained low until approximately 2 km from the centre of a wind farm (Figure 4.4.7). Numbers increased at a constant rate until approximately 8 km from a centre of a wind farm, after 8 km numbers overall remained constant.

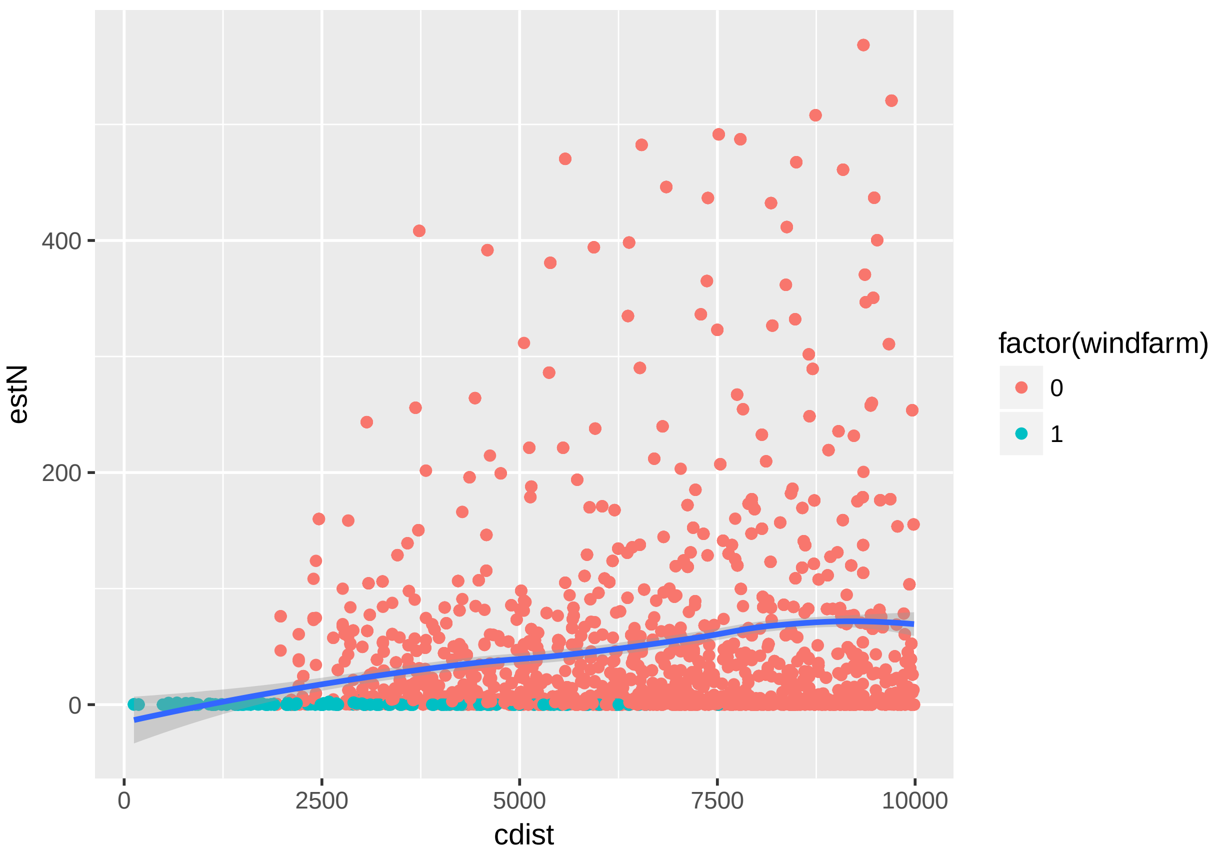

Figure 4.4.7 Estimated numbers of sitting common scoter per grid cell (estN) against the closest distance to the centre of a wind farm (cdist; m). Values have been limited to a distance of 10 km from the centre of a wind farm and colour distinguishes points outside (0) or inside (1) the footprint of a wind farm. The grey region is the 95% confidence interval around a smooth function fitted to these data.

The impact of removing the wind farms was illustrated using the February 2015 prediction data and by selecting the variable indicating the presence/absence of a wind farm (i.e. $windfarm$) and changing all records in the prediction grid indicating presence of a wind farm to indicating no wind farm. Figure 4.4.8 indicated that the numbers per grid cell increased within the footprint of the wind farm with the removal of the wind farm. The effect on overall predicted abundance within the Liverpool Bay SPA was small (Table 4.4.7).

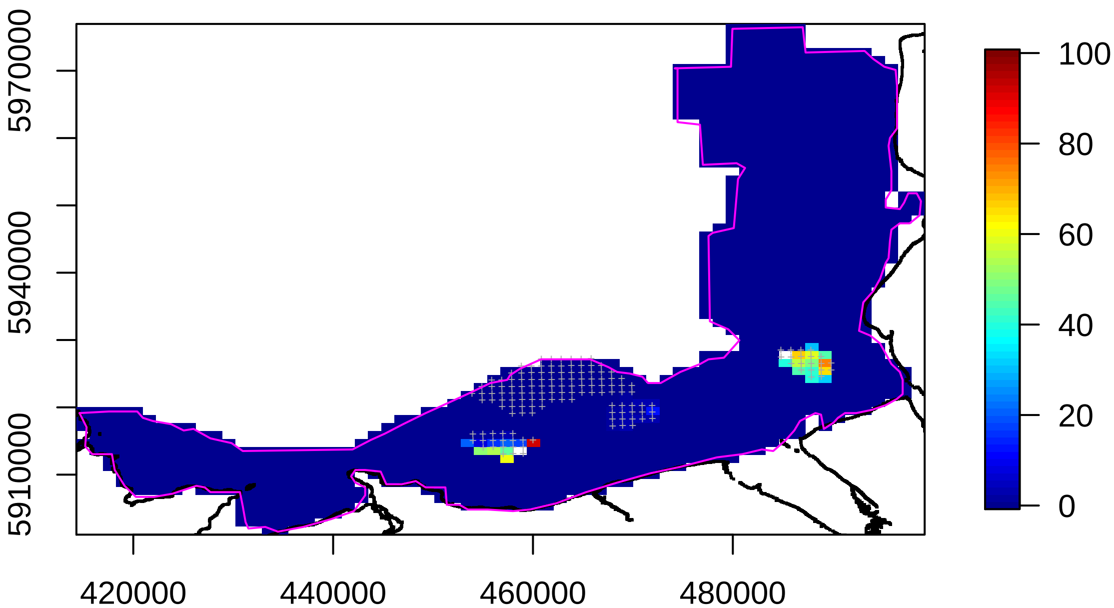

Figure 4.4.8 The differences in average predicted numbers of sitting common scoters per grid cell when the wind farms are removed using the prediction data for February 2015. Symbols indicate significant differences, an increase in the number of birds (+) and a decrease in the number of birds (o). The scale has been limited to a difference of 100 birds per grid cell.

Table 4.4.7 Estimated abundances of sitting common scoter with and without wind farms for the February 2015 prediction data.

Date	Estimated.N	CI_2.5	CI_97.5	Scenario
04/02/2015	117101	96539	168958	No change
04/02/2015	119406	98294	172960	Wind farms removed

The presence of a wind farm had the effect of reducing the numbers of birds within the footprint of the wind farm. Looking at the differences in the estimated numbers per grid cell with and without wind farms from the centre of a wind farm shows that beyond about 3 km from the centre there were no differences with and without wind farms (Figure 4.4.9).

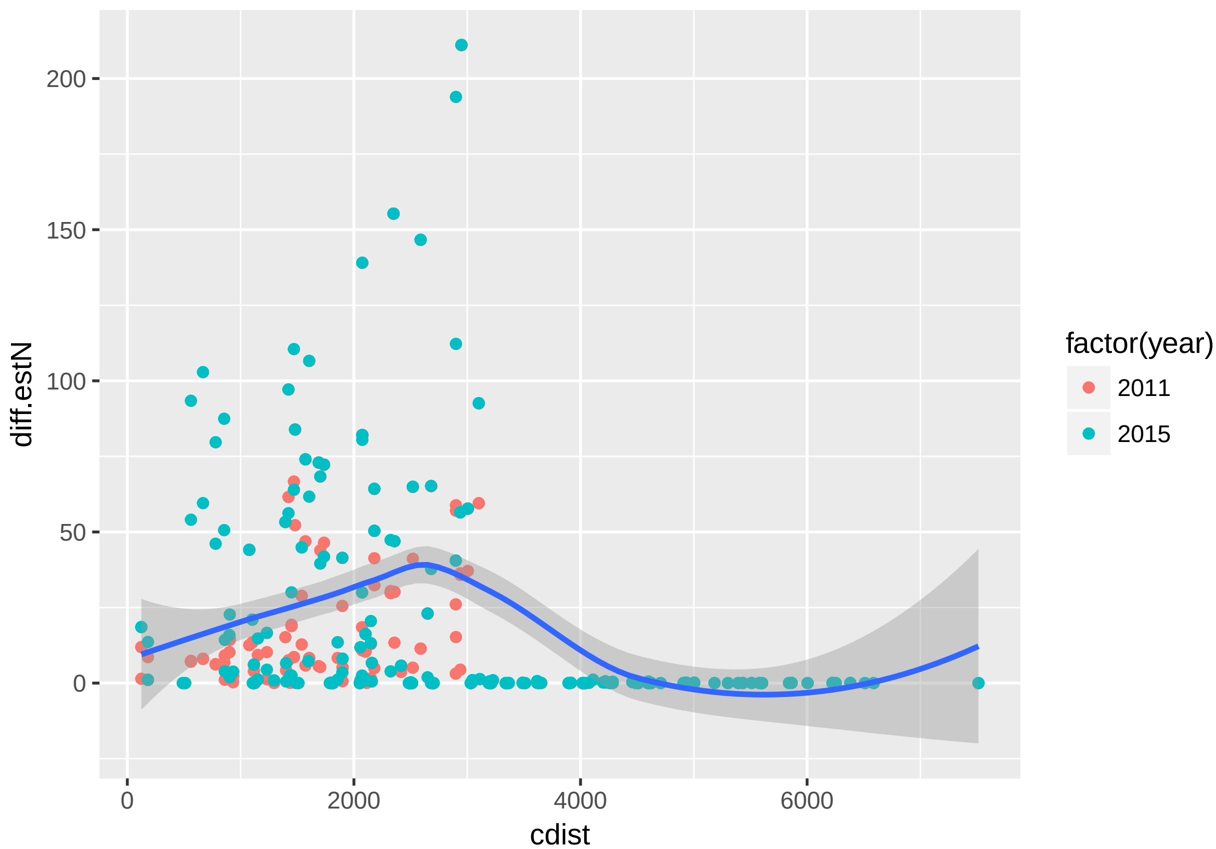

Figure 4.4.9 Difference in estimated numbers of sitting common scoter per grid cell (diff.estN) with and without wind farms against the closest distance to the centre of a wind farm (cdist, m) using all prediction data. The grey region is a 95% confidence interval around a smooth function fitted to these data.

4.5 Common scoter flying

4.5.1 Selected model

Each candidate variable was assessed individually and as with the other species it was again depth which had the highest pseudo-R^2 fit score (Table 4.5.1). Although *shipAIS*1 had the lowest mean CV and would be chosen at the first stage of the selection process, it was the first variable to be removed from the full model (see Appendix F). Therefore, the variable with the next lowest mean CV score, *shipcatAv* was selected from the group of variables (Table 4.5.1).

Table 4.5.1. Fit statistics including each term separately to model flying common scoter counts: mean CV, 2.5 and 97.5 percentile-based confidence limits, pseudo R^2 fit score (R2, a measure of the correlation between the observed values and the fitted values from the model) and probability (p.value) associated with fitting each term separately. Numbers in the Group column indicate variables which were grouped together and one variable from the group was chosen.

Variable	meanCV	lowCV	highCV	R2	p.value	Group
s(depth)	22.1	22.05	22.17	0.01697	0	
as.factor(shipAIS10)	22.21	22.2	22.23	0.008707	0.2268	
as.factor(windfarm)	22.22	22.21	22.24	0.006916	0.04712	
shiplenav	22.22	22.21	22.24	0.007063	0.1394	
as.factor(anthrop)	22.23	22.21	22.24	0.00665	0.08875	
as.factor(windcable)	22.23	22.22	22.25	0.006387	0.1631	

Variable	meanCV	lowCV	highCV	R2	p.value	Group
as.factor(shipMMO)	22.24	22.23	22.26	0.00661	0.6217	
as.factor(shipAIS5)	22.25	22.23	22.27	0.006416	0.7361	
shiplennear	22.25	22.24	22.27	0.006151	0.6508	
as.factor(shipAIS1)	22.25	22.24	22.27	0.005974	0.986	1
as.factor(shipcatAv)	22.25	22.23	22.32	0.008711	0.01769	1
as.factor(shipnumf)	22.25	22.24	22.27	0.00592	0.5573	1
as.factor(fish)	22.25	22.24	22.27	0.006061	0.5415	
as.factor(shipcatMax)	22.26	22.23	22.32	0.008722	0.01674	1
s(shiplenmax)	22.26	22.24	22.29	0.006509	0.5108	
as.factor(LBspa)	22.28	22.27	22.3	0.006029	0.9695	
s(salinity)	22.29	22.25	22.34	0.007215	0.307	
s(shipnear)	22.32	22.27	22.39	0.00648	0.1979	

Having chosen which term to include from those grouped together, the multi-collinearity of the remaining variables was assessed (Table 4.5.2). The term *shipMMO* was likely collinear with *shipcatAv* and *shipcatAv* was selected over *shipMMO*. The term *anthrop* was selected because of potentially higher predictive power (Table 4.5.1). The variables *shiplenav* and *shiplenmax* had high adjusted GVIFs but these were not greater than the threshold (>5) and so at this stage were retained.

Table 4.5.2 Table of generalized variance inflation factors (GVIF) for flying common scoter, degrees of freedom (Df) and GVIFs adjusted for the degrees of freedom (GVIF^(1/2*Df)).

	GVIF	Df	GVIF^(1/(2*Df))
as.factor(shipAIS10)	3.835	1	1.958
as.factor(windfarm)	1.004	1	1.002
as.factor(anthrop)	219340	1	468.3
as.factor(windcable)	219340	1	468.3
as.factor(shipMMO)	91.63	1	9.572
as.factor(shipAIS5)	3.979	1	1.995
as.factor(shipcatAv)	4002	6	1.996
as.factor(fish)	1.27	1	1.127
as.factor(LBspa)	1.181	1	1.087
depth	1.964	1	1.402
shiplenav	15.61	1	3.951
shiplennear	1.807	1	1.344
shiplenmax	22.94	1	4.789
salinity	1.386	1	1.177
shipnear	1.763	1	1.328

The stages in the model selection process are summarised in Table 4.5.3. The variables *shiplennear*, *shiplenav*, *shiplenmax* and *salinity* were included as linear terms, because there were problems fitting them as smooth terms (even after reducing the maximum number of knots for the smooth term to one). The mean CV score did not 'settle down' until six terms had been removed.

Table 4.5.3. The number of iterations in model selection for flying common scoter; The Model column indicates terms that were dropped from ('-') or added to ('+') the model; the mean CV and percentile based confidence limits associated with the model, pseudo-R^2 fit score and p.value which indicates the probability associated with the term excluded from, or added to, the model.

NumIter	Model	meanCV	CI_2.5	CI_97.5	R2	p.value
1	Full model	2.141e+25	51.32	7.447e+21	0.0563	NA

NumIter	Model	meanCV	CI_2.5	CI_97.5	R2	p.value
2	- shiplennear	2.739e+25	36.27	7.265e+21	0.0563	0.9747
3	- as.factor(shipAIS5)	8.482e+32	75.22	2.591e+29	0.04606	0.7687
4	- as.factor(shipAIS10)	8.576e+32	77.54	2.743e+29	0.04696	0.8296
5	- salinity	2.339e+26	132	1.501e+23	0.05114	0.4298
6	- shiplenmax	2.632e+26	49.46	4.339e+23	0.05066	0.4112
7	- as.factor(LBspa)	2.267e+27	236.9	3.63e+26	0.05187	0.3801
8	- shiplenav	22.37	22.21	22.68	0.03729	0.2153
9	- s(shipnear)	22.19	22.08	22.34	0.02734	0.1541
10	- as.factor(fish)	22.09	21.98	22.27	0.02836	0.155
11	+ s(x.pos,y.pos)	22	21.82	22.27	0.05	0.003835

The only shipping metric remaining in the model was *shipcatAv*. An interaction with this term and location was tried but was inestimable and so an interaction term was not included. The final model for flying common scoter included the following variables:

- factors, $windfarm$, *anthrop*, *shipcatAv*
- one dimensional smooth term *depth* and
- location as two-dimensional term between *x.pos* and *y.pos*

The fit score for the final model was 0.05 which was similar to that of the full model, although without the model fitting problems. This value was low but this was not surprising given the small number of segments where flying common scoter were observed and the variability of those observations when numbers were seen. The significance of the terms in the model are shown in Table 4.5.4.

Table 4.5.4 Analysis of variance table for the final model fitted to flying common scoter data; the number of degrees of freedom (Df), test statistic (X2) and *p*-value associated with each term in the model (P(>|Chi|)).

Table 25: Analysis of 'Wald statistic' Table

	Df	X2	P(>|Chi|)
as.factor(windfarm)	1	20.3	6.613e-06
as.factor(anthrop)	1	13.5	0.0002386
as.factor(shipcatAv)	6	25.8	0.0002425
s(depth)	4	83.08	0
s(x.pos, y.pos)	3	13.41	0.003835

Despite the low fit score, the residuals did not provide any cause for concern (Figure 4.5.1) and the predicted values (Figure 4.5.4.) showed agreement with the observed values (Figure 4.1.2). Further details of the model selection process and assessment for sitting common scoter are included in Appendix F.

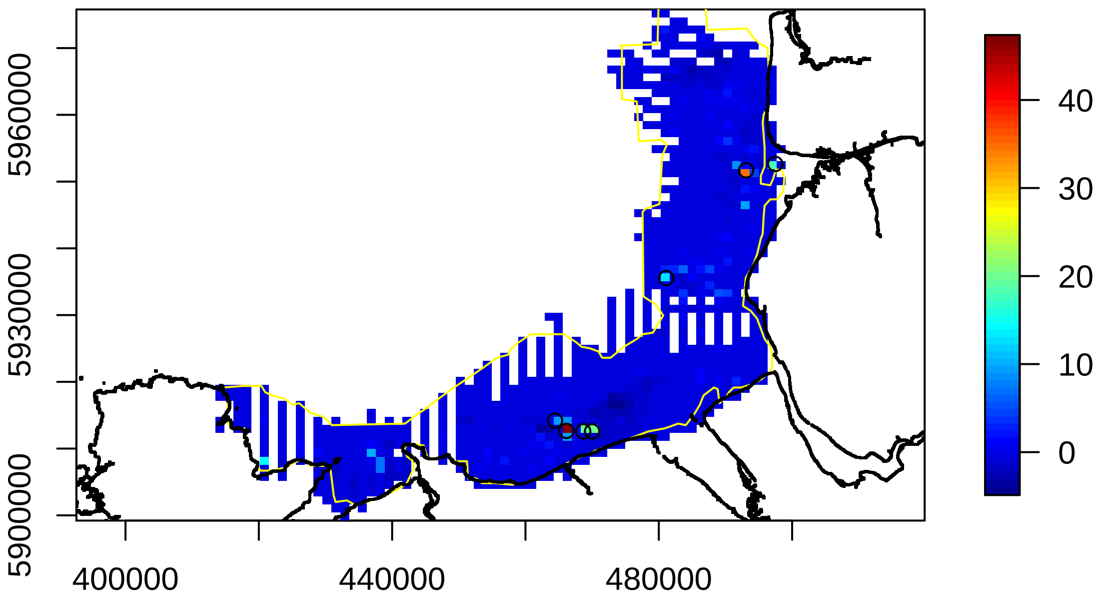

Figure 4.5.1 Plot of the residuals (difference between the observed number of birds and predicted number) averaged over all surveys. The black circles indicate segments where large numbers (>80) of common scoter were observed flying. The yellow line indicates the approximate boundary of Liverpool Bay SPA.

The relationships of the variables (factors and one-dimensional terms) to the response (i.e. numbers of flying common scoter) given the other variables in the model are shown in Figure 4.5.2. In terms of significant coefficients, there were significant negative effects due to presence of a wind farm and the presence of other anthropogenic effects compared to their absence; the presence of small ships (10 - 15 m) on the day of the survey had a significant positive effect (testing at 5% significance level), compared to the absence of a ship.

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[1] "Making partial plots"
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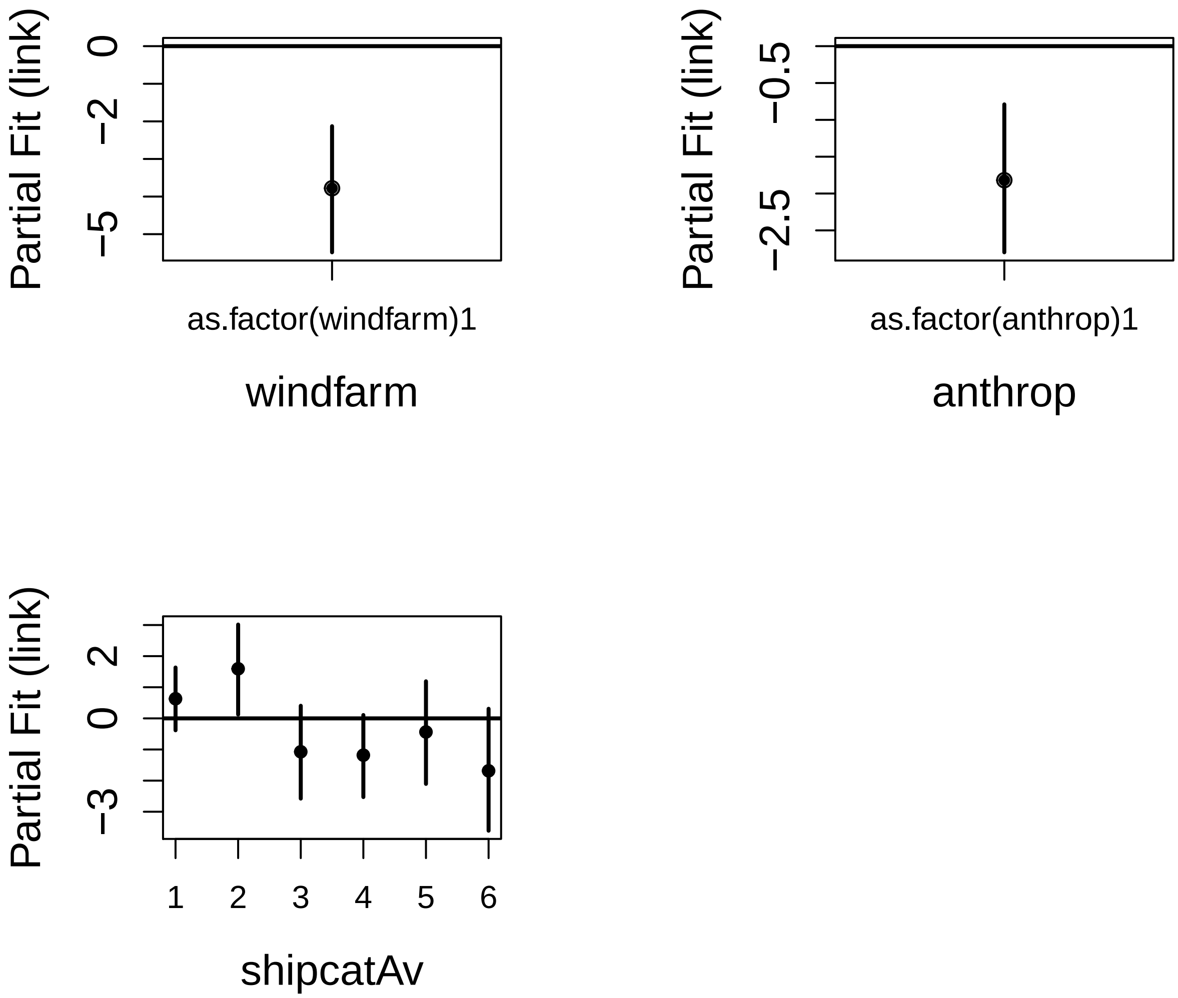

Figure 4.5.2a Fitted relationships of the factors in the final model to the numbers of flying common scoter (on a logarithmic scale) given the other variables in the model. For factors, the estimated coefficient (dot) and confidence interval (vertical line) are shown for each estimated factor coefficient; factor level 0 is used as a baseline, or reference, level. A positive value indicates an increase in the response and a negative value indicates a decrease. The presence of a wind farm and the presence of anthropogenic effects had a significant negative effect compared to their absence in a segment. Factor levels 1 and 2 for *shipcatAv* had a positive effect compared to the baseline coefficient although for level 1 this was not significant as evidenced by the confidence interval containing zero and level 2 (presence of a small ship) was significant (testing at a 5% significance level). Larger ships (factor levels 3 to 6) had a negative impact but again these were not significantly different from the baseline coefficient.

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[1] "Making partial plots"
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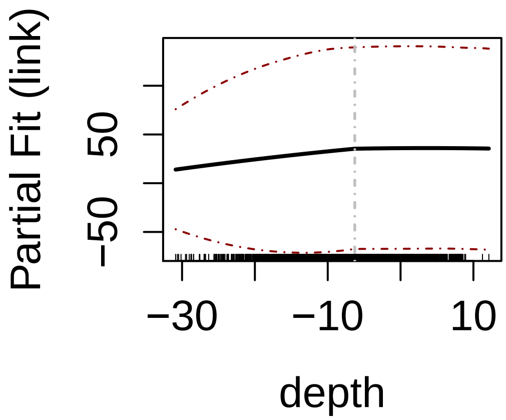

Figure 4.5.2b Fitted relationships of *depth* (m) in the final model to the numbers of flying common scoter (on a logarithmic scale) given the other variables in the model. the solid line indicates the relationship, the dashed lines show the confidence interval and the ticks along the x-axis indicate the observed values. A positive value indicates an increase in the response and a negative value indicates a decrease. Here, there appears to be a slight preference for shallower waters but there is considerable uncertainty associated with the fitted function as evidenced by the wide confidence intervals which also contain zero indicating non-significance.

4.5.2 Estimated abundances

The shipping metric in the final model was survey specific and so prediction was made using the observed values for each of the five survey dates (Figure 4.5.3) and then averaged over all surveys (Figure 4.5.4).

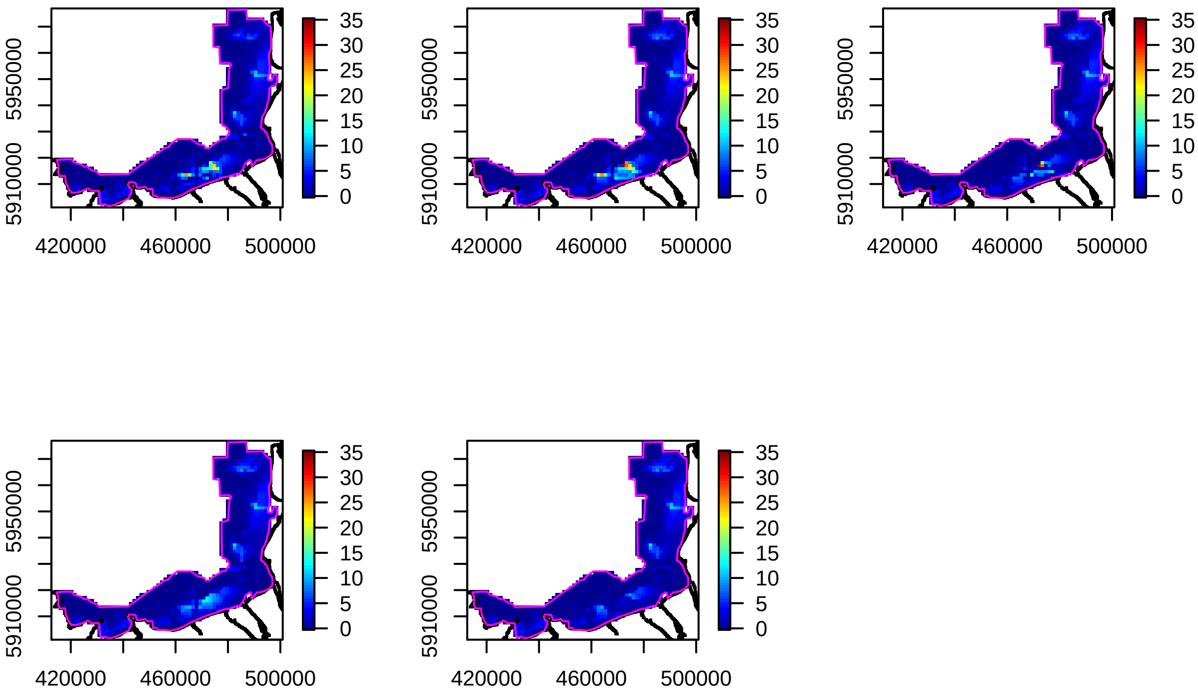

Figure 4.5.3 Estimated number of flying common scoter per grid cell (~1 km^2) based on the observed values for each survey date. The magenta line indicates the boundary of Liverpool Bay SPA.

The estimated abundances for each survey (and 95% confidence intervals) in the Liverpool Bay SPA using the observed values are shown in Table 4.5.5. Although numbers are much lower for flying common scoter than for sitting common scoter, the pattern is similar with higher numbers closer to the coast (Figure 4.5.4). There was some uncertainty associated with the estimated abundance surface; this uncertainty occurred because of large values generated during the bootstrap process for grid cells lying mostly along the seaward edge of the southern part of the SPA (Figure 4.5.5). The high uncertainty coincided with parts of the region where survey coverage was lowest (Figure 4.1.2) and where there were no observations of flying common scoter, elsewhere the uncertainty was low.

Table 4.5.5 Estimated abundances (N) and percentile-based confidence intervals for flying common scoter for each survey date.

Date	Estimated.N	CI_2.5	CI_97.5
12/02/2011	2621	1981	5719
07/03/2011	2917	2146	6157
18/03/2011	2477	1820	5824
24/01/2015	2570	1821	5976
04/02/2015	2148	1584	5104
Mean	2546	1876	5805

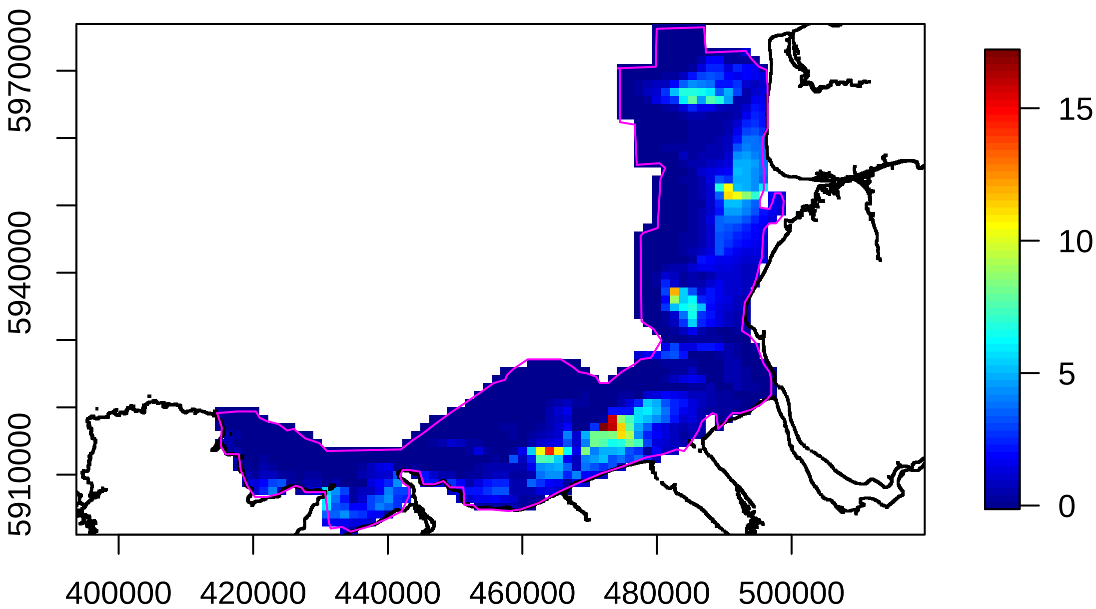

Figure 4.5.4 Estimated numbers of flying common scoter per grid cell and averaged over all survey dates.

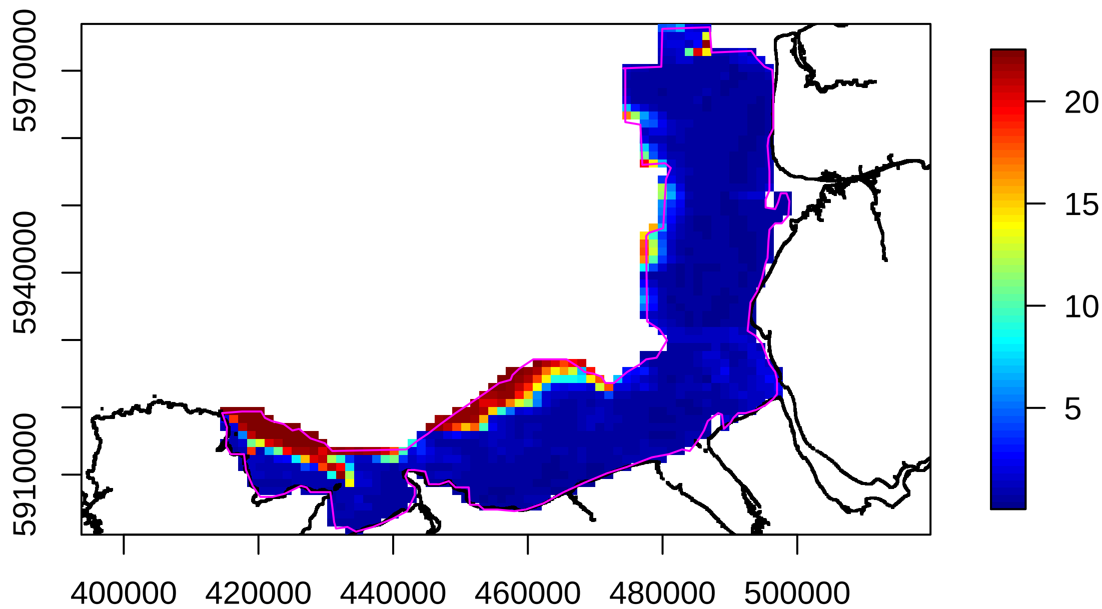

Figure 4.5.5 Coefficients of variation associated with the estimated numbers per grid cell for flying common scoter and averaged over all surveys. The magenta line indicates the approximate boundary of Liverpool Bay SPA.

4.5.3 Impact of shipping

For flying common scoter, the only shipping metric included in the final model was *shipcatAv* which described segments where ship traffic was always absent, ship traffic sometimes present (but not on the day of the survey) or ship traffic present on the day of the survey and divided into five categories based on ship length. The hypothetical scenario considered here was an increase in the length of ships in existing shipping lanes and assessing this scenario was somewhat more straightforward than for for sitting common scoter as only changes in one variable needed to be specified. To implement the scenario, the imposed change on the variable *shipcatAv* was that ships moved into the next length category, for example, ships in category 2 moved to category 3 and so on for the other categories, noting that category 6 was the longest category allowed.

The impact is shown in Figure 4.5.6 and to help interpret this plot also see the observed values for *shipcatAv* for the February 2015 survey in Appendix G and fitted values for each factor in Figure 4.5.2. Figure 4.5.6 shows that there will, in general, be no change and any changes will be small (1 or 2 birds per grid cell). The increases are likely due to ships moving from category 4 (>20 - 36 m) to category 5 (>36 - 89 m) as the coefficient associated with category 5 was slightly larger than for category 4. The effect on abundance in Liverpool Bay SPA overall is given in Table 4.5.6.

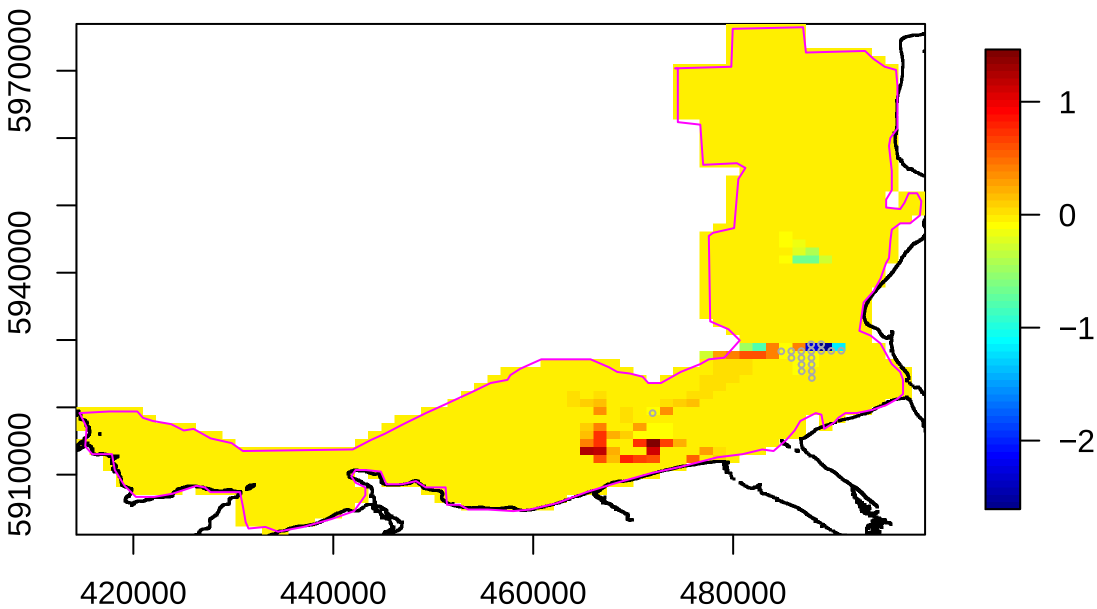

Figure 4.5.6 The differences in numbers of sitting common scoter per grid cell when the length of a ship is increased to the next category using observed values for 2015. Symbols indicate significant differences, an increase in the number of birds (+) and a decrease in the number of birds (o).

Table 4.5.6 Estimated abundances and 95 percentile-based confidence intervals for sitting common scoter under hypothesised change of an increase in the length of ships.

Date	Estimated.N	CI_2.5	CI_97.5	Change
04/02/2015	2148	1584	5104	No change
04/02/2015	2155	1565	5328	Ship length increase

4.5.4 Impact of wind farms

The estimated numbers of flying common scoter per grid cell was generally low. Plotting the estimated numbers per grid cell against the closest distance to the centre of a wind farm showed that there were no flying common scoter within about 2 km from the centre. Overall the prediction data, numbers increased slightly as the distance from the centre increased (Figure 4.5.7).

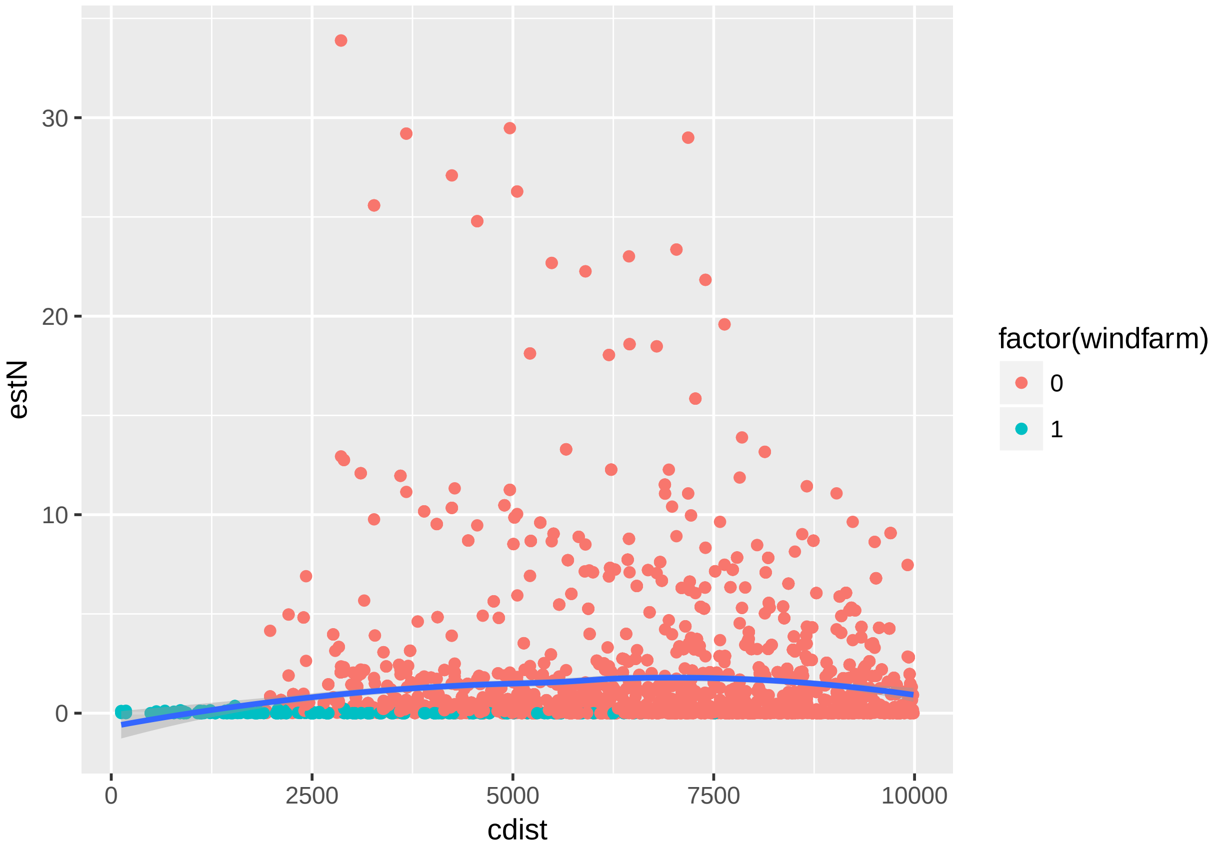

Figure 4.5.7 Estimated numbers of flying common scoter per grid cell against the closest distance to a centre of a wind farm using all the prediction data. Values have been limited to a distance of 10 km from the centre of a wind farm and colour distinguishes points outside (0) or inside (1) the footprint of a wind farm. The grey region is the 95% confidence interval around a smooth function fitted to these data.

The impact of removing the wind farms was illustrated using the February 2015 prediction data. Figure 4.5.8 indicated that the numbers per grid cell increased within the footprint of the wind farm when the wind farm was removed compared to when the wind farm was present. The increase in predicted abundance over all within the SPA is given in Table 4.5.7.

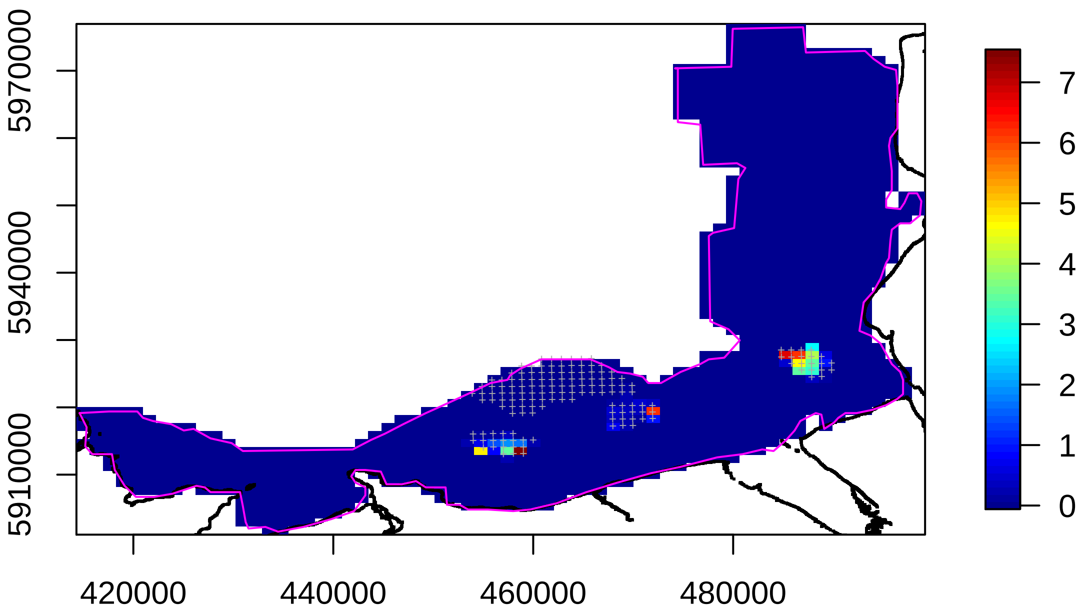

Figure 4.5.8 The differences in numbers of flying common scoters per grid cell when the wind farms were removed compared to wind farms being present using prediction data for February 2015. Symbols indicate significant differences, an increase in the number of birds (+) and a decrease in the number of birds (o).

Table 4.5.7 Estimated abundances of flying common scoter with and without wind farms for the February 2015 prediction data.

Date	Estimated.N	CI_2.5	CI_97.5	Scenario
04/02/2015	2148	1584	5104	No change
04/02/2015	2266	1724	5252	Wind farms removed

Within the footprint of a wind farm, the differences in the estimated numbers per grid cell with and without wind farms extended out to approximately 3 km from the centre of a wind farm (Figure 4.5.9).

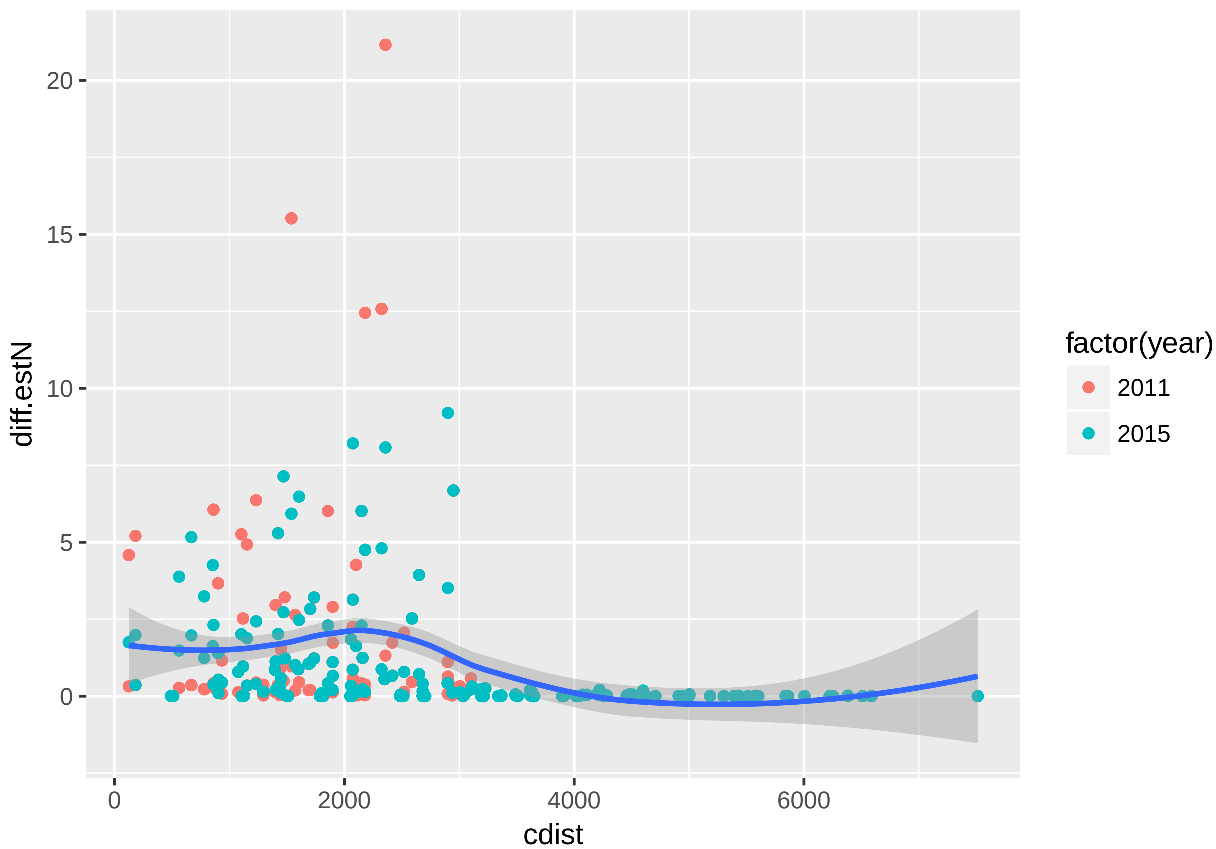

Figure 4.5.9 Differences in estimated numbers of flying common scoter per grid cell (diff.estN) with and without wind farms against the closest distance to the centre of a wind farm (cdist, m) using all prediction data. The grey region is a 95% confidence interval around a smooth function fitted to these data.

5. Discussion

5.1 Selected models

Models were fitted to data for sitting red-throated divers and sitting and flying common scoter. Backward selection was used to select from the candidate list of environmental and shipping metric variables. In terms of the fit scores, the model fitted to sitting common scoter explained the most variation observed in the data and the model fitted to flying common scoter the least. All three final models contained variables for the presence/absence of a wind farm (at the time of the survey), a one-dimensional term of depth and a two-dimensional term for location. Including location substantially improved the fit score for red-throated divers and sitting common scoter and this term is essentially a proxy for potentially many factors that affect the bird distributions.

Other variables included in the models depended on species. In terms of the metrics representing the ship traffic on the day of the survey, it was the length metrics that were selected rather than the metric describing the number of ships.

5.1.1 Red-throated diver

This was the only model to select inside/outside of Liverpool Bay SPA and the coefficients indicated an increase of numbers inside the SPA compared to outside. This perhaps was not surprising since the boundary of the SPA was defined on the basis of red-throated diver distributions. Several shipping metrics were selected in the model for red-throated divers but these were all survey specific (i.e. recorded on the day of the survey); the more general variables representing presence/absence of shipping over longer time periods were not included. The metrics included were length of the nearest ship, average length of the ships intersecting the segment and distance to the nearest ship. Based on the fitted function for distance to nearest ship, 2 km appeared to be a critical distance; numbers increased substantially as the distance increased up to approximately 2 km, beyond that distance the changes in numbers as distance increased were smaller.

The relationships of the length variables to the number of birds had opposite effects as length increased; as the length of the nearest ship increased, the numbers of birds decreased, whereas, when the average length of ships intersecting the segment increased, the numbers of birds increased. There were relatively few, large ships observed, and so particularly for the average length of a ship there were very few observations with large values and this has driven the relationship and resulted in wide confidence intervals.

5.1.2 Sitting common scoter

The model selected for sitting common scoter was the most complicated, containing shipping metrics describing the ship traffic on the day of the survey and also a more general picture of the presence/absence of ship traffic. Presence of shipping over a longer time period indicated a negative effect. The 'combination' factor described a segment in terms of ships absent from a segment, sometimes present (but not on the day of the survey) or ship traffic present and divided into categories based on average length. The estimates for these factor levels indicated that a ship being present on the day of the survey had a negative effect and the larger the boat in general, the larger the negative effect (Figure 4.4.1).

5.1.3 Flying common scoter

Common scoter were observed flying in only a small number of aerial survey segments and the simplest model was selected. The fit score indicated that the least amount of variation in the observed numbers per segment had been estimated by the model compared to the fit scores for the models fitted to the other species. There were regions where there were no observations and survey effort was lower than in other regions resulting in large uncertainties in the estimates in these regions (e.g. seaward edge of the southern part of the SPA) and hence overall the region.

The only shipping metric selected for flying common scoter was the combination variable describing a segment in terms of a ship traffic absent from a segment, sometimes present (but not on the day of the survey) or ship traffic present on the day of the survey and divided into categories based on average ship length. This variable was also selected in the model for sitting common scoter and the patterns of the estimates were similar in that the presence of large boats (greater than 15 m) had a negative effect. For flying common scoter the presence of smaller boats (10 - 15 m) showed a positive effect. This may be a coincidence in that birds may have been flying to or across regions where small boats may occur and small boats may be under represented in these data, particularly for 2011 (see later).

5.2 Impact of wind farms and other anthropogenic activities

The variable indicating presence/absence of a wind farm was selected in the final models for all species and in all cases the presence of a wind farm was associated with a significant decrease in the number of birds within the footprint of the wind farm. The buffering effect around the wind farms was assessed by plotting the estimated numbers per grid cell against the closest distance to the centre of a wind farm. For red-throated divers, numbers increased out to a distance of 3 km from the centre of the wind farm and remained constant beyond 3 km. For common scoter, the increase occurred over a distance of approximately 8 km.

The variable indicating anthropogenic effects (other than wind farms) was only selected in the model for flying common scoter and again the presence of an effect (i.e. wind export cable, gas storage, aggregate extraction) was associated with a significant decrease in the number of birds. These data, and also the variable describing the presence/absence of the wind export cable, were based on 2015 locations and thus their presence would have been over represented for the 2011 survey data.

The variable describing the presence/absence of fishing was not selected in any of the models. This may indicate that this was not important for these species or that the fishing data used did not capture the relevant information. These data were a summary of fishing activity that occurred during 2011 rather than being a description of fishing activity on the day of the survey. In addition, the 2011 fishing data may not represent the location of fishing activity during 2015 if there have been substantial changes in fishing activity between these two years.

5.3 Limitations of data

Some limitations of the data have been mentioned already and this section further describes gaps in, or limitations of, the data underlying the candidate explanatory variables.

5.3.1 Aerial survey data

On two surveys the spatial extent of Liverpool Bay SPA was not covered completely, the southern part was covered on 12/01/2011 and northern part covered on 18/03/2011. There could have been a substantial change in distribution, or abundance, of birds between these dates from one part of the SPA to the other. However, on the other three days (07/03/2011, 24/01/2015 and 04/02/2015) the spatial extent of the SPA was covered by the aerial surveys.

Data on birds along the transects were captured digitally and it has been assumed all birds within the image would be detected. Birds that were diving when the plane flew over would not be detected; this could lead to an under-representation if the birds dived in response to the plane, however, it is thought because of the altitude of the survey plane few birds would react. The species of birds may be misidentified from the digital image. To try and ensure all detections of common scoter and red-throated diver records were included, all records assessed as definitely, probably and possibly the species of interest were included and in addition records of diver sp. were treated as red-throated diver.

5.3.1 Shipping data

Only the shipais.co.uk data set could be queried by time and thus requested and compared over periods contemporary with the aerial surveys. Personal communication with Ian McConnell (owner of shipais.com) suggested that in 2011, the data set may not have included smaller fishing boats, lifeboats and private yachts, but by 2015 most of these vessels would have carried an AIS system. Navy and Coastguard vessels are not required to carry AIS, but are rarely found in Liverpool Bay.

Data from MMO Anonymised AIS derived track lines from 2011 were used to describe the general presence/absence of shipping and was applied to both the 2011 and 2015 aerial survey data. This may have under estimated the presence of shipping in 2015, particularly in regions where only smaller vessels were likely to go. Incorporating the 2015 MMO data set would reduce this problem. In terms of the model selection, it is likely that using the 2015 MMO data for 2015 aerial survey data would increase it's similarity to other variables being considered and hence not be considered in an initial model.

Comparison between the position of vessels recorded during aerial surveys and the shipais.co.uk tracks of the same day or same day and previous days showed poor correspondence. This suggested the ais data set should be viewed as a proxy for shipping activity but has omissions. Comparing the vessels recorded during aerial surveys with the AIS tracks from the 10 days comprising the 48 hour blocks around each of the surveys showed better correspondence, indicating that vessels tend to use 'lanes' which are captured in a time series of tracks, but not necessarily in daily samples.

Though recorded, speed was not used as a metric for vessel activity in this project due to constraints on time. Vessel speed is a dynamic variable, changing regularly depending on activity, thus any size vessel may travel at slower speeds at any time, though only some vessels can travel at faster speeds. Mapping this constantly changing variable across large numbers of vessels (typically around 100 in the region each day) would be challenging, though vessel name has been included in the compiled and formatted data so this could be linked back to vessel type (categorical variable) or to perhaps to the average or maximum speed recorded by that vessel that day.

The survey specific shipping metrics summarised shipping activity that had been recorded for the whole day (i.e. 24 hours) and although the aerial surveys took place over several hours there will be differences in the amount of time between a ship being present and a bird being surveyed. In some cases birds will have been surveyed before a ship was present on that day. Burger *et al.* (2016) only included shipping information up to 5 hours prior to the survey and included a 'time since last ship' variable. This could be investigated in future studies with consideration given to the time limit prior to the survey given that Burger *et al.* (2016) were interested in different species.

Information on presence/absence of fishing was derived from 2011 data but was used to represent fishing activity in both 2011 and 2015, and potentially the location of fishing activity could have changed between these two years.

5.3.2 Environmental data

Many of the environmental data sets used in previous studies had been compiled under contract for other projects and were only available commercially at additional cost. Thus, only water depth and salinity, both used in previous studies and found to be useful in modelling, were sourced where data access was granted for this project. The salinity data set was only freely available for years up to 2004 and at a course resolution. There were some problems fitting salinity as a smooth function and having salinity recorded on a finer resolution may have reduced these issues. Nonetheless, it was selected as a significant term in one of the models, however, depending on how changeable salinity is from year to year, it may have been more important for other models had more up to date information been available.

Wind farms were assumed to be present if the foundations had been constructed at the time of the survey. However, there may be different levels of activity associated with different phases of construction. The centres of the wind farms were based on the wind farm footprints defined in the prediction grid, and thus may not be exact.

The variable describing the presence/absence of wind farms was survey specific, however, for the two variables describing the presence/absence of other anthropogenic infrastructure, data from 2015 was used and applied to both the 2011 and 2015 aerial survey data. This would have over represented the infrastructure in place at the time of the 2011 survey because, for example, the wind export cables for the wind farms not constructed in 2011 were included.

Other variables considered in previous studies may also have been useful to consider here, such as sea surface temperature, chlorophyll-a, sediment type, seabed complexity and food distribution. All these can be incorporated if available (see section 5.5).

5.4 Interactive web tool

As part of this project an interactive web tool was produced to allow different scenarios to be assessed by a user. Details are available in Appendix H (in a separate document).

5.5 Further work

The analysis was conducted in R (R Core Team, 2017) and all the documents have been generated using R Markdown (Allaire *et al.* 2015) which allows text (in plain text format) and R code to be combined. All documents containing R code and the data files necessary to run the code will be provided to NE, thus allowing anyone with sufficient knowledge of R to reproduce the analyses.

As discussed some of the explanatory variables were not contemporary with the survey data (e.g. salinity, MMO AIS data and fishing data) and only a limited suite of environmental data were available to the project. Thus, any updates or additions to the explanatory variables can be incorporated. The MMO anonymised AIS derived track lines and 2015 fishing activity are now available on the data.gov website.

The impact of hypothesised changes on the numbers of birds to shipping were considered as part of this project by comparing estimated numbers before and after an imposed change in the values of relevant explanatory variables. Relatively simple scenarios were considered, for example, increasing the size of the ships where ships were already observed to be present. Considering the effects of, for example, a new shipping lane would be possible using this approach but is outside the scope of this project. Implementing this would be relatively straightforward by changing the values of the explanatory variables in the prediction grid to reflect the new shipping lane. However, the interaction of the shipping metrics would need to be carefully considered, for example, changing a presence/absence shipping metric from absence to presence may also impact on other variables, such as distance to nearest ship. The length metrics were included in the models and so the lengths of ships in the new shipping lanes would also need to be considered.

Similarly, considering the extension of a wind farm, or any of the anthropogenic activities, could also be assessed by imposing a change on the relevant variables in the prediction grid from absence to presence.

6. Conclusions

Common scoter and red-throated diver over winter in Liverpool Bay SPA and are known to be sensitive to shipping traffic. Ships regularly cross Liverpool Bay SPA to enter or leave the port of Liverpool and boats travel within the SPA to service the wind farms and other anthropogenic effects (also within the SPA) or for fishing activities.

Aerial surveys of Liverpool Bay SPA were conducted in winter 2011 and 2015 and collected information on the numbers of common scoters and red-throated divers. This project has collated and processed shipping and other anthropogenic activity data and combined it with the aerial survey data to model the distribution of wintering common scoters and red-throated divers within Liverpool Bay SPA.

A statistical modelling approach using the MRSea package (Scott-Hayward *et al.* 2017) provided a flexible framework within which to fit the statistical models and to assess the impact of shipping and other anthropogenic activities on the distribution and number of birds. Backwards model selection was used to select significant variables from a suite of candidate explanatory variables. Geographic location was included as a two-dimensional smooth term.

Statistical models were fitted to observations of red-throated diver, sitting common scoter and flying common scoter. Flying common scoter had only been recorded in a few data points and thus any models on this basis are necessarily speculative and the final model struggled to capture the variability observed in these data and resulted in uncertainty in these estimates. The models for the other species were more successful in capturing some of the variability, which was substantial for sitting common scoter.

All selected models contained terms for depth, presence/absence of a wind farm and location. Other selected terms were species specific. In all cases, the presence of a wind farm (defined by when the foundations had been constructed) had a significant negative effect on the numbers of birds per grid cell. The hypothesized change due to removing the wind farms (e.g. post operation) indicated that there would be an increase in the numbers of birds within the footprint of the wind farm but the increase in abundance within the Liverpool Bay SPA as a whole was small.

For red-throated divers other variables chosen were: inside/outside Liverpool Bay SPA and inside the SPA had a positive effect on numbers compared to outside the SPA; the nearest distance to a ship and 2 km appeared to be a critical distance with number increasing as the distance to the ship increased from 0 to 2 km; two variables described the length of ships with a mixed message. The predicted average numbers reduced as the length of the nearest ship increased but were predicted to increase as the average length of the ships present increased, however, this latter relationship might be due to a small number of large covariate values.

Several shipping metrics were included in the model for sitting common scoter and they related to both ships present on the day of the survey and the presence/absence of shipping over longer time periods. Based on the estimated model coefficients, compared to the absence of ships, there were significant negative effects associated with ships being present generally (defined by ships present in a 10 day period) and ships over 15 m being present on the day of the survey. The average length of ships present, included as a linear term, indicated a positive effect, however, there was substantial uncertainty in the fitted function for this term.

The estimated model coefficients for flying common scoter indicated that there was a negative effect with the presence of anthropogenic effects (wind export cable, mineral extraction, gas storage). The effects due to ships being present sometimes or on the day of the survey (and categorised by length) compared to ships being absent, although selected in the model, were less severe than for sitting common scoter.

The statistical models allowed various hypothesized changes to be assessed by estimating the numbers of birds using observed values of explanatory variables, imposing the required change on the values of the explanatory variables and re-estimating the number of birds. Within the scope of this project, the number of scenarios that could be considered was limited, however, these models and framework could be used further to assess impacts outside the scope of this project. Within the MRSea package (Scott-Hayward *et al.* 2017) there are specific functions to allow the impacts of hypothesized scenarios to be determined.

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Glossary

Coefficient of variation - a measure used to describe the amount of variation in a population and expressed as $standard.deviation/mean$. The larger the value, the more variation in the population.

Confidence interval (CI) - a range of values likely to contain the true value of a parameter being estimated. The width of the CI will depend on the variability of the observations being used to estimate the parameter and the number of observations. CI around estimated coefficients and fitted functions indicate the uncertainty in the coefficients/functions; the wider the interval, the more uncertainty in the estimated values.

Cross validation (CV) - an approach used to assess the fit of competing models where a smaller CV score is preferred. Data are divided into 'training' and 'validation' sets, the model is fitted to the training set and then compared to validation set. This process is repeated and the results are averages to obtain a score. In k-fold cross validation, the data are randomly divided into k equally sized subsets and each subset is used as the validation set in turn. The average of the k values is used as the CV score.

Explanatory variable - also called independent, or predictor, variable. Used to estimate the response variable.

Generalized variance inflation factor - a measure to quantify the severity of multi-collinearity in a generalized linear model.

Mean - average

Multi-collinearity - two or more explanatory (or predictor) variables are highly correlated.

p-value - probability assessing the significance of an explanatory variable in a model.

pseudo R^2 fit statistic - a measure of the squared correlation between the observed values and the values estimated from the model. It takes values between 0 (no correlation) and 1 (perfect correlation).

Response variable - the measurement of interest in a statistical model and estimated from a combination of explanatory variables. Also called the dependent variable.

Zero-inflated - zero values more frequently observed than expected for a particular distribution.

Appendix A. Summary of aerial survey data

Six digital aerial surveys were flown over the Liverpool Bay SPA on five days (Table A1). Plots of the numbers of birds per segment identified during each survey are shown overleaf. Note that the colour scales are different for each plot because of the large variation in the numbers of birds identified per segment between surveys (Table A2).

Table A1. Summary of the realised coverage for each survey; k is the number of transects, Nseg is the number of segments, L is the total length of search effort (km); w is the total strip width (km) and a (= L x w) is the area covered during the survey (km^2).

Survey	Date	k	Nseg	L	w	a
1	12/02/2011	58	711	708.4	0.175	124
2	07/03/2011	58	695	697.8	0.175	122.1
3	07/03/2011	38	587	585	0.175	102.4
4	18/03/2011	38	591	591	0.175	103.4
5	24/01/2015	44	742	742	0.5	371
6	04/02/2015	44	713	717.3	0.5	358.6
Total		280	4039	4041		1182

Table A2. The numbers (N) of common scoter (CS) and red-throated diver (RTD) identified sitting on the water (sit) and flying (fly) for each survey.

Survey	N CS sit	N CS fly	N RTD sit	N RTD fly
1	6697	29	208	3
2	4726	544	152	2
3	2390	25	61	0
4	4505	23	92	4
5	34380	946	242	3
6	41122	496	286	10
Total	93820	2063	1041	22

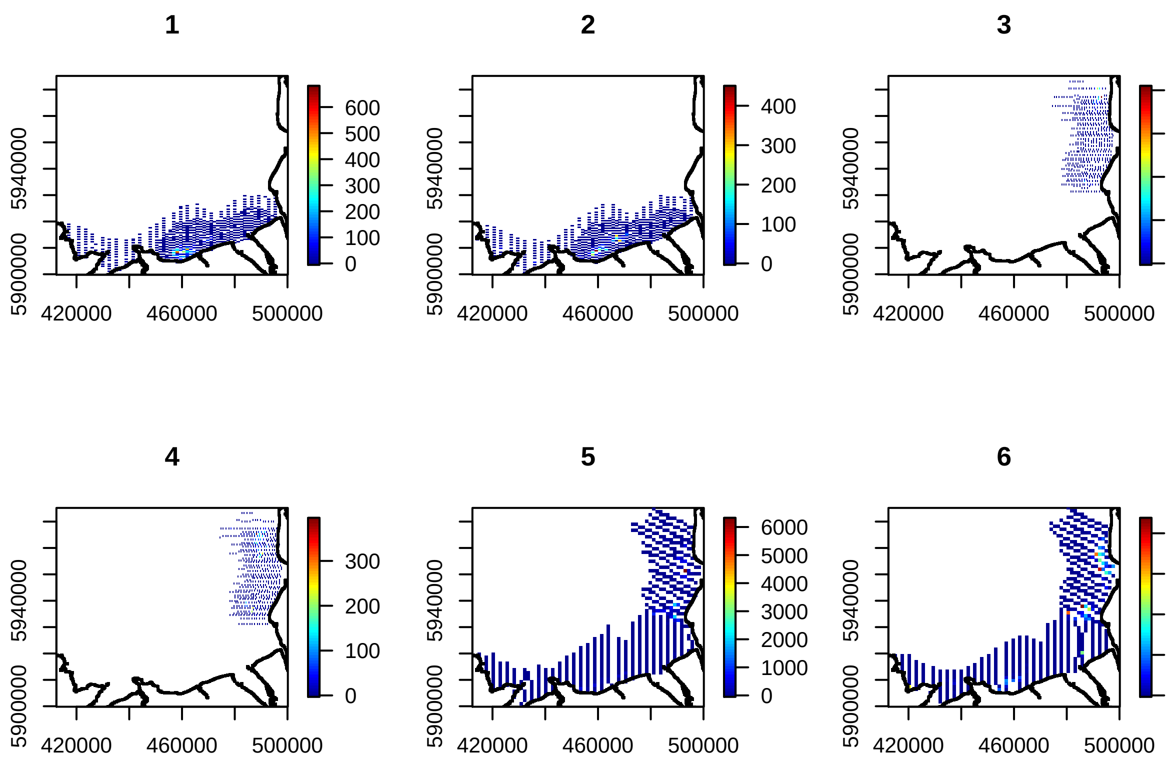


Figure A1. Numbers of common scoter sitting on the water per segment for each survey.

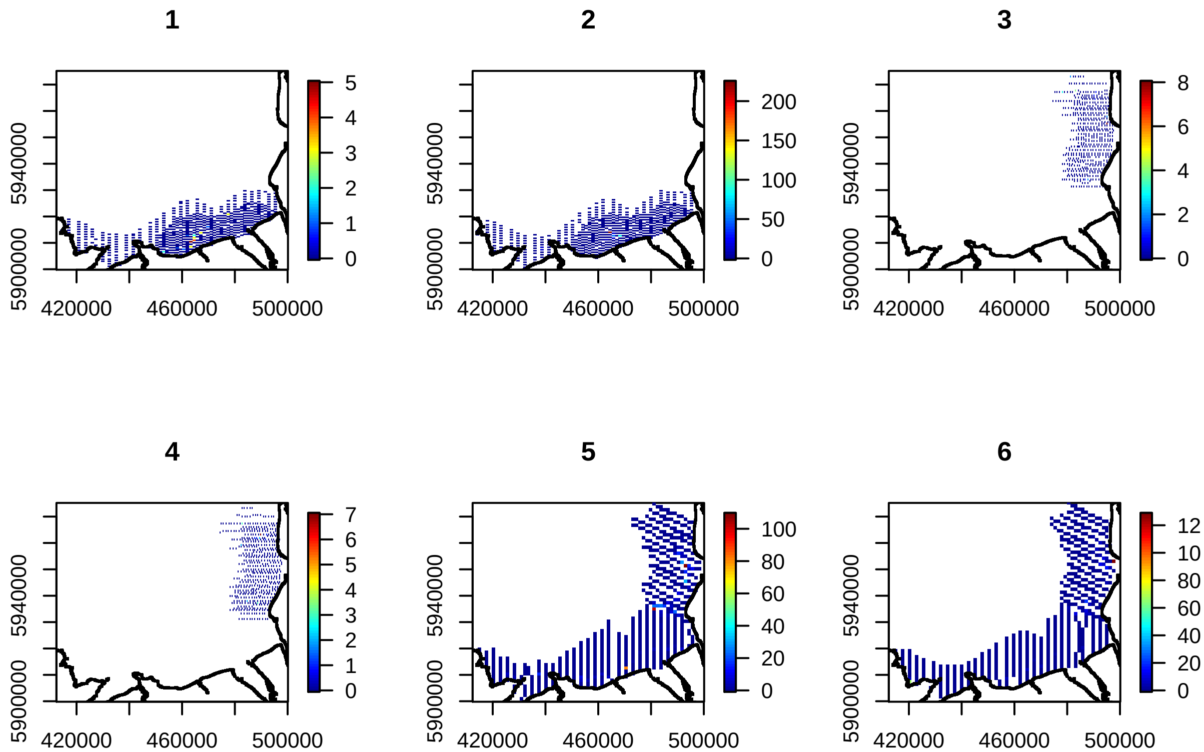


Figure A2. Numbers of flying common scoter per segment for each survey.

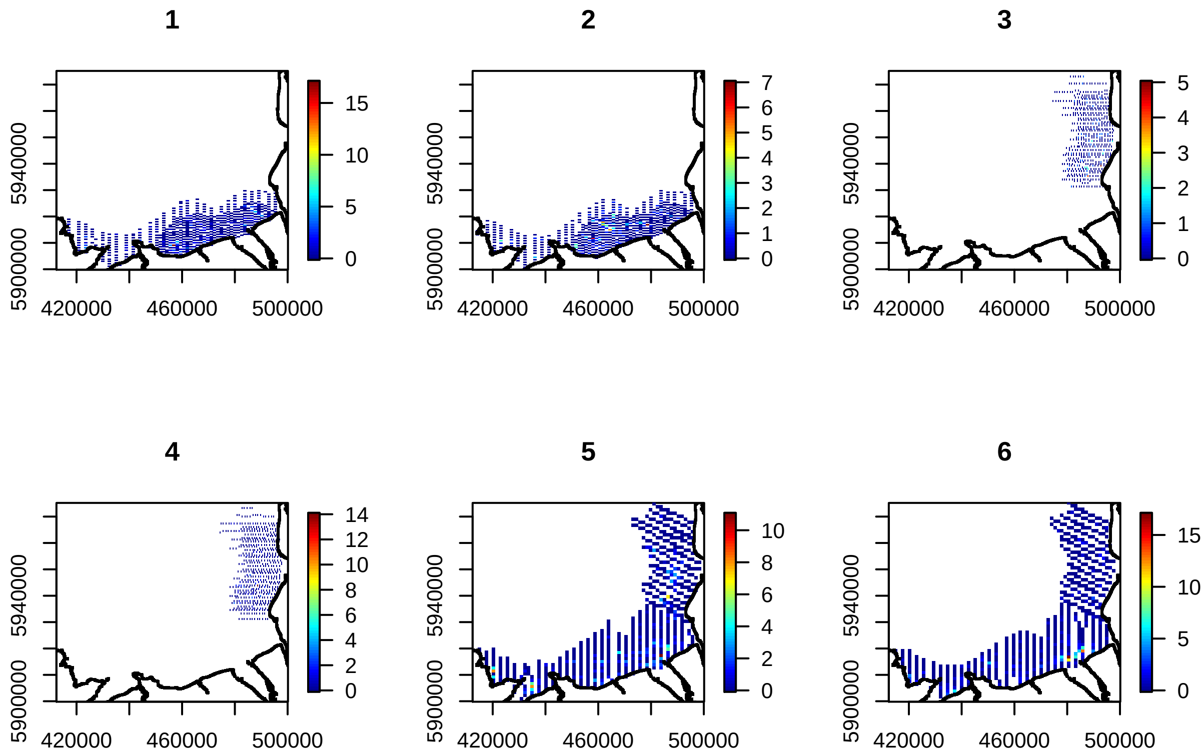


Figure A3. Numbers of red-throated divers sitting on the water per segment for each survey.

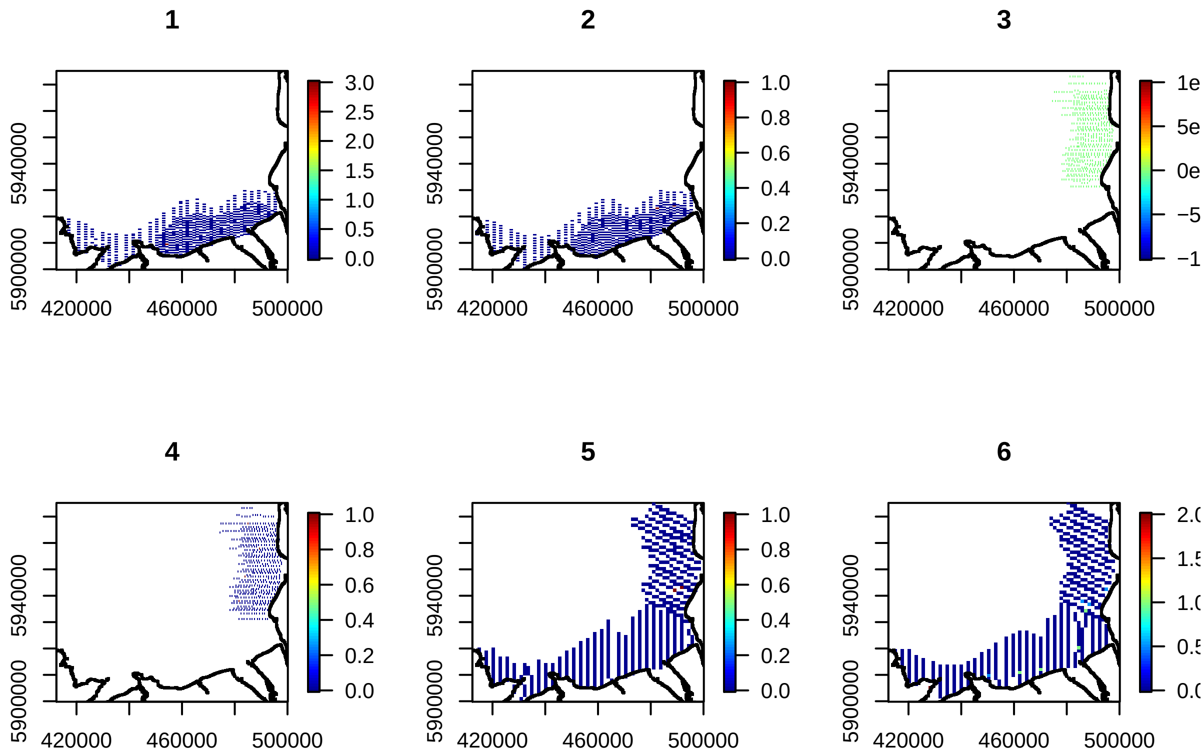


Figure A4. Numbers of flying red-throated divers per segment for each survey. No red-throated divers were identified during survey 3.

Appendix B. Shipping data

Table B1. Details of fields contained in the 2011 UK commercial fishing data for boats 15 m and over.

FieldName	Description
tottime	Total time (minutes) by all vessels
mobtime	Total time (minutes) using Mobile gear
passtime	Total time (minutes) using passive gear
totqty	Total quantity (tonnes) liveweight of fish landed by all vessels
mobqty	Total quantity (tonnes) liveweight of fish landed using Mobile gear
passqty	Total quantity (tonnes) liveweight of fish landed using passive gear
totval	Total value of fish landed by all vessels
mobval	Total value of fish landed using Mobile gear
passval	Total value of fish landed using passive gear
totkwh	Total fishing effort (kilowatt/hours) by all vessels
mobkwh	Total fishing effort (kilowatt/hours) using Mobile gear
passkwh	Total fishing effort (kilowatt/hours) using passive gear

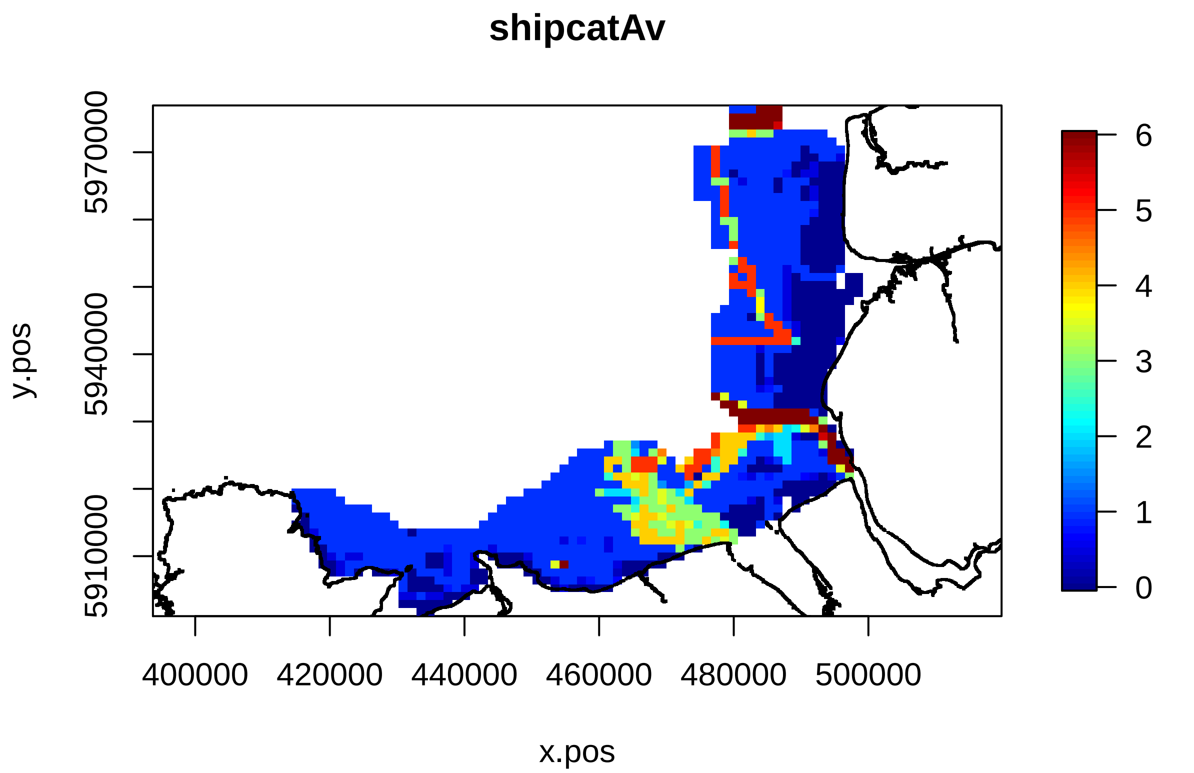
Table B2. Details of the changes made to AIS tracks. Date is in yyyymmdd format.

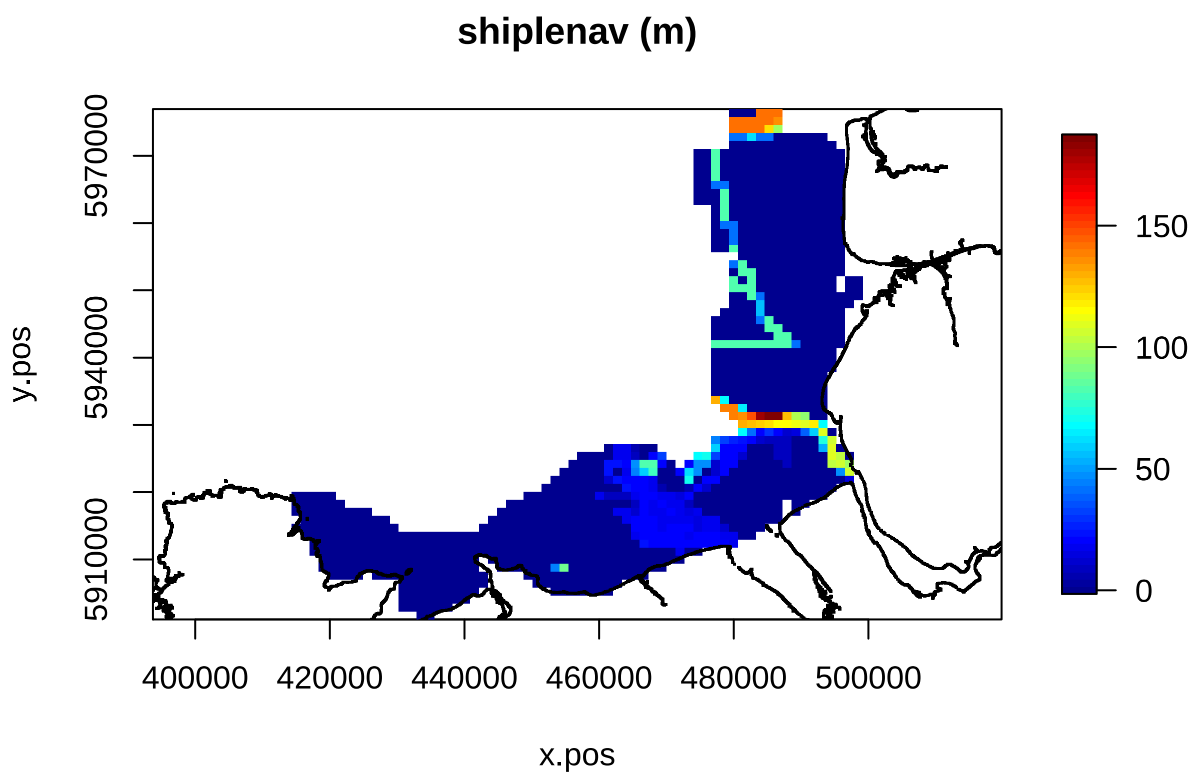
Date	Boat name	Change
20110318	South Stack	delete
20110318	Waterfall	delete part
20110318	Neptune Mariner	delete part
20110318	Ctruck Advance	delete part
20110317	South Stack	delete
20110317	Delivener	delete part
20110317	Windcat 23	delete part
20110317	Wind Transporter	delete part
20110317	Oakgarth	delete part
20110307	South Stack	delete
20110307	Oakgarth	delete
20110307	Ashgarth	delete
20110212	Oakgarth	delete
20110211	HBC Supporter	delete
20110211	HBC Reformer	delete
20110211	Sea Hex	delete
20110211	Pompeii	delete part
20110211	Normand Prosper	delete part
20110211	Henly Pioneer	delete part
20110211	Ashgarth	delete part
20110211	Oakgarth	delete part

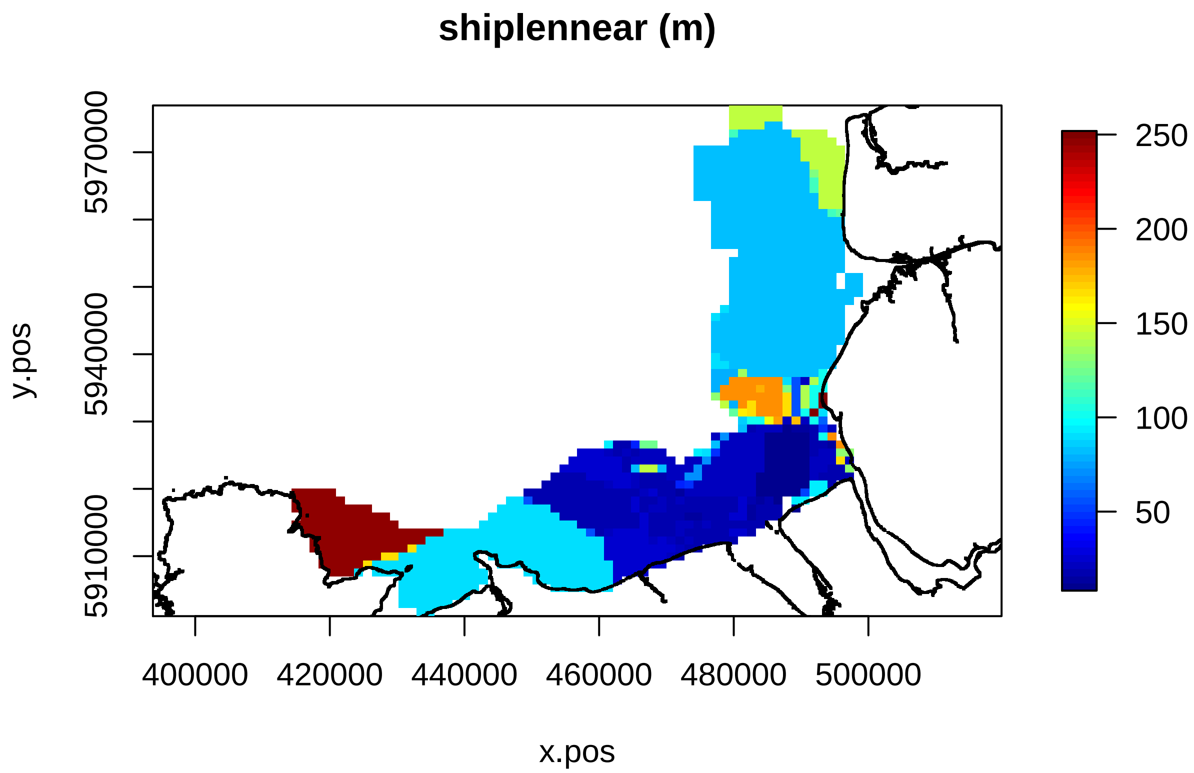
Appendix G. Plots of shipping metrics for the February 2015

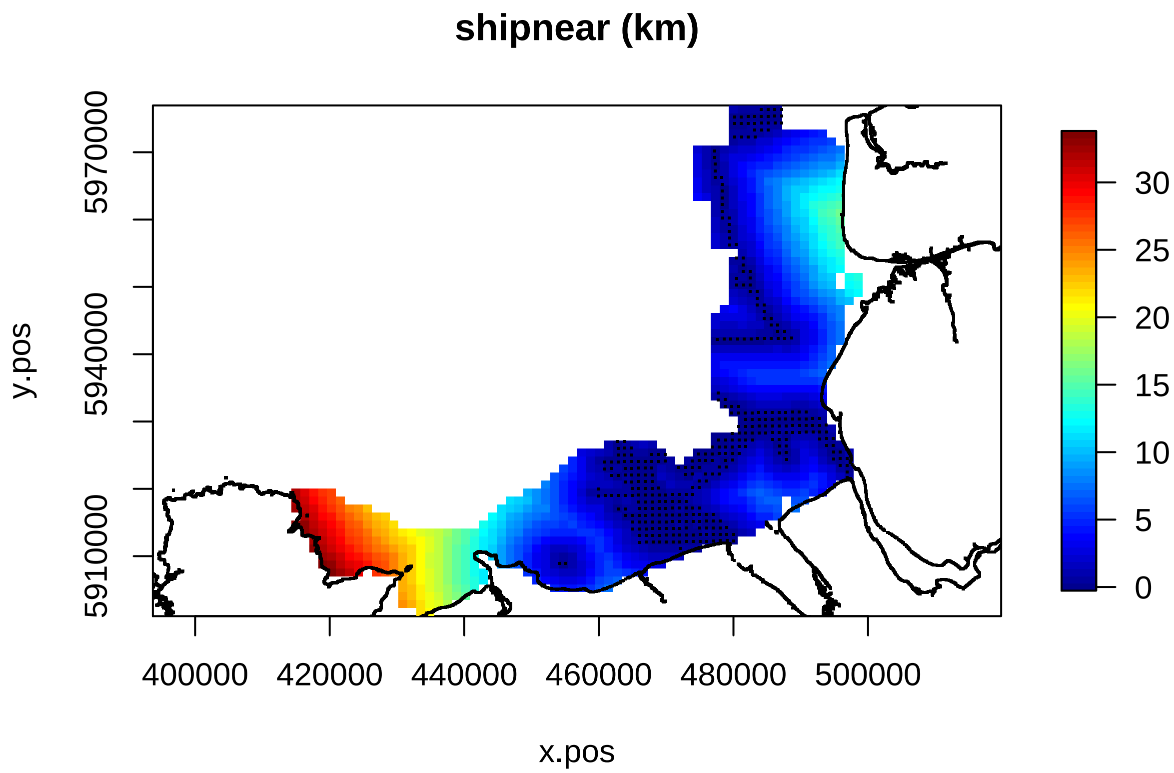
To illustrate the hypothetical changes imposed on the observed data, the shipping traffic recorded on 04/02/2015 were used. Below are plots of the variables included in the final models showing the observed values for this date throughout Liverpool Bay SPA. Other variables included in the models were not survey specific and are shown in Appendix C.

- *shipcatAv* - a factor with six levels; no ships present (0), ships present but not on the day of the survey (1) and using the average length of ships present on the day of the survey the other factor levels were, small ship 10-15m in length on average (2), ships >15-20m (3), ships >20-36m (4), ships >36-89m (5) and ships >89m in length on average (6)
- *shiplenav* - average length (m) of ships intersecting with the segment
- *shiplennear* - length (m) of the nearest ship
- *shipnear* - nearest distance to a ship (km). The black dots in this plot indicate grid cells where ships were present on the day of the survey.


shipcatAv
y.pos
5910000
5940000
5970000
400000
420000
440000
460000
480000
500000
x.pos
0
1
2
3
4
5
6


shiplenav (m)
y.pos
5910000
5940000
5970000
400000
420000
440000
460000
480000
500000
x.pos
0
50
100
150


shiplennear (m)
y.pos
5910000
5940000
5970000
x.pos
400000
420000
440000
460000
480000
500000
50
100
150
200
250


shipnear (km)
y.pos
5910000
5940000
5970000
400000
420000
440000
460000
480000
500000
x.pos
0
5
10
15
20
25
30