Seabird maps of the North Sea

A short description of methodology

Author(s): Susanne van Donk, Rob van Bemmelen, Chun Chen, Ingrid Tulp, Eleni Melis

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Client Rijkswaterstaat Water, Verkeer en Leefomgeving
Attn.: K. Portegies
Lange Kleiweg 34
2288 GK Rijswijk

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Contents

1 Assignment

This assignment is part of the 'Wind op zee ecologisch programma' (Wozep). The methods developed by this project will be used in the upcoming 'Kader Ecologie en Cumulatie' (KEC 5.0). Within KEC, the cumulative effects of planned and already built offshore windfarms on species with a protected status within natural legislation are assessed. This assignment focuses on the preparation of distribution maps for seabirds species within KEC ('Dichtheidskaarten zeevogels').

In the previous KEC studies, international and national seabird distribution maps were generated by interpolating ship- and airplane based counts of seabirds in the North Sea. For this, 'Inverse Distance Weighted' interpolation was used, which is a deterministic method that results directly from raw (averaged) counts (Leopold et al., 2014). However, this method does not provide any information on robustness or statistical uncertainty of the interpolated count data. Another shortcoming of the deterministic method was that rare observations with high number of birds get a relatively large influence on the density at a certain location. Furthermore, ecological covariates that might explain the distribution of birds were not taken into account in the previous approach. Therefore, a statistical method for estimating bird distributions was developed to address these issues. The resulting maps are based on statistical models in which the densities in space and time per species are predicted based on statistical correlations between relevant covariates abiotic and biotic conditions and human activities) and a random spatial temporal factor. In addition to the predicted densities, these maps also provide information about reliability and (statistical) uncertainty regarding the predicted densities. By including covariates, this new method provides a deeper knowledge on the ecological processes underlying the observed and expected seabird distributions. Maps were prepared for a total of nine seabird species: Northern Gannet *(Morus bassanus)*, Herring Gull *(Larus argentatus)*, Lesser Black-backed Gull *(Larus fuscus)*, Great Black-backed Gull *(Larus marinus)*, Black-legged Kittiwake *(Rissa tridactyla)*, Great Skua *(Stercorarius skua)*, Razorbill *(Alca torda)*, Common Guillemot *(Uria aalge)* and Sandwich Tern *(Thalasseur sandvicensis)*.

This report describes the applied method in terms of data preparation, use of covariates, and model use and selection. For the exploration and results part, we used the Black-legged Kittiwake as an example species. Final models and predicted maps are provided per species in the appendix. Data selection and statistical method have been changed over the course of the project due to advice of experts and challenges we encountered during data exploration and model fitting. Changes and decisions on the method are indicated in the text and further explained in the discussion. All analyses were executed in R, and the respective scripts are provided in a Github repository.

2 Material and Methods

2.1 Used datasets

2.1.1 Seabird dataset

2.1.1.1 ESAS & MWTL dataset

Two datasets were considered in the analyses. The European Seabirds At Sea (ESAS) database includes mostly ship-based counts of seabirds in the greater North Sea. This dataset is managed and updated by the Brussels 'Instituut voor Natuur- en Bosonderzoek' (INBO). The 'Monitoring Waterstaatskundige Toestand des Lands' (MWTL) dataset holds aerial surveys covering the Dutch section of the North Sea. This dataset was requested from Waardenburg ecology. For more in depth information on how data is gathered for the ESAS and MWTL datasets we refer to previous studies (Camphuysen et al., 2004; Fijn et al., 2020; van Roomen et al., 2013).

Counts from 1991 onwards were only selected when they had a valid geographical position (latitude and longitude) and a non-zero sampled surface area. Each count was assigned to a bimonthly period: December-January, February-March, April-May, June-July, August-September and October-November.

The ESAS database is collated from surveys with a wide variety of objectives (See European Seabirds At Sea (ESAS). ICES, Copenhagen, Denmark. https://esas.ices.dk). In most (standard) surveys, all species encountered were counted. However, some surveys targeted specific species or groups of species. The MWTL dataset is more consistent, as surveys have been conducted in six months over the course of the year in a standardized way. This standardized method and the survey design have been adjusted in 2014. After this change, the lower flying height allowed identification to species level of almost all groups, including Common Guillemot and Razorbill. In addition, the more extensive survey transects design resulted in a more even spread of survey effort across the Dutch continental shelf compared to the survey design before 2014.

2.1.1.2 Preparation of dataset

Distance sampling analysis

Distance sampling is a statistical technique that accounts for the lower detection of birds that are at greater distance from the observer or, in the case of ship-based and aerial surveys of seabirds at sea, the transect line (Buckland et al. 1993, 2001). Therefore, observers are required to note the distance of (each flock of) birds from the transect line. It is expected that there are less detections of birds at greater distance from the transect line. This relationship can be described by the *detection curve*. To account for non-detected birds in calculating bird densities, either the count or the surveyed area can be adjusted. In the latter case, the *effective strip width* (ESW) needs to be calculated from the detection curve. Detection curves (and the resulting ESWs) were estimated for each species using the *Distance* package (Miller et al. 2019, Miller and Clark-Wolf 2023) in R (version 4.3.1, 2023-06-16) (R Core Team 2023).

Distances from the transect line were usually recorded in distance bins. Whereas the ESAS protocols prescribe the use of four bands between 0 and 300m from the transect line (with boundaries at 50m, 100m and 200m), several survey programs used different boundaries of the distance bins. Therefore, separate models were fitted for each combination of distance bin boundaries.

Per data set, several models were constructed and compared based on the Akaike Information Criterion (AIC). Models were fitted with a half-normal or hazard-rate base function, and either without covariates but with a cosine adjustment term, or with no adjustment term and sea state as a covariate. The model with the lowest AIC value was selected as the final model, from which ESWs were calculated and used to calculate the effectively surveyed area for all segments in the original survey data used for the spatial modelling.

Survey data preparation

Survey data was prepared for spatial modelling in several steps. The appropriate selection of data was made. For each species, only survey campaigns were included where the species was included in the target taxa (species were occasionally excluded for various other reasons for instance when counting from an active fishing vessel, which attracts large numbers or gulls). For some species, identification is not always straightforward and when not identified to species level, they were registered as a species group. For example, Razorbill and Common Guillemot are morphologically similar and are often registered as being one of the two species. The same applies to large gulls. The percentage of individuals not identified to species level can be substantial in these surveys. Excluding unidentified birds would therefore lead to an underestimation of the focal species. Therefore, unidentified birds were divided over the relevant species according to their relative abundance among identified individuals of that species group recorded on that same date in the same survey.

Transects were divided in shorter segments, but this differed between survey campaigns and methods. Ship-based surveys with intervals shorter than 5 minutes were resampled to 5-minute intervals. Aerial surveys with short intervals were resampled to 1-minute intervals. The effectively surveyed area per transect segment was calculated as the segment length multiplied by the effective strip width multiplied by the number of sides of the ship or airplane where was counted.

2.1.2 Covariates

2.1.2.1 Covariates and coupling to bird datasets

Datasets, their source and the time-period that was used in the initial exploration are described in Table 2-1 and two examples plotted in Figure **2**-**1** and **Figure 2-2**. We developed an R-script that coupled the bird dataset to the covariates. This can be found at https://github.com/rvanbemmelen/MORUS. In this script, data selection and data processing and which datasets were used in the final analysis per species were defined. Besides, for the creation of the maps after analysis of the data, a raster of 10*10km was created to be able to create a prediction map. The script of the creation of the raster can also be found in the Github deposit.

2.1.2.2 Selection of data, time periods and covariates

The covariates that have been used were selected based on a short literature review and on expert knowledge regarding the relation between seabird species and covariates, but was limited by the covariate data that was available for the greater North Sea. Due to the lack of prey availability data, sea surface temperature (SST), Chlorophyll-A, and sand percentage were used as proxies for prey availability, assuming a possible correlation between these covariates and fish availability (e.g. sand eel, like fish from the *Ammodytidae* family). Distances to (large) breeding site were only included in the bimonthly periods April-May, June-July and August-September. Not all covariates that were gathered were used in the final analysis. The statistical process of selecting covariates is described under the chapter data analysis (2.2.1).

After the exploratory analysis, we decided to only include MWTL data in the analysis. This decision was made because of the unbalanced data of the ESAS data; there is almost no data of the last 10-15 years outside the Dutch part of the North Sea, (see Soudijn et al., 2022b, Figure 3-1. for an example of an effort map). Furthermore, the differences in observation method within the ESAS dataset bring along problems with analysis (ship versus airplane, incidental versus consistent). For instance, some birds are attracted to ships (gull species), while this is not the case with aerial surveys. As said, the ESAS database is collated from surveys with all kind of different objectives while MWTL dataset is more consistent as counts have been conducted in six months over the course of the year in a standardized way. Finally, there was also the wish to include a time period factor in the model for later use in KEC 5.0. This is only possible with the consistent MWTL dataset, as the ESAS dataset has too many gaps/almost no data in especially the latest 10-20 years. The time period that was included in the model differed per species. For most species we selected data from 2000 onwards. For the Common Guillemot and Razorbill, however, we only used data from 2014 onwards as these species were not distinguishable from each other before due to the methods applied.

Table 2-1 Data and covariates that are used or explored in the analyses

Type of data	Source	Time period	Frequency
ESAS raw data	available at ESAS (ICES datacenter) MWTL data, not open. https://sovon.nl/ or https://waardenburg.eco/	1991-2022	Date time stamp for every observation
Sediment (percent mud and percent sand) Depth Distance to (nearest) coast	Working Group on Spatial Fisheries Data (outputs from 2021 meeting). https://www.ices.dk/community/groups/pages/wgsfd.aspx	nvt	One value for all years
Sea surface temperature, Mass concentration of Chlorophyll A	Marine Copernicus. https://doi.org/10.48670/moi-00153, https://doi.org/10.48670/moi-00058	SST: January 1982 to December 2020, Chl-a: January 1993 to June 2022	SST: annually and monthly Chl-a: annually and monthly
Other species distribution	Waggitt, James (2019), Data from: Distribution maps of cetacean and seabird populations in the North-East Atlantic, Dryad, Dataset, https://doi.org/10.5061/dryad.mw6m905sz	nvt	One value for all years
Breeding sites Number of breeding pairs	UK breeding sites downloaded from https://app.bto.org/seabirds/public/index.jsp. Other breeding sites taken from https://ebba2.info/	Measurements done between 2013-2017	One value for all years
Shipping lanes	RWS (2017), Scheepvaart verkeersscheidingsstelsel Noordzee (Nederlands Continentaal Plat) update 1-juni-2017, https://www.nationaalgeoregister.nl/geonetwork/srv/dut/catalog.search#/metadata/5996e444-f7f3-40d2-b485-8b9af6e8aa89?tab=relations	Version of 2017	One value for all years
Mining platforms	Human activities, oil & gas platforms, boreholes and offshore installations. https://emodnet.ec.europa.eu/geoviewer/	1950-now	Moment of completion or construction in year-month
Offshore windfarms	To be requested via Wozep - Offshore Wind Ecological Programme OWPdata_HabLoss500mBuffer.gpkg, Soudijn, F. H., Hin, V., Wal, J. T. van der, & Donk, S. van. (2021). Cumulative population-level effects of habitat loss on seabirds "Kader Ecologie en Cumulatie." Wageningen Marine Research report C070/21, IJmuiden, September 2021, https://doi.org/doi.org/10.18174/553775		Moment of completion construction in years
Fishing activity	VMS data via WMR		Annual data between 2009-2020

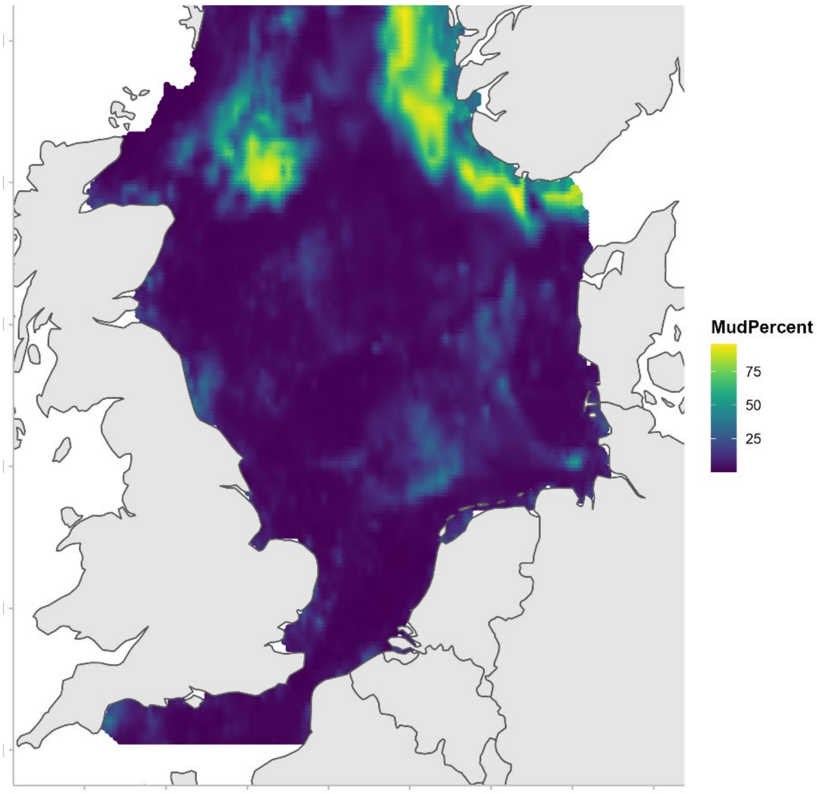

Figure 2-1 Mud percent in the North Sea. Working Group on Spatial Fisheries Data (outputs from 2021 meeting). (https://www.ices.dk/community/groups/pages/wgsfd.aspx)

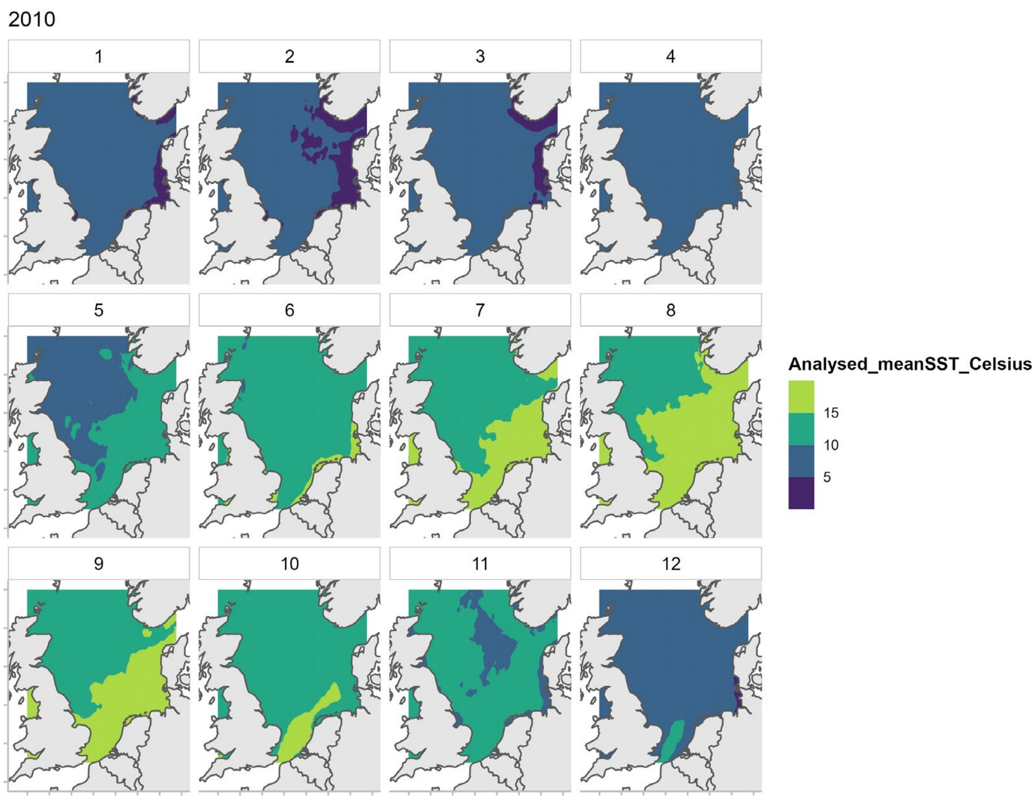

Figure 2-2 Mean sea surface temperature in the North Sea in 2010 per month. (Marine Copernicus)

2.2 Habitat modelling

2.2.1 Description general statistical method

So far, not much has been published on habitat modelling on the large spatial temporal scale of the entire North Sea over the last 30 years. Waggitt et al. (2020) published estimated density maps using a GLM for several seabirds using international observational data. Soudijn et al. (2022a) applied a GLM model under a Bayesian framework using the R-package 'INLA'. However, the uncertainty of the estimation and the ability of the model to predict density were not extensively taken into consideration, and the model runs were highly time-consuming. In this project, we applied a generalized linear/additive mixed model (GLMM/GAMM) (including spatial-temporal effects (i.e. estimated through a stochastic partial differential equation approach (SPDE)) with a sequential process of model selection using cross-validation. The modelling steps are illustrated in **Figure 2-3**. The habitat modelling and the predicted density maps are desired to tackle the following characteristics:

- Estimate high numbers of zero observations that are present in the data and over-dispersion of the density distribution;
- Provide uncertainty estimations of density distributions;
- Model the spatial-temporal autocorrelation of the density distributions;
- Predict densities at unobserved locations/times;
- Explain ecological causes of habitat preferences;
- Provide seasonal maps.

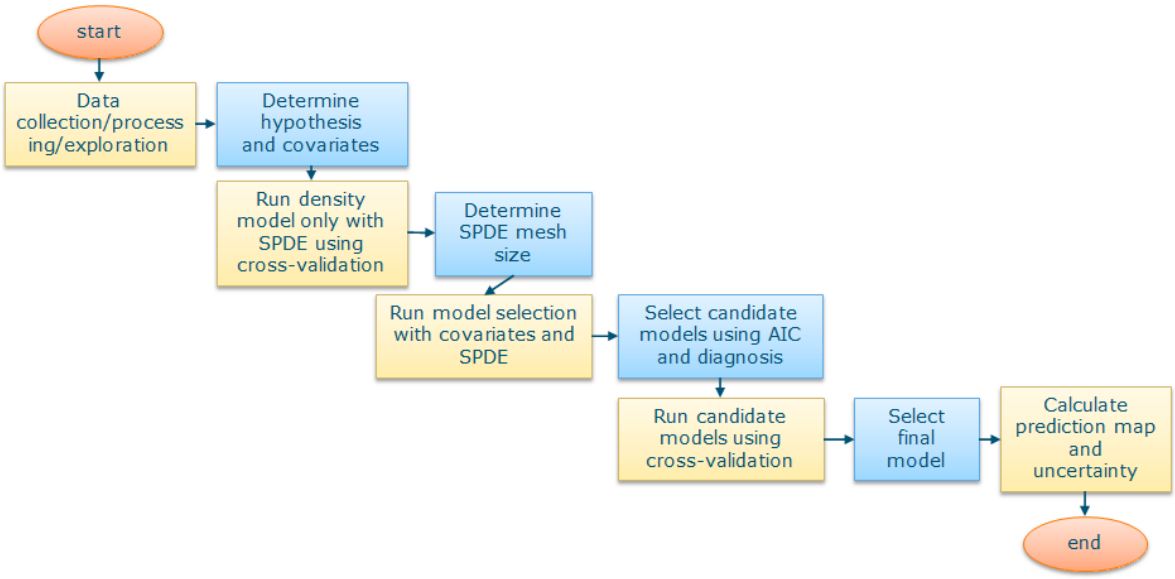

Figure 2-3 The modelling steps used in this project.

The steps are described as follows:
Step 1: data exploration, collinearity was checked among all collected variables, and a subset of covariates was selected for modelling
Step 2: ran spatial SPDE, GLMM model with varying mesh size was configured under cross-validation, and the best mesh size configuration was selected
Step 3: ran GLMM model and spatial-temporal SPDE and all selected covariates. The candidate models using AIC and model diagnosis were selected
Step 4: ran candidate models using cross-validation and selected the final model
Step 5: calculated prediction map and uncertainty

Cross-validation was employed to prevent overfitting. Due to the high complexity of the model, it was separated into two step-wise cross-validations procedures in the framework.

The GLMM/GAMM analysis was implemented using R's sdmTMB package (Anderson et.al., 2022). All the scripts with details of the model can be found in https://github.com/rvanbemmelen/MORUS.

3 Results

In this section, we show results of the habitat model. When results are shown, we used the Black-legged Kittiwake as an example species.

3.1 Statistical method

3.1.1 Data exploration

We explored data distributions, missing values, outliers and data transformations. **Figure 3-1** illustrates the relationships among pairwise covariates and bird-densities. Based on their statistical relationships, as well as ecological hypothesis, a subset of more ecologically plausible covariates were selected to test in the GLMM. Depth was strongly correlated with distance to nearest coast (**Figure 3-1**, dark red square), we therefore decided to only use depth in the analysis. For many species, we found a strong correlation between distance to (big) breeding site and depth. This was not the case for the Black-legged Kittiwake in the example shown in **Figure 3-1**, also not in the summer months. For the Kittiwake, we could therefore include both distance to big breeding site as depth in the model.

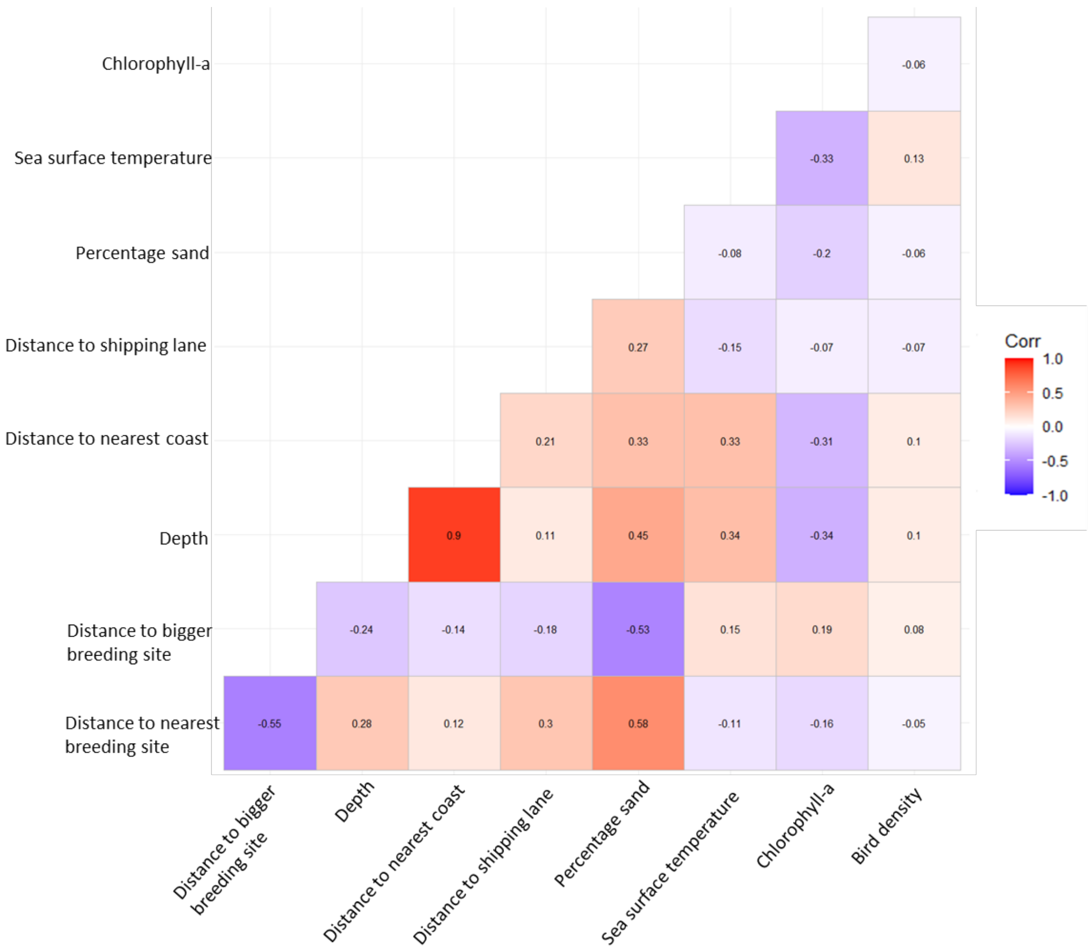

Figure 3-1 The correlation plots among variables collected in December-January for Kittiwake. A stronger color correlates with a higher correlation between two variables. Red indicates a positive correlation and blue a negative one. All variables were transformed for this correlation plot (square root or other transformation).

3.1.2 SPDE model

There are local spatial patterns that cannot be explained by global habitat covariates. These local spatial patterns can be mathematically defined as a Gaussian Markov Random Field (GMRF) (Rue and Held, 2005). To estimate the covariance of a GMRF, an SPDE model was applied. To work out the SPDE model, a spatial irregular grid structure was defined. The grid should not be too refined to prevent overfitting nor too coarse to miss the local spatial pattern. We tested four models with time-invariant spatial SPDE models (**Figure 3-2**). The mesh was defined based on the cutoff value, i.e. the minimum allowed distance between points in the mesh. After applying the cross-validation procedure, the model with a mesh cutoff of 15 km was selected. Later, however, we selected a model with a mesh cutoff of 20 km instead of the 15 km mesh, as we showed that this mesh size was better in prediction of the data.

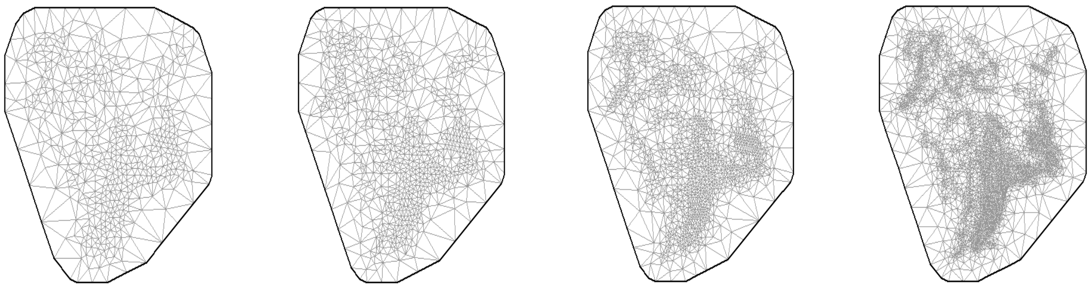

Figure 3-2 SPDE meshes tested with cross-validation for the Kittiwake model for the December-January period. The cutoff values set to construct the mesh were 20km, 15km, 10km and 5km (from left to right).

3.1.3 Covariates included in full models per species

We decided to not include the covariates effective surveyed area (ESA) and distance to platforms in the models. ESA seemed to have an effect on density in some birds, but after investigating the effect, it seemed mostly driven by a small number of large values of ESA and we could not explain the biologically meaning or the difference per species. With regards to the distance to platforms, birds on top of platforms were not counted and areas of (high) platforms are avoided at counts with airplanes. Furthermore, we took out the percentage of sand for birds that were not expected to feed substantially on sand eel. Whether or not an observation was within a windfarm was removed from the model because the amount of data within wind farms was very low. Distance to coast was replaced by water depth as covariate as these covariates are highly correlated. In **Table 3-1**, the covariates included at the start of model selection are shown per species. In the process of data exploration, we noticed that there were not enough non-zero observations for the Great Skua to run a model. Therefore, for this species, we prepared 5-year period maps using the old method of inverse distance weighting. For the species for which we could use data from 2000 onwards we added time-periods of five years (2000-2005, 2005-2010, 2010-2015-2020) to the data to include in the model as time period. For Razorbill and Common Guillemot, a time-period of one year was applied as not enough data was available to apply 5-year periods for these species.

Table 3-1 Covariates included in starting models per species

Sand % = percentage of sand of the seafloor substrate, SST = Sea Surface Temperature, Chl-a = Chlorophyll-a

Species	Depth	Proxies for prey			Distance to breeding site	Distance to shipping lane	Fishing intensity	Time period
		Sand %	SST	Chl-a				
Northern Gannet	x	x	x	x				5-year
Herring Gull	x		x	x			x	5-year
Lesser Black-backed Gull	x	x	x	x			x	5-year
Great Black-backed Gull	x		x	x	x		x	5-year
Black-legged Kittiwake	x	x	x	x	x		x	5-year
Razorbill	x	x	x	x		x		year
Common Guillemot	x	x	x	x	x	x		year
Sandwich Tern	x	x	x	x				5-year
Great Skua	IDW model							

3.1.4 Full model selection

A list of models was tested, including both fixed covariates and the spatial SPDE model as selected in Section 3.2.

$$dens_i \sim \text{Tweedie}\ (\mu_i, p)$$
$$\log(\boldsymbol{\mu}) = \text{intercept} + \boldsymbol{X} \times \boldsymbol{\beta} + \mathbf{A}\ \times \mathbf{w} \tag{1}$$

The abstract model formula is given in (1). The density was estimated as a Tweedie distribution with a log link function for the mean. The linear predictor included intercept, a series of covariates (***X***) estimated as non-linear smoother, and a spatial random field (***w***) that varied by period.

The models were tested through backward selection. We started with the full model and excluded covariates stepwise. We selected the best models based on AIC. We concluded the model selection if the full model within that round had the lowest AIC by two AIC units. We left some variables in the model no matter what because of their ecological importance or their prediction strength and/or their strong correlation with other variables. These variables were depth and the time-space variance. The final models that were used for the prediction map can be seen in **Table 3-2**. The table shows that sea surface temperature, Chlorophyll-A and fishing intensity improved the model in all bimonthly periods, while percentage of sand was only of significant importance in some bimonthly periods. Distance to the breeding site did not improve the model. In the annexes, covariates included in the final model can be found for the other species.

Table 3-2 Covariates included in final model Black-legged Kittiwake

Sand % = percentage of sand of the seafloor substrate, SST = Sea Surface Temperature, Chl-a = Chlorophyll-a

Bimonthly period	Depth	Proxies for prey			Distance to breeding site	Distance to shipping lane	Fishing intensity	Time period
		Sand %	SST	Chl-A				
Dec-Jan	x		x				x	5-year
Feb-Mrch	x	x	x	x			x	5-year
Apr-May	x		x	x			x	5-year
Jun-Jul	x		x	x			x	5-year
Aug-Sep	x	x	x	x				5-year
Oct-Nov	x	x	x	x			x	5-year

3.1.5 Prediction map

The final prediction maps for December-January are shown in the figures below (**Figure 3-3**, **Figure 3-4**, **Figure 3-5**, **Figure 3-6**). Besides the prediction and uncertainty maps, we also show a map with the effect of the covariates and the effect of the spatial factor. The coefficient of variation is lower when only making predictions for the Dutch part of the North Sea compared to the full North Sea.

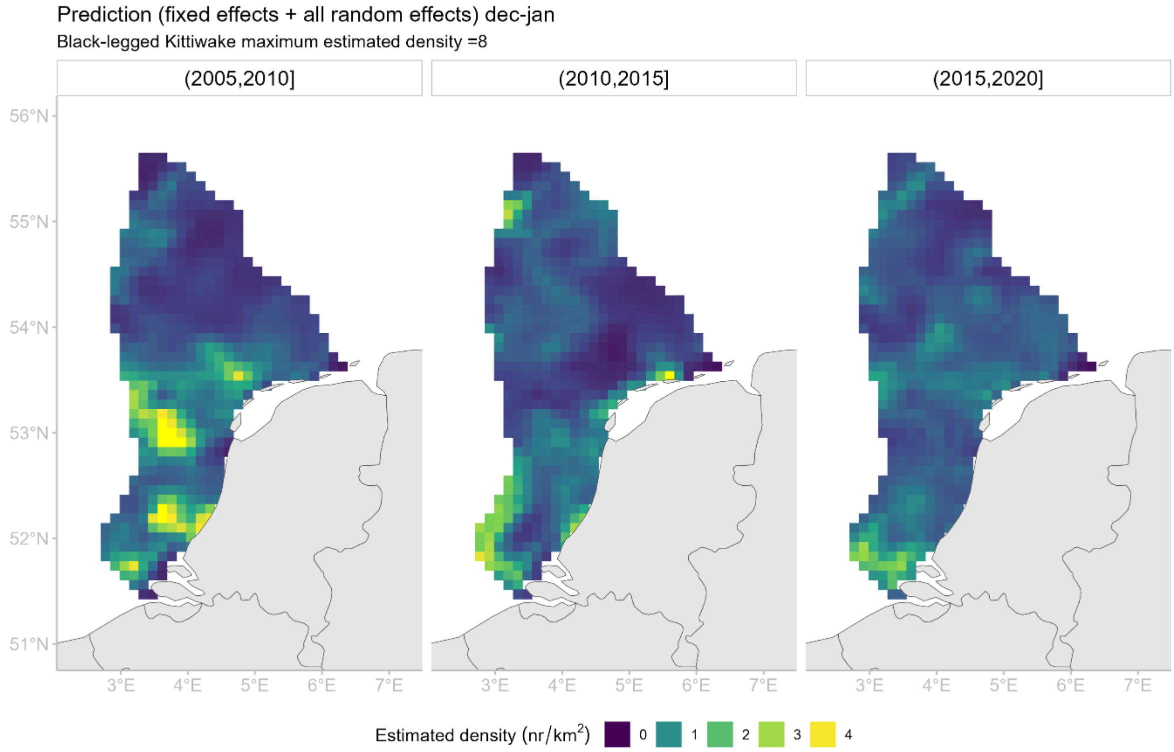

Figure 3-3 The predicted density for Kittiwake in the period December-January for the time periods 2006 to 2010 (2005,2010], 2011 to 2015 (2010,2015] and 2016 to 2020 (2015,2020].

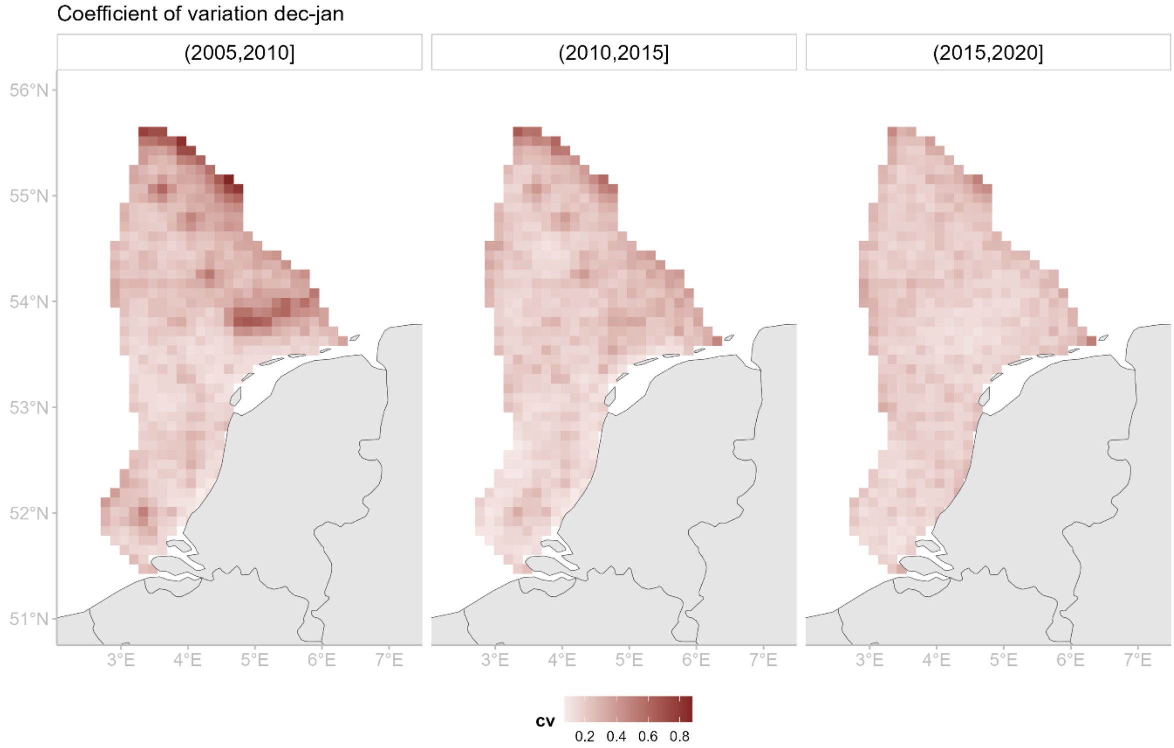

Figure 3-4 The coefficient of variation (uncertainty) for the predicted density for the time periods 2006 to 2010 (2005,2010], 2011 to 2015 (2010,2015] and 2016 to 2020 (2015,2020].

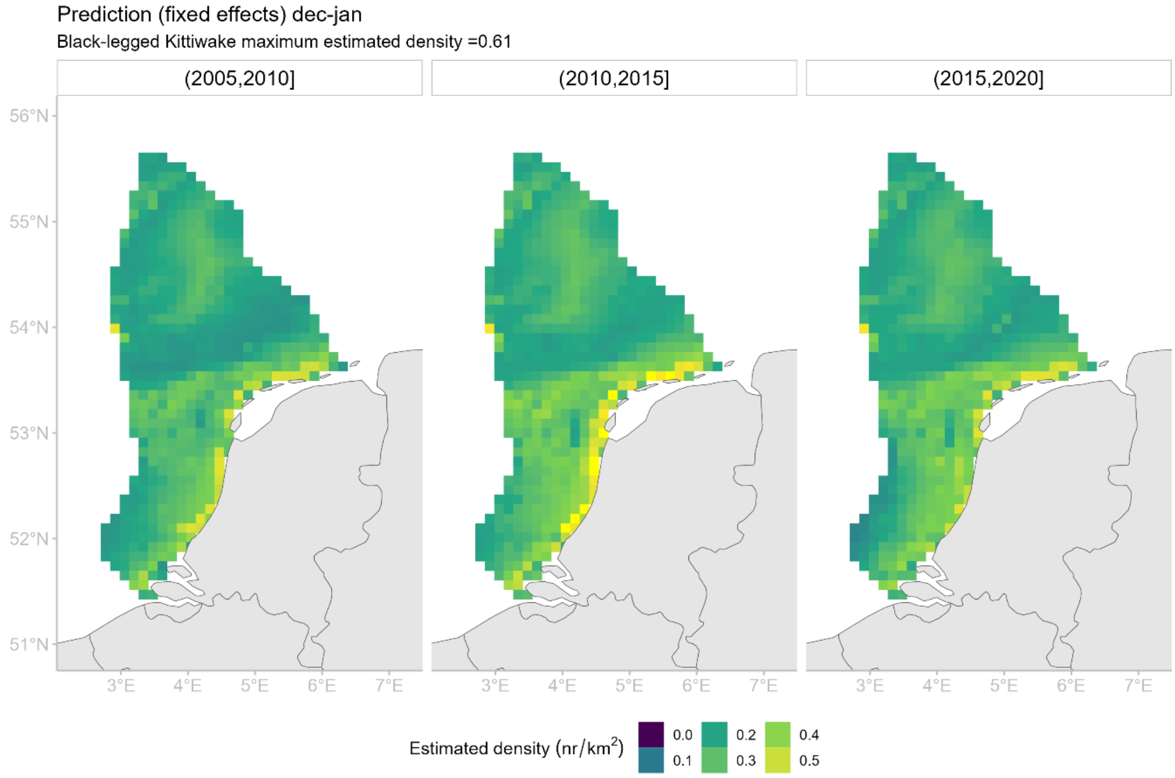

Figure 3-5 The predicted density estimated using the fixed covariates for the time periods 2006 to 2010 (2005,2010], 2011 to 2015 (2010,2015] and 2016 to 2020 (2015,2020].

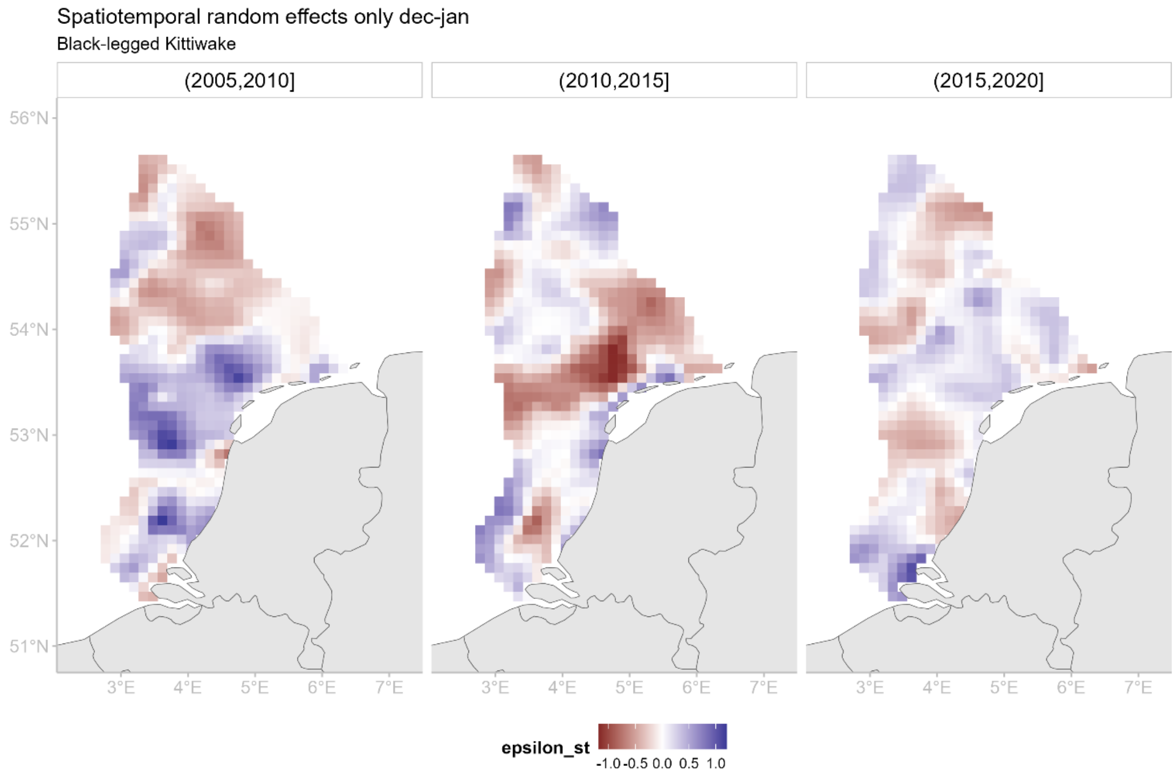

Figure 3-6 The predicted density from the local spatial random effects (SPDE) for the time periods 2006 to 2010 (2005,2010], 2011 to 2015 (2010,2015] and 2016 to 2020 (2015,2020].

3.1.6 Conditional effects

To get more insight in the relation between bird density or bird presence and covariates, we made plots of the relative relation between the predictor (bird density) and a covariate that was used in the model, while keeping the other covariates in the model on a constant value (**Figure 3-7**). In such a way, we can better understand how bird distributions are related to these covariates. Here, it appears that in the colder months (October-March) Black-legged Kittiwake densities are slightly higher in relatively shallow areas of the Dutch Sea while the opposite is true in the warmer months, especially in April-May. In this period the Black-legged Kittiwakes are probably close to breeding areas which are mostly located outside the Netherlands, and therefore closer situated to the deeper parts of the Dutch Sea. For SST, there seems to be a relatively strong effect in the colder months (October-March) and April-May. In the colder months, the kittiwakes seem to be present in higher densities in a certain range of temperatures. This means that they sometimes select the warmer waters (December-March) and sometimes the colder waters (October-November & April-May).

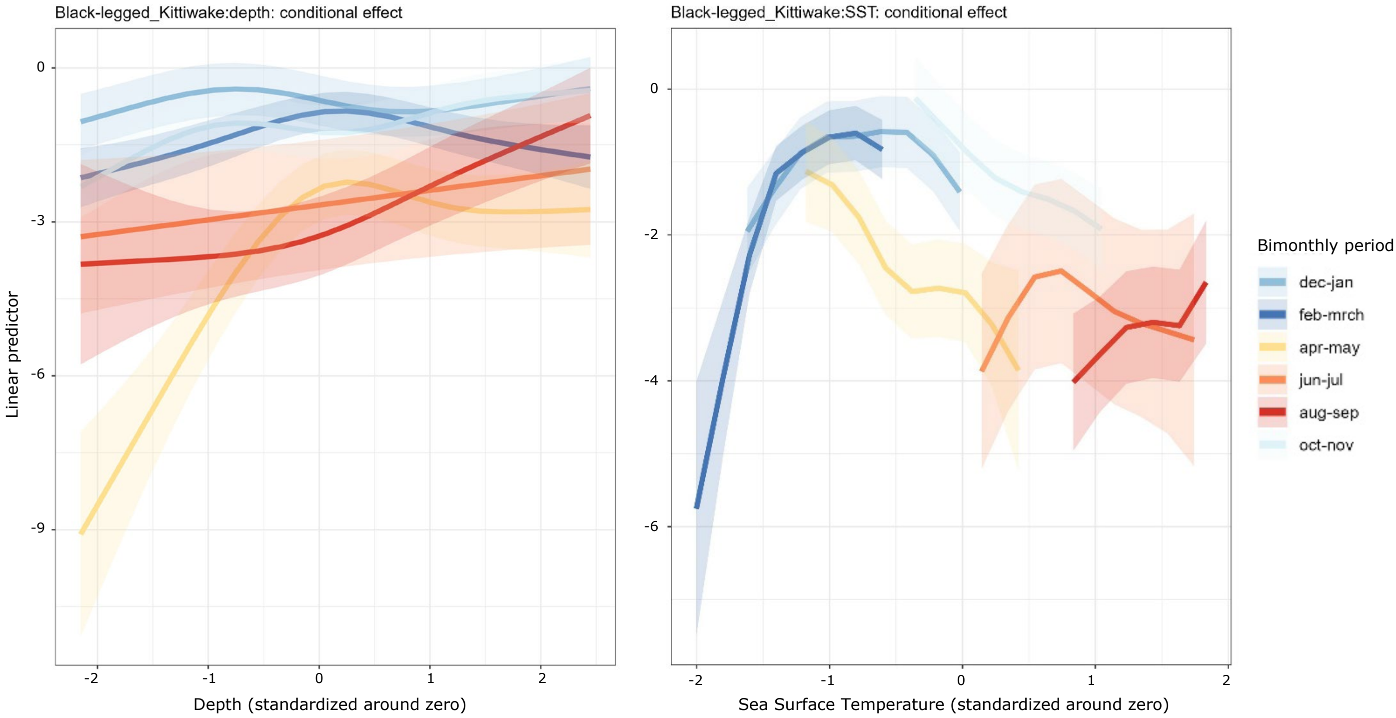

Figure 3-7 Two examples of the relative effect of two covariates on Black-legged Kittiwake density in the model while keeping the other variables on a constant value, per bimonthly period. On the x-axis the standardized value for depth (left) and standardized value for Sea surface temperature (SST, right).

4 Conclusions

During this project, new density maps covering the Dutch sector of the North Sea were created for nine seabird species. With the scripts and description of the methods, the maps can be relatively easily updated when new data becomes available. In addition, the scripts can be adapted to create density maps for other seabird species. Also, new density maps can be created for certain periods, or areas can be exclude based on uncertainty. The main aims of this project was to improve on the main shortcomings of the methodology used for earlier maps (IDW): reducing the effect of rare, very high counts and allowing the estimation of uncertainty. Both aims were fulfilled: the influence of rare, very high densities are less in the final maps compared to maps created for KEC4, which makes these maps less patchy.

Maps of the Dutch Continental Shelf

The imbalance of the national and international data was known before starting the project but difficulties with using the data in a statistical model were larger than expected. Especially, data was missing in certain parts of the North Sea (north east) and during certain important time periods (last 15 years). The differences in observation method within the ESAS dataset bring along additional problems regarding the analysis (ship versus airplane, incidental versus consistent). For instance, some birds are attracted to ships (gull species), while this is not the case with aerial surveys. We therefore decided to develop the method further by focusing on the Dutch Continental Shelf only, which restricted the analysis to the use of aerial survey data collected during the MWTL monitoring. In this way, we were better able to understand and interpret the results, and reduce the biases in the data. The project focused on creating reliable maps that can be used for calculations focused on the Dutch sector of the North Sea. Like so, we could include a time period in the model to capture changes in densities over time. Using both aerial and ship- based surveys in one analysis would require more discussion and thought.

Effect of covariates versus the random spatial-temporal factor

The random spatial-temporal factor in the model explained, relative to the fixed covariates, the most variation for almost all bimonthly periods and species. Thus, a relatively low amount of the variation in the data is explained by the fixed effects – the environmental covariates. This might be explained by fixed effects representing mainly the distribution (or habitat preference) at large spatial scales, whereas the spatial random effects likely capture small-scale spatial-temporal behaviour.

The relation between bird density or bird presence and covariates is shown as prepared conditional covariate plots, where the relative effect of the covariate on the predictor (bird density) is shown, while keeping the other covariates on a constant value (**Figure 3-7**). These plots allow a more thorough (ecological) interpretation of these relations to get more insight in seabird behaviour and distribution. This can then inform future studies, for example to exclude relations that seem to be unrealistic or that show only weak correlations with seabird densities. As in most models the spatial-temporal random effect explained most variation in the model, covariates might also compete with the other covariates in the model, especially if they show collinearity.

The models developed here result in generic density maps per bimonthly period across years. As such, these maps will not suite all purposes. For example, the frequency with which species occur at high densities in certain areas would require a different approach. Similarly, to estimate population size or wanting to know the probability that a certain species uses a specific area, other models (for instance presence absence) might be more suitable.

Model selection and model types

We used AIC for model selection and selected the simpler model in case of similar AICs. Models with too many covariates sometimes failed to converge. Adding many covariates can also result in overfitting. How to select the best model is subject of discussion and there are several alternative approaches. For instance, all selected covariates could be included in the model, no matter if they improve the model or not, which would allow to study their relative effects on seabird densities. Depth is included in all final models, and the relative effect of this covariate can be studied (Annex 1-9)

Another method that could be used is to run two or more models, using different modelling techniques or model structures, and use the average of these models for the prediction maps (Oppel et al., 2012; Woodman et al., 2019). For instance, to make a model with only the fixed effects and a model with only the random effects and take the average predicted densities of both. Such an approach may balance the pros and cons of each method.

In discussions with experts, it was suggested that the Tweedie model we used might be too sensitive for large values. Based on a comparison between the Tweedie and hurdle model, we decided to continue with Tweedie, as this model had a better fit.

We fitted one model per bimonthly period. For some species this caused problems due to too few non-zero values in certain periods (e.g., Razorbill, Great Skua). For the Razorbill, we therefore fitted one model for the warmer months (April-September; Annex 7). For the Great Skua, we used inverse distance weighting to make maps (Annex 6). Another alternative approach could be to use one statistical model per species, which includes the bimonthly period as fixed factor. A disadvantage of such a model is that it would not be possible to include or exclude certain covariates depending on the season.

Generic method versus species specific

We aimed to develop a generic method that can be used for all seabird species. However, this might not result in the best result for each species. Each species has species-specific ecology and behaviour, and models created for them separately might therefore result in better predictive models. However, the species-specific option can be very time-consuming and may be less easily transferable to new data, areas or species; whereas we aimed for a method that can be easily used in future work.

Additional ideas on selected covariates in the model

To explain bird densities, we included several covariates in the models. However, one of the most important covariates, prey density, was not available. In the future, this might be available, at least for some species and for more recent years, and can then be included. To overcome the lack of prey density information, we used three proxies for prey: percentage of sand, chlorophyll-a and sea surface temperature. Percentage of sand is known to be related to the presence of sand lance (Ammodytes), whereas chlorophyll-a and sea surface temperature are linked to primary productivity, which is expected to be reflected in the abundance of species at higher trophic levels. For some species, the importance of these variables varied between bimonthly periods. This suggests that the relation with prey and these proxies might vary seasonally or spatially.

Unfortunately, we did not have a very good measure for fishing vessel effort. The used fishing effort map is very rough, while the effect of active fishing vessels is time and space specific. More detailed information is gathered but not available for use due to privacy of fishing companies. The presence of some species is associated with other bird species (or sea mammals).

At least in the North Sea, Black-legged Kittiwakes often associate with Razorbills, that perform pursuit-dives to chase prey fish to the surface, which then become available for surface-feeding kittiwakes (Camphuysen 1999). We explored the relation between some species and density maps of Waggitt et al. (2020) as covariates. This dataset has one value per 10km^2 and showed therefore almost zero correlation with bird density. In future work, we could add real time densities or presence/absence of Razorbills to the model of Black-legged Kittiwakes.

Future directions

This project resulted in a series of maps of the distribution and densities of nine seabird species across the Dutch sector of the North Sea. The project also produced conditional plots of the relation between seabird densities and a series of covariates. However, a full evaluation of the model outcomes was unfortunately beyond the scope of this project. Future studies should therefore aim to understand and test the outcomes of our models and built on this to inform studies of more specific relationships of seabird densities with their environment. Revealing the links between environment and seabird densities is important for our understanding of the consistencies and variation in distribution of seabirds in the North Sea, which in turn can inform policies to protect seabird populations.

5 Quality Assurance

Wageningen Marine Research utilises an ISO 9001:2015 certified quality management system. The organisation has been certified since 27 February 2001. The certification was issued by DNV.

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Justification

Report C024/24
Project Number: 4316100303

The scientific quality of this report has been peer reviewed by a colleague scientist and a member of the Management Team of Wageningen Marine Research

Approved: Floor Soudijn
Researcher

Signature: DocuSigned by:
Floor Soudijn
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Date: 29th of April 2024

Approved: Tammo Bult
Director

Signature: DocuSigned by:
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Date: 29th of April 2024

Annex 1 Factsheet Northern Gannet

The models for the density distribution of the Northern Gannet show that sea surface temperature and Chlorophyll-A improved the models in almost all bimonthly periods, while percentage of sand was only of significant importance in some bimonthly periods (**Table 5-1**). As depth was not part of the model selection and was always left in the models, we showed the conditional effect of this variable. It appears that in all bimonthly periods, Gannet densities are slightly lower in relatively shallow areas of the Dutch Sea (**Figure 5-1**). This can also be seen in the maps of predicted densities, densities are low along the relatively shallow coastline (**Figure 5-2**).

Table 5-1 Covariates included in final model Northern Gannet

Sand % = percentage of sand of seafloor substrate, SST = Sea Surface Temperature, Chl-a = Chlorophyll-a

Bimonthly period	Depth	Proxies for prey			Distance to breeding site	Distance to shipping lane	Fishing intensity	Time period
		Sand %	SST	Chl-A				
Dec-Jan	x	x	x	x				5-year
Feb-Mrch	x	x		x				5-year
Apr-May	x		x	x				5-year
Jun-Jul	x	x	x	x				5-year
Aug-Sep	x		x					5-year
Oct-Nov	x		x	x				5-year

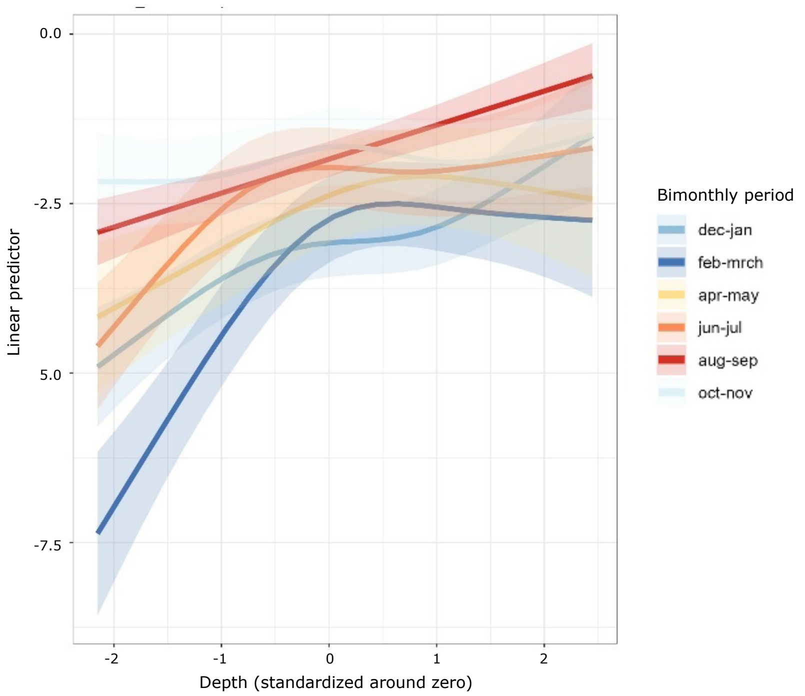

Figure 5-1 The relative effect of covariate depth on Northern Gannet density in the model while keeping the other variables on a constant value, per bimonthly period. On the x-axis the standardized value for depth; a lower value corresponds with shallower water.

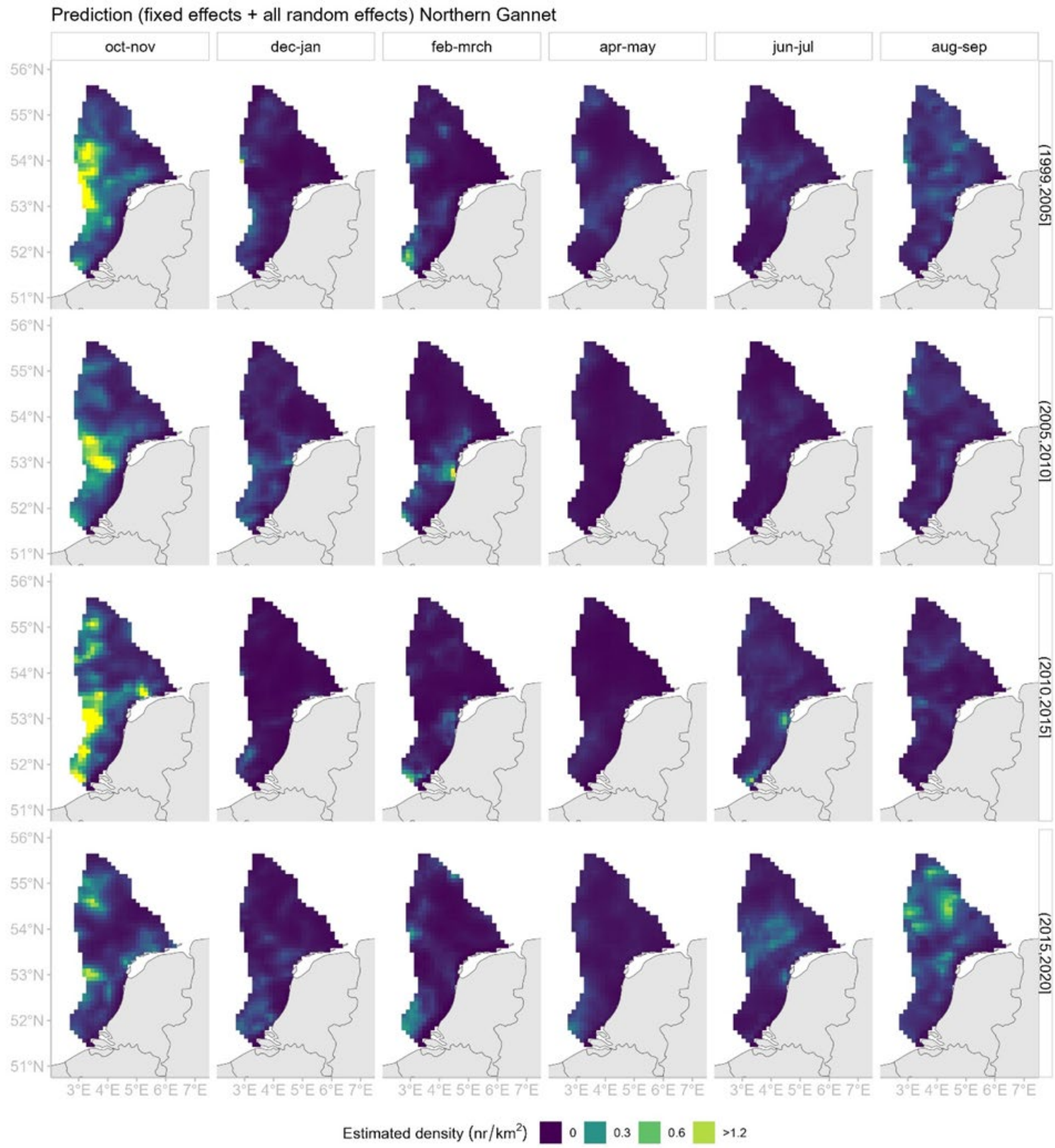

Figure 5-2 The predicted density for Northern Gannet per bimonthly period for the time periods 2000 to 2005 (1999,2005], 2006 to 2010 (2005,2010], 2011 to 2015 (2010,2015] and 2016 to 2020 (2015,2020].

Annex 2 Factsheet Herring Gull

The models for the density distribution of the Herring Gull show that sea surface temperature and Chlorophyll-A improved the model in almost all bimonthly periods (**Table 5-2**). Fishing intensity improved the models in most bimonthly periods, apart from the period between April and July. In this period, Herring Gulls probably foraged, when at sea, very close to the coast and colony and in the Wadden Sea which is not counted by MWTL. As depth was not part of the model selection and was always left in the models, we showed the conditional effect of this variable. It appears that in all bimonthly periods, Herring Gull densities were slightly lower in relatively deep areas of the Dutch Sea (**Figure 5-3**). Densities of Herring Gulls were concentrated along the coast, especially during the breeding season (April-August) (**Figure 5-4**). In winter, the predicted maps showed also higher densities further at sea (for instance in Dec-Jan).

Table 5-2 Covariates included in final model Herring Gull

Sand % = percentage of sand of seafloor substrate, SST = Sea Surface Temperature, Chl-a = Chlorophyll-a

Bimonthly period	Depth	Proxies for prey			Distance to breeding site	Distance to shipping lane	Fishing intensity	Time period
		Sand %	SST	Chl-A				
Dec-Jan	x		x				x	5-year
Feb-Mrch	x		x	x			x	5-year
Apr-May	x		x	x				5-year
Jun-Jul	x			x				5-year
Aug-Sep	x		x	x			x	5-year
Oct-Nov	x		x	x			x	5-year

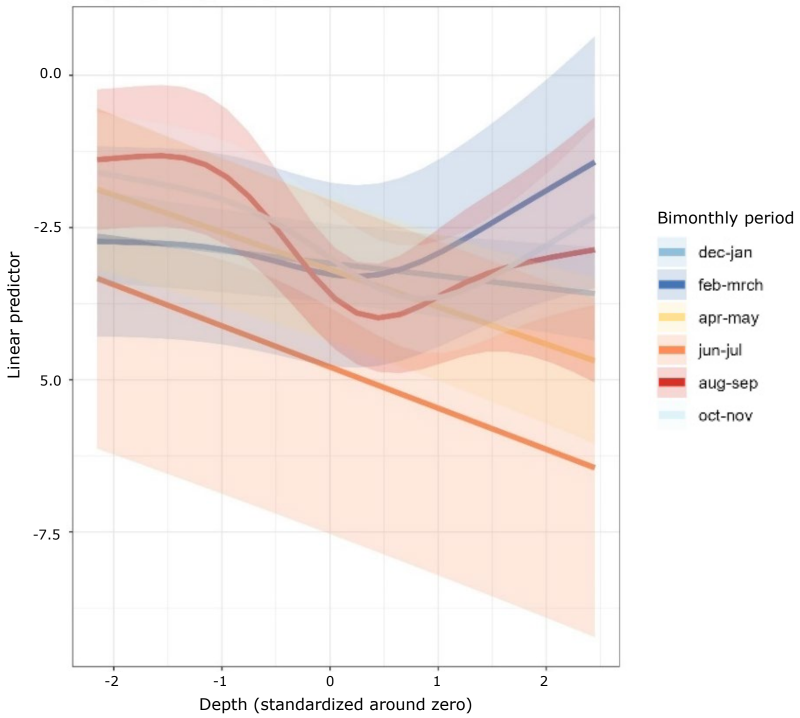

Figure 5-3 The relative effect of covariate depth on Herring Gull density in the model while keeping the other variables on a constant value, per bimonthly period. On the x-axis the standardized value for depth; a lower value corresponds with shallower water.

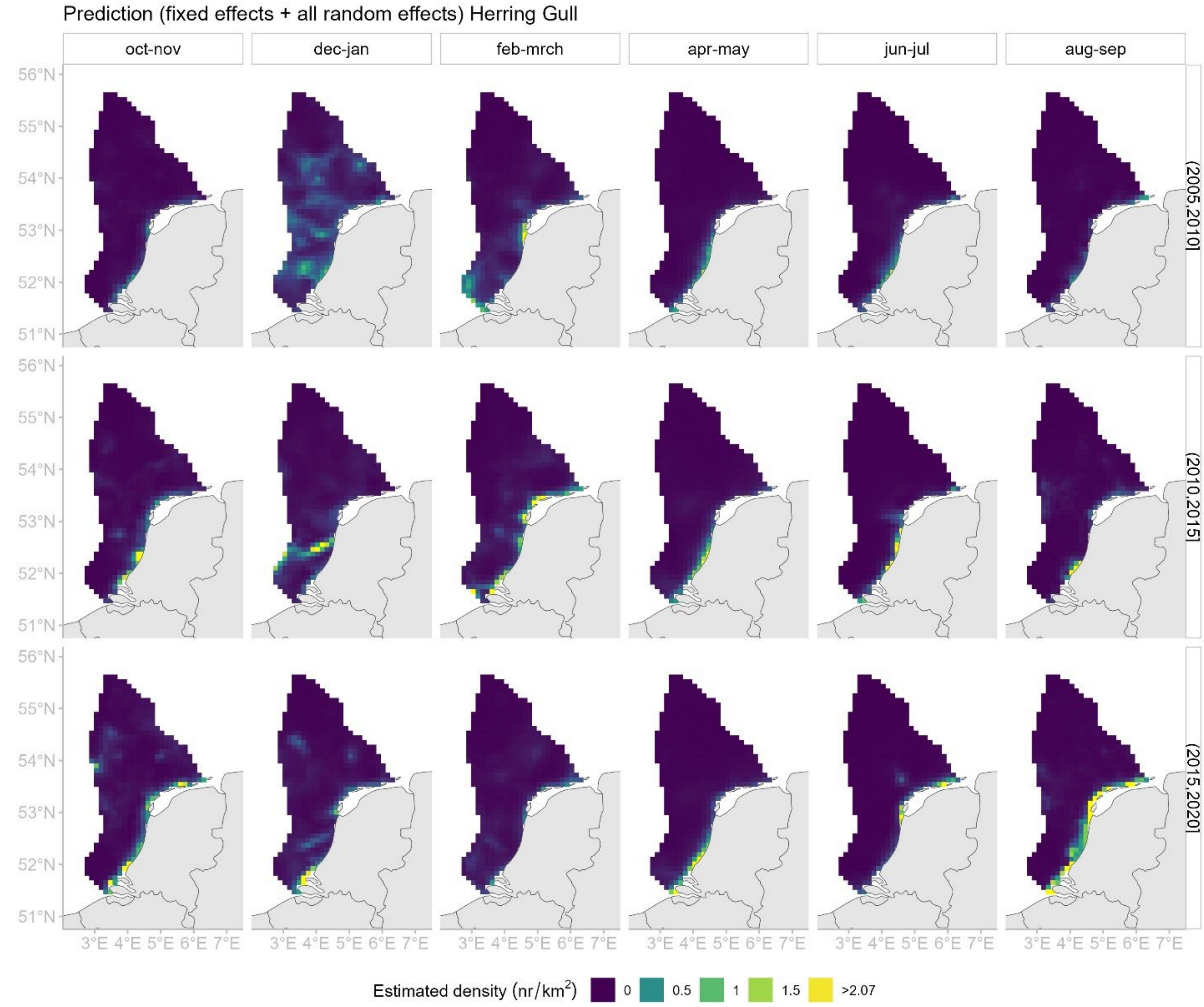

Figure 5-4 The predicted density for Herring Gull per bimonthly period for the time periods 2006 to 2010 (2005,2010], 2011 to 2015 (2010,2015] and 2016 to 2020 (2015,2020]. Time period 2000 to 2005 (1999,2005] is not predicted, as for this period fishing intensity is not available.

Annex 3 Factsheet Lesser Black-backed Gull

The models for the density distribution of the Lesser Black-backed Gull show that sea surface temperature and Chlorophyll-A improved the model in almost all bimonthly periods (**Table 5-3**). Both percentage of sand and fishing intensity was of importance in the model in the warmer months (resp. April till July, April till September). As depth was not part of the model selection and was always left in the models, we showed the conditional effect of this variable. It appears that in the colder bimonthly periods, Lesser Black-backed Gull densities were slightly lower in relatively deep areas of the Dutch Sea (**Figure 5-5**). Densities of Lesser Black-backed Gulls were concentrated along the coast, especially during the breeding season (April-August) (**Figure 5-6**). In winter, densities were close to zero when Lesser Black-backed Gulls migrated to their winter areas.

Table 5-3 Covariates included in final model Lesser Black-backed Gull

Sand % = percentage of sand of seafloor substrate, SST = Sea Surface Temperature, Chl-a = Chlorophyll-a

Bimonthly period	Depth	Proxies for prey			Distance to breeding site	Distance to shipping lane	Fishing intensity	Time period
		Sand %	SST	Chl-A				
Dec-Jan	x		x	x				5-year
Feb-Mrch	x		x	x				5-year
Apr-May	x	x	x				x	5-year
Jun-Jul	x	x	x	x			x	5-year
Aug-Sep	x		x	x			x	5-year
Oct-Nov	x		x	x				5-year

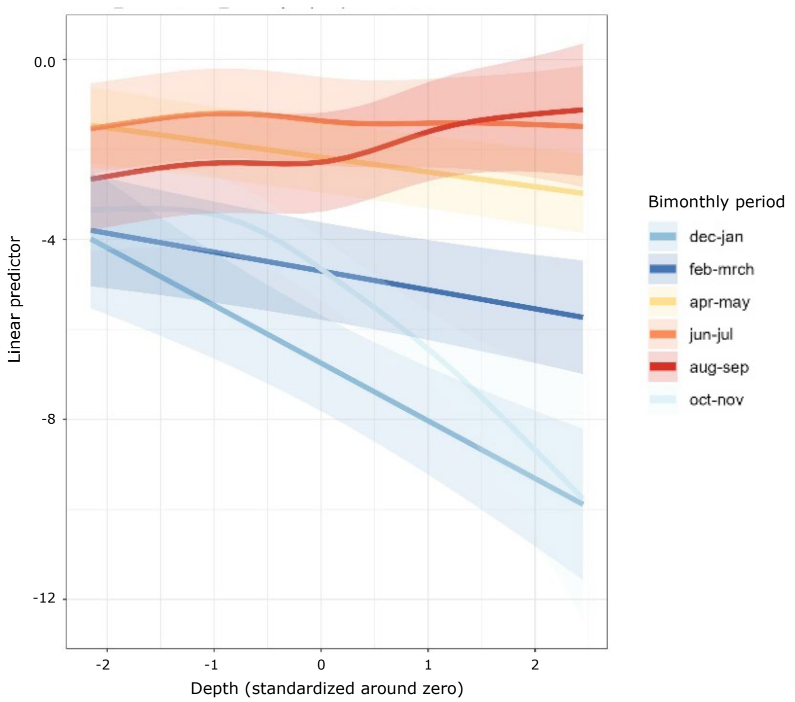

Figure 5-5 The relative effect of covariate depth on Lesser Black-backed Gull density in the model while keeping the other variables on a constant value, per bimonthly period. On the x-axis the standardized value for depth; a lower value corresponds with shallower water.

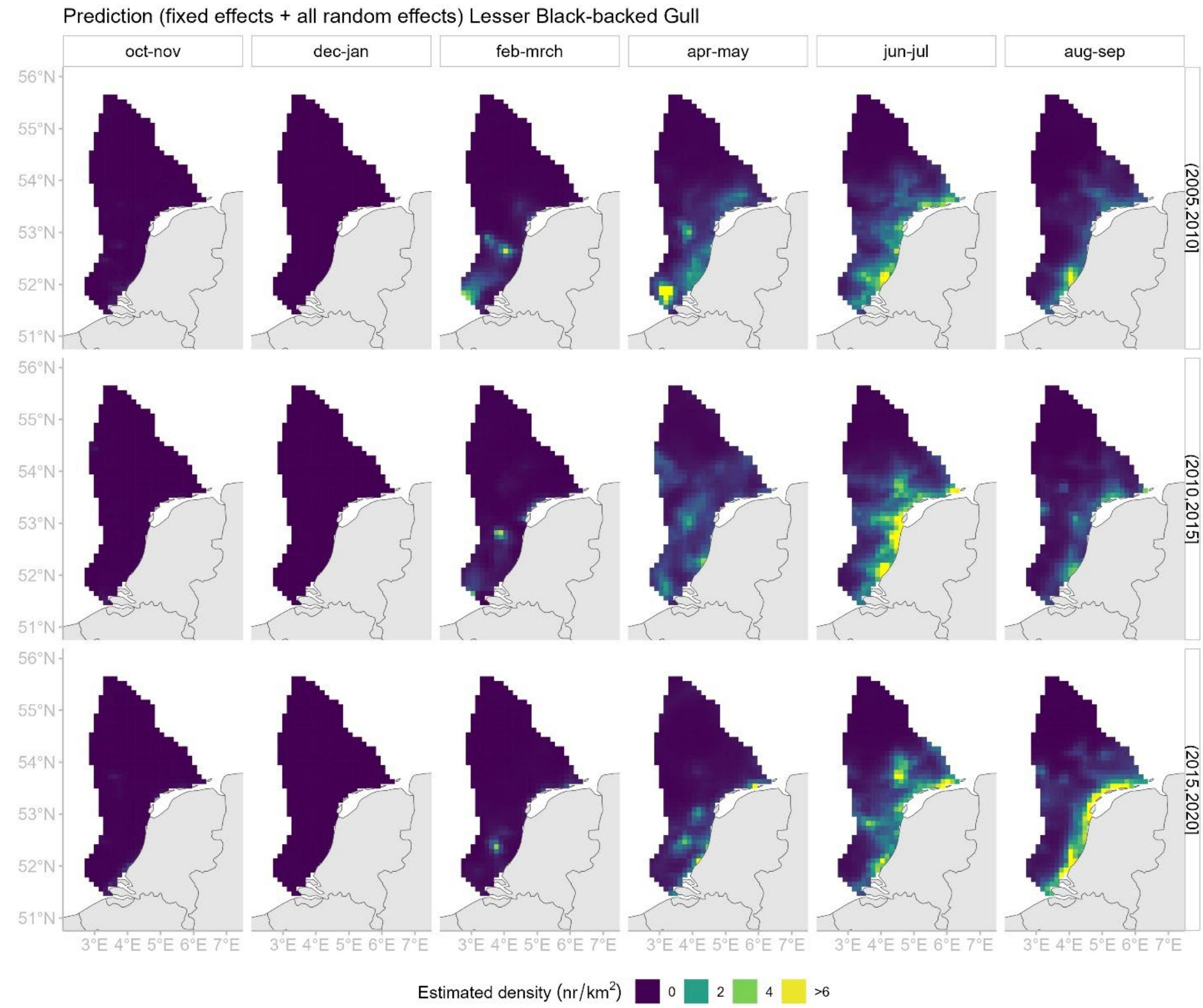

Figure 5-6 The predicted density for Lesser Black-backed Gull per bimonthly period for the time periods 2006 to 2010 (2005,2010], 2011 to 2015 (2010,2015] and 2016 to 2020 (2015,2020]. Time period 2000 to 2005 (1999,2005] is not predicted, as for this period fishing intensity is not available.

Annex 4 Factsheet Great Black-backed Gull

The models for the density distribution of the Great Black-backed Gull show that sea surface temperature and Chlorophyll-A were alternating each other (**Table 5-4**). When SST was included, Chlorophyll-A was not. Fishing intensity was of importance in the models in the period between December and July. Distance to big breeding site was included in the models between April and September, but was thrown out during model selection. As depth was not part of the model selection and was always left in the models, we showed the conditional effect of this variable. There was no clear pattern between Great Black-backed Gull densities and depth (**Figure 5-7**). Densities of Great Black-backed Gulls were usually low, but predicted to be slightly higher in the south-west part of the Dutch North Sea (**Figure 5-8**). Densities were close to zero during the breeding season (April-August).

Table 5-4 Covariates included in final model Great Black-backed Gull

Sand % = percentage of sand of seafloor substrate, SST = Sea Surface Temperature, Chl-a = Chlorophyll-a

Bimonthly period	Depth	Proxies for prey			Distance to breeding site	Distance to shipping lane	Fishing intensity	Time period
		Sand %	SST	Chl-A				
Dec-Jan	x		x				x	5-year
Feb-Mrch	x			x			x	5-year
Apr-May	x		x				x	5-year
Jun-Jul	x			x			x	5-year
Aug-Sep	x		x					5-year
Oct-Nov	x			x				5-year

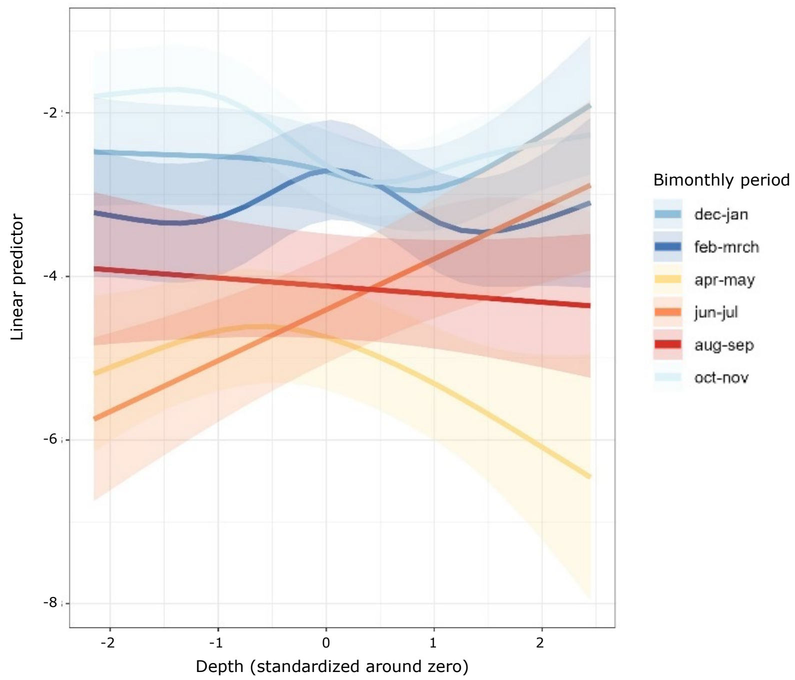

Figure 5-7 The relative effect of covariate depth on Great Black-backed Gull density in the model while keeping the other variables on a constant value, per bimonthly period. On the x-axis the standardized value for depth; a lower value corresponds with shallower water.

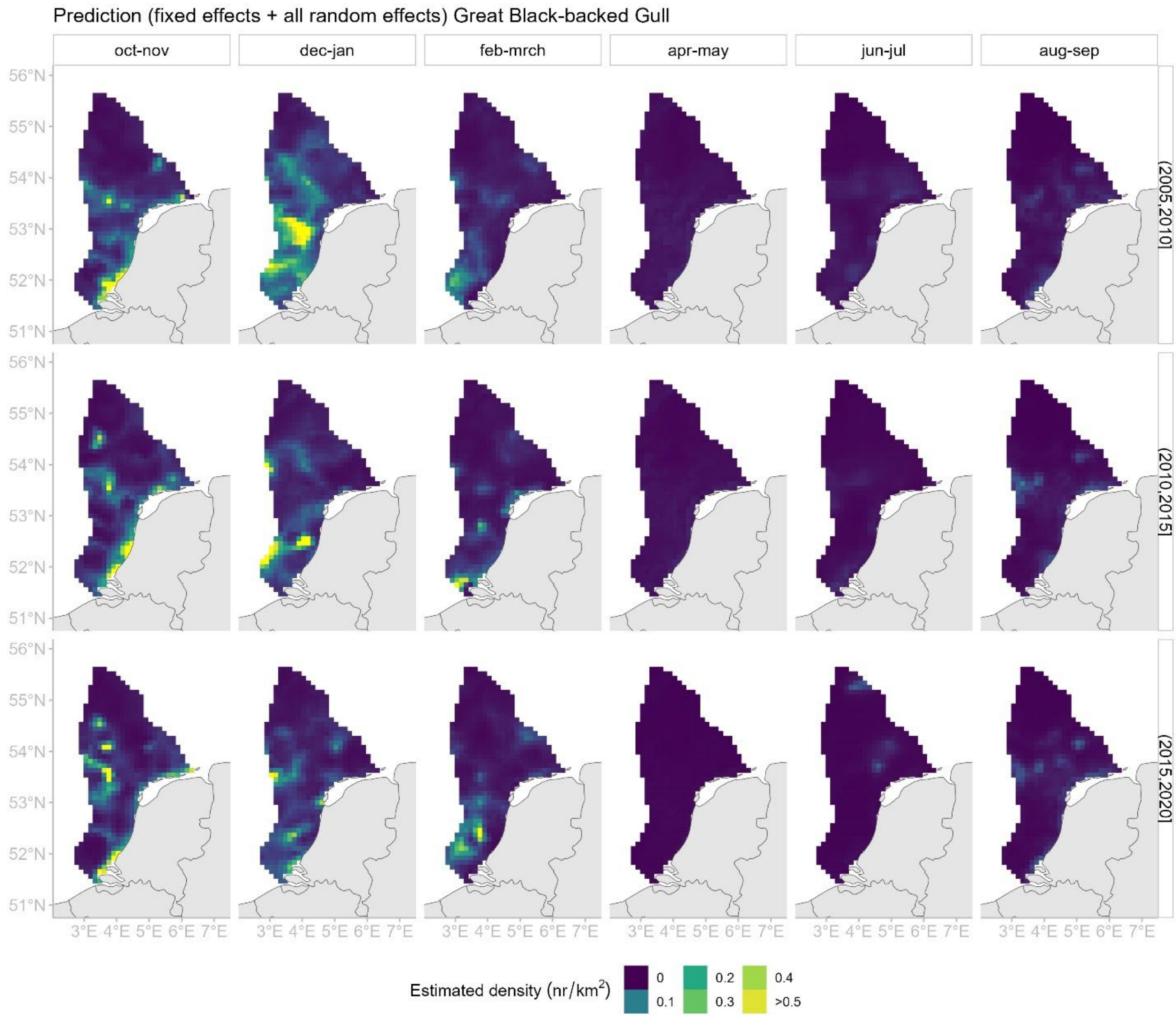

Figure 5-8 The predicted density for the Great Black-backed Gull per bimonthly period for the time periods 2006 to 2010 (2005,2010], 2011 to 2015 (2010,2015] and 2016 to 2020 (2015,2020]. Time period 2000 to 2005 (1999,2005] is not predicted, as for this period fishing intensity is not available.

Annex 5 Factsheet Black-legged Kittiwake

The table with covariates in the final model is presented and described in the main text (**Table 3-2**). The relative effect of depth is also presented in the main text (**Figure 3-7**). Black-legged Kittiwakes were a common bird in the North Sea during the colder months (October-March). In the breeding season, densities were usually a bit lower, as most bigger breeding sites are further away from the Dutch part of the Sea (**Figure 5-9**).

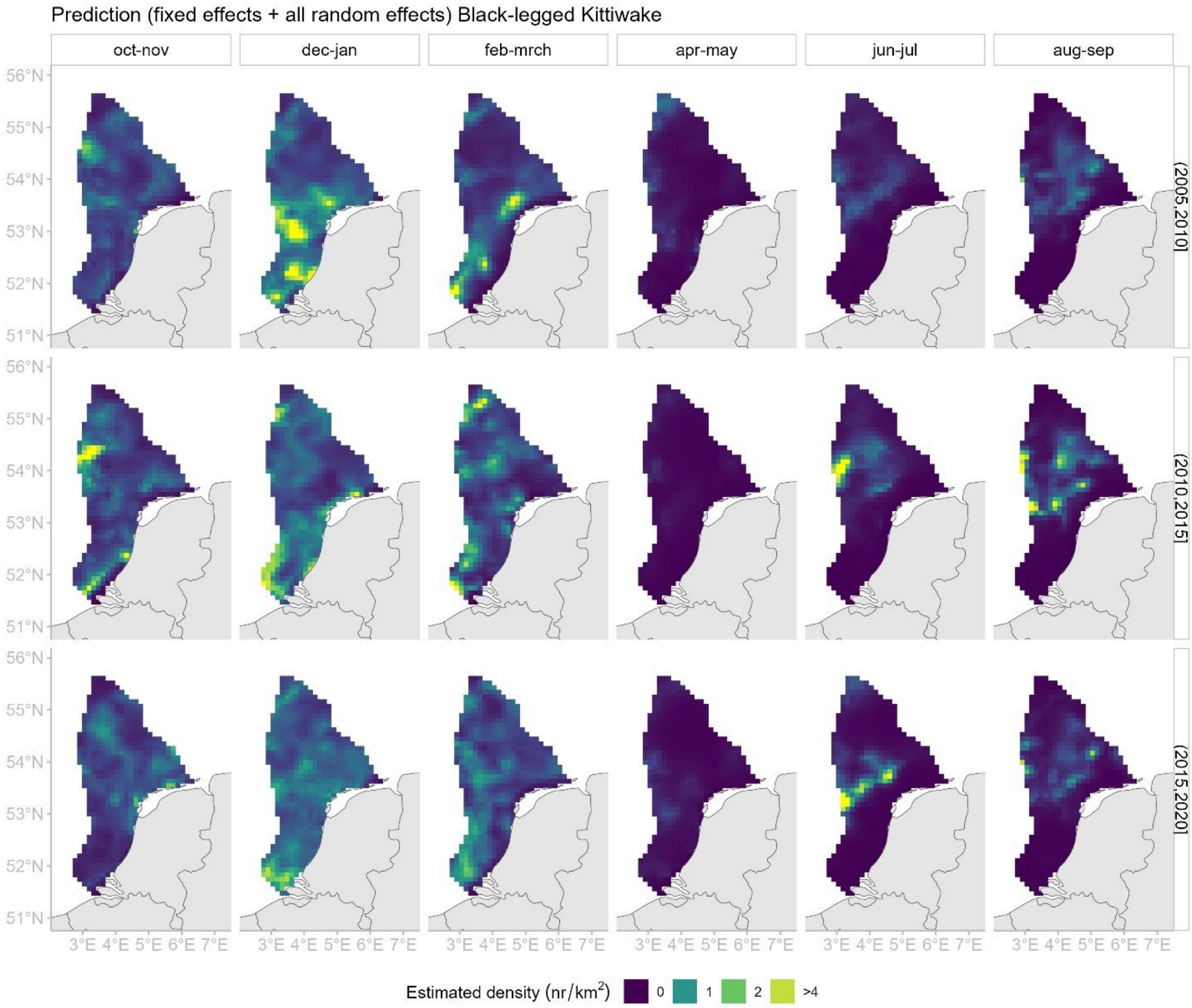

Figure 5-9 The predicted density for the Black-legged Kittiwake per bimonthly period for the time periods 2006 to 2010 (2005,2010], 2011 to 2015 (2010,2015] and 2016 to 2020 (2015,2020]. Time period 2000 to 2005 (1999,2005] is not predicted, as for this period fishing intensity is not available.

Annex 6 Factsheet Great Skua

In the process of data exploration, we noticed that there were not enough non-zero observations for the Great Skua to run a model. Therefore, for this species, we prepared 5-year period maps using the old method of inverse distance weighting. Densities of the Great Skua were very low. There was no clear pattern distinguishable (**Figure 5-10**).

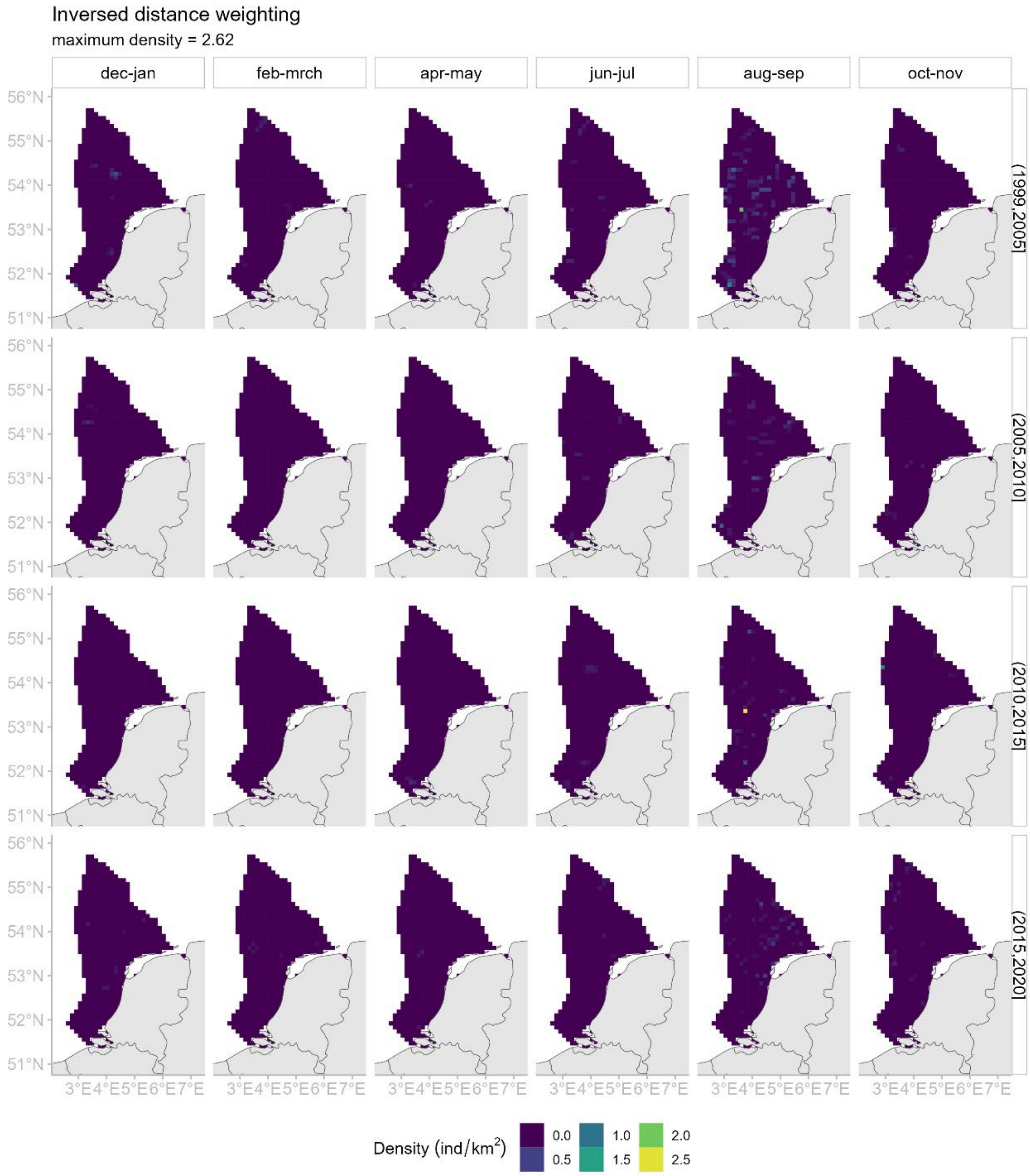

Figure 5-10 Figure 5-10 The predicted density for Great Skua per bimonthly period for the time periods 2000 to 2005 (1999,2005], 2006 to 2010 (2005,2010], 2011 to 2015 (2010,2015] and 2016 to 2020 (2015,2020].

Annex 7 Factsheet Razorbill

The models for the density distribution of the Razorbill show that sea surface temperature and Chlorophyll-A improved the model both only in one model, while percentage of sand improved the model in most cases (**Table 5-5**). Distance to shipping lane was not included in the models due to low non-zero values and models that did not convert. Due to too few non-zero datapoints, the months between April and September were merged in one model. As depth was not part of the model selection and was always left in the models, we showed the conditional effect of this variable. It appears that in all bimonthly periods and the period ‘summer’, Razorbill densities were slightly lower in relatively shallow areas of the Dutch Sea (**Figure 5-11**). This can also be seen in the maps of predicted densities, densities were low along the relatively shallow coastline (**Figure 5-12**). Densities were close to zero during the breeding season (April-August).

Table 5-5 Covariates included in final model Razorbill

Sand % = percentage of sand of seafloor substrate, SST = Sea Surface Temperature, Chl-a = Chlorophyll-a

Bimonthly period	Depth	Proxies for prey			Distance to breeding site	Distance to shipping lane	Fishing intensity	Time period
		Sand %	SST	Chl-A				
Oct-Nov	x	x						1-year
Dec-Jan	x	x		x				1-year
Feb-Mrch	x							1-year
Summer	x	x	x					1-year

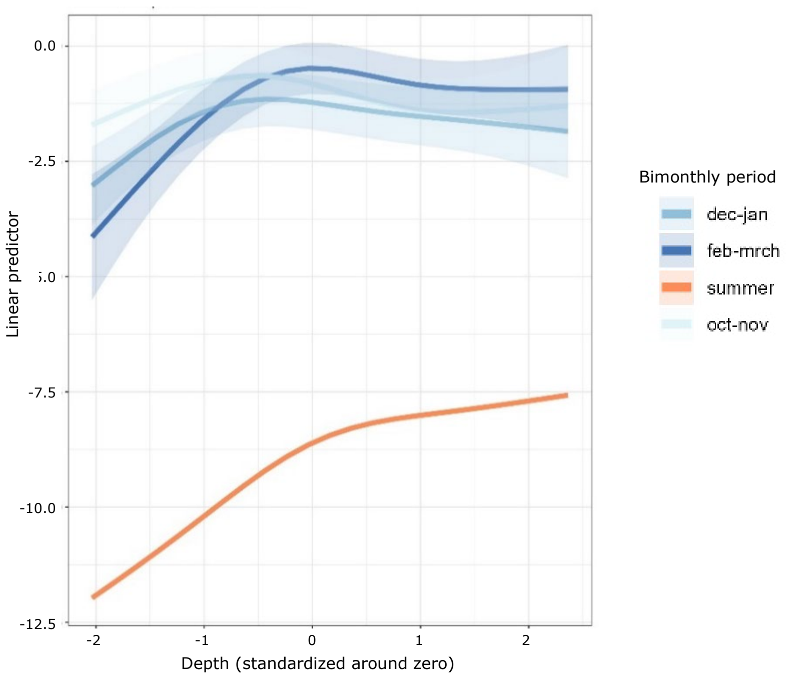

Figure 5-11 The relative effect of covariate depth on Razorbill density in the model while keeping the other variables on a constant value, per bimonthly period. On the x-axis the standardized value for depth; a lower value corresponds with shallower water.

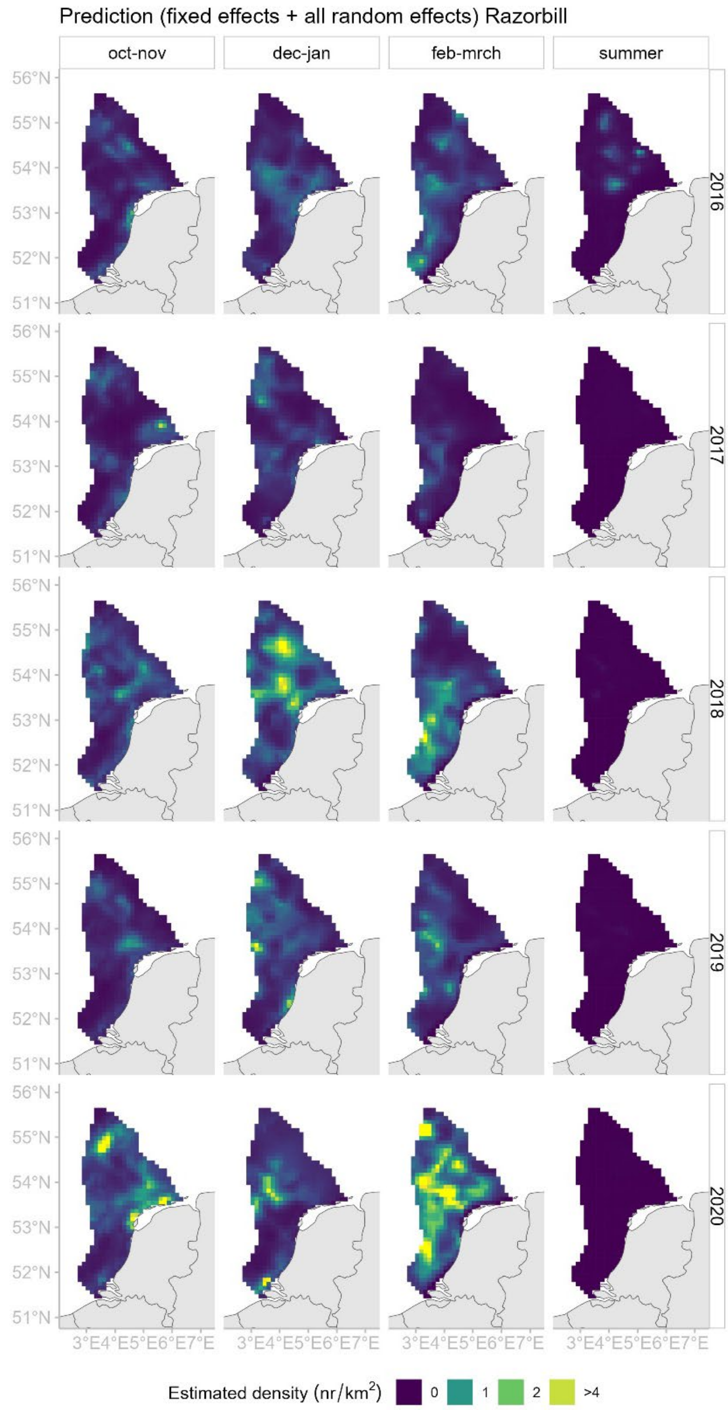

Figure 5-12 The predicted density for the Razorbill per bimonthly period per year.

Annex 8 Factsheet Common Guillemot

The models for the density distribution of the Common Guillemot show that sea surface temperature and Chlorophyll-A were alternating each other (**Table 5-6**). When SST was included in the best model, Chlorophyll-A was not apart from Oct-Nov. Distance to big breeding site was included in the models between April and September, but was only included in the model of Aug-Sep. Percentage of sand and distance shipping lane seemed to be of minor importance as they both only improved one model. As depth was not part of the model selection and was always left in the models, we showed the conditional effect of this variable. It appears that in all bimonthly periods, Guillemot densities were slightly lower in relatively shallow areas of the Dutch Sea (**Figure 5-13**). This can also be seen in the maps of predicted densities, densities were low along the relatively shallow coastline (**Figure 5-14**). There were some strikingly large areas with high densities, for instance in 2018 Aug-Sep and Feb-Mrch 2019. Densities were usually low in Jun-Jul.

Table 5-6 Covariates included in final model Common Guillemot

Sand % = percentage of sand of seafloor substrate, SST = Sea Surface Temperature, Chl-a = Chlorophyll-a

Bimonthly period	Depth	Proxies for prey			Distance to breeding site	Distance to shipping lane	Fishing intensity	Time period
		Sand %	SST	Chl-A				
Dec-Jan	x			x		x		1-year
Feb-Mrch	x			x				1-year
Apr-May	x		x					1-year
Jun-Jul	x	x		x				1-year
Aug-Sep	x		x		x			1-year
Oct-Nov	x		x	x				1-year

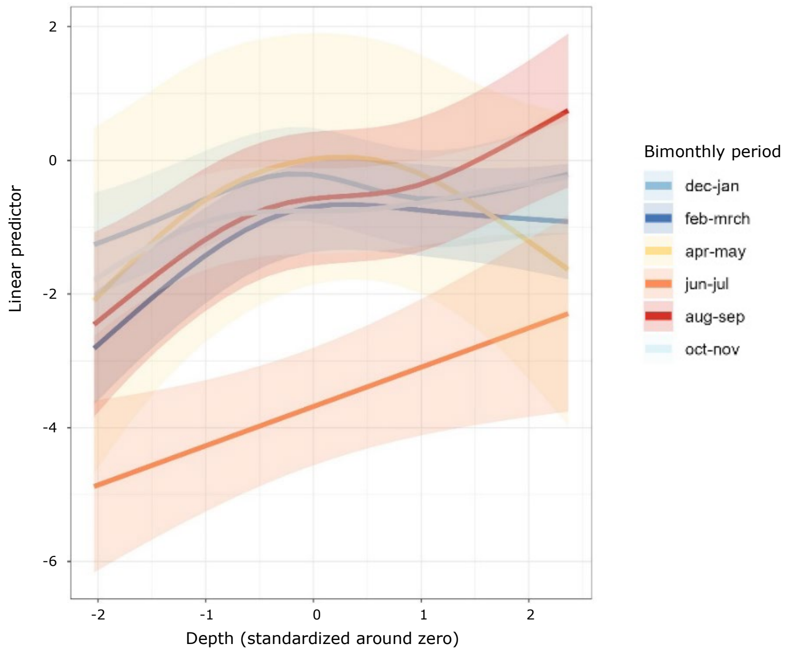

Figure 5-13 The relative effect of covariate depth on Common Guillemot density in the model while keeping the other variables on a constant value, per bimonthly period. On the x-axis the standardized value for depth; a lower value corresponds with shallower water.

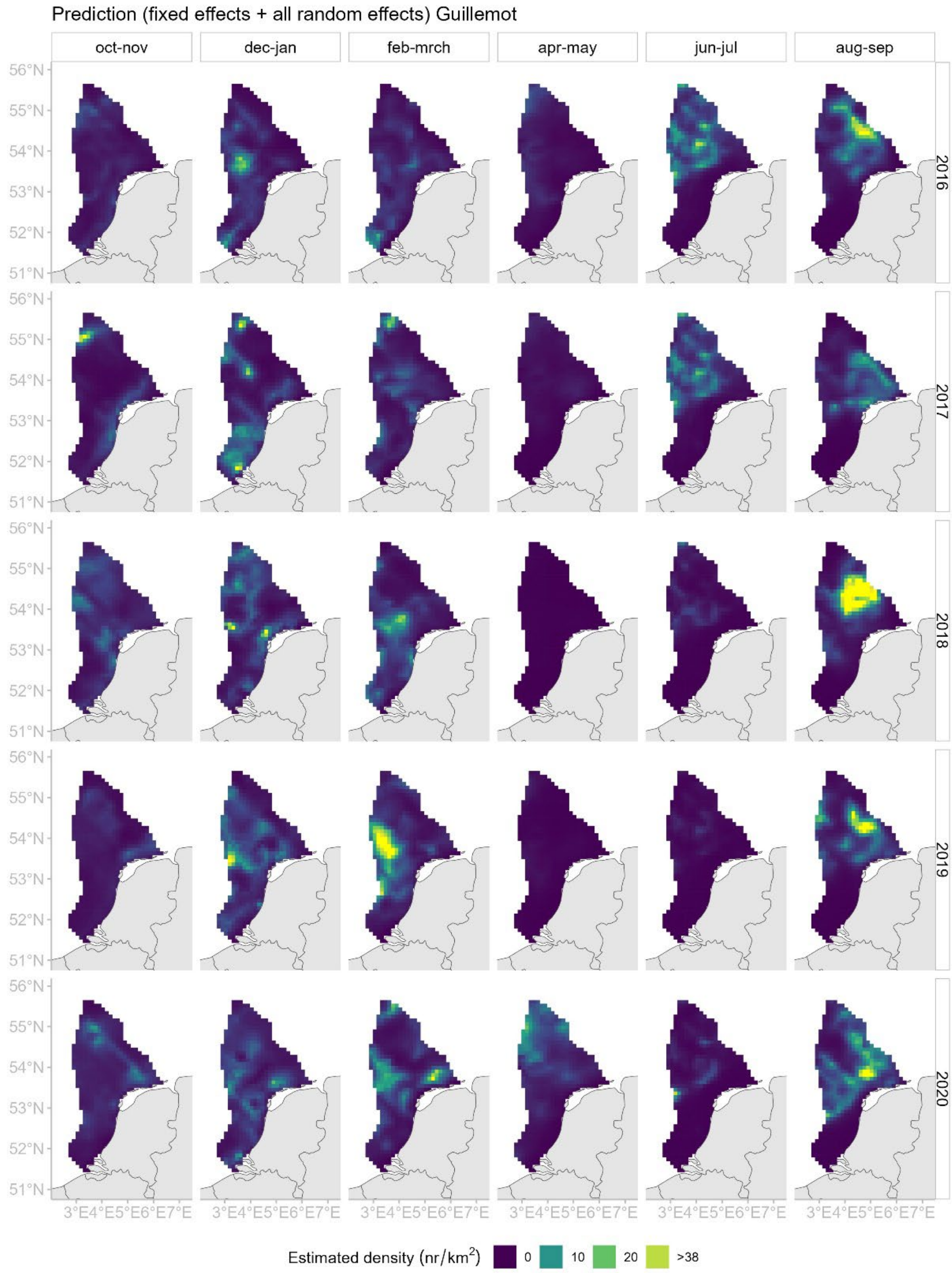

Figure 5-14 The predicted density for the Common Guillemot per bimonthly per year.

Annex 9 Factsheet Sandwich Tern

Due to too few non-zero datapoints, the winter months between December and March were not modelled. The models for the density distribution of the Sandwich Tern show that sea surface temperature and Chlorophyll-A were alternating each other in the models (**Table 5-7**). When SST was included in the best model, Chlorophyll-A was not apart, from Apr-May. As depth was not part of the model selection and was always left in the models, we showed the conditional effect of this variable. The Sandwich Tern is a coastal bird, all bimonthly periods show that Tern densities were higher in relatively shallow areas of the Dutch Sea (**Figure 5-15**). This can also be seen in the maps of predicted densities, densities were high along the coastline and close to breeding colonies (**Figure 5-16**).

Table 5-7 Covariates included in final model Sandwich Tern

Sand % = percentage of sand of seafloor substrate, SST = Sea Surface Temperature, Chl-a = Chlorophyll-a

Bimonthly period	Depth	Proxies for prey			Distance to breeding site	Distance to shipping lane	Fishing intensity	Time period
		Sand %	SST	Chl-A				
Apr-May	x		x	x				5-year
Jun-Jul	x	x	x					5-year
Aug-Sep	x	x		x				5-year
Oct-Nov	x		x					5-year

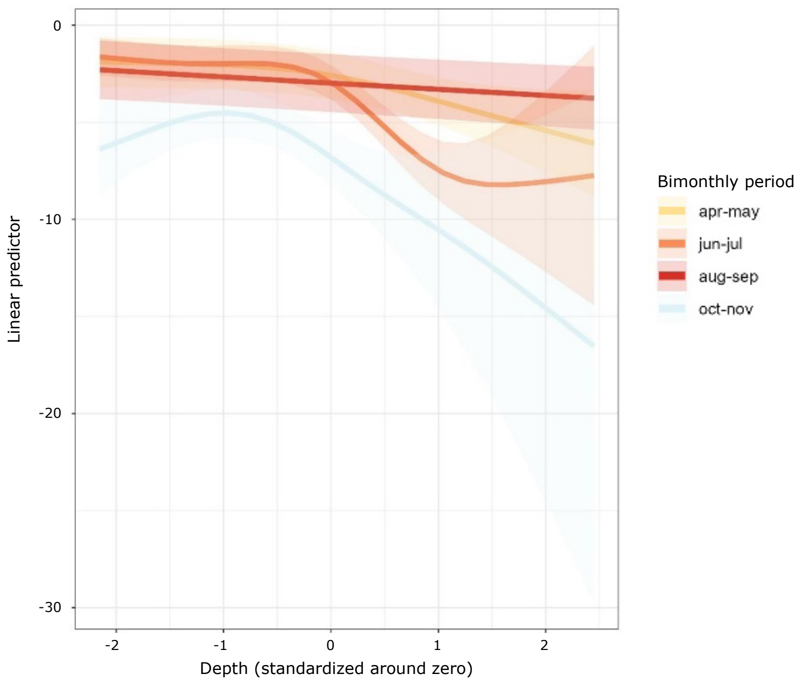

Figure 5-15 The relative effect of covariate depth on Sandwich Tern density in the model while keeping the other variables on a constant value, per bimonthly period. On the x-axis the standardized value for depth; a lower value corresponds with shallower water.

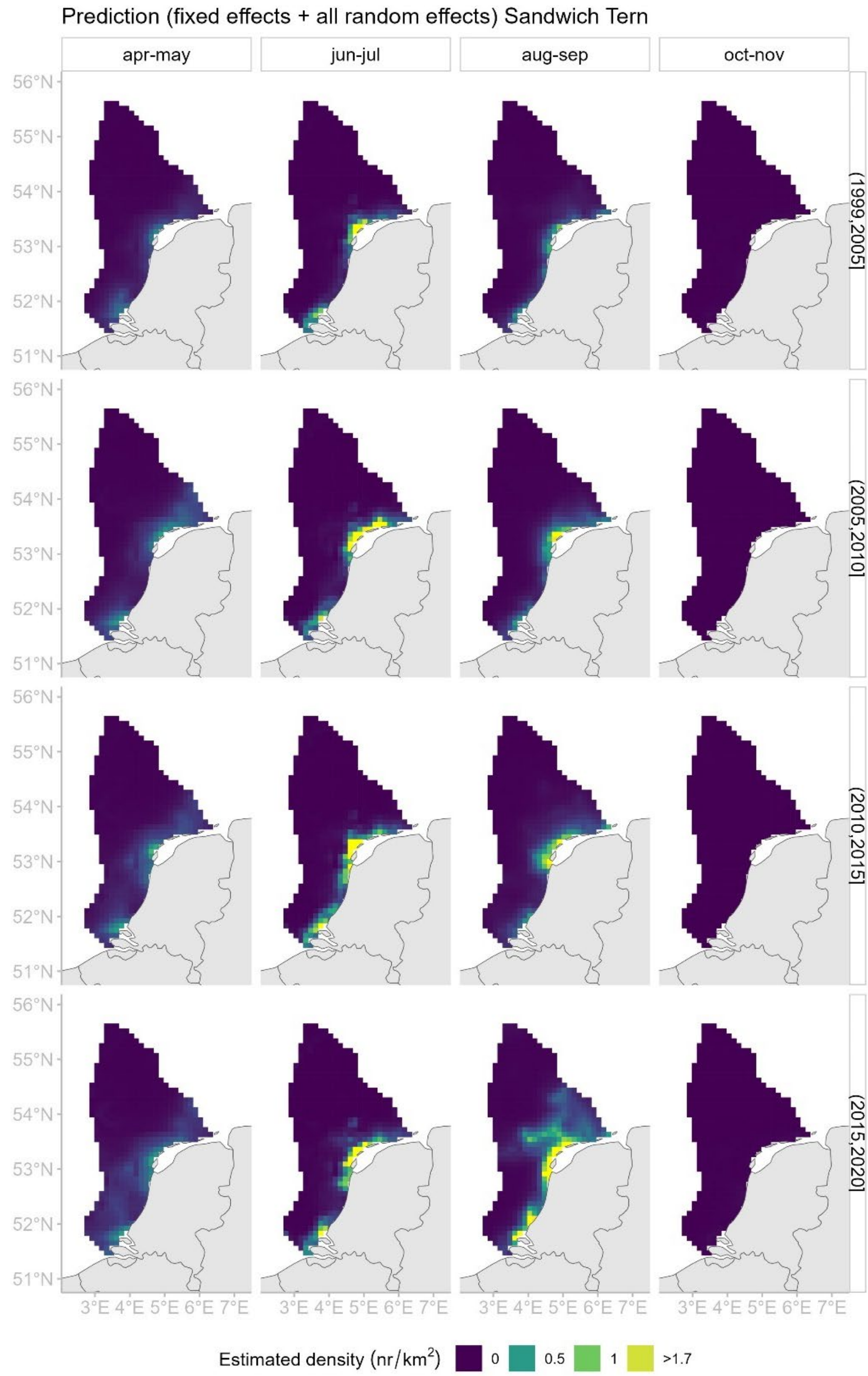

Figure 5-16 The predicted density for the Sandwich Tern per bimonthly period for the time periods 2000 to 2005 (1999,2005], 2006 to 2010 (2005,2010], 2011 to 2015 (2010,2015] and 2016 to 2020 (2015,2020].

Wageningen Marine Research
T +31 (0)317 48 70 00
E imares@wur.nl
www.wur.nl/marine-research

Visitors'adress
- Ankerpark 27 1781 AG Den Helder
- Korringaweg 7, 4401 NT Yerseke
- Haringkade 1, 1976 CP IJmuiden

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