Knowledge update seabird distribution maps for KEC6

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1 Assignment

In 2016, the Dutch Ministry of Economic Affairs commissioned Rijkswaterstaat (RWS) to establish an integrated research program to reduce knowledge gaps regarding the effects of offshore wind farms on the North Sea ecosystem: *Wind op zee ecologisch programma* (Wozep). The Wozep research results are used in the *Kader Ecologie en Cumulatie* (KEC). Through the KEC, the cumulative effect of wind farms on species with protected status under nature conservation legislation is assessed. This involves examining both existing parks and proposed planned offshore wind farms.

Rijkswaterstaat has asked Wageningen Marine Research (WMR) to build upon KEC 4.0 in a multi-year assignment. To facilitate the execution of the KEC, up-to-date distribution maps for selected marine birds, seals, and porpoise species must be available. This knowledge update contains a description of the methods used to update and create distribution maps of fourteen marine bird species. Within the KEC 6 assessment, these distribution maps will be used to assess effects of habitat loss and collision risk from Dutch wind farms at sea.

2 Materials and Methods

2.1 Map types

2.1.1 Type of maps and their names

The maps for KEC6 are – similar to KEC5 - a combination of maps for the Dutch part of the North Sea (called 'national maps') newly generated by WMR following the same approach as in van Donk et al. (2024), international maps covering the North-East Atlantic that were previously published in a scientific journal (Waggitt et al., 2020), and international maps using inverse distance weighting (IDW) that were generated for KEC5. Separate maps were used for the Dutch part of the North Sea (national maps) and the international part of the North Sea (Figure 2.1).

For the international area, no new maps were available or generated. Both the earlier used Waggitt et al. maps and the international IDW maps were mainly based on data from the "European Seabirds At Sea" (ESAS) database. Since the previous KEC (KEC5), only little data has been added to this dataset. This means that creating new international maps will not improve the reliability of the already existing maps (Figure 2.2; van Donk, 2024).

For the national area, we generated distribution maps using the method described in van Donk et al. (2024) as well as a method that is called 'Inverse Distance Weighting' (IDW) (Leopold et al., 2014) in case of data-limited species. Respectively, these maps will be referred to as 'van Donk maps' and 'IDW' throughout the document (Figure 2.1).

The van Donk maps are based on habitat suitability models. The method was developed with the aim to improve the maps used for KEC4 (Soudijn et al., 2022). In KEC4, IDW interpolation was used, which is a deterministic method that results directly from raw (averaged) counts (Leopold et al., 2014). A shortcoming of this method is that rare observations with high numbers of birds get a relatively large influence on the bird density at a certain location. This may occur e.g., when gulls are following a fishing vessel or when birds are attracted to an area with a large amount of prey, for instance during a 'feeding frenzy'. Furthermore, ecological covariates that might explain the distribution of birds are not considered in the IDW approach. The van Donk maps are an improvement on these issues and additionally provide information on robustness and statistical uncertainty that cannot be provided with the IDW method. However, sufficient positive (non-zero) observations are necessary to run these models used to create the distribution maps. For species with limited number of observations, IDW maps are therefore the only possibility ('IDW national') (Table 2.1).

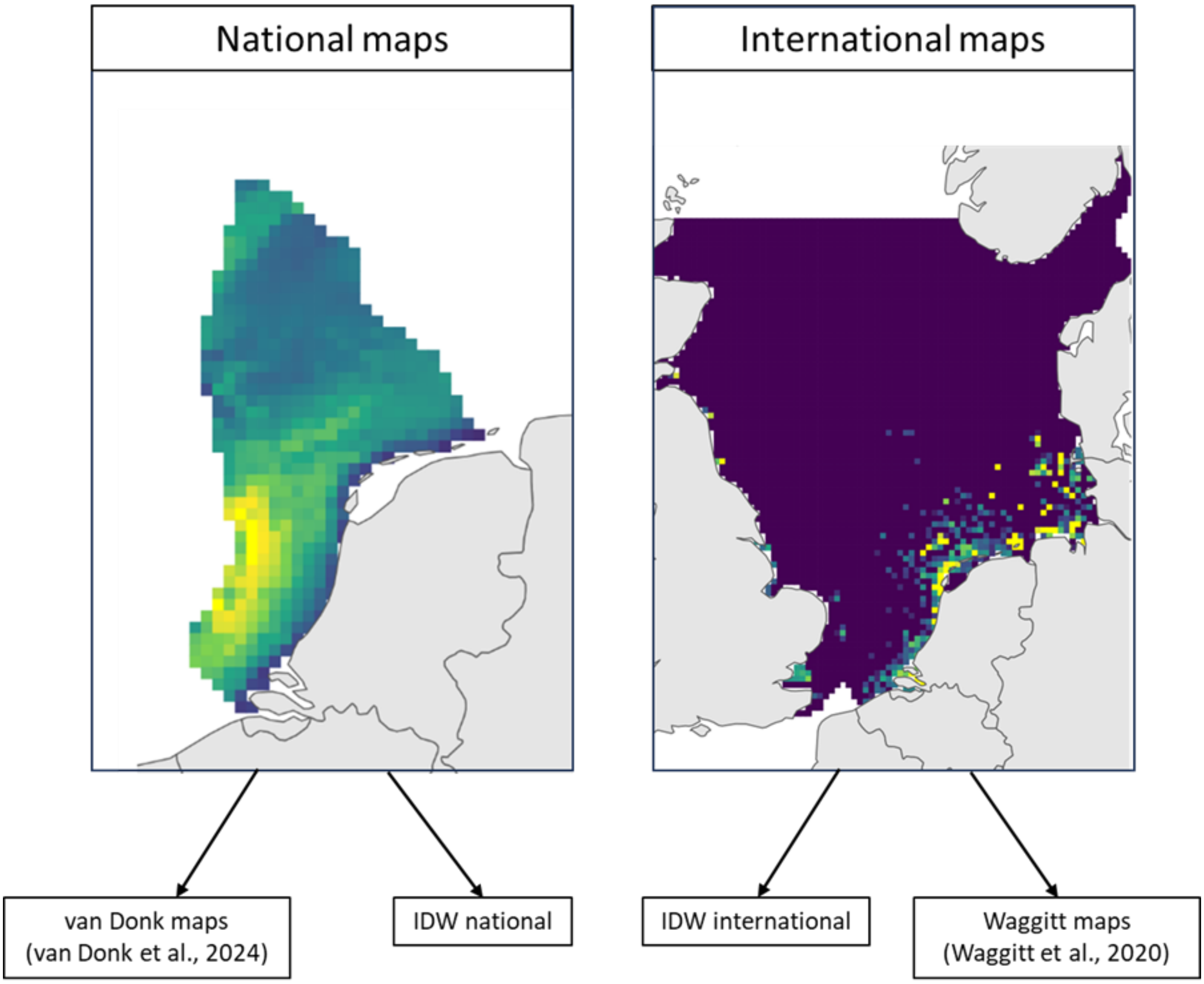

Figure 2.1 *Maps that have been created of the Dutch part (National maps) and of the international part of the North Sea (International maps). For the national area, we either created maps based on the methodology described by van Donk et al. (2024), or using Inverse Distance Weighting (IDW). The international maps are not updated for KEC6.*

Figure 2.2 *Datapoints in the ESAS database for the Greater North Sea per year show that little data has been added with public access for the international KEC area since the last KEC (KEC5) (year >2020).*

2.2 Marine bird species in KEC6

For KEC6, new distribution maps ('van Donk' or 'IDW national') were made for the following species: northern fulmar *(Fulmarus glacialis),* 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)*, little gull *(Hydrocoloeus minutus)*, Sandwich tern *(Thalasseus sandvicensis)*, great skua *(Stercorarius skua)*, Arctic skua *(Stercorarius parasiticus)*, Atlantic puffin *(Fratercula arctica),* razorbill *(Alca torda)* and common guillemot *(Uria aalge)*. Furthermore, a map has been provided combining two species, Arctic tern *(Sterna paradisaea)* and common tern *(Sterna hirundo)*, because these species cannot always be distinguished during the survey (Table 2.1). This combined species is referred to as 'commic tern' in the following. Hereafter, the terms 'seabird' and 'marine bird' are used interchangeably for all species mentioned above.

Table 2.1 *Species assessed within KEC6 and the type of map used for national and international scenarios.*

Species	Scientific name	Type map national		Type map international/	
		Source	**Time period**	**Source**	**Time period**
Razorbill	*Alca torda*	van Donk maps (2026)	2020–2025	Waggitt maps (Waggitt et al. 2020)	*1980–2018*
Arctic puffin	*Fratercula arctica*	van Donk maps (2026)	2021–2025	Waggitt maps (Waggitt et al. 2020)	*1980–2018*
Common Guillemot	*Uria alge*	van Donk maps (2026)	2020–2025	Waggitt maps (Waggitt et al. 2020)	*1980–2018*
Northern fulmar	*Fulmarus glacialis*	van Donk maps (2026)	2021–2025	Waggitt maps (Waggitt et al. 2020)	*1980–2018*
Northern Gannet	*Sula bassana*	van Donk maps (2026)	2021–2025	Waggitt maps (Waggitt et al. 2020)	*1980–2018*
Black-legged Kittiwake	*Rissa tridactyla*	van Donk maps (2026)	2021–2025	Waggitt maps (Waggitt et al. 2020)	*1980–2018*
Sandwich Tern	*Thalasseus sandvicencis*	van Donk maps (2026)	2021–2025	IDW international	1990–2020
"Commic tern" (Arctic & Common Tern)	*Sterna paradisaea/Sterna hirunda*	van Donk maps (2026)	2021–2025	IDW international	1990–2020
Herring Gull	*Larus argentatus*	van Donk maps (2026)	2021–2025	Waggitt maps (Waggitt et al. 2020)	*1980–2018*
Lesser Black-backed Gull	*Larus fuscus*	van Donk maps (2026)	2021–2025	Waggitt maps (Waggitt et al. 2020)	*1980–2018*
Great Black-backed Gull	*Larus marinus*	van Donk maps (2026)	2021–2025	IDW international	1990–2020
Little Gull	*Hydrocoloeus minutus*	van Donk maps (2026)	2021–2025	IDW international	1990–2020
Arctic Skua	*Stercorarius parasiticus*	IDW national (2026)	2021–2025	IDW international	1990–2020
Great Skua	*Stercorarius skua*	IDW national (2026)	2021–2025	Waggitt maps (Waggitt et al. 2020)	1980–2018

2.3 Datasets used

2.3.1 Marine bird data

For the new national maps that were created for KEC6, the '*Monitoring Waterstaatskundige Toestand des Lands*' (MWTL) dataset was used, holding aerial surveys covering the Dutch section of the North Sea. This dataset was requested from Waardenburg Ecology. For more in-depth information on how that data is collected, we refer to previous studies (Fijn et al., 2020; van Roomen et al., 2013).

The MWTL dataset is a relatively consistent dataset, as a standardized survey is being conducted every two months over the course of the year. The survey method and design have been adjusted in 2014. This change involved a reduced flight height, which allowed identification to species level for almost all groups, including common guillemot and razorbill. In addition, the extended survey transects design resulted in a more even spread of survey effort across the Dutch continental shelf compared to the survey design before 2014.

Preparation of this dataset has been done as described in van Donk et al. (2024). Preparation included a distance sampling analysis, which 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., 2004).

2.3.2 Covariate data

Datasets used, their source, the time-period and the data transformations that were applied in the modelling are described in Table 2.2, and one example of a covariate is plotted in Figure 2.3. The covariates that have been used were selected based on a short literature review and on expert knowledge regarding the relation between marine bird species and covariates (van Donk et al., 2024), but was limited to the covariate data that was available. 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 abundance (e.g., sandeel-like fish from the Ammodytidae family). In the future, these variables could be replaced by prey distribution maps (e.g., pelagic fish) that have recently been developed for sprat (Ransijn et al., 2026).

Table 2.2 *Data that was used to create national seabird distribution maps.*

Type of data	Source	Time period used/ available	Frequency	Data transformation for modelling procedure
Bird data in (n/km^2)	MWTL data. https://sovon.nl/ or https://waardenburg.eco/	Feb 1996 till Jul 2025	Date time stamp for every observation	Square root transformation
Sand (%),	Working Group on Spatial Fisheries Data (outputs from 2021 meeting).	N/A	One value for all years	Fourth root transformation and standardized
Depth (m)	https://www.ices.dk/community/groups/pages/wgsfd.asp x	N/A	One value for all years	Standardized
Sea surface temperature (°C),	Marine Copernicus. **https://doi.org/10.48670/moi-00059** NWSHELF_MULTIYEAR_PHY_004_009	Feb 1996 till Jul 2025	Daily	Standardized
Chlorophyll-a (mg/m^3)	Marine Copernicus. NWSHELF_MULTIYEAR_BGC_004_011 https://doi.org/10.48670/moi-00058	Feb 1996 till Jul 2025	Daily	Square root transformation and standardized
Distance to big breeding site (km)*	https://ebba2.info/	Measurements done between 2013–2017	One value for all years	Standardized
Distance to shipping lanes (km)	RWS (2017), Scheepvaart verkeersscheidingsstelsel Noordzee (Nederlands Continentaal Plat) update 1 June 2017	Version of 2017		Square root transformation and standardized
Fishing activity (hrs)	VMS data via WMR	2009–2025	Monthly data	Log transformed and standardized

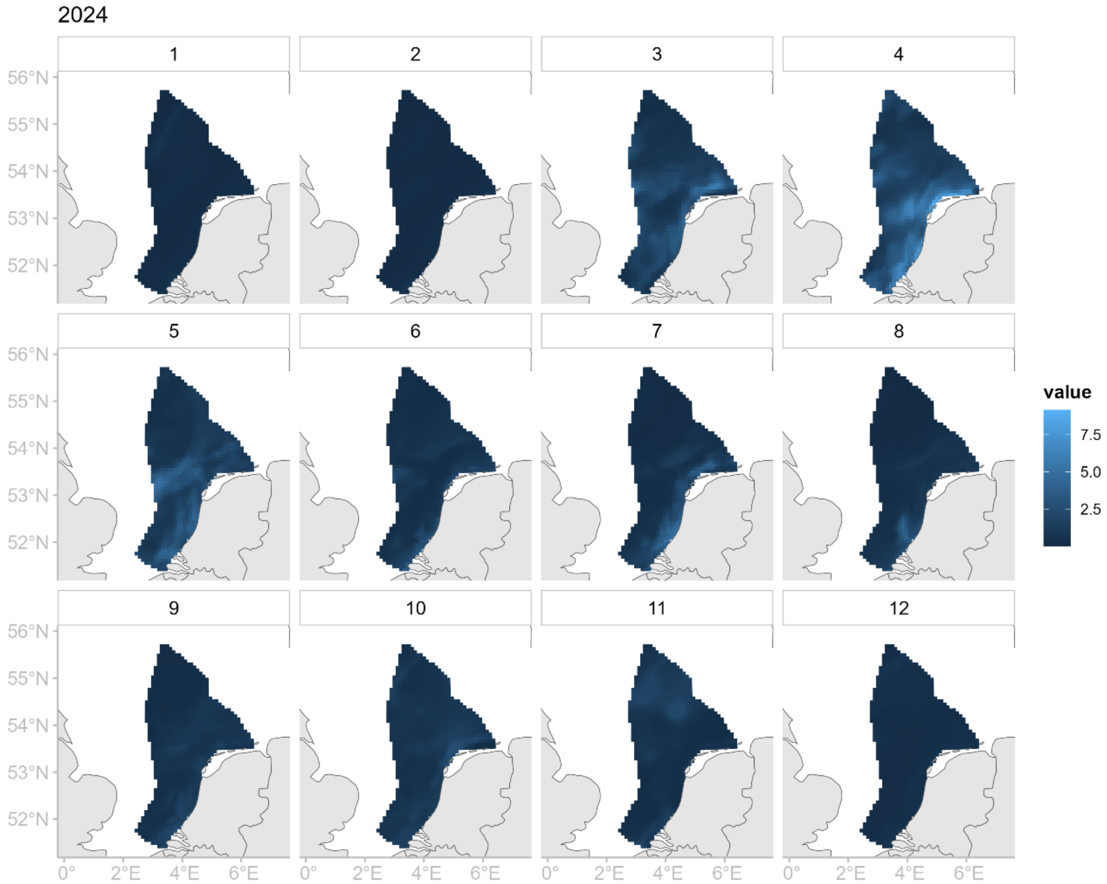

Figure 2.3 *Example of chlorophyll-a data (mg/m³) per month (1 = January, …, 12 = December) in 2024. Data obtained from the Marine Copernicus product 'NWSHELF_MULTIYEAR_BGC_004_011' (Table 2.2).*

2.3.3 Data preparation and selection

Bird data and covariates were explored and checked for missing values, unexpected patterns or outliers, and – if necessary – transformed. All covariate data was standardized (Table 2.2). Spatial bird data was coupled to the closest available covariate data in time and space or, in case of distances, the shortest distance to the nearest colony or shipping lane was calculated. We only calculated the distance to relatively large colonies to decrease the effect of very small colonies that probably only have a very small influence on total bird distribution.

The percentage of different sizes of breeding colonies was calculated per species. Large colonies were defined as breeding sites with more than 1000 breeding pairs, medium colonies as breeding sites with 100–999 breeding pairs and small colonies as breeding sites with less than 100 breeding pairs. When the percentage of large breeding colonies was greater than 25% of the total number of breeding colonies, distance to large breeding site was calculated to large colonies only. When species had no or less than 25% of large colonies, also medium sized colonies were included.

A time period factor was added to the dataset, to analyze the data in time periods of five years. In this analysis, a year starts in February and ends in January to match with the bimonthly seasons that are used in the analysis and counts (Feb–Mar, Apr–May, Jun–Jul, Aug–Sep, Oct–Nov, Dec–Jan). To be able to use the most recent data available, we added time periods 'counting back' from the most recent bird data available in 2025. This resulted in six time periods of five years: 1996–2000, 2001–2005, 2006–2010, 2011–2015, 2016–2020 and 2021–2025. Bird data for the razorbill and guillemot was only available from 2014 onwards. We therefore decided to use time periods of six years each (2014–2019, 2020–2025), to use all the data available. Bird data before 1996 was not used in the modelling procedure, because covariates chlorophyll-a and sea surface temperature were only available from 1993 onwards and no full five-year period with corresponding covariables could be added. Fishing intensity data was only available from 2009 onwards.

Consequently, for species in which fishing intensity was included in the model (Figure 2.4), only three time periods were included (2011–2015, 2016–2020 and 2021–2025).

Usually, the bird counts are executed within the bimonthly seasons that are used in the data analysis. However, sometimes bird counts (that usually takes three days) were executed slightly later. For instance, a count that is intended to be executed in January, was sometimes partly executed in February. To make sure full counts were used in the data analysis, one full survey was linked to the intended counting period. Besides the coupled dataset, a raster of 10 x 10 km was created with the average covariate values per bimonthly season and period per species to be able to create prediction maps. We used daily chlorophyll-a and SST for fitting the models, but average values over two months for the prediction raster. This sometimes resulted in differences in the range and median values for the data that has been used during the model procedure compared to the raster used for making predictions, especially in some winter months. For instance, the survey for Dec–Jan was often conducted at the end of January, sometimes continuing in February when temperatures are usually a bit lower than the average temperature of Dec–Jan. To ensure that predictions were made only within the range of values used for model fitting – and to avoid extrapolating to untested conditions – we adjusted the median values of chlorophyll-a and SST for each bimonthly season to match the medians observed in the modelling dataset.

2.4 Methodology national maps

Methods that were used to create the maps are the same as used for KEC5 (van Donk, 2024; van Donk et al., 2024). Within this chapter, only the most important steps are mentioned. Some steps in the modelling procedure were slightly adjusted and are therefore described again.

2.4.1 Van Donk maps – habitat modelling approach

2.4.1.1 Covariate selection per species

During data exploration, correlations between covariates were checked per species and bimonthly season. When a correlation between covariates was higher than 0.8, only one of these covariates was kept in the model. Distance to large breeding site was often excluded because of its high correlation with depth. For instance, chlorophyll-a was highly correlated with depth in some bimonthly seasons. In these cases, depth was kept in the models. When distance to large breeding site was included, it was only added for the bimonthly periods Apr–May, Jun–Jul and Aug–Sep (Figure 2.4). Distance to large breeding site was not included in species that do not breed in the Netherlands or breed far away (like coastal area of Scotland). This resulted in the exclusion of this covariate from all models, as the correlation between depth and distance to large breeding site was too high in species breeding in the Netherlands to be both included in the models.

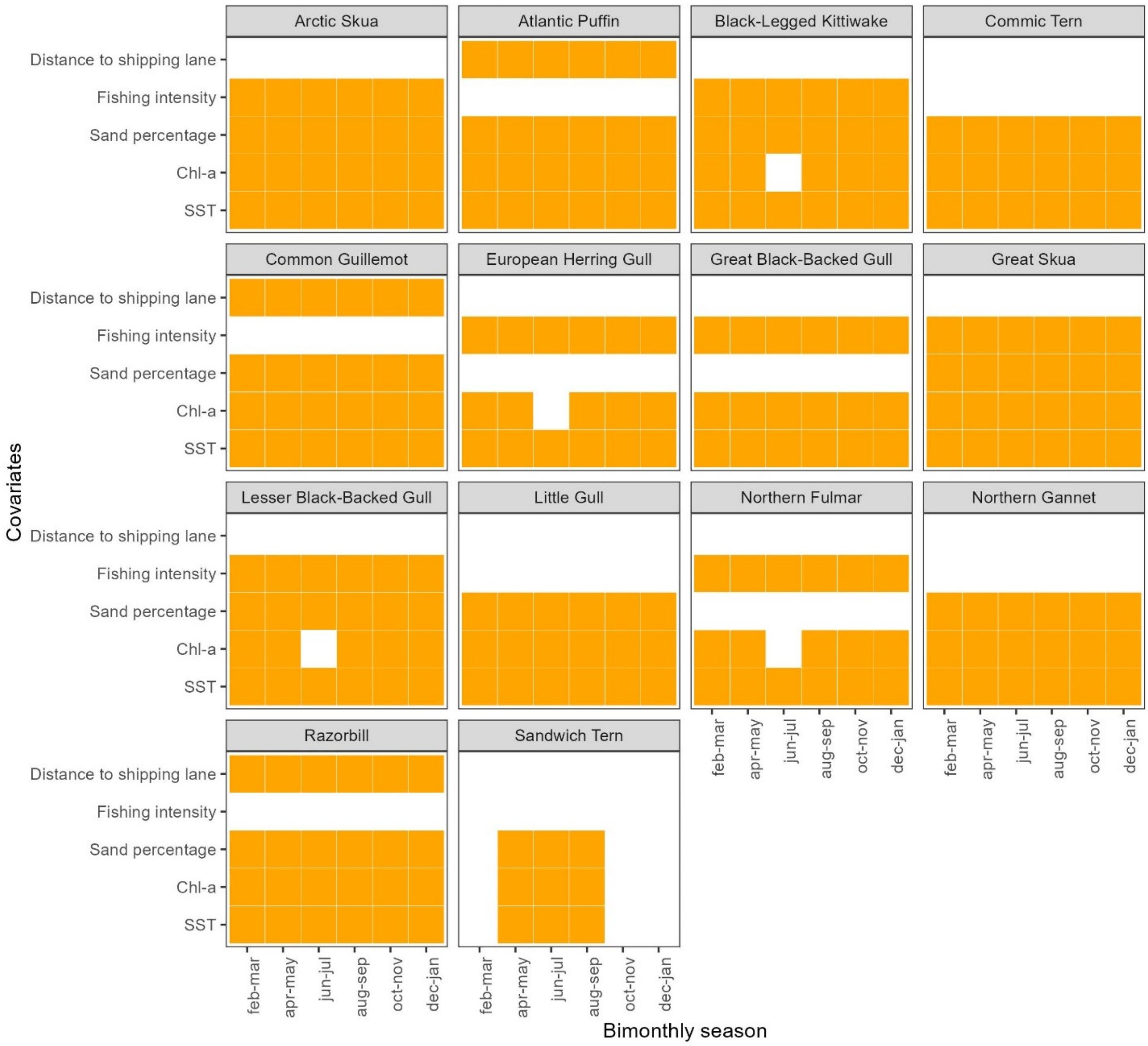

Figure 2.4 *Covariates used as starting point for backwards selection per species and bimonthly season. SST = sea surface temperature (°C), Chl-a = chlorophyll-a concentration (mg/m³).*

2.4.1.2 Model selection

A generalized linear/additive mixed model (GLMM/GAMM) was used including spatial-temporal effects (i.e. estimated through a stochastic partial differential equation approach; SPDE). This model can estimate high numbers of zero observations that are present in the data and deal with over-dispersion of the density distribution. Further, it can provide uncertainty estimations of density distributions. However, there are local spatial patterns that cannot be explained by the 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. An SPDE model with a mesh cutoff of 20 km was used in the modelling procedure.

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

The 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 selected through backward selection starting with the full set of covariates per species and bimonthly season (Figure 2.4), excluding covariates stepwise. The best models were selected based on AIC. We concluded the model selection when the full model within that round had the lowest AIC by two AIC points. When there were still two or more models at the end of model selection that were less than two AIC points of each other, the model with fewer covariates was selected. Depth and time-space variance were always retained in the model because of their ecological importance, their prediction strength and/or their strong correlation with other variables.

In some cases, models did not converge. This could be caused by too little positive (non-zero) observations in that bimonthly season or too many covariates. In these cases, raw data was checked to see whether species had a clear seasonal pattern and bimonthly seasons could be merged into a 'summer' (Apr–Sep) or 'winter' (Oct–Mar) season. If a species was not present in Dutch waters at all during some months (e.g. Sandwich tern in Oct–Mar), those bimonthly seasons were entirely left out of the model selection (Figure 2.5). If this did not solve the convergence issues, covariates were removed from the model. We started by removing distance to biggest breeding site, followed by fishing effort and distance to shipping lanes, and reran the models. If this did not help, all other covariates except for depth and the time-space variance were removed. When there were still problems with running the model, an IDW approach was chosen for that species. In some cases, there were no problems in running the models in the model selection part, but problems arose in predicting distribution as the model was able to converge but the predictive power was too low. In this case, we also removed covariates in the same order as described earlier and re-ran the prediction. This was only the case in a few species and for only one bimonthly season within that species. When that still did not work, depth was also removed to be able to make predictions, only keeping the time variable in the model.

2.4.1.3 Final covariates per species

After model selection, the final models included different sets of covariates per species and bimonthly season (Figure 2.5). For the razorbill and puffin, bimonthly seasons between April and September were merged into a summer season to be able to create a dataset with enough positive observations to run predictions. For some species and bimonthly seasons, all covariates apart from depth were removed to be able to make prediction datasets and maps. In three cases also depth was removed to be able to make predictions. This was done for little gull and great black-backed gull in Jun–Jul and lesser black-backed gull in Dec–Jan (Figure 2.5).

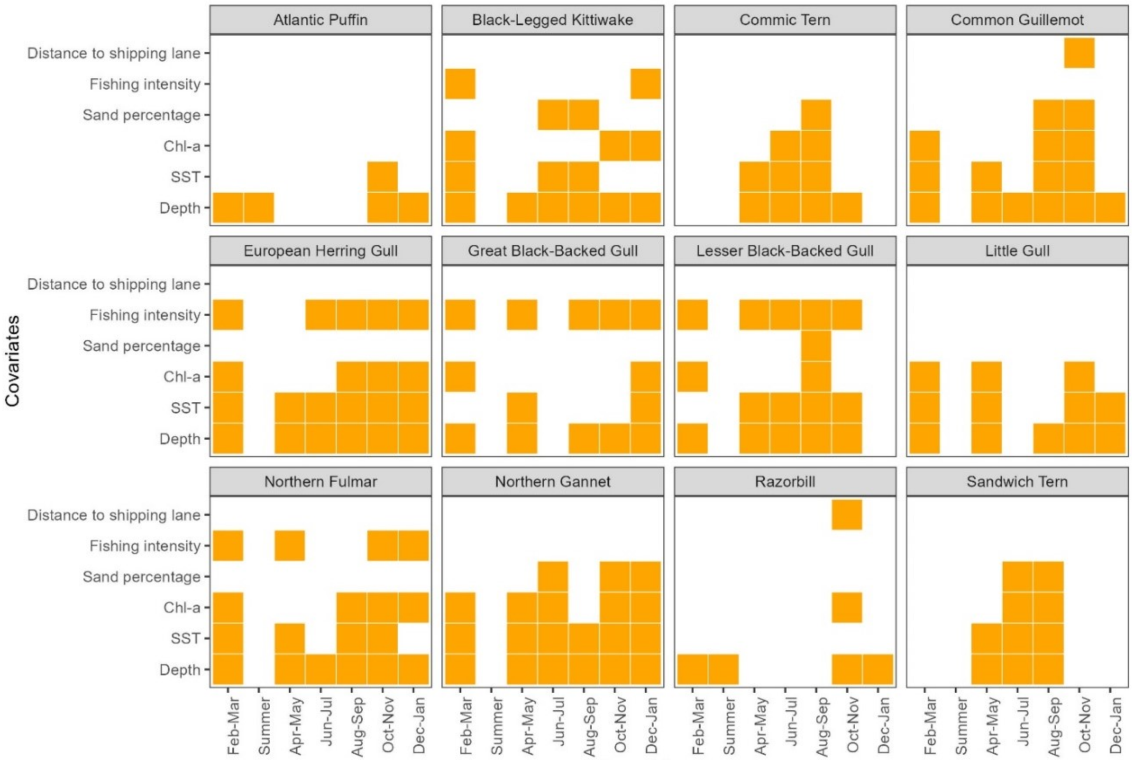

Figure 2.5 *Covariates resulting from backwards selection used in the final models per species and bimonthly season. SST = sea surface temperature, Chl-a = chlorophyll-a concentration. For razorbill and Atlantic puffin, bimonthly seasons Apr–Sep were merged into a summer season due to limited non-zero observations in these months.*

2.4.1.4 Prediction

Bird distributions (individuals per km²) were predicted on a 10 x 10 km spatial grid using data from the most recent available period. When data from this period were insufficient to support reliable spatial predictions, data from all periods were pooled to estimate bird densities. Model outputs were stored as spatial prediction maps and as corresponding parquet files. To quantify predictive uncertainty, 1,000 simulation-based predictions were generated from the final models for each species and bimonthly season. These simulations were also stored as parquet files. The resulting dataset can be used as input for KEC analyses, allowing uncertainty in bird density distributions to be incorporated into subsequent assessments.
All maps that were created on a 10 x 10 km grid. The 10 x 10 km grid was found to best fit the modelling approach (van Donk et al., 2024) and in addition, the Waggitt maps were also generated on a 10 x 10 km grid.

2.4.1.5 Checks of prediction maps

When predictions were finished, a visual check was done to assess the distribution patterns. These patterns were compared to raw average and median data. In case of unexpected patterns, relationships between bird distributions and covariates were studied followed by a re-assessment of the model used.

All analyses were performed using R version 4.4.3 (R Core Team, 2024). The GLMM/GAMM analysis was implemented using the *sdmTMB* package (Anderson et.al., 2022). All scripts with details of the model can be found in the Wozep repository (https://wozep.nl/git/wozep/kec-6.0/02-density-maps/-/tree/main/birds).

2.4.2 IDW maps

IDW national maps were generated for Arctic skua and great skua due to too few non-zero observations (Table 2.2). IDW national maps have been developed using inverse distance weight per 5-year time period on a 10 x 10 km grid (Soudijn et al., 2022; van Donk et al., 2024). IDW was performed with the R package *gstat* (Gräler et al., 2016; Pebesma, 2004). The following settings were used: the inverse distance weighting power (idp) was set to a value of two. The minimum number of observations (nmin) for predicting density was set to 5 and the maximum number of observations (nmax) to 15; to predict density, 5-15 observations were used at a specific location. These settings correspond to the settings used for the maps created for KEC4 (Soudijn et al., 2022). However, data were not averaged per year and bimonthly period. The time period for the IDW national maps is the same as for the maps generated with the modelling approach.

IDW is a deterministic interpolation method, meaning that predicted values are calculated directly from surrounding observations using distance-based weights, without relying on a statistical model of spatial variation. As a result, IDW does not provide an estimate of prediction uncertainty (e.g., variance or standard error), unlike geostatistical approaches such as the van Donk maps. Although there are methods available to estimate uncertainty for IDW by for instance using cross-validation, bootstrapping, or sensitivity analyses. These approaches either show an overall uncertainty of models (so not a variation per spatial point) or are relatively unstable and thus of limited interpretative value. An additional complicating factor is that we already use IDW for species with limited positive observations (Arctic and great skua) which further complicates the reliability of calculated uncertainty. Consequently, attempting to quantify uncertainty for IDW in these contexts is unlikely to yield robust or informative results.

3 Results

3.1 National prediction maps - van Donk

National prediction maps using the van Donk approach were created for 12 species (**Table 2.1**). A visual example shows the distribution of the common guillemot in the period 2020-2025 for the different bimonthly seasons (**Figure 3.1**). Highest concentrations in Dutch waters can be found in Aug–Sep. Distribution maps based on the van Donk maps for these 12 species are presented in Annex 1.

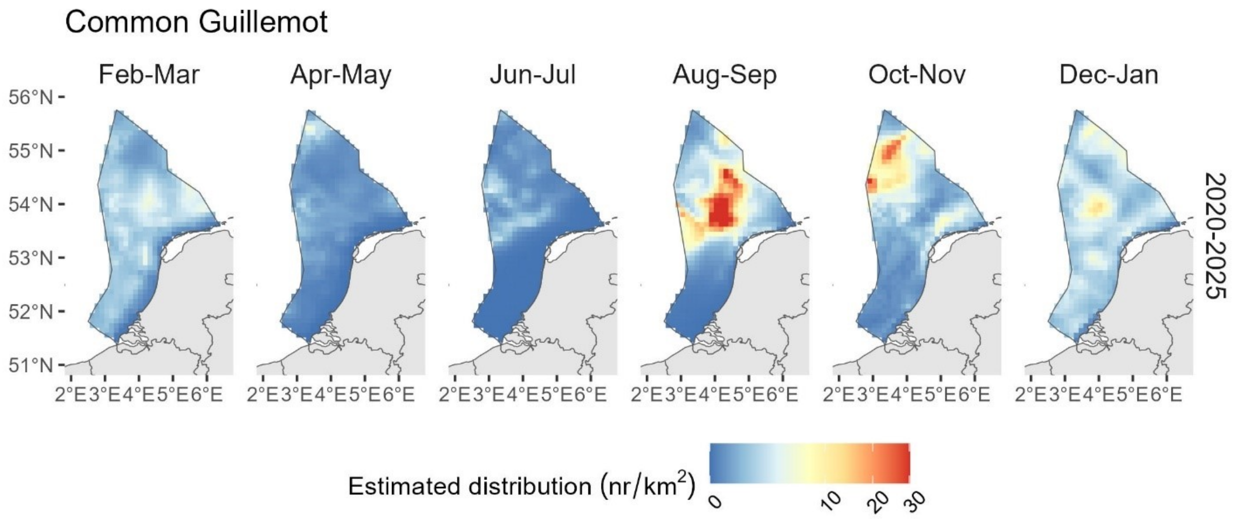

Figure 3.1 *Estimated distribution of common guillemots in Dutch waters per bimonthly period (2020–2025). Values above the 99.5 percentile were truncated for visualization purposes. A square-root transformation was applied to the color scale for display purposes only.*

3.2 National prediction maps - IDW

For the Arctic and great skua, most models did not converge, even when all covariates except depth were removed. For these species, IDW was used to prepare maps for the period 2021-2025. Both species are very rare in the Dutch part of the North Sea, resulting in too few non-zero observations for a model to converge. Visualization of these two IDW maps can be found in Annex 2.

3.3 Checks of prediction maps

3.3.1 Comparison model prediction with raw data

A visual check of the predicted distribution maps was done to assess and discuss the predicted distributions together with other seabird experts from Wageningen Marine Research and Waardenburg Ecology. Predicted distributions were compared to raw average and median data (Figure 3.2). During this visual check, the primary focus was given to whether seasonal patterns and distribution corresponded with the raw data and expectations for the species. Predicted densities are often a bit lower than the simple average of the raw data, particularly in datasets with many outliers as the bird surveys. This difference arises because the model estimates are based on the underlying distribution while accounting for variability, spatial structure, and uncertainty, rather than directly averaging raw values. Extreme observations (occasionally high bird counts) can have a disproportionately large effect on the mean of the raw data. The model, however, uses the underlying data distribution and the chance such occasionally high bird observations are done. As a result, model predictions tend to reflect the distribution of the birds robustly and are less influenced by rare, high bird observations, leading to lower predicted values compared to the raw mean. The maps are therefore a good reflection of spots where densities are usually higher or lower for certain seabird species, but less to use as population estimates.

For the common guillemot, the distributions in the predicted maps (Figure 3.2c) were comparable with distributions in the raw data maps (Figure 3.2a, b). The map with average values (Figure 3.2b) shows where high densities can be found, while the map with median values (Figure 3.2a) shows where the guillemot is consistently counted during the aerial survey.

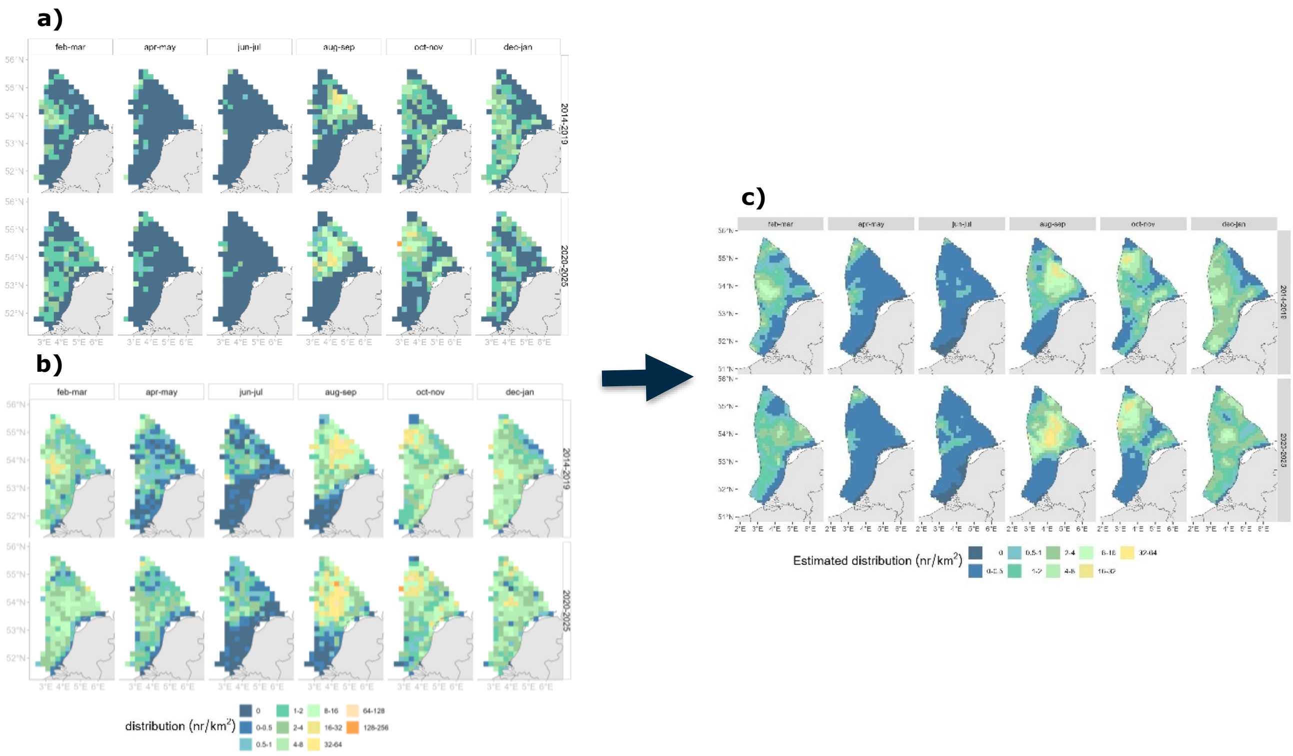

Figure 3.2 *Visual comparison between the median (a) and averaged (b) raw data (nr/km^2) on a grid of 20 x 20 km with the predicted estimated distribution (c) of the common guillemot on a 10 x 10 km grid. The numbers per km^2 are categorized in the same groups for comparison.*

3.3.2 Correlation with covariates

Final models per species and bimonthly seasons differed in covariates that seemingly played a role in the distribution of birds (Figure 2.5). While in some cases the best model following model selection included all initial covariates, in other cases the best model did not contain any covariates after model selection (apart from depth and period which were always kept in the model). For most species, the relationship between bird distribution and depth was as expected. For instance, the guillemot density is usually not high in very shallow areas, e.g., coastal areas (Figure 3.3). The relationship between guillemot distribution and sea surface temperature is less clear. In some bimonthly seasons, distribution is higher with higher temperatures (Oct–Nov) and in other seasons the pattern is reversed (Figure 3.3).

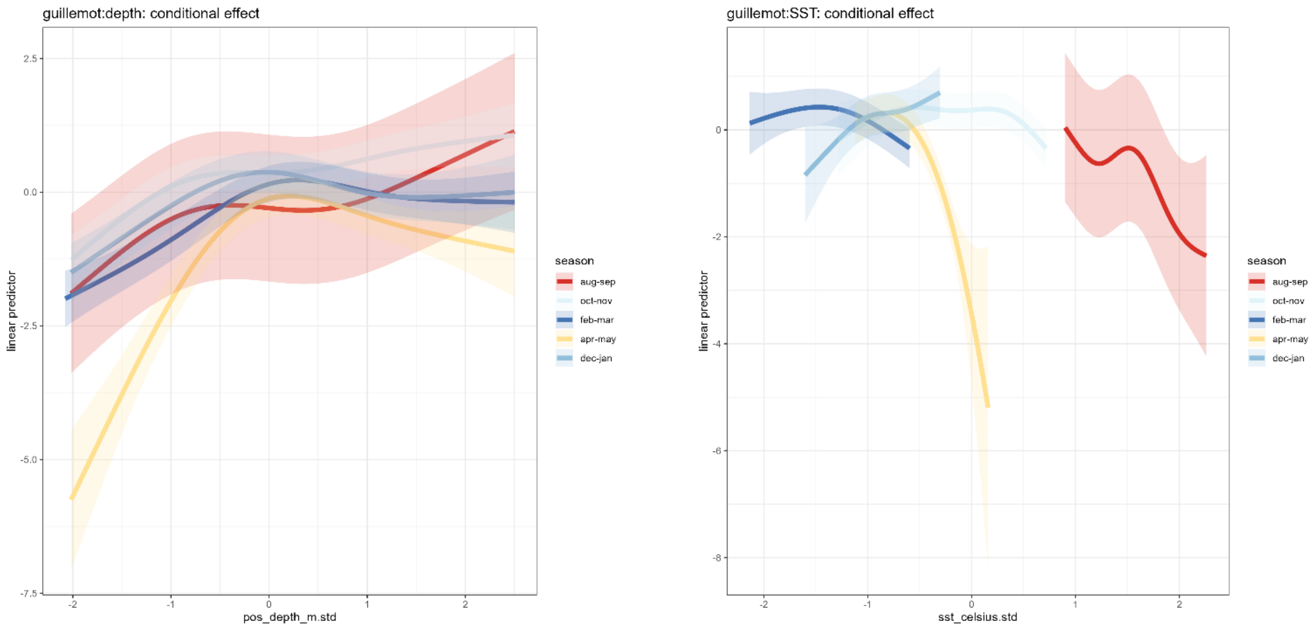

Figure 3.3 *Two examples of the relative effect of two covariates on common guillemot distribution in the model while keeping the other variables on a constant value, per bimonthly season. On the x-axis the standardized value for depth (left) and standardized value for sea surface temperature (SST, right).*

3.3.3 Adaptions after visual checks

Two species (black-legged kittiwake and razorbill) showed a distribution pattern that was strongly different compared to the raw data and to the expectations of the consulted seabird experts in two bimonthly seasons (Oct–Nov and Dec–Jan), which resulted in a prediction map with a different overall seasonal pattern. This deviating pattern was caused by the relationship of density with SST in these months. After removing this covariate from the models of these months, the predictions and especially the overall seasonal patterns were closer to expectations and the patterns that could be observed by eye in the raw data.

4 Conclusion and recommendations

During this project, national maps for the periods 2021–2025 or 2020–2025 were generated for 14 species. The procedure followed was similar to the method used for the previous KEC assessment (van Donk et al., 2024). However, there were some changes in the use of covariates and estimation procedure. Besides the use of the most recent bird data available (until July 2025), we also used more detailed covariate data for fishing effort (monthly instead of yearly means), SST and chlorophyll-a (daily instead of monthly means). Furthermore, more time and effort were spent on interpreting and discussing the prediction maps with experts, which in some cases resulted in small modifications in the covariates used for prediction. Adjusting or changing the methods more radically was out of the scope of this project, but some adjustments are suggested below.

We did not use prey density as a covariate in the models, but only covariates that are suggested to correlate to prey density (Chl-a, SST, percentage of sand). In preparation of a future assessment, prey density data could potentially be used to replace the prey proxy variables SST and Chl-a to predict bird distributions more accurately, provided prey density maps are available by then. Besides, other covariates could be considered. For instance, little gulls are often seen foraging near auks and near fronts of different water masses (Fijn et al., 2022; Schwemmer and Garthe, 2006; Vanermen et al., 2014). Including this information as covariates might result in better distribution predictions for these species.

The model approach used could be reassessed. Model selection was done using backward selection based on Akaike Information Criterion (AIC) comparison. This resulted in relatively long computational times, and models with too many covariates or bimonthly seasons with too little positive (non-zero) observation caused convergence issues. This was particularly the case for species that are not so common in the Dutch part of the sea or in certain seasons. Forward selection (adding covariates one by one) and specifically testing the predictive performance with, for instance, mean absolute error (MAE) and the root mean squared error (RMSE) might be a more time-efficient approach for the purpose of predicting maps. With this way of covariate selection, adding an extra covariate is tested and assessed on the percentage of improvement of the predictions instead of the best fit (AIC). When this improvement is very low, adding an extra covariate is probably not necessary for the predictive power and can be left out. Besides model selection, depth was always retained in the models as earlier explorations have shown that this covariate showed the strongest relation with bird distribution in almost all species. However, this could change over time (for instance because of climate change) and adding an extra step by testing the final model with and without depth could be of interest. Furthermore, new scientific insights within the scientific community might lead to reassessing the model that we used. One possibility, for example, is to run two or more models with different model types and then take an average of the results of these models for the density per grid cell (Oppel et al., 2012; Woodman et al., 2019). However, a downside of this approach is that it is more time-consuming.

The maps of the international part of the sea remain a point of attention. The biggest problem is still that there is little recent data available. Additional survey efforts at an international level are recommended to close this gap.

Predicting bird distributions using a model provides the opportunity to study the relationship between seabird density and a range of covariates. Although a full evaluation of model results was beyond the scope of this project, future studies could focus on understanding and testing the outputs of the models to elucidate the relationships between marine bird densities and environmental variables. Improved or higher quality covariate data could improve predictive ability and ecological understanding, particularly with regard to prey distributions. Studying the links between environment and seabird density is important for understanding seabird distributions in the North Sea and will benefit decision-making in order to protect seabird populations.

5 Quality Assurance

Wageningen Marine Research utilizes an ISO 9001:2015 certified quality management system, certified since February 27, 2001 by DNV. ISO 9001 is an international standard for quality management, focused on the continuous improvement of processes and ensuring customer satisfaction.

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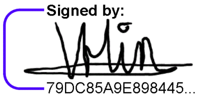
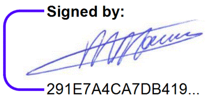
Justification

Report: C052/26
Project Number: 4315100272

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:	Dr. V Hin Researcher
Signature:	
Date:	16 June 2026

Approved:	A.M. Mouissie, PhD Business Manager Projects
Signature:	
Date:	16 June 2026

Annex 1 Distribution maps

This annex presents distribution maps for 12 seabird species based on the van Donk approach for a total of 12 species. Note that color scales differ between species.

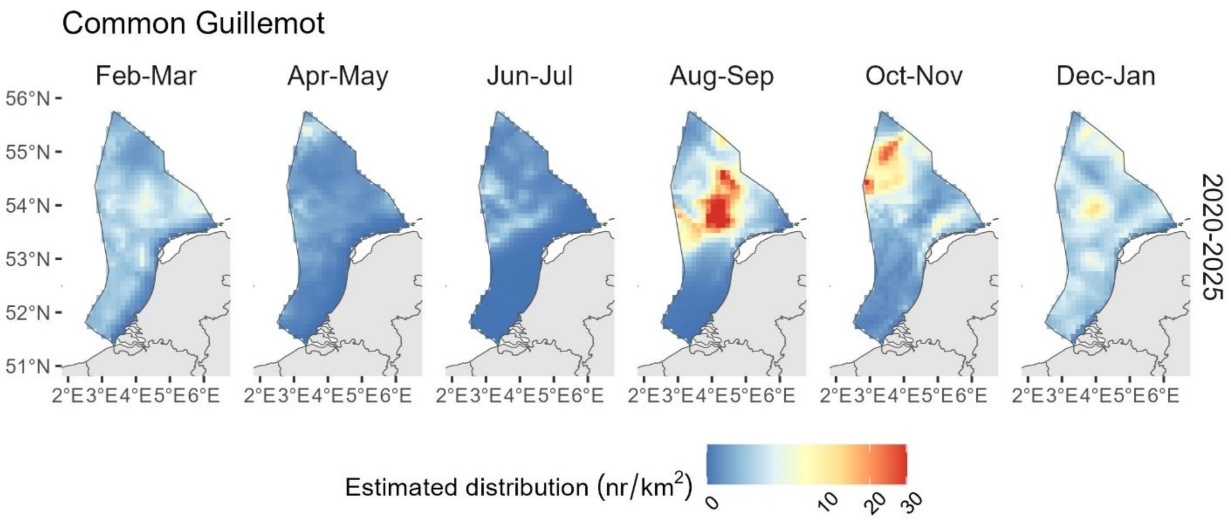


Figure 5.1 *Estimated distribution of common guillemots in Dutch waters per bimonthly period (2020–2025). Values above the 99.5 percentile were truncated for visualization purposes. A square-root transformation was applied to the color scale for display purposes only.*

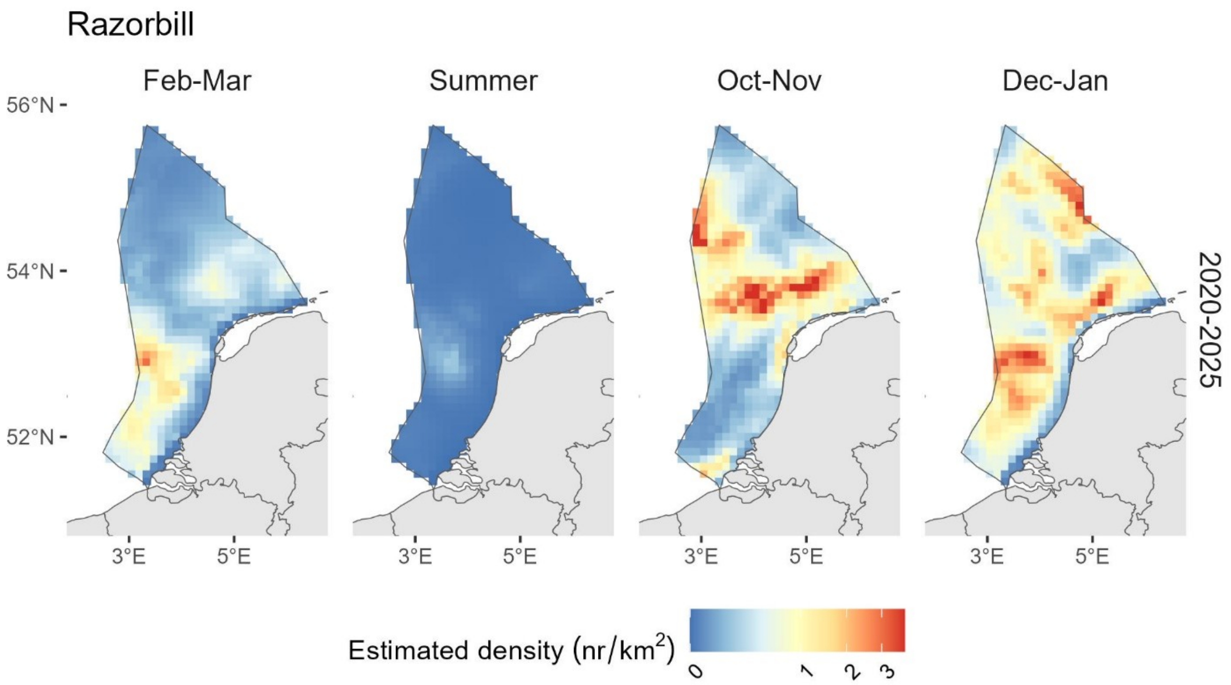


Figure 5.2 *Estimated distribution of razorbills in Dutch waters per bimonthly period (2020–2025). The months April until September were combined into one season ('summer'). Values above the 99.5 percentile were truncated for visualization purposes. A square-root transformation was applied to the color scale for display purposes only.*

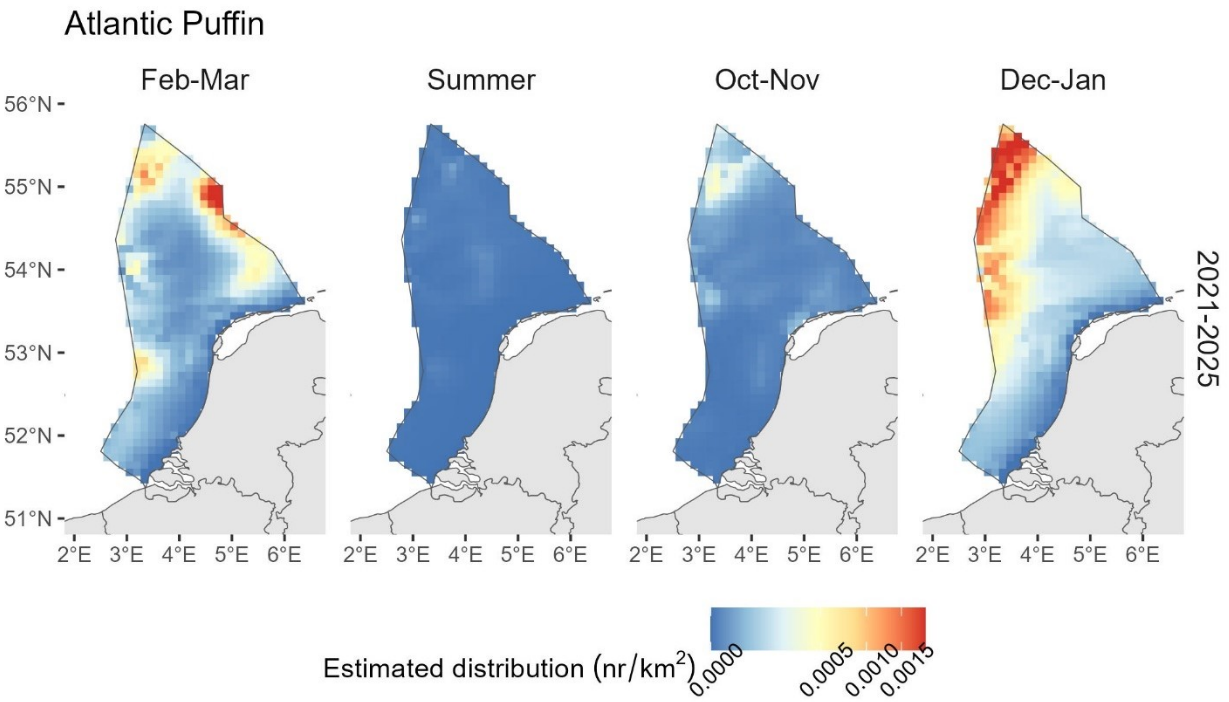


Figure 5.3 *Estimated distribution of Atlantic puffins in Dutch waters per bimonthly period (2021–2025). The months April until September were combined into one season ('summer'). Values above the 99.5 percentile were truncated for visualization purposes. A square-root transformation was applied to the color scale for display purposes only.*

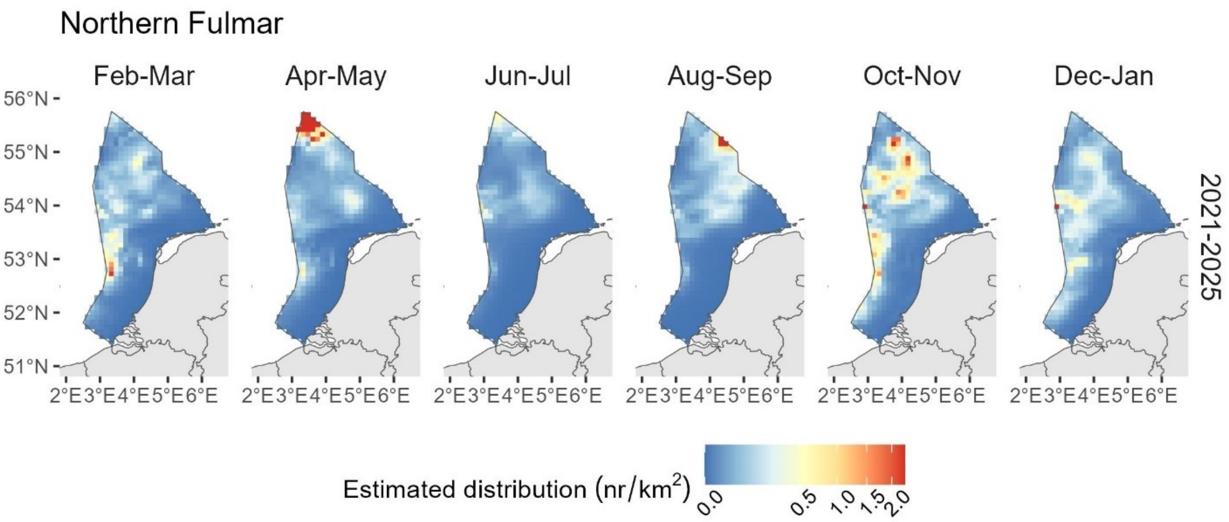


Figure 5.4 *Estimated distribution of northern fulmars in Dutch waters per bimonthly period (2021–2025). Values above the 99.5 percentile were truncated for visualization purposes. A square-root transformation was applied to the color scale for display purposes only.*

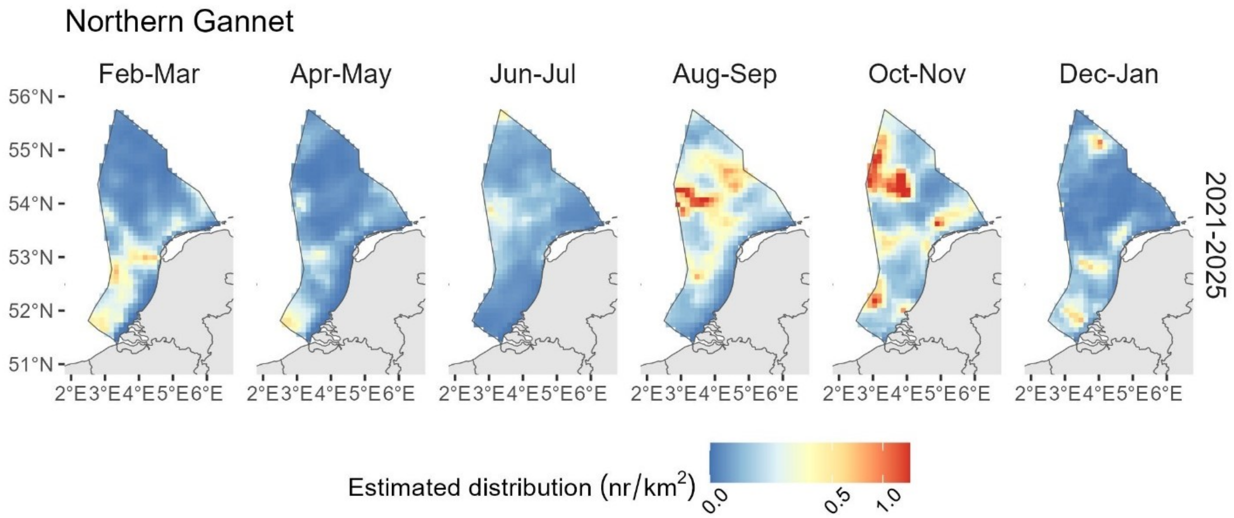


Figure 5.5 *Estimated distribution of northern gannets in Dutch waters per bimonthly period (2021–2025). Values above the 99.5 percentile were truncated for visualization purposes. A square-root transformation was applied to the color scale for display purposes only.*

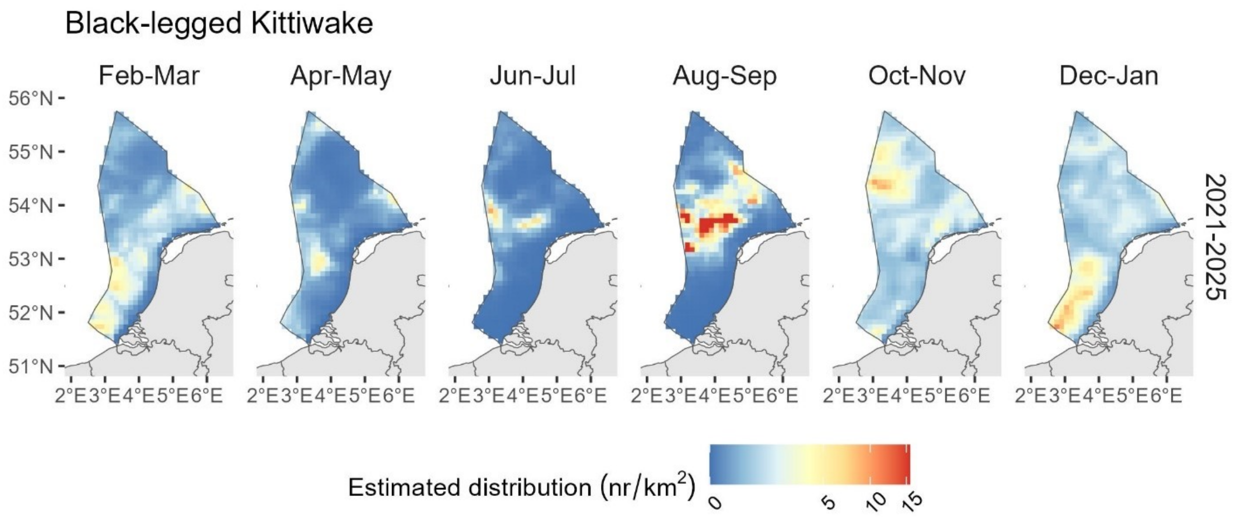


Figure 5.6 *Estimated distribution of black-legged kittiwakes in Dutch waters per bimonthly period (2021–2025). Values above the 99.5 percentile were truncated for visualization purposes. A square-root transformation was applied to the color scale for display purposes only.*

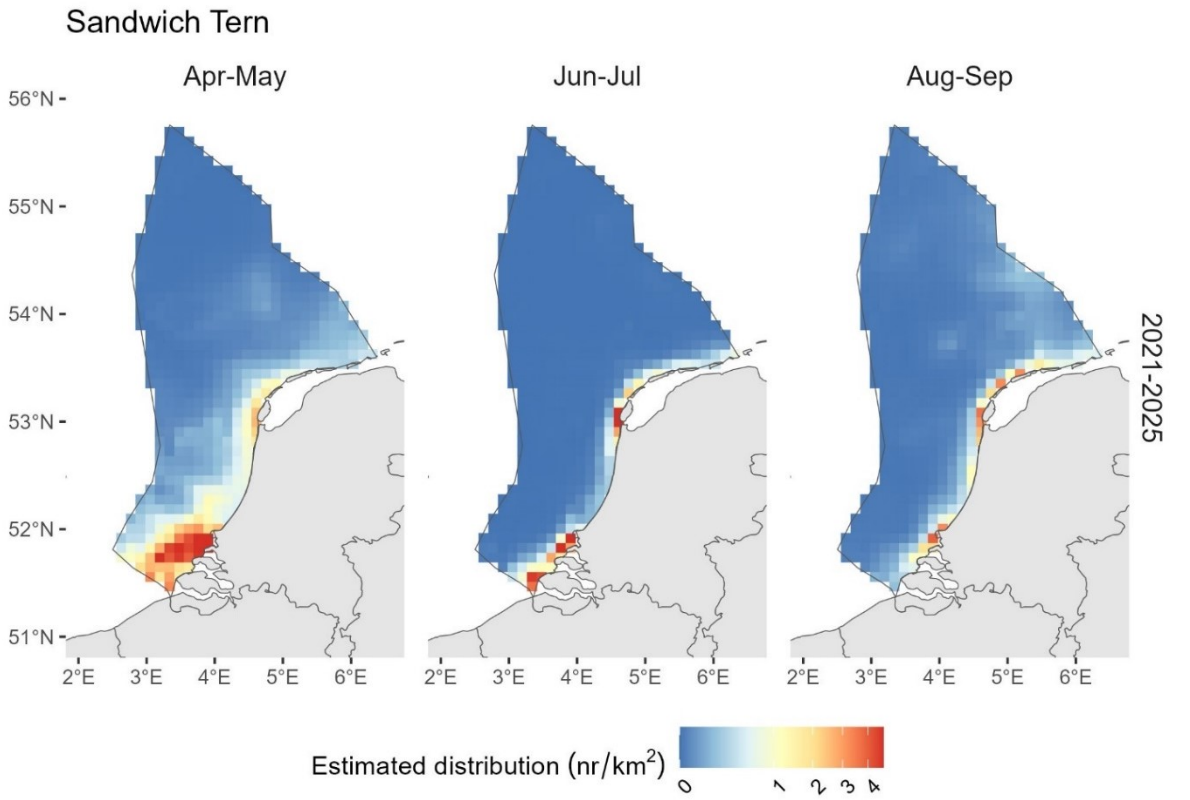


Figure 5.7 *Estimated distribution of Sandwich terns in Dutch waters per bimonthly period (2021–2025). Values above the 99.5 percentile were truncated for visualization purposes. Distribution was only estimated for the bimonthly seasons between April and September when the species is present in Dutch waters. A square-root transformation was applied to the color scale for display purposes only.*

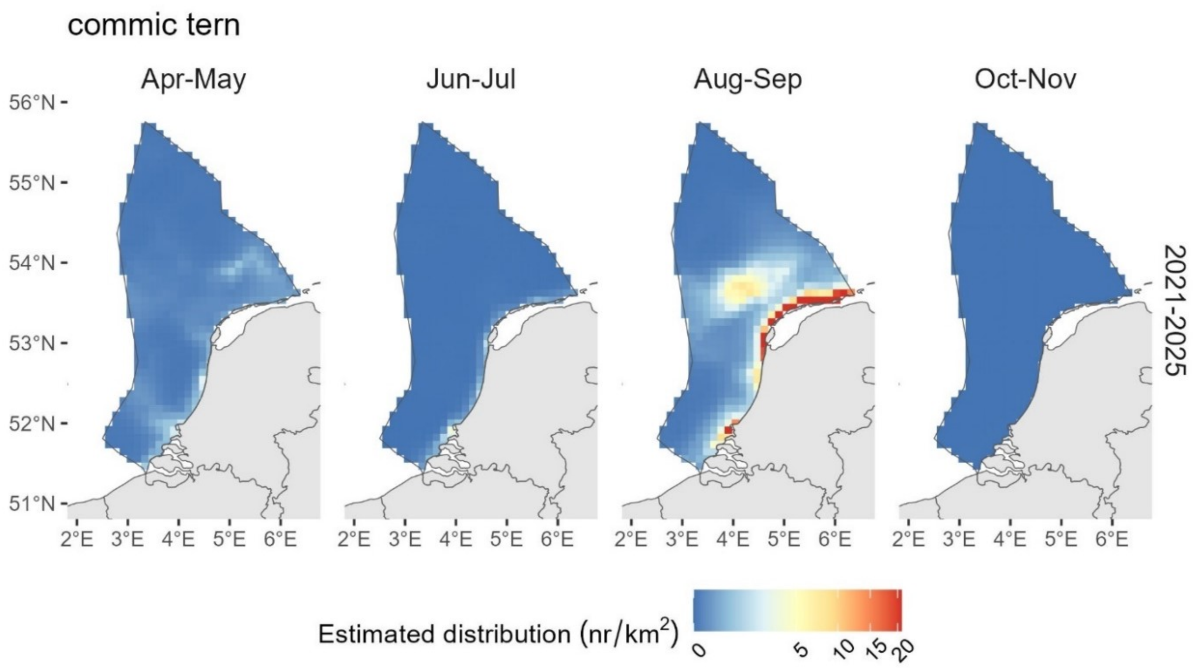


Figure 5.8 *Estimated distribution of the 'commic' tern (common tern and Arctic tern) in Dutch waters per bimonthly period (2021–2025). Values above the 99.5 percentile were truncated for visualization purposes. Distribution was only estimated for the bimonthly seasons between April and November when the species is present in Dutch waters. A square-root transformation was applied to the color scale for display purposes only.*

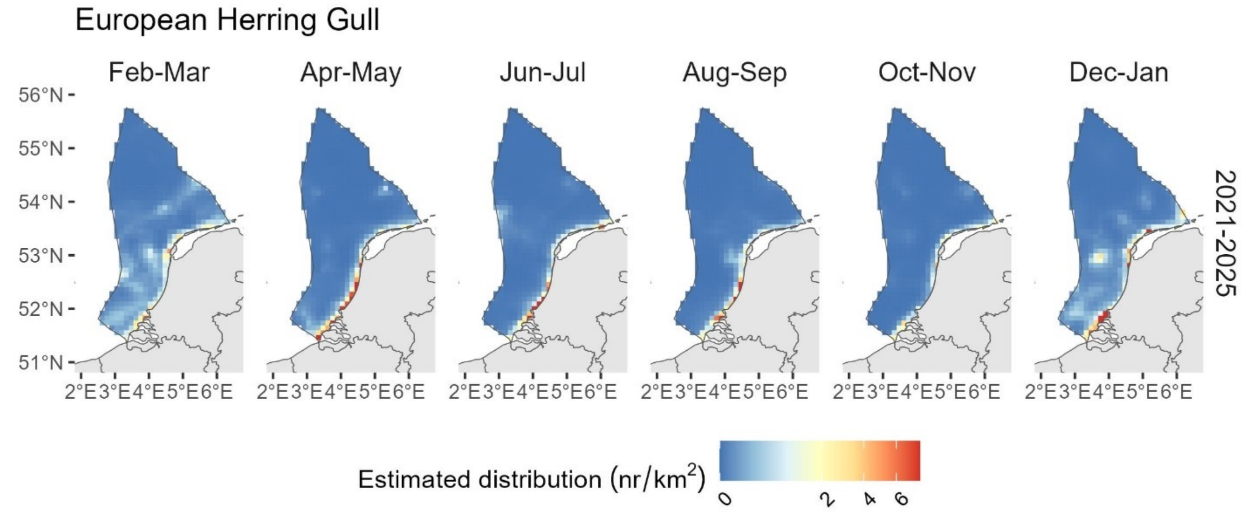


Figure 5.9 *Estimated distribution of European herring gulls in Dutch waters per bimonthly period (2021–2025). Values above the 99.5 percentile were truncated for visualization purposes. A square-root transformation was applied to the color scale for display purposes only.*

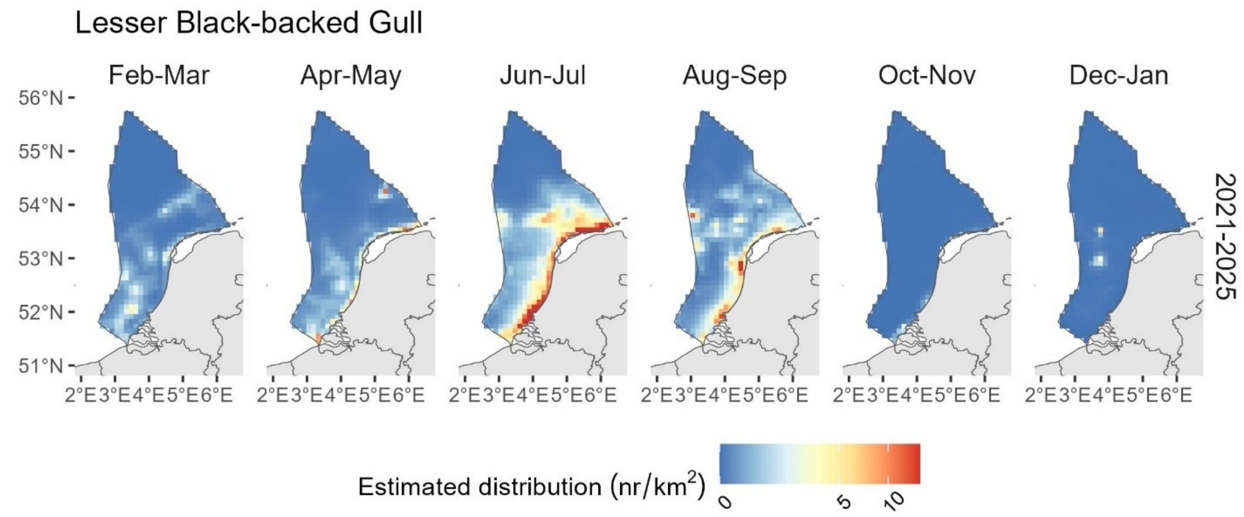


Figure 5.10 *Estimated distribution of lesser black-backed gulls in Dutch waters per bimonthly period (2021–2025). Values above the 99.5 percentile were truncated for visualization purposes. A square-root transformation was applied to the color scale for display purposes only.*

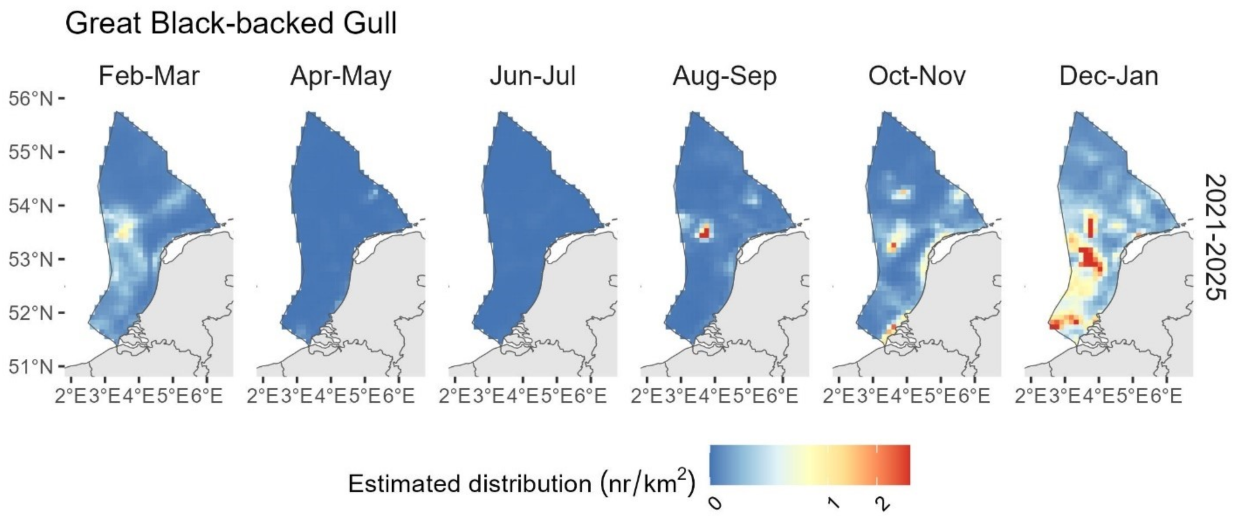


Figure 5.11 *Estimated distribution of greater black-backed gulls in Dutch waters per bimonthly period (2021–2025). Values above the 99.5 percentile were truncated for visualization purposes. A square-root transformation was applied to the color scale for display purposes only.*

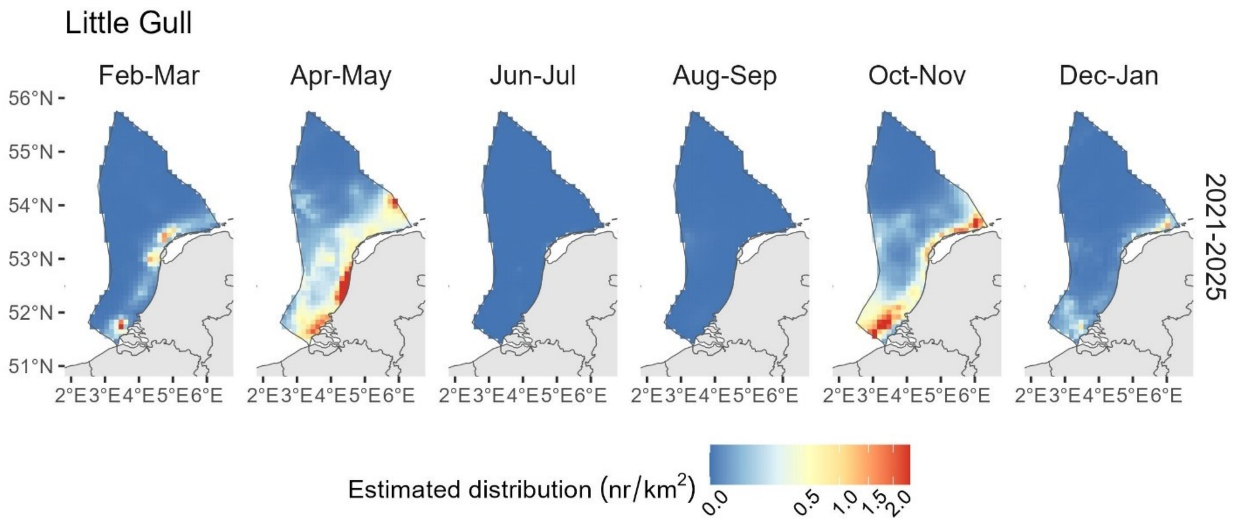


Figure 5.12 *Estimated distribution of the little gull in Dutch waters per bimonthly period (2021–2025). Values above the 99.5 percentile were truncated for visualization purposes. A square-root transformation was applied to the color scale for display purposes only.*

Annex 2 IDW maps

This annex presents distribution maps based on inverse distance weighting for two species. Note that colour scales differ between species.

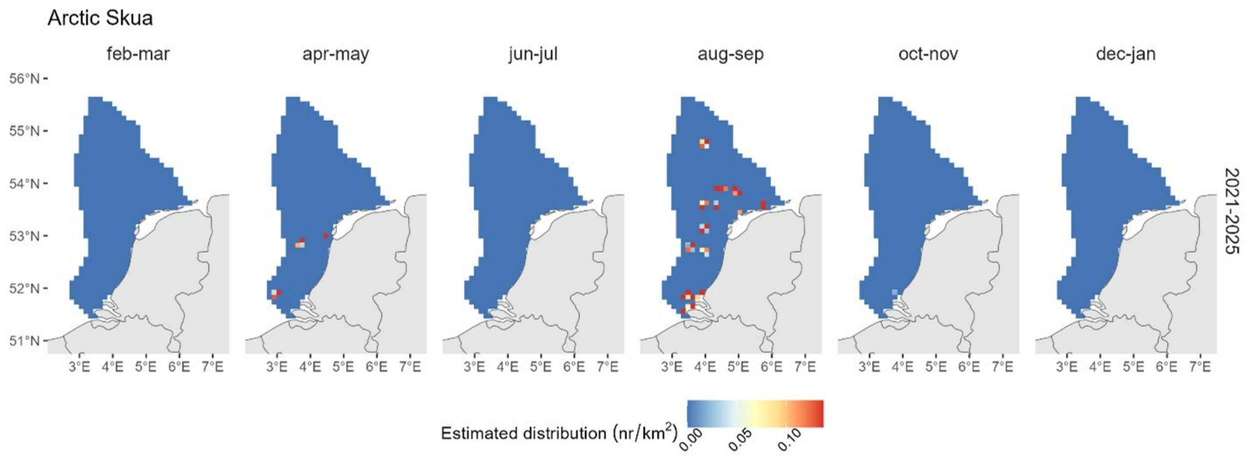


Figure 5.13 *Distribution of Arctic skuas in Dutch waters estimated with inverse distance weighting per bimonthly season (2021–2025). Values above the 99.5 percentile were truncated for visualization purposes. A square-root transformation was applied to the color scale for display purposes only.*

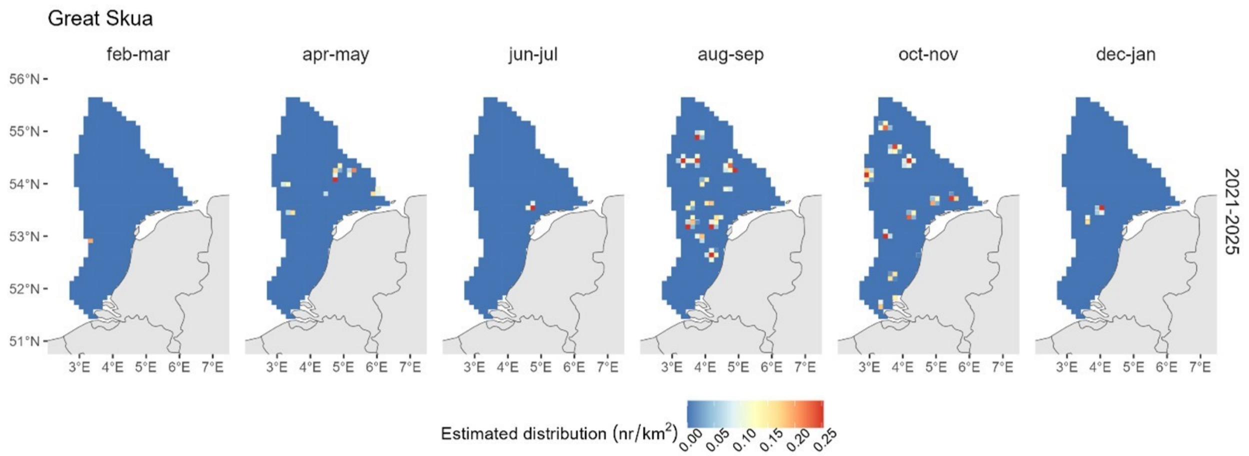


Figure 5.14 *Distribution of great skuas in Dutch waters estimated with inverse distance weighting per bimonthly season (2021–2025). Values above the 99.5 percentile were truncated for visualization purposes. A square-root transformation was applied to the color scale for display purposes only.*