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Displacement and population level effects in 5 selected species

Author(s): Tobias van Kooten, Floor Soudijn, Ingrid Tulp, Chun Chen, Daniel Benden and Mardik Leopold

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Summary

Introduction

The planned large-scale development of offshore wind farms (OWFs) in the North Sea has potential consequences for many marine organisms, including seabirds. Seabirds may suffer from habitat loss if OWFs are built in areas they use, which may in turn negatively affect the populations of seabirds using the Dutch continental shelf. Adverse effects of offshore wind farms on seabirds potentially lead to a trade-off between societal demands for marine nature conservation and clean energy. Seabirds are important target species in European conservation frameworks.

In this study, we developed and applied a method for assessing the effect of habitat loss on five seabird species: red-throated divers (*Gavia stellata*), northern gannets (*Morus bassanus*), sandwich terns (*Thalasseus sandvicensis*), razorbills (*Alca torda*) and common guillemots (*Uria aalge*). To our knowledge, this is the first study that calculates effects on the full life cycle and the larger North Sea population.

Assessment method

To assess the effect of OWF related habitat loss on the larger North Sea population of the seabirds listed above, we aim to answer the following research questions:

1. What is the importance of the areas to be occupied by OWFs, and what fraction of the populations is confronted with OWFs?
2. What is the degree of displacement by OWFs for each of the species?
3. What is the cost of habitat loss (in terms of the survival probability) as a result of the placement of OWFs?
4. What are the population consequences of these changes in vital rates?

Key aspects of the assessment method are:

- It translates effects that are measurable in the field to population level indicators that are relevant for policy
- It takes a precautionary approach in dealing with uncertainty, and is able to quantify the uncertainty in the predictions
- It can differentiate spatial configurations/locations of OWFs, and can be used for future scenario studies.
- It takes the OWF plans of other North Sea countries into account

To answer our research questions we use a research method with three steps. First, we describe the population distribution based on habitat maps that are constructed based on seabird distribution data and abiotic explanatory variables. Second, we determine the cost of habitat loss using an individual based energy-budget model, the habitat model predictions and the degree of displacement. We calculate the 'cost' of habitat loss in terms of reduced survival rates of bird redistribution due to a change in the availability and configuration of the foraging area for several OWF scenarios. Finally, we use population models to project the effect of the reduction in survival rates on the population level. We used all available information from literature and expert judgement to develop our models. Nonetheless, many steps in the calculations are characterised by uncertainties. For the individual based model and the population model we translated this uncertainty into three scenarios: a best estimate, a worst case and an extreme scenario. For the best estimate approach, we use the best available estimate for the degree of displacement, whereas in the worst case we use complete displacement. In addition to the estimated reduced survival rates we use a scenario with 90% survival of all displaced individuals (based on the previously used 10% mortality method; Leopold et al, 2014). We also use an extreme scenario of 0% survival of all displaced individuals. All three scenarios were run for situations without wind farms, for Dutch wind farms only, for foreign wind farms only and for all wind farms combined. By contrasting the last two scenarios, we obtain insight into the *additional* effect of the Dutch OWF.

Results

For three species (northern gannet, razorbill and common guillemot), habitat suitability maps covered the entire North Sea. Due to data limitations, the habitat suitability maps for red-throated diver and sandwich tern were limited to the Dutch continental shelf area. It is technically possible to calculate tern and diver abundance outside the input data locations, but doing so implies that the relationships determining bird abundance in Dutch areas translate 1:1 to the rest of the North Sea. We have no data to study whether or not this is the case and have therefore chosen not to extrapolate for these two species. All habitat models include a random spatial field. The overlap between the bird populations and Dutch OWFs was generally found to be low (0.5-2% overlap, depending on the species). For the species that were considered over the full North Sea area, the overlap with international OWFs (3.6-6.4% overlap, depending on the species) always surpasses the overlap with Dutch OWFs.

In an un-impacted situation (without wind farms), the population models predict a strongly declining red-throated diver population and a slowly declining northern gannet population. On the other hand, the sandwich tern, razorbill and common guillemot populations were all predicted to increase. The perturbation analysis of all bird population models showed that the population growth rate is more strongly affected by changes in adult survival than by changes in reproductive success or breeding probability.

Compared to a scenario without windfarms, the population model predicts a median population size of 82.7-96.6% for best estimate scenarios and 76-95.8% for worst case scenarios (percentage depends on the species). These effects are much smaller than predicted for the extreme scenario (6.1-66.5%, depending on the species). The overlap between outcomes of impacted and un-impacted populations is substantial; 42-49% of the population sizes without wind farms is smaller than the median of the outcomes for the worst-case scenarios. For the best estimate scenario, this is 44-49%. This result shows that it is unlikely that effects of OWF will be distinguishable from ambient fluctuations. The gannet population shows the strongest effect of all species in the best estimate scenario. The median population size with all windfarms is 82.7% of the median without windfarms and 42% of the outcomes without windfarms show a population size smaller than the median of the outcomes with all windfarms. Probably, because the effect of OWFs adds mortality both in the breeding and the non-breeding season, while for all other species their presence on the North Sea is seasonal.

The effects of the Dutch OWFs, either in isolation or in addition to the international wind farms, are smaller. The model predicts a median population size of 95.8-98% (worst case) or 96.4-98.3% (best estimate scenario) with Dutch windfarms compared to the situation without wind farms. For the extreme scenario, the median population size is predicted to be 56.1%-86% of the median without windfarms.

The results of the simulation modelling, which translates effects of OWF from the habitat map to effects on parameter values of the matrix population models, should be viewed as illustrations of what can be obtained with this approach. The method and implementation are still in the development and testing phase. The reason for this is that the simulations take very long to run (3 days for the calibration step, 3 days for the effect simulation step). This means that testing the method thoroughly simply takes a large amount of time. Testing procedures will continue, and will result in a fully operational method (and its application) in the first quarter of 2019.

Assumptions and uncertainties

To our knowledge, this is the first study that calculates effects on the full life cycle and the larger population. Our results indicate that the effect of habitat loss from currently planned OWFs on the five studied bird populations results, in thirty years' time, in population sizes varying between 76% and 95.8% as compared to the situation without windfarms (worst case scenario, NL and international OWFs). However, OWFs are only one of the many sources of disturbance, next to e.g. shipping. It should be noted that we have not studied cumulation with other potential pressures or effects if the spatial use and configuration of future windfarms changes, and that such cumulation can amplify effects. In addition, other bird species than the species studied here may show different patterns in overlap with the OWFs.

We used existing information to the best of our knowledge. Yet, there are still large sources of uncertainty that may influence the outcome. While our current analysis has taken into account uncertainty in the population-level parameter values, we have only used the average predicted values from the habitat models. Using higher habitat qualities for the areas where certain OWFs are added may lead to larger population effects of those OWFs. The actual effect of OWF on seabirds ultimately depends on how OWFs influence the vital rates of seabirds, which is still largely unknown.

Potential improvements

For northern gannets, razorbills and guillemots, the current assessment suffers from the disparity between the data sources in space and time. More data are available than are currently available in the ESAS database (see e.g.

https://www.ascobans.org/sites/default/files/document/2.4.1%20Mapping%20cetacean%20distributions_Evans.pdf). The coordination of collecting the data from all different sources into one database is currently lacking. That is also the reason why we could not include the area outside the DCF (Dutch Continental Shelf) for red-throated diver and sandwich tern. There is an urgent need for an updated central database.

An important source of uncertainty regarding the population parameters lies in the difficulties in disentangling mortality and migration. A good understanding of the meta-population dynamics between colonies would allow for a refinement of the calculation of mortality parameters. In addition, a better understanding of the meta-population dynamics of seabirds, also regarding the dynamics of migration between breeding and overwintering areas, would allow for a better definition of the pool of birds that is potentially affected by the OWFs in the North Sea.

1 Introduction

1.1 Background

The planned large-scale development of offshore wind farms (OWFs) in the North Sea has potential consequences for many marine organisms, including seabirds. Some seabird species avoid wind farm areas (Dierschke, Furness et al. 2016). Such species may suffer from habitat loss if OWFs are built in areas they use, which may in turn negatively affect the populations of such species using the Dutch continental shelf or the larger North Sea area. Adverse effects of offshore wind farms on seabirds potentially lead to a trade-off between societal demands for marine nature conservation and clean energy. Seabirds are also important target species in European conservation frameworks such as the Marine Strategy Framework Directive and the Bird- and Habitat directive.

Large-scale development of offshore wind farms is considered an essential part of a transition to carbon-neutral energy production in The Netherlands and other North Sea countries. In order to develop the Dutch offshore wind agenda in an ecologically sound way, as outlined in the policy document 'Energie-akkoord voor duurzame groei' (2013, English: Agreement on Energy for Sustainable Growth), the KEC ('Kader Ecologie en Cumulatie' English: Framework for Ecology and Cumulation of impacts) was compiled (RWS, 2016). This document gives an overview of species and populations that may suffer from the planned OWF development, and highlights potential mitigating measures to prevent these problems. The work presented in this report follows directly from the KEC, in which a ranking is developed of seabird species deemed most at risk from the Dutch offshore wind farms through displacement and habitat loss. In this work, we develop and apply a framework for assessing these effects on the 5 species indicated as the most sensitive in the KEC. The work in the KEC applies an identical method to a large number of species. This means that it applies strong generalizations and relies heavily on precautionary approach assumptions. By conducting a more detailed and species-specific assessment for the species indicated as most sensitive in the KEC, this study aims to reduce the uncertainty in the assessment for the given species. Hence, the KEC approach aims to rank all relevant species according to their likely sensitivity, while this study quantifies in more detail the sensitivity of those species indicated most at risk.

The aim of the work reported on here is to develop and apply an assessment method to estimate detrimental population effects from OWF plans in Dutch waters, caused by OWF-induced habitat loss.

Key aspects of the assessment method are:

- It translates effects that are measurable in the field to population level indicators that are relevant for policy
- It takes a precautionary approach in dealing with uncertainty, and is able to quantify the uncertainty in the predictions
- It can differentiate spatial configurations/locations of OWFs, and can be used for future scenario studies.
- It takes the OWF plans of other North Sea countries into account
- It is reproducible and built on the basis of good scientific practice

1.2 Research questions

The aim of this analysis is to quantify the effects, as a result of habitat loss, of OWF development in Dutch waters on the population development of five seabird species: red-throated diver (*Gavia stellata*), northern gannet (*Morus bassanus*), sandwich tern (*Thalasseus sandvicensis*), razorbill (*Alca torda*) and common guillemot (*Uria aalge*). This analysis consists of a number of elements of OWF-induced habitat loss which together allow us to assess the (potential) influence of habitat loss for individual birds on the population of these birds. Four sub-questions can be formulated that are the focus of different parts of the analysis and which together address the overall goal. The sub-questions are:

1. What is the importance of the areas to be occupied by OWFs, and what fraction of the population is displaced?
2. What is the (direct) cost of this habitat loss (in terms of time and/or energy)? And, how do the results of the above questions combined change the population vital rates (e.g. reproduction, survival) as a result of the placement of Dutch OWFs?
3. What are the population consequences of these changes in vital rates?

The approach to each of the elements of this analysis is based on a common framework for the five species studied here (Figure 1.1). It is adapted to reflect species-specific knowledge regarding the ecology, life history and the data availability for each of the species.

Question 1 will be answered using state-of-the-art habitat models, which couple bird observational count data to biotic and abiotic independent variables.

Question 2 will be answered using individual based energy-budget models. The habitat model will be used, together with the OWF scenarios to be developed and the degree of displacement, to calculate the energetic costs of bird redistribution due to a change in the availability and configuration of the foraging area. Finally, we determine the 'cost' of the scenarios in terms of reduced survival rates. This requires a translation of energetic costs into changes in survival and will be done using a behavioural simulation model.

Question 3 will be answered using population models. These models will also be used to conduct estimates of sensitivity of the results to parameter uncertainty.

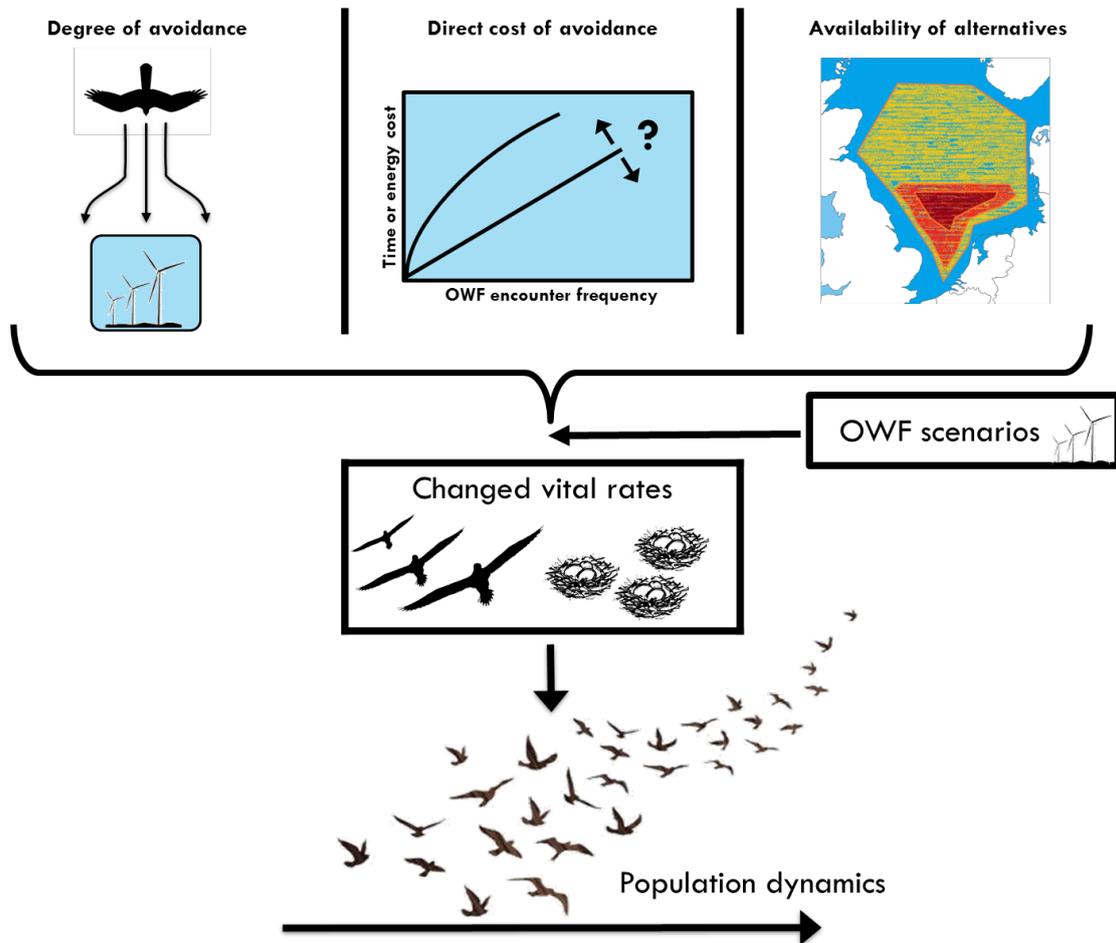


Figure 1.1 Schematic representation of the analysis. Studies on the degree of avoidance, the cost of avoidance and the availability of alternative foraging habitat are aimed at calculating expected changes in vital rates (growth, reproduction, survival) given the OWF development scenario under study. These changed rates are then used to study the effects of each scenario on the population dynamics.

1.3 Scope of this study

1.3.1 Spatial

We restrict our analysis to the area between -4° and 10° longitude and between 50° and 62° . This covers the greater North Sea area (Figure 1.2). Within this area we ignore waters that are not part of the 'Greater North Sea' (e.g. the Wadden Sea, Bristol Channel and Irish Sea). For all prediction maps (result of the habitat modelling) and effect calculations (individual-based simulation models) we use a spatial resolution of 0.01° in each direction, corresponding to pixel sizes of approximately 1.1km (north-south) by 0.6 km (east-west). This resolution ensures that even the smallest OWFs will encompass several map pixels.

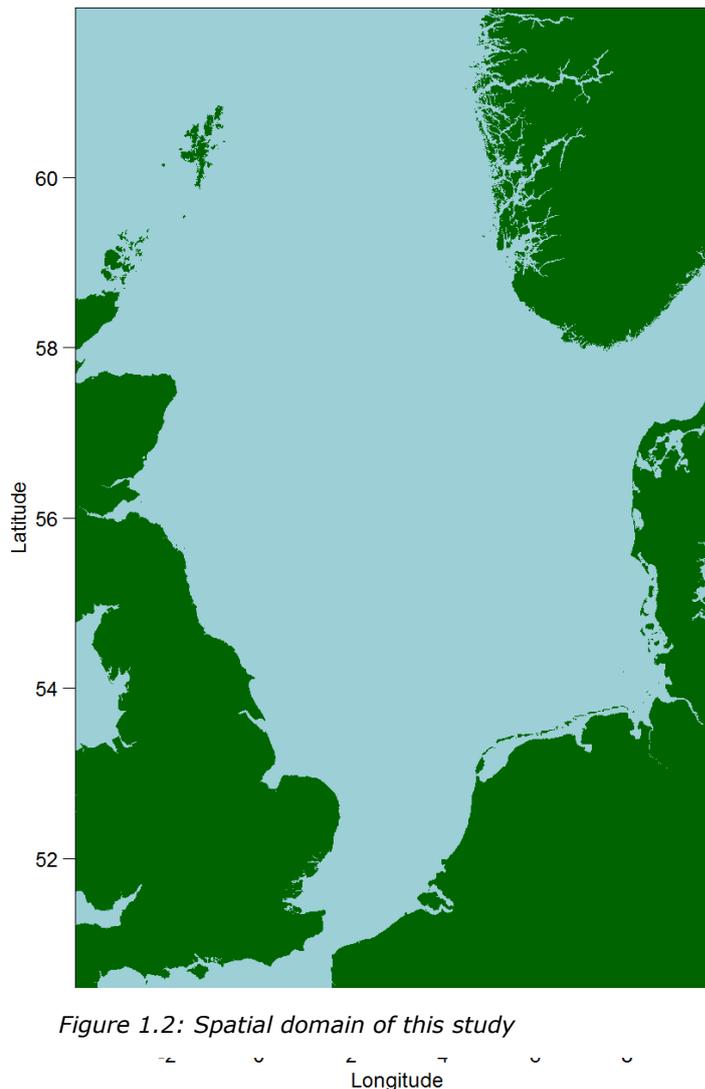


Figure 1.2: Spatial domain of this study

1.3.2 Temporal

The seabird survey data we use include all annual sightings in the period between 1991 and 2017. These data are a collation of many incidental and more systematic surveys, and are collected throughout the year. The habitat models do not use any time-dependent explanatory variables, like temperature or salinity (other than within-season). While this may limit their fit to the data, such models would be unusable for our purpose, as they would require our scenario studies (individual-based simulation models and population models) to also include future predictions for those time-dependent variables. This is beyond the scope of this work, as we are interested in quantifying the general effects of OWF on populations. Because of the calculation method we use (R-INLA), a significant proportion of the variation that is caused by time-dependent explanatory variables is now covered by the spatial field.

1.3.3 Populations

The research questions for this study pertain to the population-level effects of OWF on the Dutch Continental Shelf (DCS). Hence, we are primarily interested in the subset of birds which can be expected to frequently visit the DCS. For colony breeders, this implies that we include all breeding colonies of which the members are expected to use the DCS (this means, for example, that we exclude colonies on the British west coast, although they may interbreed with individuals from east coast colonies). There are three important issues associated with this approach:

1. It is impossible to assign birds sighted at sea to a breeding colony
2. There is always exchange of birds between colonies that do and those that do not use the DCS, and the magnitude of this exchange is largely unquantified.
3. Population models require 'closed' populations, where birth, growth and death, rather than emigration and immigration, are the dominant processes affecting population dynamics.

The first issue means that we cannot know from observations which are the relevant colonies. The second issue implies that even if we choose the relevant colonies, we can't be sure that they are actually a population in the sense of the 3rd issue. For the colony breeders (all except red-throated diver) we deal with these issues by considering all breeding colonies in a wide range around our focus area as part of the relevant population (Table 2.32.3).

For the birds that are mainly confronted with OWFs on the DCS during the winter season, we consider the birds that use the Southern North Sea during the winter season as "the population". This implies that we consider the Southern North Sea as a "closed" area, in which the population resides during the whole winter season. We consider this a precautionary approach assumption, because mixing with other populations would effectively increase the population size, thereby decreasing the per capita effect and hence the effect of OWF on population growth rate.

1.3.4 Effect scenarios

OWF placement scenarios

The OWF scenarios we study are focused on establishing the effects of the Dutch OWF development. However, the Dutch OWFs cannot be studied in isolation, but must be viewed in the context of international OWF developments. Therefore, we study 3 OWF placement scenarios:

1. The addition of only the Dutch OWFs
2. The addition of only the non-Dutch OWFs
3. The addition of the Dutch OWF's when all non-Dutch OWFs are already present

With these 3 scenario's we cover the effects of the Dutch plans in isolation as well as the Dutch plans within the context of the wider development of OWF in the North Sea. We use the OWF data as presented in van der Wal et al (2018, in prep.), which document the areas of all existing and planned North Sea OWFs.

Displacement and mortality scenarios

We study the effects of the OWF placement scenarios above using a best estimate, a worst case and an extreme scenario (Table 1.1). For the best estimate approach, we use the best available estimate for the degree of displacement, whereas in the worst and extreme case we use complete displacement: all birds inside planned wind farms will move elsewhere. In the extreme scenario, 0% of all displaced individuals survive. In the worst and best estimate scenarios we use two mortality scenarios. The first assumes 90% survival of displaced birds, based on the 10% mortality assumption previously proposed for the effect of habitat loss (Leopold, Boonman et al. 2014). The second is based on the IBM calculations, the best estimate uses the mean of the estimated effect size of OWF on survival, while the worst-case approach uses the 5th percentile of the survival frequency distribution. For the 5th percentile, survival will be equal to or smaller than the value used in only 5 out of 100 estimations, whereas in 95 of 100 estimates it will be higher.

The 10% mortality is assumed to occur over a single season of presence in the area with OWFs. Survival of the red-throated diver, razorbill and common guillemot, OWFs is thus affected in the non-

breeding season (see Table 2.1). Gannets are affected both in the summer and winter period, while sandwich terns are affected only in the breeding season.

For red-throated diver, razorbill and common guillemot, OWFs are assumed to affect survival only in the non-breeding season. The distribution of those species during the breeding season is strongly constrained by the locations of breeding colonies. Though some OWFs are planned close to specific colonies, we have assumed here that plasticity in the breeding locations prevents OWF-induced mortality during the breeding season.

Software problems

Until very late in this study, we were troubled by an error in the IBM software, which we developed to estimate the population-level effect on survival from the habitat models. We have only just located and repaired the error. Therefore, in the current report, we have produced output using the individual-based simulation model, but this output has not yet been used to do the population-level effect calculations. Hence, the scenarios marked 2. in Table 1.1 are not part of this report yet. These computations will be completed in an update to this report, to be published in the first quarter of 2019.

Table 1.1 Mortality and displacement scenarios

Population model scenario	Degree of displacement	Survival of displaced individuals
Extreme	100%	0%
Worst case	100%	1. 90%
		2. 5 th percentile of simulation model estimate ¹
Best estimate	Best available estimate for each species	1. 90%
		2. Median (50 th percentile) of simulation model estimate ¹

¹ These scenarios are not part of the current report, but will be delivered in an updated version by March 31st, 2019.

2 Materials and Methods

2.1 Outline of the analysis

The analysis framework applied here consists of 3 steps.

The first step is a habitat model, which couples bird observations to abiotic variables at the time and place of the sighting. This model can be used to generate a habitat map, which predicts abundance at each location on the map based on the relevant abiotic variables at that location. Because we are interested in estimating the effects of planned OWFs, rather than in explaining spatiotemporal patterns in the past, we are limited to using abiotic variables that are constant in time, such as depth. For example, if we would use temperature data, we would need spatially resolved temperature predictions for the next 30 years. While this means our model may be crude compared to some published seabird distribution models, those models are simply not usable for our purpose.

Once we have a prediction map, we use an individual-based simulation model to assess the effect of OWF on seabird survival. Using the values on the prediction map as a measurement of habitat quality, this model simulates a large number of individual birds, moving around on the prediction map. Each individual in the simulated population has an energy budget, which it can increase in good locations and which is used up in bad locations. Once energy runs out, an individual is assumed to die. This model does not include reproduction. We calibrate the model so that at the end of the season (Table 2.1), without OWFs, the survival corresponds to a known value for each specific bird and life stage. We then add the OWFs and displacement to the model and run it again. This yields the new survival value in the presence of OWFs. This method assesses only the direct effect of the inaccessibility of the areas where OWFs are located. It does not take into account the effect of reduced carrying capacity, because we have no indications that this form of density-dependence plays a role in regulating seabird populations.

The final step in our analysis is to compare the survival values derived above, with and without OWFs, and using a number of scenarios ('best estimate', 'worst case' and 'extreme') in a stochastic matrix population model. This allows us to study the OWF effects on population growth rate, population development over 30 years, and a number of other relevant criteria.

2.2 Habitat suitability models

2.2.1 Data sources

Habitat suitability modelling requires data on the spatial distribution of birds and on the other (biotic and abiotic) conditions. We have used the following data sources for the habitat models:

2.2.2 Bird observation data

For modelling at-sea seabird distribution, data are needed on seabird counts at sea (density estimates) that are geo-referenced. We used two sources of data:

ESAS contains both ship-based (ESAS-ship) and aerial surveys (ESAE-fly), which were treated separately.

1. the ESAS (European Seabirds At Sea) database (mostly ship-based counts of seabirds), kept at JNCC, Aberdeen, covering the entire North Sea and,
2. for the Dutch section of the North Sea only, the MWTL database (Monitoring Waterstaatkundige Toestand des Lands, plane-based counts, available via Noordzeeloket, Rijkswaterstaat), also including the ship-based Shortlist Masterplan Wind data collected in 2010-2011 (Van Bemmelen, Geelhoed et al. 2011)

From each database, only observations were used from 1991 to the most recent data available (2017). An overview of the locations of observations in these two data sets, see figure 2.1.

2.2.3 Handling bird data

Distance sampling is a widely used methodology for estimating animal density or abundance (Buckland and Turnock 1992, Buckland, Anderson et al. 1993). A key underlying concept is that the probability of detecting an animal decreases as its distance from the observer increases. The distance sampling methodology is based on detection functions, which model the probability of detecting an animal as a function of distance from the observer trajectory in transects. Distance sampling was applied to arrive from the observed sightings to densities.

ESAS ship

ESAS Sampling effort is strongly directed by specific projects often connected to wind farm locations or special protection zones. The ship-based observations in ESAS are made using a strip-count with series of strips on one or both sides of the ship. Based on density sampling theory and on the assumption that the birds were evenly distributed before the observing ship entered the area, and that equal densities should be present at all distances from the ship's track line, species-specific correction factors were derived to compensate for birds missed at greater perpendicular distances (Table 4.2 in Leopold, Boonman et al. 2014).

MWTL

The survey design of this programme has been restructured both temporally and spatially in 2014 and was shifted from a strip-transect analysis to line-transect (Distance) analysis. In the analysis we did not correct for this transition in methods.

From an airplane with a survey altitude of 500 ft as conducted in the MWTL monitoring programme a number of sea bird species is indistinguishable from each other, e.g. 'razormots', i.e., razorbills/common guillemots. For these, the ship-based observations from the same season and area have been used to split these 'combi-species' into the respective single species, using the method previously described by Leopold, Boonman et al. (2014).

The small divers, red-throated diver and black-throated diver, are difficult to distinguish in the field, but we also know that red-throated divers greatly outnumber black-throated divers in the North Sea. Therefore, we refer to red-throated divers throughout the text.

Sampling surface was calculated as effective-strip-width × speed × time.

For every bird species, first the species-specific appropriate seasons were determined for which habitat models should be formulated. This was based on the spatial and temporal coverage of different surveys (by mapping monthly distribution for each species). For Razorbill, common guillemot and red-throated diver winter (non-breeding period) numbers were used. For sandwich tern the breeding season and for northern gannet both the non-breeding season and the breeding season were selected, but gannets visiting Dutch waters during the breeding season were assumed to be non-breeding individuals (juveniles and/or 'floaters').

Table 2.1. The selected months for every species used in the habitat and IBM models.

Species	Selected months	Period for which a habitat model was constructed
red-throated diver	Oct-March	non-breeding season
northern gannet	Sept-March	non-breeding season
northern gannet	April-Aug	breeding season
sandwich tern	April-August	breeding season
razorbill	Oct-March	non-breeding season
common guillemot	July-April	non-breeding season

2.2.4 Abiotic data

The explanatory variables are the other (a-)biotic factors prevailing at the time and location of each observation. For all species the same set of abiotic variables was considered in the habitat models:

- depth (smoother)
- day of season
- distance to the nearest colony (common guillemot, razorbill, northern gannet. For sandwich tern distance to coast was highly correlated to distance to colony, so only distance to coast was used)
- distance to the nearest coast
- sediment type
- slope of sea floor
- aspect of the sea floor
- survey (sampling) type

An overview of several of the above variables is given in Figure 2.2. The distribution of the different species is likely to be affected by the combination of all these (abiotic) parameters. However, in the final selection of the relevant parameters, the ultimate goal of the habitat models was leading: to arrive at a time-invariant predicted density map. Because of this we could not include explanatory variables which change in time and for which future predictions are not readily available (temperature and salinity). For the same reason, a year effect was not included. Given that all species considered are long-lived, we also do not expect a strong year effect. Aspect of the seafloor (the direction of the slope) was also considered as an explanatory variable, but to properly include it we would need to use a cyclic cubic regression spline, which would further increase the already large computational demands of the model fitting. Therefore, we did not use aspect of the seafloor.

Due to computational limits no interactions between explanatory variables were considered.

An important variable which is missing in the above list is the (fish) food for the seabirds. While we have some knowledge of the long-term average distribution of the various species in the diet of the birds, its spatiotemporal distribution is highly variable. The explanatory relationship found with some of the above variables may hence describe a relationship with prey fish, which in turn are related to seabird abundance. For example, sandeel are important prey fish, which have a strong association with particular sediment types. A relationship between seabird abundance and sediment could thus be a proxy for a relationship between sandeel and seabirds. Because adequate data on sandeel distribution is unavailable, our analysis does not deal with such causal nuances.

Distance to coast

Coastline data were obtained from OpenStreetMap at <http://openstreetmapdata.com/data/coastlines>. Zoom level 5 was used in all calculations.

Day of season

For each observation, day of season was calculated as the number of days between the start of the current season (Table 2.1) and the observation date. This captures seasonal variation but not variation between years.

Water depth

Bathymetry data were obtained at a 30 arc-second resolution from the GEBCO Digital Atlas published by the British Oceanographic Data Centre on behalf of the Intergovernmental Oceanographic Commission and the International Hydrographic Organization, 2014.

Sediment

Seafloor habitat data were obtained from Emodnet. We used the dataset 'EUSeaMap 2016: Marine Strategy Framework Directive MSFD Benthic Broad Habitat Types'. The classifications used include aspects other than sediment type. We used a simplification of the habitat classification in the data (Table 2), because the full classification includes depth information, which we included separately.

Slope

The slope of the seafloor (in degrees) was calculated from the depth map, based on the depth difference with adjacent grid cells, using the function `terrain()` in the R package 'raster'.

Table 2.2. *Eunis classification level 5 and simplified groups.*

type	Description sediment	Grouped category
A5.13	infralittoral coarse sediment	coarse sediment
A5.14	circalittoral coarse sediment	coarse sediment
A5.15	deep circalittoral coarse sediment	coarse sediment
A5.23	infralittoral fine sand	fine sand/muddy sand
A5.24	infralittoral muddy sand	fine sand/muddy sand
A5.25	circalittoral fine sand	fine sand/muddy sand
A5.26	circalittoral fine sand	fine sand/muddy sand
A5.27	deep circalittoral sand	sand
A5.33	infralittoral sandy mud	sandy mud
A5.35	circalittoral sandy mud	sandy mud
A5.37	deep circalittoral fine mud	fine mud
A5.44	circalittoral mixed sediments	mixed

Distance to colony

For common guillemots, razorbills and northern gannets, information on breeding colony locations was obtained from 'Seabird populations of Britain and Ireland' (Mitchell, Newton et al. 2004). For guillemots the Helgoland colony was excluded because it is small in comparison to other colonies, and its inclusion would lead to an inflated assignment of observed birds to that colony, meaning that many more bird observations would have these small colonies as 'nearest colony' than actually breed there. The colony locations were simplified to combine clusters of adjacent colonies (Table 2.3). For sandwich tern, colony data were examined but since distance to colony was highly correlated with distance to coast, only the latter was used.

Table 2.3: *Locations of breeding colonies of gannets, common guillemots and razorbills (WGS84 coordinates).*

Species	Colony	longitude	latitude
northern gannet	Shetland Islands	-1.194546	60.406036
	Bass Rock	-2.640667	56.077719
	Bempton Cliffs	-0.126189	54.132481
	Troup Head	-2.297285	57.700378
	Guernsey	-2.239297	49.704769
	Helgoland	7.897865	54.18325
	Scottish mainland south	-1.994228	55.780047
	Norway	5.635605	59.108856
razorbill	Bempton Cliffs	-0.126189	54.132481
	Shetland Islands	-1.194546	60.406036
	Orkney Islands	-2.805229	59.031799
	Scottish mainland north	-1.998647	57.314904
	Scottish mainland south	-1.994228	55.780047
common guillemot	Bempton Cliffs	-0.126189	54.132481
	Shetland Islands	-1.194546	60.406036
	Orkney Islands	-2.805229	59.031799
	Scottish mainland north	-1.998647	57.314904

R-INLA

The bird data we are dealing with are complex. The reason for this is that birds are behaving in clusters, resulting in spatially and temporally correlated data: An observation at one point in space is more similar to a point close by than a point further away. The same holds for points in time: the number in year 1 is more similar to the number in year 2 than in the year 5. Data are correlated in both space and time and we need to account for this in the analysis. Furthermore, we are dealing with data that come from different sources, collected from planes and ships, by different observers, and these sources of variation also need to be taken into account. That can be done by using hierarchical models: models that take into account variation on different levels that we know affect the observations, but that we are not necessarily interested in.

Hierarchical models are widely used in ecology to represent complex dependency structures in data. The most advanced way to incorporate all these requirements to the data analysis is using R-INLA and Gaussian Markov random field, under the Bayesian statistics framework (Rue, Martino et al. 2009, Lindgren, Rue et al. 2011)

Hurdle model

In the analysis we applied a two-step hurdle model. In a hurdle model we focus on two questions, namely (i) what is driving absence and presence of birds? And (ii) once birds are present, what is driving their abundance? The first question requires a Bernoulli GLM (or GAM) and the second part a log-normal GLM (or GAM).

In the model we estimate a spatially correlated random effect. To estimate this term, a mathematical model is imposed on the covariance matrix of the spatial random effects, namely the so-called Matérn correlation function. This function dictates that sites close to each other have similar spatial random effects, and the further sites are away from each other, the less similar are the spatial random effects. A so-called mesh is defined for the study area. This means that a large number of connecting triangles are created; see Annex 1. The mesh consists of a large number of nodes (i.e. the vertices of the triangles). Instead of estimating the spatial random effects directly, we will estimate one value at each node. The mesh we used has 820 nodes, which means that the software will estimate values for each node. Once we have these values, the spatially correlated random value is calculated as a weighted average of the surrounding values. The mesh is also used to calculate the parameters of the Matérn correlation. The number of vertices was 820, of which the maximum edge length was defined as 50 km (see Annex 1). The largest allowed triangle edge length was cut off at 30 km. For simplicity the same mesh is applied to both the first (presence-absence) and second model (abundance). Note that any estimation outside the sampled area is extrapolated and thus should be interpreted with care.

For the abundance model we tried different distributions: truncated Poisson (for count), gamma (for square root transformed density). A log-normal distribution was chosen because it provided the best model diagnostics and is relatively simple.

For every species we applied a model with and without the spatial random field to investigate whether applying a spatial random field improves the model. These models are compared using the Deviance Information Criterion (DIC). Models with lower DIC value indicate a better fitting.

An important aspect of our type of data is that they suffer from an observer effect: different observers have differing detection probabilities. This is a well-known problem of bird count data (Van der Meer and Camphuysen 1996), which can be corrected for. However, our long-term data set contains too many observers (>100) and this factor contains too many missing values to carry out a meaningful correction. Therefore, we have not taken this into account.

The main purpose of this study is to use environmental covariates to interpret and extrapolate density (i.e. provide a best fitted distribution map), rather than understanding the causal relationships. Therefore, we did not apply strict rules to prevent correlated covariates, such as depth, distance to coast, and distance to colony, or survey type vs. area.

Most ESAS samples were collected in very few years, the data in terms of year, survey type and spatial distribution are therefore very unbalanced (cf. Fig. 2.1). However, we assume that there is no change in the relationship between seabirds and explanatory variables over the years and thus ignore the year effect and serial correlated spatial random field. As a result, we are able to obtain a time-invariant density map.

In the end, the following Bernoulli GAM with time-invariant spatial random field was fitted for presence-absence of bird:

$$bird_i^{01} \sim \text{Bernoulli}(\pi_i)$$

$$E(bird_i^{01}) = \pi_i, \quad \text{var}(bird_i^{01}) = \pi_i \times (1 - \pi_i)$$

$$\text{logit}(bird_i^{01}) = \text{intercept} + f(\text{depth}) + \text{slope}_i + \text{dis_coast}_i + \text{dis_colony}_i + \text{days_season}_i + \text{data_source}_i + \text{sediment}_i + u_i$$

The response variable $bird_i^{01}$ refers to the absence and presence of the bird at location i , which follows a Bernoulli distribution with a probability π_i of presence. Model covariates are described in Section 2.2.4: water depth, slope, distance to coast, distance to colony, days after the beginning of breeding (or non-breeding) season, data sources, sediment type. Water depth effect was modelled as a smoother using cubic regression spline (knots=4). Additionally, a spatial random effect u_i was included to estimate the spatial correlated effect.

The following log-normal GAM with time-invariant spatial random field was fitted for the positive density:

$$\log(bird_i^+) \sim N(\mu_i, \sigma^2)$$

$$E(\log(bird_i^+)) = \mu_i, \text{var}(\log(bird_i^+)) = \sigma^2$$

$$\log(bird_i^+) = \text{intercept} + f(\text{depth}) + \text{slope}_i + \text{dis_coast}_i + \text{dis_colony}_i + \text{days_season}_i + \text{data_source}_i + \text{sediment}_i + u_i$$

The response variable $bird_i^+$ refers to the positive density of the bird at location i . The log transformed density follows a Normal distribution with mean μ_i and variance σ^2 . To be consistent with the presence-absence model, the same covariates were kept in the log-normal GAM model.

The statistical analysis was conducted using (R Core Team 2014) and R-INLA package at www.r-inla.org (Rue, Martino et al. 2009, Lindgren, Rue et al. 2011, Zuur, Ieno et al. 2017).

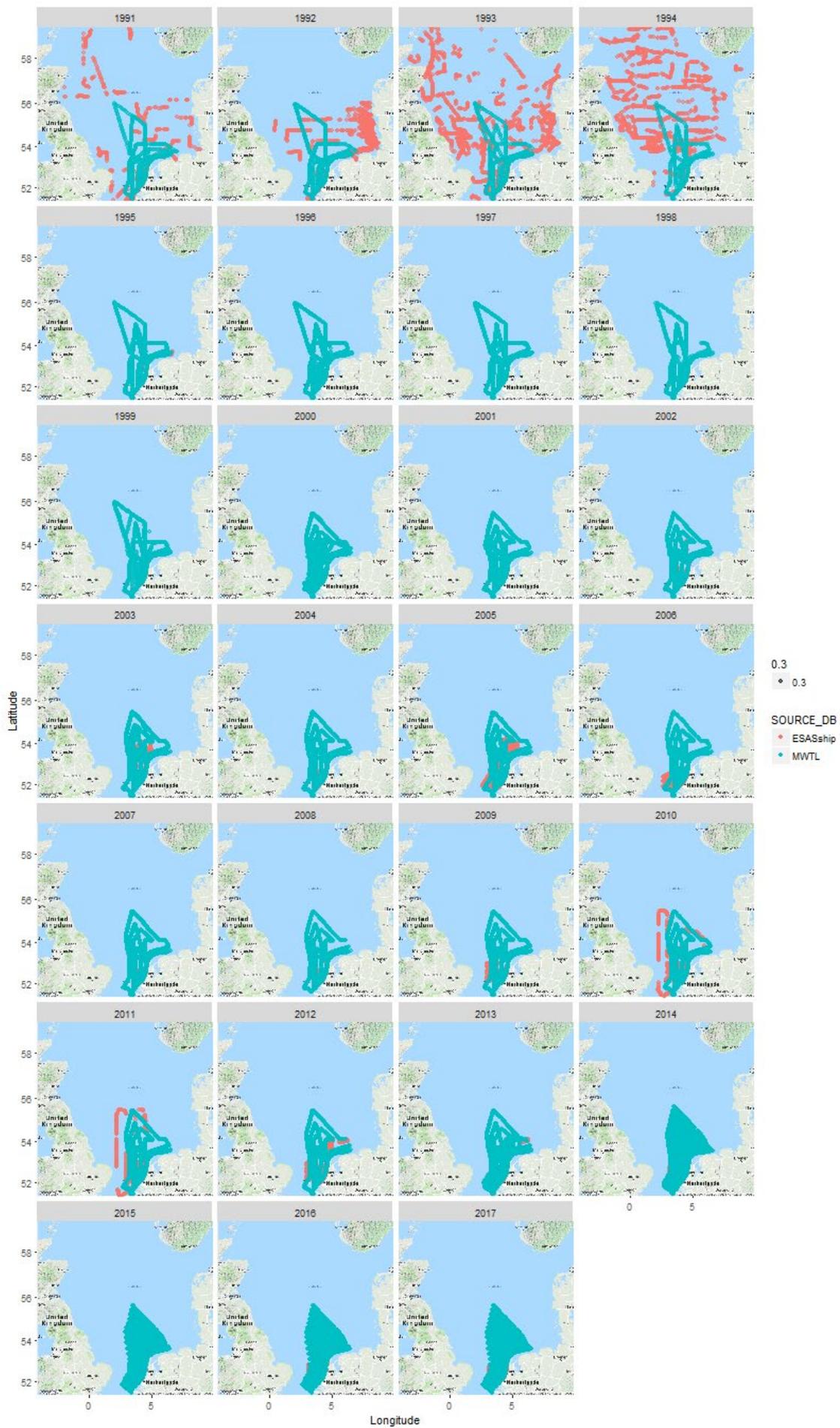


Figure 2.1. Overview of observer effort per year for the two data sources.

Prediction maps

To obtain the final mean density map, we conducted a simulation-based approach. First, we simulate a set of regression parameters and spatial random effects from their joint posterior distribution, from which we simulate 1000 observations (variance depends on the likelihood distribution). In model 2, since the response is based on log-transformed data, we apply the exponential function to back-transform these simulated observations to the original scale. We can then estimate the mean of these observations for this set of parameters. We repeat this process again for 1000 times. This way, the posterior distribution for 1) the mean presence probability and 2) the mean positive density are obtained, at each point in the map. We also calculated the 95% credible intervals (the Bayesian analogue to confidence intervals) for both means. The product of these two mean values gives the final estimated mean density. The density estimates are based on the population sizes at the median date during the period they are in the area.

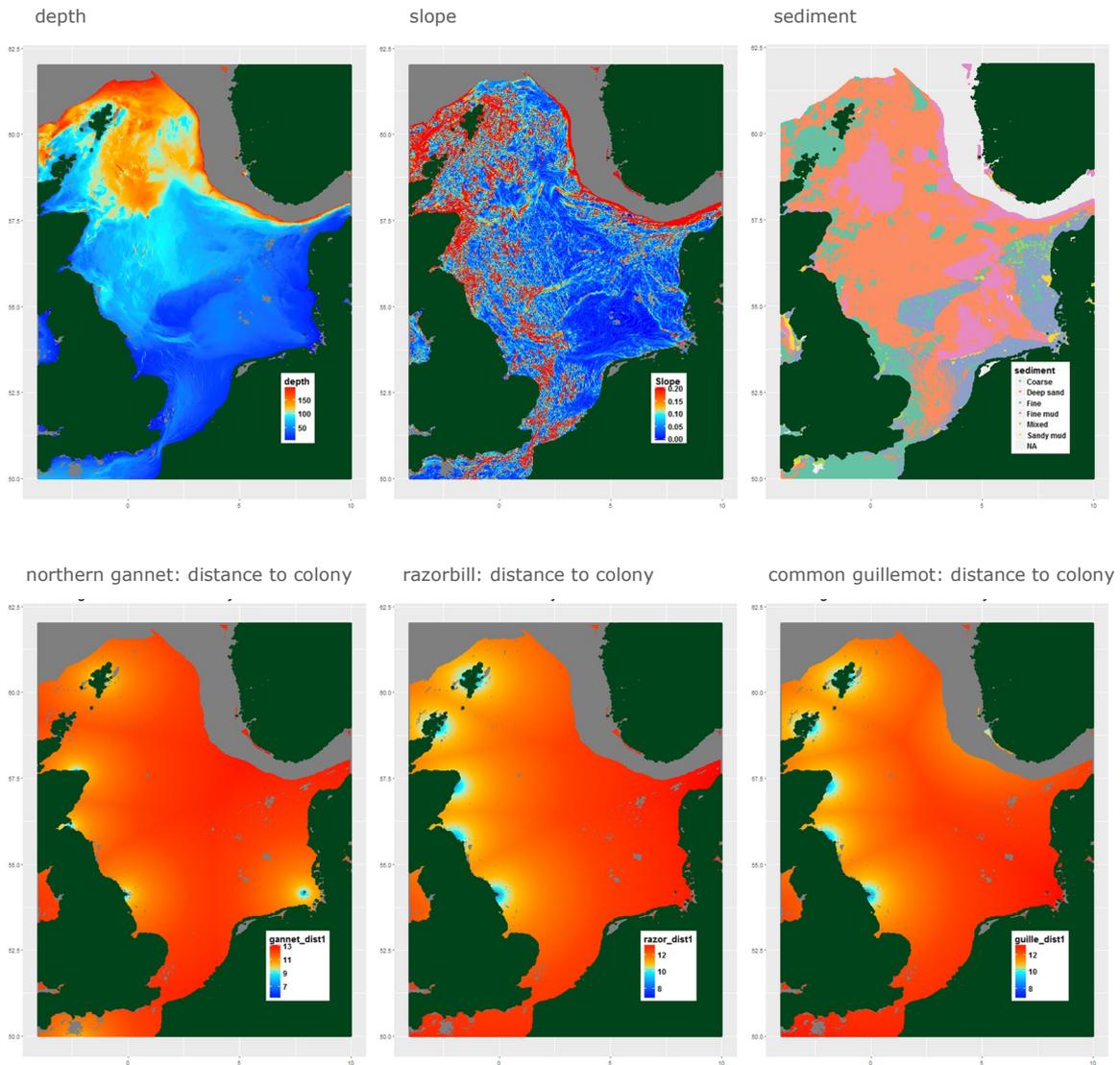


Figure 2.2. Covariates used in the habitat models. The grey areas (Norwegian coast and far north) are very deep, and there were very few bird observations for this area. Any prediction for this area would be very speculative and hence we exclude it from the prediction.

2.3 Individual based model

For each species we used an individual based simulation model to assess the effect of OWF-related habitat loss on survival rate. This model used an energy budget approach to quantify this effect. In a first step, the model was calibrated in absence of planned OWFs to yield the survival which is known from the literature. The calibrated model was then used to calculate the change in survival as a result of adding the planned OWFs.

2.3.1 Behavioural simulation

The model simulates a large number of birds (100,000) each occupying a location on a map, which is the output from the habitat model for that species, normalized by the maximum abundance on the map. Individual birds move to adjacent map cells each 4 hours. OWFs are implemented as cells on the map which are (partially) inaccessible, with the accessibility set to zero in the 'worst case' scenario and to a species-specific estimated value in the 'best estimate' scenario (Table 1.1). Survival is calculated as number of individuals at the end of the simulation relative to the number at the start of the simulation. Simulations are run for the relevant species-specific season length (Table 2.1).

As an illustration of this process, Figure 2.3 shows the spatial distribution of simulated Razorbills at the end of a simulation. The OWFs are visible as shadows between the birds (shown in white). We can see that the distribution closely follows the habitat quality and that the birds clearly avoid the windmill areas but not completely.

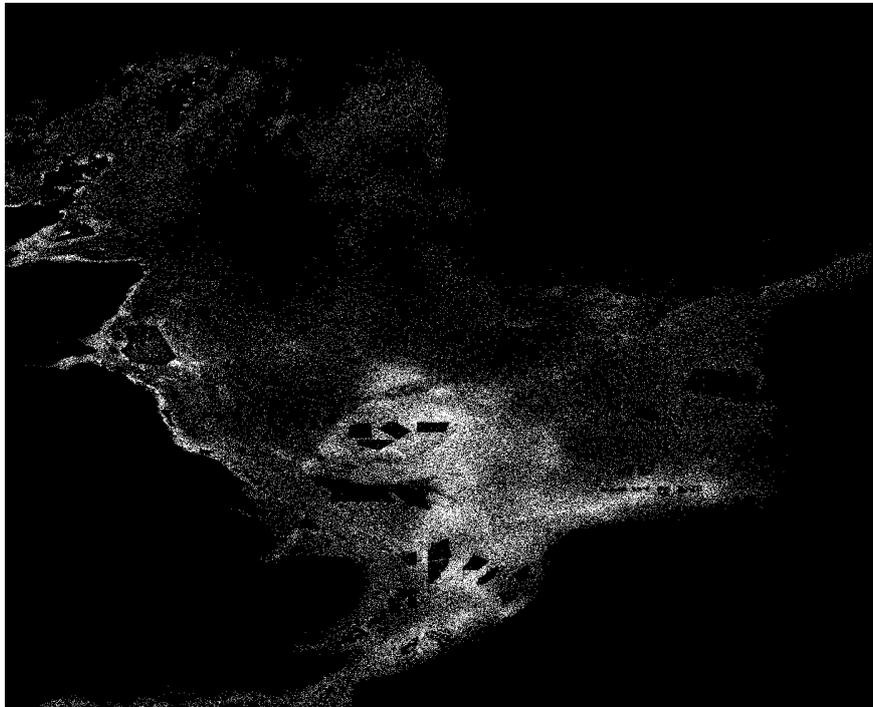


Figure 2.3 Spatial Razorbill distribution at the end of a best estimate displacement simulation.

2.3.2 Individual model

Energetics

The model assumes individual birds have an energy budget defined as:

$$E(t) = E(t - 1) + I(t) - T.$$

Where $E(t)$ is the available energy at time t , $E(t - 1)$ available energy at time $t - 1$, $I(t)$ the energy acquired at time t and T the energetic costs per unit time. We assume that T is constant over time. We assume that when $E(t) \leq 0$, the individual dies. Because we are only interested in the relative effect of OWF, not the absolute change in E , we can assume arbitrary units for E , T and I . Here, we choose to express E in 'normalized habitat quality', and $I(t)$ equals the habitat quality of the location

occupied by the bird at time t . This way, updating $E(t)$ means that we add the value of the current location of the normalized habitat map underlying the simulation to $E(t - 1)$.

Behaviour

We assume that individuals either stay where they are or move to adjacent cells (8 nearest neighbour cells) on the map. The chance to move to any potential location is proportional to the relative habitat quality of the 9 cells (8 nearest neighbour cells plus the current location). If one or more adjacent cells are on land, outside the map or inside OWF areas, there is a reduced chance to move to those locations (either zero or a reduced chance in case of partial displacement). This is included in the relative habitat quality, which hence can be zero. The individual then moves randomly following the derived probability distribution. For OWF locations the relative habitat qualities of the OWF cells are downscaled, so that individuals are less likely to move into and more likely to leave OWFs (Table 2.5). The chance to move to an OWF cell c_i is downscaled with $1 - displacement$, while the remainder $c_i \cdot displacement$ is distributed over the neighbouring non OWF cells proportionally to the habitat quality of each non-OWF cell, such that the chance to move there becomes higher. The displacement values are given in Table 2.5.

2.3.3 Calibration

The goal of the calibration is to tune T in such a way that the survival (the number of birds at the end of the simulation divided by the numbers at the start) equals the correct value, which we take from the literature. We find the value T^* corresponding to the desired survival probability by solving $S - S(T) = 0$. We solve the equation using the bisection method. For each value of T we run the model 10 times, and T^* is reached when the desired value for survival equals the mean of the simulations for a given T . The number of runs is low due to computational time constraints. For calibration we use a scaled habitat map without the projected Dutch OWFs. The calibration procedure is carried out separately for each stage or age class in each population model which has its own survival parameter value.

2.3.4 OWF effects on survival

In order to estimate the effects of OWFs, we use the T^* derived in the calibration step, incorporate the OWF scenario in the habitat map, then re-run the simulation to obtain the survival probability corresponding to the OWF scenario. We do this last step a large (1000) number of times so that we can estimate the effect of the stochasticity inherent in the movement process. Going forward to the population models, we use the survival value at the 5th percentile of the distribution for the worst-case scenario, and for the 'best estimate' scenario we use the median survival.

2.3.5 Initial conditions

For both calibration and simulation the model needs an initial energy and an initial position on the habitat map for each bird. For the initial energy we use 2 times the mean value of the habitat map. A weighted discrete random distribution is used to determine the initial position of each bird. For each cell on the map the chance for a bird to start in this cell is weighted with the value of that cell in the habitat map.

2.3.6 Parameterization

Table 2.4 describes the general parameters used for calibration and simulations. The survival probabilities were only used during calibration. The season length is equal to the number of months a bird population uses the study area (Table 2.1). Although razorbills and guillemots are present all year, their dispersal follows other rules due to the central-place foraging associated with breeding. Gannets appear all over the area throughout the breeding season (but with a different distribution), and therefore we have conducted separate simulations for the breeding and non-breeding season. To

calculate the number of time steps, we use the season length and the assumptions that birds move to another cell every 4 hours and that each month has 30 days.

For each species we defined a survival scenario (see Table 2.4). The annual survival S_y is scaled to seasonal survival S_m where m is the length of the season in months. The scaling follows:

$$S_m = e^{\frac{m \ln(S_y)}{12}}.$$

The best estimates for the displacement rates (Table 2.5) are based on the review by Dierschke, Furness et al. (2016) of bird displacement by wind farms in European waters. In the review, diver and northern gannet are categorized as “strong avoiders” of wind farms, while razorbill, guillemot and sandwich tern are qualified as “weak avoiders” of wind farms. In addition, a mean displacement score is calculated. The review does not explicitly define a best estimate of displacement. To estimate this value we used the information of areas for which displacement was quantified. Resulting in the following values per species:

- For the diver, non-significant displacement >80% was found in one study area (Dierschke, Furness et al. 2016). We chose a value of 0.8 as a best estimate of the displacement rate for the diver.
- Observations of gannets show a significant displacement >50% in two areas and a non-significant effect >80% in another area (Dierschke, Furness et al. 2016). We chose a value of 0.8 as a best estimate of the displacement rate for the gannet.
- For the sandwich tern, observations show a significant displacement >50% in one area, while multiple studies report indifference (Dierschke, Furness et al. 2016). We chose a value of 0.5 as a best estimate of the displacement rate for the sandwich tern.
- Razorbill observations show significant displacement <50% in 2 areas and non-significant displacement >50% in 3 areas (Dierschke, Furness et al. 2016). We chose a value of 0.5 as a best estimate of the displacement rate for the razorbill.
- Guillemot observations show significant displacement >50% in two areas, non-significant displacement >80% in one area, significant displacement < 50% in one area and no signs of displacement were found in three areas (Dierschke, Furness et al. 2016). We chose a value of 0.5 as a best estimate of the displacement rate for the guillemot.

Table 2.4 general parameters for calibration and simulations

Species	Season length (m)	Time steps	Annual survival
red-throated diver	7 months	1260	0.84
northern gannet (breeding)	5 months	900	0.9
northern gannet (non breeding)	7 months	1260	0.9
sandwich tern	5 months	900	0.95
Razorbill	7 months	1260	0.9
common guillemot	10 months	1800	0.94

Table 2.5 Windfarm displacement parameters

Species	Best estimate	Worst case
red-throated diver	0.8	1
northern gannet (breeding)	0.8	1
northern gannet (non-breeding)	0.8	1
sandwich tern	0.5	0.8 ¹
Razorbill	0.5	0.8 ¹
common guillemot	0.5	0.8 ¹

¹ These scenarios are not as defined in the introduction (Table 1.1), we will update these values for the new version by March 31st, 2019.

2.3.7 Stability, accuracy and precision

We tested the model for stability, accuracy and precision of the obtained solution. The model is invariant to the initial conditions, so the simulated survival is equally independent of the initial conditions. The model also has high accuracy: the simulation returns a survival very close to the survival used during the training if we run it without any OWFs. The precision is defined as the difference between the 95% percentile and the 5% percentile of the survival distribution. The precision of the model is ± 0.001 .

A more detailed description of the results and methods can be found in Annex 4

2.4 Population models

2.4.1 Matrix model structure

We use stage-structured matrix population models for all five bird species. Depending on the species, we choose a different number of life stages. A higher number of stages can be used when the resolution of the knowledge of life-history parameters is higher. Below we describe the setup and analysis of the matrix models in general terms. Per species we discuss the stage structure of the model, the setup of the projection matrices, the parameter values and sources of population data. For stages that comprise multiple year classes, transition rates are estimated based on the assumption of a stable age distribution. Following (Crouse, Crowder et al. 1987):

$$P_i = \left(\frac{1 - p_i^{d_i-1}}{1 - p_i^{d_i}} \right) p_i, \quad (1)$$

the probability of surviving and remaining in the same stage P_i , is calculated based on p_i , the annual survival probability, and d_i , the number of years individuals remaining in the stage. The probability that an individual survives and passes to the next stage G_i is given by:

$$G_i = \frac{p_i^{d_i}(1-p_i)}{1-p_i^{d_i}}. \quad (2)$$

Survival and aging from one breeding season to the next is described by the matrix M_w . This is an example based on a model with four stages (sandwich tern):

$$M_w = \begin{pmatrix} P_1 & 0 & 0 & 0 \\ G_1 & P_2 & 0 & 0 \\ 0 & G_2 & P_3 & 0 \\ 0 & 0 & G_3 & P_4 \end{pmatrix}. \quad (3)$$

In the breeding season, reproduction occurs following matrix M_s . Each reproducing adult produces F_i offspring in the breeding season. Part B_A of the adults skips reproduction (so-called 'floaters'). This results in the following matrix based on a model with a total of four life stages, two of which are reproducing stages:

$$M_s = \begin{pmatrix} 1 & 0 & (1 - B_A)F_3 & (1 - B_A)F_4 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix}. \quad (4)$$

The annual projection matrix is calculated as $A = M_w * M_s$. The order of the seasonal matrices in the matrix multiplication implies that the annual projection matrix calculates the number of birds after the winter, just before the breeding season begins. At this point, newborns from the previous year have (in model terms) already become 1 year old. Turning the multiplication of the seasonal matrices around would result in a different annual projection matrix. However, analysis of this matrix would result in an identical population analysis. It would just be looking at the population at a different moment in the year.

2.4.2 Model analysis

To analyse the models, we calculate the population growth rate and do a perturbation analysis of the population growth rate to changes in the values of the parameters.

The population growth rate is equal to λ , the real part of the dominant eigenvalue of the annual projection matrix (Caswell 2001). To test the effect of small changes in the parameter values on the population growth rate, we do a sensitivity and elasticity analysis of the population growth rate. Sensitivities of λ to lower-level parameters are given by (Caswell 2001). For any parameter x , it holds that:

$$\frac{\partial \lambda}{\partial x} = \sum_{i,j} \frac{\partial \lambda}{\partial a_{ij}} \frac{\partial a_{ij}}{\partial x}. \quad (5)$$

The sensitivity of λ to changes in parameter x depends on partial derivatives of all matrix elements a_{ij} to parameter x and the partial derivative of λ to matrix element a_{ij} .

Elasticities of λ to lower-level parameters (x) are given by:

$$\frac{x}{\lambda} \frac{\partial \lambda}{\partial x} = \frac{x}{\lambda} \sum_{i,j} \frac{\partial \lambda}{\partial a_{ij}} \frac{\partial a_{ij}}{\partial x}. \quad (6)$$

This is equal to the sensitivity of λ to changes in parameter x , multiplied by x divided by the population growth rate. This means that elasticities are sensitivities, corrected so that they are comparable across parameters.

We use the software package R for all model analyses (R Core Team 2014). Population projections are done using the R-package "popbio".

2.4.3 Parameter uncertainty

We determine uncertainty in the model output due to uncertainty in the model parameters using a Monte Carlo (MC) method. In short, we calculate a large number (50,000) of projection matrices, each based on a set of parameter values drawn randomly from the probability distributions of the parameter estimates. This method assumes that the different parameters vary independently (they are uncorrelated to each other) and are constant through time. This method thus results in fully deterministic matrix models. A comparison of the MC method with stochastic matrix models shows that the MC method gives the most cautionary results for uncertainty in the model outcomes (for a detailed discussion of the methods for uncertainty calculations see annex 2).

In most cases, the data underlying the parameter values are binomially distributed. The survival probability, breeding success and skipped breeding probability either take the value "0" or "1" on the individual level. As a consequence, the variability around the mean parameter values $\bar{\mu}$ and variance σ follows a beta distribution, with parameters $\alpha = \bar{\mu}^2 (\frac{1-\bar{\mu}}{\sigma^2} - \frac{1}{\bar{\mu}})$ and $\beta = (\alpha - \bar{\mu} \alpha) / \bar{\mu}$. A beta distribution is appropriate to describe the uncertainty around the mean chance of a 'failure/success' type of process, such as survival and producing a single offspring. Since we generally do not have access to the original datasets used to estimate the life history parameters and do not know the original sample sizes, we do Monte Carlo simulations of the distributions around the mean parameter values. We use reported mean values and standard deviations to calculate the distribution parameters α and β . In case there are no standard deviations available, we use the range rule to estimate the standard deviation. This rule defines the standard deviation as $(\mu_{max} - \mu_{min})/4$.

Sandwich terns and red-throated divers produce either 0, 1 or 2 fledglings and fecundity data thus follow a multinomial distribution. For these species we assume a sex ratio of 50% and use female offspring for the fecundity parameter so that the variability in the value can be described using a beta distribution.

2.4.4 Scenarios

The effect of OWF-related habitat loss is modelled as a “press disturbance”. In other words, the bird populations suffer from the same additional mortality due to the windfarms throughout the 30-year period that we consider. We subtract the estimated mortality probability due to windfarms from the estimated survival probabilities for all stages in the model. We thus assume that the effect of the wind farms affects individuals in all bird life stages equally for all species. Using these estimates for average survival probabilities for the scenarios, we repeat the model analysis described above, except for the elasticity and sensitivity analyses. For the model uncertainty analysis, we assume that only the mean of the parameter values is affected by the presence of OWFs, but that the variance is not.

The population level effect of offshore wind farm deployment is calculated for nine different scenarios. First, we determine the percentage of the population that is affected by Dutch windfarms, international windfarms, or Dutch and international windfarms together based on the outcomes of the habitat suitability model (see outcomes in Table 3.23). As a worst-case scenario, we assume 100% displacement of the birds by the OWFs, leading to full displacement of the part of the population that is predicted to overlap with OWFs. Alternatively, we use the best estimate for realistic displacement, based on a review by Dierschke, Furness et al. (2016, see Table 2.5). Finally, we assume either an extreme of 100% or an arbitrary 10% mortality of displaced individuals for the scenario with 100% avoidance and 10% mortality for the scenario with best estimate avoidance. The assumption of 10% mortality of displaced individuals corresponds to what is used in earlier effect studies of OWF-related habitat loss (Leopold, Boonman et al. 2014). In the results section, we use the term ‘realistic’ to indicate the best estimate displacement and 10% mortality, ‘worst case’ to indicate 100% displacement and 10% mortality, and ‘extreme’ to indicate 100% avoidance and 100% mortality. This last scenario is mostly used for comparison: a stronger effect of OWF-related displacement is not possible, and calculating this scenario allows us to better interpret the magnitude of the effect in the other scenarios. From this, we calculate the proportion of the population that will die as a result of OWF-induced habitat loss (see Table 3.17 in the results section).

2.4.5 Metrics of population-level OWF effects

We use four metrics to quantify the population-level effect of OWF:

- Population growth rate (PGR), with its 5th and 95th percentile
- Percentage of the outcomes that show a population decline of 10% or more after 30 years (P10%30Y)
- Ratio of impacted to unimpacted (No OWFs) median population size after 30 years
- Percentage of unimpacted (No OWFs) PGRs that lie beneath the median impacted PGR, and thus also have a smaller population size.

Note that our metrics relate to the ‘percentage of x...’ rather than to the ‘chance that x...’ or ‘probability that x...’. While equivalent in practice, it would be technically incorrect if we used the latter formulation, because of the Monte Carlo approach we use. In this method, the parameter values for each of a large number of model simulations are sampled from representative distributions, but are constant within each simulation. Strictly speaking, our method hence calculates the frequency (expressed as a percentage of the total) with which ‘x’ occurs. The ‘chance that x’ formulation would be correct if the outcome of our model simulation itself would vary.

PGR

The population growth rate is an accepted metric to indicate the health of a population and to measure population-level effects of disturbance (Caswell 2001, Cook and Robinson 2016). A value >1 indicates an exponentially growing population, while a smaller value indicates a declining population. We present the 5th and 95th percentile, based on the Monte Carlo analysis described above. Given the

uncertainty in the parameter values, 90% of our outcomes predict a PGR above (5th) or below (95th) these values.

Population decrease of 10% over 30 years

A population decrease of 10% or more occurs when the annual population growth rate is equal to or smaller than $\sqrt[3]{0.9} = 0.996$. By keeping track of this statistic for all simulations in the Monte Carlo analysis, we obtain the P10%30Y metric. We have chosen 10% because it is reasonable to assume that such a change can be detected in a well-studied population, and 30 years because it is the period of validity of recent Dutch OWF permits as well as the current life expectancy of an OWF. Hence, this metric indicates the likelihood of a measurable reduction in the abundance of the population after the planned lifetime of an OWF. It is strongly related to the PGR, but integrates the effect of parameter uncertainty into a single metric.

Relative population size

The relative median population size after 30 years is equal to the ratio between the median population size in the Monte Carlo simulations with OWFs divided by that without OWFs. Since the population size at the start of the time period is the same for all scenarios, we calculate this metric based on the PGR. The ratio between the population growth rates over a 30-year period (PGR^{30}) is equal to the ratio between the population sizes after 30 years. A value <1 means indicates a smaller population size as a result of OWFs. This metric is related to the OWF-induced relative change in PGR, but is more intuitive and relates to the planned lifetime of OWFs.

Overlap of unimpacted and impacted

The percentage of unimpacted PGRs that lie beneath the median impacted PGR (Figure 2.4) is the most complex but also the most informative metric. Essentially, this metric indicates the overlap between the outcomes of the unimpacted and impacted scenarios. It indicates the chance that a population develops similarly to an unaffected population, given the magnitude of the OWF effect and the parameter uncertainty. If it is far below 50%, it is highly unlikely that a population will develop 'as if it were unaffected'. It is the chance (expressed as a percentage) that an unaffected population has a smaller PGR than the median (50th percentile) of the affected population and thus has a smaller population size. If an OWF has no effect at all, its value would be 50%, as the distributions (and medians) would be identical, so that half the Monte Carlo simulation outcomes would be below the median of the OWF-affected population. A value $<50\%$ indicates a negative effect of OWFs.

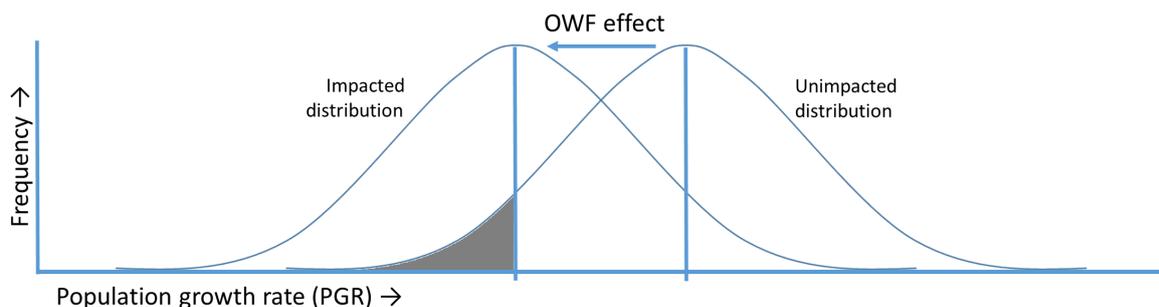


Figure 2.4: Diagram illustrating the 'percentage of un-impacted (No OWFs) PGRs that lie beneath the median impacted PGR' concept. The arrow indicates the effect of OWF on the median of the PGR distribution, shifting it from the un-impacted to the impacted distribution. The grey area under the un-impacted curve is the part that is at or below the median of the un-impacted distribution. An important aspect of this criterion is that it becomes smaller both with larger distance between the means (larger effect) and with narrower distributions (less uncertainty). An effect size of zero would imply the distributions are perfectly overlaid, and exactly half (or 50%) of the un-impacted distribution would be below the median of the impacted distribution.

2.4.6 Red-throated diver model

The diver model contains a juvenile *DJ* (ages 0 and 1), immature *DI* (age 2) and adult *DA* (age 3+) life stage. We choose three stages based on the available mortality estimates (Table 2.4). Survival has been

estimated for individuals at age 0, age 1 and age 3+. Since reproduction starts at age 3 (Horswill and Robinson 2015), we define an immature stage for individuals with age 2.

Survival and aging from one breeding season to the next are described by matrix M_{Dw} :

$$M_{Dw} = \begin{pmatrix} \left(\frac{1-S_{DJ}^1}{1-S_{DJ}^2}\right)S_{DJ} & 0 & 0 \\ \frac{S_{DJ}^2(1-S_{DJ})}{1-S_{DJ}^2} & 0 & 0 \\ 0 & S_{DA} & S_{DA} \end{pmatrix}. \quad (7)$$

With survival of juveniles S_{DJ} , and immatures and adults S_{DA} .

Part of the adults produces offspring in the breeding season. In the breeding season, reproduction occurs following matrix M_{Ds} :

$$M_{Ds} = \begin{pmatrix} 1 & 0 & F_{DA}(1-B_{DA}) \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix}. \quad (8)$$

Adults produce F_{DA} female offspring. The probability that individuals skip reproduction equals B_{DA} . The annual projection matrix is calculated as:

$$A_D = M_{Dw} * M_{Ds} \\ = \begin{pmatrix} \left(\frac{1-S_{DJ}^1}{1-S_{DJ}^2}\right)S_{DJ} & 0 & S_{DJ}\left(\frac{1-S_{DJ}^1}{1-S_{DJ}^2}\right)F_{DA}(1-B_{DA}) \\ \frac{S_{DJ}^2(1-S_{DJ})}{1-S_{DJ}^2} & 0 & \frac{S_{DJ}^2(1-S_{DJ})}{1-S_{DJ}^2}F_{DA}(1-B_{DA}) \\ 0 & S_{DA} & S_{DA} \end{pmatrix}. \quad (9)$$

2.4.6.1 Diver parameter values

Parameter values for the diver are taken from the review by (Horswill and Robinson 2015). There are not many reports of life-history parameters for this species. A measure of the variance of the values is not available for the survival probabilities. The (relatively low) fecundity reported by Horswill and Robinson (2015) is based on studies at Shetland and Orkney, while Hemmingsson and Eriksson (2002) refer to studies in Sweden. Maximal clutch size is 2 eggs.

There is no information on the probability of skipping reproduction for the red-throated diver. The incidence of skipped breeding is expected to be between 40-60% (Poot, van Horssen et al. 2011) in adult divers based on an adult body size of about 1.6 kg (Robinson 2005).

Table 2.4 Default parameter values red-throated diver

symbol	mean	unit	variance	description	remark	source
F_{DA}	0.348	Year ⁻¹	0.088 (SD)	fledged female offspring, age 5+	average across Sweden (0.41) and UK (0.2855)	1, 2, 3
B_{DA}	0.48		0.4-0.6 (min-max) 0.05 (SD range rule)	skipped breeding probability, all adult stages	estimate based on body size (1600 g). 0.4-0.6	4, 5
S_{DJ}	0.61	-	0.014 (SD)	annual survival probability age 0-1	the SD value is quite low, but there are only two estimates available and they are very close	1, 2
S_{DA}	0.88	-	0.06 (SD)	annual survival probability immatures & adults, age 2+		2, 6
a_{Dm}	3	Years		age at recruitment		1

¹Horswill & Robinson (2015); ²Hemmingsson and Eriksson (2002); ³Dierschke, Furness et al. (2017); ⁴Poot, van Horssen et al. (2011); ⁵Robinson (2005); ⁶Schmutz (2014).

2.4.7 Northern gannet model

The model contains the juvenile stages GJ_0 (age 0), immature stages GI_1 (age 1) and GI_2 (age 2), GI_3 (age 3) and GI_4 (age 4) and adult stage GA (age 5+).

Survival and aging from one breeding season to the next is described by matrix M_{GW} :

$$M_{GW} = \begin{pmatrix} 0 & 0 & 0 & 0 & 0 & 0 \\ S_{G0} & 0 & 0 & 0 & 0 & 0 \\ 0 & S_{G1} & 0 & 0 & 0 & 0 \\ 0 & 0 & S_{G2} & 0 & 0 & 0 \\ 0 & 0 & 0 & S_{G3} & 0 & 0 \\ 0 & 0 & 0 & 0 & S_{GA} & S_{GA} \end{pmatrix}. \quad (10)$$

With survival of juveniles S_{G0} , survival of immatures $S_{G1...G3}$ and survival of adults S_{GA} .

Adults produce offspring in the breeding season. Only part of the adults reproduces and we introduce a probability for reproduction. In the breeding season, reproduction occurs following matrix M_{GS} :

$$M_{GS} = \begin{pmatrix} 1 & 0 & 0 & 0 & 0 & \frac{F_{GA}}{2}(1 - B_{GA}) \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{pmatrix}. \quad (11)$$

Adults produce $\frac{F_{GA}}{2}$ female offspring. The probability that individuals skip reproduction equals B_{GA} for young and old adults.

The annual projection matrix is calculated as:

$$A_G = M_{GW} * M_{GS},$$

$$= \begin{pmatrix} 0 & 0 & 0 & 0 & 0 & 0 \\ S_{G0} & 0 & 0 & 0 & 0 & S_{G0} \frac{F_{GA}}{2}(1 - B_{GA}) \\ 0 & S_{G1} & 0 & 0 & 0 & 0 \\ 0 & 0 & S_{G2} & 0 & 0 & 0 \\ 0 & 0 & 0 & S_{G3} & 0 & 0 \\ 0 & 0 & 0 & 0 & S_{GA} & S_{GA} \end{pmatrix}. \quad (12)$$

2.4.7.1 Northern gannet parameter values

Parameter values for the gannet are taken from the review by Horswill and Robinson (2015). There are a number of reports of life-history parameters for this species. The values in the review are based on studies of gannet colonies in the UK. Maximal clutch size is 1 egg (Wanless, Frederiksen et al. 2006).

Based on a body weight of 3000 g (Robinson 2005), the incidence of skipped breeding is estimated to be between 25-75% (Poot, van Horssen et al. 2011). No standard deviation was available for the incidence of skipped breeding. Therefore, we calculated the SD for this parameter based on the range rule $((\max - \min)/4)$.

Table 2.5 Northern gannet life-history parameters

Symbol	Mean value	Variance	unit	Description	Remark	Source
F_{GA}	0.7	0.082 (SD) 0 - 1 (min-max)	Year ⁻¹	Fledged offspring, national average UK	Area specific estimates (UK), available	1
B_{GA}	0.5	0.125 (SD) range rule) 0.25-0.75 (min-max)	-	Skipped breeding probability, all adult stages	Weight based estimate (3000 g)	1, 2, 3
S_{G0}	0.424	0.007 (SE)	-	Annual survival probability age 0		1
S_{G1}	0.829	0.004 (SE)	-	Annual survival probability age 1		1

Symbol	Mean value	Variance	unit	Description	Remark	Source
S_{G2}	0.891	0.003 (SE)	-	Annual survival probability age 2		
S_{G3}	0.895	0.003 (SE)	-	Annual survival probability age 3		1
S_{Ga}	0.919	0.042 (SD)	-	Annual survival probability immatures & adults, age 4+		1
a_{Gm}	5		Years	Age at recruitment		1

¹Horswill & Robinson (2015); ²Robinson (2005); ³Poot, van Horsen et al. (2011);

2.4.7.2 Northern gannet windfarm scenarios

The gannet population distribution overlaps with the OWFs both in the breeding and the non-breeding season. The effect of the windfarms is therefore calculated in two steps. We assume that in the summer, the whole population is present and deduct the mortality probability from the summer survival (normally 1 on the diagonal of matrix M_{Gs}). Since in winter, only part of the population stays at the North Sea, we multiply the mortality in winter due to the windfarms with the estimated proportion of the population that is present compared to the summer population.

2.4.8 Sandwich tern model

We use a juvenile TJ (age 0), immature TI (age 1 and 2), young adult TM (age 3 and 4) and old adult TA (age 5+) stage. The immature and young adult stage each last two years. We group immatures of one and two years old together because estimated mortality rates are identical. Maturation in the sandwich tern occurs at age 3 (Van der Jeugd, Ens et al. 2014). Adults of age 3 and 4 have a significantly lower breeding success than adults of 5 years and older (Veen 1977). Therefore, we define an adult class for inexperienced (young) and an adult class for experienced (old) adults separately.

Survival and aging from one breeding season to the next is described by matrix M_{Tw} :

$$M_{Tw} = \begin{pmatrix} 0 & 0 & 0 & 0 \\ S_{TJ} & \left(\frac{1-S_{TI}}{1-S_{TI}^2}\right)S_{TI} & 0 & 0 \\ 0 & \frac{S_{TI}^2(1-S_{TI})}{1-S_{TI}^2} & \left(\frac{1-S_{TA}}{1-S_{TA}^2}\right)S_{TA} & 0 \\ 0 & 0 & \frac{S_{TA}^2(1-S_{TA})}{1-S_{TA}^2} & S_{TA} \end{pmatrix}. \quad (13)$$

With survival of juveniles S_{TJ} , survival of immatures S_{TI} and survival of adults S_{TA} .

Part of the adults produce offspring in the breeding season. In the breeding season, reproduction occurs following matrix M_{Ts} :

$$M_{Ts} = \begin{pmatrix} 1 & 0 & F_{TM}(1-B_{TA}) & F_{TA}(1-B_{TA}) \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix}. \quad (14)$$

Young and old adults produce respectively F_{TM} and F_{TA} female offspring. The probability that individuals skip reproduction equals B_{TA} for young and old adults.

The annual projection matrix is calculated as:

$$A_T = M_{Tw} * M_{Ts},$$

$$= \begin{pmatrix} 0 & 0 & 0 & 0 \\ S_{TJ} & \left(\frac{1-S_{TI}}{1-S_{TI}^2}\right)S_{TI} & S_{TJ} \frac{F_{TM}}{2}(1-B_{TA}) & S_{TJ} \frac{F_{TA}}{2}(1-B_{TA}) \\ 0 & \frac{S_{TI}^2(1-S_{TI})}{1-S_{TI}^2} & \left(\frac{1-S_{TA}}{1-S_{TA}^2}\right)S_{TA} & 0 \\ 0 & 0 & \frac{S_{TA}^2(1-S_{TA})}{1-S_{TA}^2} & S_{TA} \end{pmatrix}. \quad (15)$$

2.4.8.1 Sandwich tern parameter values

The parameter values (Table 2.6) are based on studies of the Wadden Sea sandwich tern colonies. Survival probabilities and breeding success are based on a recent study (Van der Jeugd, Ens et al. 2014), which uses 40 years of ringing data from Griend to estimate survival. Breeding success measurements of the same colony from 1990 to 2010 are included in the study. Sandwich terns brood size varies between 1-2 eggs per brood.

Breeding success is reported to be much lower in 3- and 4-year-old adults than in adults of age 5 and older (Veen 1977, page 54). Veen (1977) reports that the breeding success for 3- and 4-year-old individuals is about 30% of that of older adults. For individuals with age 5+, we have used a weighted average based on colony size (unpublished data Hans Schekkerman, SOVON). For the younger adults we use a value of 30% of the older adult fecundity number.

There is no information on the probability of skipping reproduction for the sandwich tern. The incidence of skipped breeding is expected to be between 10-40% (Poot, van Horssen et al. 2011) in adult sandwich terns based on an adult body size of about 250 g (Robinson 2005). The incidence of skipped breeding is taken equal for all reproducing stages.

Table 2.6 Default parameter values sandwich tern

Symbol	Mean value	Variance	unit	Description	Remark	Source
F_{TM}	$0.3 F_{TA}$	Depends on values for F_{TA}	Year ⁻¹	Fledged female offspring, adults age 3 and 4		1
F_{TA}	0.275	0.095 (SD)	Year ⁻¹	Fledged female offspring, adults age 5+	Weighed reproduction (based on colony size)	2
B_{TA}	0.1	0.075 (SD range rule) 0.1-0.4 (min max)	-	Skipped breeding probability, all adult stages	Estimate based on body weight (250 g)	3, 4
S_{TJ}	0.302	0.125 (SD)	-	Annual survival probability juveniles, age 0		5
S_{TI}	0.956	0.028 (SD)	-	Annual survival probability immatures, age 1 and 2		5
S_{TA}	0.945	0.099 (SD)	-	Annual survival probability adults, age 3+		5
a_{TM}	3	-	Years	Age at maturation		5

¹Veen (1977); ²Data Sovon; ³Poot, van Horssen et al. (2011); ⁴Robinson (2005); ⁵Van der Jeugd, Ens et al. (2014).

2.4.9 Razorbill model

The model contains the juveniles RJ (ages 0 and 1), immatures RI (ages 2-4) and adults RA (age 5+). Survival and aging from one breeding season to the next is described by matrix M_{RW} :

$$M_{RW} = \begin{pmatrix} \left(\frac{1 - S_{RJ}^1}{1 - S_{RJ}^2} \right) S_{RJ} & 0 & 0 \\ \frac{S_{RJ}^2 (1 - S_{RJ})}{1 - S_{RJ}^2} & \left(\frac{1 - S_{RA}^2}{1 - S_{RA}^3} \right) S_{RA} & 0 \\ 0 & \frac{S_{RA}^3 (1 - S_{RA})}{1 - S_{RA}^3} & S_{RA} \end{pmatrix}. \quad (16)$$

With survival of juveniles S_{RJ} and survival of immatures and of adults S_{RA} .

Part of the adults produce offspring in the breeding season. Reproduction occurs following matrix M_{RS} :

$$M_{RS} = \begin{pmatrix} 1 & 0 & \frac{F_{RA}}{2}(1 - B_{RA}) \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix}. \quad (17)$$

Adults produce $\frac{F_{RA}}{2}$ female offspring. The probability that individuals skip reproduction equals B_{RA} .

The annual projection matrix is calculated as:

$$A_R = M_{RW} * M_{RS},$$

$$= \begin{pmatrix} \left(\frac{1 - S_{RJ}^2}{1 - S_{RJ}^3}\right) S_{RJ} & 0 & \left(\frac{1 - S_{RJ}^2}{1 - S_{RJ}^3}\right) S_{RJ} \frac{F_{RA}}{2} (1 - B_{RA}) \\ \frac{S_{RJ}^3 (1 - S_{RJ})}{1 - S_{RJ}^3} & \left(\frac{1 - S_{RA}^1}{1 - S_{RA}^2}\right) S_{RA} & \frac{S_{RJ}^3 (1 - S_{RJ}) F_{RA}}{1 - S_{RJ}^3} \frac{1 - B_{RA}}{2} \\ 0 & \frac{S_{RA}^2 (1 - S_{RA})}{1 - S_{RA}^2} & S_{RA} \end{pmatrix}. \quad (18)$$

2.4.9.1 Razorbill parameter values

Parameter values for the razorbill (table 2.7) are taken from the review by Horswill and Robinson (2015). There are a number of reports of life-history parameters for this species. The values in the review are based on studies of razorbill colonies in the UK. Yet, the juvenile survival estimate is based on a ringing program in Canadian razorbill colonies. Maximum clutch size is one egg.

Based on a body weight of 710 g (Robinson 2005), the incidence of skipped breeding is estimated to be between 25-50% (Poot, van Horssen et al. 2011). Horswill and Robinson (2015) give an estimate of only 3% for the incidence of missed breeding. We use the latter value as it is based on species specific observations. No standard deviation was available for the incidence of skipped breeding. Therefore, we calculated the SD for this parameter based on the range rule $((\max - \min)/4)$.

Table 2.7 Default parameter values Razorbill

Symbol	Mean value	variance	unit	Description	Remark	Source
F_{RA}	0.57	0.247 (SD)	Year ¹	Fledged offspring, age 5+		1
B_{RA}	0.03	0.125 (SD range rule) 0.0-0.5 (min-max)	-	Skipped breeding probability, all adult stages	Estimate based on body weight (710g)	2,3
S_{RJ}	0.788	0.133 (SD)	-	Annual Survival probability age 0 and 1	Based on Canadian colonies, derived annual value from original study	1, 4
S_{RA}	0.895	0.067 (SD)	-	Annual Survival probability immatures & adults, age 2+		1
a_{Rm}	5	-	Years	Age at recruitment		1

¹Horswill and Robinson (2015); ²Robinson (2005); ³Poot, van Horssen et al. (2011); ⁴Lavers, Jones et al. (2008);

2.4.10 Common guillemot model

The guillemot matrix model contains the juvenile stages UJ_0 (age 0), UJ_1 (age 1) and UJ_2 (age 2), immatures UI (age 3-5) and adults UA (age 6+). Survival and aging from one breeding season to the next is described by matrix M_{Uw} :

$$M_{UW} = \begin{pmatrix} 0 & 0 & 0 & 0 & 0 \\ S_{U0} & 0 & 0 & 0 & 0 \\ 0 & S_{U1} & 0 & 0 & 0 \\ 0 & 0 & S_{U2} & \left(\frac{1-S_{UA}^2}{1-S_{UA}^3}\right)S_{UA} & 0 \\ 0 & 0 & 0 & \frac{S_{UA}^3(1-S_{UA})}{1-S_{UA}^3} & S_{UA} \end{pmatrix}. \quad (19)$$

With survival of juveniles S_{U0} , S_{U1} and S_{U2} , and survival of immatures and adults S_{UA} . Adults produce offspring in the breeding season. Only part of the adults reproduces and we introduce a probability for reproduction. In the breeding season, reproduction occurs following matrix M_{Us} :

$$M_{Us} = \begin{pmatrix} 1 & 0 & 0 & 0 & \frac{F_{UA}}{2}(1-B_{UA}) \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{pmatrix}. \quad (20)$$

Adults produce $\frac{F_{UA}}{2}$ female offspring. The probability that individuals skip reproduction equals B_{UA} for young and old adults.

The annual projection matrix is calculated as:

$$A_U = M_{UW} * M_{Us}$$

$$= \begin{pmatrix} 0 & 0 & 0 & 0 & 0 \\ S_{U0} & 0 & 0 & 0 & S_{U0} \frac{F_{UA}}{2} (1-B_{UA}) \\ 0 & S_{U1} & 0 & 0 & 0 \\ 0 & 0 & S_{U2} & \left(\frac{1-S_{UA}^2}{1-S_{UA}^3}\right)S_{UA} & 0 \\ 0 & 0 & 0 & \frac{S_{UA}^3(1-S_{UA})}{1-S_{UA}^3} & S_{UA} \end{pmatrix}. \quad (21)$$

2.4.10.1 Common guillemot parameter values

Parameter values for the guillemot (Table 2.8) are taken from the review by Horswill and Robinson (2015). There are a number of reports of life-history parameters for this species. The values in the review are based on studies of common guillemot colonies in the UK. The incidence of skipped breeding is estimated to be between 5-10% (Harris and Wanless 1995). No standard deviation was available for the incidence of skipped breeding. Therefore, we calculated the SD for this parameter based on the range rule ((max-min)/4). Maximum clutch size is one egg.

Table 2.8 Default parameter values common guillemot

symbol	mean value	variance	unit	description	remark	source
F_{UA}	0.627	0.147 (SD)	Year ⁻¹	fledged offspring, age 5+	area specific estimates (UK), available	1
B_{UA}	0.08	0.0125 (SD) 5-10% (min-max)	-	skipped breeding probability, all adult stages	SD based on range rule	1,2
S_{U0}	0.56	0.013 (SD)	-	annual survival probability age 0		1
S_{U1}	0.792	0.034 (SD)	-	annual survival probability age 1		1
S_{U2}	0.917	0.022 (SD)	-	annual survival probability age 2		
S_{UA}	0.939	0.067 (SD)	-	annual survival probability immatures & adults, age 3+		1
a_{UM}	6	-	Years	age at recruitment		1

¹Horswill & Robinson (2015); ²Harris and Wanless (1995)

3 Results

In this chapter the results per species are presented. For every species we present:

1. The resulting habitat suitability map (the predicted distribution based on the habitat models), that provides input to the next step.
2. The habitat suitability map is then used in the individual based models, to calculate the proportion of birds that will be affected through reduced survival because of habitat loss under different OWF- scenarios.
3. The resulting changes in survival rates are incorporated in population models to arrive at population projections under the different OWF-scenarios.

3.1 Red throated diver

3.1.1 Density predictions

For red-throated diver the area was limited to the Dutch Continental Shelf only, because it is a highly coastal species and there are insufficient data for the UK coast. It is technically possible to calculate diver abundance outside the input data locations, but doing so implies that the relationships determining bird abundance in Dutch areas translate 1:1 to the rest of the North Sea. We have no data to study whether or not this is the case and have therefore chosen not to extrapolate to other areas.

Significant predictors for presence-absence (model 1) are slope, distance to coast, day of season, data source and sediment. Numbers increased with increasing slope, decreased with distance to coast, increased with day of the season and were lower in the MWTL database. Some sediment categories (deep sand and fine mud) showed higher densities than others. For areas where divers are present (model 2), densities increased with slope, were higher in the MWTL data and lower in areas with fine sediment. Water depth was included as a smoother and showed clearly that red-throated divers occur mainly up to a depth of 25 m, with the highest densities in the shallowest part (Annex 1). The DIC shows that for both models the model including the covariates and the spatial random field fits better than the models without the spatial random field (Table 3.2).

Table 3.1: Coefficients and significance of covariates in the habitat model for red-throated diver. Significant covariates are printed bold.

Species		model 1 (presence-absence) coefficient	model 2 (density) coefficient
red-throated diver	covariate		
	Intercept	-5.01633	1.425925
	slope	0.045033	0.050955
	distance to coast	-1.79805	-0.22824
	day of season	0.224881	-0.0223
	data source_MWTL	-1.3976	0.14553
	sediment_deep_sand	0.766361	0.034593
	sediment_fine	0.051037	-0.23341
	sediment_fine_mud	1.099596	-0.33112
	sediment_mixed	-0.41883	-0.43178
	sediment_sandy_mud	0.27502	-0.0318

Table 3.2. DIC values of the two models with and without a spatial random field. The best models are indicated by the lowest DIC value.

Model	Covariates only	Covariates + SRF
model presence/absence	24421.2	23438.9
model positive density	10590.08	10034.69

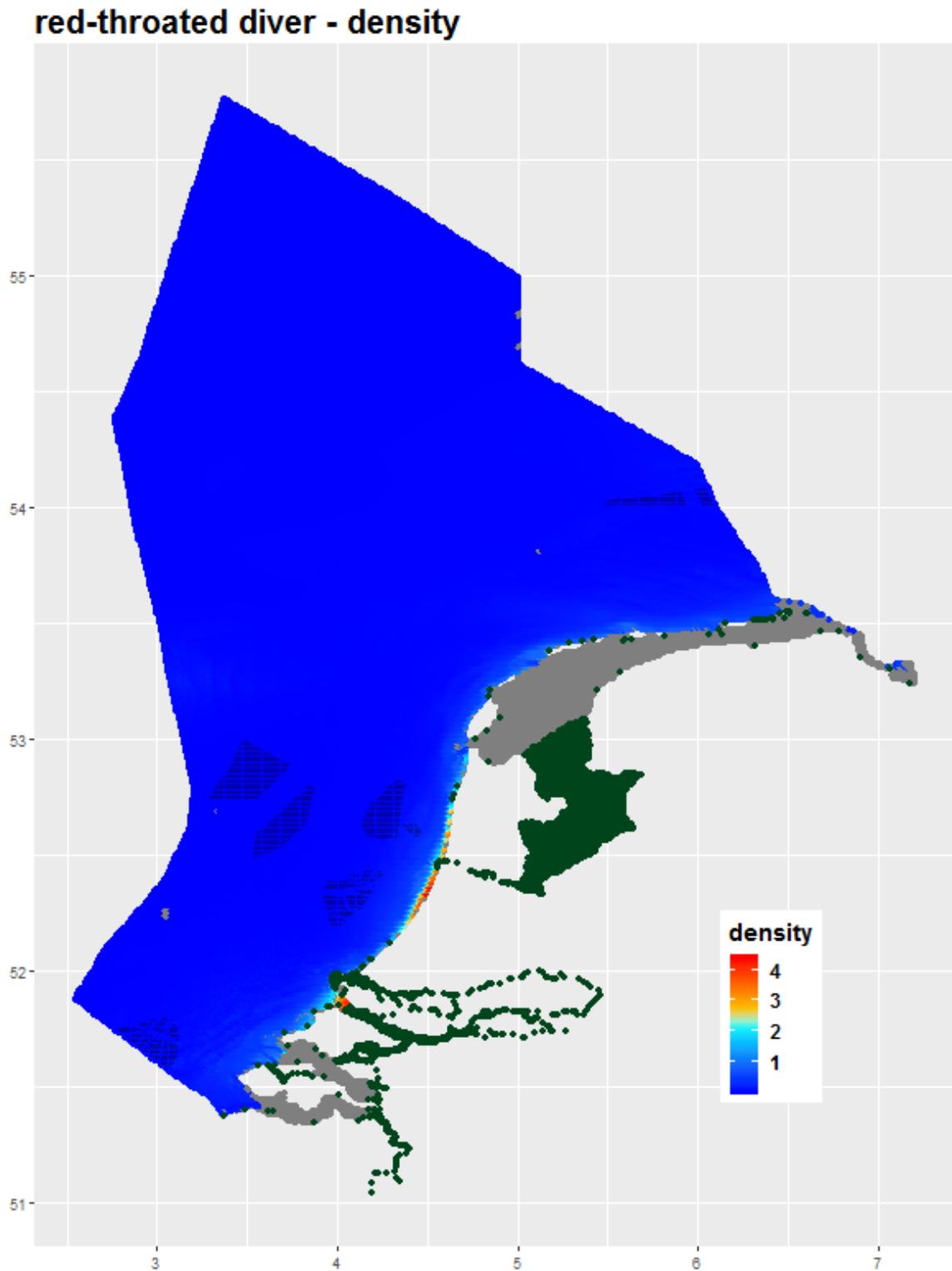


Figure 3.1. Habitat suitability map for red-throated diver. Black hatched areas are Dutch planned and constructed OWFS. Grey areas are areas of missing data or too far outside the parameter range of the data.

3.1.2 Population level effect

Since the habitat model for red-throated diver was limited to the NCP, we can only study effects of Dutch OWFs on the red-throated diver population (overlap 1%, Table 3.23). The red-throated diver population model predicts a decline of the population without wind farms. The median diver population growth rate is 0.953 (Table 3.3). While an increase of the population is included in the 90% range of possible outcomes of the model, the majority of the outcomes predict a decrease of the population (Figure 3.2). Without wind farms, a population decline of 10% or more over a 30-year period is shown by 80% of the outcomes. For the extreme scenario this number rises to 87%, for the best estimate scenario it is 81%.

The population growth rate decreases only slightly with additional mortality (Figure 3.2), but if all displaced individuals die (extreme scenario), the small effect adds up to a substantial reduction of the relative population after 30 years. The median population size would be 0.67 of the median population size without wind farms. Yet, even for this extreme scenario, 42% of the outcomes without OWFs predict a population size lower than the median with OWFs (Table 3.3). In contrast, both the worst case and best estimate scenarios show a negligible effect of OWF mortality on all population metrics. In summary, we do not find a strong effect of OWF related habitat loss on the population level for divers, unless we assume an unrealistically strong survival rate of displaced birds.

The perturbation analysis for divers (Annex 2) shows that population growth rate is most strongly affected by changes in adult survival, which have an order of magnitude larger effect per unit change (elasticity) than any other parameter.

Table 3.3 Diver population growth rate for all model scenarios. The median annual population growth rate (PGR), the 5% and 95% percentile, the proportion of the calculations (out of 50,000) that predict a 10% decline (or greater) of the population over a period of 30 years, the median population size after 30 years relative to the scenario without OWFs for all model scenarios and the percentage of the results without OWFs that predict a population size under the median of the results for each of the OWF scenarios

	PGR	5% percentile	95% percentile	P10%30yr	relative population size after 30 years	percentage results unaffected lower than median affected
without OWFs	0.953	0.834	1.028	80%		
extreme scenario						
<i>Dutch OWFs</i>	0.940	0.825	1.017	87%	0.665	42%
worst case scenario						
<i>Dutch OWFs</i>	0.951	0.834	1.027	81%	0.958	49%
best estimate scenario						
<i>Dutch OWFs</i>	0.952	0.834	1.027	81%	0.964	49%

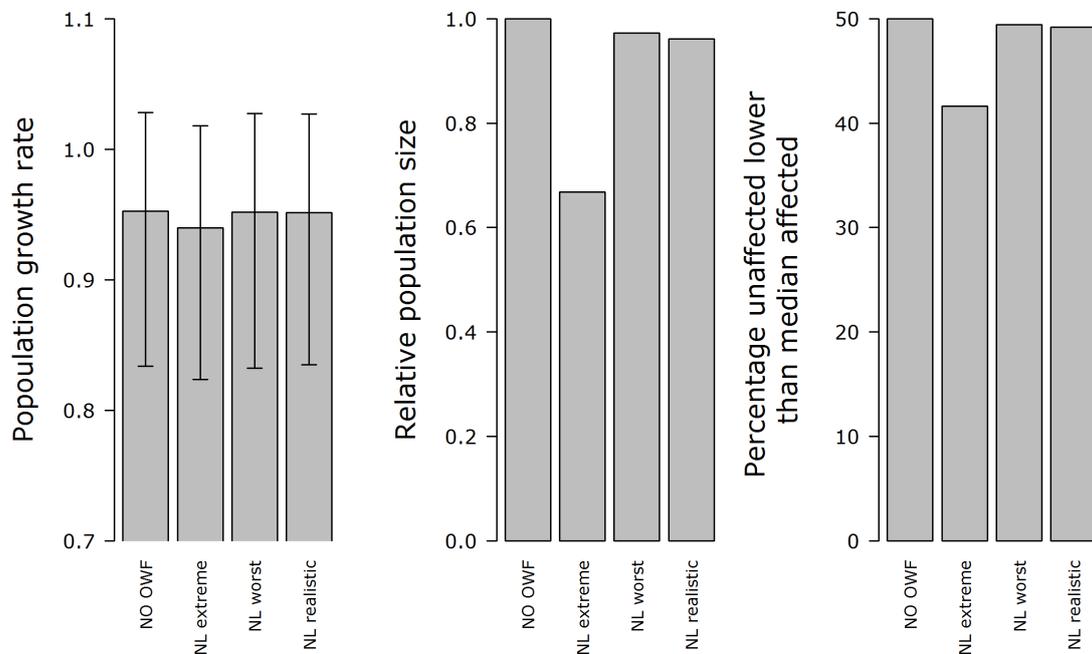


Figure 3.2 Red-throated diver median population growth rate, with 5 and 95% percentile, relative median population size after 30 years and percentage of outcomes of the scenario without OWFs that lies lower than the median of the results for each of the scenarios with Dutch OWFs.

3.2 Northern gannet

3.2.1 Density predictions

Non-breeding gannets:

Significant predictors for presence-absence (model 1) were: distance to colony, day of season and data source. Presence decreased with distance to colony, increased with day of season and was lower in MWTL data. Densities (model 2) decreased with distance to colony, decreased with day of the season, were higher in the MWTL set and in fine mud. In the non-breeding season gannets occur mainly deeper than 25 m (Annex 1).

The DIC shows that for both models the model including the covariates and the spatial random field fits better than the models without the spatial random field (Table 3.4).

Breeding gannets:

Significant predictors for presence-absence (model 1) were: slope, distance to coast, day of season, data source, sediment (deep sand, fine mud). Presence decreased with day of season and was lower in the MWTL data. Densities (model 2) increased with day of season and were higher in MWTL. Similar to non-breeding birds, the depth distribution of breeding gannets is mainly limited to areas of 25 m or deeper (Annex 1).

The DIC shows that for both models the model including the covariates and the spatial random field fits better than the models without the spatial random field (Table 3.5).

Table 3.4. Coefficients and significance of covariates in the model for northern gannet in the non-breeding period and for non-breeding gannets in the breeding period. Significant covariates are printed bold.

Species		model 1 (presence-absence)	model 2 (density)
northern gannet breeding	covariate	coefficient	coefficient
	Intercept	211.4576	0.605138
	slope	-0.0137	0.04385
	distance to coast	-0.02262	-0.01912
	distance to colony	-0.42959	-0.09945
	day of season	0.062422	-0.05778
	data source_MWTL	-0.6109	0.097146
	sediment_deep_sand	-0.02229	0.052198
	sediment_fine	0.084492	-0.03663
	sediment_fine_mud	0.084802	0.182566
	sediment_mixed	0.527542	0.123171
	sediment_sandy_mud	-0.1341	0.094206
	northern gannet non-breeding	Intercept	265.9615
slope		-0.00715	-0.00309
distance to coast		-0.06124	-0.00232
distance to colony		-0.35705	0.035008
day of season		-0.6184	0.033482
data source_MWTL		-0.48162	0.213265
sediment_deep_sand		-0.01166	0.032611
sediment_fine		0.098544	-0.03979
sediment_fine_mud		-0.05606	0.102193
sediment_mixed		-0.89871	0.179755
sediment_sandy_mud		0.160599	0.05712

Table 3.5. DIC values of the two models with and without a spatial random field. The best models are indicated by the lowest DIC value.

	model	covariates only	covariates + SRF
northern gannet breeding	model presence/absence	43986.3	42389.9
	model positive density	22200.81	16605.22
northern gannet non-breeding	model presence/absence	52041.71	49929.42
	model positive density	23255.41	18014.1

northern gannet - density

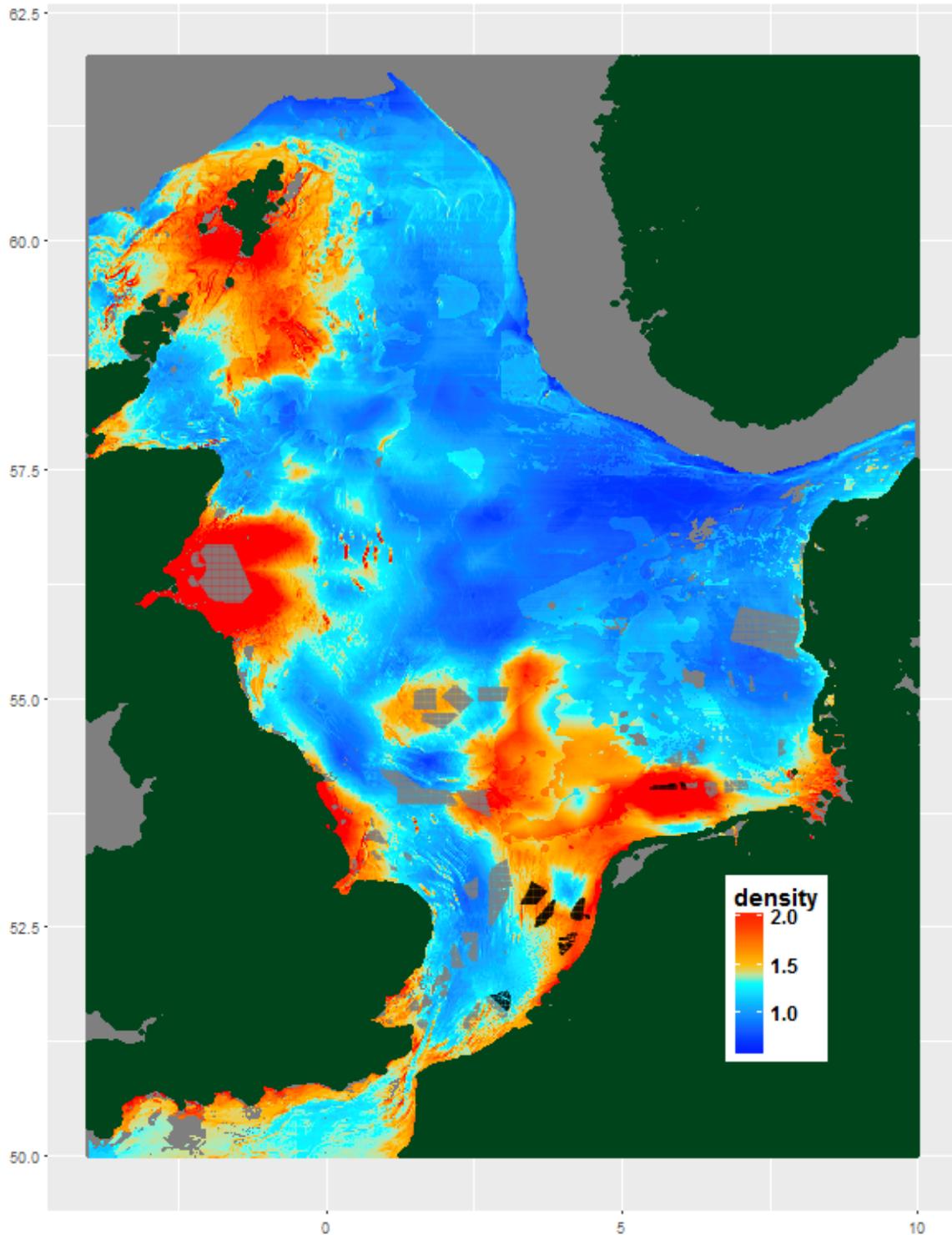


Figure 3.3. Habitat suitability map for northern gannets in the breeding season. Grey areas with hatch superimposed are the internationally planned OWFs, black areas are Dutch planned and constructed OWFs. Grey areas without hatch are areas of missing data or too far outside the parameter range of the data.

northern gannet - density

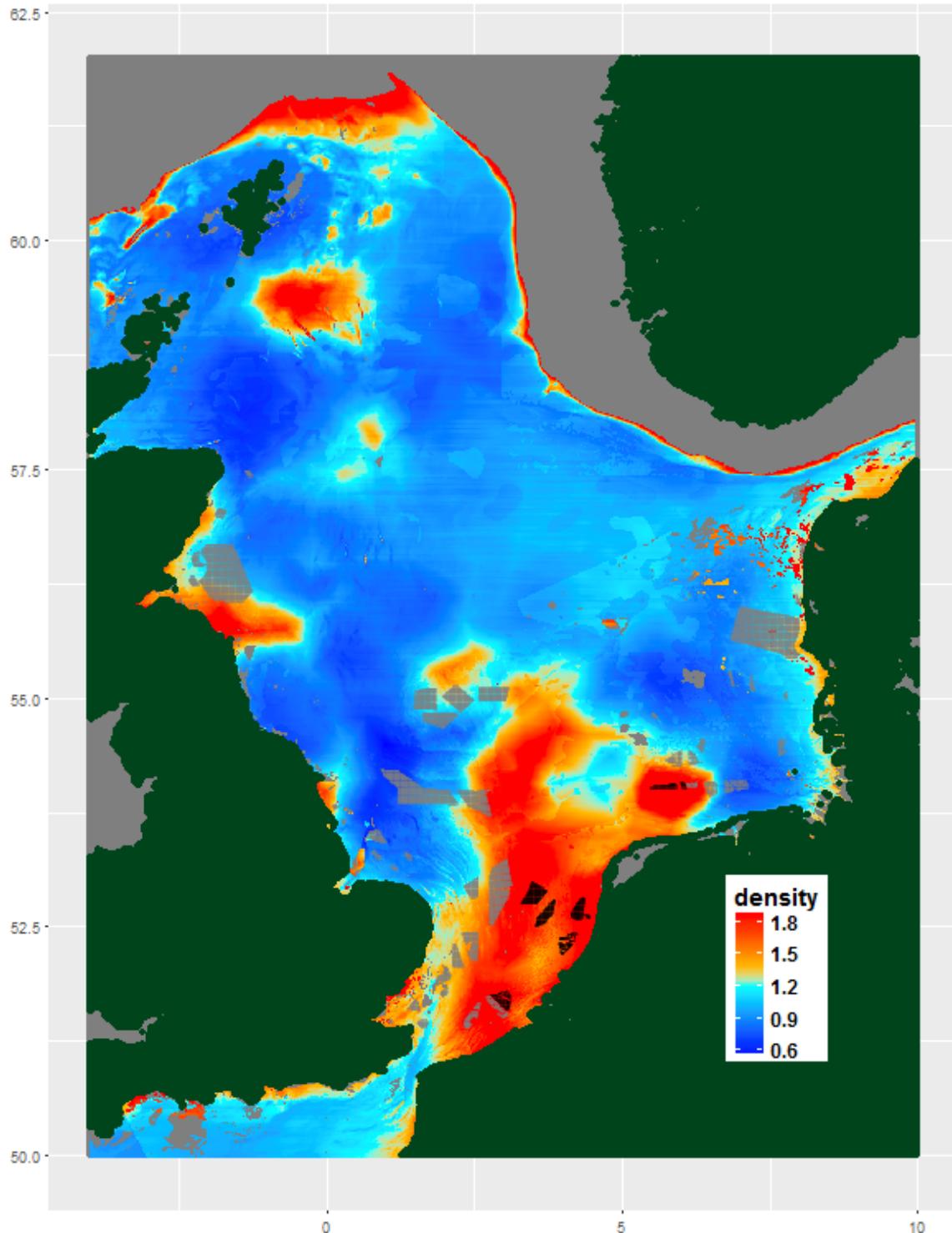


Figure 3.4. Habitat suitability map for northern gannets in the non-breeding season. Grey areas with hatch superimposed are the internationally planned OWFs, black areas are Dutch planned and constructed OWFs. Grey areas without hatch are areas of missing data or too far outside the parameter range of the data.

3.2.2 OWF effects on survival probability

Table 3.5 shows the simulated survival probability of northern gannet using realistic displacement, with and without the international OWFs. Table 3.6 shows the same results for the worst case displacement, again with and without the international OWFs.

The additional mortality is the percentage change between the median or the 5th percentile and the survival probability used during the calibration.

Generally, there is very little variation in outcomes, which means that the differences between the 5th and the 50th percentile (the median) are minimal, indicating that all simulations give a highly similar outcome.

Table 3.5 Effects of OWF (best estimate scenario) on northern gannet survival probabilities: 5th percentile, median and median fraction decreased survival from OWFs

	<i>Survival without OWF</i>	<i>Survival at 5th percentile</i>	<i>Survival at median</i>	<i>Median survival decrease from OWF</i>	<i>5th percentile survival decrease from OWF</i>
All OWF					
<i>breeding</i>	0.9	0.896	0.898	0.3%	0.4%
<i>non-breeding</i>	0.9	0.860	0.861	4.3%	4.5%
Dutch OWF					
<i>breeding</i>	0.9	0.899	0.900	0.0%	0.2%
<i>non-breeding</i>	0.9	0.861	0.863	4.1%	4.3%

Table 3.6 Effects of OWF (worst case scenario) on northern gannet survival probabilities: 5th percentile, median and median fraction decreased survival from OWFs.

	<i>Survival without OWF</i>	<i>Survival at 5th percentile</i>	<i>Survival at median</i>	<i>Median survival decrease from OWF</i>	<i>5th percentile survival decrease from OWF</i>
All OWF					
<i>breeding</i>	0.9	0.896	0.897	0.3%	0.4%
<i>non-breeding</i>	0.9	0.860	0.862	4.3%	4.4%
Dutch OWF					
<i>breeding</i>	0.9	0.899	0.900	0.0%	0.2%
<i>non-breeding</i>	0.9	0.861	0.863	4.1%	4.3%

3.2.3 Population level effect

The northern gannet population overlaps most strongly with the international (non-Dutch) wind farms (3.3-3.6%, Table 3.23). Only 0.4-0.5% of the population overlaps with Dutch wind farms. Without wind farms, the gannet population model predicts a slow decline of the population. The median of the population growth rates is 0.975 (Table 3.7). While the possibility of a population growth rate larger than one is included in the 90% of possible outcomes of the model, the majority of the outcomes predicts a decrease of the population (Figure 3.5). Without wind farms, 74% of the outcomes predict a population decline of 10% or larger over a period of 30 years. For the extreme scenario with all windfarms this increases to 100%, while for the best estimate scenario the number is 80%.

The population growth rate decreases only slightly due to the additional OWF mortality, except for the scenario for which all displaced individuals die and the international windfarms are included (Figure 3.5). With all windfarms and in case all displaced individuals die, the median population size is 0.09 of the median population size without wind farms. For this extreme scenario, 5% of the outcomes without OWFs predict a population size lower than the median (Table 3.7). Yet, for all scenarios that

are considered to be more realistic (e.g. 10% mortality), the median population size is at least 0.8 of the median population size without wind farms. In addition, a substantial 42% of the outcomes without OWFs predict population sizes lower than the median with all OWFs. In summary, we find a small effect of OWF related habitat loss on the population level for the gannet for all best estimate scenarios.

When the Dutch OWFs are considered alone, the effect on all the metrics that we consider is negligible.

The perturbation analysis for gannets (Annex 3) shows that population growth rate is most strongly affected by changes in adult survival, which have over an order of magnitude larger effect per unit change (elasticity) than any other parameter.

The additional effect of the Dutch OWFs when the international OWFs are already present (the difference between 'foreign OWFs and 'all OWFs' in Table 3.7) causes a very small change to the outcome of the assessment for gannets. The effect is limited even in the extreme scenario, and virtually non-existent in the worst case and best estimate scenarios.

Table 3.7: Northern gannet population growth rate for all model scenarios. The median annual population growth rate (PGR) with 5% and 95% percentile, the proportion of the calculations (out of 50,000) that predict a 10% decline (or greater) of the population over a period of 30 years, the median population size after 30 years relative to the scenario without OWFs for all model scenarios and the percentage of the results without OWFs that predict a smaller population size than the median of the OWF scenarios.

	PGR	5% percentile	95% percentile	P10%30yr	relative population size after 30 years	percentage results unaffected lower than median affected
without OWFs	0.975	0.898	1.023	74%		
extreme scenario						
<i>Dutch OWFs</i>	0.966	0.891	1.014	82%	0.766	41%
<i>foreign OWFs</i>	0.909	0.840	0.959	100%	0.124	7%
<i>all OWFs</i>	0.901	0.832	0.951	100%	0.094	5%
worst case scenario						
<i>Dutch OWFs</i>	0.974	0.899	1.022	75%	0.961	49%
<i>foreign OWFs</i>	0.969	0.893	1.016	80%	0.820	43%
<i>all OWFs</i>	0.968	0.893	1.015	81%	0.797	42%
best estimate scenario						
<i>Dutch OWFs</i>	0.974	0.898	1.022	74%	0.983	49%
<i>foreign OWFs</i>	0.970	0.894	1.018	79%	0.861	45%
<i>all OWFs</i>	0.969	0.894	1.017	80%	0.827	44%

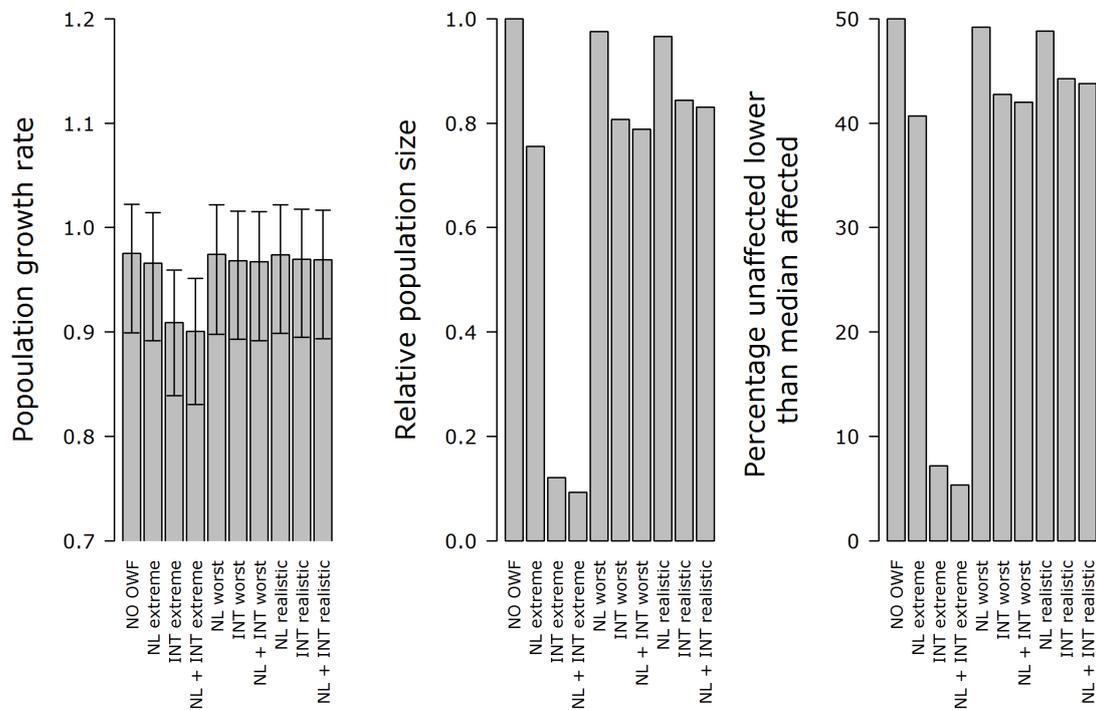


Figure 3.5 Northern gannet median PGR, with 5 and 95% percentile, relative population size after 30 years and the percentage of outcomes without OWFs that predicts a population size smaller than the median for each of the scenarios.

3.3 Sandwich tern

3.3.1 Density predictions

Because our sandwich tern data was limited to the Dutch Continental Shelf, we were forced to focus the habitat model only on that area. Even though the species occurs along the UK, Belgian, Danish and German coasts as well, the habitat model fitted only on the Dutch data cannot be used reliably to predict distributions along other coasts.

Significant predictors for presence-absence (model 1) were: slope, distance to coast, data source (Table 3.8). Presence increased with slope and decreased with distance to coast and was higher in the MWTL data. Densities (model 2) increased with slope. The depth smoother showed that sandwich terns occur mainly in the zone up to 25 m depth and within that zone densities tend to be highest in the shallowest part (Annex 1).

The DIC shows that for both models the model including the covariates and the spatial random field fits better than the models without the spatial random field (Table 3.9).

Table 3.8: Coefficients and significance of covariates in the model for sandwich tern. Significant covariates are printed bold.

species		model 1 (presence-absence) coefficient	model 2 (density) coefficient
sandwich tern	covariate		
	Intercept	-4.43369	1.403966
	slope	0.097131	0.040045
	distance to coast	-1.15674	-0.18875
	day of season	0.005745	-0.02069
	data source_MWTL	0.414829	0.038241

species		model 1 (presence-absence) coefficient	model 2 (density) coefficient
sandwich tern	covariate		
	sediment_deep_sand	0.148702	0.136699
	sediment_fine	0.019506	-0.00012
	sediment_fine_mud	0.118629	0.308908
	sediment_mixed	-0.4642	0.261901
sediment_sandy_mud	-0.4677	0.073392	

Table 3.9: DIC values of the two models with and without a spatial random field. The best models are indicated by the lowest DIC value.

model	covariates only	covariates + SRF
model presence/absence	30897.92	29110.92
model positive density	13442.5	13282.5

sandwich tern - density

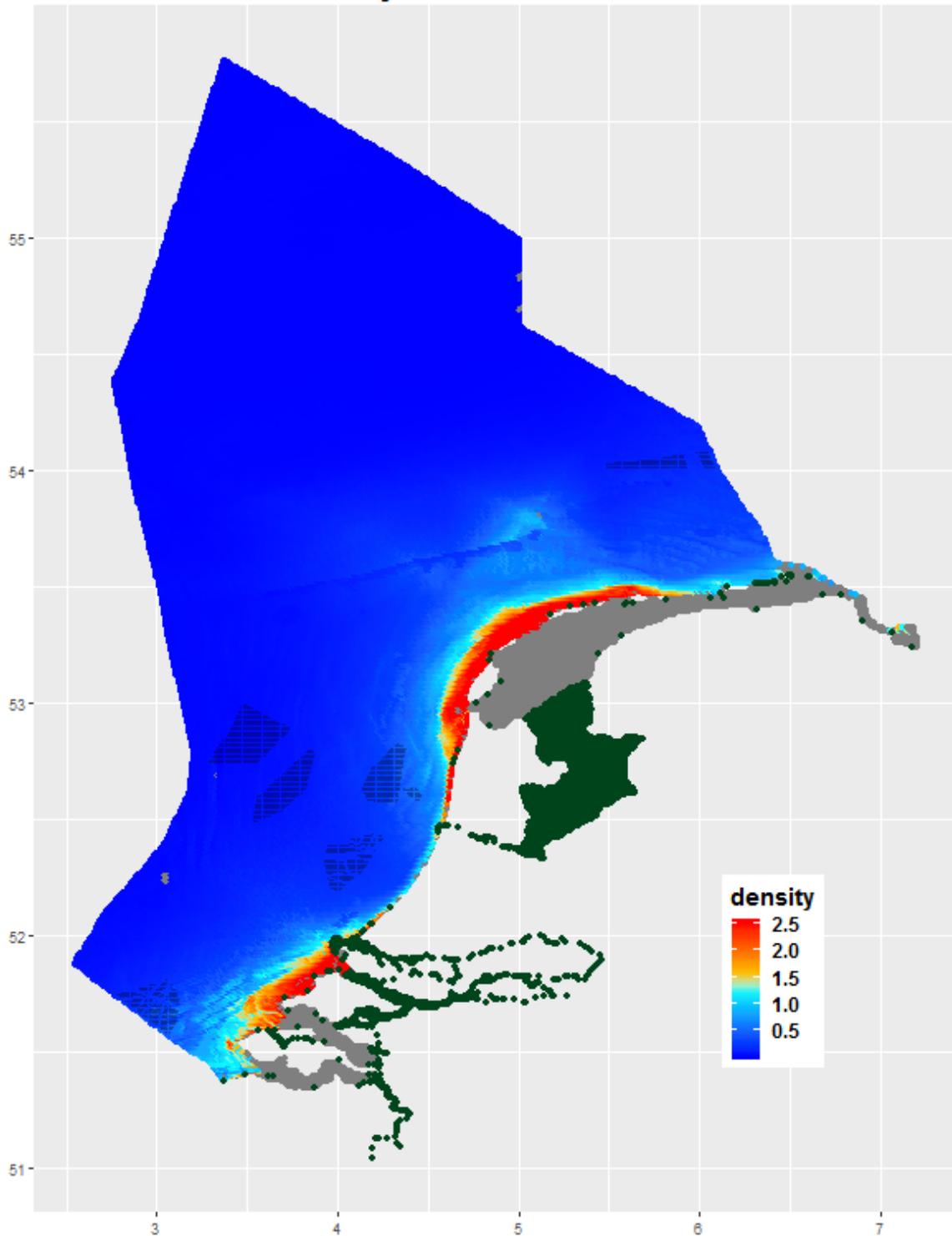


Figure 3.6. Habitat suitability map for the sandwich tern in the breeding season. Black hatched areas are Dutch planned and constructed OWFS. Grey areas are areas of missing data or too far outside the parameter range of the data.

3.3.2 Population level effect

Since the habitat model is limited to the DCF, the sandwich tern population we modelled, only overlaps with Dutch wind farms (Table 3.23). Even though there is exchange between Dutch and other colonies, we are currently unable to quantify this exchange and hence the effects of OWF-related habitat loss in non-Dutch waters. Two percent of the population in the DCF occurs in OWF's. Without wind farms, the sandwich tern population model predicts an increase of the population. The median of the population growth rates is 1.037 (Table 3.12). While a decrease of the population is included in

the inner 90% of model outcomes, the minority of the outcomes predicts a decrease of the population (Figure 3.7). Without wind farms, 25% of the outcomes predicts a population decline of 10% or more over a period of 30 years. For the extreme scenario with windfarms, this is 33%, and, for the best estimate scenario, this is 25%, the same as without wind farms.

There is a very small effect of the additional mortality due to OWFs on the population growth rate (Figure 3.7). If all displaced individuals would die, this results in a substantially smaller median population size over a period of 30 years. The median population size would be 0.56 of the median population size without wind farms. Still, even for this extreme scenario, 34% of the outcomes without OWFs predict a population size lower than the median with OWFs (Table 3.12). All best estimate scenarios show a negligible effect of OWF mortality on all population metrics. In summary, we do not find a strong effect of OWF related habitat loss on the population level for the sandwich tern.

The perturbation analysis for sandwich terns (Annex 3) shows that population growth rate is most strongly affected by changes in adult survival, which has almost an order of magnitude larger effect per unit change (elasticity) than any other parameter. The population growth rate is particularly insensitive to changes in the breeding success of young adults and the breeding probability.

Table 3.12 Sandwich tern population growth rate for Dutch OWF scenarios. The median annual population growth rate (PGR) with 5% and 95% percentile, the proportion of the calculations (out of 50,000) that predict a 10% decline (or greater) of the population over a period of 30 years, the median population size after 30 years relative to the scenario without OWFs for all model scenarios and the percentage of the results without OWFs that show a population size smaller than the median of the results for each of the OWF scenarios.

	PGR	5% percentile	95% percentile	P10%30yr	relative population size after 30 years	percentage results unaffected lower than median affected
without OWFs	1.037	0.817	1.083	25%		
extreme scenario						
<i>Dutch OWFs</i>	1.018	0.803	1.063	33%	0.561	34%
worst case scenario						
<i>Dutch OWFs</i>	1.035	0.815	1.081	26%	0.948	48%
best estimate scenario						
<i>Dutch OWFs</i>	1.036	0.816	1.082	25%	0.966	49%

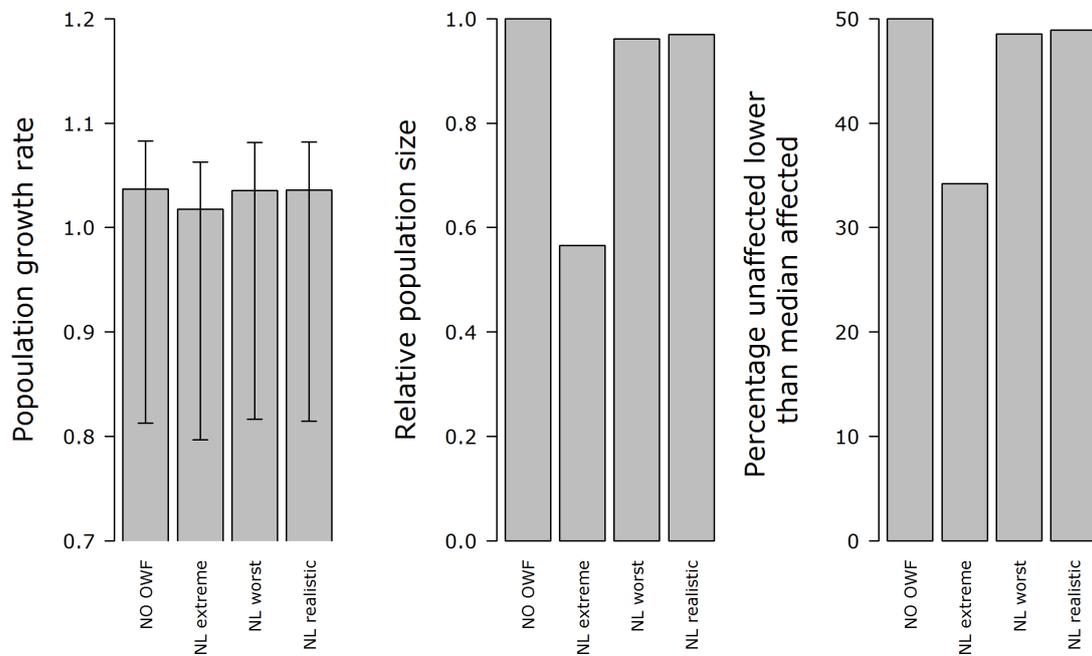


Figure 3.7 Sandwich tern median PGR with 5 and 95% percentile, relative population size and percentage of results without OWFs that shows a population size smaller than the median of the results for each of the scenarios.

3.4 Razorbill

3.4.1 Density predictions

Significant predictors for presence-absence (model 1) were: slope, day of season, data source, sediment (mixed, sandy mud, Table 3.13). Presence decreased with slope and increased with day of the season, was lower in the MWTL database and was higher in mixed and sandy-mud sediment. Densities (model 2) only showed significantly lower values in the MWTL data. The depth smoother shows an optimum at depths of 25-50 m. Occurrence shallower and deeper is lower compared to this zone. Densities decrease with depth (Annex 1). The DIC shows that for both models the model including the covariates and the spatial random field fits better than the models without the spatial random field (Table 3.14).

Table 3.13. Coefficients and significance of covariates in the model for razorbill. Significant covariates are printed bold.

species		model 1 (presence-absence) coefficient	model 2 (density) coefficient
razorbill	covariate		
	Intercept	-2.66816	1.41566
	slope	-0.04263	-0.00151
	distance to coast	0.001868	0.148471
	distance to colony	-0.28734	0.022792
	day of season	0.136457	0.012843
	data source_MWTL	-0.71421	-1.04223

species		model 1 (presence-absence) coefficient	model 2 (density) coefficient
razorbill	covariate		
	sediment_deep_sand	-0.13245	0.038652
	sediment_fine	0.075727	-0.03033
	sediment_fine_mud	-0.10365	0.11218
	sediment_mixed	0.604687	-0.10614
sediment_sandy_mud	0.234285	0.13044	

Table 3.14. DIC values of the two models with and without a spatial random field. The best models are indicated by the lowest DIC value.

Model	covariates only	covariates + SRF
model presence/absence	70440.09	69560.83
model positive density	31969.25	30971.74

razorbill - density

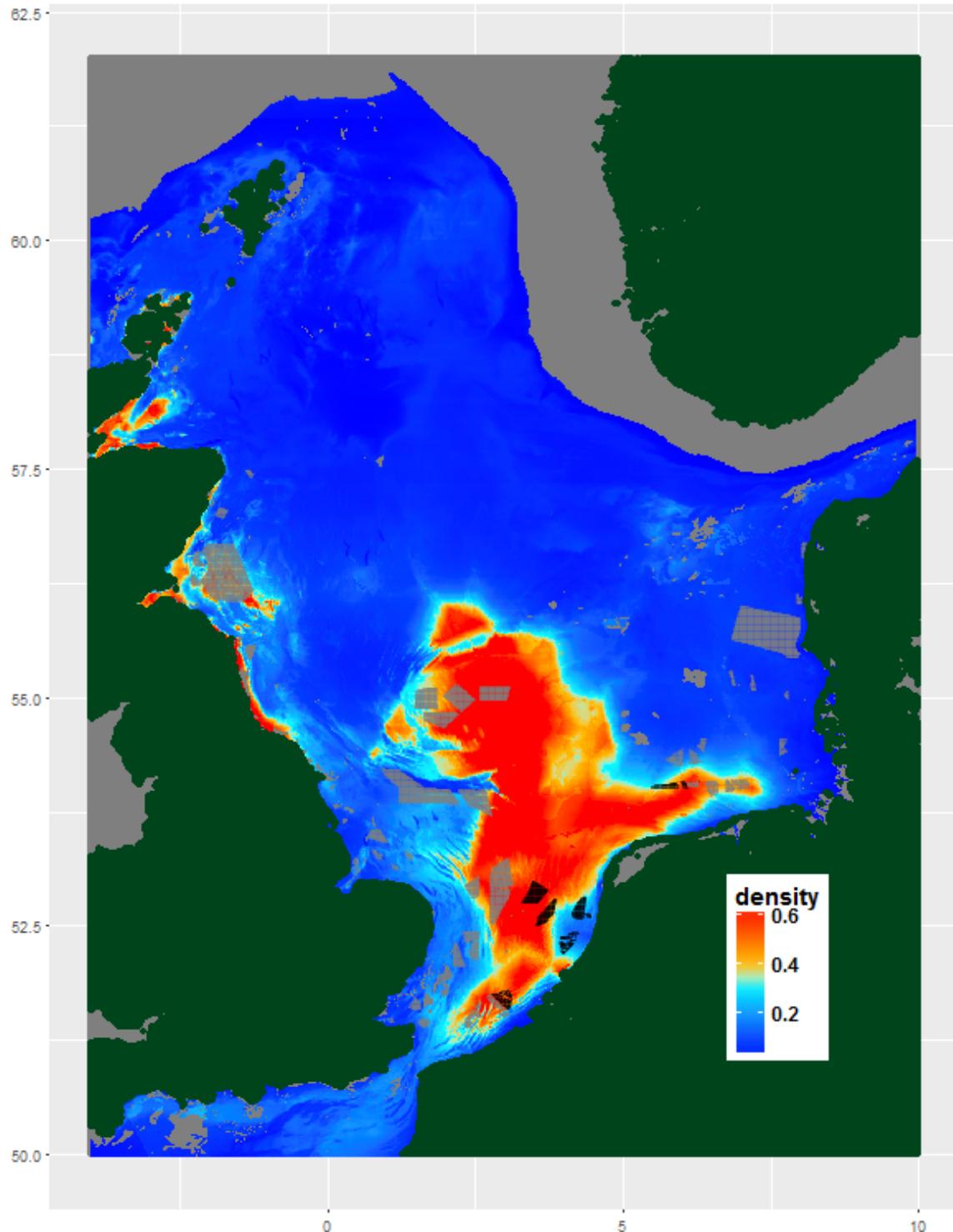


Figure 3.8: habitat suitability map for the razorbill in the non-breeding season. Grey areas with hatch superimposed are the internationally planned OWFs, black areas are Dutch planned and constructed OWFs. Grey areas without hatch are areas of missing data or too far outside the parameter range of the data.

3.4.2 OWF effects on survival probability

Table 3.15 shows the simulated survival probability of razorbills using realistic displacement, with and without the international OWFs. Table 3.16 shows the same results for the worst case displacement, again with and without the international OWFs.

The additional mortality is the percentage change between the median or the 5th percentile and the survival probability used during the calibration.

Generally, there is very little variation in outcomes, which means that the differences between the 5th and the 50th percentile (the median) are minimal, indicating that all simulations give a highly similar outcome.

Table 3.15 Effects of OWF (best estimate scenario) on razorbill survival probabilities: 5th percentile, median and median fraction decreased survival from OWFs.

<i>Survival without OWF</i>	<i>Survival at 5th percentile</i>	<i>Survival at median</i>	<i>Median survival decrease from OWF</i>	<i>5th percentile survival decrease from OWF</i>
<i>All OWF</i>				
0.9	0.896	0.897	0.3%	0.4%
<i>Dutch OWF</i>				
0.9	0.897	0.897	0.3%	0.4%

Table 3.16 Effects of OWF (worst case scenario) on razorbill survival probabilities: 5th percentile, median and median fraction decreased survival from OWFs.

<i>Survival without OWF</i>	<i>Survival at 5th percentile</i>	<i>Survival at median</i>	<i>Median survival decrease from OWF</i>	<i>5th percentile survival decrease from OWF</i>
<i>All OWF</i>				
0.9	0.896	0.897	0.3%	0.4%
<i>Dutch OWF</i>				
0.9	0.897	0.897	0.3%	0.4%

3.4.3 Population level effect

The razorbill population overlaps more with the international wind farms than with the Dutch ones (6.2 vs 1 %, Table 3.23). Without wind farms, the razorbill population model predicts an increase of the population. The median of the population growth rates is 1.016 (Table 3.17). While the possibility of a population growth rate smaller than one is included in the inner 90% of model outcomes, most outcomes predict an increase of the population (Figure 3.9). Without wind farms, 41% of the outcomes show a population decline of 10% or more over a period of 30 years. For the extreme scenario with all windfarms, this doubles to 82%. For the best estimate scenario the effect of all OWFs is small: the number increases to 43%.

The population growth rate decreases slightly due to additional OWF mortality, except for the extreme scenario in which all displaced individuals die and the international windfarms are included (Figure 3.9). With all windfarms and 100% mortality, the median population size after 30 years is 0.06 of the median population size without wind farms. For this extreme scenario, 15% of the outcomes without OWFs show a smaller population than the median with OWFs (Table 3.17). Yet, for both the best estimate and worst case scenarios, the median population size after 30 years is at least 0.76 of the median population size without wind farms. In addition, a substantial 45% of the outcomes without OWFs predict population sizes lower than the median with all OWFs. In summary, we find only a small effect of OWF related habitat loss on the population level for the razorbill for all best estimate scenarios. When the Dutch OWFs are considered alone, the effect on all the metrics that we consider is negligible in the best estimate scenarios.

The perturbation analysis for razorbills (annex 3) shows that population growth rate is most strongly affected by changes in adult survival, which has a more than 3-fold larger effect per unit change (elasticity) than any other parameter.

The additional effect of the Dutch OWFs when the international OWFs are already present (the difference between 'foreign OWFs' and 'all OWFs' in Table 3.17) causes a very small change to the

outcome of the assessment for razorbills. The effect is limited even in the extreme scenario, and virtually non-existent in the worst case and best estimate scenarios.

Table 3.17 Razorbill population growth rate for all model scenarios. The median annual population growth rate (PGR), the 5% and 95% percentile, the proportion of the calculations (out of 50,000) that predict a 10% decline (or greater) of the population over a period of 30 years (P10%30yr), the median population size after 30 years relative to the scenario without OWFs for all model scenarios and the percentage of the results without OWFs that show a population size smaller than the median of each of the OWF scenarios

	PGR	5% percentile	95% percentile	P10%30yr	relative population size after 30 years	percentage results unaffected lower than median affected
without OWFs	1.016	0.861	1.133	41%		
extreme scenario						
Dutch OWFs	1.003	0.849	1.122	47%	0.683	44%
foreign OWFs	0.939	0.792	1.060	77%	0.093	19%
all OWFs	0.926	0.784	1.049	82%	0.061	15%
worst case scenario						
Dutch OWFs	1.015	0.859	1.131	41%	0.961	49%
foreign OWFs	1.008	0.854	1.126	45%	0.782	46%
all OWFs	1.007	0.851	1.124	45%	0.760	45%
best estimate scenario						
Dutch OWFs	1.015	0.862	1.132	41%	0.968	49%
foreign OWFs	1.012	0.858	1.129	43%	0.884	48%
all OWFs	1.011	0.857	1.128	43%	0.870	48%

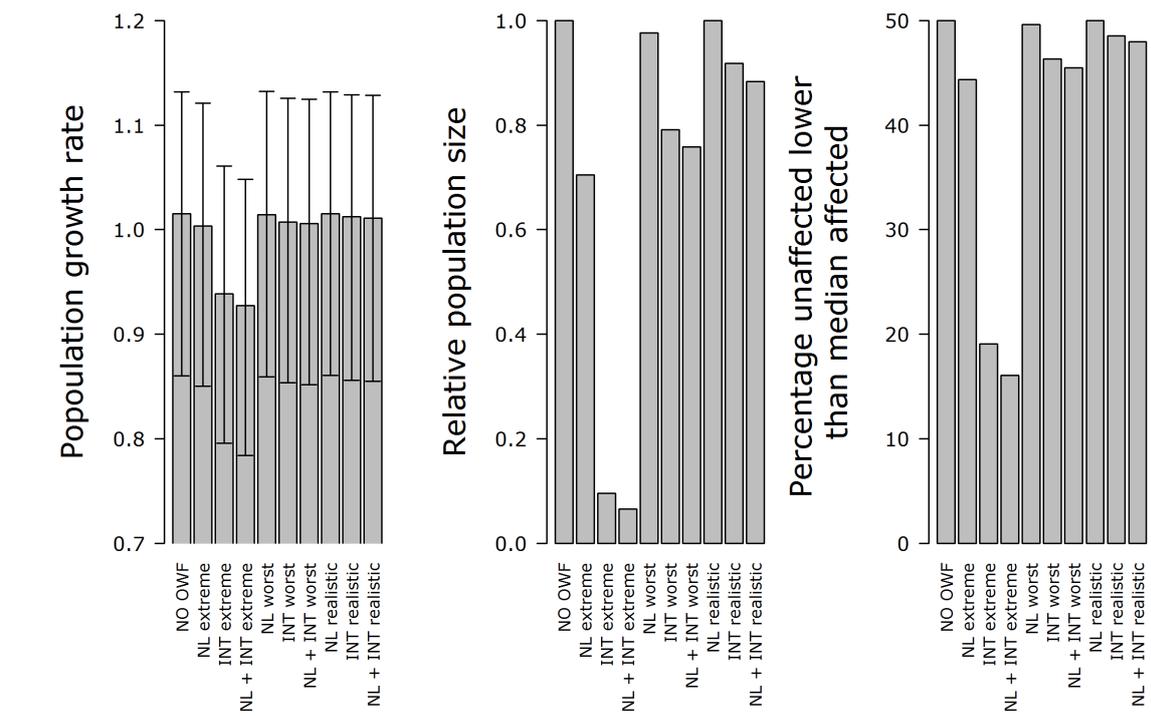


Figure 3.9 Razorbill median PGR, with 5 and 95% percentile, relative population size and percentage of results without OWFs that shows a population size lower than the median of each of the scenarios.

3.5 Common guillemot

3.5.1 Density predictions

Significant predictors for presence-absence (model 1) were: slope, distance to coast, distance to colony, day of season, data source, sediment (fine, sandy mud, Table 3.18). Presence showed decrease with slope and distance to colony, increase with distance to coast, increase with day of the season, was lower for the MWTL set and was higher in fine sediment and sandy mud. Densities (model 2) were lower further from the coast, further from the colonies at a later day in the season and were lower in the MWTL set and differed depending on sediment. Occurrence of common guillemot increases with depth but densities decrease in the range between 0 towards 50 m depth (Annex 1). The DIC shows that for both models the model including the covariates and the spatial random field fits better than the models without the spatial random field (Table 3.19).

Table 3.18: Coefficients and significance of covariates in the model for common guillemot. Significant covariates are printed bold.

species		model 1 (presence-absence) coefficient	model 2 (density) coefficient
common guillemot	covariate		
	Intercept	-1.4588	1.42561
	slope	-0.03813	0.003278
	distance to coast	0.323664	-0.18215
	distance to colony	-0.58643	-0.10273
	day of season	0.057627	-0.19656
	data source_MWTL	-1.68776	-0.27071
	sediment_deep_sand	-0.04471	0.11442
	sediment_fine	0.093759	0.051989
	sediment_fine_mud	-0.0334	0.188292
	sediment_mixed	-0.35696	-0.46817
	sediment_sandy_mud	0.203859	0.179814

Table 3.19: DIC values of the two models with and without a spatial random field. The best models are indicated by the lowest DIC value.

model	covariates only	covariates + SRF
model presence/absence	175732.4	172342.6
model positive density	31969.25	30971.74

common guillemot - density

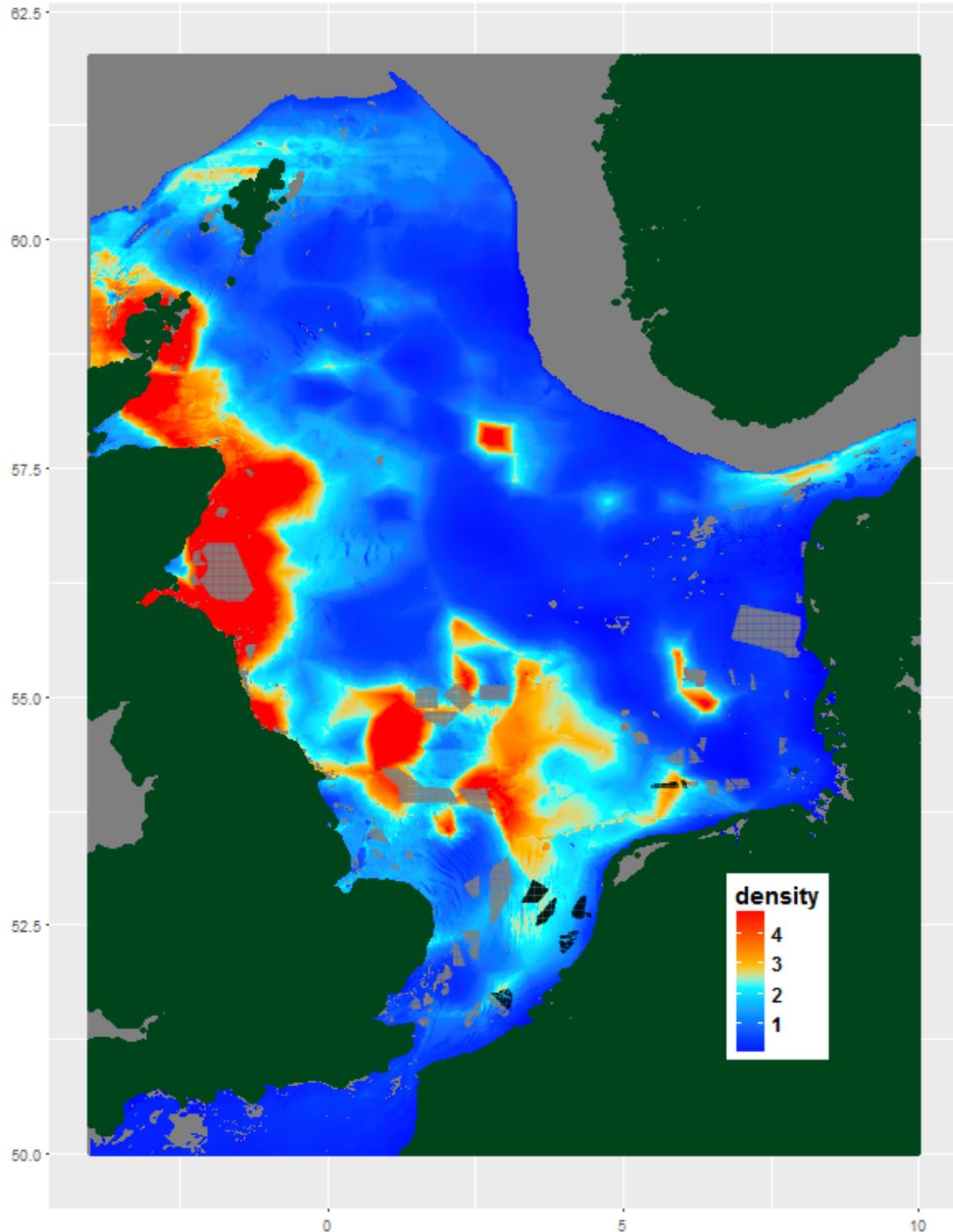


Figure 3.10. Habitat suitability map for the common guillemot in the non-breeding season. Grey areas with hatch superimposed are the internationally planned OWFs, black areas are Dutch planned and constructed OWFs. Grey areas without hatch are areas of missing data or too far outside the parameter range of the data.

3.5.2 OWF effects on survival probability

Table 3.20 shows the simulated survival probability of Guillemots using best estimate displacement, with and without the international OWFs. Table 3.21 shows the same results for the worst case displacement, again with and without the international OWFs.

The additional mortality is the percentage change between the median or the 5th percentile and the survival probability used during the calibration.

Generally, there is very little variation in outcomes, which means that the differences between the 5th and the 50th percentile (the median) are minimal, indicating that all simulations give a highly similar outcome.

Table 3.20: Effects of OWF (best estimate scenario) on guillemot survival probabilities: 5th percentile, median and median fraction decreased survival from OWFs.

	Survival without OWF	Survival at 5th percentile	Survival at median	Median survival decrease from OWF	5th percentile survival decrease from OWF
All OWF	0.94	0.939	0.940	0.0%	0.1%
Dutch OWF	0.94	0.939	0.940	0.0%	0.1%

Table 3.21: Effects of OWF (worst case scenario) on Guillemot survival probabilities: 5th percentile, median and median fraction decreased survival from OWFs.

	Survival without OWF	Survival at 5th percentile	Survival at median	Median survival decrease from OWF	5th percentile survival decrease from OWF
All OWF	0.94	0.939	0.940	0.0%	0.1%
Dutch OWF	0.94	0.939	0.940	0.0%	0.1%

3.5.3 Population level effect

The guillemot population overlaps more with the international than with the Dutch wind farms (6.4 vs 0.4%, Table 3.23). Without wind farms, the guillemot population model predicts an increasing population. The median population growth rate is 1.043 (Table 3.22). While the possibility of a population growth rate smaller than one is included in the inner 90% of model outcomes, the majority of the outcomes predicts an increase of the population (Figure 3.11). Without wind farms, 24% of the outcomes shows a population decline of 10% or greater over a period of 30 years. For the extreme scenario with all windfarms, this is 78%. For the best estimate scenario, this is 26%. In case only the Dutch OWFs are considered, this is the same as without wind farms, 24%.

The population growth rate decreases only slightly due to additional OWF mortality, except for the extreme scenario in which all displaced individuals die and the international windfarms are included (Figure 3.11). With all windfarms and in case all displaced individuals die, the median population size is 0.07 of the median population size without wind farms. For this extreme scenario, only 13% of the outcomes without OWFs have a population size smaller than the median with OWFs (Table 3.22). However, for the worst case and best estimate scenarios (e.g. 10% mortality), the median population size is at least 0.77 of the median population size without wind farms. In addition, a substantial 43% of population sizes without OWFs are smaller than the median with all OWFs. In summary, we find only a small effect of OWF related habitat loss on the population level for the guillemot for both worst case and best estimate scenarios. When the Dutch OWFs are considered alone, the effect on all metrics is negligible.

The perturbation analysis for guillemots (Annex 3) shows that population growth rate is most strongly affected by changes in adult survival, which has over an order of magnitude larger effect per unit change (elasticity) than any other parameter.

The additional effect of the Dutch OWFs when the international OWFs are already present (the difference between 'foreign OWFs' and 'all OWFs' in Table 3.15) causes a very small change to the outcome of the assessment for guillemots. The effect is limited even in the extreme scenario, and virtually non-existent in the worst case and best estimate scenarios.

Table 3.22 Common guillemot population growth rate for all model scenarios. The median annual population growth rate (PGR), the 5% and 95% percentile, the proportion of the calculations (out of 50,000) that predict a 10% decline (or greater) of the population over a period of 30 years (P10%30yr), the median population size after 30 years relative to the scenario without OWFs and the percentage of the results without OWFs that show a population size smaller than the median of each of the OWF scenarios.

	PGR	5% percentile	95% percentile	P10%30yr	relative population size after 30 years	percentage results unaffected lower than median affected
without OWFs	1.043	0.897	1.089	24%		
extreme scenario						
<i>Dutch OWFs</i>	1.037	0.893	1.087	26%	86%	46%
<i>foreign OWFs</i>	0.959	0.834	1.035	75%	8%	14%
<i>all OWFs</i>	0.954	0.827	1.031	78%	7%	13%
worst case scenario						
<i>Dutch OWFs</i>	1.042	0.897	1.089	24%	98%	49%
<i>foreign OWFs</i>	1.034	0.891	1.085	28%	77%	43%
<i>all OWFs</i>	1.034	0.890	1.085	28%	77%	43%
best estimate scenario						

	PGR	5% percentile	95% percentile	P10%30yr	relative population size after 30 years	percentage results unaffected lower than median affected
Dutch OWFs	1.042	0.896	1.089	24%	98%	50%
foreign OWFs	1.038	0.894	1.087	26%	88%	47%
all OWFs	1.038	0.891	1.087	26%	87%	46%

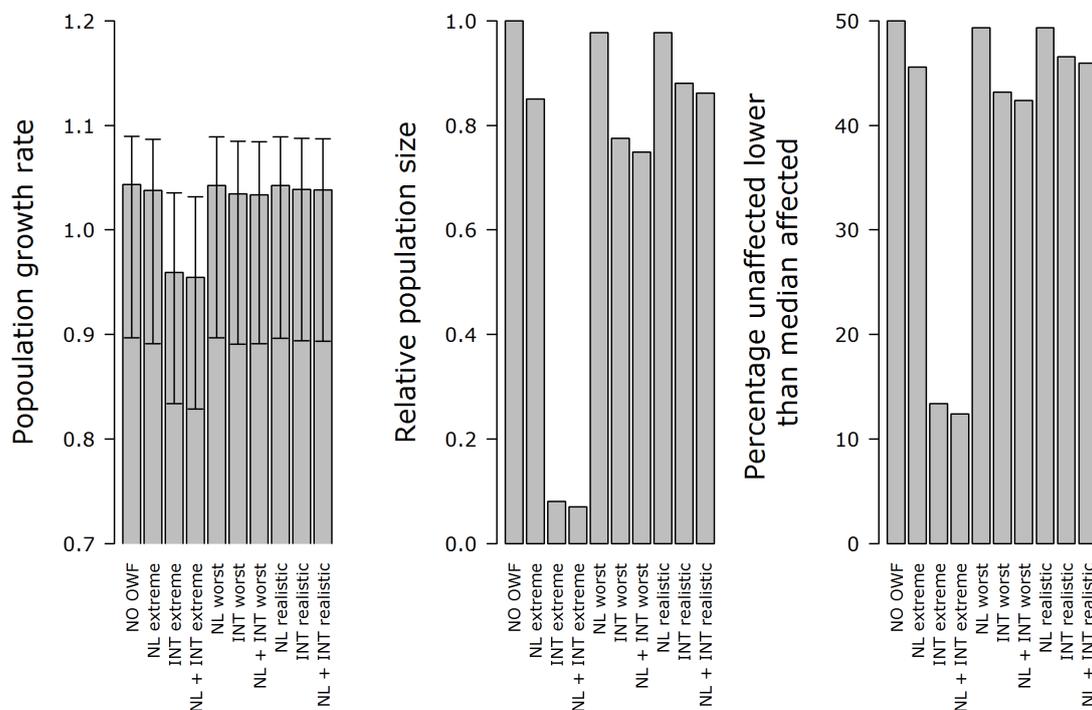


Figure 3.11 Common guillemot annual population growth rate with 5% and 95% percentile, relative median population size after 30 years and percentage of predictions without OWFs that show a population size smaller than the median of each of the scenarios.

3.6 Mortality estimates

Table 3.23 gives a summary of the density predictions for all bird species based on the habitat suitability maps. These are obtained by multiplying the predicted bird density at each map grid cell by the size of each cell, and summing all cells on the map. Based on the percentage of the bird populations found in Dutch, and international wind farms we estimate additional OWF mortality (Table 3.24) for the “extreme”, “worst case” and “best estimate” scenarios (see section 2.3.4). We use these mortality estimates in the results presented in section 3.1-3.5 to calculate population level effects of OWF deployment in the North Sea.

Table 3.23. Population estimates (based on habitat suitability models: estimates of number of birds in whole study area at the median date, in Dutch and non-Dutch wind farms). In sandwich tern and red-throated divers the estimated number based on the habitat map cannot be compared to previous estimates, as the latter include a larger area than the NCP.

bird species	total estimated number	previous estimates	birds in NL-OWFs	birds in international-OWFs
red-throated diver	2458	49.000 ¹	24 (1%)	0
northern gannet non-breeding	615.182		3288 (0.5%)	20.122 (3.3%)
northern gannet breeding	712.981	1.300.000 ²	3023 (0.4%)	25.432 (3.6%)
sandwich tern	11.986	36.000 ³	242 (2%)	0
razorbill	84.949	324.000 ¹	821 (1%)	5.242 (6.2%)
common guillemot	842.640	1.562.000 ¹	3297 (0.4%)	54.081 (6.4%)

¹ Skov, Durinck et al. (2007); ² Birdlife Red list 2015; ³ Sovon: <https://www.sovon.nl/nl/soort/6110>

Table 3.24. Population effect estimates (based on habitat suitability models, displacement and mortality scenarios: % annual mortality due to OWF related displacement).

OWF	scenario	red-throated diver	gannet breeding	gannet nonbreeding	tern	razorbill	guillemot
NL	extreme	1.00%	0.40%	0.50%	2.00%	1.00%	0.40%
	worst	0.10%	0.04%	0.05%	0.20%	0.10%	0.04%
	best estimate	0.08%	0.03%	0.04%	0.10%	0.05%	0.02%
INT	extreme		3.60%	3.30%		6.20%	6.40%
	worst		0.36%	0.33%		0.62%	0.64%
	best estimate		0.29%	0.26%		0.31%	0.32%
NL + INT	extreme		4.00%	3.80%		7.20%	6.80%
	worst		0.40%	0.38%		0.72%	0.68%
	best estimate		0.32%	0.30%		0.36%	0.34%

4 Discussion

4.1 Habitat models

The habitat maps show distributions for five species during the period they are present. For red-throated diver, northern gannet, razorbill and common guillemot the analysis was limited to the non-breeding season, for sandwich tern to the breeding season and for northern gannet the analysis was carried out both for the breeding and non-breeding season. Seasonal variation is accounted for by incorporating day of the season in the models (and making the predictions for the situation at the median date). Sandwich tern and red-throated divers are confined to the coastal area, whereas northern gannets, razorbills and common guillemot have a much wider distribution. In the habitat models we did not use any time-dependent explanatory variables, like temperature, salinity or food (other than within-season). This was a deliberate choice as such models would be unusable for our purpose, since they would require our scenario studies to include future predictions for those time-dependent variables. However, this greatly reduces the explanatory power (and thus also predictive power) of the simplified habitat models we used. Part of this unexplained variation will be covered by the spatial random field that we apply. This is illustrated by the fact that in all cases models with a spatial random field performed better.

The habitat models describe the general distribution of the five species in the seasons in which they use the North Sea. This is based on the information of the period since 1991. Most ESAS samples were collected in very few years (Figure 2.1). Therefore, the data in terms of year, survey and spatial distribution are very unbalanced. We assumed that there is not much change of the bird density distribution over the years and thus ignore the year effect and serial correlated spatial random field. Major changes in both seabird and sea mammal redistribution took place in the period just before 1990, possibly related to shifting food distributions (Camphuysen 2004, Frederiksen, Furness et al. 2007, Anderson, Evans et al. 2014). Our predicted distributions are based on the more recent situation. Any major shifts in food distribution in the future may alter the habitat maps considerably.

In the habitat mapping we multiplied the distributions resulting from two models: presence-absence and positive densities. For both these models, uncertainties were calculated. For the combined model this was not possible, which makes the judgement of the precision of the habitat maps difficult. The quality of the habitat maps greatly depends on the quantity and quality of the bird data they are based on. The area covered by the MWTL data has a higher resolution than the remaining areas. E.g. the German Bight and the area off the UK coast are only covered in four years in the whole period. This pattern is also visible in several habitat maps where the MWTL area stands out, despite the fact that it was incorporated in the model as a covariate. For the coastal species, red-throated diver and sandwich tern this is not a problem. However, for razorbill, common guillemot and northern gannet the suggestion that the NCP is the preferred habitat over other areas is unrealistic².

4.1.1 Improvement of habitat models

At the moment the aerial survey program of MWTL covers the coastal zone (up to approximately 25 km offshore) in April and June and the entire DCF in August, November, January and February. Yet, the sandwich terns maximum foraging range extends the 25 km coastal zone (Fijn, de Jong et al. 2017). Terns have been recorded much further offshore (e.g. Poot, van Horssen et al. 2011 - Shortlist Masterplan Wind), especially in the months prior to and after breeding (March - April, July - October). Sandwich terns are absent from the DCF (or present in very low numbers) during the MWTL counts that cover the entire DCF in Nov/Jan/Feb. In addition, the April and June MWTL surveys are expected to only partly cover the sandwich tern distribution in the Dutch North Sea. Therefore, the distribution

² This will be further addressed in an update to this report, where we will update the habitat models to better deal with this issue. This update will be finalized at the end of Q1, 2019.

of the sandwich tern in the period just before and after breeding (outside the coastal zone) is not well documented.

In order to improve the distribution map of sandwich terns for the entire North Sea, the survey area in April and June should be extended. Either to cover the entire DCF (expanding the survey program similar to the extension of the Aug/Nov/Jan/Feb surveys), or the parts where sandwich terns can be expected in larger numbers (the extension also applied in the Shortlist Masterplan - up to 80 km offshore (Van Bemmelen, Geelhoed et al. 2011)).

For the other species it would be good to complement the ESAS data with more recent data. There is currently no central organisation of the database and the database is not kept up to date.

4.2 Population models

4.2.1 Red-throated diver

The red-throated diver is very sensitive to disturbance. Birds have been reported to take flight in response to approaching vessels several kilometres away (Schwemmer, Mendel et al. 2011). One of the consequences of this behaviour is that the birds are hard to count at sea. There is very little information about the diver population (trends) in Europe. It is therefore impossible to compare the negative population trend that our population model predicts with population data. While the divers return to the same lake each year to breed, the breeding sites are widely spread out and the sizes of breeding populations are not well known either. As a result, the population trends are uncertain in most places (BirdLife International 2015b). The divers undertake long distance migrations and the origin of individuals in the North Sea is unknown.

The quality of the parameter estimates is low for this species. There is no measure of the variance in survival probabilities of juvenile divers (Horswill and Robinson 2015). The measures of breeding success are more reliable since individuals return to the same lake to breed each year.

4.2.2 Northern gannet

The population model predicts a decreasing population. However, gannet breeding colonies have been observed to increase everywhere in Europe (BirdLife International 2015c). Especially Scottish colonies, which display exponential growth (Murray, Harris et al. 2015). The parameter estimates that we use are based on colonies in the UK. This area contains most of the breeding individuals that are relevant for the North Sea area. Yet, these do not predict the expected growing population. The population growth rate is relatively close to 1. A good estimate of breeding probability is lacking. Increasing the breeding probability to a value around 1 would result in a positive population growth rate (see Annex 3). The value that we currently use seems on the high side and is based on an across species dataset (based on the relationship between body mass and percentage floaters, Poot, van Horssen et al. 2011). Yet, there are no studies available that measure the incidence of skipped breeding for the northern gannet specifically (Horswill and Robinson 2015).

4.2.3 Sandwich tern

The population model predicts an increase in the sandwich tern population. Fluctuations or positive trends are both common in sandwich tern populations across Europe (BirdLife International 2015d). In the months prior to and after breeding (and even within the breeding period itself), the sandwich tern is known to forage outside the coastal zone on the Dutch Continental Shelf (Fijn, de Jong et al. 2017). This is the area in which the OWFs have been and are being planned. In addition to a suboptimal documentation of the distribution of the birds in this period (see section 4.1.1), there is no information available on the origin of these birds.

The sensitivity analysis of the population model in our study shows that the population growth rate is highly sensitive to the adult survival probability. Currently, for the Netherlands only for the Wadden Sea population survival estimates are available. Outside the Netherlands, there is not much

information available to estimate sandwich tern survival (Horswill and Robinson 2015). Adult survival rates greatly depend on exchange rates between colonies. Exchange between nearby colonies is known to occur frequently in the sandwich tern. It is unclear how often birds change colonies over larger distances. The emigration and immigration to and from colonies outside the Dutch/Belgian area could have a strong effect on the population dynamics. If many adult birds would leave or arrive, this would have a similar effect as a change in the mortality rate in the adult stage in our model.

4.2.4 Razorbill

The median population growth rate shows an increase of the razorbill population. The razorbill abundance increases in some areas of Europe and decreases in others (BirdLife International 2015a). The source colonies of overwintering birds have not been resolved, and it is thus not possible to link to specific colonies.

The razorbill is quite common in the North Sea area. Some signs of density dependence have been observed in the Isle of May colony (Harris, Newell et al. 2015) by reduced population growth rates. Yet, it is unclear whether density dependence affects the razorbill at the meta-population level of the North Sea overwintering population. For example, razorbill colonies in Norway (Fauchald, Anker-Nilssen et al. 2015) do not show any sign of reduction in growth rates. Birds from Scandinavian colonies also use the North Sea as overwintering area.

The range of outcomes is rather large. This stems from high SD values reported by Horswill and Robinson (2015). The breeding success seems variable. For juvenile survival only few data are available, which were collected in Canada. The razorbill population model is highly dependent on adult survival estimates. Individuals display high colony-fidelity, which reduces the risk of overestimation of the adult survival rates.

4.2.5 Common guillemot

The median population growth rate shows an increase of the guillemot population. The abundance of the guillemot increases in some areas of Europe and decreases in others (BirdLife International 2015e). The source colonies of overwintering birds have not been resolved, and it is thus not possible to link to specific colonies.

The guillemot is quite common in the North Sea area. Similar to the razorbill, some signs of density dependence have been observed in guillemot colonies in the UK (Crespin, Harris et al. 2006, Votier, Birkhead et al. 2008, Harris, Heubeck et al. 2015). Yet, it is unclear whether density dependence affects the guillemot at the meta-population level of the North Sea overwintering population. For example, guillemot colonies in Norway (Fauchald, Anker-Nilssen et al. 2015) do not show any sign of slow growth. Birds from Scandinavian colonies also use the North Sea as overwintering area (SEAPOP). The parameter estimates of this species are generally good. Adults tend to return to the same colonies to breed, reducing the risk of overestimation of the adult survival rates. Juveniles however may switch between colonies, affecting the measurability of juvenile survival.

4.2.6 Density dependence

Our analysis assumes that no density-dependence acts on the populations. In other words, the populations are assumed to be unregulated: $PGR > 1$ leads to a population that exponentially grows to infinity, while $PGR < 1$ implies a population exponentially declines to zero. While we do not consider this realistic for seabird populations, there are a number of good reasons for this assumption. First, density dependence is very hard to measure in the field and it is even harder to determine the cause. Some information may be available for one or a few very well-studied breeding colonies, but how do colony-level processes scale up to the population? The details of inter-colony metapopulation dynamics are crucial here, but there is very little information on this aspect of seabird life history. Finally, we consider a population without density dependence as the correct implementation of the precautionary approach. Any density dependence would mean that some of the effects of additional mortality from OWFs is buffered in reduced density-dependent mortality or increased density-dependent productivity. Hence, density-dependence weakens the effect of OWF-derived habitat loss.

The only exception is where increased densities as a result of habitat loss would lead to increased resource- or interference competition. This could potentially lead to an effect of OWF closures which is more than proportional to the habitat lost, but survival would only be affected if food or space were in limited supply compared to the population requirements. There is some evidence that the food supply is limiting for colony-breeding seabirds during the breeding (Wakefield, Bodey et al. 2013, Bolton, Conolly et al. 2018). However, we are not aware of any such evidence for the non-breeding season which we focus on. Individuals require less energy during the non-breeding season, (no chick to feed), though this may be offset by higher energetic demands of lower temperatures in winter. However, they also have much more space available (no nest to return to) and have more time to feed (no time lost flying back and forth). It seems intuitively unlikely that space or food are limiting on the population level during the non-breeding season. However, the lack of evidence should not be interpreted as evidence for absence.

It is important to note that when total areas covered by OWFs increase much further, it is inevitable that food availability in the non-breeding season will eventually start to play a role. In its current form, our framework is not suitable to study such extreme cases.

4.3 OWF scenarios

4.3.1 OWF effects

In all best estimate and worst-case scenarios, the effect of windfarms on the population level of the five bird species is small (much smaller than for the unrealistic 'extreme' scenario). For the effect of the Dutch windfarms alone, either in isolation or in addition to the international wind farms, the effects are even smaller. The northern gannet, razorbill and common guillemot population show a negligible effect of Dutch windfarms (except in the unrealistic 'extreme' scenario). The sandwich tern and red-throated diver populations are only affected by Dutch OWFs in the extreme scenario. Amongst all species, the gannet population is affected most strongly, probably because the effect of OWFs adds mortality both in the breeding and the non-breeding season, while for all other species their presence on the North Sea is seasonal. However the OWFs are only one of the many sources of disturbance, next to e.g. shipping. The fact that we find only small effects of OWFs does not preclude an effect in combination with other potential pressures.

Since the habitat model is limited to the DCF for the sandwich tern and diver population, we considered only the effect of Dutch wind farms for these species. It is known that the winter distribution of the diver includes areas outside the DCF. Yet, we have no data to extrapolate from the DCF to other areas. Also, there is exchange between Dutch and foreign sandwich tern colonies. However, we are currently unable to quantify this exchange and hence are limited to calculating the effects of OWF-related habitat loss in non-Dutch waters only.

We have incorporated the effect of OWFs on survival in a simplified matter. Changes in survival are assumed to be stage independent. While this complies with a cautionary approach, sandwich terns generally spend a few years in more Southern areas before returning to the North Sea area to start breeding (we will incorporate this for the new version by March 31st, 2019). In the current report, we have assumed that the 10% mortality rule is based on OWF exposure during a single season. Yet, the duration of the season that is considered differs per species (see Table 2.1). This results in a disparity in the consideration of the effect of OWFs between the species. We will consider an explicit time dependency of the 10% mortality rule for the report due by March 31st, 2019.

4.3.2 Uncertainty of Population estimates

The population numbers that are estimated by the habitat models are a rough estimate of the actual population size at the median date during the period they are in the area. Both parts of the habitat model (presence/absence and densities) had large uncertainties (not shown), which means that also the resulting population size is very imprecise. Moreover, in reality the population may be larger than

estimated, because birds could continuously enter and leave the area that we consider. However, the approach that we have chosen allows for the calculation of the maximum effect on the population level, by assuming that all birds are present throughout the season, so that the population experiences the maximum exposure level.

The population level indicators that we have chosen to use are independent of population density. The population indicators are all calculated based on the population growth rates, which are determined based on the life history parameters only.

4.3.3 Displacement behaviour

The estimates of displacement are mostly based on comparisons of counts of birds inside and outside windfarms (Dierschke, Furness et al. 2016). These observations do not take factors such as feeding behaviour into account. Therefore, the worst-case scenario assumes 100% avoidance for the mortality calculations. On the other hand, many of the observations on avoidance of OWFs are done during or shortly after the construction phase. It is likely that habituation to the OWFs may occur for all species studied here, except perhaps for the red-throated diver. The red-throated diver is very sensitive to disturbance (Schwemmer, Mendel et al. 2011) and the regular presence of a maintenance boat such as is common for wind farms may be enough to chase the bird away from OWF areas. For the sandwich tern, northern gannet, razorbill and common guillemot this would mean they may not lose foraging habitat in the long run, meaning that our best estimate scenario assumes more impact than will occur in reality. For the gannet however, not avoiding OWFs may result in an increase of the risk of collision mortality. The first studies of habituation of seabirds to OWFs have only recently been done. So far, there is no clear picture of habituation behaviour of the birds that we studied here.

4.3.4 Timing of OWF effects and OWFs already present

In addition to a number of choices in developing our assessment framework, our implementation of the OWF scenario is also 'worst case', as we implement all planned OWFs up to 2030 simultaneously from the start of the simulations. We allow no habituation and no transition period with fewer OWFs. In our 'no OWF' scenario we have assumed that all OWFs which are already present in the North Sea are not there. While this is potentially problematic because in some of the distributional data and some of the data underlying parameter estimates of the population models, these OWFs were already present, this means that in the distributions and parameter estimates their effects are already included. However, these OWFs are few and small compared to the planned OWFs for the next decade, so we expect this effect to be small. In any case, it conforms to the precautionary approach because if anything, our approach results in an overestimation of the OWF effects.

4.3.5 Effects on fecundity

Our analysis has focused on OWF effects on survival, rather than effects on fecundity. This has several reasons. Our elasticity analysis shows that for all species, adult survival is by far the most important determinant of population growth rate – and hence all other population metrics. This is not surprising, because all species are long-lived and have low annual fecundity. It does imply that OWF effects on fecundity, although they may be present and even may be substantial, will have relatively little effect on the population metrics. A further reason that the effect on fecundity is likely to be smaller, is plasticity in nesting location. If a nesting location becomes severely affected by nearby OWFs, birds are likely to relocate to other areas, either because individual birds move or because offspring do not return to their parental breeding location. Including this dynamic would not only necessitate the inclusion of explicit colony dynamics but also an assessment of the availability of unused breeding locations, both of which are beyond the scope of this study.

4.3.6 Effects of habitat change

The large scale at which windfarms are currently planned may also involve considerable changes in the underwater habitat. The predominant habitat currently consisting of sandy bottom will partly be replaced by hard structures. In addition, the placement of the piles may affect mixing of water layers

and both effects may change fish communities and can have both positive and negative effects on predators. Finally, harvesting wind energy can alter the transfer of energy from air to sea, affecting waves and currents. These system-level changes are not part of the current study, but would affect the results in this study, as it would affect both wind patterns and the distribution of prey fish for these seabirds.

4.4 Conclusions and recommendations

We have calculated the population effects of OWF avoidance on 5 seabird species in the North Sea. To our knowledge, this is the first study which calculates effects on the full life cycle and the larger population. Most studies of this effect focus on the reproductive success of a single breeding colony. The framework we use for these calculations relies on established methodological components, but the combination of components to scale up from local OWF-related habitat loss to effects on populations is novel. We find, generally, that effects of Dutch OWFs are small compared to those of the other countries surrounding the North Sea. The Dutch OWF plans up to 2030, which we used in our test scenario, have a comparatively small effect on the 30-year (the expected lifetime of an OWF) population development of these five seabirds. While our current analysis has taken into account uncertainty in the population-level parameter values, we have only used the average predicted values from the habitat models. Using higher habitat qualities for the areas where certain OWFs are added may lead to larger population effects of those OWFs³.

We expect that our results for red-throated divers and sandwich terns will also hold for other strongly coastal species: the Dutch OWFs simply have no effect because they are too far offshore. We also expect our results for northern gannets, common guillemots and razorbills to hold for similar colony-breeding birds which have their breeding grounds well outside the Netherlands: the total international North Sea OWF plans will have a measurable (but limited) effect on the populations, but the contribution of the Dutch OWFs to this effect will be negligible, because they form a very small part of the population distribution. If additional locations for OWFs elsewhere on the Dutch Continental Shelf would be appointed, novel calculations of the Dutch contribution to population effects would have to be conducted. The assessment framework developed in this study is readily available to conduct such further analyses.

4.4.1 Recommendations for improved future assessment quality

Improving habitat modelling

For sandwich terns, because they are so strongly coastal, the MWTL sampling program is sufficient in space. However, an extension in time to better cover the breeding- and postbreeding seasons would strongly strengthen the knowledge base for assessment of OWF (and other anthropogenic) effects.

Red-throated divers are difficult to count because they are so easily disturbed. One potential improvement to data collection for this species may be the use of high definition cameras from planes flying at high altitude.

We are confident that the coverage of the Dutch part of the North Sea has been good and that all existing data, brought together in the MWTL and ESAS databases, were available for this study. Unfortunately, this was not the case for other parts of the North Sea, and the habitat model quality for gannets, razorbills and guillemots has suffered as a result. Maintaining the ESAS database has proved difficult in the last ten years or so, and not all survey data collected in these years has been forwarded to ESAS, and incorporated in the database. In addition, new parties have emerged that have been collecting seabirds at sea data and these have not all become ESAS partners. That survey data are missing from the ESAS database is evident if analysis results made in different countries are compared (see e.g., Evans 2018; Mendel et al. 2019). Moreover, much of the national survey effort, including in The Netherlands, has been directed solely towards national waters and more widely ranging, international surveys have become increasingly rare. For future, international studies of seabird distribution patterns in the North Sea, a revitalization of ESAS is thus urgently needed as is new,

³ This work will be part of an update to this report, to be finished by the end of Q1, 2019.

international survey effort that covers the entire North Sea, rather than just national waters. These two might go hand in hand, and new, jointly undertaken survey work may entice parties to update ESAS. Within ESAS, suggestions have been made to ask ICES to host the (new) ESAS database and to work towards international cooperation with the fisheries institutes around the North Sea, by working towards a coupling between fisheries surveys and seabird surveys. A backing up from the governments of the North Sea countries, e.g., via the ICES delegates could be a great help here.

Improving population modelling

An important source of uncertainty in the population modelling is that it is hard to disentangle mortality and migration. A good understanding of the metapopulation dynamics between colonies would greatly help. This would allow for a refinement of the mortality parameters as we gain better understanding of how to offset them with immigration and emigration.

4.4.2 Additional planned analysis for first quarter of 2019

4.4.2.1 Habitat models

- use the uncertainty in the habitat model to follow precautionary principles (95% credible interval)
- Improve the habitat modelling for diver and sandwich terns, so that we focus on DCF area only
- Explore effects of (and methods to deal with) the unbalanced nature of the MWTL and ESAS data

4.4.2.2 Individual based models

- Test of the sensitivity of the method to loss of good foraging areas by stepwise exclusion of the best foraging areas (e.g. 5%, 10%, 15%)
- re-evaluate our choice to not use density dependence as a result of habitat loss in the simulation model (More discussion on relevance of the assumption and if needed a sensitivity analysis to decide if it matters with the current OWF plans).
- Conduct intensive testing to verify correctness of results produced

4.4.2.3 Population models

- Calculate population level effects of IBM mortality estimates
- Adjust 10% mortality rule to the number of months that we consider in the IBMs (length of season) – use 10% mortality on an annual basis
- Make OWF exposure scenarios age-specific for the sandwich tern and perhaps also other species.
- Make overview of evidence regarding density dependence in our study species
- Adjust the implementation of the floater stage, the estimated numbers include subadults that we have already excluded from reproduction through an age of recruitment to the reproducing pool.

4.4.2.4 Discussion and conclusions

- More complete explanation of the habitat model output: what covariates explain the high/low density

5 Quality Assurance

Wageningen Marine Research utilises an ISO 9001:2015 certified quality management system (certificate number: 187378-2015-AQ-NLD-RvA). This certificate is valid until 15 December 2018. The organisation has been certified since 27 February 2001. The certification was issued by DNV Certification B.V.

References

- Anderson, H. B., P. G. H. Evans, J. M. Potts, M. P. Harris and S. Wanless (2014). "The diet of Common Guillemot *Uria aalge* chicks provides evidence of changing prey communities in the North Sea." *Ibis* **156**(1): 23-34.
- BirdLife International (2015a). Supplementary material *Alca Torda* (Razorbill). European Red List of Birds. Luxembourg, Office for Official Publications of the European Communities.
- BirdLife International (2015b). Supplementary material *Gavia stellata* (Red-throated loon). European Red List of Birds. Luxembourg, Office for Official Publications of the European Communities.
- BirdLife International (2015c). Supplementary material *Morus basannus* (Northern gannet). European Red List of Birds. Luxembourg, Office for Official Publications of the European Communities.
- BirdLife International (2015d). Supplementary material *Thalasseus sandvicensis* (Sandwich tern). European Red List of Birds. Luxembourg, Office for Official Publications of the European Communities.
- BirdLife International (2015e). Supplementary material *Uria aalge* (Common Murre). European Red List of Birds. Luxembourg, Office for Official Publications of the European Communities.
- Bolton, M., G. Conolly, M. Carroll, E. D. Wakefield and R. Caldow (2018). "A review of the occurrence of inter-colony segregation of seabird foraging areas and the implications for marine environmental impact assessment." *Ibis* **in press**
- Buckland, S. T., D. R. Anderson, K. P. Burnham and J. L. Laake (1993). DISTANCE Sampling: Estimating abundance of biological populations, Chapman & Hall, London, reprinted 1999 by RUWPA, University of St. Andrews, Scotland.
- Buckland, S. T. and B. J. Turnock (1992). "A robust line transect method." *Biometrics* **48**: 901-909.
- Camphuysen, C. J. (2004). "The return of the harbour porpoise (*Phocoena phocoena*) in Dutch coastal waters." *Lutra* **47**: 135-144.
- Caswell, H. (2001). Matrix population models. Sunderland, Sinauer Associates, Inc.
- Cook, A. S. C. P. and R. A. Robinson (2016). Testing sensitivity of metrics of seabird population response to offshore wind farm effects. JNCC Report **553**.
- Crespin, L., M. P. Harris, J. D. LEBRETON, M. Frederiksen and S. Wanless (2006). "Recruitment to a seabird population depends on environmental factors and on population size." *Journal of Animal Ecology* **75**(1): 228-238.
- Crouse, D. T., L. B. Crowder and H. Caswell (1987). "A Stage-Based Population Model for Loggerhead Sea Turtles and Implications for Conservation." **68**(5): 1412-1423.
- Dierschke, V., R. W. Furness and S. Garthe (2016). "Seabirds and offshore wind farms in European waters: Avoidance and attraction." *Biological Conservation* **202**: 59-68.
- Dierschke, V., R. W. Furness, C. E. Gray, I. K. Petersen, J. Schmutz, R. Zydalis and F. Daunt (2017). Possible Behavioural, Energetic and Demographic Effects of Displacement of Red-throated Divers. **605**.
- Evans P., Waggitt J. & Hiddink J. 2018. Mapping cetacean distributions in NW European Seas. Presentation given at ASCOBANS AC 2018.
https://www.ascobans.org/sites/default/files/document/2.4.1%20Mapping%20cetacean%20distributions_Evans.pdf

- Fauchald, P., T. Anker-Nilssen, R. T. Barrett, J. O. Bustnes, B.-J. Bårdsen, S. Christensen-Dalsgaard, S. Descamps, S. Engen, K. E. Erikstad and S. A. Hanssen (2015). "The status and trends of seabirds breeding in Norway and Svalbard."
- Fijn, R. C., J. de Jong, W. Courtens, H. Verstraete, E. W. M. Stienen and M. J. M. Poot (2017). "GPS-tracking and colony observations reveal variation in offshore habitat use and foraging ecology of breeding Sandwich Terns." Journal of Sea Research **127**: 203-211.
- Frederiksen, M., R. W. Furness and S. Wanless (2007). "Regional variation in the role of bottom-up and top-down processes in controlling sandeel abundance in the North Sea." Marine Ecology Progress Series **337**: 279-286.
- Harris, M. and S. Wanless (1995). "Survival and non-breeding of adult Common Guillemots *Uria aalge*." Ibis **137**(2): 192-197.
- Harris, M. P., M. Heubeck, M. A. Newell and S. Wanless (2015). "The need for year-specific correction factors (k values) when converting counts of individual Common Guillemots *Uria aalge* to breeding pairs." Bird Study **62**(2): 276-279.
- Harris, M. P., M. A. Newell and S. Wanless (2015). "The use of k values to convert counts of individual Razorbills *Alca torda* to breeding pairs." Seabird **28**: 30-36.
- Hemmingsson, E. and M. O. G. Eriksson (2002). "Ringing of red-throated diver *Gavia stellata* and black-throated diver *Gavia arctica* in Sweden." Newsletter Diver/Loon Specialist Group, Wetlands International **4**: 8-13.
- Horswill, C. and R. A. Robinson (2015). Review of Seabird Demographic Rates and Density Dependence. Peterborough, UK.
- Lavers, J. L., I. L. Jones, A. W. Diamond and G. J. Robertson (2008). "Annual survival of North American Razorbills (*Alca torda*) varies with ocean climate indices." Canadian Journal of Zoology **86**(1): 51-61.
- Leopold, M. F., M. Boonman, M. P. Collier, N. Davaasuren, R. C. Fijn, A. Gyimesi, J. de Jong, R. H. Jongbloed, B. Jonge Poerink, J. C. Kleyheeg-Hartman, K. L. Krijgsveld, S. Lagerveld, R. Lensink, M. J. M. Poot, v. d. W. J.T and M. Scholl (2014). A first approach to deal with cumulative effects on birds and bats of offshore wind farms and other human activities in the Southern North Sea.
- Lindgren, F., H. Rue and L. J. (2011). "An explicit link between Gaussian fields and Gaussian Markov random fields: The SPDE approach (with discussion)." Journal of the Royal Statistical Society, Series B **73**: 423-498.
- Mendel B., Schwemmer P., Peschko V., Müller S., Schwemmer H., Mercker M. & Garthe S. 2019. Operational offshore wind farms and associated ship traffic cause profound changes in distribution patterns of Loons (*Gavia* spp.). Journal of Environmental Management **231**: 429-438.
- Mitchell, P. I., S. F. Newton, N. Ratcliffe and T. E. Dunn (2004). Seabird populations of Britain and Ireland. London, T. & AD Poyser.
- Murray, S., M. Harris and S. Wanless (2015). "The status of the gannet in Scotland in 2013-14." Scottish Birds **35**(1): 3-18.
- Poot, M. J., P. W. v. W. V. Horssen, M. P. Collier, R. Lensink and S. Dirksen (2011). Effect studies offshore wind Egmond aan Zee: cumulative effects on seabirds: 220-220.
- R Core Team (2014). "R: A language and environment for statistical computing, version 3.1.1 (2014-07-10). R Foundation for Statistical Computing, Vienna, Austria. URL <http://www.R-project.org>."
- Robinson, R. A. (2005). "BirdFacts: profiles of birds occurring in Britain & Ireland." BTO Research Report 407 Retrieved November, 2018, from <https://www.bto.org/about-birds/birdfacts>.
- Rue, H., S. Martino and N. Chopin (2009). "Approximate Bayesian inference for latent Gaussian models using integrated nested Laplace approximations (with discussion)." Journal of the Royal Statistical Society, Series B **71**: 319-392.

RWS (2016). "Kader Ecologie en Cumulatie t.b.v. uitrol windenergie op zee". Rijkswaterstaat.

Schmutz, J. A. (2014). "Survival of adult Red-throated Loons (*Gavia stellata*) may be linked to marine conditions." Waterbirds **37**(Special Publication 1): 118-124.

Schwemmer, P., B. Mendel, N. Sonntag, V. Dierschke and S. Garthe (2011). "Effects of ship traffic on seabirds in offshore waters: implications for marine conservation and spatial planning." Ecological Applications **21**(5): 1851-1860.

SEAPOP. "SEATRACK Seabird tracking." Retrieved November, 2018, from <http://seatrack.seapop.no/map/>.

Skov, H., J. Durinck, M. F. Leopold and M. L. Tasker (2007). "A quantitative method for evaluating the importance of marine areas for conservation of birds." Biological Conservation **136**(3): 362-371.

Van Bemmelen, R. S. A., S. C. V. Geelhoed and M. F. Leopold (2011). Shortlist Masterplan Wind Ship-based monitoring of seabirds and cetaceans. IMARES (Report / IMARES Wageningen UR C099/11) - 90.

Van der Jeugd, H., B. J. Ens, M. Versluijs and H. Schekkerman (2014). Geïntegreerde monitoring van vogels van de Nederlandse waddenzee: 208-208.

Van der Meer, J. and C. J. Camphuysen (1996). "Effect of observer differences on abundance estimates of seabirds from ship-based strip transect surveys." Ibis **138**(3): 433-437.

Van der Wal et al. 2018 in prep.

Veen, J. (1977). "Functional and Causal Aspects of Nest Distribution in Colonies of the Sandwich Tern (*Sterna s. sandvicensis* Lath.)." Behaviour Suppl. **XX**(20): 1-193.

Votier, S. C., T. R. Birkhead, D. Oro, M. Trinder, M. Grantham, J. A. Clark, R. H. McCleery and B. J. Hatchwell (2008). "Recruitment and survival of immature seabirds in relation to oil spills and climate variability." Journal of Animal Ecology **77**(5): 974-983.

Wakefield, E. D., T. W. Bodey, S. Bearhop, J. Blackburn, K. Colhoun, R. Davies, R. G. Dwyer, J. A. Green, D. Gremillet, A. L. Jackson, M. J. Jessopp, A. Kane, R. H. W. Langston, A. Lescroel, S. Murray, M. Le Nuz, S. C. Patrick, C. Peron, L. M. Soanes, S. Wanless, S. C. Votier and K. C. Hamer (2013). "Space Partitioning Without Territoriality in Gannets." Science **341**(6141): 68-70.

Wanless, S., M. Frederiksen, M. P. Harris and S. N. Freeman (2006). "Survival of Gannets *Morus bassanus* in Britain and Ireland, 1959-2002." Bird Study **53**(1): 79-85.

Zuur, A. F., E. N. Ieno and A. A. Saveliev (2017). Spatial, Temporal and Spatial-Temporal Ecological Data Analysis with R-INLA. Highland Statistics Ltd.

Justification

Report C088/18

Project Number: 4315100085

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. Geert Aarts
Scientist



Signature:

Date: 30 November 2018

Approved: Dr. Joep de Leeuw
Senior scientist



Signature:

Date: 30 November 2018

Approved: Drs. J. Asjes,
Manager integration

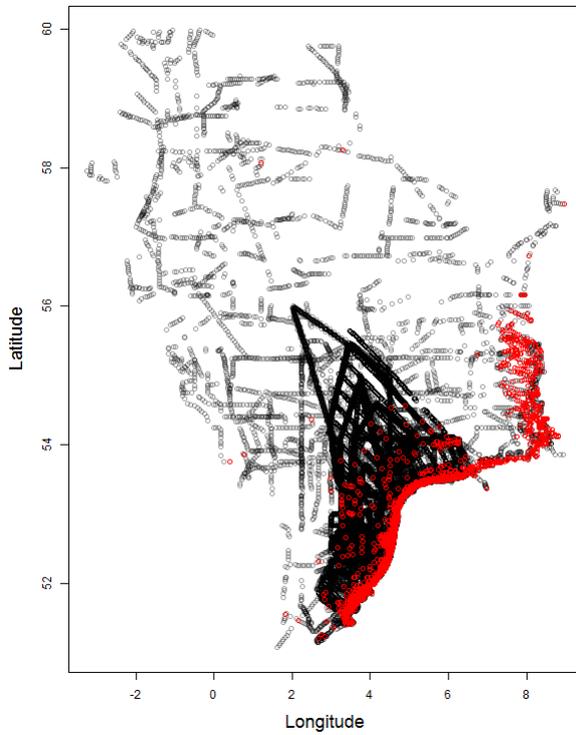


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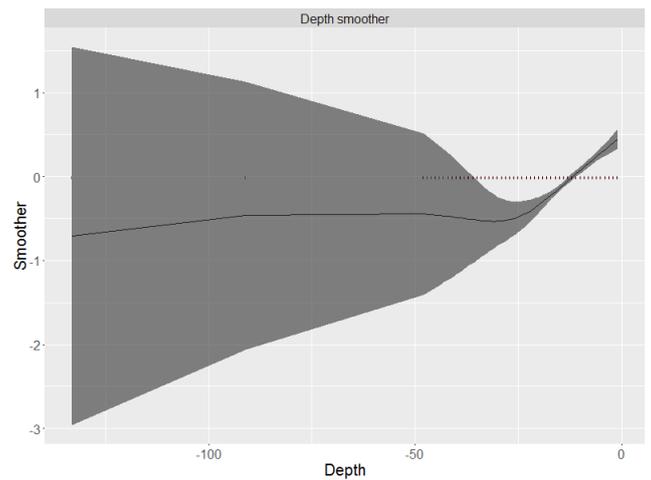
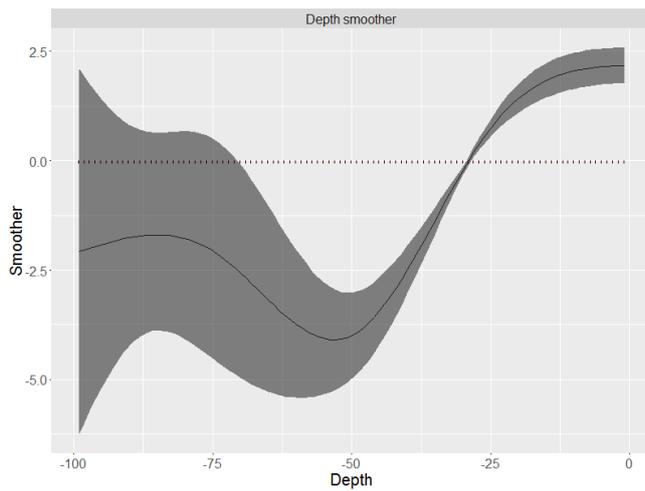
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1 Annex: Details on habitat modelling

red-throated diver

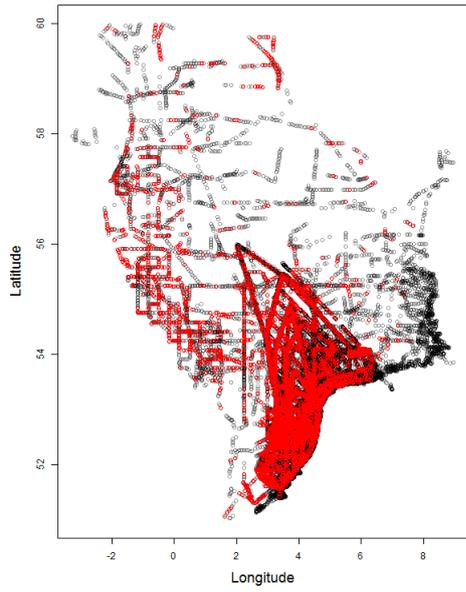


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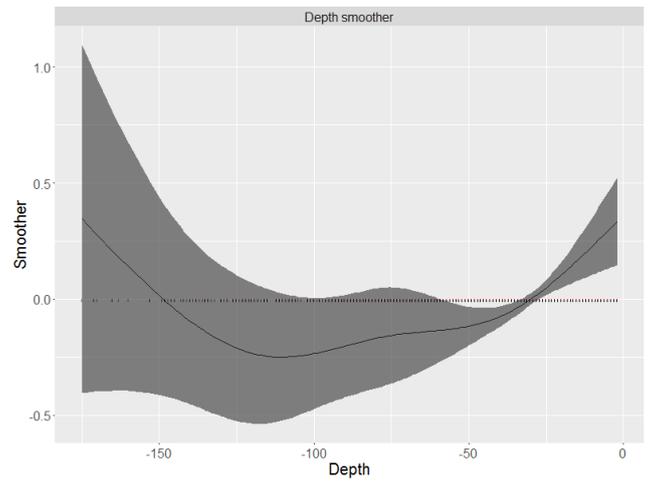
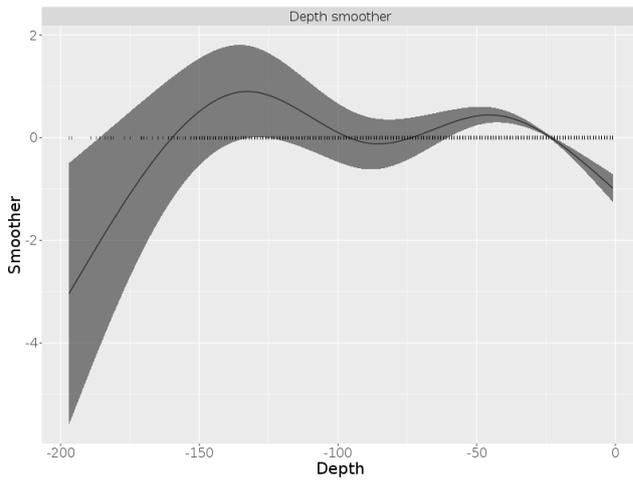


Relationship between presence of red-throated diver and depth (left, model 1) and between density and depth (right, model 2)

northern gannet non-breeding

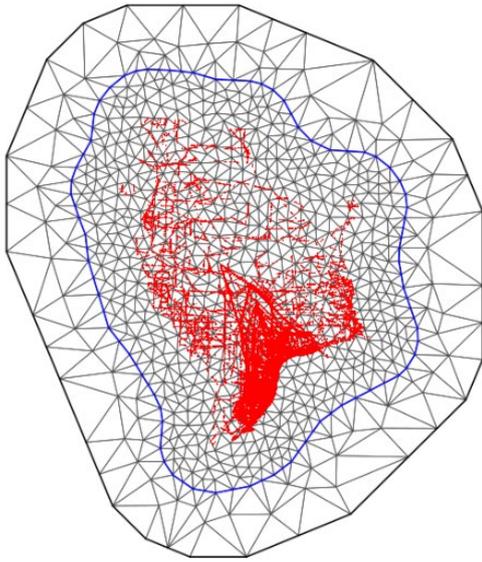


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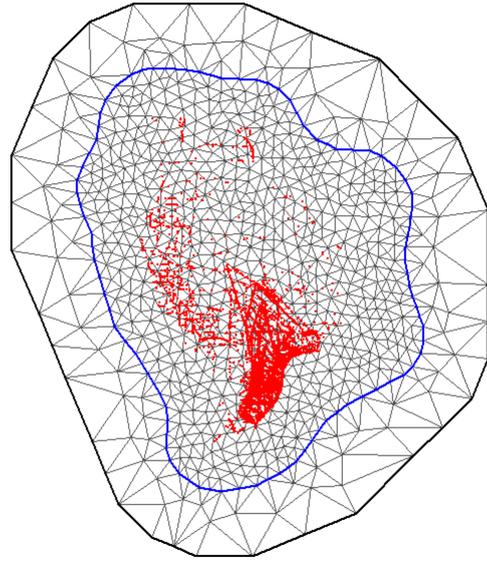


Relationship between presence of northern gannet in the non-breeding period and depth (left, model 1) and between density and depth (right, model 2)

Constrained refined Delaunay triangulation

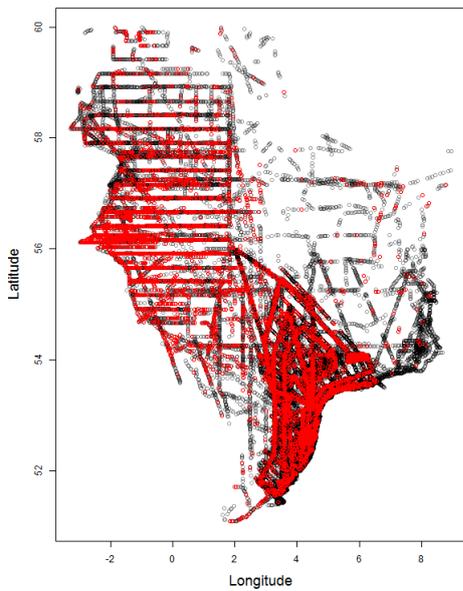


Constrained refined Delaunay triangulation

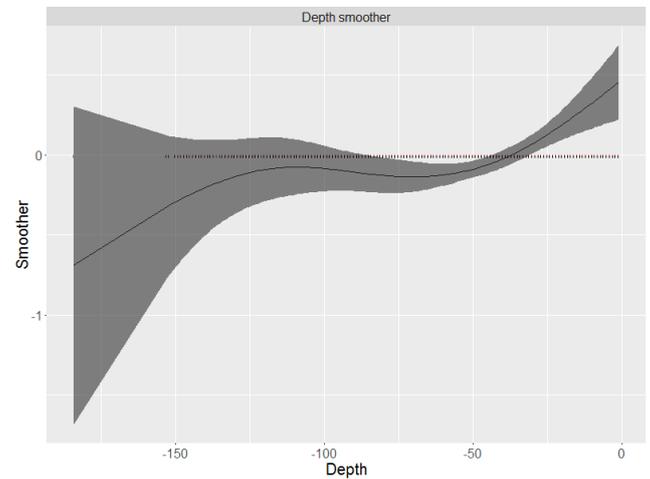
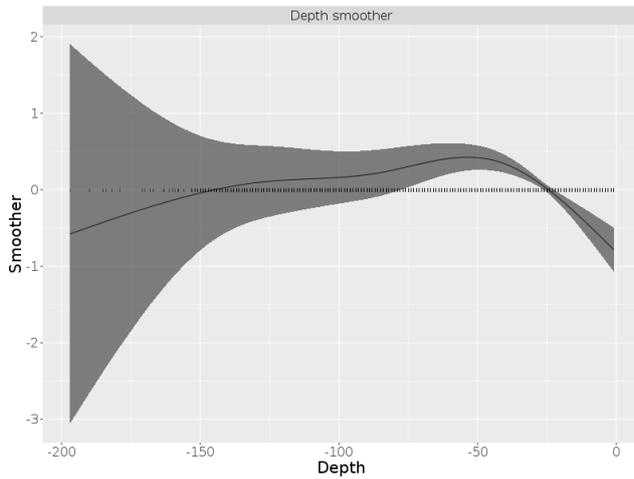


Mesh and sampling points for model 1 (left) and model 2(right, only non-zero observations)

northern gannet breeding

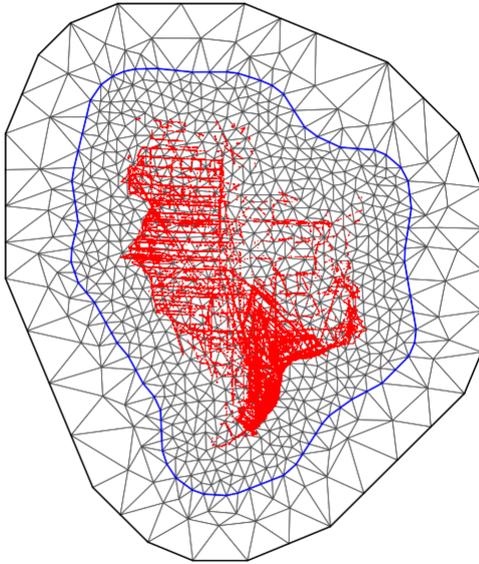


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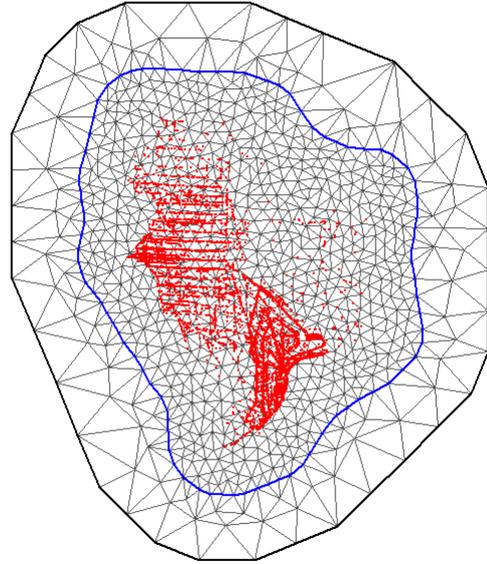


Relationship between presence of northern gannet in the breeding period and depth (left, model 1) and between density and depth (right, model 2)

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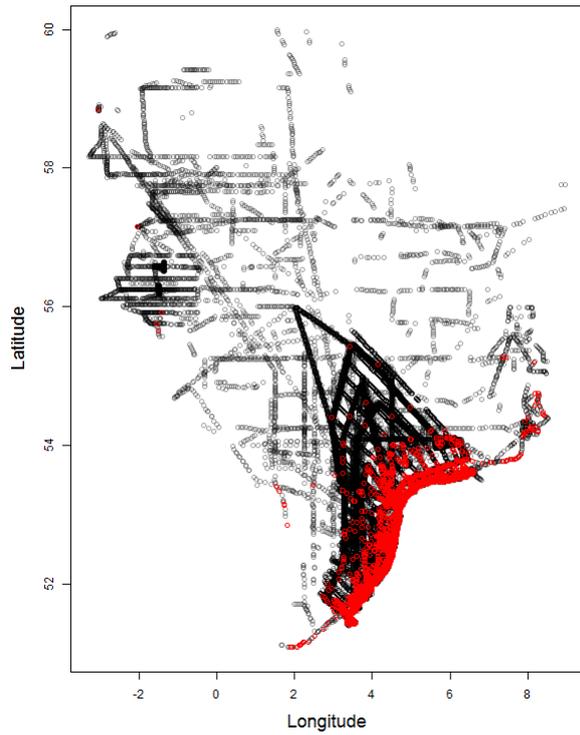


Constrained refined Delaunay triangulation

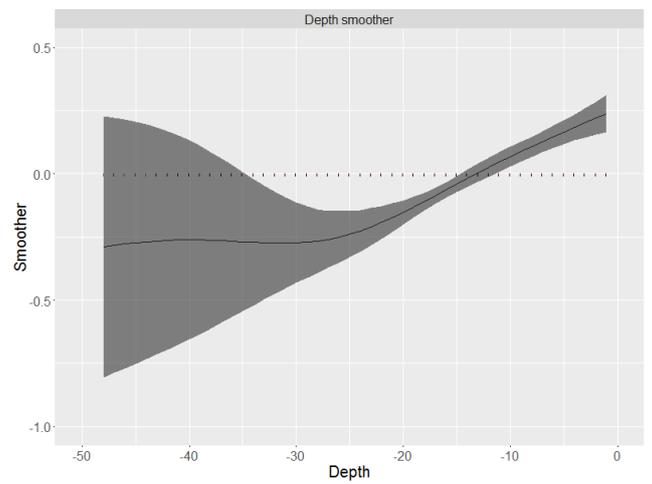
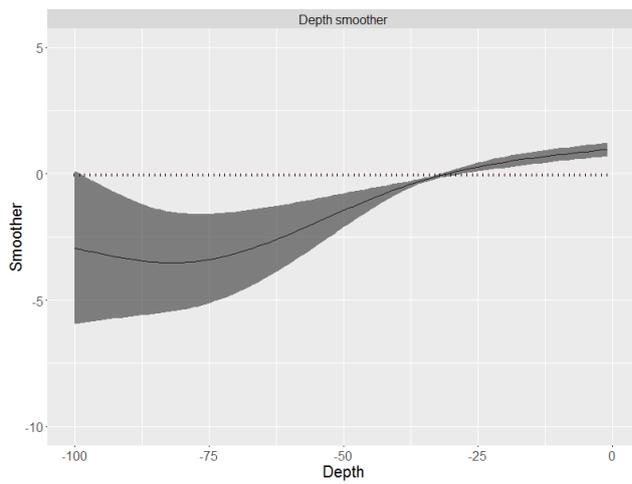


Mesh and sampling points for model 1 (left) and model 2(right, only non-zero observations))

sandwich tern

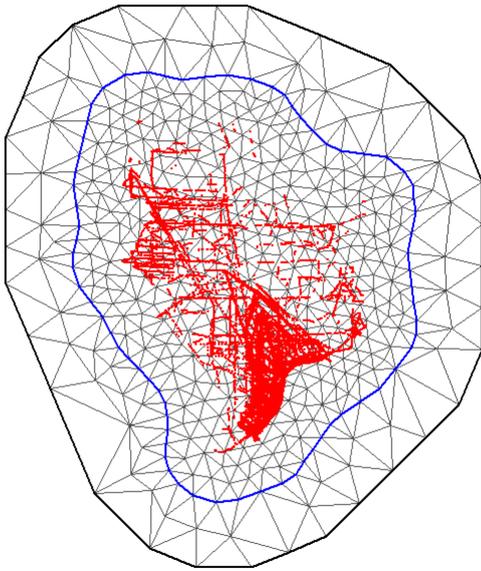


Presence (red) and absence (black)

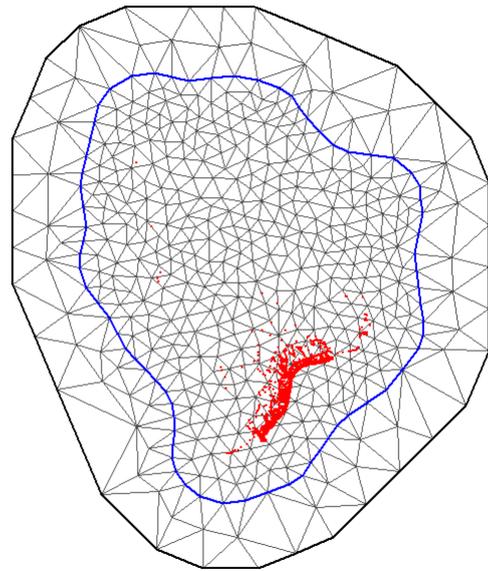


Relationship between presence of sandwich tern and depth (left, model 1) and between density and depth (right, model 2)

Constrained refined Delaunay triangulation

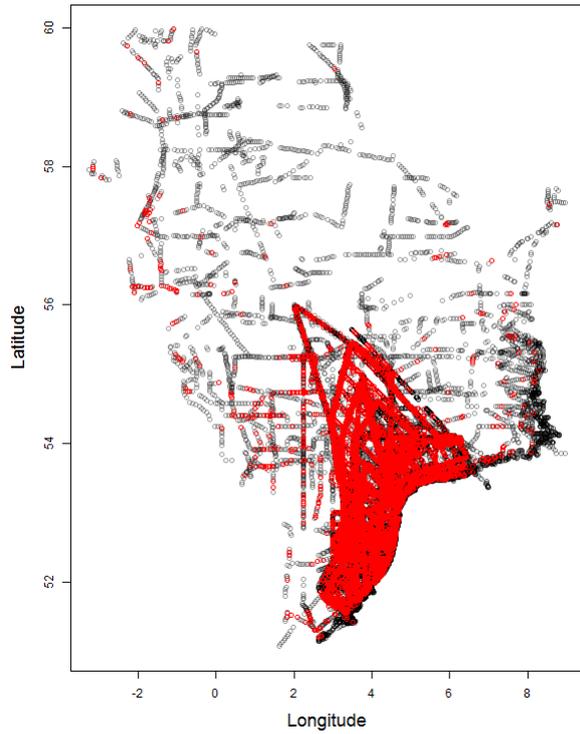


Constrained refined Delaunay triangulation

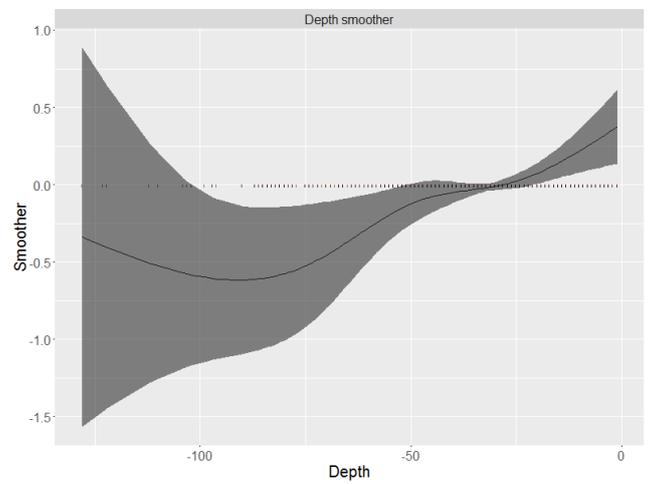
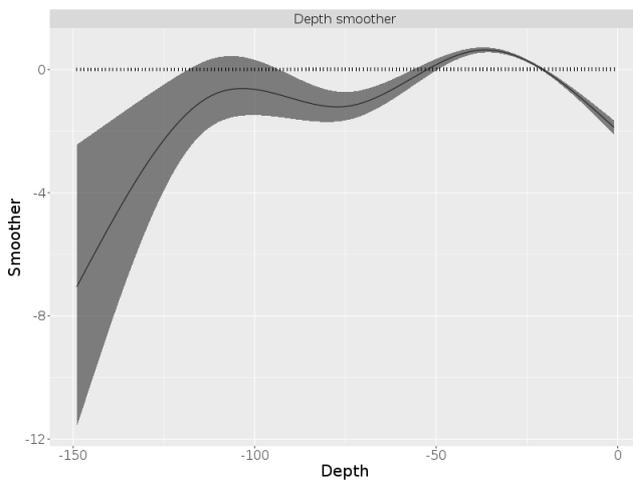


Mesh and sampling points for model 1 (left) and model 2(right, only non-zero observations)

Razorbill

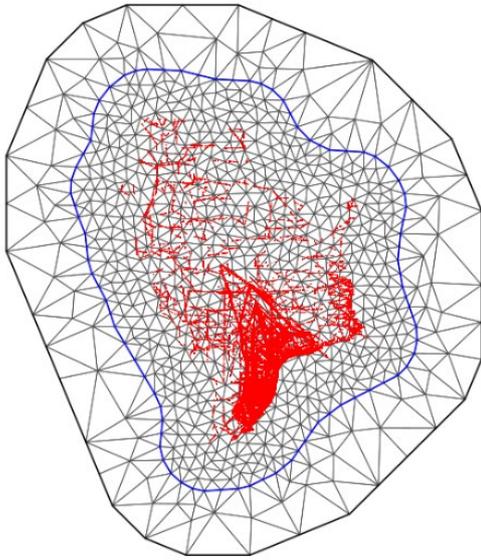


Presence (red) and absence (black)

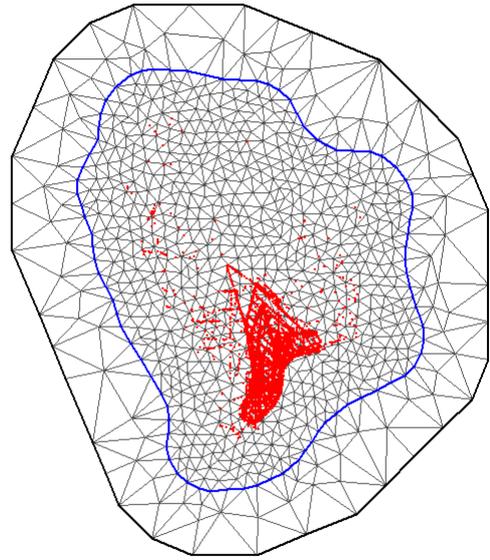


Relationship between presence of razorbill and depth (left, model 1) and between density and depth (right, model 2).

Constrained refined Delaunay triangulation



Constrained refined Delaunay triangulation



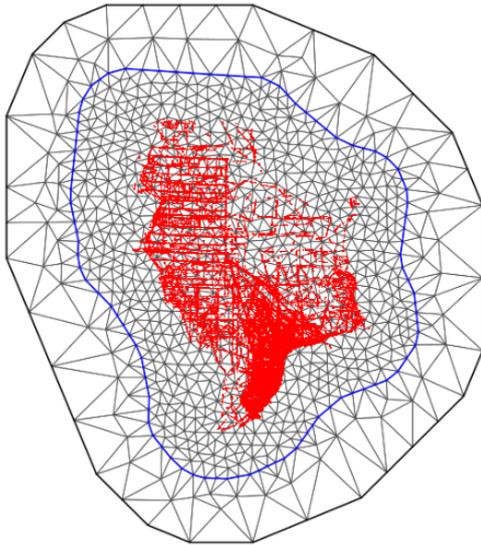
Mesh and sampling points for model 1 (left) and model 2 (right, only non-zero observations)

common guillemot

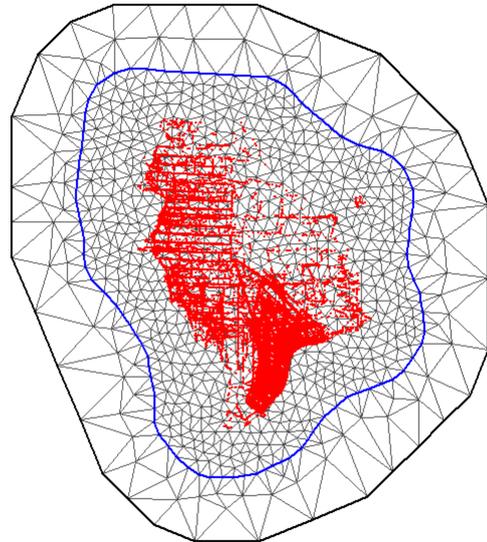
Presence (red) and absence (black)

Relationship between presence of common guillemot and depth (left, model 1) and between density and depth (right, model 2)

Constrained refined Delaunay triangulation



Constrained refined Delaunay triangulation



Mesh and sampling points for model 1 (left) and model 2(right, only non-zero observations)

2 Annex: Implementation methods for analysis parameter uncertainty

A. Potiek, F.H. Soudijn & T. van Kooten

2.1 Introduction

Parameter estimates are usually reported with a measure of variance, often in the form of a standard deviation. Variability in parameter values may stem from measurement error and/or natural variability in parameter values. Measurement error is an inherent part of any measurement and the measurement process. For example, if the measured adult survival rate is 90%, it is possible that the 'true' survival is actually 91%. A large measurement error indicates that the estimate is relatively uncertain. Natural variability in parameter values is caused by fluctuations in environmental conditions such as food availability and the weather. In a year with favourable environmental conditions, survival and fecundity are likely to be higher than in other years. It is often not possible to separate the causes for variability in the parameter values. However, the impact of the two on the outcome of a population model may strongly differ.

Here, we study to what extent the source of parameter uncertainty (measurement error or natural variability) matters for the outcome of our main study, the effect of OWF-related displacement on the population dynamics of seabirds.

In theory, if all variance is explained by measurement error, the demographic rate is (slightly) under- or overestimated every single year in the population model. Hence, the effect adds up over time. In contrast, variation between years results in some years with above-average parameter values, and some years with below-average parameter values. Over time, the average will move towards the estimated value. Several demographic rates vary between years. In our population models, input parameters are juvenile survival, immature survival, adult survival, fecundity and probability of non-breeding. These demographic rates may vary independently, or the variation may be correlated. Such correlations would occur if natural variability was caused by 'good' and 'bad' years, in which all parameters would be positively or negatively affected. In addition to the source of the variation, we study the effect of correlated variability in parameter values.

This is essentially an analysis of model assumptions. The effect of the various assumptions will be qualitatively similar for any of our studied species. Therefore, we do the analysis only for the common guillemot, for which we have the best data on variance of parameter values. The results can, in a qualitative sense, be extrapolated to the other species.

These results will allow us to choose the most appropriate way to incorporate parameter value uncertainty in our main analysis. An important guiding principle in this choice will be the precautionary principle. If one assumption will lead to larger effects of OWFs and we have no data to choose between the different possibilities, the precautionary principle requires us to choose the most conservative method.

2.2 Aim

This report covers four different subprojects:

- Measurement error
 1. Test the impact of measurement error on the uncertainty of the outcomes of the population model.
- Natural variability

2. Test the effect of stochastic fluctuations in the parameter values through time on the uncertainty of the outcomes of the population model. In contrast to the analysis on the impact of measurement error (1), the parameter values are here (2) assumed to vary between years.
 3. Test the effect of within-year correlations between values of the parameters (survival and fecundity) on the uncertainty of the outcomes of the population model. In subproject 2, we assumed that demographic rates varied independently, whereas in subproject 3 we run the model for different strengths of correlations.
- Empirical natural variability: evidence for correlated demographic rates
 - 4. Analyse multi-annual parameter datasets of some of our model species (WOZEP habitat loss and collision victims) to determine how parameter values naturally vary through time and to what extent demographic rates are correlated.

2.3 Methods

We study the effect of the source of measurement error (subprojects 1-3) using the population model of the common guillemot. The model details are described in the main section of this report.

2.3.1 Measurement error

2.3.1.1 Subproject 1

The uncertainty in the model output due to measurement error can be estimated using Monte Carlo methods. This method implies random sampling from the probability distributions of all parameter estimates. For subproject 1, we follow the assumption that the deviation from the mean in parameter values is independent for each parameter. In addition, this method assumes that the uncertainty stems from inaccurate measurements of parameter values rather than from temporal changes. Hence, parameter values do not vary in time. The choice for the probability distributions of the parameter estimates depends on the availability of the data for the species that is under study. If very little data are available for a certain species, the range from which a parameter value is drawn will be wider than when good data are available.

We calculate all model output (e.g. population growth rates, sensitivity analysis and population sizes) for a large number of random draws from the parameter probability distributions. Based on the results of these simulations we determine confidence intervals around the model output.

2.3.2 Natural variability

2.3.2.1 Subproject 2

A stochastic matrix model allows for variability of the parameter values through time. At each time step, parameter values are drawn randomly from a probability distribution of the parameter values. The shape of the probability distributions is based on the information that is available for the species under study. Using this method, we run 10,000 simulations, in which demographic rates are independently, randomly drawn from the probability distribution. Based on the results of the simulations we determine confidence intervals around the model output.

2.3.2.2 Subproject 3

We also investigate the effect of covariance between the parameter values on the model outcome. If the correlation between survival and reproduction is strong, this means that a good year for survival is also a good year for reproduction. In contrast, if they are uncorrelated, survival and fecundity vary independently. To analyse the impact of such a correlation, we use a similar approach as described for subproject 2. However, we define an additional parameter C , which is the degree of correlation between demographic rates. This parameter C varies between 0 and 1, corresponding to uncorrelated to completely correlated demographic rates.

2.3.3 Empirical natural variability: correlation in measured parameters

2.3.3.1 Subproject 4

Using datasets of life history parameters that consist of multiple years of data from the same colony, we analyse the effect of “natural” environmental stochasticity on the model output. The previous step in the analysis will help us understand how correlated parameter values may affect the model outcomes. A dataset with “natural” environmental stochasticity shows us how strong the correlation between parameter values and also the frequency of “good” and “bad” years is in reality. The previous step in the analysis is needed because there is not a lot of multi-year data of life history parameters available. As the level of correlation between parameter values varies between species, we perform this analysis for several species. However, this analysis requires high-quality and long-term data, the availability of which will be limited.

We searched the literature for papers reporting survival rates as well as fecundity. An overview of the available data is shown in Table 1. Correlations between demographic rates in the same year were tested on significance, as well as delayed effects of survival in the previous year on breeding success in the present year.

Table 3.1 Overview of data used for testing correlations

In addition to the data found in published literature, more recent data from Isle of May was collated based on annual newsletters from the CEH long-term monitoring programme, in which among others guillemot, kittiwake, puffin and razorbill are monitored ([https://www.ceh.ac.uk/our-](https://www.ceh.ac.uk/our-science/projects/isle-may-long-term-study)

Source	Species	Parameters	Area	Time period
Meade <i>et al.</i> (2013)	Guillemot	immature survival, adult survival, breeding success	Skomer (UK)	1992-2004
Crespin <i>et al.</i> (2006a, b)	Guillemot	immature survival, adult survival, breeding success	Isle of May (UK)	1983-1994
Ebbinge <i>et al.</i> (2002)	Brent goose	adult survival, breeding success (% juveniles in winter)	Western Europe (wintering area)	1956-1998
CEH monitoring programme	Guillemot, kittiwake, razorbill, puffin	return rate, breeding success	Isle of May (UK)	2007-2018

science/projects/isle-may-long-term-study). These newsletters report breeding success (fledglings per breeding pair) and return rates for adults. Return rates can be used as a proximate for annual survival. Although return rates underestimate annual survival, it can be assumed that this is the case for all years within the monitoring programme (2007-2018).

2.3.4 Input data population models, basis for subproject 1-3

2.3.5 Species: common guillemot

We assume that the data underlying all parameter values follow a binomial distribution. Therefore, uncertainty around a mean parameter value \bar{S}_a with variance $\sigma_{S_a}^2$ can be described by a beta distribution with $\alpha = \bar{S}_a^2 \left(\frac{1-\bar{S}_a}{\sigma_{S_a}^2} - \frac{1}{\bar{S}_a} \right)$, $\beta = (\alpha - \bar{S}_a \alpha) / \bar{S}_a$.

As we do not have the data and we do not know n_i , we simulate data based on the beta distributions as described above. We repeat this for all parameter values. The variance is taken as the standard deviation cubed. Note that although the used parameter distribution is the same for subprojects 1-3, the assumed source of variation differs. In the first subproject, we assume that the variation is due to measurement error. The parameter values are drawn at the start of a simulation, and used for each year within that simulation. For a new simulation, new parameter values are drawn. Hence, each simulation uses different demographic rates, which are constant over time. In the second subproject, demographic rates vary over time. Within each simulation, new values for each demographic rate are drawn every year. For the third subproject, the simulation starts with the definition of the degree of correlation. Subsequently, a parameter defining year quality is drawn. Depending on the degree of correlation, the effect of year quality on demographic rates can be strong (high degree of correlation) or weak (low degree of correlation).

Table 3.2: Parameter values and sources used in the population model

Symbol	Mean value	Variance	unit	Description	Remark	Source
F_a	0.627	0.147 (sd)	Year ⁻¹	Fledged offspring, age 5+		1
D	0.08	0.03 (sd)	-	Skipped breeding probability, all adult stages	No source for SD, the value is arbitrary	1
S_0	0.56	0.013	-	Annual Survival probability age 0		1
S_1	0.792	0.034	-	Annual Survival probability age 1		1
S_2	0.917	0.022	-	Annual Survival probability age 2		
S_a	0.939	0.067 (sd)	-	Annual Survival probability immatures & adults, age 3+		1
a_m	6		Years	Age at recruitment		1

¹Horswill & Robinson 2015

2.4 Results

For each of the scenarios, we show a frequency distribution of the population growth rates, calculated over 10,000 runs.

2.4.1 All variation due to measurement error

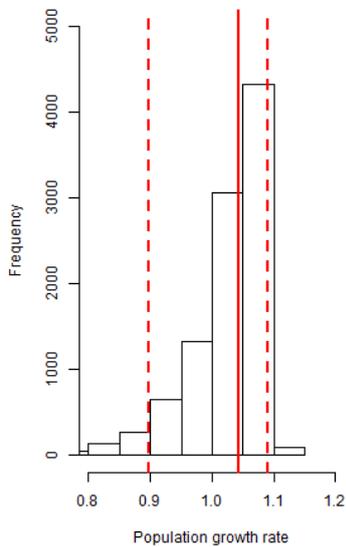


Figure 3.1 Population growth rates (with mean, red solid line and 5% and 95% edge of results, red dashed lines) and inner 90% of population projections (with mean of all projections, red solid line) for Monte Carlo simulations. Parameter values are as given in Table 2.

2.4.2 All variation due to natural variability

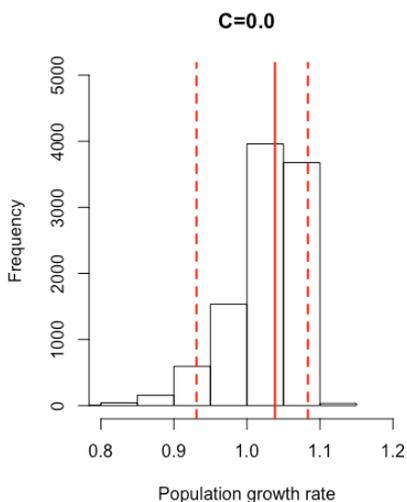


Figure 3.2 Frequency distribution of population growth rates assuming all variation is due to natural variability. Demographic rates within years are assumed to be independent (not correlated, $C=0$). Continuous line represents median population growth rate, and dashed lines the 90% confidence interval.

2.4.3 All variation due to natural variability; Impact of correlated demographic rates

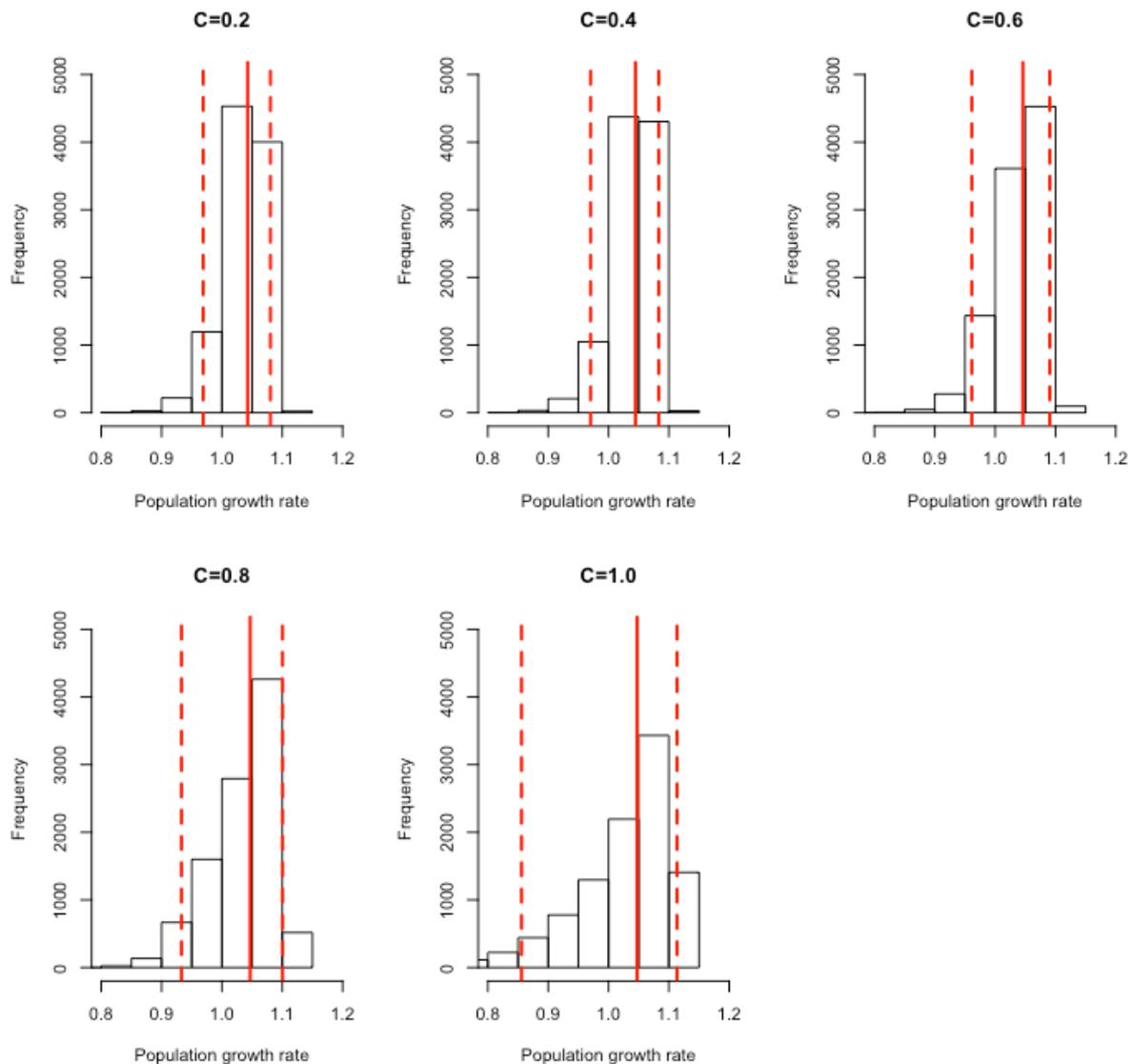


Figure 3.3 Frequency distribution of population growth rates with varying degree of correlation between parameters (Low C: weak correlation, C=1: fully correlated values). Continuous line represents median population growth rate, and dashed lines the 90% confidence interval.

2.4.4 Empirical natural variability: correlation in measured parameters

Demographic rates for guillemots reported by Meade et al. (2013) and Crespin et al. (2006a, b) were not significantly correlated.

For brent goose, we analysed data from Ebbinge et al. (2002) to test for correlations between demographic rates. In this study, breeding success in year i is defined as the percentage of first-winter birds in the following winter. We tested for correlations between breeding success and adult survival in the year prior to the breeding season, as well as to the year following the breeding season. We found no correlation between the breeding success and the adult survival in the following year. However, we found a significant negative correlation between adult survival prior to the breeding season and breeding success (Figure 3.4). This significant negative correlation suggests that a year with low adult survival is likely followed by high breeding success. This was contrasting with our expectation that individuals are in poorer body condition after a strong winter with high mortality, and therefore have lower breeding success. This has been interpreted as density-dependence in reproductive output (Ebbinge et al 2002), but might also be an artefact of the type of data collection. With both measures depending on the number of adults, a relatively low number of adults in a certain year suggests low adult survival compared to other years. In the calculation of breeding success, the number of first-

year individuals is divided by a relatively low number of adults. In case the number of first-years is comparable between years, this gives a relatively high proportion of first-years.

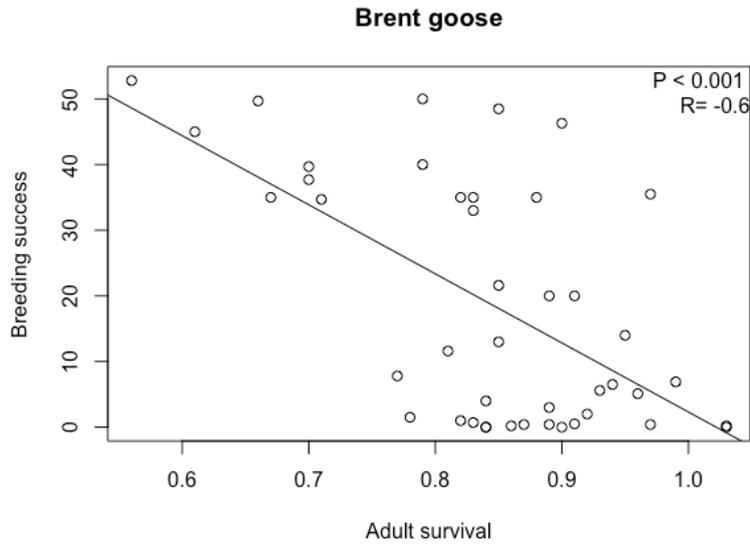


Figure 3.4 Relation between adult survival from year i to $i+1$ and breeding success in year $i+1$.

Data on the breeding success and return rates of guillemot, kittiwake, razorbill and puffin from the CEH long-term monitoring programme did not show significant correlations for kittiwake and razorbill. For both guillemot and puffin, there seems to be a significant positive relationship between breeding success and return rate in the year before as well as after the breeding season (Figure 3.5). However, the cause of these correlations is a single data point of extremely low breeding success. In all cases, the exclusion of this data point results in a non-significant correlation.

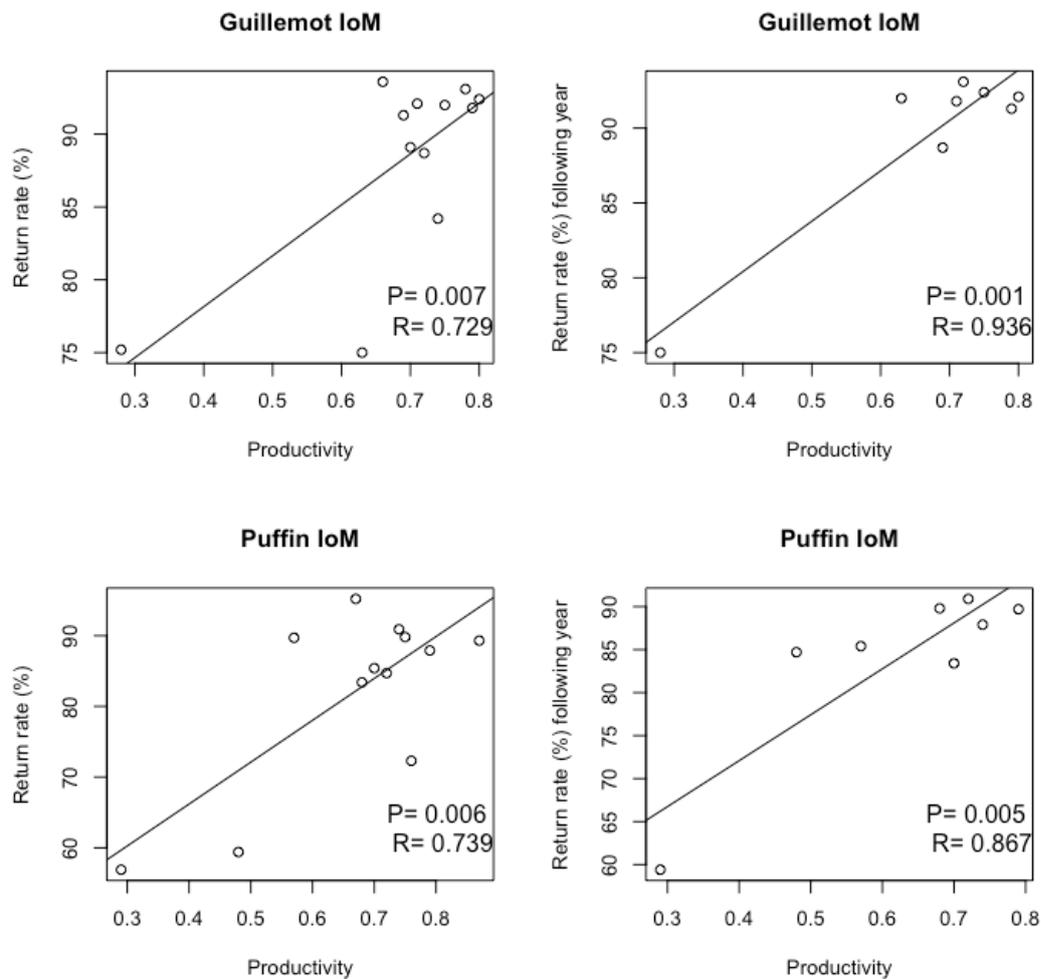


Figure 3.5 Correlations between breeding success and the return rate of the year prior to the breeding season (left panel), and between breeding success and the return rate of the year following the breeding season (right panel).

2.5 Conclusions

- Stochastic simulations with complete correlation give the widest variance in population growth rate distribution, but we see no support for such strong correlations in any of the data examined.
- Uncorrelated and weakly correlated temporal variation of parameter values leads to the narrowest population growth rate distributions
- Time-invariant measurement error (Monte Carlo approach) leads to higher variation in population growth rate distribution.
- There is no empirical basis to distinguish between temporal variations in parameter values and measurement error.
- Applying the precautionary approach leads us to choose the Monte Carlo approach, because it results in the highest uncertainty among assumptions with equal plausibility.
- Long-term studies and repeated measures of parameters are needed to empirically distinguish between the assumptions tested here.

3 Annex: sensitivity analysis population models

Red-throated diver

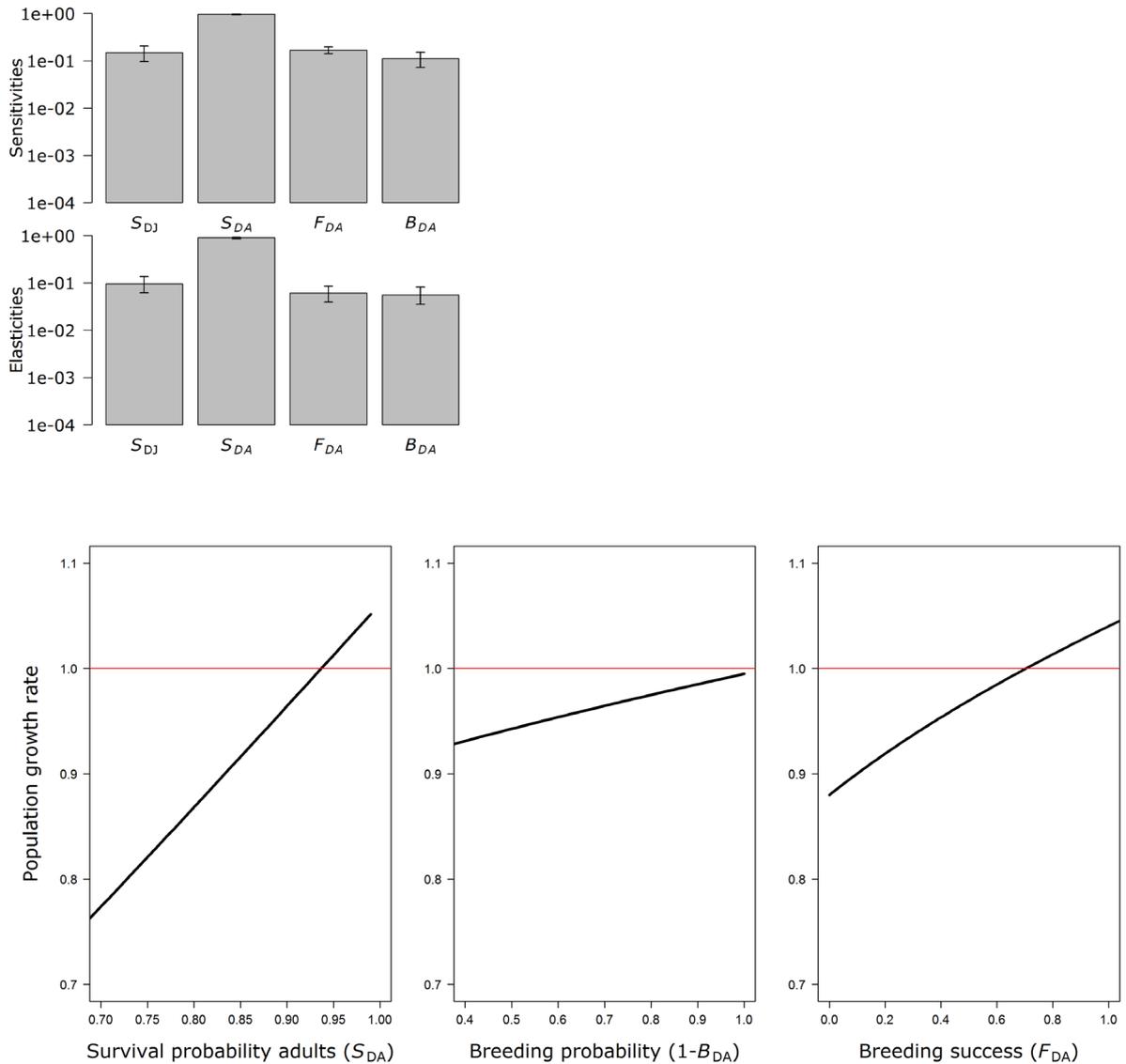


Figure 4.1 Diver perturbation analysis of (annual) population growth rate (without OWFs). Elasticities and sensitivities of population growth rate to individual parameters, error bars represent 5% and 95% percentile of the outcomes. Population growth rate as a function of the diver adult survival probability S_{DA} , the breeding probability B_{DA} and the breeding success F_{DA} , the red solid line indicates the boundary where a population increase switches to a decrease. Note the log axis for sensitivities and elasticities.

northern gannet

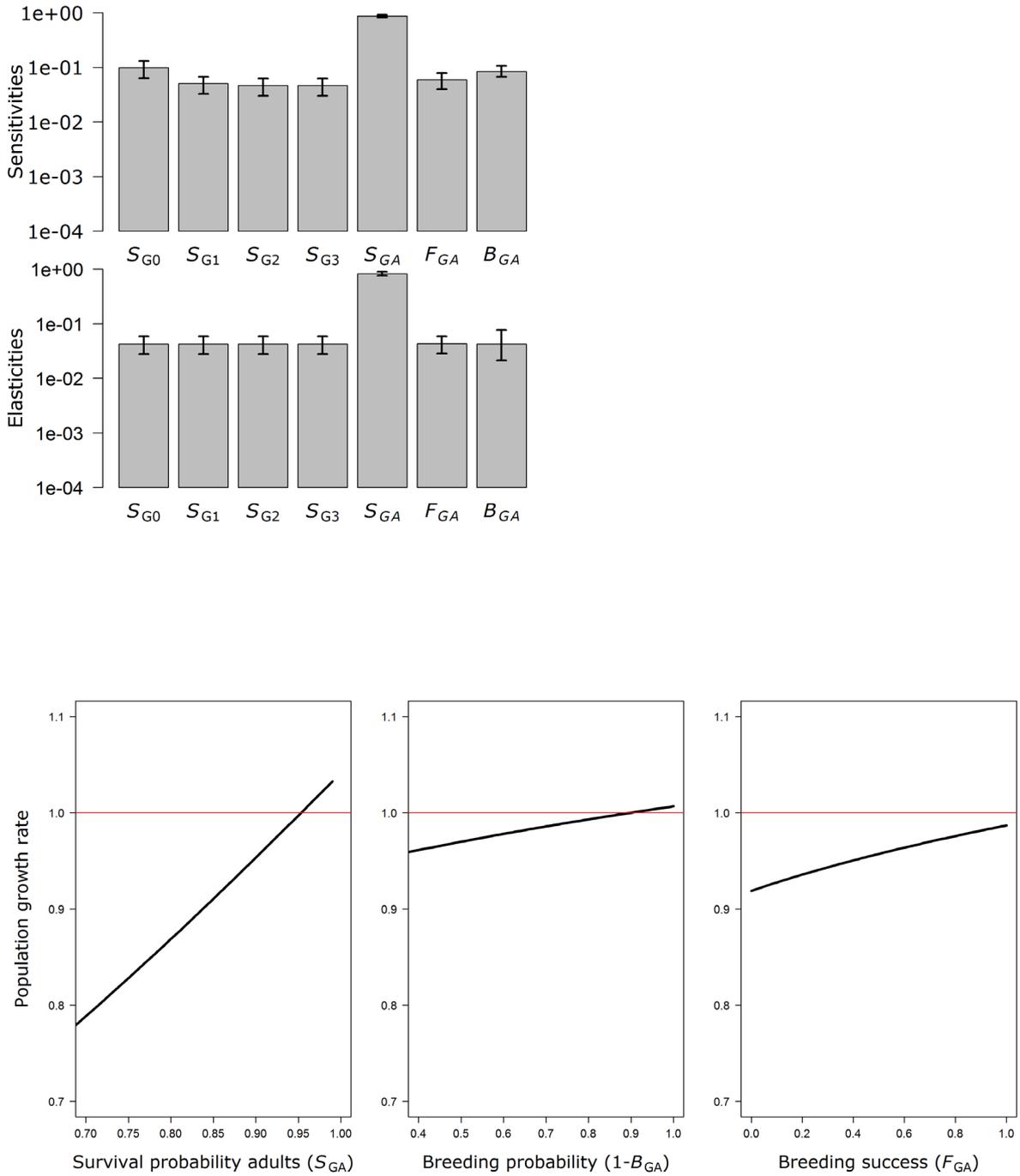


Figure 4.2 Northern gannet perturbation analysis of (annual) population growth rate (without OWFs). Elasticities and sensitivities of population growth rate to individual parameters, error bars represent 5% and 95% percentile of the outcomes. Population growth rate as a function of the gannet adult survival probability S_{GA} , the breeding probability B_{GA} and the breeding success F_{GA} , the red solid line indicates the boundary where a population increase switches to a decrease. Note the log axis for sensitivities and elasticities.

sandwich tern

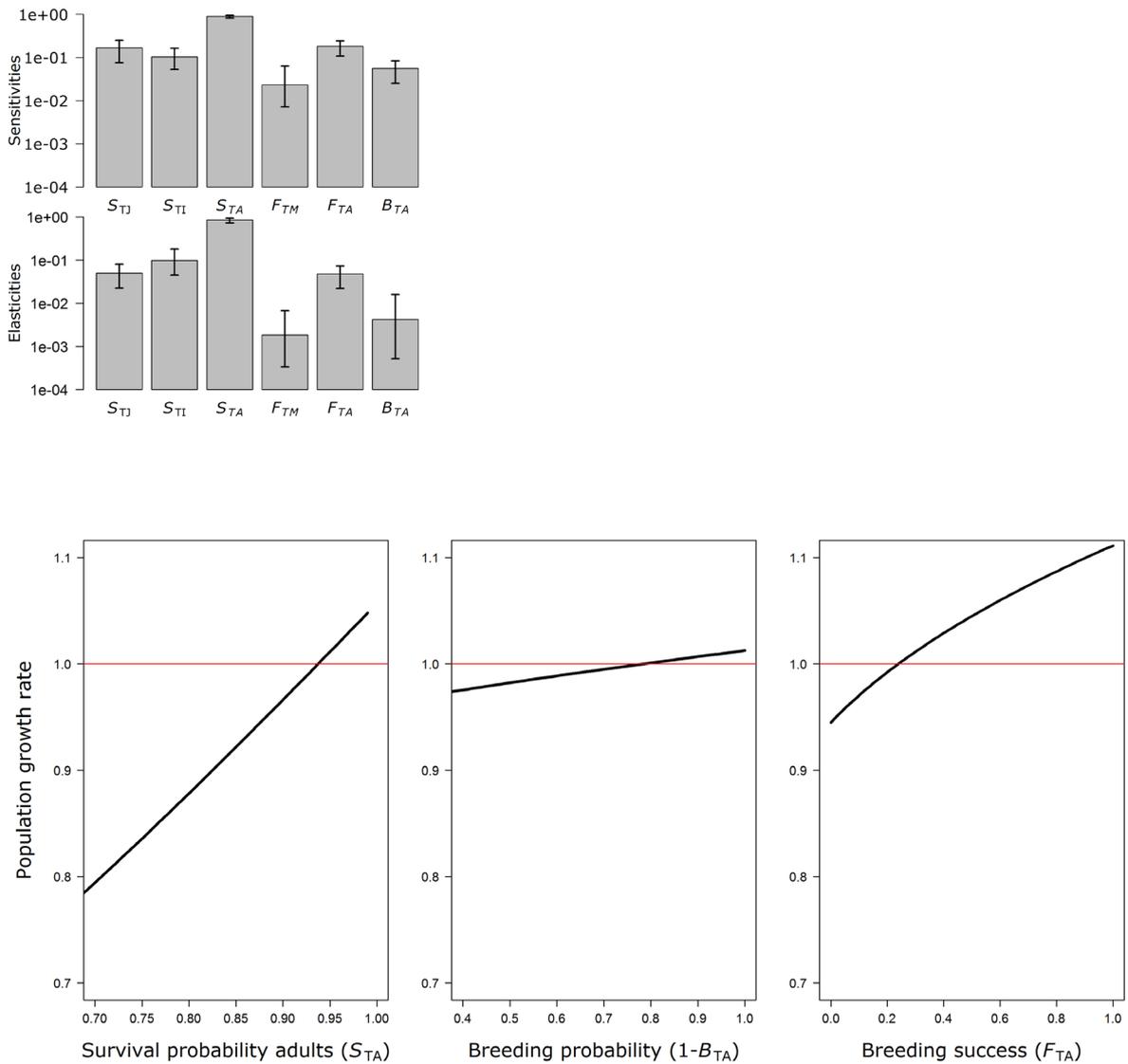


Figure 4.3 Sandwich tern perturbation analysis of (annual) population growth rate (without OWFs). Elasticities and sensitivities of the population growth rate to individual parameters, error bars represent 5% and 95% percentile of the outcomes. Population growth rate as a function of the tern adult survival probability S_{TA} , the breeding probability B_{TA} and the breeding success F_{TA} , the red solid line indicates the boundary where a population increase switches to a decrease. Note the log axis for sensitivities and elasticities.

razorbill

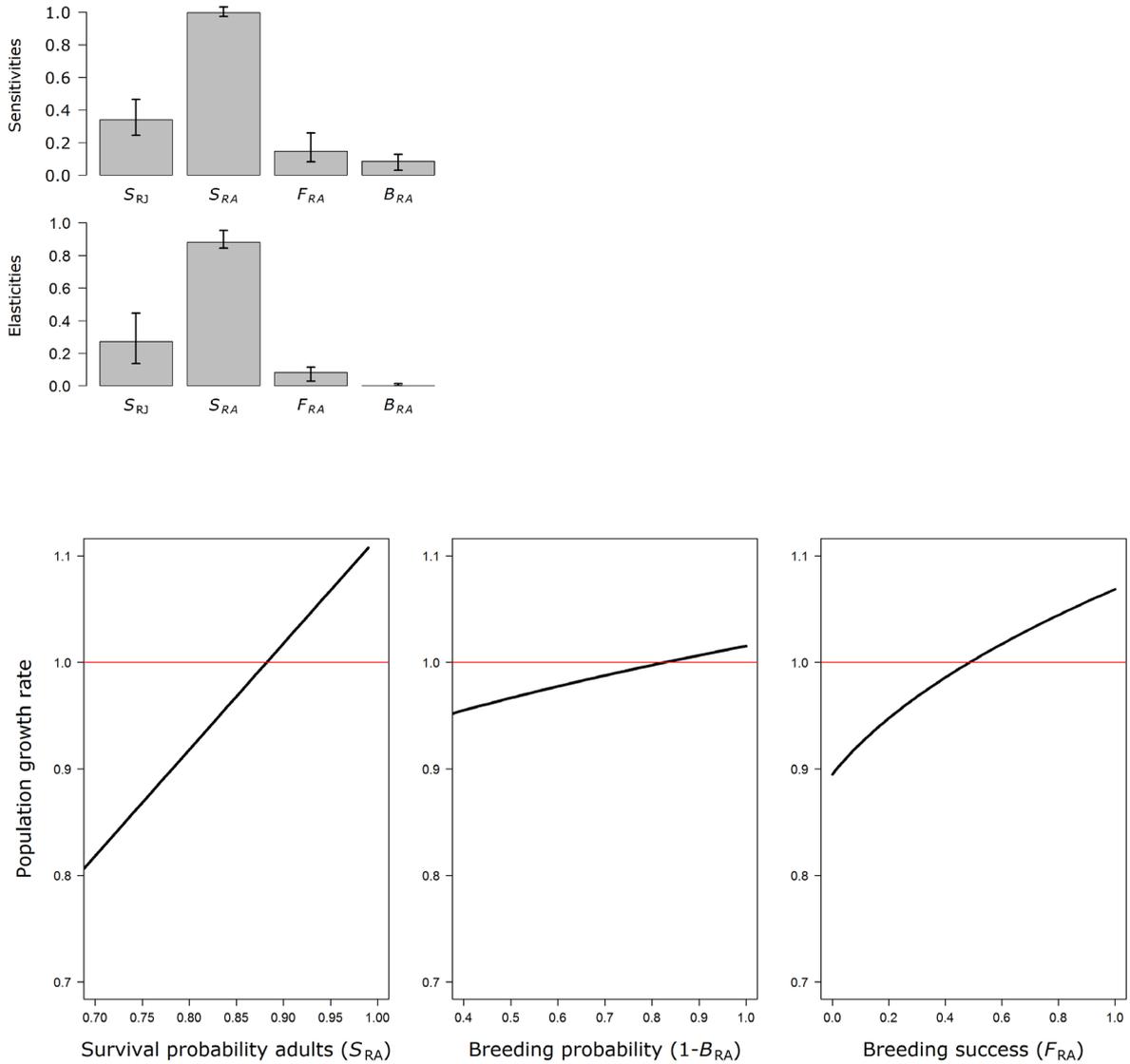
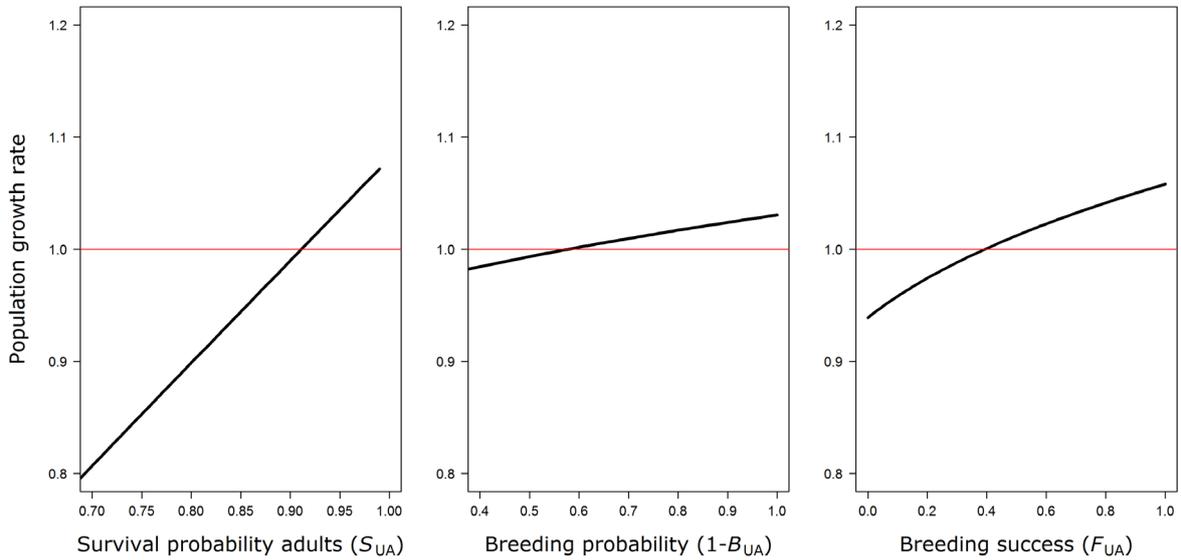
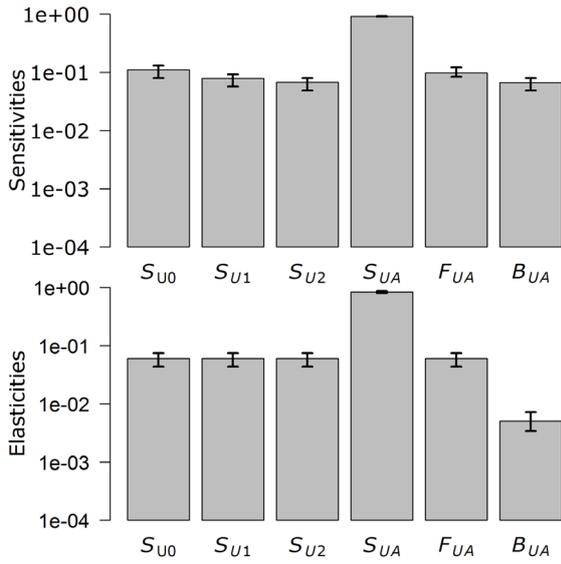


Figure 4.4 Razorbill perturbation analysis of (annual) population growth rate (without OWFs). Elasticities and sensitivities of the population growth rate to individual parameters, error bars represent 5% and 95% percentile of the outcomes. Population growth rate as a function of the razorbill adult survival probability S_{RA} , the breeding probability B_{RA} and the breeding success F_{RA} , the red solid line indicates the boundary where a population increase switches to a decrease. Note the log axis for sensitivities and elasticities.

common guillemot



Common guillemot perturbation analysis of (annual) population growth rate (without OWFs). Elasticities and sensitivities of the population growth rate to individual parameters, error bars represent 5% and 95% percentile of the outcomes. Population growth rate as a function of the guillemot adult survival probability S_{UA} , the breeding probability B_{UA} and the breeding success F_{UA} , the red solid line indicates the boundary where a population increase switches to a decrease. Note the log axis for sensitivities and elasticities.

4 Annex: Stability, Accuracy and Precision of the individual-based simulation model

For the individual based model, we did a stability analysis for the initial energy and the number of time steps. We used the Razorbill parametrisation with an annual survivability of 0.9. For the simulation we ran the model 200 times without any OWF locations. We expected that the survival probability calculated by the simulation would be equal to the true survival rate, that is the survival rate used during the calibration and thus independent of the initial energy and of the number of time steps. Also we say something about the accuracy and precision of the model. The accuracy of the mode is defined as the absolute difference between the 50% percentile to the true survival probability. The precision is defined as the difference between the 95% percentile and the 5% percentile.

For the different initial energies we used a multiple of the mean of the habitat quality values, as multiplication factors we used: 0.001, 0.01, 0.1, 0.25, 0.5, 1, 2.5, 5, 10. The result is shown in Figure A here we see that the simulated survival probability is as expected very close to the true survival probability. Figure B shows how precise and accurate the model is. We see that the simulated survivability is fairly close to the true survival probability and that the precision is a bit under 0.002. This means that the results of the model can be interpreted as having a precision of ± 0.001 .

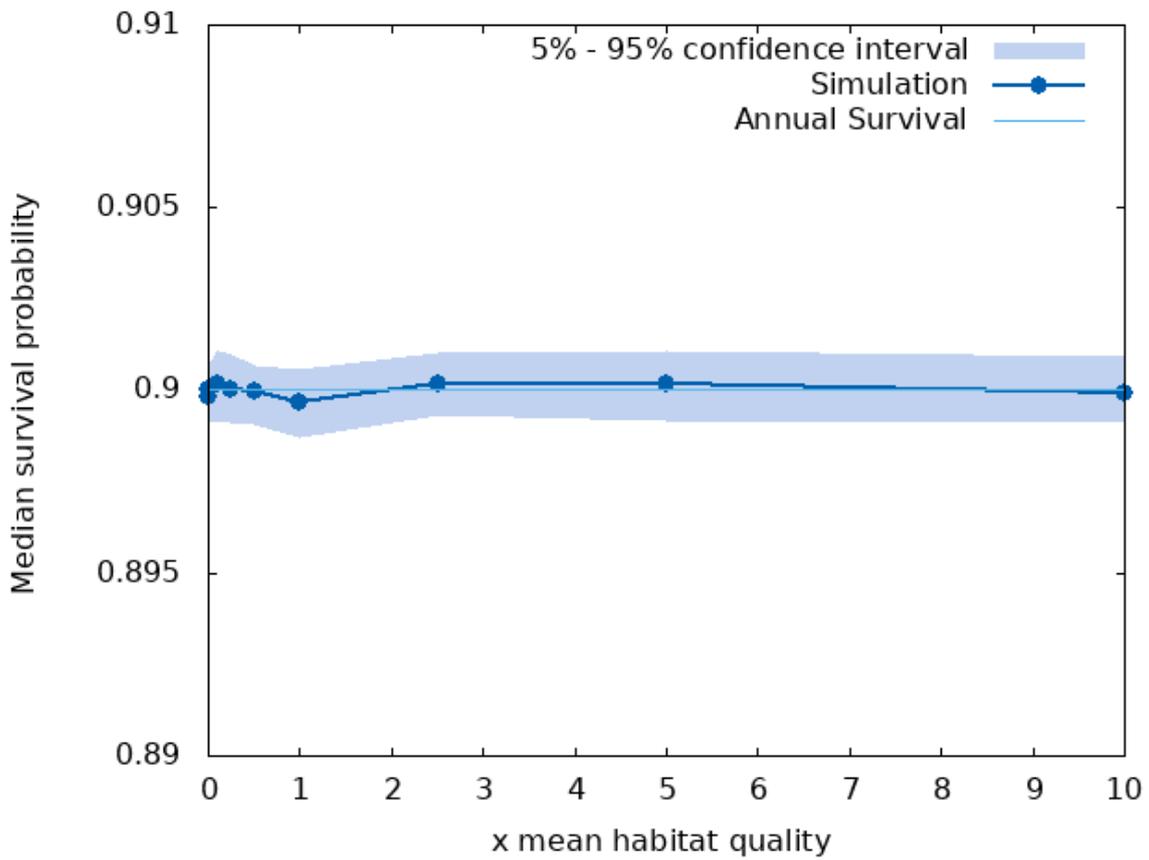


Figure A Results of the stability analysis for the individual based model varying the initial energy

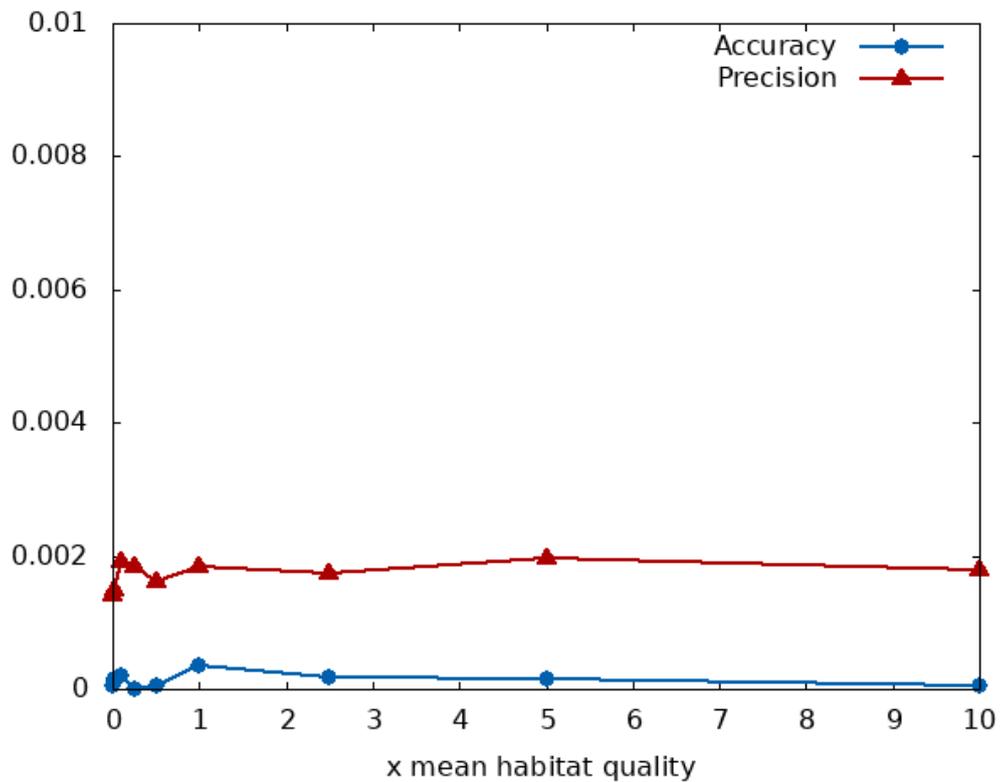


Figure B Accuracy and Precision of Individual based model

For the number of time steps, we varied the hours between moving to a different cell. Again we used the Razorbill parametrisation with an annual survivability of 0.9.

We used 3040, 1520 760 for the number of time steps, corresponding with moving to another cell every 2 hours, every 4 hours every 2 hours.

Also in this case we see as expected that the simulated survival probability matches the true survival

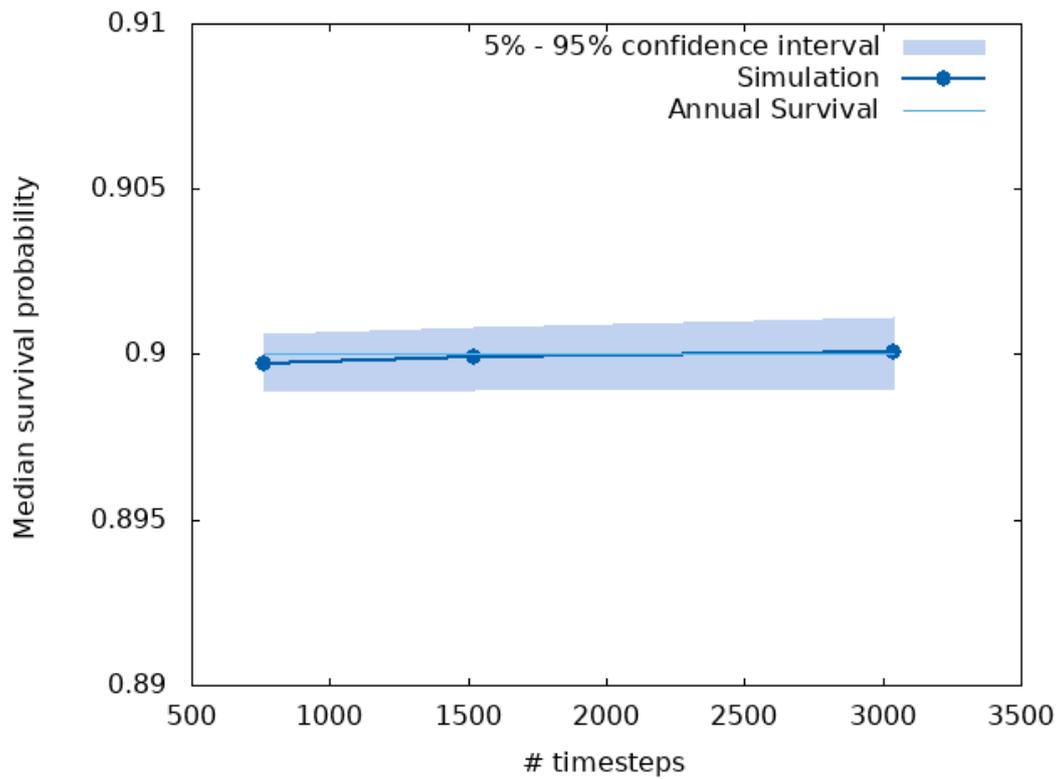


Figure C Results of the stability analysis for the individual based model while varying the number of time steps.

probability very close. If we look at the accuracy and precision in Figure D we see again that the accuracy is very high and the precision around 0.002. Again indicating that the simulation outcome can be interpreted as having a precision of ± 0.001

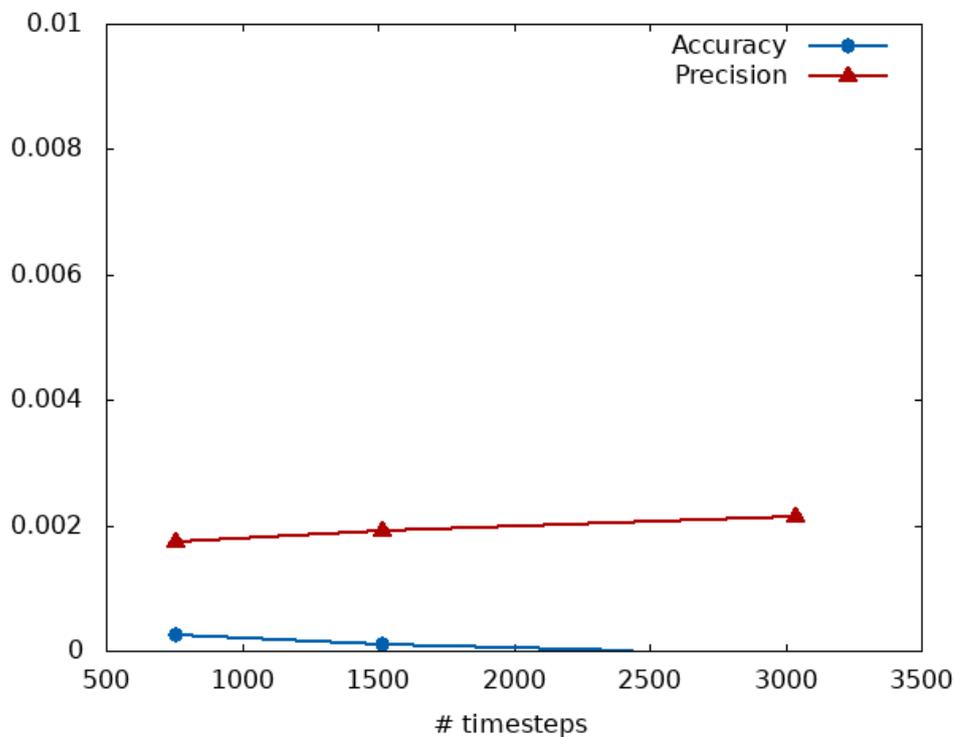


Figure D Accuracy and precision of the individual based model while varying the number of time steps.

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Wageningen University & Research:

is specialised in the domain of healthy food and living environment.

The Wageningen Marine Research vision

'To explore the potential of marine nature to improve the quality of life'

The Wageningen Marine Research mission

- To conduct research with the aim of acquiring knowledge and offering advice on the sustainable management and use of marine and coastal areas.
- Wageningen Marine Research is an independent, leading scientific research institute

Wageningen Marine Research is part of the international knowledge organisation Wageningen UR (University & Research centre). Within Wageningen UR, nine specialised research institutes of the Stichting Wageningen Research Foundation have joined forces with Wageningen University to help answer the most important questions in the domain of healthy food and living environment.
