

Modelled changes to seabird presence and abundance across the MarPAMM region in response to predicted changes in climatic and oceanographic variables

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Executive summary

1. Seabirds are the world's most threatened group of birds, and have globally declined by a conservative estimate of 70% over recent decades. There are many factors driving seabird declines, including overfishing, by-catch, pollution, disease and predation by non-native invasive species. The negative effects of climate change, however, are amongst the anthropogenic threats likely to have the largest impact across seabird populations. As part of the suite of work for the BTO Northern Ireland Science Plan 2023–2028 for DAERA/NIEA, BTO was asked to provide an analysis and associated report to investigate climate change related change in seabird populations in and around Northern Ireland.
2. In this report, we update previously estimated projections of change in seabird populations (Davies et al. 2023) based on newly available datasets, including data from Seabirds Count and updated NEMO and C3S oceanographic data. We also discuss the reliability of existing Interreg VA/MarPAMM projected changes, and the likely extent to which climate change is already driving alterations to seabird abundance.
3. To assess how seabird populations in the Interreg VA/MarPAMM region may be affected by future predicted climate change, we updated the model used by Davies et al. (2023). In Davies et al. (2023), an INLA-based hurdle model was used to quantify both the predicted change in presence and abundance of seabird species in Britain and Ireland by 2050 in response to an array of climatic and oceanographic variables. National census data of seabirds from the Seabird Colony Register and Seabird 2000 were included in this previous study. Here, we update this previous analysis to incorporate updated oceanographic data, and the most recent national census of seabirds in Britain and Ireland, Seabirds Count. We present results for the Interreg VA/MarPAMM region for 19 breeding seabird species for which there were sufficient data, out of a possible 22.
4. We predict that 16 species breeding in the study region will decline in their presence probability and abundance by 2050, ranging from -2.2% (Sandwich Tern) to -98.8% (Arctic Skua) for presence probability, and from -8.6% (Little Tern) to -94.9% (Great Skua) for abundance. Although the median predicted abundance change was negative for most species, uncertainty was very high: credible intervals for future abundance included current abundance for all species. Temperature-related environmental variables (both climatic and oceanographic) were the strongest apparent drivers of these declines. The results of these updated analyses broadly aligned with those identified in Davies et al. (2023), though the generally shallower predicted changes likely reflected the shorter time period over which predictions were made (c. 29 vs 50 years).
5. There were several seabird species known to breed in Northern Ireland and the wider Interreg VA/MarPAMM region for which it was not possible to run models, generally due to insufficient data on these populations being available, or because there were too few colonies extant. In addition, limitations inherent to: 1) modelling data with high levels of fine-scale spatial variation, 2) attempting to adequately represent the environmental conditions experienced by seabirds, and 3) the nature of the ecological processes through which environmental conditions influence seabird presence and abundance, may have limited ability of the models to identify fitted relationships.
6. Overall, the population of seabirds in the Interreg VA/MarPAMM region is predicted to decline in presence and abundance by 2050 under climate change.

1. Introduction

Seabirds are one of the most threatened vertebrate groups with many species on a path to extinction (Paleczny et al. 2015). Amongst the anthropogenic threats faced by seabirds, including overfishing, by-catch, pollution, disease and predation by non-native invasive species, climate change is one of those likely to have the greatest impact on national and global populations (Dias et al. 2019). Climate change associated effects, such as marine heatwaves and increased storminess, amongst other factors, are all likely to have direct negative impacts on seabird populations (Mölter et al. 2016, Frölicher et al. 2018). Indirect effects of climate change may also arise through bottom-up processes, manifested as changes in oceanography, primary production and prey species availability and abundance (Johnston et al. 2025). The pace at which climate change could impact seabird populations may be such that long-term data are required to understand how populations may change over time. However, gathering comprehensive data at national scales is incredibly time-consuming and resource intensive, and such effort is only possible periodically. Although annual monitoring of seabirds is undertaken, there are notable gaps in coverage and the species covered (e.g. the BTO/JNCC Seabird Monitoring Programme, see Harris et al. (2024)).

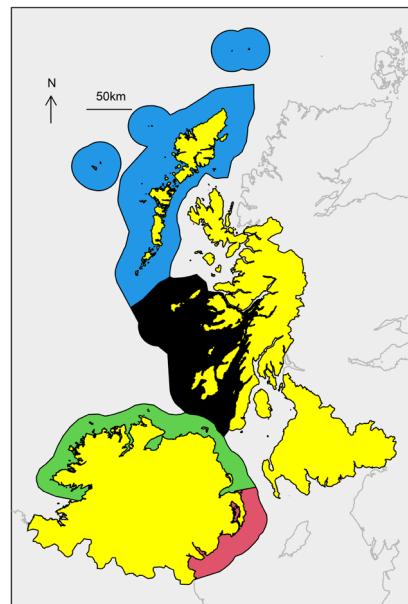
In Britain, Ireland, the Channel Islands and Isle of Man (hereafter 'Britain and Ireland'), national censuses are undertaken approximately every 15 years with the aim of capturing the national-level trends in abundance for 25 breeding seabird species. Up to 2023, these censuses included: Operation Seafarer (Cramp et al. 1974), Seabird Colony Register (hereafter 'SCR Census'; Lloyd et al. 1991), and Seabird 2000 (Mitchell et al. 2004). The data arising from these censuses are well-placed to assess how seabirds may respond to changes in both terrestrial and oceanographic variables over time and space (with the exception of urban-nesting gulls, which were overlooked in earlier censuses and then latterly it was not possible to survey all urban areas where gulls are likely to nest). Accordingly, Davies et al. (2023) used these data with a hierarchical spatial modelling approach to predict how seabird populations in Britain and Ireland may change in their abundance and distribution under the Representative Concentration Pathway (RCP) 8.5 climate scenario that assumes average global warming of 2°C by 2050. In addition, Davies et al. (2023) tested how the predicted effects may vary between both the generalised habitat use and foraging mode of species to further understand the responses of species to future climate scenarios. Overall, Davies et al. (2023) predicted future declines of many of the modelled species across Britain and Ireland as a result of projected climate change, particularly for marine specialists. The most recent national census, Seabirds Count (Burnell et al. 2023), has been published and offers the most comprehensive assessment of the population size of Britain and Ireland's seabirds to date. This publication of the Seabirds Count data presents an opportunity to update and refine Davies et al.'s (2023) predictions to include this most recent census, and potentially examine how seabird populations are already being affected by climate change by utilising updated environmental data.

Northern Ireland hosts internationally important populations of seabirds and waterbirds, many of which are declining or under threat of decline (Booth Jones & Haddad 2024). During the summer breeding season, 25 species of seabird breed on the British and Irish coastlines, on islands, cliff faces, and harbours, as well as at inland lakes and in urban areas. These include a diverse range of species, such as gulls Larinae and terns Sterninae (both of which are subfamilies of the Laridae), which arrive at colonies in terrestrial habitats during the spring and summer to nest, and auks Alcidae that may return to their colonies from early autumn (Bennett et al. 2022).

MarPAMM was a cross-border project which ran until 2022, designed to monitor and manage mobile species along with their respective coastal and marine environments. One of the key outputs was predictions of future population numbers for seabird colonies within: 1) the Interreg VA region (Figure 1), which includes Northern Ireland, the border counties of Ireland, and the west of Scotland, and 2) Britain and Ireland (project report written up as Davies et al. (2021), and then published as Davies et al. (2023). As part of a suite of work for the Northern Ireland Environment Agency (NIEA) funded through the Department of Agriculture, Environment and Rural Affairs (DAERA) Environment Fund, we updated the work of Davies et al. (2023) to incorporate the most recently available data.

Throughout the rest of the report, we refer to the geographic region encompassed by the INTERREG VA area as 'the MarPAMM region' alone. Specifically, we estimate how populations of the 16 seabird species known to breed in the MarPAMM region, and that have sufficiently rich datasets, may be affected by future predicted changes to climatic and oceanographic conditions.

Figure 1. INTERREG VA area (yellow) and MarPAMM management regions (blue, Outer Hebrides; black, Argyll; red, Co. Down – Co. Louth; green, North Coast Ireland – North Channel). Figure and text taken from Davies et al. (2021).



2. Methods

2.1. Methodological approach

To quantify predicted changes in seabird abundance and distribution across the MarPAMM region, we updated the recent analysis conducted by Davies et al. (2023) which used seabird abundance data from two censuses: the SCR Census for 1985–1988 (Lloyd et al. 1991) and Seabird 2000 for 1998–2002 (Mitchell et al. 2004). Davies et al. (2023) related seabird presence and abundance to climatic and oceanographic variables using a Bayesian hurdle model with spatial random effects, projecting change in seabird abundance by 2050 according to the UK Climate Projections 2018 (UKCP18) RCP8.5 scenario. We updated this analysis to include the most recent seabird census, the Seabirds Count 2015–2021 (Burnell et al. 2023), alongside climatic and oceanographic variables relevant for this time period. Further, we were able to include the two Stercoraridae species known to breed in the MarPAMM region, omitted from Davies et al. (2023), owing to there now being sufficient data to meaningfully assess change for these species. As done in Davies et al. (2023), for model fitting we included all available seabird data across Britain and Ireland, to include as much information as possible on the relationship between climate/oceanography and seabird presence/abundance, in order to maximise our ability to predict population changes within the comparatively small MarPAMM region. All data preparation and analysis were carried out in R version 4.2.1 (R Core Team 2024).

2.2. Seabird presence and abundance data

Seabird presence and abundance data across Britain and Ireland were taken from the three most recent seabird censuses. Collectively, these national censuses provide robust information on spatial and temporal changes in seabird distribution and abundance since the second half of the 20th century. We did not have access to Seabird Count census data for Manx Shearwater (*Puffinus puffinus*) or European Storm Petrel (*Hydrobates pelagicus*), so these species were omitted from our study. We also omitted Roseate Tern (*Sterna dougallii*) and Mediterranean Gull (*Larus melanocephalus*) from our study as these species had fewer presence cells within the MarPAMM region than the number of parameters in the model. In addition, following Davies et al. (2023), SCR Census counts for Leach's Storm Petrel (*Hydrobates leucorhous*) were omitted, as counts were based on expert assessment rather than surveys. Otherwise, data were included for all census sites in Britain and Ireland with a presence of seabird species, amounting to 5,631 sites in the SCR Census, 1,917 in Seabird 2000, and 9,743 in Seabirds Count. Counts for Atlantic Puffin (*Fratercula arctica*, hereafter 'Puffin') are adjusted in the census methodologies, and predictions have larger uncertainty than other species due to this species being a burrow-nester, which tend to be difficult to survey. For Lesser Black-backed Gull (*Larus fuscus*) and Herring Gull (*L. argentatus*), census data were only available for the natural nesting birds. Given the large proportion of Lesser Black-backed Gulls (83.8%) and Herring Gulls (74.3%) nesting in urban locations in Great Britain (Burnell et al. 2023), and the likelihood that population trends of natural and urban nesters differ, predictions may incompletely capture climate–species interactions and underestimate predicted presence or abundance for these species.

The spatial resolution of the censuses were aggregated to that of the UKCP18 atmospheric climate data (12 × 12 km cells). Seabird abundance for each census period was calculated as the summed count for each species within each cell. When a census-site spanned more than one cell (affecting 282 and 1,667 sites in SCR Census and Seabird 2000, respectively), the count for that census-site was divided among those cells in proportion to

the length or area of the site spanning those individual cells and rounded to the nearest integer. For Seabirds Count, it could not be determined whether sites spanned multiple cells as the extent of site (i.e. their start and end latitude and longitude) were not available from the Joint Nature Conservation Committee (JNCC).

Zero counts were inconsistently recorded in the seabird censuses, hence we could not always differentiate between when a species had not been counted as opposed to when they were not present at the site. Zero counts represented 2.6% of all recorded counts (representing 1.9% of cells) in the SCR Census, 11.2% of all recorded counts (representing 5.6% of cells) in Seabird 2000, and 22.1% of all recorded counts (representing 9.2% of cells) in Seabirds Count. The proportion of counts recorded as zero also varied considerably between species. It is unclear how surveyors would decide between recording an absence as a zero or as a blank (information is not provided on this in Mitchell et al. (2004) or Burnell et al. (2023)). Following Johnston et al. (2013) and as done in Davies et al. (2023), given that the periodic seabird censuses aim to count all seabirds at all sites present, we assumed that species were not present at census-sites that were visited in a particular year, but at which they were not recorded. We consider this assumption to be relatively inconsequential for inference about most species, with the possible exception of the few species that moved colonies between years (e.g. tern species). The available dataset for a given species in a given census therefore consisted of count data (mostly positive but some zeros) for some cells and non-count data (i.e. zeros) for all remaining cells containing seabird census sites.

Between the censuses, there were some differences in the boundaries used to define sites. These issues introduced unavoidable error into the derived relationships between seabird abundance and environmental variables, as it is possible that some apparent site-level abundance change between censuses was due to differing spatial delineation over time. However, we consider these issues to be minor, at least for the first two censuses, because: 1) most counts came from relatively small census-sites (79.6 and 83.9% of counts came from census-sites with a length of <2 km in SCR Census and Seabird 2000, respectively), and 2) few counts came from sites that spanned multiple cells (2.1 and 6.8% in SCR Census and Seabird 2000, respectively). For Seabirds Count, no information was available regarding the extent of the site, so there may have been some minor changes to site delineation compared to previous censuses.

2.3. Climatic and oceanographic data

As done in Davies et al. (2023), we derived relationships between seabird presence/abundance and climatic and oceanographic variables (summarised in Table 1). In common with other studies (Johnston et al. 2013, Russell et al. 2015), air temperature and precipitation were selected to represent atmospheric climatic variation as these variables can impact productivity and survival (Johnston et al. 2025), which can in turn affect population growth rate (Sandvik et al. 2012). Observed maximum monthly temperature, minimum monthly temperature and total monthly precipitation data for the UK and Ireland were taken from the Had-UK (Met Office et al. 2024) and Met Éireann (Met Éireann, 2024) interpolated datasets at a 1 km resolution. Modelled atmospheric data for the same variables for 1980–2080 were taken from Met Office UKCP18 data (Met Office Hadley Centre 2018) for the RCP8.5 climate scenario. RCP8.5 was used in Davies et al.'s (2023) analysis and represents the most aggressive and realistic future greenhouse gas concentration scenario (Schwalm et al. 2020), equivalent to approximately 2°C global warming by 2050 compared to 1986–2005 levels (IPCC 2014). The RCP 8.5 scenario currently represents that most consistent with observed global trends (Schwalm et al. 2020). For the UKCP18 data, projections were available from 12 different global and regional models. Since there was no a priori reason to select any particular model, the median of the 12 projections was taken for each month. Four climate variables were derived in total, summarising winter and breeding season temperature and precipitation. Given evidence that the trajectories of bird populations are more heavily influenced by changes in climate extremes than mean climate (Pearce-Higgins et al. 2015), atmospheric climate variables were designed to represent conditions associated with seasonally-related changes in temperature and extremes of precipitation.

Sea surface temperature (SST) and potential energy anomaly (PEA), along with bathymetry (see 2.4), were used to represent oceanographic variation. PEA is a proxy measure of ocean stratification, which in turn impacts marine food web dynamics across trophic levels (Mann 1993). PEA describes the energy required to fully mix a column of water, and low PEA values correspond to a well mixed water column, whereas more intensively stratified water columns have higher PEA values (Holt et al. 2010). These variables are commonly included in studies investigating the influence of oceanographic variables on seabird abundance, distribution and demography (Nur et al. 2011, Satterthwaite et al. 2012, Bertrand et al. 2014, Carroll et al. 2015, Trevail et al. 2019).

Davies et al. (2021, 2023) used oceanographic data from the Scottish Shelf Model, but these were not available for the Seabirds Count timestep. Therefore, SST and PEA data for the periods covering Seabird 2000, Seabirds Count and the future 2050 scenario were derived from the Nucleus for European Modelling of the Ocean dataset (NEMO; Tinker 2023) at 7 km horizontal resolution. Like UKCP18, data were available for 12 ensemble models, so the median value across the ensembles for each month was taken. NEMO data were not available for the SCR Census, so SST data were instead taken from the Copernicus Climate Change Service (Copernicus Climate Change Service (C3S), 2019) at 0.05° spatial resolution. PEA data were not available for the SCR Census and so values for this census were imputed by INLA. Each oceanographic variable was then averaged over species-specific mean maximum foraging ranges, derived from the review by Woodward et al. (2024). For a given species count in a given census cell, the mean of each oceanographic variable was taken over the species' mean maximum foraging range, weighted by the inverse distance (distance + 0.1 km to avoid dividing by zero) of the oceanographic grid cells from the midpoint of the census cell. For a given cell, all oceanographic variables were left blank if no ocean-containing cells were within the foraging area, i.e. in inland areas. Because PEA of waters on and off the continental shelf differed by several orders of magnitude (with greater PEA in deeper waters beyond the shelf), PEA values were omitted for waters > 200 m, as done in Davies et al. (2023). The PEA values then included in the model were effectively for on-shelf areas only with the average on-shelf PEA across the foraging range supplied for each species. Only four of the study species have foraging ranges that are likely to reach the edge of the shelf (Puffin, Lesser Black-backed Gull, Black-legged Kittiwake *Rissa tridactyla*, hereafter 'Kittiwake', Great Skua *Stercorarius skua*, and Northern Fulmar *Fulmarus glacialis*, hereafter 'Fulmar'), and only from a small proportion of their colonies in the study region. As such, it is unlikely that the exclusion of PEA data beyond the shelf had a large impact on model predictions.

All climatic and oceanographic variables were treated the same way as in Davies et al. (2023). First, all variables were aggregated to the 12-km cell scale of the UKCP18 data. Second, variables were averaged over the five years leading up to the median year of each census (1982–1986, 1995–2000 and 2013–2018 for SCR Census, Seabird 2000 and Seabirds Count respectively), following the assumption that climate influences seabird abundance through its effects on several consecutive years of productivity and survival. Third, climate and oceanographic data were calculated for winter (December–February) and species-specific breeding seasons (Table S1), with breeding seasons defined as the months during which eggs or chicks can be present (Campbell & Ferguson-Lees 1972).

2.4. Other environmental data

Bathymetry data (depth of water column in m) were derived from the UKCP09 marine projections (Hadley Centre for Climate Prediction and Research 2017). Bathymetry data were averaged over the species' foraging ranges (as in Section 2.3). Although strictly speaking, bathymetry is affected by sea level rise and sea level rise projections were available, the same bathymetry data were used for the historical and future periods. This is because bathymetry data were used with the intent to represent meso-scale oceanographic characteristics in the species foraging areas, and predicted sea level changes are negligible (on the order of tens of cm; Met Office Hadley Centre 2018) compared to the range of bathymetry data in the region (which span c. 5 km). Further, bathymetry data sourced are to the nearest metre, and so are not precise enough for calculating habitat loss from sea-level rise on the order of a few cm. As such the models employed here do not account for potential habitat loss for coastal breeders caused by sea level rise which have been raised as a concern by Leonard (2024).

Following Davies et al. (2023), three additional environmental variables were included to account for further causes of spatial variation in seabird abundance: 'coastal', an indicator variable that was true when a cell was entirely within 5 km from the coast; 'islands', an indicator variable that was true when a cell contained any islands that were less than 15 km² in area; and 'coastline length', the length of coastline within a cell from the 'esriGeometryPolyline' shapefiles of the study area available from ArcGIS (©Esri US). Although these variables may be poor descriptors of the physical variables that are likely to directly influence seabird presence and abundance at this scale (such as cliff height or length), such data could not be easily derived from large-scale datasets in a way that is relevant for each species. Therefore, although we expected models to be relatively weak predictors of spatial variation in seabird abundance for species where such features are important, this does not necessarily mean that they are not good predictors of the overall geographic and climatic component of such distributions (Johnston et al. 2013) or of temporal variation in seabird presence and abundance.

Table 1. Environmental variables included in models of seabird presence and abundance. SST = sea surface temperature. PEA = potential energy anomaly. See Table S1 for species-specific breeding seasons.

Variable category	Variable name	Calculation
Climate	Winter minimum temperature	Five-year December–February mean minimum monthly temperature
	Breeding season maximum temperature	Five-year mean maximum temperature of (yearly) warmest month in species-specific breeding season
	Winter precipitation	Five-year mean total December–February precipitation
	Breeding season precipitation	Five-year mean total precipitation of (yearly) wettest month in species-specific breeding season
Oceanography	Winter SST	Distance-weighted-mean 24 yr mean December–February SST within species-specific foraging area
	Breeding season SST	Distance-weighted-mean 24 yr mean SST over species-specific breeding season within species-specific foraging area
	Winter PEA	Distance-weighted-mean 24 yr mean December–February PEA within species-specific foraging area
	Breeding season PEA	Distance-weighted-mean 24 yr mean PEA over species-specific breeding season within species-specific foraging area
	Bathymetry	Distance-weighted-mean depth of water within foraging area
Geographical variables	Coastal	Whether cell was entirely (0) >5 km from the coast or not (1)
	Islands	Whether cell contains any islands of <15 km ² area (1) or not (0)
	Coastline length	Length of coastline (km) within cell

2.5. Statistical modelling

Seabird presence and abundance should be subject to both intrinsic and extrinsic causes of spatial autocorrelation (Beale et al. 2010). To infer the relationship between climate, oceanography and seabird presence and abundance while properly accounting for spatial autocorrelation, we fitted spatial models using integrated nested Laplace approximation (INLA; Rue et al. 2009). As INLA fits models in a Bayesian framework by approximating (rather than sampling from) the posterior distribution, INLA provides major gains in computational efficiency compared to traditional Markov chain Monte Carlo (MCMC) methods for fitting spatial models to large datasets. Models were fitted using the R package INLA (Rue et al. 2009).

Following Davies et al. (2023), we used INLA to fit hurdle models (Sadykova et al. 2020) which separately modelled presence-absence (with a binomial likelihood) and abundance conditional on presence (with a zero-truncated negative binomial likelihood). The hurdle models were fitted for each species individually. To account for spatial autocorrelation, we modelled seabird presence and abundance as a function of both fixed effects (environmental variables) and a single spatial random effect with a Matérn correlation structure. Presence and abundance-given-presence were assumed to be driven by slightly different processes, so parameters for the explanatory variables and spatial random effect were estimated separately for the two model components. To account for potential non-linear relationships (Hansen et al. 2021), both linear and quadratic terms were included in the full model for all continuous variables. The full model for each species therefore comprised nine environmental covariates, nine quadratic terms for the environmental covariates and three geographical variables (Table 1).

Default priors (as per the INLA package version 24.03.29) were specified for the fixed effects in the model. The priors for the Matérn covariance function of the spatial random effect were specified according to its empirical range r and marginal standard deviation σ (Bakka et al. 2018). Reasonably vague prior parameters were given: $P(r > 0.3) = 0.5$; $P(\sigma > 10) = 0.01$. Coordinates and environmental covariates were scaled to mean 0 and standard deviation 1 before inclusion in the model, to avoid numerical issues.

The fitted models for each species were then used to project future seabird presence probability and abundance across Britain and Ireland in 2050, using projected atmospheric climate and oceanographic data for 2050 under the RCP8.5 climate scenario. Predictions were then made from these models for the MarPAMM region.

2.6. Model diagnostics and validation

Success of model convergence was assessed using the Kullback–Leibler distance (KLD) of each parameter. KLD measures the ability for the normal distribution to approximate the posterior probability distribution for a given parameter and should be close to zero if successful (Wang & Ghosh 2011).

By way of validation, the ability of the model to predict spatial variation in seabird presence and abundance was assessed for each species using presence and abundance data from 70% of randomly selected cells (the ‘spatial fine-scale predictive ability assessment’). Using the fitted model, the species’ presence and abundance were then predicted at the remaining 30% of the census sites. The predictive performance of the model was assessed by: 1) the area under the curve (AUC; the discrimination ability of a classifier) of the receiver operating characteristic for the predicted and observed presences, and 2) the R^2 of the relationship between the predicted and observed abundances. These statistics varied depending on the random sample of census sites withheld, so the median of each statistic was taken over 20 model runs (as done in Davies et al. 2023). We defined three discriminatory ability categories for AUC: moderate (0.7–0.8), good (0.8–0.9) and excellent (>0.9). Following Pearce-Higgins et al. (2011), we defined four predictive ability categories for R^2 : very poor (<0.01), poor (0.01–0.06), moderate (0.06–0.25) and good (>0.25). Model fit as assessed in this way is not necessarily an estimate of the proportion of variation in the response variables explained by the fixed effects alone because some of the variation in the response variables is explained by the spatial random effect. In addition, estimates of predictive ability may be underestimated because PEA data were not available for the SCR Census timestep (predictions for this timestep were made with PEA data imputed by INLA).

2.7. Prediction of seabird presence and abundance

Predictions of future presence and abundance probability in 2050 were made using the full model (i.e. using all data, rather than the validation model) for each species. In the core results we present predicted changes at the family level with species-level results available in the supplementary material. In Davies et al.’s (2023) analysis, models typically mispredicted known species abundance in a given cell, including overprediction of low population sizes for some species. These overpredictions probably arose due to the complex spatially-autocorrelated and overdispersed structure of seabird abundance, which is difficult to account for at the spatial scale of the model (see Davies et al. (2023) for further details). As a result, Davies et al. (2023) estimated future abundance by multiplying observed abundance at the then-most recent census, Seabird 2000, by the predicted change in abundance (calculated as predicted abundance in 2050 / predicted abundance in 2000). To further improve comparability, UKCP18 modelled data were used for predicting abundance in both 2000 and 2050 (rather than using observed HadUK and Met Éireann data for predicting abundance in 2000) to ensure all the projected changes in seabird abundance were due to projected changes in climatic variables rather than potential differences between observed and projected values. In this analysis, we followed the same approach as Davies et al. (2023), by estimating relative change in abundance and presence probability between Seabirds Count (the current-most recent census) and 2050.

To predict abundance and associated uncertainty at individual sites, a frequency distribution of predicted change in presence and abundance was generated for each cell. This was done by sampling one random draw x and y from the posterior distributions of the predicted abundance in 2018 (the median year of Seabirds Count) and 2050, respectively, and then dividing y by x . This calculation was repeated 10,000 times for each cell to derive a frequency distribution of predicted change in abundance for that cell. The observed

abundance in 2018 was multiplied by the 2.5th, 50th and 97.5th percentile of this frequency distribution to give the median abundance (with credible interval) for each cell. This abundance (and credible interval) was apportioned among the constituent census-sites in the cell proportionally according to the relative size of their counts during Seabirds Count.

Following Davies et al. (2023), to assess the ability of the model to predict temporal change in seabird presence and abundance, we examined its accuracy in predicting changes in recorded abundance between the Seabird 2000 and Seabirds Count censuses. For each species, we summed predicted and observed abundance across all withheld cells (for a different random sample of withheld cells for each species) for Seabird 2000 and Seabirds Count, respectively, to give predicted and observed proportional change in aggregated abundance. We then assessed the correlation between predicted and observed summed abundances for the withheld cells across species. This assessment is hereafter called the 'temporal large-scale predictive ability assessment', to contrast with the 'spatial fine-scale predictive ability assessment' described in Section 2.6.

Focusing on abundance change solely at sites where a species was present during Seabirds Count ignores the capacity for colonisation, which can potentially compensate for declines or enhance increases in abundance. As a metric of the capacity for colonisation of new sites, we present the median predicted change in presence probability across cells unoccupied during Seabirds Count. This metric should only be considered a maximum capacity for colonisation because not all of the unoccupied area is potentially colonisable by all species, due to factors such as variation in breeding habitat suitability and species interactions.

2.8. Climate–seabird relationships with feeding ecology and habitat specialism

We assessed whether species' fitted relationships with climate and oceanography varied with feeding ecology and habitat specialism. We defined two categories of feeding ecology, capturing whether species feed in the water column or benthos: 'diving species' – species that mainly do so, and 'surface-feeding species' – species that rarely or never do so (OSPAR Commission 2016), Table S1. We defined two categories of habitat specialism, capturing whether species feed in terrestrial or freshwater habitats: 'marine specialists' – species that never do so, and 'habitat generalists' – species that sometimes do so, Table S1.

For each climate or oceanographic variable, for each hurdle model sub-component (presence–absence or abundance), a t-test was carried out with the parameter estimate as the response variable and feeding group as the explanatory variable. We repeated these t-tests, replacing habitat specialism as the explanatory variable to test for differences between marine specialists and generalists. Because some species were more closely related than others, and thus were potentially not independent in their relationships with climate and oceanography, a phylogenetic covariance structure was used in the linear model. A phylogenetic tree was averaged from 1,000 Ericson backbone trees (trees downloaded from www.birdtree.org, accessed 8 March 2021; Jetz et al. 2012). The model was fitted using 'MCMCglmm' (Hadfield 2010).

3. Results

3.1. Model performance and fit

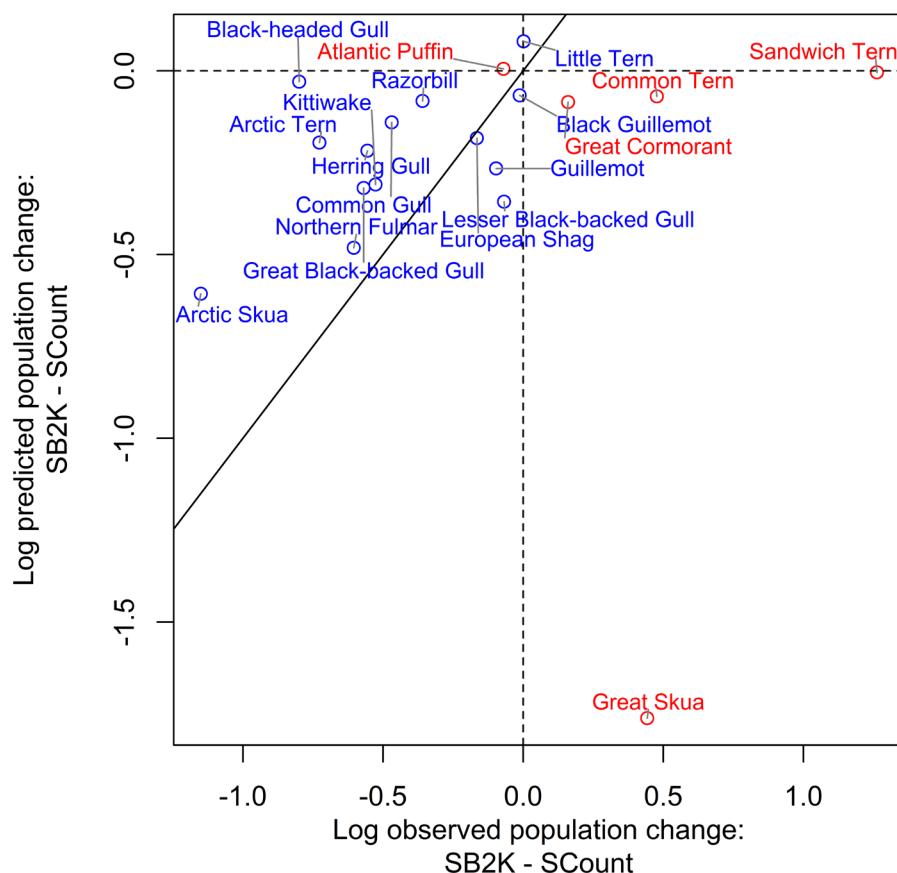
In addition to the species omitted from our study due to insufficient data (see Section 2.2), we were not able to model populations of Northern Gannet (*Morus bassanus*) and Leach's Storm Petrel as their abundance was too low to achieve model convergence. Results for the remaining 19 species are presented below. KLD scores (a measure of model convergence) were <0.1 for all modelled species, indicating successful convergence. In the spatial fine-scale predictive ability assessment, R^2 values (indicating the ability of the model to predict abundance) were highly variable, ranging from <0.01 (Razorbill *Alca torda*, Common Guillemot *Uria aalge*, hereafter 'Guillemot', Black Headed Gull *Chroicocephalus ridibundus*, Sandwich Tern *Thalasseus sandvicensis*) to 0.36 (Black Guillemot *Cephus grylle*; Table 2). R^2 predictive ability was classified as very poor for four, poor for six, moderate for six, and good for three species. However, AUC values (indicating the ability of the model to predict presence–absence) were better, classified as moderate for three, good for 12 and excellent for four species (Table 2).

Table 2. Area under the curve (AUC), R² scores and R² predictive ability (classified according to Pearce-Higgins et al. 2011) for the models run for each species.

Species scientific name	Species common name	AUC	R ²	R ² Predictive Ability
<i>Alca torda</i>	Razorbill	0.88	<0.01	Very poor
<i>Cephus grylle</i>	Black Guillemot	0.94	0.36	Good
<i>Fratercula arctica</i>	Atlantic Puffin	0.89	0.01	Poor
<i>Uria aalge</i>	Common Guillemot	0.90	<0.01	Very poor
<i>Chroicocephalus ridibundus</i>	Black-headed Gull	0.83	<0.01	Very poor
<i>Larus argentatus</i>	Herring Gull	0.85	0.03	Poor
<i>Larus canus</i>	Common Gull	0.90	0.35	Good
<i>Larus fuscus</i>	Lesser Black-backed Gull	0.78	0.24	Moderate
<i>Larus marinus</i>	Great Black-backed Gull	0.88	0.06	Moderate
<i>Sterna hirundo</i>	Common Tern	0.80	0.01	Poor
<i>Sterna paradisea</i>	Arctic Tern	0.88	0.35	Good
<i>Sterna albifrons</i>	Little Tern	0.83	0.08	Moderate
<i>Thalasseus sandvicensis</i>	Sandwich Tern	0.77	<0.01	Very poor
<i>Rissa tridactyla</i>	Black-legged Kittiwake	0.86	0.07	Moderate
<i>Galosus aristotelis</i>	European Shag	0.89	0.05	Poor
<i>Phalacrocorax carbo</i>	Great Cormorant	0.77	0.01	Poor
<i>Fulmarus glacialis</i>	Northern Fulmar	0.92	0.19	Moderate
<i>Stercorarius parasiticus</i>	Arctic Skua	0.94	0.01	Poor
<i>Stercorarius skua</i>	Great Skua	0.98	0.11	Moderate

Figure 2. shows the relationship between observed and predicted population change for each species. In the temporal large-scale predictive ability assessment, the model had relatively poor ability to predict species' overall changes in population size across all withheld cells for all species (linear model; slope = 0.04, R² = 0.02, p = 0.55; Figure 2). Predictive ability was much worse for Great Skua than other species. Removing Great Skua made a large improvement to the R² and p-value (linear model; slope = 0.08, R² = 0.20, p = 0.06). Uncertainty was generally high: for all species, the 95% credible intervals of the projected future abundance overlapped with current abundance (Table 3). However, the direction of change was correctly predicted for 14 of the 19 modelled species (Figure 2).

Figure 2. Observed and predicted population change by species. Each point is the log observed and log predicted change in abundance between Seabird 2000 and Seabirds Count, where abundance is summed across all cells for which data were withheld from the model. Colour shows whether species were correctly attributed to overall increase or decline (blue: correctly attributed; red: incorrectly attributed). Solid line: $y = x$; dashed lines: $x = 0$ and $y = 0$.



3.2. Overall predicted change in presence and abundance

Table 3 shows predicted presence and abundance change for each species for the overall MarPAMM region. Species-level graphs of predicted abundance and presence change are shown in Supplementary Information – Section 6.2.

Table 3. Projected future abundance and presence change for 19 seabird species under climate change for the MarPAMM region. We indicate overall species trend by colour: increasing (green), stable, i.e. between -5 and +5 (orange), and declining (red).

Species	Family	Seabirds Count total	Population size (95% CI)	Median predicted changes by 2050	
				Presence change for unoccupied cells %	Abundance change % (95% CI)
Razorbill	Alcidae	71,794	65,460 (18,685 - 195,522)	-74.7	-8.8 (-74.0 - 172.4)
Black Guillemot	Alcidae	12,993	10,144 (3,632 - 25,070)	-52.8	-21.9 (-72.0 - 93.0)
Atlantic Puffin	Alcidae	231,402	90,048 (7,522 - 823,974)	-61.1	-61.1 (-96.7 - 256.1)
Guillemot	Alcidae	299,654	362,989 (86,634 - 1,297,160)	-57.3	21.1 (-71.1 - 332.9)
Black-headed Gull	Laridae	16,125	19,518 (4,840 - 79,869)	-14.5	21.0 (-70.0 - 395.3)
Herring Gull	Laridae	14,334	7,077 (2,453 - 20,011)	-18.9	-50.6 (-82.9 - 39.6)
Common Gull	Laridae	4,621	3,369 (974 - 10,923)	0.80	-27.1 (-78.9 - 136.4)
Lesser Black-backed Gull	Laridae	7,040	4,515 (971 - 21,234)	-9.20	-35.9 (-86.2 - 201.6)
Great Black-backed Gull	Laridae	2,737	1,987 (635 - 5,968)	-22.4	-27.4 (-76.8 - 118.1)
Common Tern	Laridae	3,352	3,583 (881 - 14,637)	-8.60	6.90 (-73.7 - 336.7)
Arctic Tern	Laridae	5,699	2,947 (457 - 14,880)	1.90	-48.3 (-92 - 161.1)
Little Tern	Laridae	152	139 (12 - 1,121)	0.10	-8.6 (-92.3 - 703.24)
Sandwich Tern	Laridae	2,398	1,378 (236 - 49,818)	-2.20	-42.6 (-90.1 - 1,977.5)
Kittiwake	Laridae	36,149	22,590 (5,262 - 79,993)	-63.3	-37.5 (-85.4 - 121.3)
European Shag	Phalacrocoracidae	8,372	6,516 (2,501 - 16,318)	-61.1	-22.2 (-70.1 - 94.9)
Great Cormorant	Phalacrocoracidae	2,475	1,971 (597 - 6,039)	79.4	-20.4 (-75.9 - 144.0)
Northern Fulmar	Procellariidae	59,436	26,294 (8,049 - 69,481)	-69.0	-55.8 (-86.5 - 17.0)
Arctic Skua	Stercorariidae	140	49 (7 - 667)	-98.8	-64.8 (-94.9 - 376.3)
Great Skua	Stercorariidae	707	36 (1 - 4,945)	-60.4	-94.9 (-99.8 - 599.5)

For predicted abundance, credible intervals were very large, echoing the poor performance of the abundance model components. We therefore focus on median estimates for this section. Only one of the four Alcidae species was predicted to increase in the MarPAMM region by 2050; Common Guillemot *Uria aalge*, hereafter 'Guillemot' by 21.1%. The credible intervals for Puffin (7,522–823,974), and to a lesser degree Razorbill, were relatively broad compared to other Alcidae, likely due to greater imprecision associated in the counts of this burrow-nesting species. All Laridae gull species were predicted to decline, with the exception of Black-headed Gull which was predicted to increase by 21.0% in the MarPAMM region by 2050. By 2050 the populations of both Great Black-backed Gull (*L. marinus*) and Common Gull (*L. canus*) could reach fewer than 1,000 predicted individuals in the MarPAMM region (635 and 974 total count respectively). Three of the four tern species (Arctic *Sterna paradisea*, Little *Sternula albifrons* and Sandwich Tern) were predicted to decline by 2050 in the MarPAMM region, with Common Tern (*S. hirundo*) remaining relatively stable (predicted change: +6.9%). Both Phalacrocoracidae species (European Shag *Gulosus aristotelis*, hereafter 'Shag', and Great Cormorant *Phalacrocorax carbo*, hereafter 'Cormorant') were predicted to decline by 2050 at a similar rate: -22.2% and -20.4% respectively. Populations of Fulmar, the only Procellariidae species modelled, were predicted to halve in the MarPAMM region, with a predicted decline of -55.8%. Finally, the two Stercorariidae species, Arctic *Stercorarius parasiticus* and Great Skua, had the most severe decline of any species in the MarPAMM region of -64.8% and -94.9% by 2050 respectively.

Only four species (Common Gull, Arctic Tern, Little Tern and Cormorant) were predicted to have a greater probability of presence at currently unoccupied cells in 2050. However, for three of those species (Little Tern, Common Gull and Arctic Tern), the predicted increase in presence probability was very small (0.1%, 0.8% and 1.9% respectively). Consequently, colonisation of new areas would be unlikely to compensate for the losses of abundance predicted for these species (-8.6%, -27.1% and -48.3% respectively).

Overall, across families, broad trends in predicted future presence and abundance by the current study were in agreement with those in Davies et al. (2023; Table 4). Generally, the only major discrepancy between the two studies was that changes predicted by the current study were shallower than those predicted by Davies et al. (2023).

Table 4. A comparison of the overall predicted trends in presence and abundance by Davies et al. (2023) and the current study for each of the five seabird families modelled. '+' indicates an overall positive trend, '-' indicates an overall negative trend. The trends in abundance for each family between the Seabird 2000 and Seabirds Count census are provided for context.

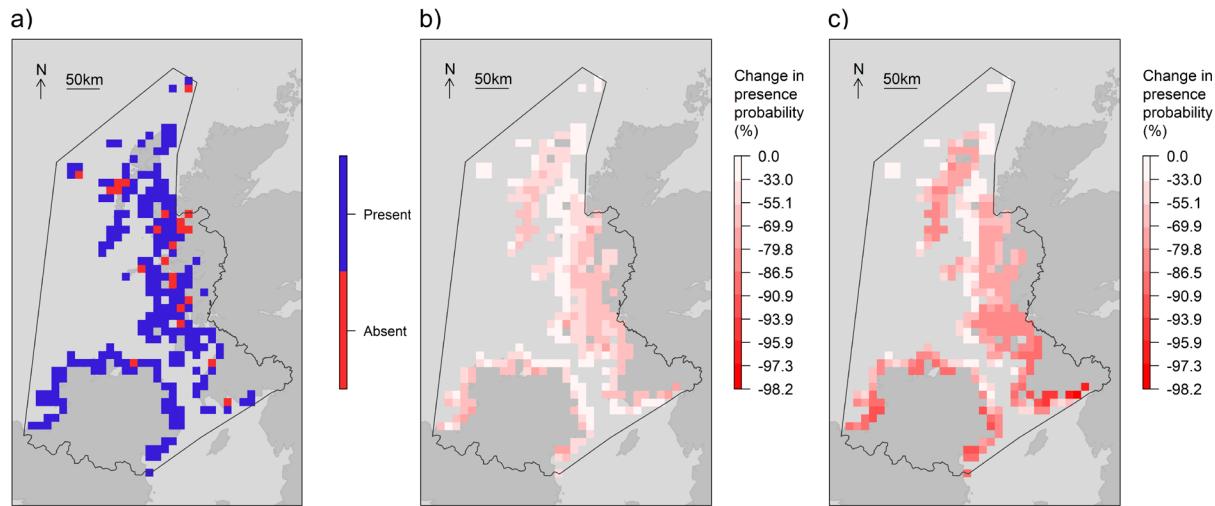
		Predicted Seabirds Count 2000–2050 change (Davies et al. 2023)		Predicted Seabirds Count 2000–2050 change (current study)	
Family	Observed Seabird 2000– Seabirds Count abundance	Presence probability	Abundance	Presence probability	Abundance
Alcidae	-	-	-	-	-
Laridae	-	-	-	-	-
Phalacrocoracidae	-	+	+	+	-
Procellariidae	-	-	-	-	-
Stercorariidae	-	not modelled	not modelled	-	-

3.3 Family-level predicted future presence

3.3.1. Alcidae

At the time of the Seabirds Count census, Alcidae species had a widespread distribution throughout the MarPAMM region (Figure 3a). Using the updated model incorporating data from the Seabirds Count census, declines in presence probability were predicted across much of the MarPAMM region, particularly in the more inland areas (Figure 3b). In contrast, Davies et al. (2023) predicted that there would be sharper declines, particularly in the south MarPAMM region (Figure 3c).

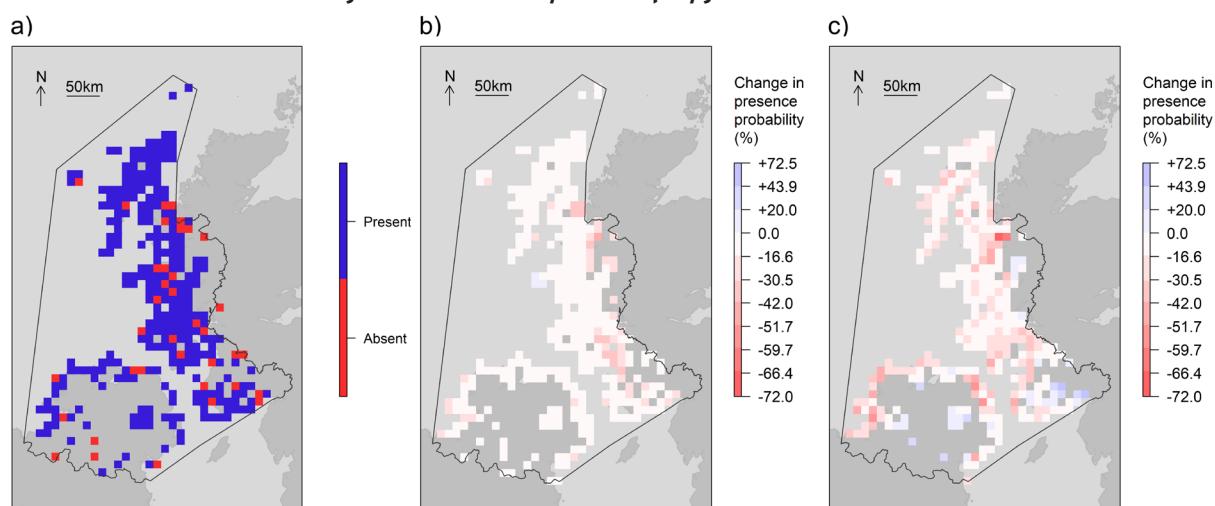
Figure 3. a) The realised presence of modelled Alcidae species (n species = 4) in the Seabirds Count census, and model predictions of the change in presence probability by 2050 from **b)** Seabirds Count as estimated by the current study, and **c)** from the Seabird 2000 census as estimated by Davies et al. (2023). The extent of the MarPAMM region is indicated by a black polygon.



3.3.2. Laridae

Laridae were present through much of the MarPAMM region at the time of the Seabirds Count census, with scattered areas of absence (Figure 4a). Using the current study's revised model, in most cases, Laridae species were predicted to show little change in presence probability throughout much of the MarPAMM region by 2050, with a small number of areas with declines and a few isolated areas of slight increase (Figure 4b).. Broadly, Davies et al. (2023) predicted more extreme increases and decreases of presence probability than the current study (Figure 2c).

Figure 4. a) The realised presence of modelled Laridae species (n species = 10) in the Seabirds Count census, and model predictions of the change in presence probability by 2050 from **b)** Seabirds Count as estimated by the current study, and **c)** from the Seabird 2000 census as estimated by Davies et al. (2023). The extent of the MarPAMM region is indicated by a black polygon.

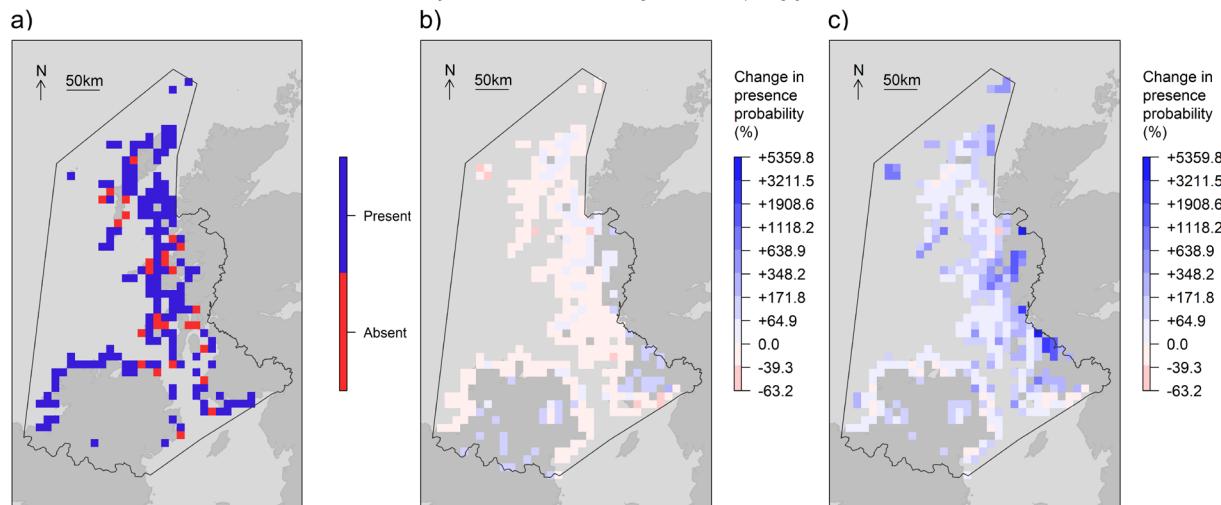


3.3.3. Phalacrocoracidae

Phalacrocoracidae species were present throughout the MarPAMM region at the time of the Seabirds Count census with scattered absences (Figure 5a). Using the current study's model incorporating the Seabirds

Count data, Phalacrocoracidae were predicted to have a slight decrease in the probability of presence by 2050 across the majority of the MarPAMM region. There were few areas predicted to have increased presence, particularly in more inland areas (indicating change in Cormorants as the only one of the two Phalacrocoracidae species to breed away from the coast). Sharper declines were predicted for some isolated parts of the more northern islands where Shags are the more dominant species (Figure 5b). The predictions of change in the probability of presence by Davies et al. (2023) were more positive, with increases in the probability of presence almost across the entire MarPAMM region (Figure 5c).

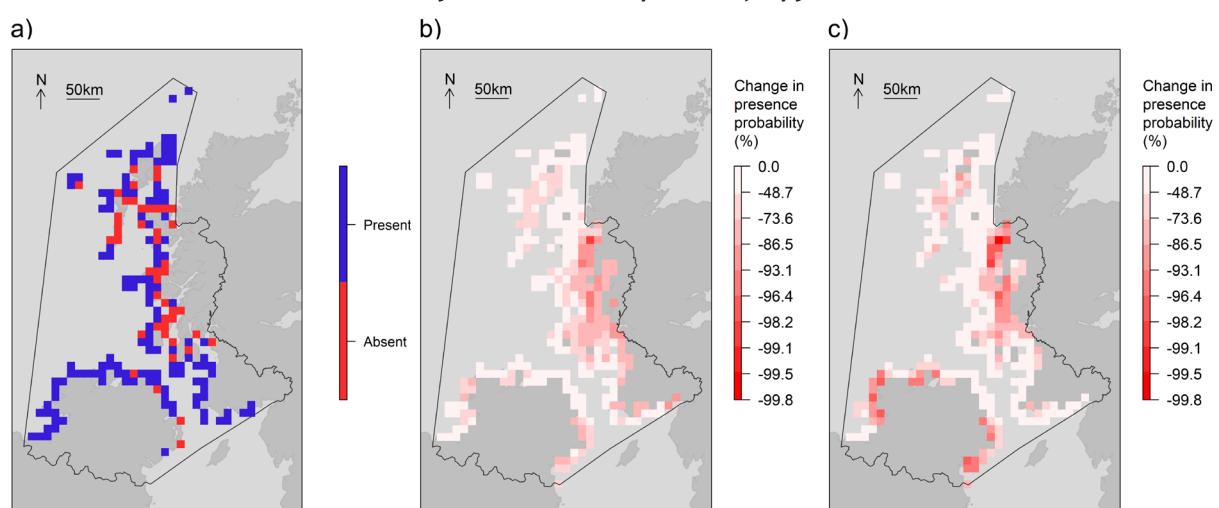
Figure 5. a) The realised presence of modelled Phalacrocoracidae species (n species = 2) in the Seabirds Count census, and model predictions of the change in presence probability by 2050 from **b)** Seabirds Count as estimated by the current study, and **c)** from the Seabird 2000 census as estimated by Davies et al. (2023). The extent of the MarPAMM region is indicated by a black polygon.



3.3.4. Procellariidae

Procellariidae species, here only Fulmar, were absent in approximately a third of cells in the MarPAMM region during the Seabirds Count census (Figure 6a). Using the updated model produced in the current study incorporating those Seabirds Count census data, declines of varying magnitude were predicted across much of the MarPAMM region by 2050 (Figure 6b). The predictions in Davies et al. (2023) indicated a similar overall spatial pattern of probability change, but with sharper predicted declines than the current study (Figure 6c). In both the current study and Davies et al. (2023), declines were focussed in the central part of the MarPAMM region.

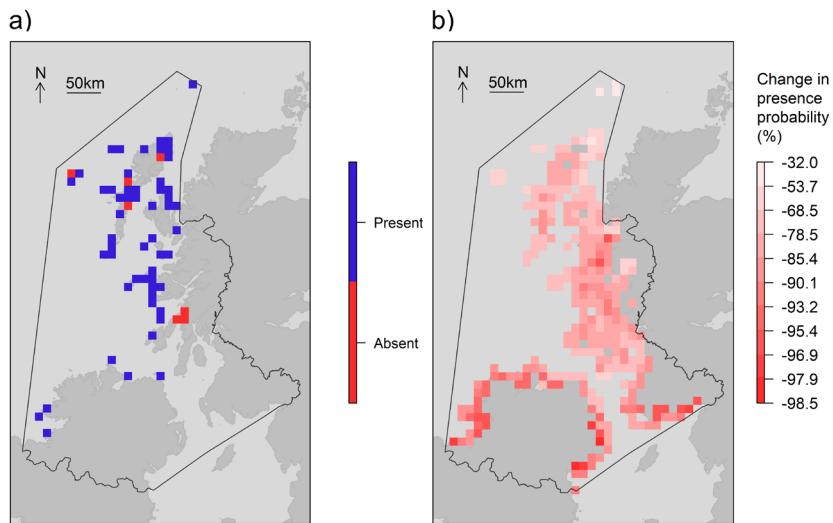
Figure 6. a) The realised presence of Fulmar (the only Procellariidae species modelled) in the Seabirds Count census, and model predictions of the change in presence probability by 2050 from **b)** Seabirds Count as estimated by the current study, and **c)** from the Seabird 2000 census as estimated by Davies et al. (2023). The extent of the MarPAMM region is indicated by a black polygon.



3.3.5 *Stercorariidae*

Stercorariidae species were found throughout the north and west of the MarPAMM region, including in few squares around Northern Ireland during the Seabirds Count Census (Figure 7a). The current study predicts that the presence of the species' is likely to decline greatly throughout the MarPAMM region by 2025, particularly in the south of the region (Figure 7b).

Figure 7. a) The realised presence of *Stercorariidae* (n species = 2) in the Seabirds Count census, and model predictions of the change in presence probability by 2050 from b) Seabirds Count as estimated by the current study. The extent of the MarPAMM region is indicated by a black polygon.

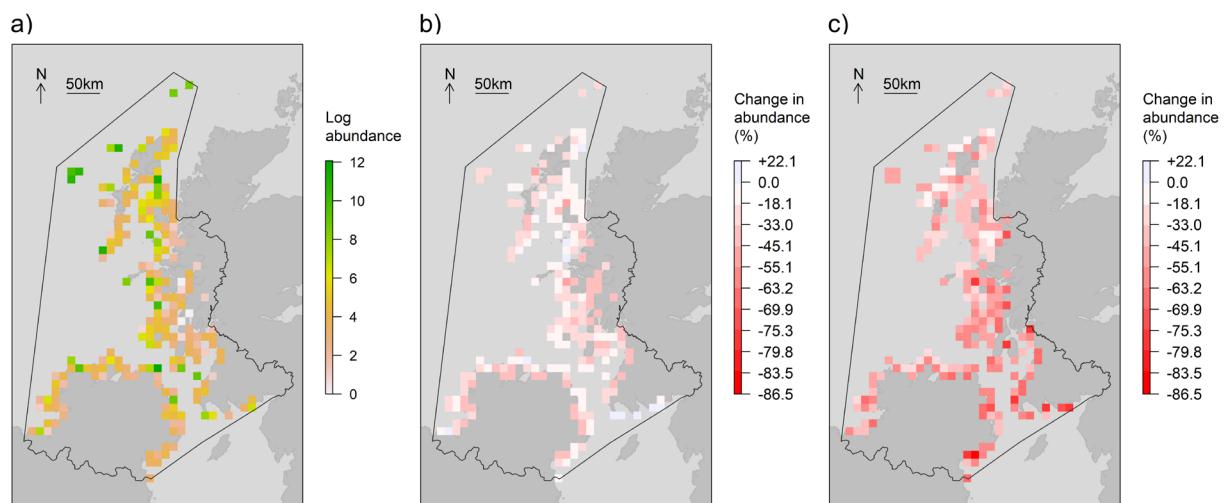


3.4 Family-level predicted future abundance

3.4.1. *Alcidae*

Following the Seabirds Count census, *Alcidae* species were observed to have peaks in abundance on offshore islands, with some scattered mainland cells with similarly large abundance (Figure 8a). Using the current study's improved model, *Alcidae* species were either predicted to show declines or remain relatively stable throughout the MarPAMM region by 2050 with just a few regions in the south showing a slight increase (Figure 8b). Davies et al. (2023) predicted that declines in *Alcidae* species would be more severe than those predicted in the current study (Figure 8c).

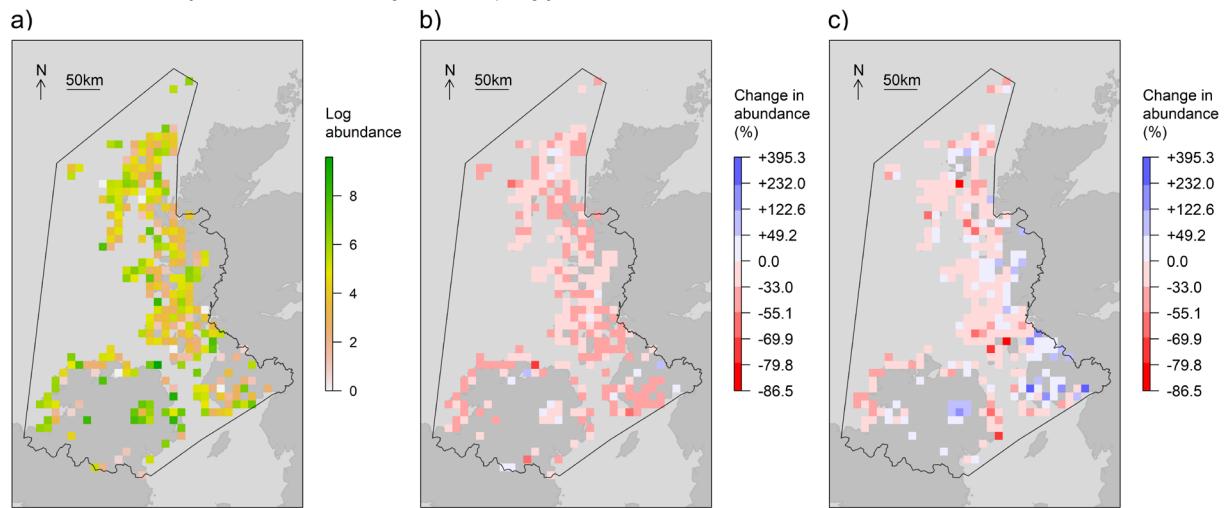
Figure 8. a) The realised abundance of modelled *Alcidae* species (n species = 4) in the Seabirds Count census, and model predictions of the change in abundance by 2050 from b) Seabirds Count as estimated by the current study, and c) from the Seabird 2000 census as estimated by Davies et al. (2023). The extent of the MarPAMM region is indicated by a black polygon.



3.4.2. Laridae

There were no apparent spatial patterns in the abundance of Laridae species in the MarPAMM region in the Seabirds Count census (Figure 9a). Using the model in the current study incorporating those Seabird Count census data, Laridae species were predicted to decline throughout the majority of the MarPAMM region by 2050 with some small increases in isolated cells (Figure 9b). The predictions of Davies et al. (2023) were broadly similar to those in the current study, however Davies et al. (2023) predicted more areas of increase for Laridae by 2050 (Figure 9c).

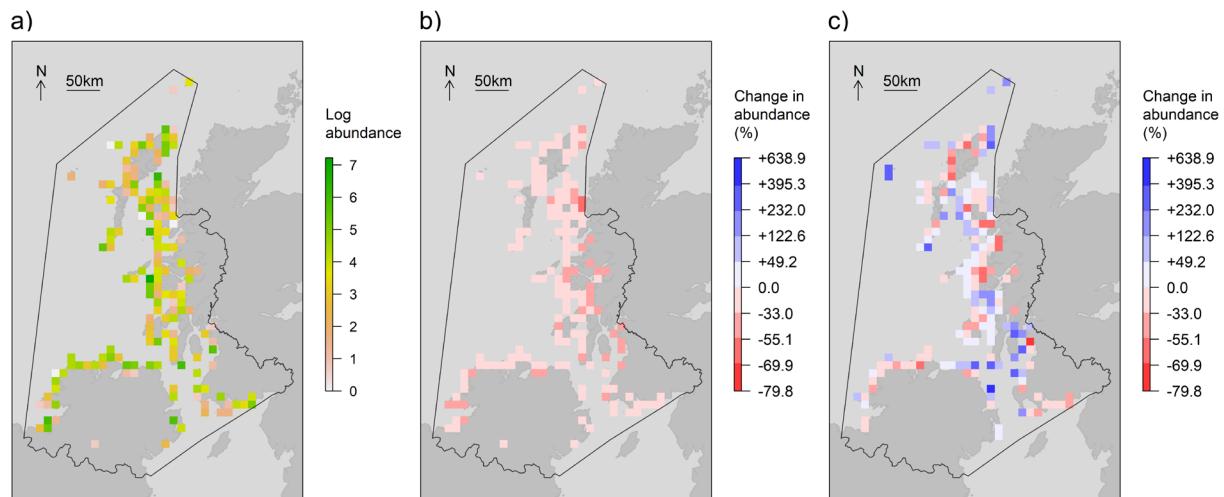
Figure 9. a) The realised abundance of modelled Laridae species (n species = 10) in the Seabirds Count census, and model predictions of the change in abundance by 2050 from b) Seabirds Count as estimated by the current study, and c) from the Seabird 2000 census as estimated by Davies et al. (2023). The extent of the MarPAMM region is indicated by a black polygon.



3.4.3. Phalacrocoracidae

Phalacrocoracidae species showed a high relative abundance on the west coast of Northern Ireland and in isolated cells further north in the MarPAMM region in the Seabirds Count census (Figure 10a). Using the model in the current study, Phalacrocoracidae species were predicted to show declines throughout the entire MarPAMM region by 2050 (Figure 10b). In contrast, Davies et al. (2023) predicted that Phalacrocoracidae species would increase in more than half of cells by 2050 (Figure 10c).

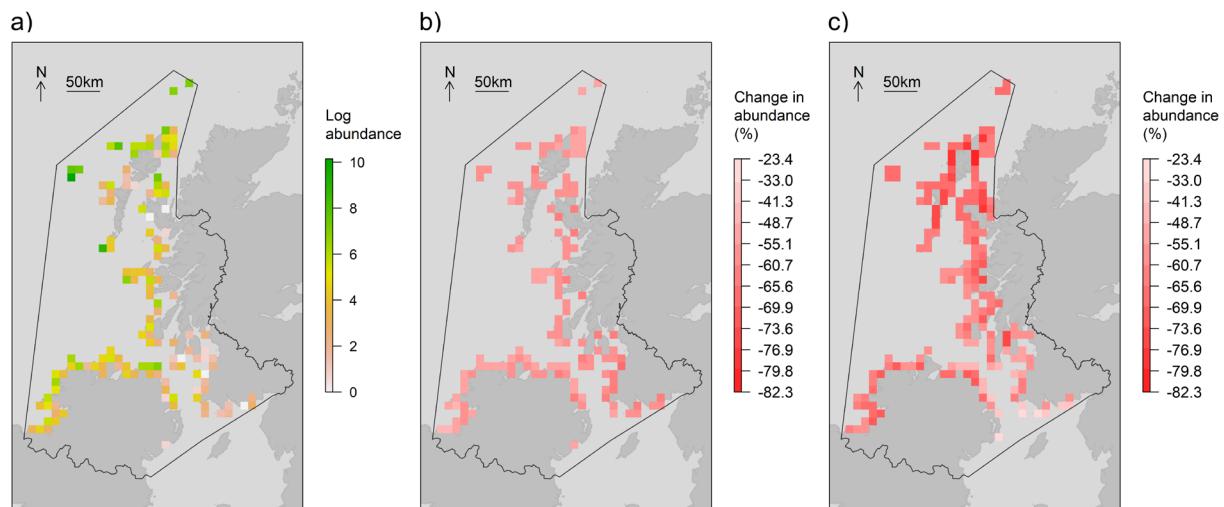
Figure 10. a) The realised abundance of modelled Phalacrocoracidae species (n species = 2) in the Seabirds Count census, and model predictions of the change in abundance by 2050 from b) Seabirds Count as estimated by the current study, and c) from the Seabird 2000 census as estimated by Davies et al. (2023). The extent of the MarPAMM region is indicated by a black polygon.



3.4.4 Procellariidae

As of the Seabirds Count census Procellariidae species, here solely Fulmar, were most abundant in the north and west of the MarPAMM region (Figure 11a). In the current study, Fulmar was predicted to decline throughout every cell in the MarPAMM region by 2050 (Figure 11b). Davies et al. (2023) similarly predicted declines for Fulmar throughout the entire MarPAMM region, however these were predicted to be more severe (Figure 11c).

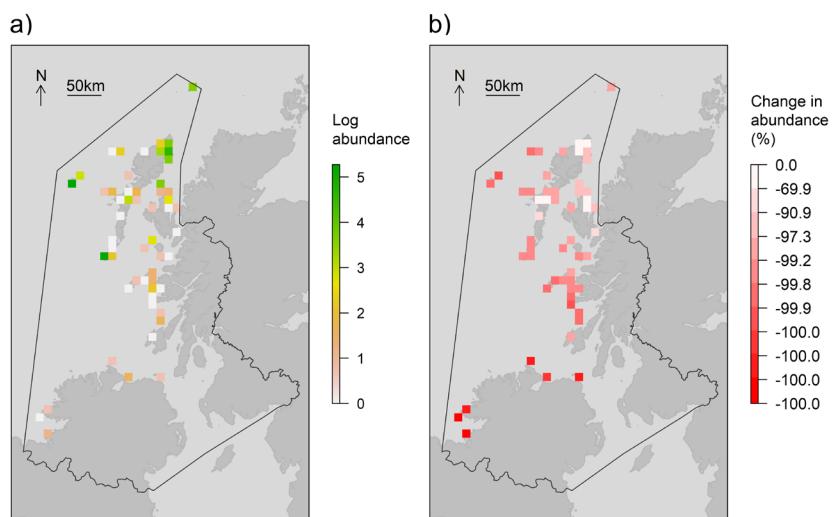
Figure 11. a) The realised abundance of Fulmar (the only Procellariidae species modelled) in the Seabirds Count census, and model predictions of the change in abundance by 2050 from b) Seabirds Count as estimated by the current study, and c) from the Seabird 2000 census as estimated by Davies et al. (2023). The extent of the MarPAMM region is indicated by a black polygon.



3.4.5 Stercorariidae

The largest populations of Stercoraciidae species were found in the north and west of the MarPAMM region in the Seabirds Count census (Figure 12a). By 2050 the species' are predicted by the current study to decline substantially at all southern most colonies, with no increases predicted anywhere in the MarPAMM region (Figure 12b). Some of the largest colonies are predicted to remain stable by 2050 however (Figure 12b).

Figure 12. a) The realised abundance of Stercoraciidae (n species = 2) in the Seabirds Count census, and model predictions of the change in abundance by 2050 from b) Seabirds Count as estimated by the current study. The extent of the MarPAMM region is indicated by a black polygon.



3.5. Relationships between seabird presence and abundance and environmental variables

Species-level graphs of the parameter estimates for the relationships between seabird presence or abundance with climate and oceanographic variables are given in Supplementary Information – 6.3. A relationship was considered 'significant' if the 95% credible intervals did not overlap zero. The following analysis of parameter estimates was conducted for the 19 species for which projections are included in the main text, and for linear terms only. Linear terms were of greater magnitude than the quadratic terms and were therefore considered to be of greater importance, as also done in Davies et al. (2023) (mean absolute linear term was 2.43 x the mean absolute quadratic term; linear model, slope = -0.59, $R^2 = 0.02$, $p < 0.01$).

In general, relationships between environmental variables and seabird presence or abundance varied across the different species (Figure S20). The only estimated relationship for which the 95% credible interval of the mean parameter estimate (across species, after accounting for phylogeny) did not overlap with zero was the negative relationship between species presence and breeding season maximum temperature (effect size = -1.91, 95% CI = -3.05, -0.70), and the positive relationship between species presence and SST (effect size = 1.65, 95% CI = 0.48, 2.79). A minimum of three significant effects on either species presence or abundance were found for all species except Common Tern, Little Tern and Sandwich Tern, for which 2, 1 and zero significant relationships were found respectively.

Coefficient estimates for the relationships of any given environmental variable with seabird presence and abundance were significantly correlated with each other (linear model; slope = 0.35, $R^2 = 0.30$, $p < 0.01$). Coefficient estimates for scaled climate variables were of significantly greater magnitude than those for scaled oceanographic variables (paired t-test; mean difference = 0.98, $t = 3.59$, $df = 151$, $p < 0.01$) and there was a greater number of significant effect sizes for climatic variables (75) than oceanographic variables (18).

3.5.1. Climate variables

For climate variables, predicted coefficients of breeding season variables had a greater magnitude than winter variables (paired t-test; mean difference = 0.30, $t = 2.52$, $df = 75$, $p = 0.01$).

Where significant, warmer winter temperatures and cooler breeding season temperatures were generally related to higher seabird presence and abundance. Winter temperature was significantly associated with the presence of 12 and abundance of six species, with positive relationships for all species except Black-headed Gull. Breeding season temperature was significantly associated with the presence and abundance of 12 species each, with negative relationships for all species except Black-headed Gull and Common Tern, which exhibited increased abundance with warmer breeding season temperatures.

Where significant, both winter and breeding season precipitation were negatively related to seabird presence and abundance. Lower winter precipitation was significantly associated with increased presence of 10 and abundance of nine species, whereas breeding season precipitation was related to reduced presence and abundance of five and 9 species respectively.

3.5.2. Oceanographic variables

For oceanographic variables, there was no significant difference between the magnitude of breeding season and winter variables (paired t-test; mean difference = -0.17, $t = -1.38$, $df = 75$, $p = 0.17$).

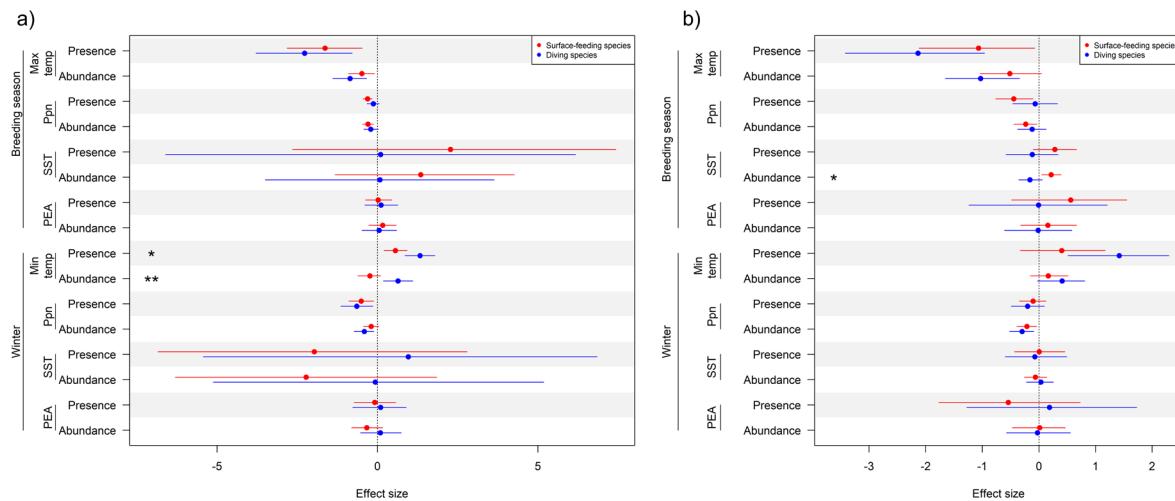
For 10 species, oceanographic variables did not have any significant effect on either presence or absence. However, for some species (Black Guillemot, Guillemot, Kittiwake and Great Skua), either winter or breeding season SST had the largest effect on presence probability. Where significant relationships with either SST or PEA were found, winter and breeding season variables consistently had opposing effects. For example, cooler winter and warmer breeding season SST were associated with higher presence probability and abundance for Great Skua. In contrast, warmer winter and cooler breeding season SST were linked to higher presence probability for Black Guillemot, with the same pattern found for the effects of PEA on Fulmar presence. Oceanographic variables had fewer significant relationships with species abundance (six) compared to presence probability (12).

3.6 Environment-seabird relationships with feeding ecology and habitat specialism

In the current study, surface-feeding and diving species only significantly differed in their relationship with winter minimum temperature, where diving species had a more positive relationship for both abundance and

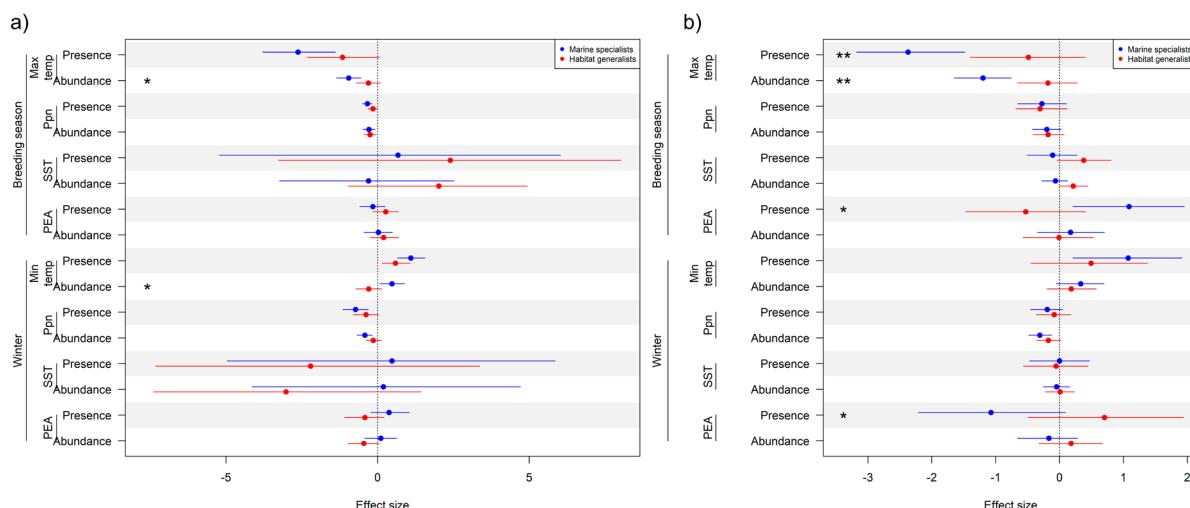
presence (Figure 13a). This clear difference in effect size was not apparent in Davies et al. (2023) – Figure 13b. However, Davies et al. (2023) did identify a more positive relationship between abundance and breeding season SST for surface-feeding species that was not apparent in the current study due to much wider credible intervals (Figure 13b). For all other variables, the relative effect sizes between the current study and Davies et al. (2023) were relatively similar.

Figure 13. Parameter estimates (dots) and associated 95% credible intervals (lines) of the relationships of surface-feeding species (red) and diving species (blue) with environmental variables, for a) the current study and b) Davies et al. (2023). Parameters where estimates significantly differed between feeding groups are indicated by asterisk(s). **<0.01, *0.01-0.05. 'Ppn' = precipitation.



Both the current study and Davies et al. (2023) identified a more negative relationship between breeding season maximum temperature and presence and abundance of marine specialists compared to habitat generalists (Figure 14a and b). The relative effect sizes identified were also comparable between the studies. The effects of a more positive relationship between PEA and species presence for habitat generalists in the winter, and the opposite in the summer found in Davies et al. (2023) were not present in the current study. For all other variables, the effect sizes in both studies were broadly similar.

Figure 14. Parameter estimates (dots) and associated 95% credible intervals (lines) of the relationships of habitat generalists (red) and marine specialists (blue) with environmental variables, for a) the current study and b) Davies et al. (2023). Parameters where estimates significantly differed between feeding groups are indicated by asterisk(s). **<0.01, *0.01-0.05. 'Ppn' = precipitation.



4. Discussion

4.1. Overall summary

Overall, the model performed well at predicting presence–absence. The model was considerably weaker, however, at predicting change in abundance, although the direction was correctly predicted for most species. With this caveat, we predicted that 15 out of the 19 species modelled would decline in presence probability, and 16 in abundance, in the MarPAMM region by 2050. The scale of declines in presence probability was highly variable from -2.2% (Sandwich Tern) to -98.2% (Arctic Skua, *Stercorarius parasiticus*). Little Terns had the smallest predicted decline in abundance of -8.6%, with a skua species again – this time Great Skua – having the highest (-94.9%). The results show broad agreement with those trends identified in Davies et al. (2023), although trends in the current study were generally shallower. These shallower trends may have resulted from the shorter time period over which the current study's model was making predictions (29 years, current study, v 50 years, Davies et al. 2023). Many climate variables had stronger effects on predicted presence and abundance during the breeding season compared to the winter. Oceanographic variables, however, had a relatively similar effect size between the breeding and winter. Overall, temperature-based variables including SST, maximum breeding season temperature and minimum winter temperature, had the largest effects on predicted presence and abundance across species foraging ecologies and habitat specialisms.

4.2. Predicted changes in presence and abundance

The general trend of predicted seabird population decline identified here was in broad agreement with other previous modelling studies based on future climate scenarios at the national scale (Johnston et al. 2013, Häkkinen et al. 2023). Generally across all species groups the predictions of changes in presence and abundance were similar to those in Davies et al. (2023), but generally less severe, i.e. deviating less from zero. With that, it is important to caveat that the current study predicted change between 2018–2050 based on more recent national census data, whereas Davies et al. (2023) predicted change between 2000–2050 with Seabird 2000 being the most up to date data used. In most cases the trends predicted by Davies et al. (2023) agreed with those observed by the Seabirds Count census. Consequently, the discrepancy between trends identified in the current study and Davies et al. (2023) may be simply reflective of 15 years of changes in populations, predominantly declines, having already taken place.

In terms of understanding drivers of change in population numbers and demographic rates such as breeding success and survival, quantification of the diet of seabirds is key. Although the diet of some seabirds (e.g. Kittiwake, Guillemot and Shag) are relatively well-studied, much of the information is for seabirds foraging in the northern North Sea. There is an urgent need for data on the diet of seabird breeding in colonies adjacent to the Celtic and Irish Sea (Johnston et al. 2025). We also have very little empirical data on what seabirds feed on outside the breeding season.

Broadly, the predictions for the future predicted presence of species generally aligned with that of Russell et al. (2015), which predicted an overall decrease in the range of these species. There were some differences to the Russell et al. (2015) study, however, on the species level, e.g. the range of Guillemots was predicted to contract to the south of the study region in Northern Ireland, whereas we identify a larger decline in the north of the region around the Outer Hebrides. However, Russell et al. (2015) were not applying the most severe climate predictions in their study and were not able to include data from the most recent national seabird census, as we did in the current study. The difference in climate scenario applied may then explain some species-level differences observed. Given that we are now likely heading towards the current worst case climate scenario (Kemp et al. 2022) we would recommend that future studies also adopt this scenario, and potentially project beyond this for a realistic prediction of what future seabird populations may look like.

Alcidae

The most severe predicted decline in the abundance of Alcidae species in the south of the MarPAMM region in Northern Ireland is in agreement with those trends identified in the most recent Seabirds Count report (Burnell et al. 2023). Specifically for Guillemot and Razorbill, which have been observed to decline in the MarPAMM region, while increasing further south outside of this region. Further, across the MarPAMM region Alcidae were also predicted to decline in presence probability, particularly in mainland colonies around Argyll. A similar pattern in presence trend was observed in both presence probability and abundance by Davies et al. (2023), though predicted declines were marginally shallower, despite showing similar spatial

variation. As yet, no convincing rationale for the pattern of trend observed and predicted in Alcidae has been offered. In addition changes in prey distribution, abundance or quality may affect the distribution and abundance of seabirds, particularly in those species that do not range as widely year-round, such as many Alcidae (Burnell et al. 2023). Little is known of the movements of prey species of seabirds in Britain and Ireland, though it is likely that future changes of prey under a changing marine environment may affect, and already be affecting, seabird populations that may explain the pattern observed in this study.

Laridae

For Laridae, predicted presence decline was marginally more pronounced towards the south of the MarPAMM region. Spatial trends in predicted abundance were less apparent than in other seabird families modelled, with predictions being relatively consistent across much of the MarPAMM region. Generally, predicted change in presence and abundance were of lower magnitudes than those predicted by Davies et al. (2023). The difference in the scale of predicted trends between the current study and Davies et al. (2023) may arise from the shorter timescale over which the former is predicting. Gull species are generally difficult to monitor, particularly the urban-breeding component of the population. As a result, there was relatively low confidence and coverage in the more recent census counts for these species (Burnell et al. 2023). Despite these difficulties, at present it is believed that the urban-nesting proportions of the populations of Herring and Lesser Black-backed Gulls have increased while the natural-nesting populations have declined (Burnell et al. 2023). Further, the overall populations of many other Laridae species have declined nationally between the Seabird 2000 and Seabirds Count censuses, with the exception of Sandwich and Common Tern. Indeed, some gull species, such as Kittiwake, have been declining in Britain and Ireland since at least the 1980s, though the trend has also varied within regions over this period (Heubeck et al. 1999). It is perhaps unsurprising then that the current study predicts a smaller additional decline to 2050 (as part of the decline predicted by Davies et al. (2023) will already have occurred). The drivers of the declines in addition to climate change impacts likely include, but are not limited to: historic persecution of many Laridae species, reduced prey availability, and disease including most recently, outbreaks of high pathogenicity avian influenza (HPAI) (Coulson 2015, Burnell et al. 2023, Tremlett et al. 2025). Laridae, in particular, have shown high susceptibility to HPAI at present (Tremlett et al. 2025). Given the already present strong declines in many species and the likelihood of further declines under future climate change, were HPAI outbreaks to continue the realised presence and abundance of Laridae may be worse than predicted here.

Phalacrocoracidae

There was reasonable contrast between the current study's predictions in presence and abundance for Phalacrocoracidae species, and that of Davies et al. (2023). Previously, Phalacrocoracidae were predicted to substantially increase overall by 2050 according to Davies et al. (2023), whereas the current study predicted a slight decline throughout the majority of the region. To examine the current study's findings more closely, Shag were predicted to decrease in presence and abundance, in some areas strongly so (Figure S14). Cormorant presence probability was predicted to increase in inland areas but decrease in more coastal locations, while abundance was predicted to decline across the current range (Figure S15). Up to the Seabird 2000 census Cormorant was predicted to be strongly increasing, while Shag had a reasonable decline throughout the MarPAMM region (Burnell et al. 2023). In Seabirds Count the increase of Cormorants had bottomed out into a slight decline, while the decline in Shags increased. Given the additional information on the trends of both of these species available to the current study, it then follows that the overall trend in this family is different to that in Davies et al. (2023). There are several additional likely drivers outside of climate change that may be contributing to the decline of Cormorants and Shags in many parts of their range, e.g. pollution (Velando et al. 2005) and licenced control (Newson & Austin 2021). Notably, the species have suffered many large wrecks in Britain and Ireland in recent years that have impacted both adults and juveniles (Acker et al. 2021). Such wrecks are driven by extreme weather events the likes of which are likely to increase under future climate change scenarios, potentially exacerbating the declines in population trajectory predicted in this study.

Procellariidae

The Fulmar suffered clear declines between Seabird 2000 and Seabirds Count, and this study predicted that these declines are expected to continue. There was little spatial patterning in the declines in presence and

abundance identified in this study, though declines in presence were marginally more likely in colonies closer to mainland Scotland. Fulmar was predicted to decline in presence probability and abundance by Davies et al. (2023), and by the current study with a similar spatial patterning. Based on Burnell et al. (2023), Fulmar declined greatly in abundance between the Seabird 2000 and Seabirds Count census (-57% in Northern Ireland and -37% in Scotland). Both Davies et al. (2023) and the current study predict that the losses in Fulmar populations will continue through to 2050. Such declines for Fulmar are mirrored in other studies that find long-term declines in abundance and survival for this species (Cordes et al. 2015). Many additional drivers of the long-term declines in Fulmar have been identified, largely relating to declining prey availability and shifting of prey distribution (MacDonald et al. 2015), as Fulmars are at particular risk of by-catch in fisheries (Beck et al. 2021, Kühn et al. 2024). Clearly, given the multitude of factors already severely impacting Fulmar populations, and the likely worsening of this under further climate change, this species is at particular risk of cascading impacts on populations.

Stercoraridae

Predicted declines in presence and abundance were clear across the MarPAMM region in the current study, particularly in the south. There are few studies predicting the future trends in either species nationally, partly resulting from the more limited distribution of the species within the UK; both species are predominantly or entirely found in Scotland. Great Skuas had shown some slight increase between Seabird 2000 and Seabirds Count (+14%; Burnell et al. 2023). However, Great Skuas were one of the species hardest hit by the HPAI outbreak in 2021 and 2022; Tremlett et al. (2024) estimated that Great Skuas had declined by 73% by 2023 as a result of the HPAI outbreaks. Consequently, the likely future change in presence and abundance for this species may be even worse than predicted in this study, where they were identified as the species with the greatest rate of future decline. Further, populations of Arctic Skuas had declined by 66% between the Seabird 2000 and Seabirds Count censuses (Burnell et al. 2023), placing them in an already vulnerable position. However, there is some anecdotal evidence that Arctic Skua populations may now be increasing in areas where Great Skua have declined following HPAI, due to the decrease in kleptoparasitism pressure. Overall, due to the additional impacts on both species (but particularly Great Skuas) since collection of the data used to parameterise models in this study, less confidence may be had in the predictions of these species as population trends are likely to be more negative than estimated.

Colonisation and arrival of new species

The overall potential for predicted abundance declines in established colonies to be offset by establishment of new colonies across species was limited. Probability of presence at unoccupied cells was only predicted to increase for Common Gull, Arctic Tern, Little Tern and Cormorant. For three of those species, the probability of increased presence was very small in comparison to predicted abundance declines: increased probability of presence was only predicted at 0.1%, 0.8% and 1.9% of modelled cells for Little Tern, Common Gull and Arctic Tern, compared to projected abundance declines of -8.6%, -27.1% and -48.3% respectively. Further, this measure represents the upper limit of potential colonisation, as not all unoccupied cells would be suitable for all species due to variation in breeding habitat suitability and species interactions. As such, the predictions show minimal potential for colonisation of new areas to compensate for seabird population declines across the MarPAMM region.

Redistribution of species under climate change may result in historically absent or less abundant seabird species establishing breeding populations in Britain and Ireland in the future. One recent example of this is the Mediterranean Gull, which is a rapidly increasing and recently arrived breeding species in Britain and Ireland (Eaton & Rare Breeding Birds Panel 2022). The arrival of new breeding species could lead to increased pressures on current British and Irish breeding species through, for example, competition for resources. Consequently, the accuracy of future studies investigating climate-mediated threats on seabirds may be improved by accounting for the potential impact of future colonising species on current seabird populations.

4.3. Fitted relationships between environmental variables and seabird presence and absence

Generally, we found that the effects of environmental variables on presence and abundance were not correlated with one another for individual species, in agreement with Davies et al. (2023). Similar to the conclusions of Davies et al. (2023), we found that fitted relationships of climate and oceanography on seabirds varied across species, although increased presence and abundance was typically related to cooler breeding season temperature and warmer winter temperature. For the most part, temperature-related

variables (both climatic and oceanographic) had the largest impact on presence and abundance, and this was most evident in marine specialists, as in Davies et al. (2023). Further, in the current study we again show that diving and surface feeders were similarly affected by environmental variables. Both diving and surface-feeding species showed a negative response to increases in breeding season temperature, despite the expectation that diving species should be able to buffer more strongly due to a greater foraging niche. Multiple studies have documented direct negative impacts of increased breeding season temperature on some seabird species, such as heat stress that may drive birds to leave their nests unattended (Gaston et al. 2002, Oswald et al. 2008). The causal mechanism of the relationship between breeding season temperature and seabird presence and abundance in this study is unclear, with indirect factors such as storminess or prey abundance also likely contributing to observed effects. Since few direct effects of minimum winter temperature on seabirds have been documented, the impact of SST on seabird presence and abundance is likely to be indirect, such as through prey abundance (Davies et al. 2023). Negative relationships between breeding season temperature and seabird productivity have also been identified previously (all species in this study: Häkkinen et al. 2023; Kittiwake: Moe et al. 2009). Studies testing how seabird presence (or persistence at a site) and overall abundance vary in relation to environmental variables are few, due to the large data requirements to address this question robustly. However, those few studies testing how the suitability of the environment for seabirds may alter with likely future climatic scenarios commonly identify declines in likely range in response to increasing SST and land temperature (Russell et al. 2015, Häkkinen et al. 2023). As terrestrial temperatures and SST are predicted to increase under climate change, it is then likely that the negative effects on seabirds observed here will continue into the future.

4.4. Limitations

There were a number of limitations of the study that merit discussion to aid interpretation and interrogation of the results. Like the original Davies et al. (2023) study, it was not possible to run the model for all species breeding in the MarPAMM region due to either low abundance or insufficient available data. However, as the populations of these species were therefore relatively small, their omission is unlikely to significantly impact overall predictions of seabird presence and abundance across the region. Crucially though, as in Davies et al. (2023), the abundance component of the models had moderate to good performance. The model performance may have been impacted by several methodological limitations due to: 1) fine-scale variation in seabird abundance, 2) mapping oceanographic conditions to seabird populations, and 3) the nuance of how environmental effects may impact seabird populations, which we discuss below.

Firstly, data with high levels of fine-scale spatial variation, such as seabird abundance, are challenging to accurately model using comparatively coarse-scale environmental data. The fine-scale variation in abundance may then have limited the model's ability to detect an effect of environmental variables, even with use of a hurdle model with a spatial random effect (especially since the seabird and environmental data were aggregated to match the 12-km resolution of the UKCP18 climate data). An alternative approach to address this limitation could be to use a spatial random effect with a much finer resolution. However, this would require fine-scale environmental and seabird abundance data which are not readily available, at least across such large spatial scales. Collecting such data would require extensive field surveys, which would necessitate large amounts of human effort, and high-resolution observed or modelled environmental data.

Secondly, the data used may not have adequately represented the environmental conditions experienced by seabird populations, particularly oceanographic conditions. We determined which spatial cells seabird populations would have had access to, and so been exposed to the conditions of, from their estimated foraging ranges. However, intraspecific variation in foraging ranges may be hugely variable (Woodward et al. 2024) and can vary with many factors, including prey availability (Fayet et al. 2021), environmental conditions (Trevail et al. 2019), and population size (Ashmole 1963), amongst others. Variability in foraging ranges may also co-vary with the maximum foraging range of a species: species that can forage at greater distances have more variable foraging ranges (Woodward et al. 2024). It then follows that the credible intervals for the fitted effect of PEA were wider for species with larger, and so more variable, foraging ranges (e.g. those >50 km). Given that foraging data are not available for each individual year, species and colony modelled, a reasonable compromise on the foraging ranges included must be made. Overall, we used foraging ranges obtained from a literature review of all available studies on foraging ranges for the species modelled (Woodward et al. 2024), which represent the most robust known mean estimates available.

A related additional consideration with the oceanographic variables was that PEA data for modelled cells beyond the continental shelf were omitted, and as a result, could not be related to species with foraging ranges extending beyond the shelf. Deeper areas of the sea, such as those beyond the shelf, typically experience greater PEA than shallower areas (Horsburgh et al. 2020). Consequently, there is potential for the PEA values included in the model to be biased towards lower values than those experienced by all birds. However, only four of the study species have foraging ranges that are likely to reach the edge of the shelf, and only from a small proportion of their colonies in the study region: Puffin, Lesser Black-backed Gull, Kittiwake and Fulmar. As such, it is unlikely that the exclusion of PEA data beyond the shelf had a large impact on model predictions. Further, PEA were not available for the SCR Census and so the fitted relationships between PEA and seabird presence and abundance were partially derived using PEA values imputed by the INLA model. These imputed values by the INLA are assumed to be a reasonable approximation of the likely PEA experienced during the SCR census, but will not be as appropriate as the data included for Seabirds 2000 and Seabirds Count. Fortunately, due to the wealth of oceanographic and seabird population data available for the latter two censuses, impacts on model uncertainty were as minimal as feasible for a study of this scale. Overall, there are key considerations and caveats associated with the oceanographic data included in this study. However, pragmatic decisions were made throughout to ensure the incorporation of as comprehensive and appropriate oceanographic data as feasible.

Finally, the nature of the ecological processes through which climate and oceanography impact seabirds could have limited the ability of the model to identify fitted relationships. For example, the modelled environmental variables may impact seabird presence and abundance through indirect processes that we could not account for in the model, such as prey availability (Frederiksen et al. 2007, Carroll et al. 2015, Johnston et al. 2021). In addition, inherent to our modelling framework is the assumption that relationships between seabird populations and environmental variables remain constant over time and space. However, processes such as plasticity and evolution (Hansen et al. 2021) or density dependence (Ehrlén & Morris 2015) may cause these relationships to vary. Density dependence is influenced by population demography and structure, and since many of the species have significantly changed in population size between the census periods (Burnell et al. 2023), relationships with environmental variables effects may have changed as a result. Seabird response to environmental change may also be subject to a time lag, such as decreased breeding success manifesting as reduced recruitment some years later (Sandvik et al. 2012). It is therefore possible that comparing concurrent data on seabird populations and environmental variables may not identify these potentially lagged relationships. Future work could focus on incorporating spatiotemporal variation in environment–presence/abundance relationships or accounting for density dependence. An alternative approach could be to investigate the effects of climate and oceanography on individual demographic parameters that influence presence and abundance over time, such as productivity, survival and dispersal. However, doing so would require vast amounts of data collected from individual seabirds across multiple census periods.

Overall, despite the above limitations, the current study presents several improvements over that of Davies et al. (2023). For all species, we were able to incorporate one additional timestep of census data (Seabirds Count) and two additional timesteps of oceanographic data (for Seabirds Count and SCR Census). Consequently, we were able to estimate the relationships between oceanography and seabird species using temporal (rather than only spatial) oceanographic variation. Additionally, we were able to produce predictions for three additional species: Arctic Skuas, Great Skuas and Little Terns, therefore providing greater coverage for those species breeding throughout the MarPAMM region.

4.5. Conclusions

From the results of the Seabirds Count census it is apparent that many British and Irish breeding seabird populations have decreased since the start of the century. The results of this study demonstrate that such declines are likely to continue for many species under a severe, but likely, climate scenario. There was no evidence that the rates of losses have accelerated since the publication of Davies et al.'s (2023) study. The current study and Davies et al. (2023) were largely in agreement on the likely environmental drivers of change and their impacts on seabird populations, hence confirming that relationships are more likely to be causative rather than purely correlational. Seabird populations are, of course, negatively impacted by many anthropogenic-driven factors of which climate change is just one, and can be mediated by both indirect and

direct effects. Consequently, it is difficult to determine the true scale at which climate change has been instrumental in driving change in seabird presence and abundance. However, there is little doubt that the changing climate has, largely negatively, affected seabird populations and shall continue to do so for the foreseeable future.

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6. Supplementary Material

6.1 Species taxonomy, breeding and foraging ecology

Table S1: Species taxonomy, breeding and foraging ecology for modelled bird species. Species-specific foraging ranges from Woodward et al. (2024) and breeding season timings from Campbell & Ferguson-Lees (1972), or from BTO BirdFacts* if not listed. [†]Seabird foraging range from Thaxter et al. (2012) instead (see Methods). ¹Feeding ecology as determined by OSPAR Commission (2016). ² Feeding ecology determined by expert opinion. ³ Habitat specialism as determined by expert opinion.

Scientific name	Common name	Family	Breeding season	Foraging range (km) [†]	Feeding ecology ¹	Habitat specialism ²
<i>Alca torda</i>	Razorbill	Alcidae	Apr-Aug	88.7	Diving	Marine specialist
<i>Cephus grylle</i>	Black Guillemot	Alcidae	May-Sep	4.8	Diving	Marine specialist
<i>Fratercula arctica</i>	Atlantic Puffin	Alcidae	Apr-Sep	137.1	Diving	Marine specialist
<i>Uria aalge</i>	Guillemot	Alcidae	Apr-Aug	73.2	Diving	Marine specialist
<i>Chroicocephalus ridibundus</i>	Black-headed Gull	Laridae	Apr-Sep	18.5	Surface feeding	Habitat generalist
<i>Larus argentatus</i>	Herring Gull	Laridae	Apr-Aug	58.8	Surface feeding	Habitat generalist
<i>Larus canus</i>	Common Gull	Laridae	Apr-Aug	50	Surface feeding	Habitat generalist
<i>Larus fuscus</i>	Lesser Black-backed Gull	Laridae	Apr-Sep	127	Surface feeding	Habitat generalist
<i>Larus marinus</i>	Great Black-backed Gull	Laridae	Apr-Aug	73	Surface feeding	Habitat generalist
<i>Sterna hirundo</i>	Common Tern	Laridae	May-Sep	18.0	Surface feeding	Habitat generalist
<i>Sternula albifrons</i>	Little Tern	Laridae	*Apr-Sep	5	Surface feeding	Marine specialist
<i>Sterna paradisaea</i>	Arctic Tern	Laridae	May-Aug	25.7	Surface feeding	Marine specialist
<i>Thalasseus sandvicensis</i>	Sandwich Tern	Laridae	Apr-Sep	34.3	Surface feeding	Marine specialist
<i>Rissa tridactyla</i>	Kittiwake	Laridae	May-Sep	156.1	Surface feeding	Marine specialist
<i>Gulosus aristotelis</i>	European Shag	Phalacrocoracidae	Jan-Oct	13.2	Diving	Marine specialist
<i>Phalacrocorax carbo</i>	Great Cormorant	Phalacrocoracidae	Mar-Sep	25.6	Diving	Habitat generalist
<i>Fulmarus glacialis</i>	Northern Fulmar	Procellariidae	May-Sep	542.3	Surface feeding	Marine specialist
<i>Stercorarius parasiticus</i>	Arctic Skua	Stercorariidae	May-Aug	63.3†	Surface feeding ³	Marine specialist
<i>Stercorarius skua</i>	Great Skua	Stercorariidae	May-Sep	443.4	Surface feeding ³	Marine specialist

6.2 Individual species-level predictions of presence and abundance change

Figure S1. Predicted change in a) presence probability and b) abundance between 2018 (Seabirds Count census) and 2050 for Razorbill across the MarPAMM region (extent indicated by a black polygon).

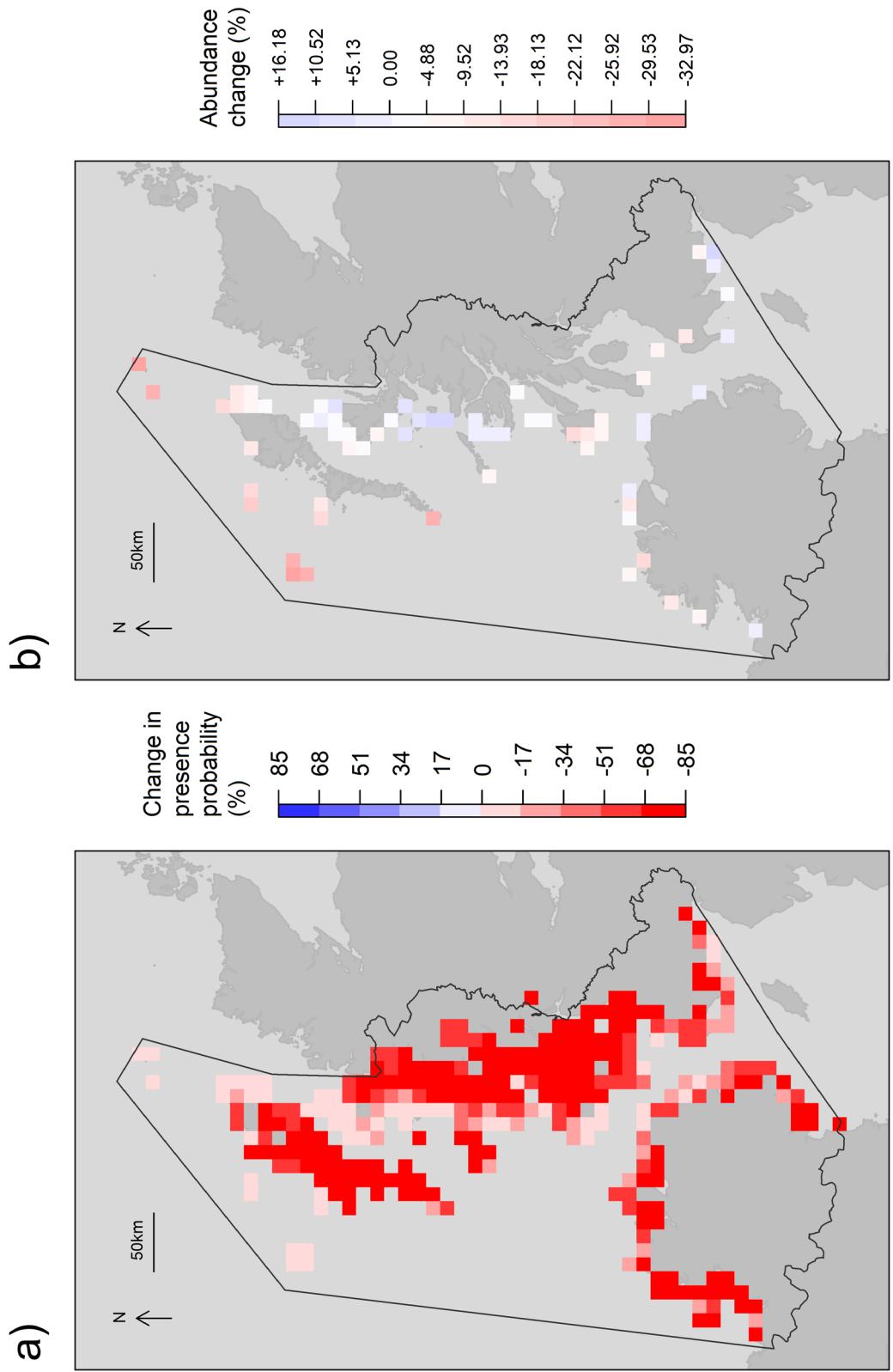


Figure S2. Predicted change in a) presence probability and b) abundance between 2018 (Seabirds Count census) and 2050 for Black Guillemot across the MarPAMM region (extent indicated by a black polygon).

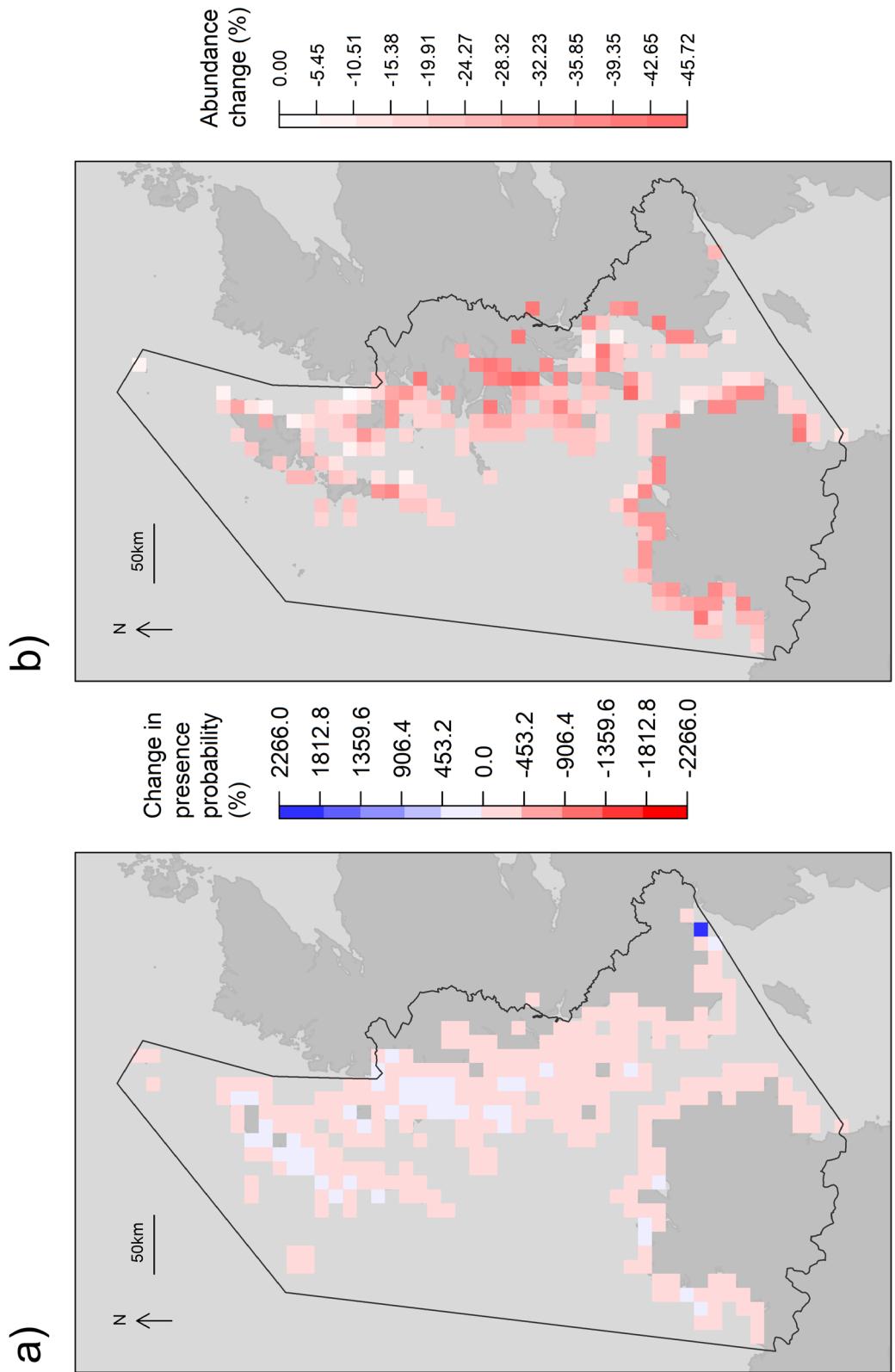


Figure S3. Predicted change in a) presence probability and b) abundance between 2018 (Seabirds Count census) and 2050 for Puffin across the MarPAMM region (extent indicated by a black polygon).

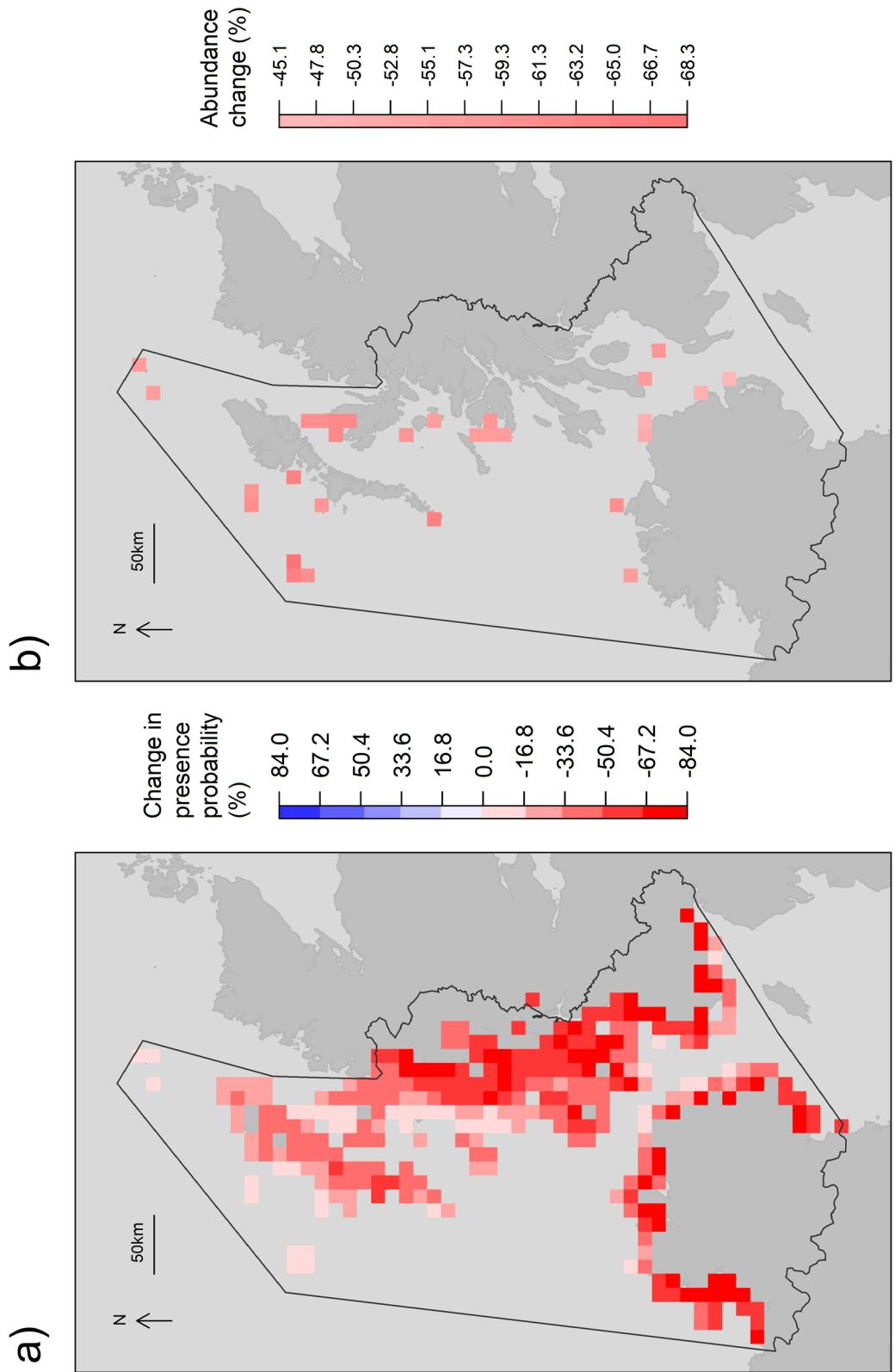


Figure S4. Predicted change in a) presence probability and b) abundance between 2018 (Seabirds Count census) and 2050 for Guillemot across the MarPAMM region (extent indicated by a black polygon).

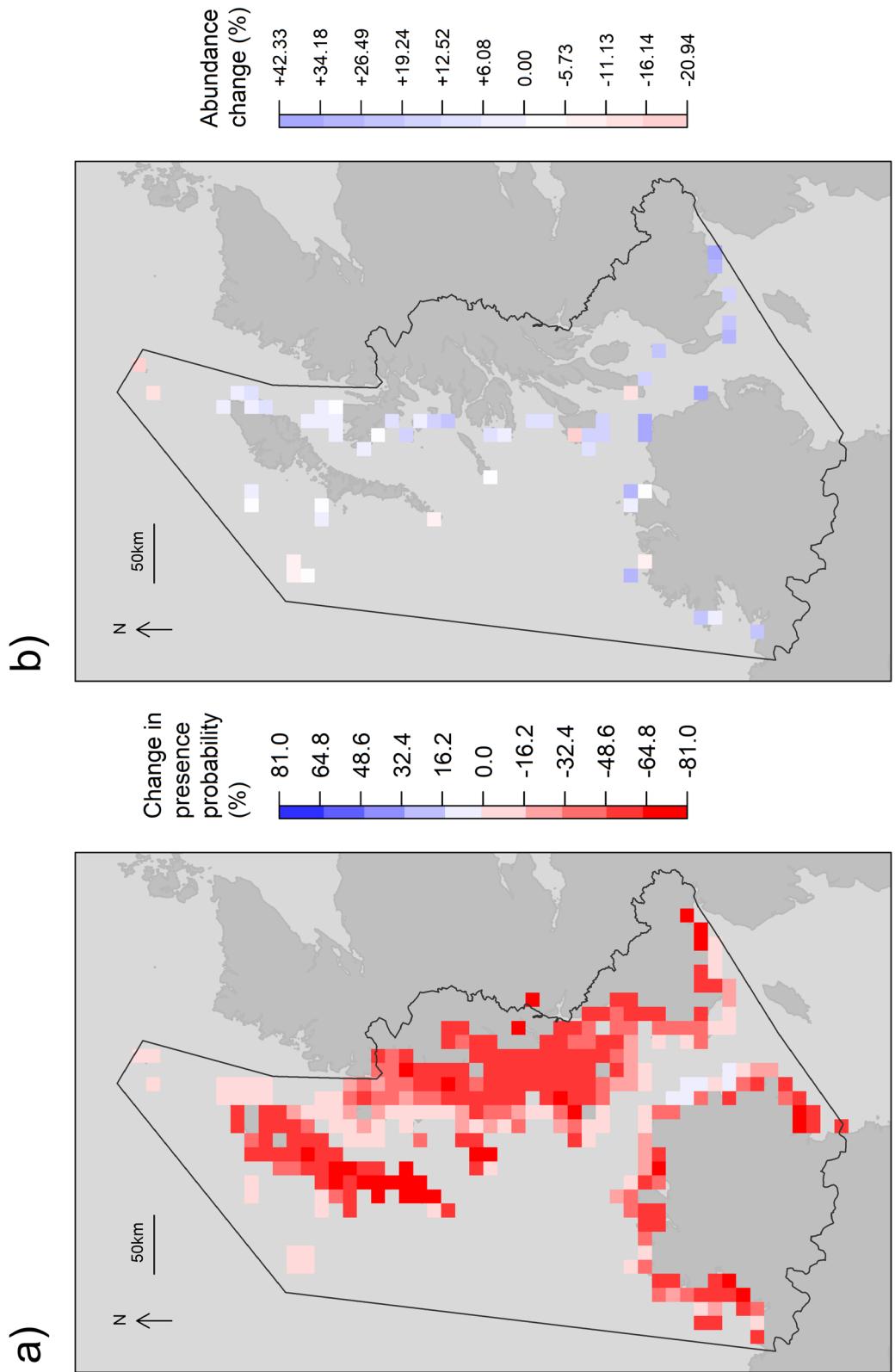


Figure S5. Predicted change in a) presence probability and b) abundance between 2018 (Seabirds Count census) and 2050 for Black-Headed Gull across the MarPAMM region (extent indicated by a black polygon).

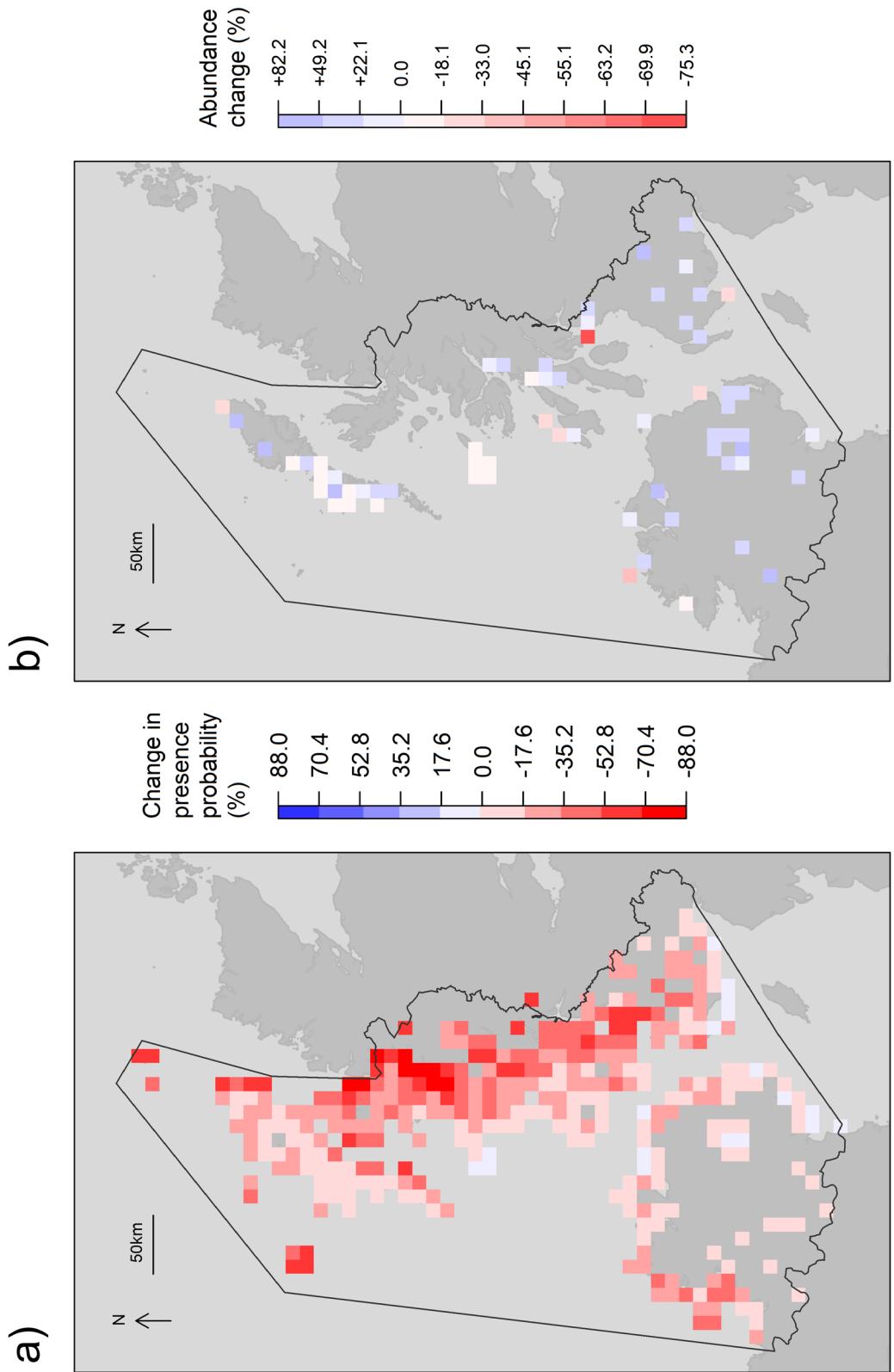


Figure S6. Predicted change in a) presence probability and b) abundance between 2018 (Seabirds Count census) and 2050 for Herring Gull across the MarPAMM region (extent indicated by a black polygon).

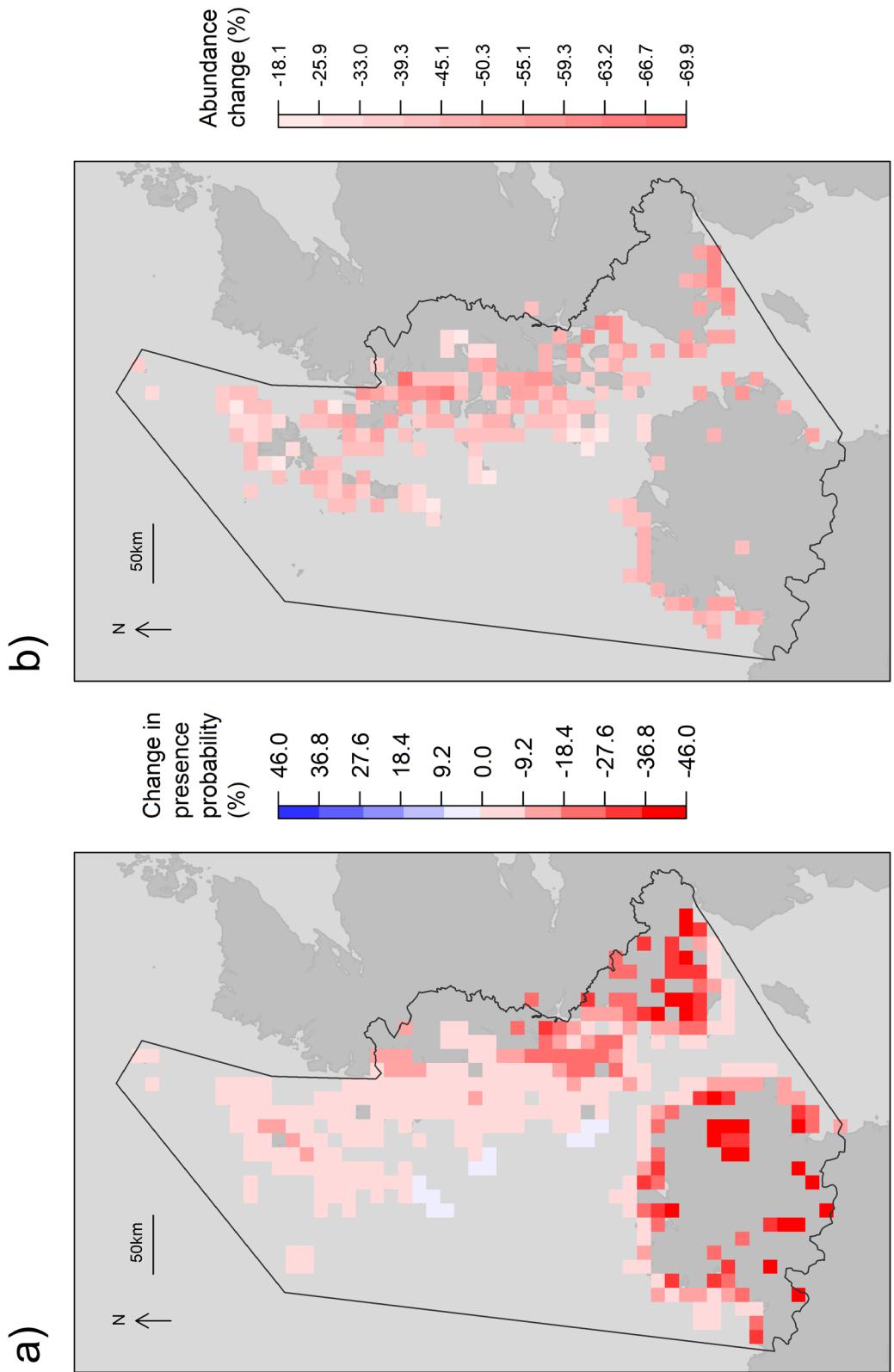


Figure S7. Predicted change in a) presence probability and b) abundance between 2018 (Seabirds Count census) and 2050 for Common Gull across the MapPAMM region (extent indicated by a black polygon).

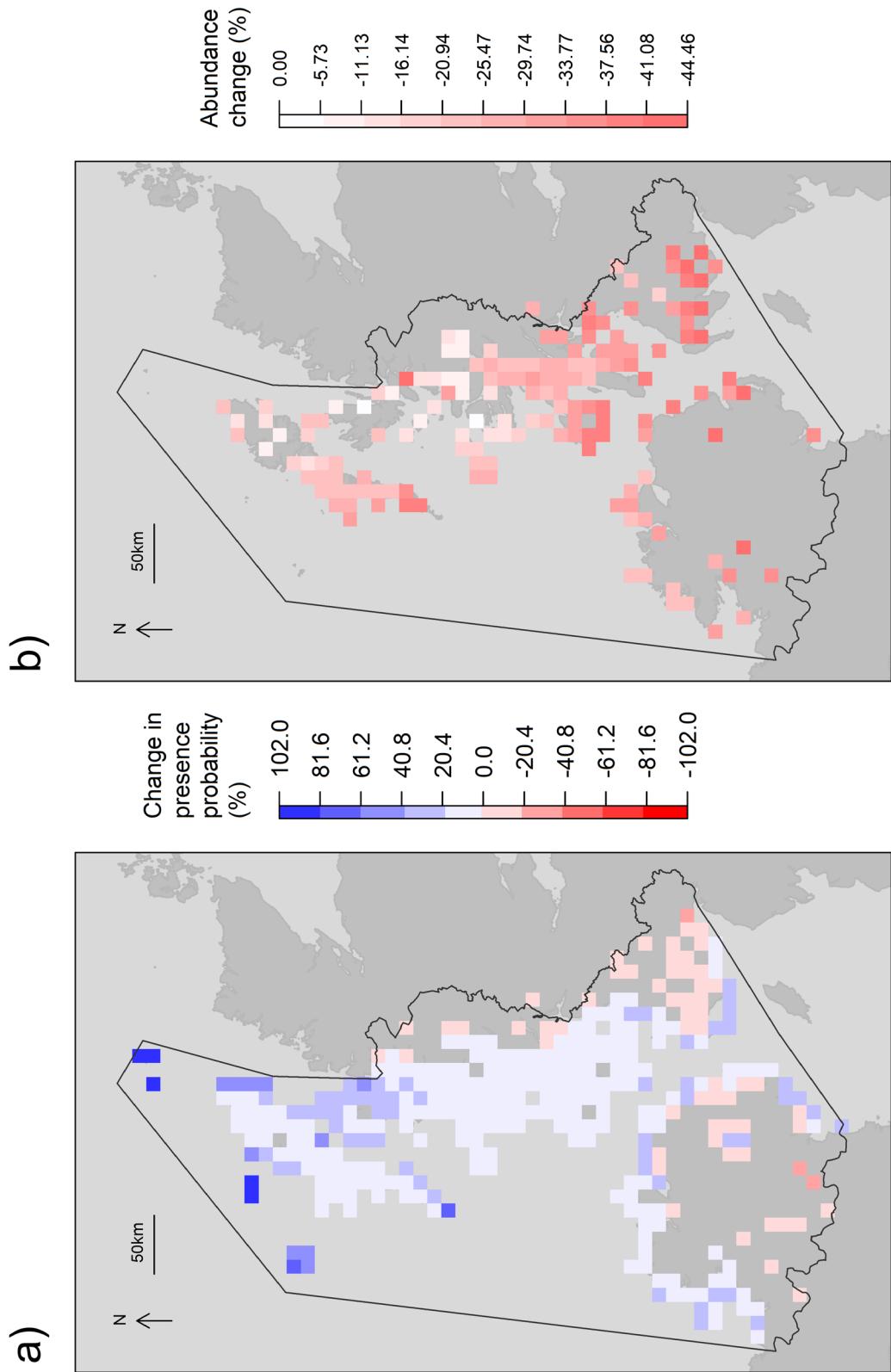


Figure S8. Predicted change in a) presence probability and b) abundance between 2018 (Seabirds Count census) and 2050 for Lesser Black-backed Gull across the MarPAMM region (extent indicated by a black polygon).

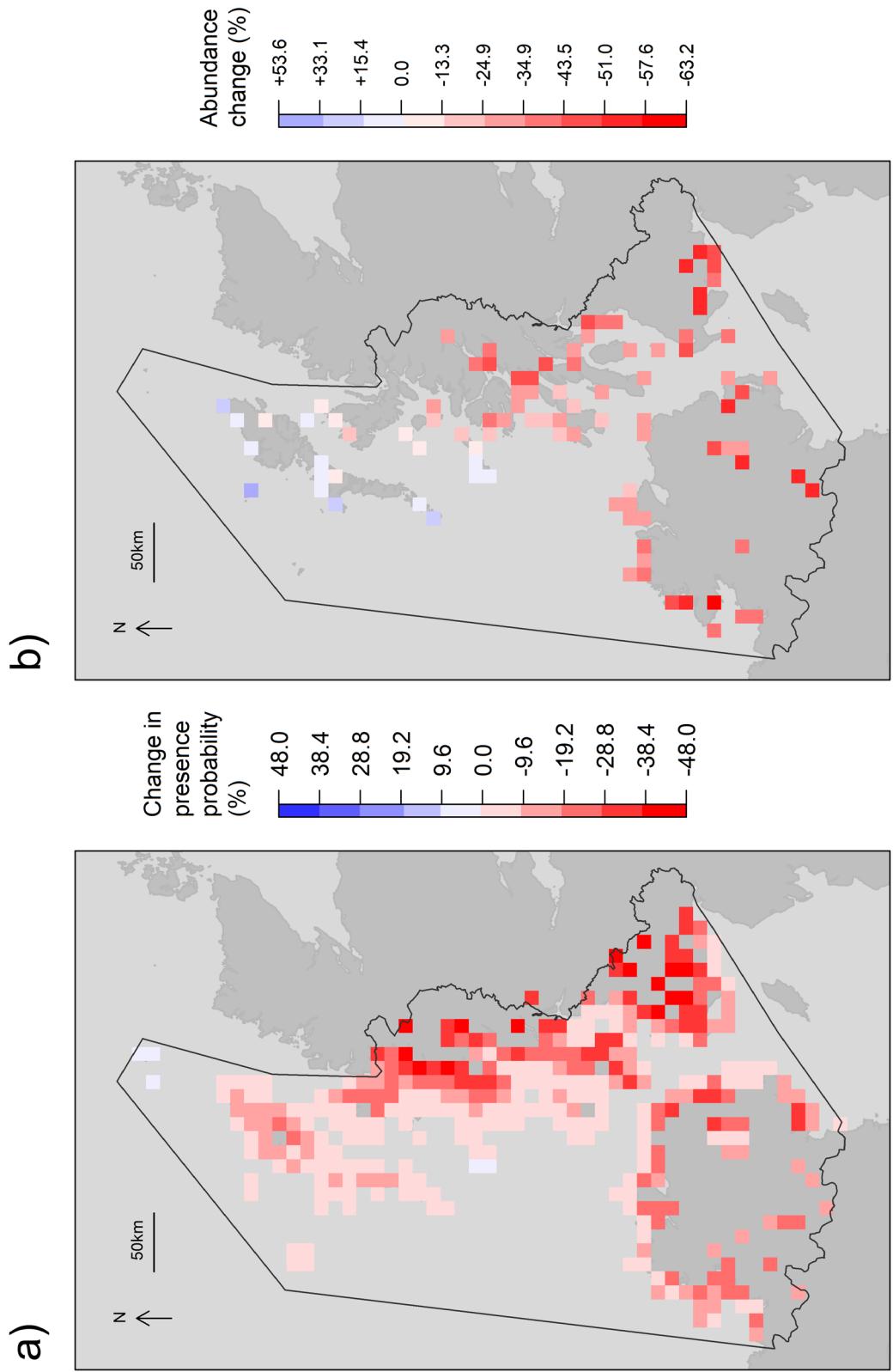


Figure S9. Predicted change in a) presence probability and b) abundance between 2018 (Seabirds Count census) and 2050 for Great Black-backed Gull across the MarPAMM region (extent indicated by a black polygon).

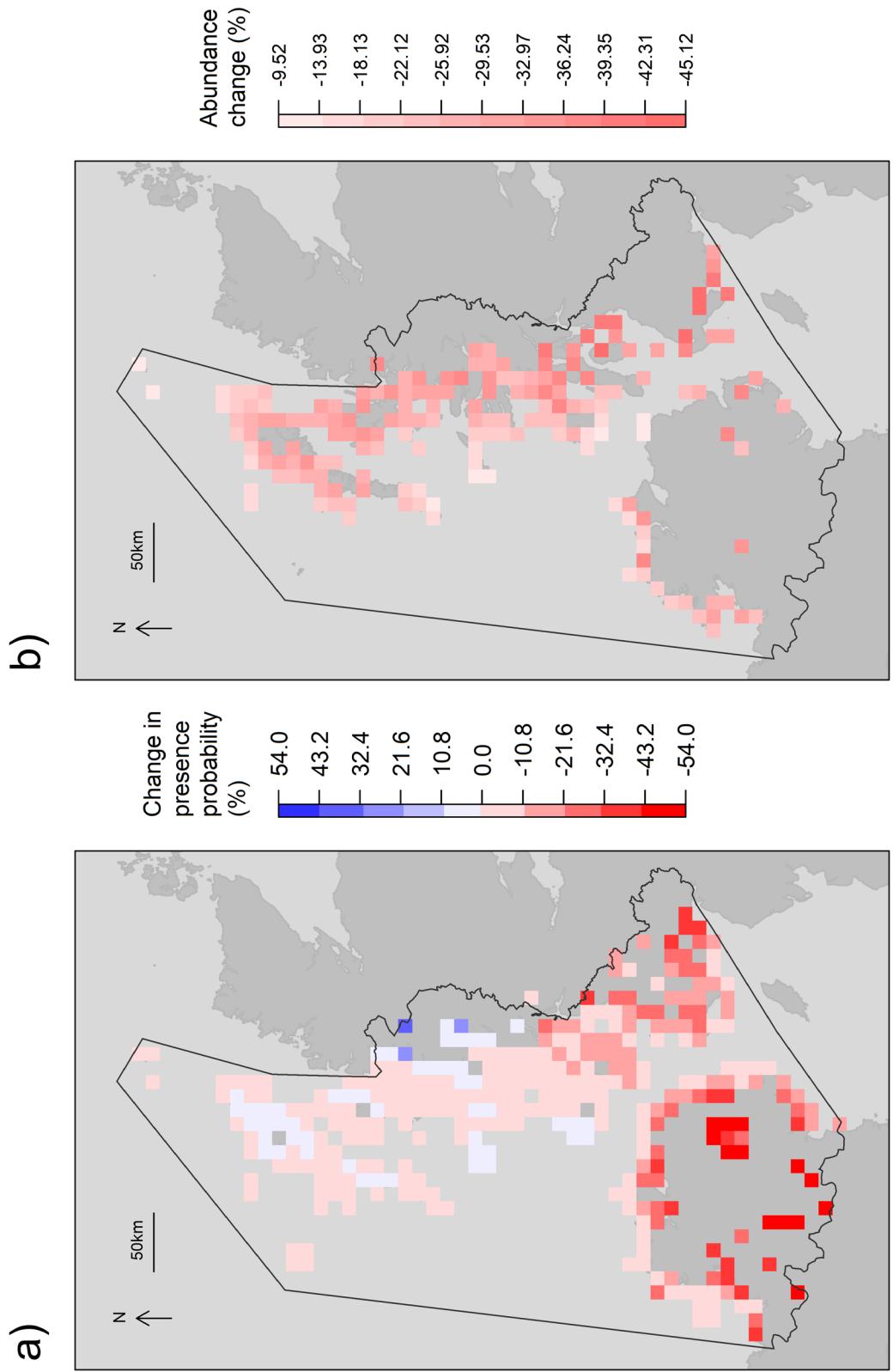


Figure S10. Predicted change in a) presence probability and b) abundance between 2018 (Seabirds Count census) and 2050 for Common Tern across the MarPAMM region (extent indicated by a black polygon).

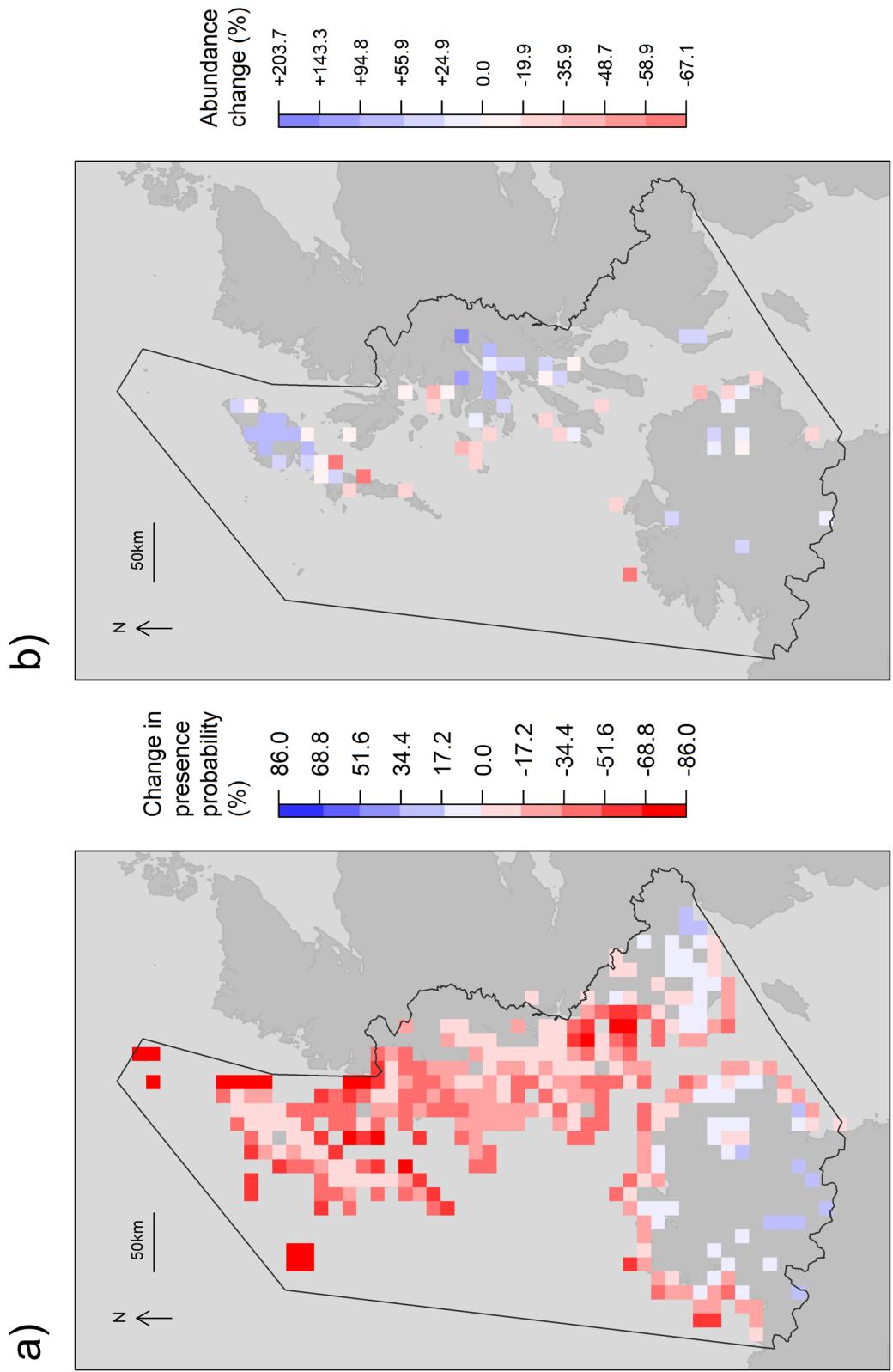


Figure S11. Predicted change in a) presence probability and b) abundance between 2018 (Seabirds Count census) and 2050 for Arctic Tern across the MarPAMM region (extent indicated by a black polygon).

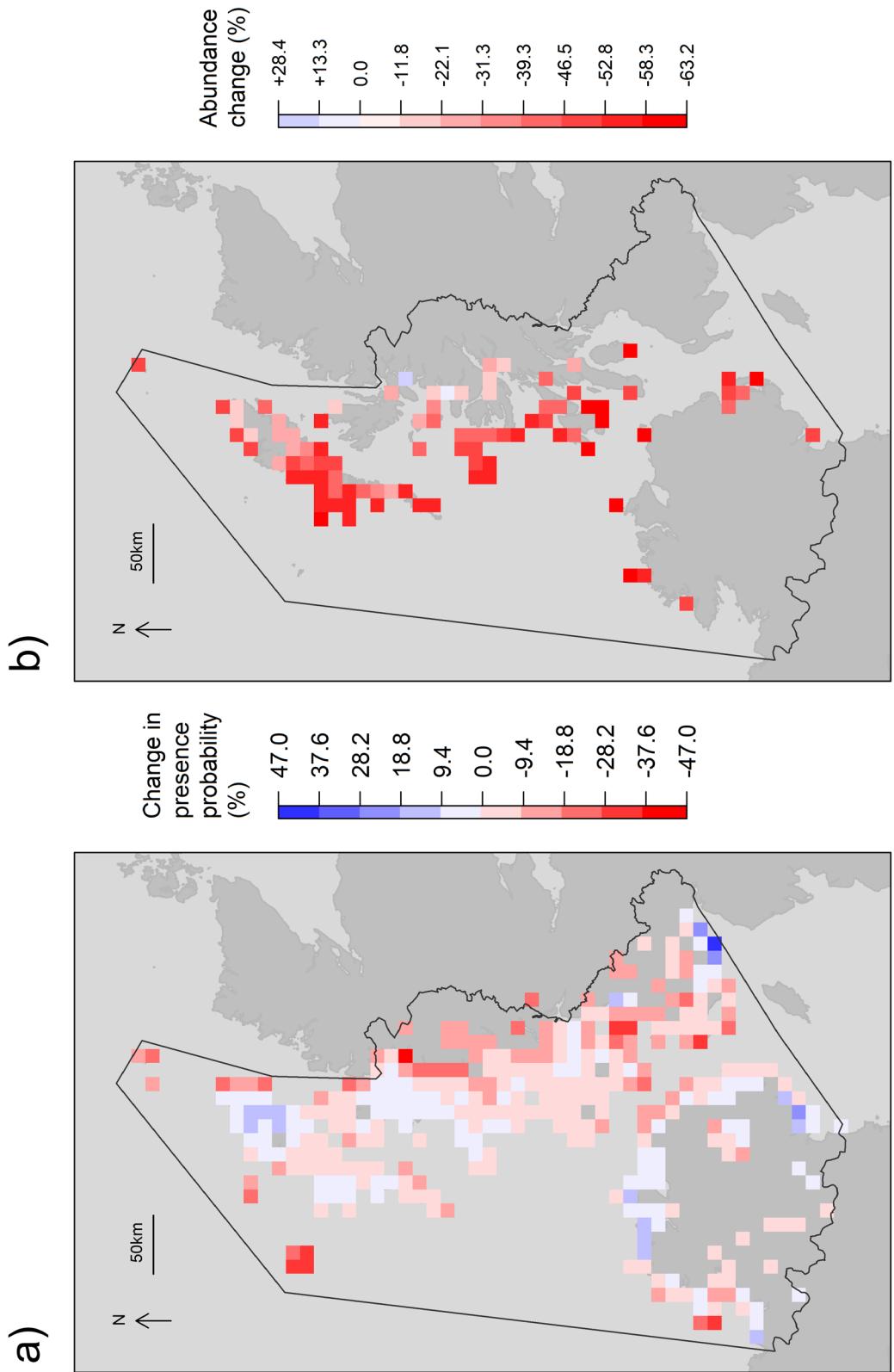


Figure S12. Predicted change in a) presence probability and b) abundance between 2018 (Seabirds Count census) and 2050 for Sandwich Tern across the MarPAMM region (extent indicated by a black polygon).

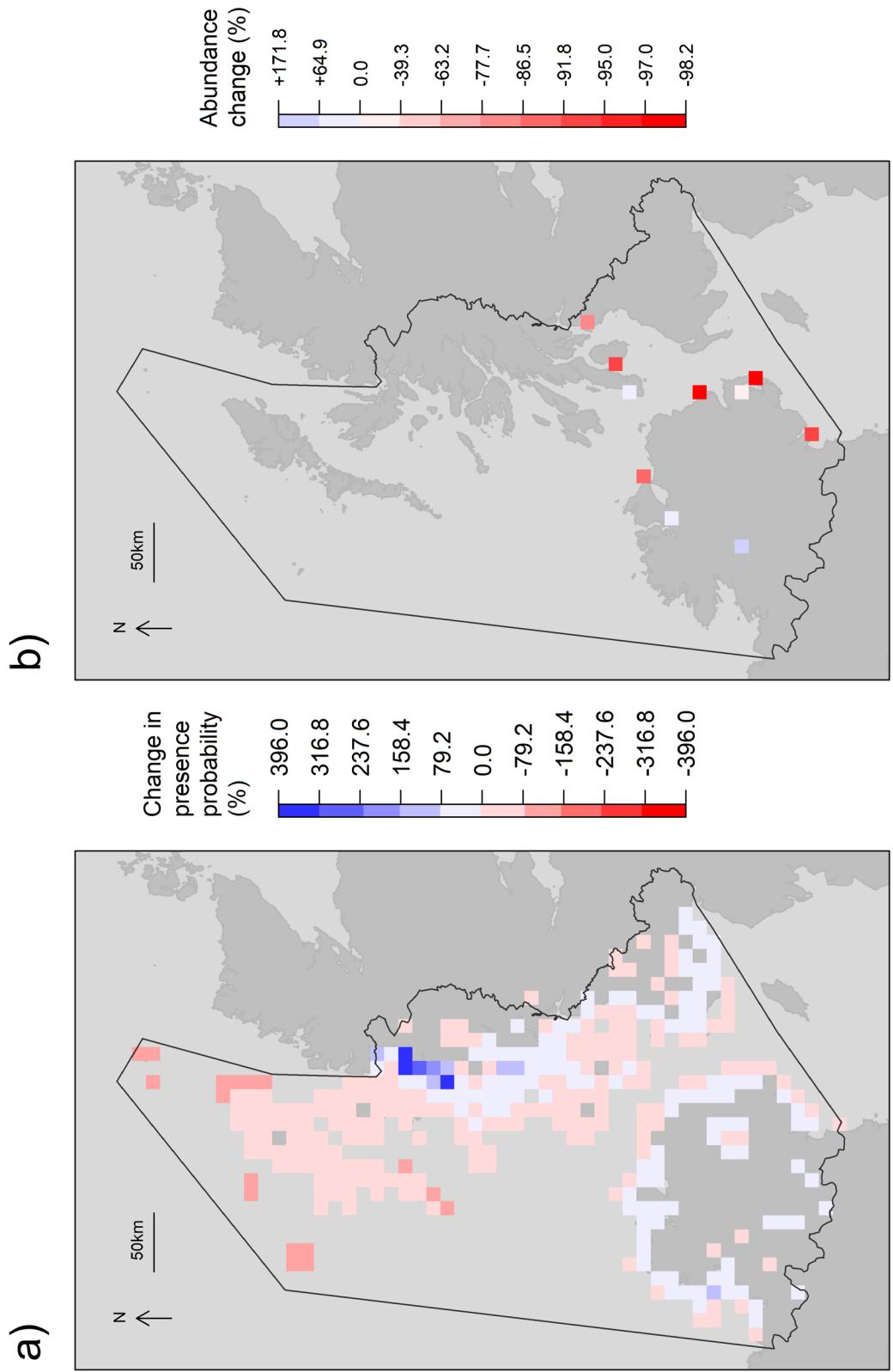


Figure S13. Predicted change in a) presence probability and b) abundance between 2018 (Seabirds Count census) and 2050 for Kittiwake across the MarPAMM region (extent indicated by a black polygon).

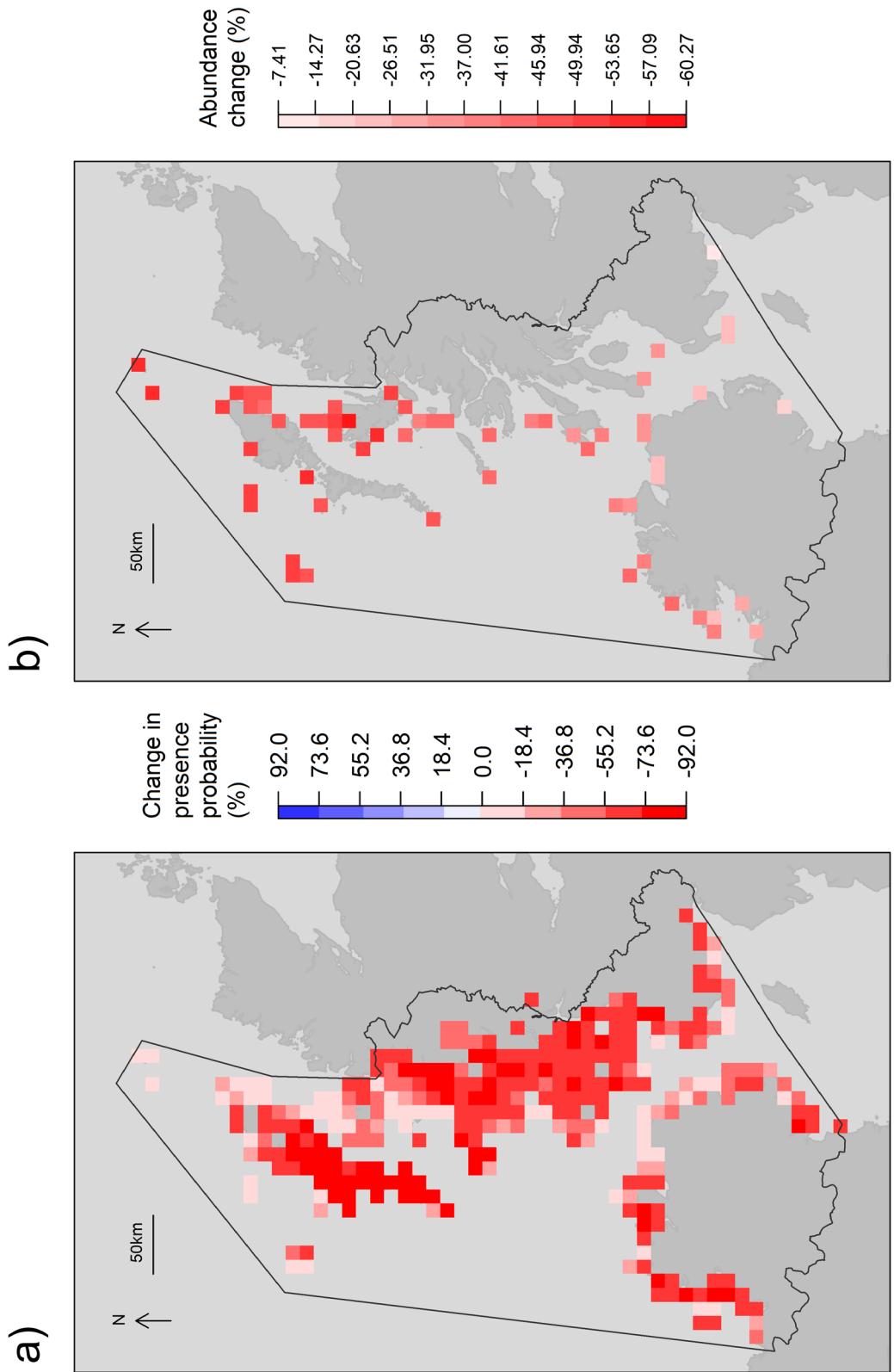


Figure S14. Predicted change in a) presence probability and b) abundance between 2018 (Seabirds Count census) and 2050 for Shag across the MarPAMM region (extent indicated by a black polygon).

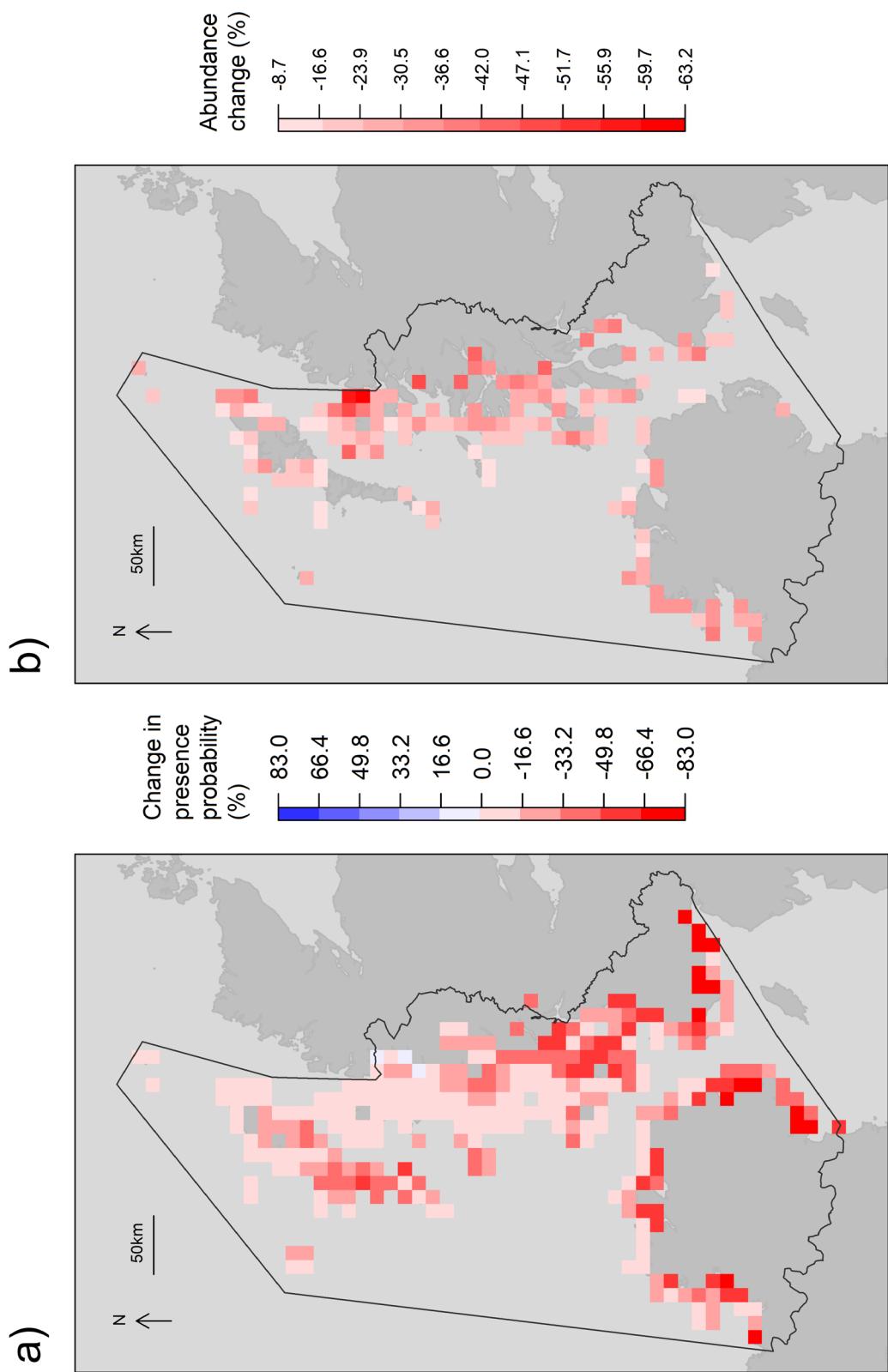


Figure S15. Predicted change in a) presence probability and b) abundance between 2018 (Seabirds Count census) and 2050 for Cormorant across the MarPAMM region (extent indicated by a black polygon).

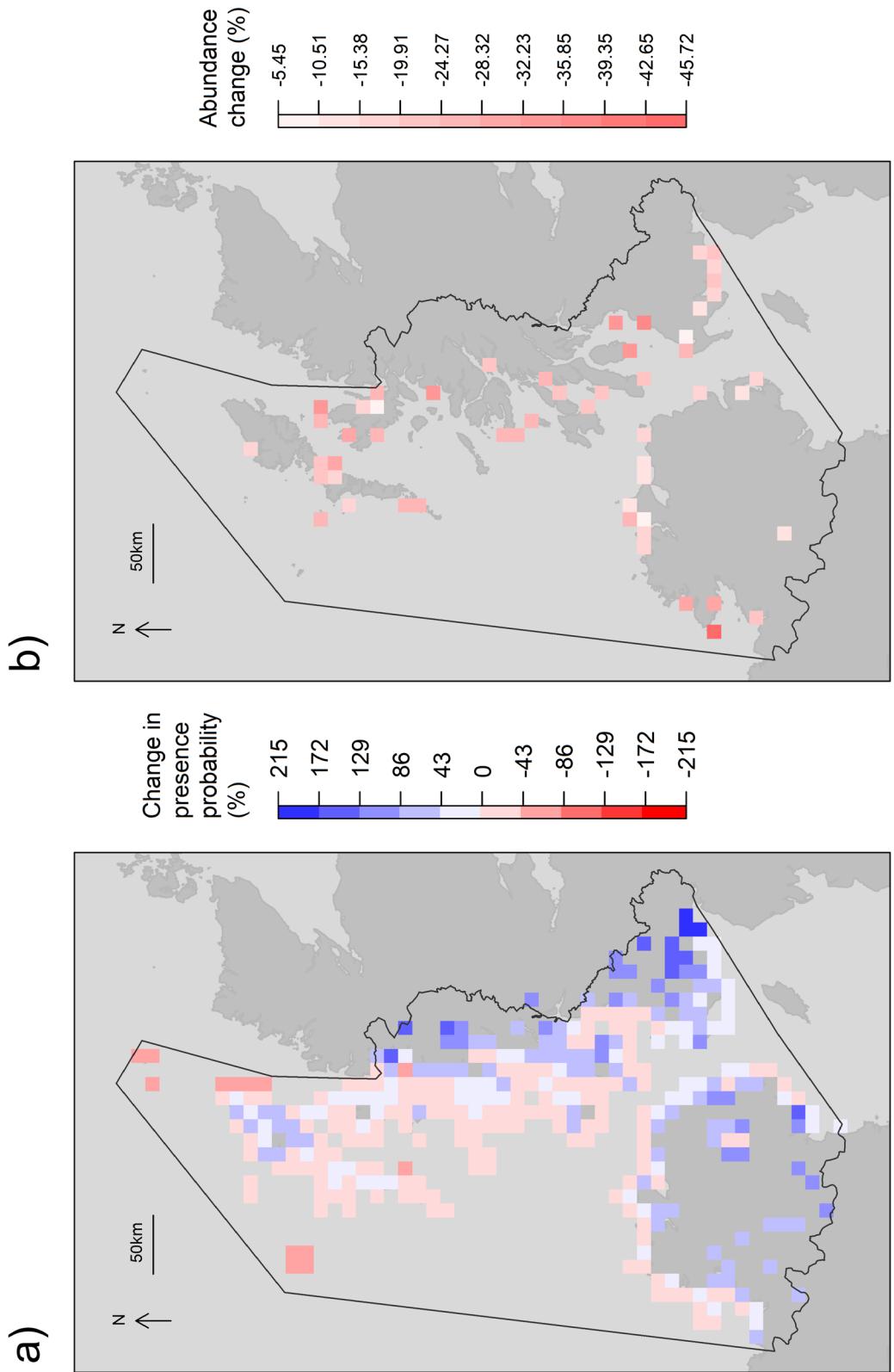


Figure S16. Predicted change in a) presence probability and b) abundance between 2018 (Seabirds Count census) and 2050 for Fulmar across the MarPAMM region (extent indicated by a black polygon).

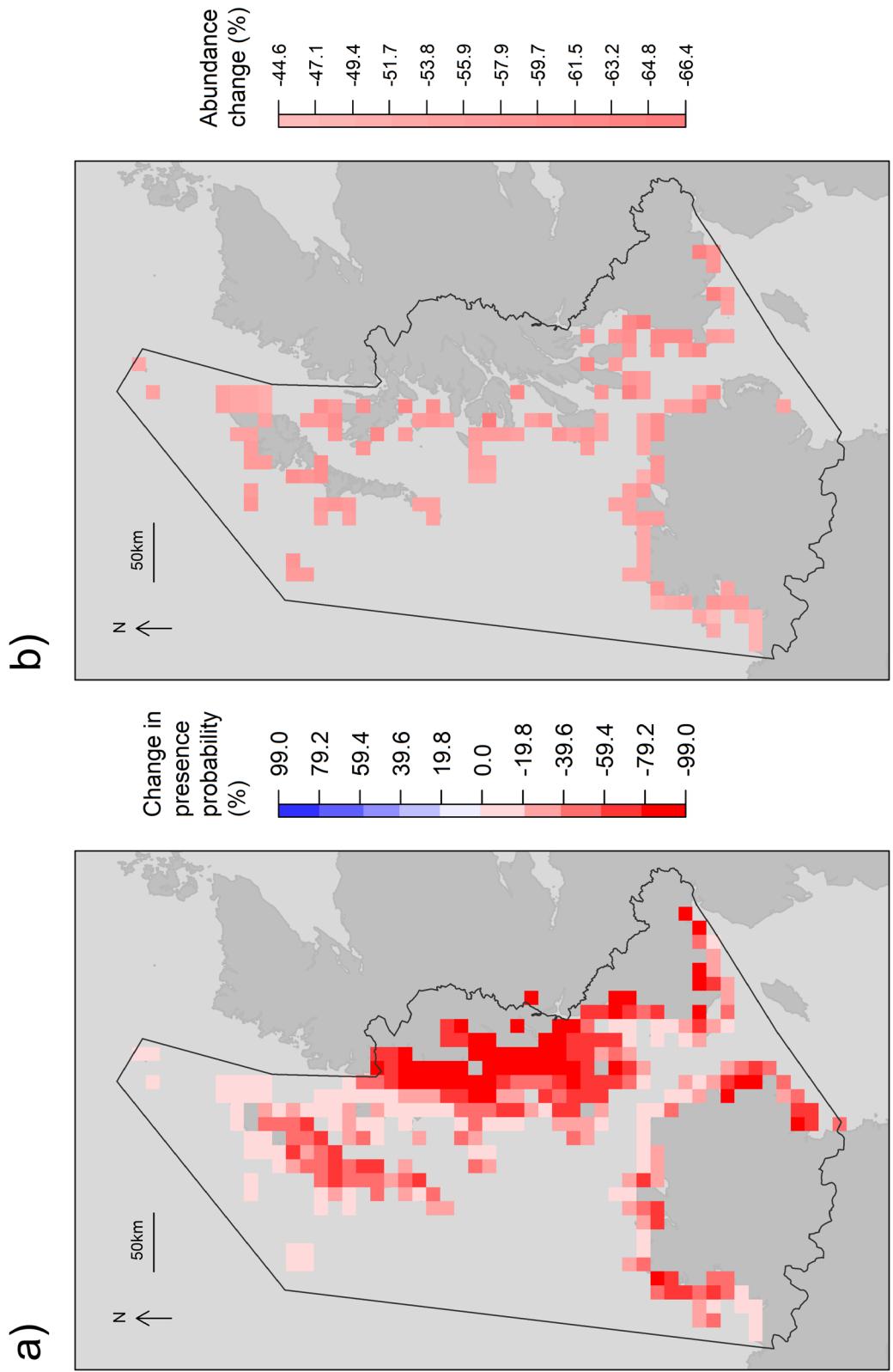


Figure S17. Predicted change in a) presence probability and b) abundance between 2018 (Seabird Census) and 2050 for Little Tern across the MarPAMM region (extent indicated by a black polygon).

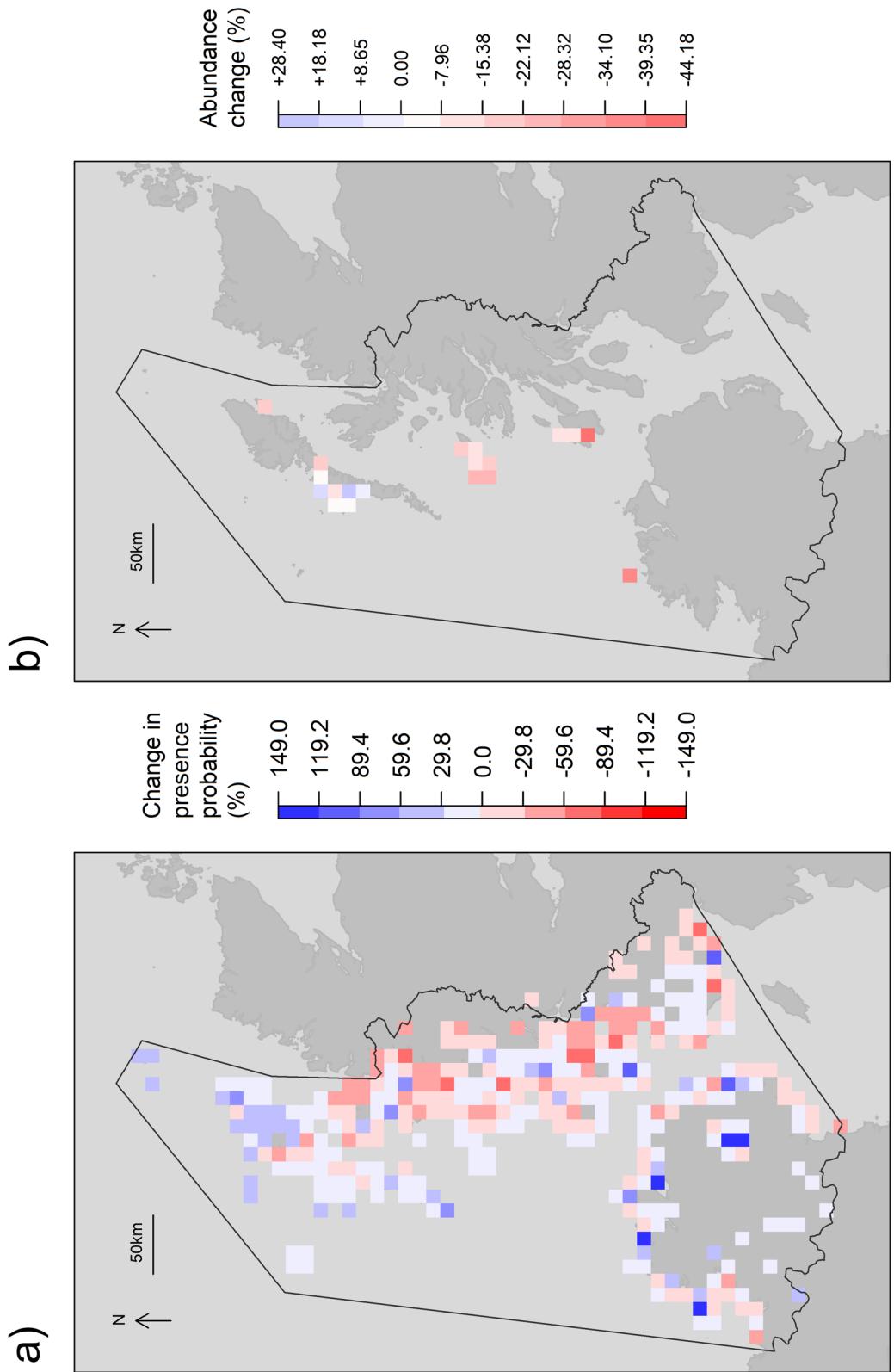


Figure S18. Predicted change in a) presence probability and b) abundance between 2018 (Seabird Census) and 2050 for Arctic Skua across the MarPAMM region (extent indicated by a black polygon).

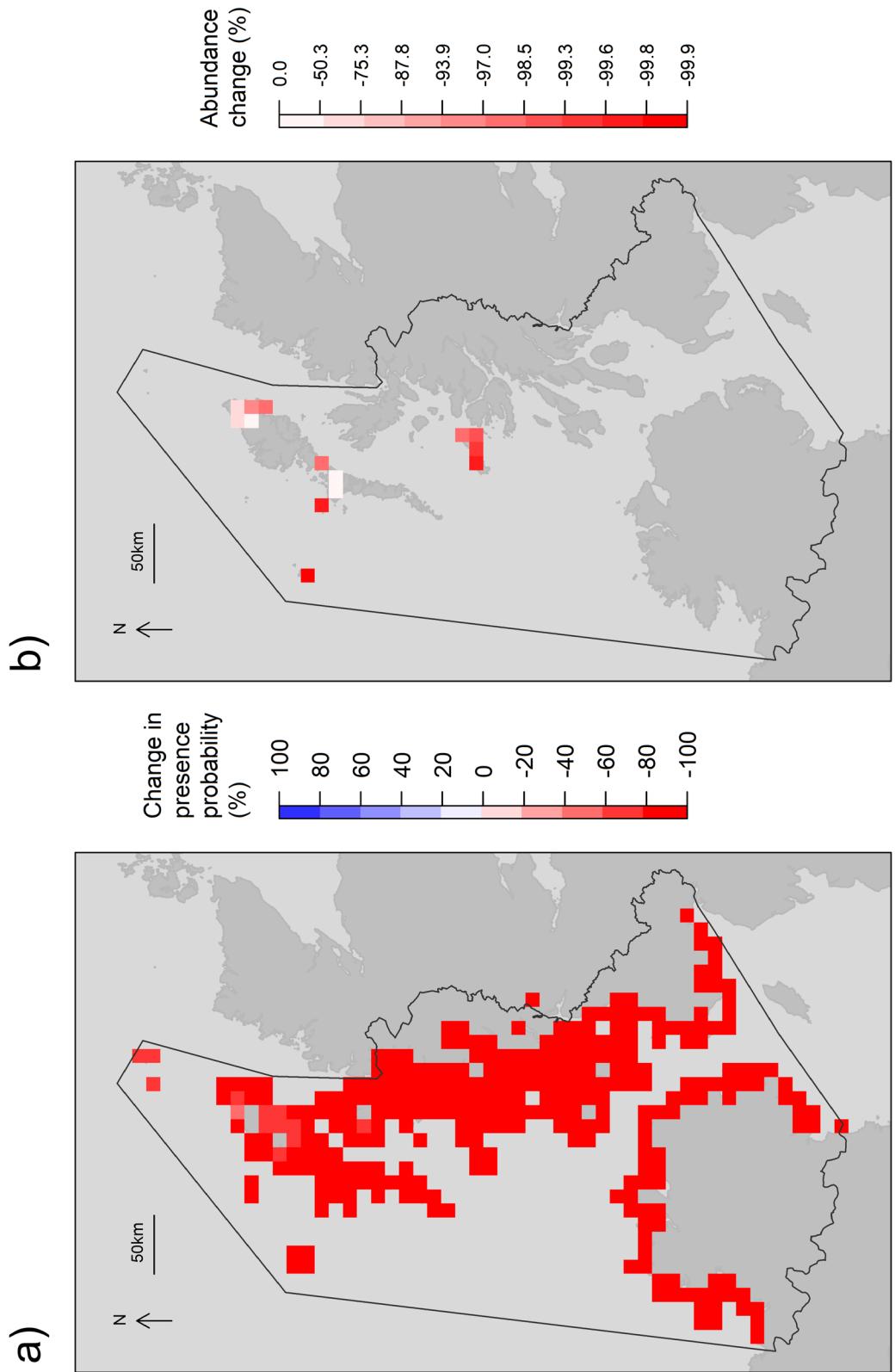
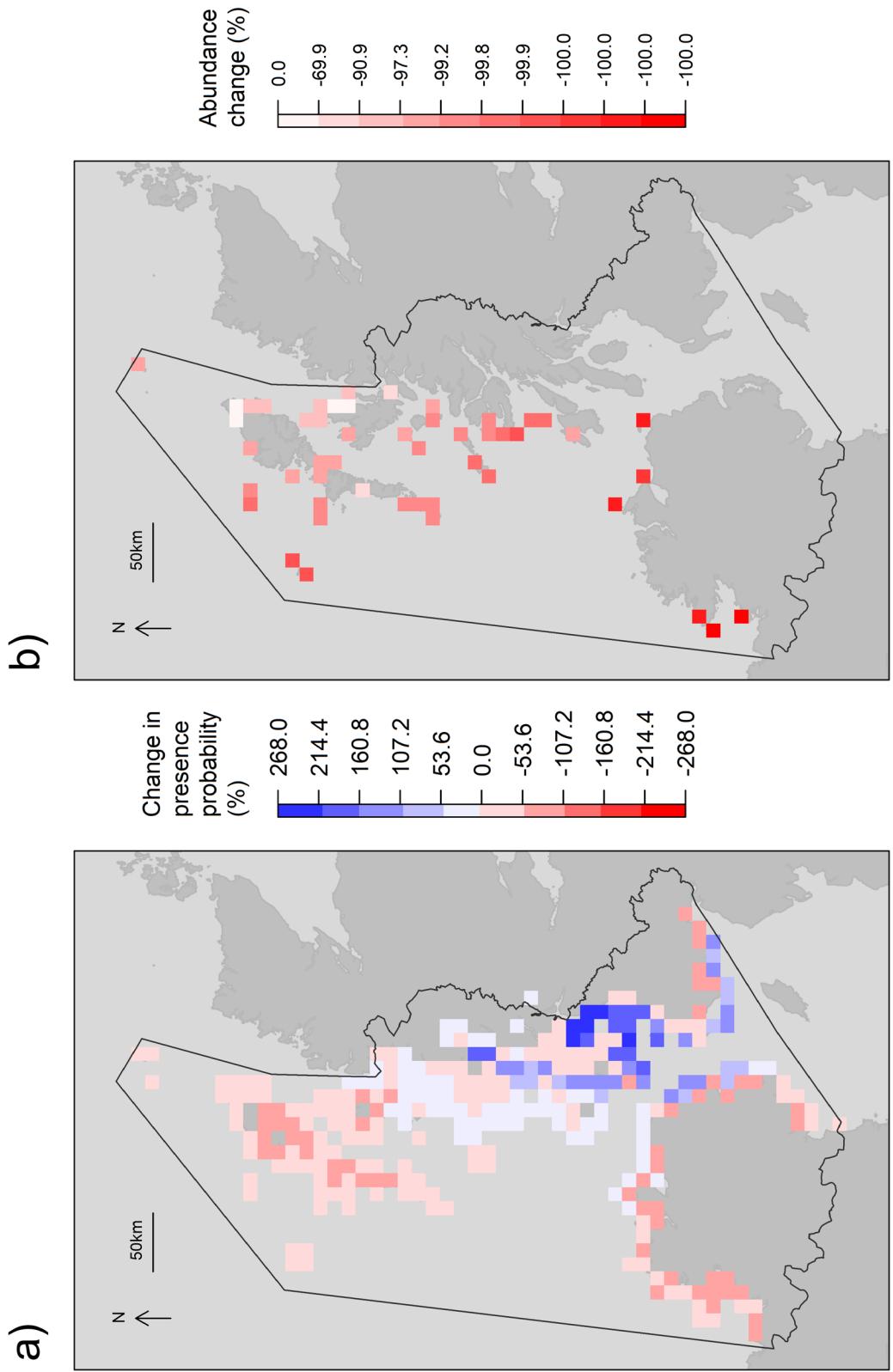
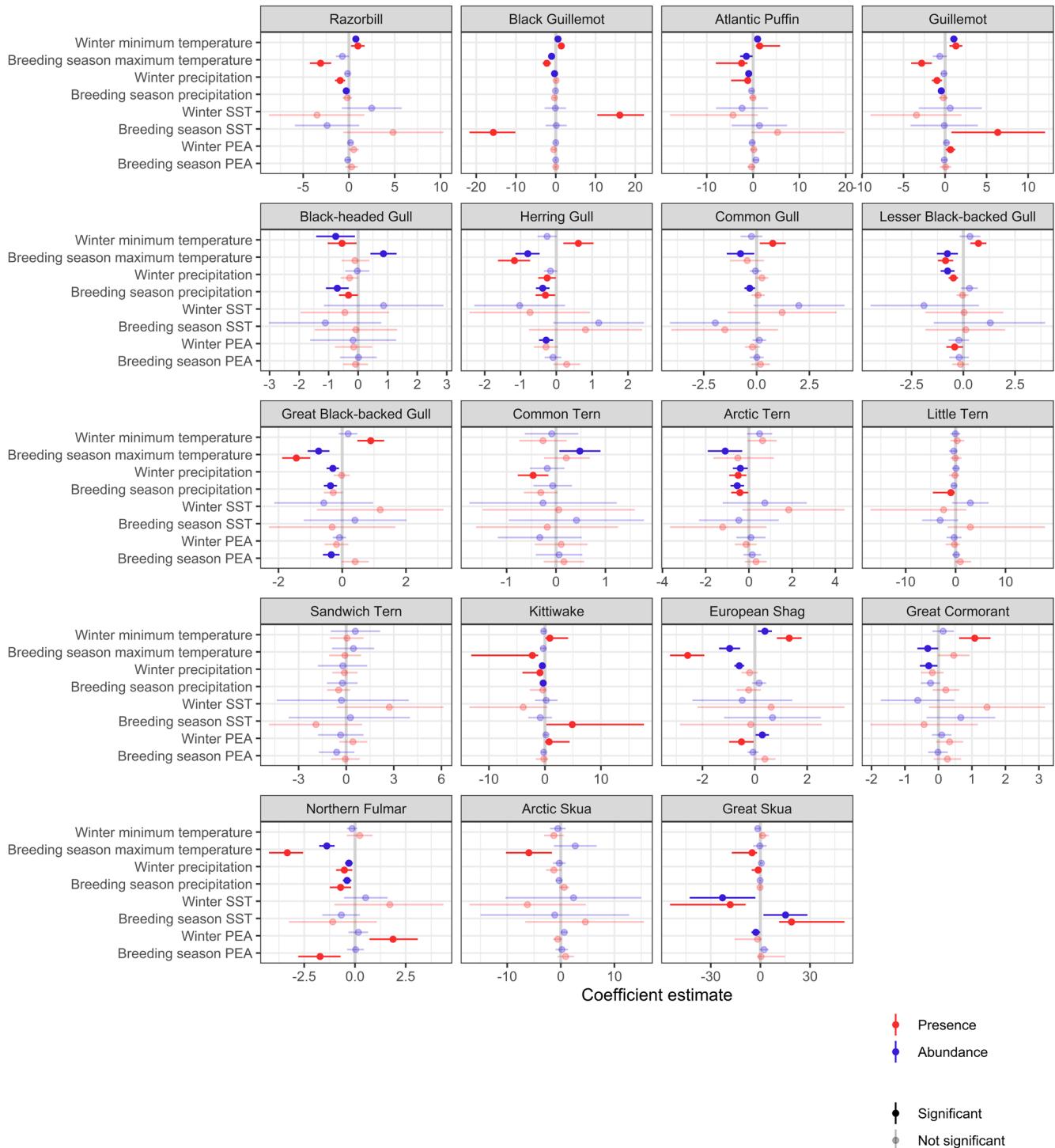


Figure S19. Predicted change in a) presence probability and b) abundance between 2018 (Seabird Census) and 2050 for Great Skua across the MarPAMM region (extent indicated by a black polygon).



6.3. Parameter estimates for relationships between presence or abundance with climate or oceanography

Figure S20: Parameter coefficient estimates and comparison of effect sizes for relationships between seabird presence and abundance with climate and oceanography. Note only linear terms are shown. 'Significance' is determined by whether or not the credible intervals overlap zero.





Cover image: Razorbill, by Sam Langlois / BTO; back cover image: Fulmar, by Philip Croft / BTO

Modelled changes to seabird presence and abundance across the MarPAMM region in response to predicted changes in climatic and oceanographic variables

As part of the suite of work for the BTO Northern Ireland Science Plan 2023–2028 for DAERA/NIEA, BTO was asked to provide an analysis and associated report to investigate climate change related change in seabird populations in and around Northern Ireland.

In this report, we update previously estimated projections of change in seabird populations (Davies et al. 2023) based on newly available datasets, including data from Seabirds Count and updated NEMO and C3S oceanographic data. We also discuss the reliability of existing Interreg VA/MarPAMM projected changes, and the likely extent to which climate change is already driving alterations to seabird abundance. Overall, the population of seabirds in the Interreg VA/MarPAMM region is predicted to decline in presence and abundance by 2050 under climate change.

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