Predicting at-sea habitat suitability of Alcids in the San Juan Islands, Washington

Sierra J. Gillman[1, 2]

Ecology and Conservation of Marine Birds and Mammals
Summer 2021

[1]Friday Harbor Laboratories, University of Washington, Friday Harbor, WA 98250
[2]School of Environmental and Forest Sciences, University of Washington, Seattle, WA 98195

Contact Information:
Sierra J. Gillman
School of Environmental and Forest Sciences, University of Washington
University of Washington
1410 NE Campus Parkway
Seattle WA 98195
sgillm@uw.edu

Keywords: Alcids, Pigeon Guillemot, Marbled Murrelet, Rhinoceros Auklet, San Juan Islands, species distribution models

Abstract
Important bird areas (IBAs) are an integral part of effective seabird conservation, however, IBAs require a clear understanding of the spatial and temporal distribution of birds. To determine potential IBAs in the San Juan Archipelago, I developed species distribution models for three Alcids species (Pigeon Guillemots [*Cepphus columba*], Rhinoceros Auklets [*Cerorhinca monocerata*], and Marbled Murrelets [*Brachyramphus marmoratus*]) based on at-sea survey observations for May-July 2013 and May-July 2018 and oceanographic variables (e.g., distance to shore, chlorophyll a concentration). Results indicated areas in the southern Lopez Island were of high habitat suitability for all three species but is currently not listed as an IBA. Distance to shore was a consistent predictor for suitable habitat but importance of environmental factors shifted temporally. The predictive maps for Marbled Murrelets showed the smallest area of suitable habitat in the region, whereas both the Pigeon Guillemot and Rhinoceros Auklet and several areas with highly suitable habitat. The preliminary results from my study indicate that San Juan Archipelago has several areas that should be considered for designation as IBAs.

Keywords: Alcids, Pigeon Guillemot, Marbled Murrelet, Rhinoceros Auklet, San Juan Islands, species distribution models

Introduction

Human activities have irrevocably and appreciably altered the Earth with clear evidence that the resulting global changes have exerted considerable stress on marine ecosystems (Halpern et al. 2008, Grémillet and Boulinier 2009). For instance, while seabirds are considered important indicators of ecosystem function (Furness and Camphuysen 1997), seabirds are susceptible to anthropogenic pressures such as marine pollutants, overexploitations of forage fish, and climate change (Schreiber 2002, Grémillet and Boulinier 2009). Additionally, anthropogenic at-sea mortality has been linked to declines in seabird populations (Lewison et al. 2004); yet, foraging grounds and nonbreeding sites are often undetermined with little or no protection (Thaxter et al. 2012, Lavers et al. 2014).

Determining important bird areas (IBAs) that can be designated as areas that need protection requires a full understanding of the spatial distribution of seabirds at sea (Oppel et al. 2012). During the breeding season seabirds can be central foragers, and the location of important foraging areas at sea are influenced by different factors such as prey availability and foraging ranges (Thaxter et al. 2012). However, the identification of candidate IBAs for the protection of seabirds can be challenging due to highly dynamic and temporally shifting distribution of individuals with unknown spatial trends (Game et al. 2009, Lavers et al. 2014). One technique that can be used to determine potential IBAs is species distribution modeling (SDM) which allows observational data to be statistically linked to environmental predictors to determine suitable habitat for seabirds. SDMs also allows the prediction of species distributions in unsurveyed areas to facilitate the identification of IBAs (Lascelles et al. 2012, Cleasby et al. 2020).

The Salish Sea, a body of water spanning British Columbia, Canada, and Washington State, USA, supports 172 bird species that inhabit the region, of which 72 are dependent on intertidal and marine habitats (Gaydos and Pearson 2011). Increased anthropogenic pressures have threatened the biodiversity in the Salish Sea ecosystem (Chittenden et al. 2018). In particular, due to loss of forage fish from overfishing, pursuit diving seabirds (e.g., Alcids) have been declining since the 1990s (Vilchis et al. 2015), and while there are several IBAs designated in the Salish Sea, none appear to be near the San Juan Archipelago (Bayard et al. 2019). In this study, I used oceanographic variables to develop SDMs for three Alcid species. I combined at-sea survey data collected for two years, capturing both inter-seasonal and inter-annual variation with environmental factors to predict the distribution of these seabirds in the San Juan Archipelago as a first step in developing candidate IBAs for the region.

Methods

Study area and Species | The transect-based surveys were conducted in the Conservation Zone 1 of the Recovery Plan for the Marbled Murrelet located in the Salish Sea (U.S. Fish and Wildlife Service 1997). The Salish Sea is a 16,925 km^2 inland sea extending from Olympia, Washington, USA, north to Campbell River, British Columbia, Canada. Within Conservation Zone 1, there are three geographic strata based on Marbled Murrelet density and ecology: Stratum 1: Strait of Juan de Fuca; Stratum 2: San Juan Islands, Whidbey and Camano islands, Port Townsend, Admiralty Inlet, and northern Hood Canal; Stratum 3: central/south Puget Sound (Figure 1). In this area of the Salish Sea, the interaction of freshwater mixing, tidally driven currents, and dissolved oxygen and salinity levels influence productivity and species composition and structure (Ebbesmeyer and Barnes 1980). I focused my analysis on three seabirds in the family Alcidae: Pigeon Guillemots (*Cepphus columba*), Rhinoceros Auklets (*Cerorhinca monocerata*), and Marbled Murrelets (*Brachyramphus marmoratus*). All three bird species are pursuit divers that feed primarily on forage fish such as Pacific herring (*Clupea pallasii*), sand smelt (*Atherina presbyter*), and Pacific sand lance (*Ammodytes hexapterus*). All three species are near shore foragers and are susceptible to anthropogenic pressures and loss of forage fish (Vilchis et al. 2015).

Data collection | US Fish and Wildlife Services (USFWS) collected the data during the annual Marbled Murrelet populations summer at-sea surveys. Each observation was collected during survey methods described by Raphael et al. (2007). Briefly, data were collected from mid-May to end of July for the year 2013 and 2018. Each stratum was divided into primary sampling units (PSUs), each of which was approximately 20 km of coastline. Thirty PSUs were randomly selected prior to starting the sampling program and were sampled both years. Each PSU was divided into four equal segments that were roughly 5 km in length. In Strata 1 and 2, each PSU was further divided into nearshore and offshore subunits. Transects 5 km in length were established at random distances from shore to distribute the sampling effort throughout the PSU. USFWS sampled 5 PSUs in Stratum 1, 20 PSUs in Stratum 2, and 5 PSUs in Stratum 3 and sampled each PSU twice during the survey season, and a random sampling unit selection approach was used to spread the survey effort in space and time by selecting a Stratum randomly and then randomly selecting PSUs within that Stratum to build a survey week (Figure 1). During the surveys, USFWS observers recorded the species and GPS point for every sea bird seen and these GPS points were used for presence data in the SDM analyses.

I separated data into 15 data sets. For Pigeon Guillemot and Rhinoceros Auklet, there were six data sets: May 2013, June 2013, July 2013, May 2018, June 2018, July 2018. For Marbled Murrelets, data sets were limited to June 2013, June 2018, and July 2018 due to too few observations in the other available months.

Environmental Variables | To predict at sea suitable habitat, I used four environmental predictors that could be correlated with seabird distribution. I used two static variables: bathymetry (m), derived from the ETOPO1 dataset hosts on the NOAA server (Amante and Eakins 2009), and minimum distance to shore (m) for each raster cell which I derived using a major shoreline raster provided by Washington Department of Fish and Wildlife. For dynamic oceanographic data, I used average monthly sea surface temperature (SST, °C) and chlorophyll *a* concentration (CHL-*a,* mg*m^{-3}) for May, June, and July in the years 2013 and 2018. I downloaded monthly SST and CHL from Terra MODIS satellite imagery via the OceanColor data portal (https://oceancolor.gsfc.nasa.gov/). I chose to use SST and CHL as proxies for prey availability because in the marine environment, SST and CHL-*a* are used to map patterns of primary productivity and commonly used in seabird distribution studies (Suryan et al. 2012, Lavers et al. 2014) because forage fish abundance was unavailable for the area of interest. The original data sources consisted of digital maps in raster format and raster data were stacked and resolution was converted to 1km for each layer prior to analysis.

Species Distribution models | Seabird habitat suitability were modelled using maximum entropy machine learning algorithm, implemented in Maxent version 3.4.1 (Phillips et al. 2006). Maxent is an approach to calculate the distribution of a species when only presence data is available. Maxent differentiates environmental conditions at presence locations against the overall conditions prevailing in the study area, based on background locations, to find the probability distribution that maximizes the entropy while fitting the best possible distribution of the species (Phillips et al. 2017). All modeling were conducted in R version 4.1 (R. Core Team 2018) with RStudio version 4.2 (RStudio Team 2020) with the *SDMtune* package (Vignali et al. 2020)I randomly generated 2,000 background points for each species within the waters of the Salish Sea in the study area, bound in the range of 47°N to 49°N by -123°W to -122°W. For each of the 15 data sets, I randomly split the observations with 70% used for training the model and the remaining 30% used for testing the final models, respectively, and I used fourfold cross validation. I fine-tuned the hyperparameters for each model with the *optimizeModel* function, checking for the increase in the mean validation via area under the receiver operating characteristic (ROC) curve (AUC) across the four cross validation folds (Fielding and Bell 1997). The best set of hyperparameters were searched with: 1) feature classes combinations: lq, lh, lqp, lqh, lph, lqph, with *l* representing linear, *q* quadratic, *p* product and *h* hinge and 2) regularization multiplier ranging from 0.1 to 4.88 with increments of 0.02 for a total of 1200 hyperparameter combinations. I kept the maximum number of iterations constant at 500 in all models. After determining the best hyperparameters for each model, I fit the final optimized model with all data, and determined model performance with AUC. Each of the final models were projected to the San Juan Archipelago to display the probability of suitable habitat for each species across the different time periods by applying the "cloglog" transformation to the raw outputs of the models (Phillips et al. 2017, Vignali et al. 2021).

Results

A total of 4,463 and 5,198 observations of the three seabird species were documented in 2013 and 2018, respectively. Rhinoceros Auklet were the most observed species, followed by Pigeon Guillemot and Marbled Murrelet (Table 1). All 15 models performed well with ≥ 0.90 AUC, indicating high accuracy in predicting suitable habitat probability for the three seabird species, independent of season or species (Table 2).

Overall, for Pigeon Guillemot and Marbled Murrelet, distance to shore was the most influential variable across months and year followed by CHL-*a*, based on percent contribution and permutation importance (Table 3 & 4). There was greater variability in which environmental factor contributed to Rhinoceros Auklet habitat predictability, with SST, CHL-*a*, and distance to shore contributing the highest to the predictions (Table 5). There did not appear to be consistent temporal or species-specific trends in which environmental predictors determined suitable habitat. In both 2013 and 2018, suitable habitat was predicted in the northern portion of the San Juan Archipelago for Pigeon Guillemot. In the subsequent months, habitat suitability shifted further south towards the Strait of Juan de Fuca and the lower regions of Lopez Island (Figure 2). I observed similar trends in Rhinoceros Auklets in 2013. In May of 2013, suitable habitat for Rhinoceros Auklet was predicted around Sidney Island, in Canada and in between Shaw, San Juan, and Lopez Islands (Figure 3). In the June for both 2013 and 2018, habitat suitability shifted south towards the Strait of Juan de Fuca, but by July of both years, suitable habitat shifted back northeast near Deception Pass (Figure 3). Marbled Murrelets were predicted to have the lowest amount of suitable habitat in the San Juan Archipelago (Figure 4), but also appeared to have the most suitable habitat near the Strait of Juan de Fuca in June (Figure 4). For all three species, the southern portion of Lopez Island was consistently indicated as suitable habitat throughout each month and years.

Discussion

Understanding what oceanic drivers influence suitable seabird habitat at-sea is crucial for conservation and management. I combined at-sea observations of three Alcids between two years with data on the physical and biological features of the marine environment to predict the suitable habitat of seabirds in the San Juan Archipelago. While the ocean presents a dynamic and variable environment, across all species, there were consistent areas that was suitable habitat for Pigeon Guillemot, Rhinoceros Auklet, and Marbled Murrelets, specifically, the southern portion of Lopez Island, an area currently not listed as an IBA. The results also highlight that suitable habitat might not be constant and effective conservation efforts might require large ranges to be protected in order to ensure that specific species are able to meet their ecological needs as environmental conditions shift across time. The predictive maps from this study are an important first step in defining marine IBAs in the San Juan Archipelago.

Limitations and Future Directions

I was unable to include forage fish abundance in the models as a predictor which could be one of the largest influences for seabird distribution at sea. Additionally, I was only able to consider four environmental variables at a course resolution. In the future, I plan to add oceanographic predictions to the model and will seek to include forage fish data across time. Once more environmental variables are included, I hope to combine multiple years together to better predict specific-species distributions and use forecasted climate and oceanographic shifts in order to predict how habitat suitability could shift overtime.

Acknowledgements

Thank you to Drs. B. Tyler and E.M. Anderson as well as M. Kuruvilla for their thoughtful inputs and guidance throughout this research project.

This material is based upon work supported by the National Science Foundation Graduate Research Fellowship Program under Grant No. 1000263298. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the National Science Foundation.

Literature Cited

Amante, C., and B. W. Eakins. 2009. ETOPO1 arc-minute global relief model: procedures, data sources and analysis.

Bayard, T., G. Slater, K. Spragens, and A. Summers. 2019. Recommendations for a Puget Sound Estuary Avian Monitoring Strategy. A synthesis report to the Puget Sound Ecosystem Monitoring Program and Puget Sound Partnership. Tacoma.

Chittenden, C. M., R. Sweeting, C. M. Neville, K. Young, M. Galbraith, E. Carmack, S. Vagle, M. Dempsey, J. Eert, and R. J. Beamish. 2018. Estuarine and marine diets of out-migrating Chinook Salmon smolts in relation to local zooplankton populations, including harmful blooms. Estuarine, Coastal and Shelf Science 200:335–348.

Cleasby, I. R., E. Owen, L. Wilson, E. D. Wakefield, P. O'Connell, and M. Bolton. 2020. Identifying important at-sea areas for seabirds using species distribution models and hotspot mapping. Biological Conservation 241:108375.

Ebbesmeyer, C. C., and C. A. Barnes. 1980. Control of a fjord basin's dynamics by tidal mixing in embracing sill zones. Estuarine and Coastal Marine Science 11:311–330.

Fielding, A. H., and J. F. Bell. 1997. A review of methods for the assessment of prediction errors in conservation presence/absence models. Environmental conservation 24:38–49.

Furness, R. W., and K. (C. J.) Camphuysen. 1997. Seabirds as monitors of the marine environment. ICES Journal of Marine Science 54:726–737.

Game, E. T., H. S. Grantham, A. J. Hobday, R. L. Pressey, A. T. Lombard, L. E. Beckley, K. Gjerde, R. Bustamante, H. P. Possingham, and A. J. Richardson. 2009. Pelagic protected areas: the missing dimension in ocean conservation. Trends in Ecology & Evolution 24:360–369.

Gaydos, J. K., and S. F. Pearson. 2011. Birds and mammals that depend on the Salish Sea: a compilation. Northwestern Naturalist 92:79–94.

Grémillet, D., and T. Boulinier. 2009. Spatial ecology and conservation of seabirds facing global climate change: a review. Marine Ecology Progress Series 391:121–137.

Halpern, B. S., S. Walbridge, K. A. Selkoe, C. V. Kappel, F. Micheli, C. D'Agrosa, J. F. Bruno, K. S. Casey, C. Ebert, H. E. Fox, R. Fujita, D. Heinemann, H. S. Lenihan, E. M. P.

Madin, M. T. Perry, E. R. Selig, M. Spalding, R. Steneck, and R. Watson. 2008. A Global Map of Human Impact on Marine Ecosystems. Science 319:948–952.

Lascelles, B. G., G. M. Langham, R. A. Ronconi, and J. B. Reid. 2012. From hotspots to site protection: Identifying Marine Protected Areas for seabirds around the globe. Biological Conservation 156:5–14.

Lavers, J. L., M. G. R. Miller, M. J. Carter, G. Swann, and R. H. Clarke. 2014. Predicting the Spatial Distribution of a Seabird Community to Identify Priority Conservation Areas in the Timor Sea. Conservation Biology 28:1699–1709.

Lewison, R. L., L. B. Crowder, A. J. Read, and S. A. Freeman. 2004. Understanding impacts of fisheries bycatch on marine megafauna. Trends in Ecology and Evolution.

Oppel, S., A. Meirinho, I. Ramírez, B. Gardner, A. F. O'Connell, P. I. Miller, and M. Louzao. 2012. Comparison of five modelling techniques to predict the spatial distribution and abundance of seabirds. Biological Conservation 156:94–104.

Phillips, S. J., R. P. Anderson, M. Dudík, R. E. Schapire, and M. E. Blair. 2017. Opening the black box: an open-source release of Maxent. Ecography 40:887–893.

Phillips, S. J., R. P. Anderson, and R. E. Schapire. 2006. Maximum entropy modeling of species geographic distributions. Ecological Modelling 190:231–259.

R. Core Team. 2018. R: A language and environment for statistical computing. Vienna, Austria: R Foundation for Statistical Computing.

Raphael, M. G., J. Baldwin, G. A. Falxa, M. H. Huff, M. Lance, S. L. Miller, S. F. Pearson, C. J. Ralph, C. Strong, and Chris. Thompson. 2007. Regional population monitoring of the marbled murrelet: field and analytical methods. Page PNW-GTR-716. U.S. Department of Agriculture, Forest Service, Pacific Northwest Research Station, Portland, OR.

RStudio Team. 2020. RStudio: integrated development environment for R.

Schreiber, E. A. 2002. Climate and weather effects on seabirds. Biology of marine birds:179–216.

Suryan, R., J. Santora, and W. Sydeman. 2012. New approach for using remotely sensed chlorophyll a to identify seabird hotspots. Marine Ecology Progress Series 451:213–225.

Thaxter, C. B., B. Lascelles, K. Sugar, A. S. C. P. Cook, S. Roos, M. Bolton, R. H. W. Langston, and N. H. K. Burton. 2012. Seabird foraging ranges as a preliminary tool for identifying candidate Marine Protected Areas. Biological Conservation 156:53–61.

U.S. Fish and Wildlife Service. 1997. Recovery Plan for the Marbled Murrelet in Washington, Oregon, and California. U.S. Fish and Wildlife Service, Portland, OR, USA:286.

Vignali, S., A. G. Barras, R. Arlettaz, and V. Braunisch. 2020. SDMtune: An R package to tune and evaluate species distribution models. Ecology and evolution 10:11488–11506.

Vignali, S., F. Lörcher, D. Hegglin, R. Arlettaz, and V. Braunisch. 2021. Modelling the habitat selection of the bearded vulture to predict areas of potential conflict with wind energy development in the Swiss Alps. Global Ecology and Conservation 25:e01405.

Vilchis, L. I., C. K. Johnson, J. R. Evenson, S. F. Pearson, K. L. Barry, P. Davidson, M. G. Raphael, and J. K. Gaydos. 2015. Assessing ecological correlates of marine bird declines to inform marine conservation. Conservation Biology 29:154–163.

Tables

Table 1 | Number of observations per month and year for Pigeon Guillemot (PIGU), Rhinoceros Auklet (RHAU), and Marbled Murrelet (MAMU) based on at-sea surveys conducted in the Conservation Zone 1 of the Recovery Plan for the Marbled Murrelet located in the Salish Sea by the US Fish and Wildlife Services.

Species	Month	Year	Number of Observations
PIGU	May	2013	322
PIGU	June	2013	657
PIGU	July	2013	618
PIGU	May	2018	636
PIGU	June	2018	898
PIGU	July	2018	503
RHAU	May	2013	403
RHAU	June	2013	1227
RHAU	July	2013	798
RHAU	May	2018	650
RHAU	June	2018	769
RHAU	July	2018	1047
MAMU	June	2013	197
MAMU	June	2018	260
MAMU	July	2018	170

Table 2 | Performance metrics for parameter settings regarding regularization multiplier (RMs), and feature classes (FCs) used for creating final models for Pigeon Guillemot (PIGU), Rhinoceros Auklet (RHAU) and Marbled Murrelet (MAMU). Model performance was measured as the area under the receiving operating characteristic (ROC) curve (AUC). The AUC is provided for the training (Training AUC) and testing (Testing AUC) datasets.

PIGU	RMs	FCs	Trained AUC	Test AUC
May 2013	0.56	lh	0.96	0.96
June 2013	3.7	lqpht	0.94	0.93
July 2013	2.66	lqpht	0.93	0.93
May 2018	1.66	lqph	0.95	0.95
June 2018	1.86	lqpht	0.94	0.94
July 2018	0.28	lqpht	0.95	0.94

RHAU	RMs	FCs	Trained AUC	Test AUC
May 2013	0.83	lqpht	0.94	0.91
June 2013	0.64	lqpht	0.92	0.9
July 2013	0.68	lqpht	0.93	0.91
May 2018	0.56	lqph	0.95	0.95
June 2018	0.84	lqpht	0.96	0.95

July 2018	0.67	lqpht	0.96	0.94

MAMU	RMs	FCs	Trained AUC	Test AUC
June 2013	2.66	lqpht	0.94	0.93
June 2018	0.56	lqph	0.96	0.95
July 2018	0.68	lqph	0.96	0.95

Table 3 | Estimates of relative contribution of the environmental variables to the final models for Pigeon Guillemot in the San Juan Archipelago: Distance to Shore (m), Sea Surface Temperature (°C), Chlorophyll *a* concentration ($mg*m^{-3}$), and bathymetry (m).

May 2013	Percent Contribution	Permutation Importance
Distance to Shore	47.46	55.01
Sea Surface Temperature	24.69	17.02
Chlorophyll *a* concentration	17.22	17.76
Bathymetry	10.64	10.21

June 2013	Percent Contribution	Permutation Importance
Distance to Shore	45.01	64.85
Chlorophyll *a* concentration	27.04	15.26
Bathymetry	22.68	16.26
Sea Surface Temperature	5.27	3.63

July 2013	Percent Contribution	Permutation Importance
Chlorophyll *a* concentration	66.22	20.64
Distance to Shore	32.28	71.29
Bathymetry	1.36	7.47
Sea Surface Temperature	0.14	0.60

May 2018	Percent Contribution	Permutation Importance
Distance to Shore	58.70	62.31
Chlorophyll *a* concentration	22.42	16.64
Bathymetry	10.08	15.15
Sea Surface Temperature	8.80	5.90

June 2018	Percent Contribution	Permutation Importance
Distance to Shore	48.65	58.77
Sea Surface Temperature	24.66	14.47
Chlorophyll *a* concentration	15.93	13.51
Bathymetry	10.76	13.25

July 2018	Percent Contribution	Permutation Importance
Distance to Shore	30.53	60.18
Chlorophyll *a* concentration	30.14	10.77
Bathymetry	20.77	17.56
Sea Surface Temperature	18.57	11.49

Table 4 | Estimates of relative contribution of the environmental variables to the final models for Marbled Murrelet in the San Juan Archipelago: Distance to Shore (m), Sea Surface Temperature (°C), Chlorophyll *a* concentration (mg*m^{-3}), and bathymetry (m).

June 2013	Percent Contribution	Permutation Importance
Distance to Shore	31.37	58.41
Chlorophyll *a* concentration	24.15	13.66
Sea Surface Temperature	22.98	17.46
Bathymetry	21.50	10.47

June 2018	Percent Contribution	Permutation Importance
Distance to Shore	36.20	56.27
Sea Surface Temperature	31.42	28.48
Bathymetry	16.49	8.15
Chlorophyll *a* concentration	15.90	7.10

July 2018	Percent Contribution	Permutation Importance
Distance to Shore	38.41	31.17
Chlorophyll *a* concentration	27.31	32.34
Sea Surface Temperature	19.76	14.13
Bathymetry	14.52	22.35

Table 5 | Estimates of relative contribution of the environmental variables to the final models for Rhinoceros Auklet in the San Juan Archipelago: Distance to Shore (m), Sea Surface Temperature (°C), Chlorophyll *a* concentration (mg*m^{-3}), and bathymetry (m).

May 2013	Percent Contribution	Permutation Importance
Sea Surface Temperature	32.57	20.07
Distance to Shore	32.55	52.98
Bathymetry	19.95	14.58
Chlorophyll *a* concentration	14.94	12.36

June 2013	Percent Contribution	Permutation Importance
Sea Surface Temperature	52.47	13.39
Distance to Shore	17.70	43.62
Chlorophyll *a* concentration	17.41	24.36
Bathymetry	12.42	18.63

July 2013	Percent Contribution	Permutation Importance
Sea Surface Temperature	31.46	20.91
Distance to Shore	25.48	38.60
Bathymetry	25.16	27.19
Chlorophyll *a* concentration	17.89	13.30

May 2018	Percent Contribution	Permutation Importance
Chlorophyll *a* concentration	33.90	40.83
Sea Surface Temperature	28.82	18.99
Bathymetry	18.70	20.31
Distance to Shore	18.57	19.87

June 2018	Percent Contribution	Permutation Importance
Bathymetry	38.27	19.64
Sea Surface Temperature	24.42	20.99
Distance to Shore	21.87	41.68
Chlorophyll *a* concentration	15.45	17.70

July 2018	Percent Contribution	Permutation Importance
Chlorophyll *a* concentration	43.077	30.305
Distance to Shore	23.692	42.543
Sea Surface Temperature	18.824	16.648
Bathymetry	14.408	10.505

Figure Legends

Figure 1 | The three strata within in Northwest Forest Plan's Marbled Murrelet (*Brachyramphus marmoratus*) Conservation Zone 1 located in the Salish Sea, Washington, USA. (A) The northern region of Stratum 2, (B) southern section of Stratum 2 and entirety of Stratum 3, and (C) Stratum 1, located in the Strait of Juan de Fuca. Green sections indicate location of Primary Sampling Units that were surveyed using distance sampling during 2013 and 2018. Figure provided by Washington Department and Fish and Wildlife.

Figure 2 | Predictive maps of Pigeon Guillemot (*Cepphus columba)*, probability of suitable at-sea habitat for (A) 2013 (May-July) and (B) 2018 (May-July) based on the optimal Maxent models using location data collected in the in the Salish Sea, Washington, USA during the same period. Predicted values are the "cloglog" output of the species-specific Maxent model with values ranging from 0 to 1 depicted by a blue to red scale. Note that values are only provided for marine areas, excluding land.

Figure 3 | Predictive maps of Rhinoceros Auklet (*Cerorhinca monocerata*), probability of suitable at-sea habitat for (A) 2013 (May-July) and (B) 2018 (May-July) based on the optimal Maxent models using location data collected in the in the Salish Sea, Washington, USA during the same period. Predicted values are the "cloglog" output of the species-specific Maxent model with values ranging from 0 to 1 depicted by a blue to red scale. Note that values are only provided for marine areas, excluding land.

Figure 4 | Predictive maps of Marbled Murrelet (*Brachyramphus marmoratus*), probability of suitable at-sea habitat for June 2013, June 2018, and July 2018 based on the optimal Maxent models using location data collected in the in the Salish Sea, Washington, USA during the same period. Predicted values are the "cloglog" output of the species-specific Maxent model with values ranging from 0 to 1 depicted by a blue to red scale. Note that values are only provided for marine areas, excluding land.

Figures

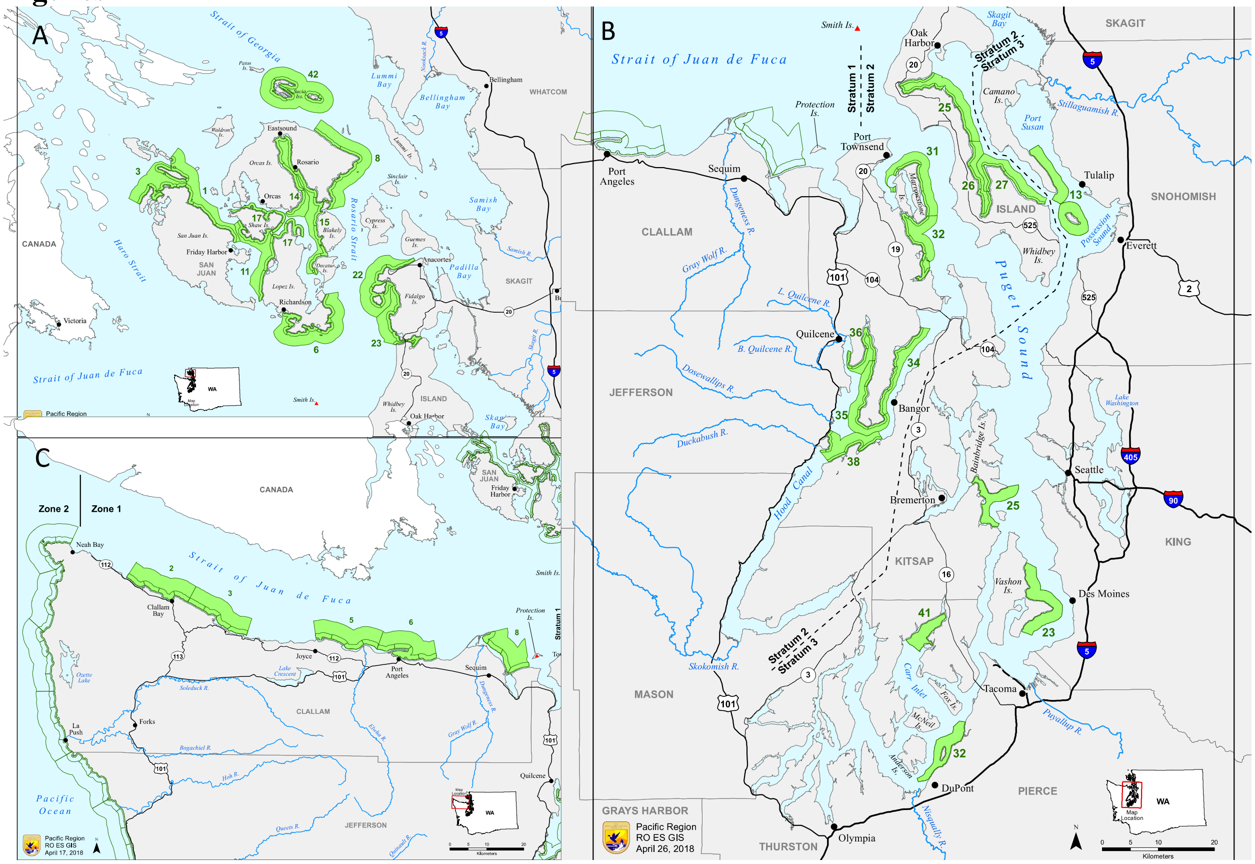

Figure 2 | The three strata within in Northwest Forest Plan's Marbled Murrelet (*Brachyramphus marmoratus*), Conservation Zone 1 located in the Salish Sea, Washington, USA. (A) The northern region of Stratum 2, (B) southern section of Stratum 2 and entirety of Stratum 3, and (C) Stratum 1, located in the Strait of Juan de Fuca. Green sections indicate location of Primary Sampling Units that were surveyed using distance sampling during 2013 and 2018. Figure provided by Washington Department and Fish and Wildlife.

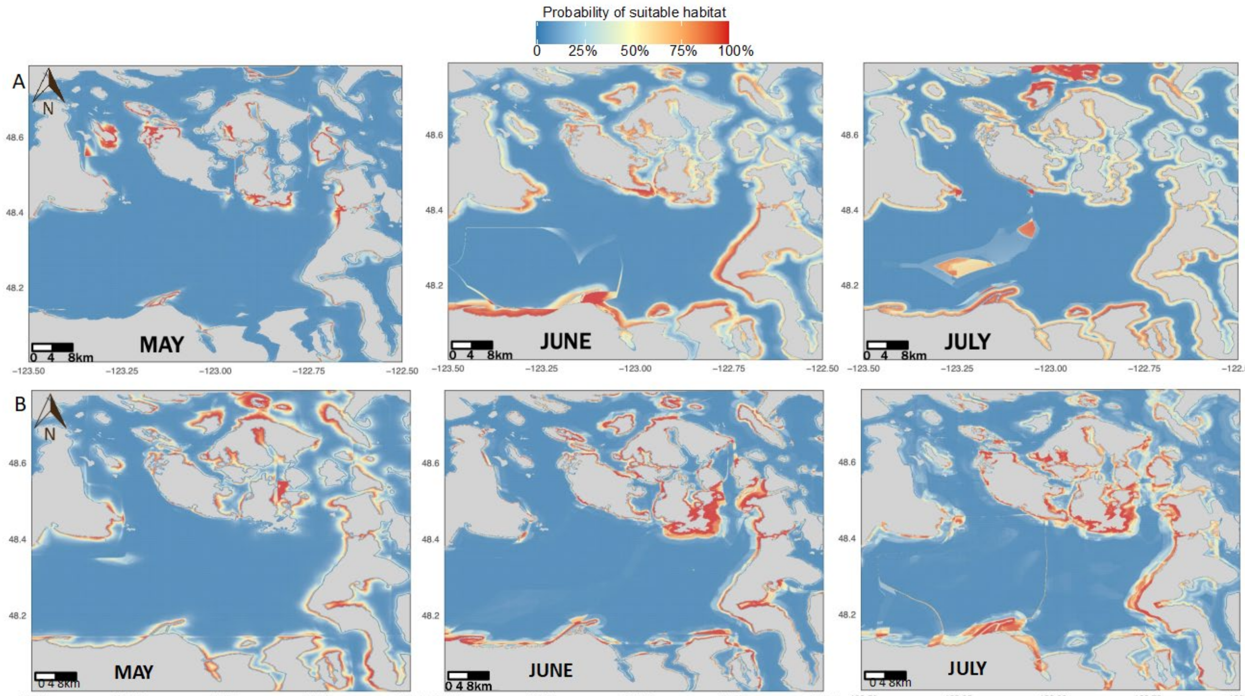

Figure 2 | Predictive maps of Pigeon Guillemot (*Cepphus columba)*, probability of suitable at-sea habitat for (A) 2013 (May-July) and (B) 2018 (May-July) based on the optimal Maxent models using location data collected in the in the Salish Sea, Washington, USA during the same period. Predicted values are the "cloglog" output of the species-specific Maxent model with values ranging from 0 to 1 depicted by a blue to red scale. Note that values are only provided for marine areas, excluding land.

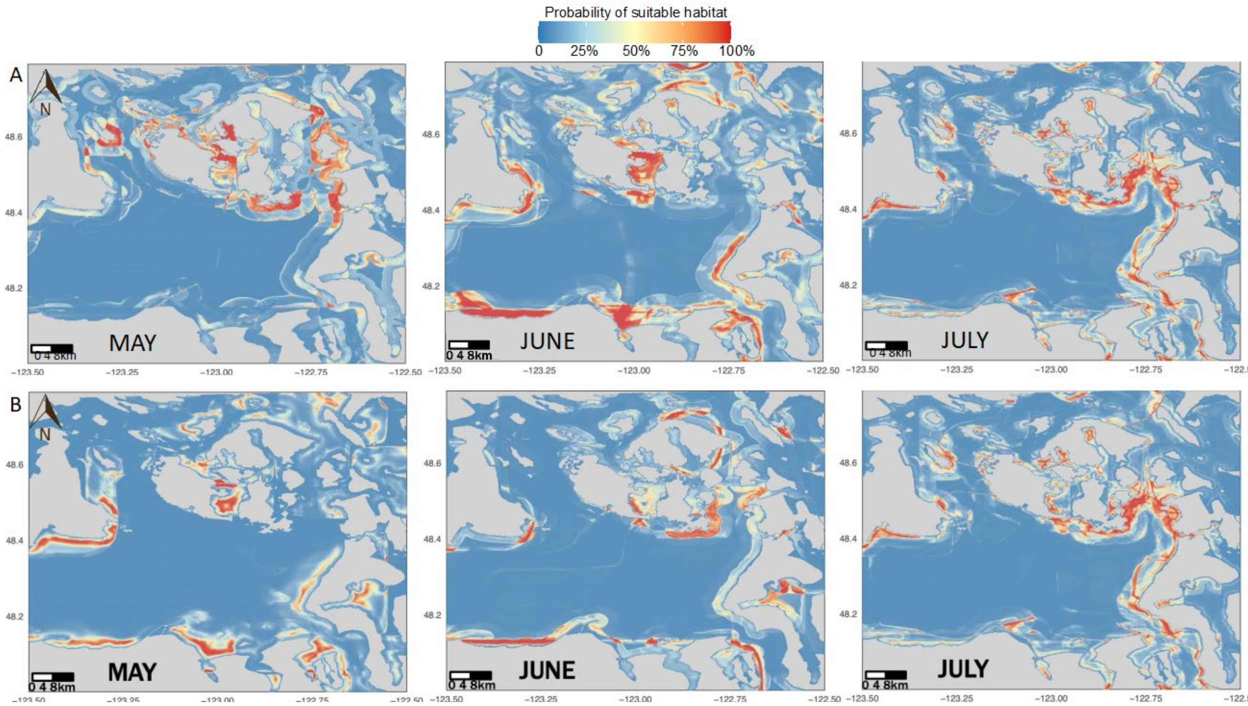

Figure 3 | Predictive maps of Rhinoceros Auklet (*Cerorhinca monocerata*), probability of suitable at-sea habitat for (A) 2013 (May-July) and (B) 2018 (May-July) based on the optimal Maxent models using location data collected in the in the Salish Sea, Washington, USA during the same period. Predicted values are the "cloglog" output of the species-specific Maxent model with values ranging from 0 to 1 depicted by a blue to red scale. Note that values are only provided for marine areas, excluding land.

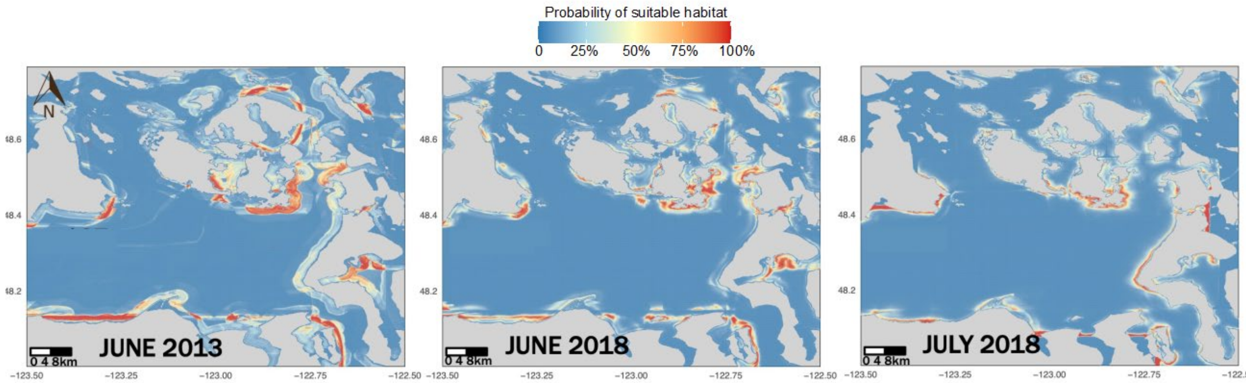

Figure 4 | Predictive maps of Marbled Murrelet (*Brachyramphus marmoratus*), probability of suitable at-sea habitat for June 2013, June 2018, and July 2018 based on the optimal Maxent models using location data collected in the in the Salish Sea, Washington, USA during the same period. Predicted values are the "cloglog" output of the species-specific Maxent model with values ranging from 0 to 1 depicted by a blue to red scale. Note that values are only provided for marine areas, excluding land.