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Using citizen-science data to identify local hotspots of species occurrence

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Abstract

Seabirds have been identified and used as indicators of ecosystem processes such as climate change, and anthropogenic activity in nearshore ecosystems around the globe. Temporal and spatial trends have been documented at large spatial scales, but few studies have examined fine scale spatial patterns, by species or functional group. In this paper, we apply spatial occupancy models to assess the spatial patchiness and interannual trends of 18 seabird species in the Puget Sound region (Washington state, USA). Our dataset, the Puget Sound Seabird Survey, is unique in that represents a seven year study, collected in winter months (October – April), and is collected at an extremely fine spatial scale (62 sites in the current analysis). Despite historic declines of seabirds in the region over the last 50 years, results from our study are optimistic, suggesting increases in probabilities of occurrence for 14 of the 18 species included. We found support for declines in occurrence for white-winged scoters, brants, and 2 species of grebes. The declines of Western grebes in particular are troubling, but in agreement with other recent studies that have shown support for a range shift south in recent years, to the California Current.

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Introduction

Ecologists and conservation practitioners have long focused on describing species distribution and estimating changes in abundance (Holmes 2001) or occurrence through time (MacKenzie et al. 2006). Identifying hotspots of a species' distribution has multiple implications for science and management. From a conservation perspective, incorporating spatial variation in models may assist in selecting areas to protect or where species are likely to persist (Cabeza & Moilanen 2001; Naujokaitis-Lewis et al. 2009). From a theoretical ecology perspective, null or neutral models of species' occurrence may be useful in predicting species diversity or community assembly (Gotelli 2000; Gotelli & McGill 2006). Finally, the inclusion of spatial variation may help in forecasting how species may respond to future environmental conditions, such as climate change (Jetz et al. 2007).

Trends in occurrence through time may be spatially structured as well. Habitat conditions, behavior, or prey availability all contribute to spatial structure (Ward et al. 2010). Anthropogenic drivers of change in species distribution may also exhibit spatial variability (e.g. wildfires, oil spills, climate change, urbanization). Ignoring underlying spatial variation when it exists may lead to poor estimation of trends through time (Hoeting et al. 2008).

Models that incorporate both spatial and temporal variation represent a rapidly evolving field in ecology (Hooten & Wikle 2008; Latimer et al. 2006; Shelton et al. 2014). While many of these methods have been in the statistical literature for decades (Banerjee et al. 2005; Cressie & Wikle 2011), ecological data often present a unique set of challenges relative to data from other fields, and the computational advances necessary to run these models have only occurred very recently. Compared to other disciplines, ecological data on species abundance is often corrupted by observation error, representing uncertainty arising from taking measurements or sampling a

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fraction of the population (Holmes 2001). Similarly, in conducting studies of species presence-absence, detections may be missed, resulting in false-negatives (MacKenzie et al. 2006).

Declining budgets for monitoring programs in recent years have increased the need for cost efficient survey techniques. In the face of recent reductions, one potentially underutilized resource is citizen-science. Participation in these volunteer based programs appears to have increased in recent years (Silvertown 2009), and some of the longest running citizen-science programs in North America are related to bird-watching. Large-scale volunteer programs like the Audubon Christmas Bird Count and the North American Breeding Bird Survey (BBS) have been effective at collecting vast amounts of survey data on commonly occurring bird species (Sauer et al. 2014). The strength of these programs is their duration, large spatial extent, and consistent methodologies over time, enabling them to be useful in monitoring species assemblages and distribution shifts in response to changing climate (Hitch & Leberg 2007). Regional-scale citizen-science programs, such as the Coastal Observation and Seabird Survey Team (COASST; Hamel et al. 2009; Litle et al. 2007; Parrish et al. 2007), or the British Columbia Coastal Waterbird Survey (Crewe et al. 2012) have also been developed to address conservation questions and establish baseline monitoring. A collective limitation of some of these surveys is that few have any consistent measures of survey effort.

Citizen science may be a useful tool for conducting baseline environmental monitoring, or helping to inform management actions or restoration activities (Cooper et al. 2007). One of the areas in in the USA that has been prioritized for restoration actions is in the Puget Sound (Washington state), where one of the largest ecosystem restoration programs in the nation is underway (Puget Sound Partnership 2014). The Puget Sound ecosystem is part of the Salish Sea (which also includes the Strait of Juan de Fuca and the Strait of Georgia), and it has been affected by widespread environmental degradation largely associated with increased urbanization (effects summarized in Puget Sound Partnership 2009; Ruckelshaus & McClure 2007). The Puget Sound consists of over 4,000 km of coastline with a suite of high-value ecosystem services, including commercial fisheries and various recreation opportunities (e.g. Tallis & Polasky 2009). A portfolio of ecosystem indicators have been developed and implemented in restoration goals for the Puget Sound region to monitor ecological condition, including seabirds (Kershner et al. 2011; Puget Sound Partnership 2013).

To date, the largest seabird-monitoring effort in Puget Sound has been an annual winter aerial survey conducted by the Washington Department of Fish and Wildlife (WDFW) (Anderson et al. 2009). These annual transects occur in 13-18% of the nearshore (<20m depth) and 3-6% of the offshore (>20m depth) marine waters seabird habitat in Puget Sound, ranging from southern Puget Sound to the Canadian border. Results from the WDFW aerial seabird surveys suggested that the density of some species, includingWestern Grebes (*Aechmophorus occidentalis*), have declined over the last two decades (Bower 2009; Evenson 2010; Vilchis et al. 2014). However, the cause(s) of these declines and the effects of environmental drivers on seabird density remain largely unknown.

To complement the WDFW seabird survey both spatially and temporally, and to establish baseline monitoring of local seabird species occurrence and abundance in winter months (October - April), Seattle Audubon initiated the shore-based Puget Sound Seabird Survey (PSSS) in 2007. This program is unique in Puget Sound, in that it is the only one that monitors seabirds repeatedly throughout the winter months in nearshore habitat. This survey also represents one of the more scientifically rigorous citizen-science efforts, because survey effort is quantified and volunteers are trained annually (and the subject of ongoing validation studies to quantify biases).

Recent research has demonstrated that rigorous statistical models can be applied to volunteer based surveys, yielding a relatively large impact, particularly when agency or industry-led data collection efforts are limited (Thorson et al. 2014a). The primary objective of our analysis was to apply spatiotemporal models to data from the Puget Sound seabird surveys to evaluate relative hotspots of occurrence. Using output from these models, a second objective was to evaluate species-specific trends in occurrence over time. These estimates may be useful to refine the list of indicator species to include spatial as well as temporal components.

Methods

Data Collection

Beginning in October 2007, pairs of volunteer birdwatchers were trained by Seattle Audubon staff to collect data on birds in the nearshore environment of Puget Sound. Though the species encountered includes waterfowl, we collectively refer to all species as 'seabirds'. Each observer team was responsible for monthly surveys (October – April) at selected sites. Many of the seabird species in the region overwinter in Puget Sound, and are of highest abundance from late fall – early spring. The PSSS survey sites were selected non-randomly due to dependence on public access (parks, beach access), but they were selected to be spaced at least 1.6 km apart. Observer teams recorded all species present out to 300m for a minimum of 15 minutes, but some site visits lasted up to 60 minutes. To minimize the variability of weather conditions, tidal stage, and the risk of double counting birds at multiple survey sites, volunteer teams completed their monthly surveys on the same date within a specific four-hour window (two hours on either side of high tide) on the first Saturday of each month. In each subsequent year of surveys, we added

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sites to cover parts of northern and southern Puget Sound. For this study, we limited our analysis to 62 sites with at least 15 visits (Table 1).

Species Selection

Over the first seven years of the PSSS (the most recent ending in spring 2014), observer teams recorded 75 unique seabird species. While many of these species may be useful as indicators of various ecosystem processes or anthropogenic impacts, we focused our analysis on 18 species that have previously been identified as useful seabird indicator species in the region (Table 2; Pearson & Hamel 2013). These species can be aggregated into five distinct groups: alcids, cormorants, grebes, loons, and waterfowl. Some of the species breed locally in Puget Sound, while others are transient in the Sound, breeding elsewhere (Table 2). Similarly, the species represent a range of diets and behaviors (Pearson & Hamel 2013), from piscivores (alcids, loons and grebes) to omnivores (cormorants, waterfowl).

Statistical Modeling

For each species, we constructed matrices of presence-absence, dimensioned by the number of unique month-year combinations (t = 49) and sites (n = 62). Sites that were not visited during a given month were treated as NA values. We constructed a spatial occupancy model separately for each species, to incorporate spatial patchiness, as well as annual and seasonal variation. The model describing the probability of species presence can be represented as $z_{i,j} \sim Ber(\phi_{i,j})$, where $z_{i,j}$ represents the unobserved presence-absence (1, 0), and $logit(\phi_i) = BX_i + ET_i + \varepsilon$, where ϕ_i represents the site-specific occupancy probabilities at time i, X_i represents a matrix of covariates (Intercept, Month, Month^2, Year, Year^2), B represents a vector of estimated coefficients (shared across sites and time periods), E represents a linear offset coefficient for sampling effort (T_i), and ε represents a vector of spatially correlated random

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effects. We included time spent (T_i in minutes, ranging from 15 – 60) as a measure of effort to account for the higher chance of recording a species present during longer visits. The spatially correlated random effects are assumed to have the distribution $\varepsilon \sim MVN(0, \Sigma)$. For simplicity, we modeled the covariance matrix Σ as an exponential covariance function, $\Sigma_{i,j} = \sigma^2 \cdot \mathrm{I}_{i,j} + \tau \cdot \exp(-d_{i,j}/\gamma)$, where I represents an identity matrix, $d_{i,j}$ is the Euclidian distance between sites *i* and *j*, and the scaling parameters (τ, γ) control how quickly covariance decays as a function of distance (Banerjee et al. 2005; Ward et al. 2012). Our model could be modified to include more complex covariance functions (Cressie & Wikle 2011) or spatial random effects that also vary temporally (Shelton et al. 2014). Because our model also includes an observation error component, however, we chose to make these spatial deviations temporally constant. The observation model, linking latent unobserved states ($z_{i,j}$) to data ($y_{i,j}$) can be written as $y_{i,j} | z_{i,j} \sim Ber(p \cdot z_{i,j})$ (Royle & Kery 2007), where *p* represents the probability of detection when a species is present.

All Markov Chain Monte Carlo (MCMC) estimation was conducted in R and JAGS (Plummer 2003; R Core Team 2014), using the R2jags package (Su & Yajima 2014). We ran five parallel MCMC chains for each species, with a burn-in of 100,000 draws and additional sampling of 50,000 MCMC draws. Trace plots were used to visually assess convergence, and the Gelman-Rubin statistic (Gelman & Rubin 1992) was used to quantify successful convergence. Not surprisingly, the only parameters that did not successfully converge (potential scale reduction factor > 1.05) were several latent states (*z*) at sites that were not visited by observers in certain months. For the purposes of visualizing predicted hotspots of occupancy in Puget Sound, we used our model output to generate predictions (spatial maps, temporal trends) of species occupancy for a standardized 15-minute survey. In addition to making these predictions for each of the 18 species included in our analysis, we generated specific occupancy probabilities for the five seabird groups: alcids, cormorants, loons, grebes, and waterfowl. For each group, the probability of occupancy for a group (corresponding to any species from that group being present) was calculated as $1-\prod_{i=1}^{sp}(1-\phi_i)$.

Results

Our species occupancy maps reveal some localized hotspots of occurrence in Puget Sound for some alcid and cormorant species (rhinoceros auklet, pelagic cormorant, Brandt's cormorant (Fig. 1) as well as loons and some waterfowl spp. like harlequin ducks (Fig. 2). The individual species maps show that some species are ubiquitous in all nearshore habitat (horned grebes, goldeneyes, scoters), while others have a much more patchy distribution of occurrence (loons, rhinoceros auklets, pigeon guillemots). Some maps of very rare or very common species may not be informative, but areas of high bird density become more apparent when our estimated occupancy probabilities are calculated by group (Fig. 3). For example, each loon species in the surveys is relatively rare (Fig. 2), but the aggregated spatial distribution of all loons shows several patches of high and low occurrence , with the highest density of occurrence in the central-south Puget Sound (Fig. 3).

The 18 species included in our analysis showed a range of seasonal variation, with waterfowl species (bufflehead, common goldeneye, surf scoter) and grebes varying the most and peaking in December – January (Fig. 4). Several species exhibited monotonic increases throughout the winter (pelagic cormorant, pigeon guillemot), however most of the 18 species had relatively small variation over the 7-month survey. Of the 18 seabird species, the probabilities of trends in occurrence being positive over the 7-year survey were greater than 80% for 14 species

(Fig. 5). Western grebes, white-winged scoters, and brants showed relatively strong negative trends in occurrence (probabilities of negative trends > 99%, 84%, 79%, respectively).

The 18 species in our analysis represent a gradient of both occurrence probabilities and trends over space. Several species from each group were relatively rare in central and south Puget Sound; the most rare species included two of the alcids (common murre, marbled murrelet), western grebes, all three loon species, and three of the waterfowl species (brant, harlequin duck, white-winged scoter; Fig. 5). In contrast, horned grebes and three different waterfowl species (bufflehead, common goldeneye, surf scoter) were the most widely occurring (Fig. 5).

Discussion

Analyses that incorporate both spatial and temporal variation are becoming increasingly common in ecology. These types of analyses are widely applicable to virtually any type of observed data, from presence-absence to continuous observation measurements (Johnson et al. 2013; Shelton et al. 2014). Incorporating spatially structured random effects introduces a layer of statistical complexity, however in many cases, this complexity is warranted, because predicted density estimates (both in space and time) are more precise (Thorson et al. 2014b).

Spatially-structured citizen-science datasets have been used at a large spatial scale, particularly in quantifying shifts in phenology linked to climate. One of the most frequently documented changes by citizen-science efforts have been shifts in breeding seasons (Hitch & Leberg 2007; Hurlbert & Liang 2012; Mayer 2010). Spatially-structured statistical models have been fit to these types of datasets to improve estimates of trends (Hurlbert & Liang 2012; Thorson et al. 2014a), but few analyses have applied spatiotemporal models to data from citizen-science efforts to identify hotspots or areas of conservation concern at a fine spatial scale. Citizen-science programs, such as the Puget Sound Seabird Survey data analyzed here, offer a unique opportunity, because both the temporal and spatial scales of data collection are much finer than national (Breeding Bird Survey) or regional (WA Department of Fish and Wildlife) efforts. If volunteer-driven science can result in relative indices of occurrence or abundance, it provides an extremely cost effective approach for identifying local areas of risk (Hass et al. 2012) or potential hotspots of diversity that may be useful in conservation planning (e.g., establishing reserves) or permitting activities.

Utilizing citizen-science data – either by including it to complement existing datasets or to fill in data gaps when other surveys are absent – is particularly important for areas or habitats at risk. The PSSS may be a good model for adopting similar citizen science efforts, either in other regions or for other species, as there are a number of risk factors to the food web that initially motivated the development of the citizen-science effort behind the PSSS. In addition to the historic decline of many seabird species (Bower 2009), there are a number of additional human impacts that have caused shifts or reorganization in the prey base (Rice et al. 2012) or competitors of seabirds (Harvey et al. 2012). These impacts could include effects of overfishing (and associated impacts of derelict fishing gear; Good et al. 2009), climate change, toxins, habitat loss (Raphael et al. 2014), altered freshwater flow regimes, and the recovery of many top predators to historic levels (pinnipeds, harbor porpoise, bald eagles).

Although many seabird species in the Puget Sound region are thought to be depleted relative to abundances in the 1960s-1970s (Bower 2009), our results present a more optimistic picture for many seabird species in the region over the last decade. Of the 18 species included in our analysis, we found strong support for 14 becoming more common, and these results are in agreement with recent studies in the region (for example, nesting surveys suggest Rhinoceros auklets are also increasing; Pearson et al. 2013). Many of the species that are occurring more frequently are those that breed in the region (Table 2). In the list of indicator species compiled by Pearson et al. (2013), some of these species (scoters, murrelets) were declining significantly when considering trends based on total abundance, so it is possible that, for species in decline, the spatial distribution increases at low densities (making them detected more frequently). Of the species not declining, one species provided weak support for declining occurrence (white-winged scoter), and three species provided strong support for continued declines in occurrence (brant, western grebe, red-necked grebe). These three species in decline are also concerning because they are already rarely seen species in the PSSS data (Fig. 5).

There is no obvious mechanism for why the three declining species in our analysis exhibit a declining trend in occupancy, but some of these declines may be related to shifts in prey abundance. Some recent evidence suggests that there have been changes in forage fish in the region (Rice et al. 2012), and over-wintering seabird species that rely on forage-fish are declining (Vilchis et al. 2014). Another mechanism that may also be related to shifts in the spatial distribution of prey are large-scale shifts in seabird species' ranges. For example, Wilson et al. (2013) used citizen-science data to show that western grebes appear to have shifted out of the Puget Sound region to the southern California Current. Our estimated declines in occupancy over the last seven years are largely in agreement with a continued decline in the occurrence of western grebes in the region. Like western grebes, brants and white-winged scoters over-winter in Puget Sound, but breed elsewhere, and thus may be affected by threats in other ecosystems. Though the exact mechanisms responsible for these trends are not known, our trend estimates may be useful in prioritizing monitoring efforts or refining existing marine bird or ecosystem indicators in the region (Kershner et al. 2011; Pearson & Hamel 2013).

Though the focus of our volunteer-driven surveys in the Puget Sound region are focused on identifying spatial hotspots and improving estimates of annual trends, citizen-science efforts like the Puget Sound Seabird Survey may provide additional valuable baseline monitoring. For example, in the event of an oil spill in the region, PSSS data could provide 7+ years of baseline information on seabird distribution and abundance before thespill for comparison. Such citizen-science efforts may also be scalable to different types of data collection that also involve spatially structured threats to marine ecosystems (harmful algal blooms, ocean acidification, etc).

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Table 1. Name, latitude, and longitude of the 62 sites included in our analysis

Site	Lat (N)	Lon (W)	Site	Lat (N)	Lon (W)
60th St Viewpoint	47.6723	122.4062	Mee Kwa Mooks	47.5637	122.4070
Alki Beach	47.5784	122.4144	Mukilteo State Park	47.9478	122.3071
Boston Harbor	47.1396	122.9029	Myrtle Edwards Park	47.6268	122.3775
Brace Point	47.5152	122.3964	Narrows Park	47.2671	122.5641
Brown's Point	47.3058	122.4443	Normandy Beach Park	47.4116	122.3401
Burfoot County Park	47.1310	122.9046	North Redondo Boardwalk	47.3507	122.3238
Carkeek Park	47.7125	122.3796	Olympia waterfront	47.0582	122.9020
Cromwell East	47.2709	122.6110	Owens Beach Pt Defiance	47.3128	122.5280
Cromwell West	47.2714	122.6191	Penn Cove Pier	48.2228	122.6883
Dash Pt State Park	47.3204	122.4141	Penrose State Park	47.2601	122.7450
DeMolay Boys Camp (E)	47.2777	122.6662	Pier 57	47.6062	122.3429
DeMolay Boys Camp (W)	47.2775	122.6668	Pier 70	47.6149	122.3573
Discovery Park West	47.6674	122.4227	Point No Point	47.9122	122.5265
Dumas Bay Park	47.3263	122.3853	Pt Wilson	48.1441	122.7538
Duwamish Head	47.5954	122.3876	Purdy Spit South	47.3817	122.6348
Edmonds north	47.8114	122.3891	Raft Island north	47.3318	122.6700
Edmonds south	47.8033	122.3947	Raft Island south	47.3261	122.6675
Elliott Bay Water Taxi Pier	47.5898	122.3800	Richmond Beach	47.7636	122.3858
Fox Island Fishing Pier	47.2287	122.5898	Ruston Way	47.2948	122.4990
Frye Cove County Park	47.1152	122.9643	Saltwater State Park	47.3728	122.3249
Golden Gardens	47.6928	122.4056	Seahurst Park	47.4781	122.3638
Howarth State Park	47.9642	122.2407	Sinclair Inlet	47.5398	122.6621
Jack Hyde Park	47.2758	122.4622	South Redondo Boardwalk	47.3434	122.3328
Kayak Point State Park	48.1373	122.3668	The Cove	47.4428	122.3563
Kopachuck	47.3101	122.6874	Thea's Park	47.2620	122.4398
Les Davis Pier	47.2836	122.4813	Three Tree Point	47.4522	122.3792
Libbey Beach County Park	48.2322	122.7668	Titlow Beach	47.2469	122.5536
Lincoln Park	47.5263	122.3949	Tolmie State Park	47.1209	122.7761
Lowman Park	47.5403	122.3974	Totten Inlet	47.1540	122.9645
Luhr Beach	47.1008	122.7272	West Point north	47.6624	122.4335
Magnolia Bluff	47.6313	122.3954	West Point south	47.6610	122.4330

Table 2. The 18 species included in our analysis of the Puget Sound Seabird Survey. Rows in bold represent species that breed locally (in Puget Sound).

Common name	Scientific name	Group
Common murre	*Uria aalge*	Alcids
Marbled murrelet	***Brachyramphus marmoratus***	**Alcids**
Pigeon guillemot	***Cepphus columba***	**Alcids**
Rhinoceros auklet	***Cerorhinca monocerata***	**Alcids**
Brandt's cormorant	***Phalacrocorax penicillatus***	**Cormorants**
Pelagic cormorant	***Phalacrocorax pelagicus***	**Cormorants**
Horned grebe	*Podiceps auritus*	Grebes
Red-necked grebe	*Podiceps grisegena*	Grebes
Western grebe	*Aechmophorus occidentalis*	Grebes
Common loon	*Gavia immer*	Loons
Pacific loon	*Gavia pacifica*	Loons
Red-throated loon	*Gavia stellata*	Loons
Brant	*Branta bernicla*	Waterfowl
Bufflehead	*Bucephala albeola*	Waterfowl
Common goldeneye	*Bucephala clangula*	Waterfowl
Harlequin duck	***Histrionicus histrionicus***	**Waterfowl**
Surf scoter	*Melanitta perspicillata*	Waterfowl
White-winged scoter	*Melanitta deglandi*	Waterfowl

Figure 1. Estimated probability of occurrence for the 62 sites included in our analysis. Presented estimates are for alcids, cormorants, and grebes in December 2013.

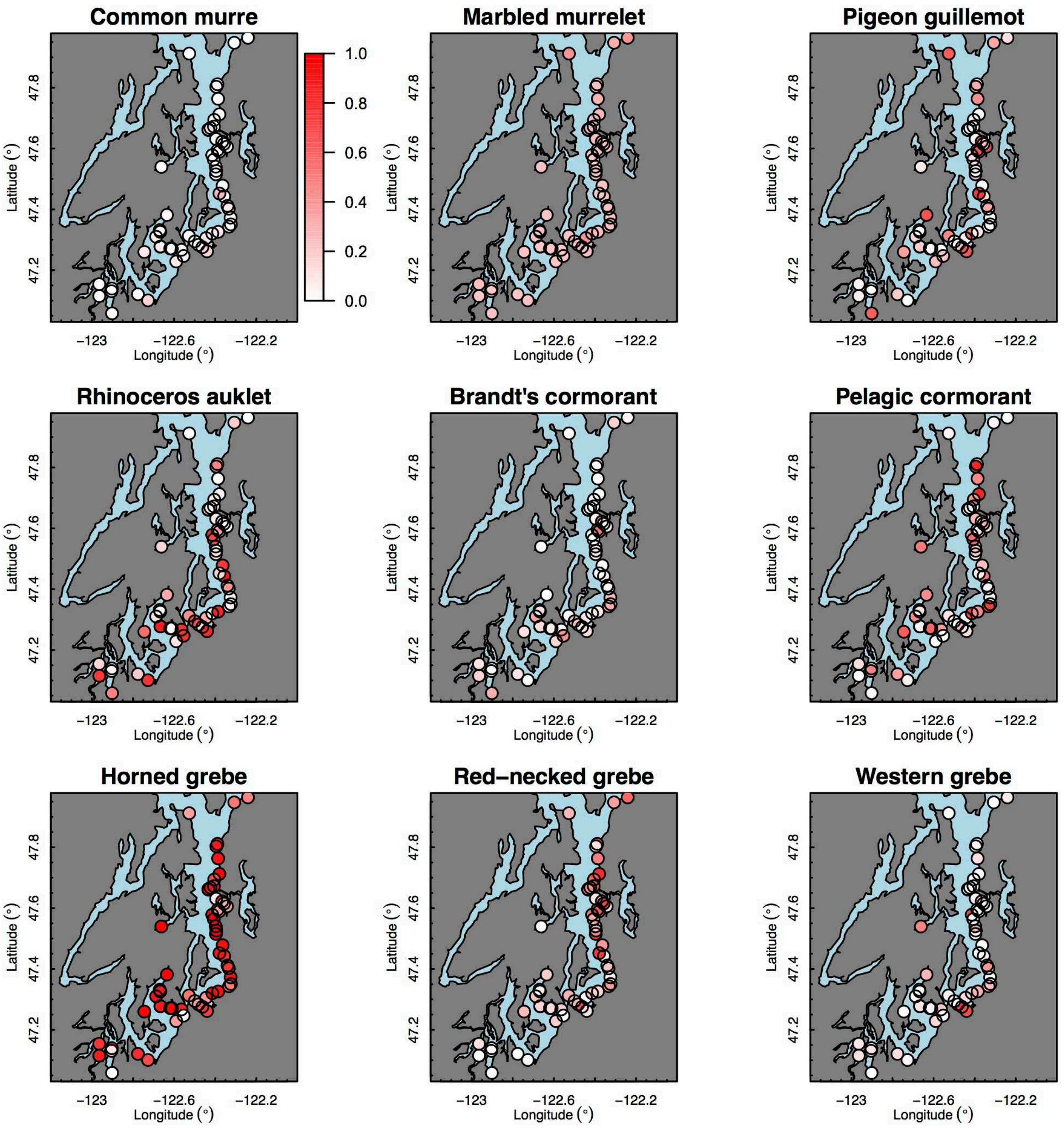
Common murre
Marbled murrelet
Pigeon guillemot
Rhinoceros auklet
Brandt's cormorant
Pelagic cormorant
Horned grebe
Red–necked grebe
Western grebe

Figure 2. Estimated probability of occurrence for the 62 sites included in our analysis. Presented estimates are for loons and waterfowl in December 2013.

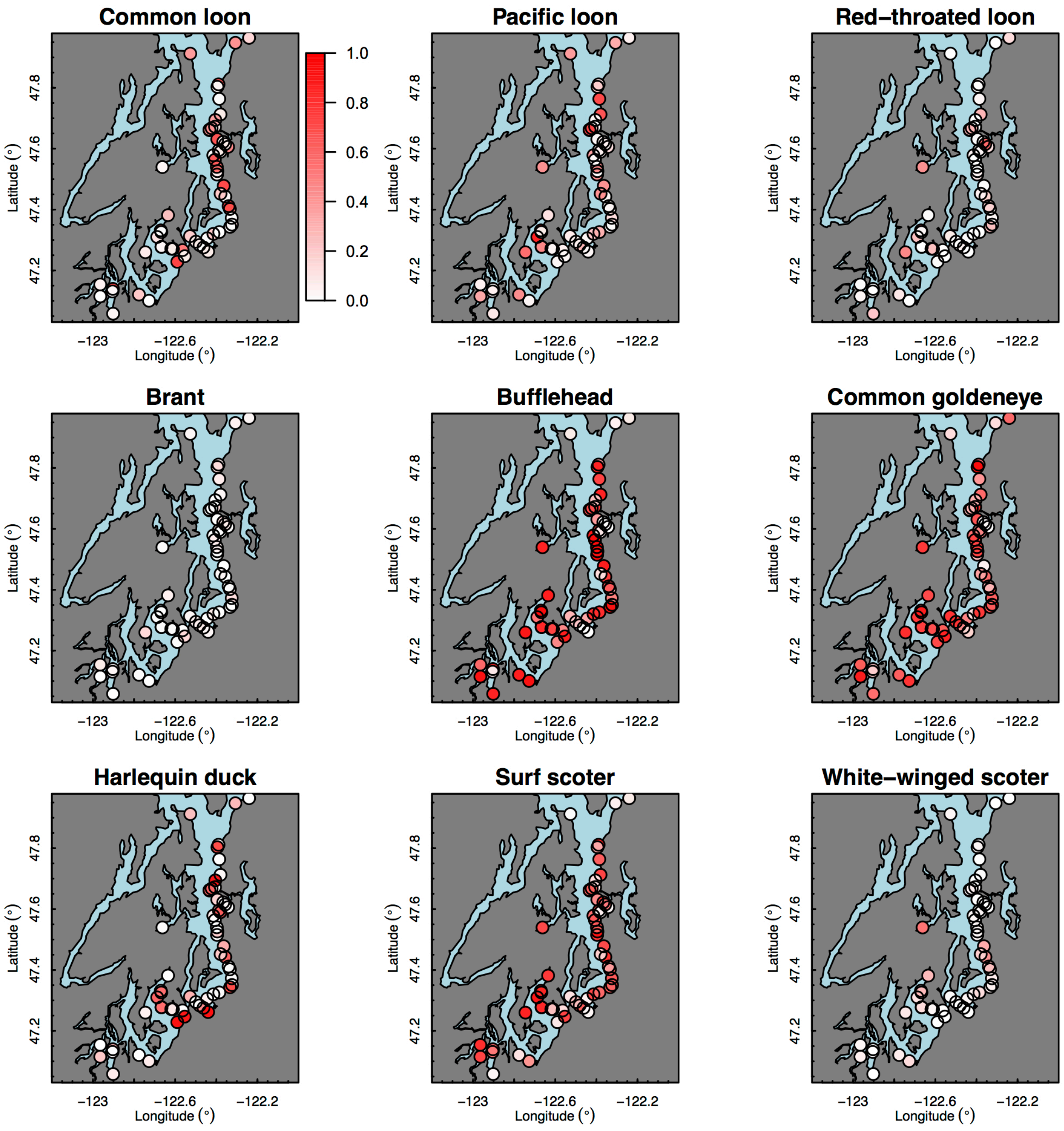

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Figure 3. Aggregated probabilities of occurrence for each of the 5 groups in our analysis, as well as for all species. For groups, these represent the probability of seeing any bird that is a member of that group; for all species, these represent the probability of seeing at least 1 bird (of the 18 species in our analysis). Estimates are shown for December 2013.

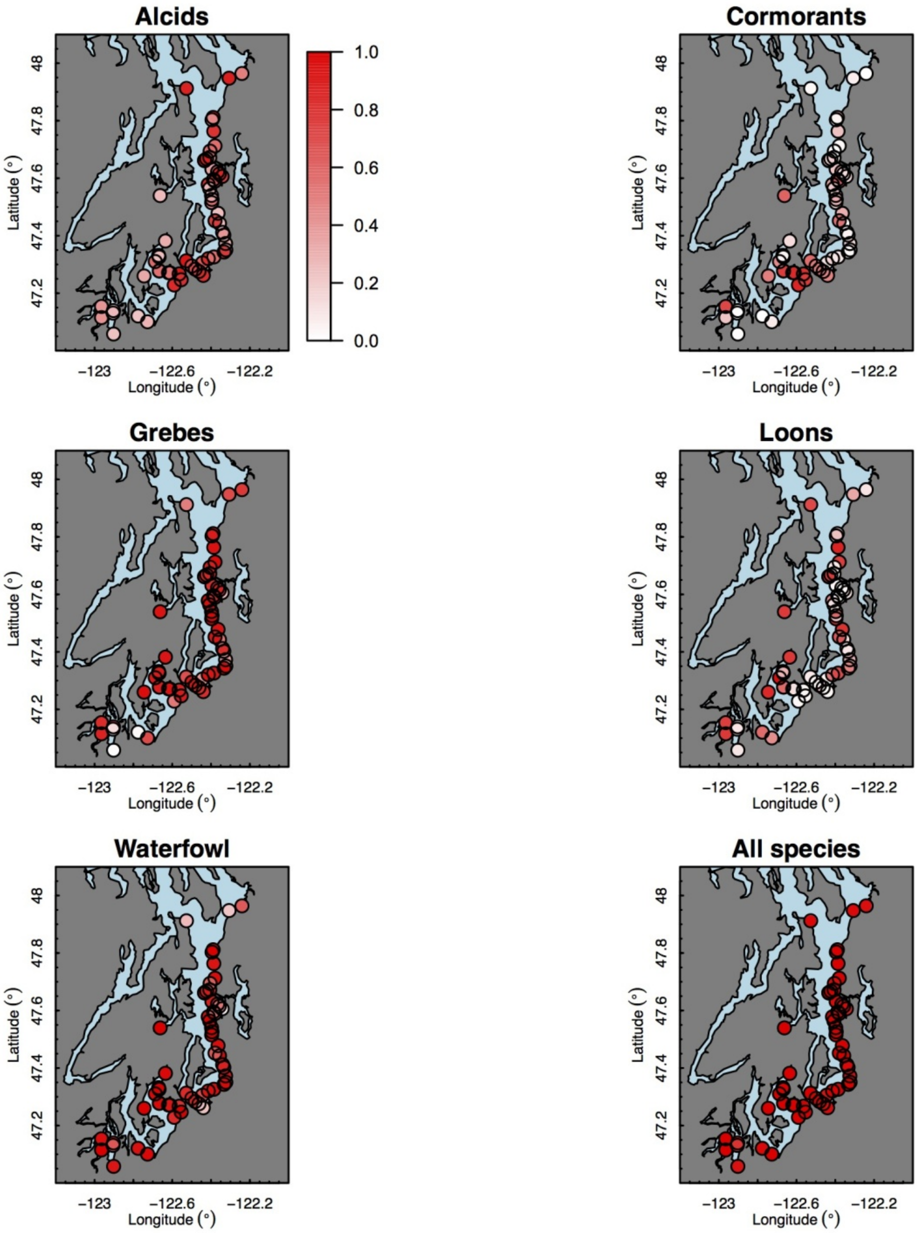


Figure 4. Estimated median probabilities of occurrence by month. Estimates are shown for the most recent year (October 2013- April 2014). Estimates for November, January, and March are not shown.

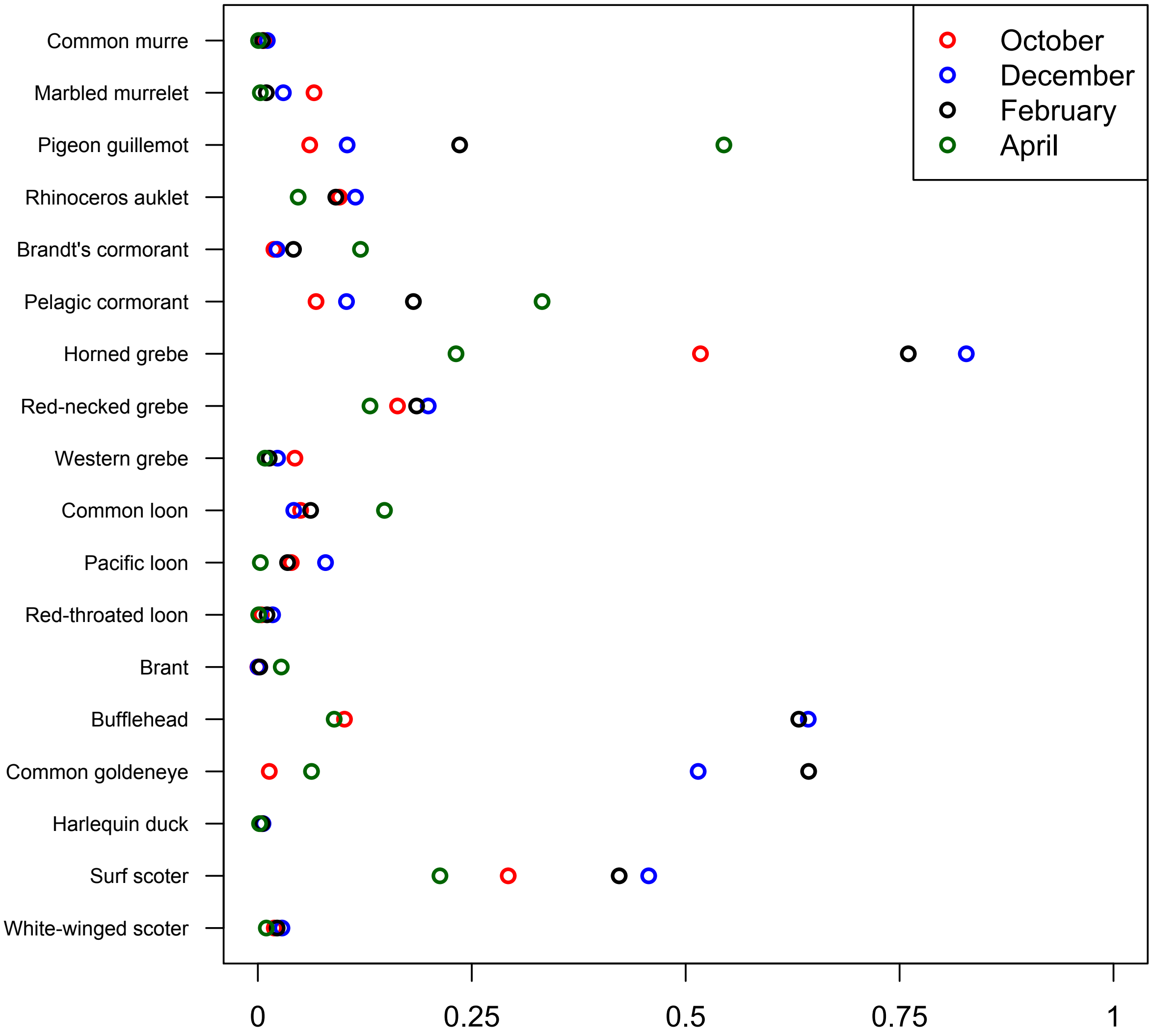
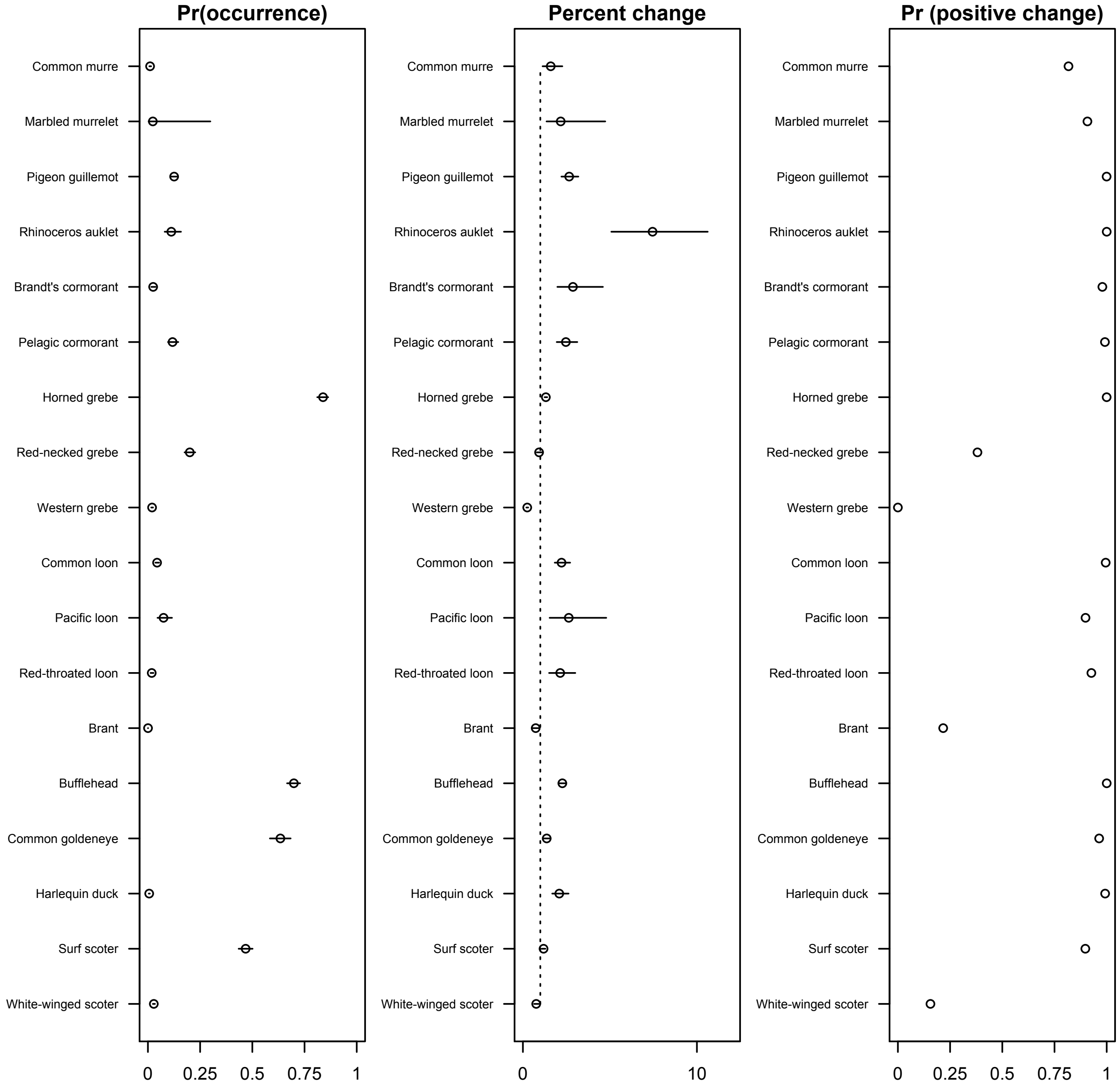


Figure 5. Estimated probability of occurrence in the 2013-2014 seabird survey (with 25%, 50%, 75% intervals), percent change in the probability of occurrence from 2007-2013 (25%, 50%, 75% intervals), and the probability of the annual rate of change from 2007-2013 has been positive. All data (2007-2013) are used to estimate intra- and inter-annual trends.



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