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Research Paper

Spatially explicit population trend estimates of owls in the Maritime provinces of Canada and the influence of call playback

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ABSTRACT. Documenting and interpreting trends in the abundance and distribution of bird populations is critical to monitoring their status and setting conservation priorities. This process requires standardized monitoring and robust analytical techniques, which can resolve trends at spatial scales of management interest while disentangling the influence that various data collection protocols can have on the interpretation of results. We used a 19-year citizen-science-collected dataset (2001–2019), the Nocturnal Owl Survey, to assess abundance trends in Barred Owl (*Strix varia*), Northern Saw-whet Owl (*Aegolius acadicus*), and Great Horned Owl (*Bubo virginianus*) at both fine and broad-scales. To achieve this, we used a spatially explicit modeling approach that facilitates the borrowing of information across spatial boundaries, allowing for more robust trend estimates at finer spatial scales. Further, we assessed the potential influence of the call-playback protocol on trend estimates. At fine spatial scales, we found that a data collection protocol that includes call playbacks provided more precise results to assess relative changes in abundance (i.e., reduced uncertainty). At broader spatial scales, trend estimates were unaffected by data collection methodology (i.e., silent listening versus call playback). Specifically, at the scale of the region or province, we found that populations of focal owl species in the Maritimes of Canada have remained stable over the past 19 years. However, at finer scales, trends are more variable and may create opportunities to test alternative hypotheses about drivers of population change and the effects of management actions at scales amenable to conservation action. The statistical analyses are anticipated to form a national, publicly accessible framework for status assessments of owls in Canada and will provide resource managers and researchers a base from which to evaluate the influence of land management and conservation practices on owl populations across the nation.

Estimations spatialement explicites de la tendance des populations de Strigidés dans les provinces maritimes du Canada et influence de l'utilisation d'enregistrements sonores

RÉSUMÉ. La documentation et l'interprétation de la tendance en matière d'abondance et de répartition des populations d'oiseaux sont essentielles pour qu'on puisse surveiller leur statut et établir les priorités de conservation. Ce processus requiert des techniques de suivis normalisés et d'analyses robustes, qui peuvent résoudre les tendances à des échelles spatiales d'intérêt pour la gestion tout en examinant l'influence que les divers protocoles de collecte de données peuvent avoir sur l'interprétation des résultats. Nous avons utilisé un ensemble de données collectées par des citoyens depuis 19 ans (2001-2019), l'Inventaire des Strigidés nocturnes, pour évaluer la tendance de l'abondance de la Chouette rayée (*Strix varia*), de la Petite Nyctale (*Aegolius acadicus*) et du Grand-duc d'Amérique (*Bubo virginianus*) à des échelles fines et larges. Pour ce faire, nous avons utilisé une approche de modélisation spatialement explicite qui facilite l'emprunt d'informations à travers les frontières spatiales, permettant d'obtenir des estimations de tendance plus robustes à des échelles spatiales plus fines. De plus, nous avons évalué l'influence potentielle du protocole relatif à l'utilisation d'enregistrements sonores sur les estimations des tendances. À des échelles spatiales fines, nous avons constaté qu'un protocole de collecte de données qui inclut l'utilisation d'enregistrements sonores fournissait des résultats plus précis pour évaluer les changements relatifs dans l'abondance (c.-à-d. une incertitude réduite). À des échelles spatiales plus larges, les estimations des tendances n'ont pas été influencées par la méthodologie de collecte de données (c.-à-d. l'écoute silencieuse par rapport à l'utilisation d'enregistrements). Plus précisément, à l'échelle de la région ou de la province, nous avons constaté que les populations des espèces de Strigidés examinées sont restées stables au cours des 19 dernières années. Cependant, à des échelles plus fines, les tendances sont plus variables et peuvent représenter des occasions de tester d'autres hypothèses quant aux facteurs de changement des populations et aux effets des mesures de gestion à des échelles se prêtant à des mesures de conservation. Les analyses statistiques devraient former un cadre national accessible au public dans le cadre de l'évaluation de la situation des Strigidés au Canada et fourniront aux gestionnaires de ressources et aux chercheurs une base à partir de laquelle ils pourront évaluer l'influence des pratiques de gestion et de conservation sur les populations de Strigidés dans tout le pays.

Key Words: *Bayesian hierarchical model; citizen science; conditional autoregressive model; Nocturnal Owl Survey; relative abundance trends; status assessment*

INTRODUCTION

Effective wildlife conservation requires well-designed, large-scale monitoring schemes be deployed to collect information about the status of populations. In turn, these monitoring schemes can be used to assess environmental and human-induced stressors, from which we can establish benchmarks to track our management successes and failures over time (Baillie 1990). Count data collected by volunteer citizen scientists have proven to be invaluable for assessing changes in populations of many bird species, especially songbirds, at multiple spatial scales (Hudson et al. 2017). For example, the North American Breeding Bird Survey (BBS) is a gold standard, large-scale, citizen-science-led survey. Since its inception in the 1960s, it has expanded to include information from more than 5400 survey routes covering much of the United States and Canada and portions of northern Mexico and now provides robust trends and annual indices of abundance for more than 500 species (Sauer et al. 2017). These data are regularly analyzed to estimate how landbird populations have changed (e.g., Smith et al. 2014), have been incorporated into hundreds of independent research publications (Hudson et al. 2017), and are the quantitative foundation for bird conservation in North America (Rosenberg et al. 2016, NABCI 2019). Further, its free and easily accessible data products make it one of the most productive citizen-science projects for generating scientific outputs (Kullenberg and Kasperowski 2016). Although there is much to be celebrated, not all avian groups are well monitored by the BBS. Specifically, nocturnal species that breed outside the BBS survey period (28 May–7 July) and sing outside the daily survey window (beginning at or near dawn) often have insufficient data to establish long-term trends (Knight et al. 2021). Owls are often among these data deficient species and, as a result, their conservation status remains poorly resolved (Domahidi et al. 2019). To address this challenge, targeted monitoring programs that maximize detection can be employed (e.g., Tozer et al. 2016).

In Canada, volunteer-based owl surveys were pioneered by James and Patricia Duncan in the early 1990s (Duncan 2021). In 1999, a national workshop was hosted that resulted in the development and adoption of standard owl survey guidelines (Takats et al. 2001). Like the BBS, the Nocturnal Owl Survey (NOS) was designed to be the national standard for monitoring this otherwise overlooked avian group. The primary objectives of the NOS are to (1) provide robust and consistent counts of owls that can be used to obtain scientifically credible measures of the status and trends of owls at continental and regional scales, (2) identify priority species for conservation, and (3) provide resource managers with annual occurrence and abundance data for model-based conservation planning. Further, the program is intended to offer an organized opportunity for volunteer citizen scientists to contribute to our understanding of owl ecology and increase public appreciation for this rarely seen avian group. The Canadian NOS is unmatched globally for its data coverage and longevity. Smaller scale studies in the United States have adopted similar protocols (Hodgman and Gallo 2004), and long-term studies in Finland have monitored territoriality and nest success of nocturnal birds of prey using disparate methods (Saurola 2009).

A key feature of the NOS data collection protocol is that it was designed to reduce detection error, which gives it an advantage over other survey methodologies. Detection error occurs when an

individual bird is present but is not detected during the survey because it does not provide a visual or acoustic cue (availability), or it is missed by the observer (perceptibility; Marsh and Sinclair 1989). Nocturnal species such as owls are often poorly monitored by protocols that begin at or near dawn, when nocturnal birds have low availability. To overcome this, NOS is done during the night when owl call rates are highest and regularly incorporate a call playback to decrease detection error (Takats et al. 2001), which in turn can improve precision and predictive performance of statistical models used to generate abundance trends (Isaac et al. 2020). Now that a standardized NOS protocol has been in use for 20 years across several Canadian provinces, a rigorous investigation using these data can be realized.

The primary objectives of the current study were to (1) estimate abundance trends of owls at a spatial scale appropriate for evaluating the ecological drivers of change and (2) investigate the influence of call playback on trend estimates. To accomplish this, we employed a modified analytical approach previously developed for BBS (Link and Sauer 2002, Sauer and Link 2011) and the Christmas Bird Count (CBC; Link et al. 2006, Soykan et al. 2016) using three species regularly detected by the NOS in the Canadian Maritime provinces of New Brunswick, Nova Scotia, and Prince Edward Island (PEI). The Maritime provinces were selected for model development because several other provincial NOS datasets were not fully digitized and cleaned at the time of writing.

The standard BBS and CBC analytical frameworks resolve long-term trends from heterogeneous citizen science data across large, hierarchically nested spatial scales including states, provinces, Bird Conservation Regions (BCR), and their intersections. The analytical methods used by these programs have evolved considerably over time as new statistical approaches have been developed. Specifically, the BBS analyses have moved from graphed indices of the ratios of area-weighted average counts (Erskine 1978), to route regressions (Link and Sauer 1998), estimating equations (Link and Sauer 1994), and, currently, hierarchical Bayesian models (e.g., Link and Sauer 2002, Sauer and Link 2011, Smith et al. 2014). Although the standard models employed by BBS and CBC enable a flexible and robust process suitable for hundreds of species, the implementation of these analyses is computationally intensive because of the use of Markov chain Monte Carlo (MCMC) to estimate model parameters for relative abundance. Further, whereas trends can be scaled up to larger spatial units, they cannot be scaled down using these methods, limiting their application to assessments of finer-scaled drivers of population change (Meehan et al. 2019).

We adopted an approach that allows for the spatial structure of counts to be taken into consideration for finer-scale assessment of abundance trends (e.g., Thogmartin et al. 2004, Bled et al. 2013, Ethier and Nudds 2015, Smith et al. 2015, Meehan et al. 2019). Specifically, spatial dependencies between count sites were included in the model to facilitate the borrowing of information across spatial boundaries and, subsequently, the generation of more robust trend estimates at finer spatial scales and in areas where data are sparse (Bled et al. 2013). This approach also reduces the amount of spatial autocorrelation in model residuals, which can lead to more reliable inferences about trends (Zuur et al. 2017). Ultimately, these models allow investigations of

abundance trends in relation to finer-scale processes, such as local land cover change or climatic variability (Thogmartin et al. 2004, Meehan et al. 2019). Further, land managers can locally test and tailor management practices to meet the needs of species across various jurisdictional boundaries (Ethier and Nudds 2015).

Although it was beyond the scope of this study to assess the influence of environmental covariates and call playback on species detection probabilities (e.g., using an occupancy framework), we chose to investigate the influence of call playback on long-term trend estimates to determine if this sampling approach creates a bias and to help identify the best response variable for future analyses. To do this, we compared trends and indices derived using count data collected during the first 2-minute silent listening period (also called the passive listening period) to those using the full listening period (i.e., passive listening and call-playback periods) to determine if and to what extent trends (e.g., direction, magnitude, and precision) are influenced by call playback. Given that owl call propensity often increases after call playback of conspecifics and/or heterospecifics (McGarigal and Fraser 1985, Francis and Bradstreet 1997, Bosakowski and Smith 1998, Neri et al. 2018), we predicted that the magnitude and direction would be similar regardless of the count period used for trend estimation, but that uncertainty around parameter estimates of trends would be lower when using counts from the full listening period (Conway and Gibbs 2005). This is because (1) detection probability for most species will improve following call playback (Francis and Bradstreet 1997), and (2) detection probability will increase as a result of the longer sampling period associated with the full listening period (Sólymos et al. 2013), effectively increasing sample size in both instances (i.e., reducing zero counts). However, if systematic bias exists because of factors that affect detection probability over time (e.g., landscape changes or technology improvements), we expect the relationship between trend estimates (i.e., silent versus full listening) to deviate from the expected one-to-one relationship.

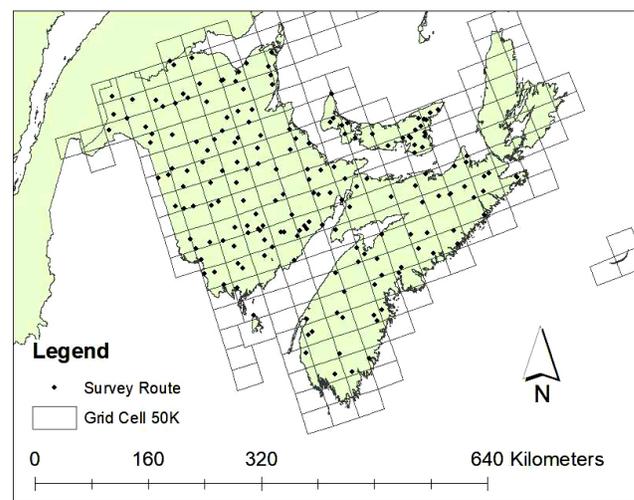
METHODS

Data collection

Like the BBS, the NOS consists of a roadside survey protocol in which citizen scientists collect counts of owls at evenly spaced stops during the breeding season. In the Maritimes, these surveys occurred between 1 April and 15 May of each year. Each route was made up of ten stops, spaced 1.6–2 km apart to reduce the likelihood of detecting an individual owl at multiple stops per route (Takats et al. 2001; Fig. 1). At each stop, a citizen scientist, trained in owl vocalization identification using audio demos and educational webinars, conducted a 2-minute point count (silent listening period) and, subsequently, played a standardized set of owl calls over a speaker to elicit responses from target species. This consisted of calls of Boreal Owl (*Aegolius funereus*) and Barred Owl (*Strix varia*) alternating with timed listening periods. In New Brunswick and PEI, the full listening period was approximately 13 minutes, whereas in Nova Scotia the full listening period was approximately 9 minutes because there are two fewer Barred Owl call playbacks and accompanying listening periods (approximately 2 minutes each). Based on a formal test of detection probability, we anticipated that all included species would have been detected by the end of the 9-minute listening period, if present, with an

approximate 95% cumulative detection probability, with few detections thereafter (Lima et al. 2020), making these protocols comparable. Surveys began 30 minutes after sunset and took approximately 3 hours to complete. Routes were sampled at least once per year, often by the same observer. Most routes were surveyed every year, but some routes became active or inactive over time depending on the availability of citizen scientists to conduct surveys and the suitability of the survey route over time. In addition to counting the number of each species detected, citizen scientists also recorded auxiliary information on survey conditions including local environmental covariates. This information was used to standardize detection probability using an index-based approach (Nichols et al. 2009), similar to the BBS (USGS 2020). Data were entered through a customized online data entry system available on NatureCounts (www.naturecounts.ca), a service provided by Birds Canada. Data were manually reviewed for form accuracy by Birds Canada staff. Raw data can be made available for download directly into R using the *naturecounts* package (LaZerte and Lepage 2019). More details about the NOS survey protocol can be found in the *Guidelines for nocturnal owls monitoring in North America* (Takats et al. 2001).

Fig. 1. Map of nocturnal owl survey routes start points in the Maritimes region of Canada, including 50 km² grid cells used for the spatially explicit analysis of relative abundance and trends, from 2001–2019.



Data cleaning

Like the BBS (USGS 2020), the NOS uses strict standardizations on survey timing and weather condition. These standardized procedures enable the generation of unbiased estimates of trends in relative abundance of a species over time without explicitly modeling imperfect detection (Nichols et al. 2009). Wind velocity, precipitation, and temperature are among the variables known to affect owl calling propensity (e.g., Lima et al. 2020) and are regularly measured by NOS citizen scientists. Therefore, we removed routes run below the minimum temperature cut off of -15 °C and those that were run when wind speeds exceeded 20 km (Beaufort scale > 3) or during a precipitation event (rain or snow), as measured at the start of the survey route.

Because our aim was to focus on species that are persistent, abundant, and biologically associated with the areas under study, we excluded rarely detected species from our analyses, i.e., species that had a mean abundance per year \leq five and species that were detected in fewer than half of the survey years. Three species were subsequently retained for the analysis: Barred Owl, Northern Saw-whet Owl (*Aegolius acadicus*), and Great Horned Owl (*Bubo virginianus*).

Model development

The basic statistical unit of the analysis was the sum of owls of the three focal species counted on a survey route within a given year, collected either during the first 2-minute silent listening period only or over the entire listening period, i.e., including after call playbacks. Owls marked as a repeat by the observer were removed to better ensure individuals were counted only once per route. Routes on which a species was never detected were dropped from the species-specific analysis. Our model describes the sum of counts of each species $\lambda_{p,k,t}$ for grid cells i encompassing unique combinations of observer routes k during a year t , where routes were assigned to cells on a regular grid. A grid size of 50 km² was used for the analysis because this was the scale at which routes were systematically assigned during survey development (Whittam 2001). In total, our analysis encompassed 105 grid cells containing 183 NOS routes within the provinces of New Brunswick (number of routes, 108), Nova Scotia (51), and PEI (24; Fig. 1). There was an average number of 6.23 neighbourhood links.

Counts were modeled from a negative binomial count distribution for y , that is, $y|\epsilon \sim \text{Poisson}(\mu\epsilon)$ and $\epsilon \sim \text{Gamma}(\Phi^{-1}, \Phi^{-1})$ (Lindén and Mäntyniemi 2011). This differs from the BBS and CBC approach, which includes an observation-level random effect to deal with overdispersed Poisson counts (Sauer and Link 2011, Soykan et al. 2016), that is, $y|\epsilon \sim \text{Poisson}(\mu\epsilon)$ and $\epsilon \sim \text{Normal}(\mu, \sigma)$. The negative binomial is expected to produce similar results to the standard BBS and CBC approach; however, it reduces computing time and size of the posterior sample because it returns a single dispersion estimate (Meehan et al. 2019). Assessing species-specific distributional assumptions using model selection is also an option, which could be tested in future iterations of this analysis.

Expected counts per grid cell $\mu_{i,t}$ were assumed to be a function of spatially structured grid cell and year effects plus unstructured variation among observer routes and cell years. The linear predictor took the following form:

$$\log(\mu_{it}) = \alpha_i + \tau_i T_{ikt} + \kappa_k + y_{it} \quad (1)$$

Parameters included a cell-specific random intercept α_i with an intrinsic conditional autoregressive (CAR) structure (Besag et al. 1991), which allowed for information on relative abundance to be shared across neighbouring cells. Specifically, values of α_i came from a normal distribution with a mean value related to the average of adjacent cells and with a conditional variance proportional to the variance across adjacent cells and inversely proportional to the number of adjacent cells. Parameters τ_i were modeled as spatially structured, cell-specific, random slope coefficients for the year effect using the CAR structure, with

conditional means and variances as described above. Spatial structure was incorporated into τ_i to allow for information about year effects to be shared across neighbouring cells. Year T was transformed such that the maximum year was zero, and each preceding year was a negative integer. This scaling means that the posterior median of cell-specific estimates of α_i represents the index of relative abundance during the final year of the time series. Differences in relative abundance among observer-route combinations, which could arise because of difference in habitat condition or observer experience, was accounted for with an independent and identically distributed (idd) random effect. To derive an annual index of abundance, we included a random effect per cell and year with an idd and combined these effects with α and τ .

Model implementation

Models were fit using a Bayesian framework with Integrated Nested Laplace Approximation (INLA) using the R-INLA package (Rue and Martino 2009) for R statistical computing (version 4.0.2; R Core Team 2020). The spatial structure parameters α_i and τ_i were scaled such that the geometric mean of marginal variances was equal to one (Sørbye and Rue 2014, Riebler et al. 2016, Freni-Sterrantino et al. 2018), and priors for precision parameters were penalized complexity (PC) priors, with parameter values UPC = 1 and PC = 0.01 (Simpson et al. 2017). Precision for the random-observer route and cell-year effects were assigned a PC prior with the same parameter values. In general, the weakly informed priors we used tend to shrink the structured and unstructured random effects toward zero in the absence of a strong signal (Simpson et al. 2017). Model fit was assessed by visually inspecting the histograms generated with cross-validation probability integral transformation (PIT; Dawid 1984), which approximates a uniform distribution if fit was reasonably good (Cazado et al. 2009, Held et al. 2010).

Following model analysis and validation, posterior medians and 95% credible intervals (CI) were computed per cell for α_i and τ_i . Posterior summaries were then mapped to visualize spatial variation in relative abundance indices and trends. We also aggregated 50 km² results to the provincial and regional level because these scales may be of interest to resource managers designing and implementing policies in Maritime region of Canada. Trend coefficients were aggregated at each scale by averaging trends for all equal area grid cells where the cell centroid fell within the area of interest.

Using a Spearman's rank correlation at the scale of the grid cell, we compared abundance and trends derived using count data collected during the first 2-minute silent listening period only to those derived using count data collected during the full listening period (i.e., including call playback). We also evaluated uncertainty estimates τ_i by comparing credible interval widths using a one-tailed t-test. Aggregated trend coefficients were also compared at the provincial and regional scales for consistency in direction, magnitude, and significance.

RESULTS

The number of grid cells and routes on which at least one species was detected was greater when call playback was used (i.e., full listening period) as compared to the 2-minute silent listening

Table 1. Aggregated relative abundance trends (annual percent change) for Barred Owl (*Strix varia*), Great Horned Owl (*Bubo virginianus*), and Northern Saw-whet Owl (*Aegolius acadicus*) in the Maritime provinces of Canada, from 2001–2019, calculated separately for the 2-minute silent listening period and full listening period, which included call playbacks. If lower and upper credibility intervals (CI) include zero, trends are considered non-significant.

| | | Silent listening | | | | | | Full listening | | | | | |
|-----------------------|----------------------|------------------|----------|----------|-------|----------|----------|----------------|----------|----------|-------|----------|----------|
| | | alpha | lower CI | upper CI | tau | lower CI | upper CI | alpha | lower CI | upper CI | tau | lower CI | upper CI |
| Barred Owl | New Brunswick | 1.02 | 0.61 | 2.08 | 1.19 | -7.09 | 12.81 | 2.63 | 1.73 | 5.41 | 0.81 | -6.11 | 13.57 |
| | Nove Scotia | 0.77 | 0.53 | 1.07 | 3.53 | -2.98 | 10.37 | 2.20 | 1.55 | 3.15 | 3.26 | -2.40 | 10.56 |
| | Prince Edward Island | 0.78 | 0.53 | 1.04 | 1.59 | -4.72 | 7.96 | 2.28 | 1.53 | 3.28 | 2.38 | -6.60 | 9.61 |
| | Maritime Provinces | 0.87 | 0.56 | 1.85 | 2.21 | -5.81 | 11.40 | 2.43 | 1.62 | 4.79 | 1.81 | -5.42 | 12.10 |
| Great Horned Owl | New Brunswick | 0.20 | 0.11 | 0.35 | -3.59 | -10.39 | 4.44 | 0.33 | 0.18 | 1.22 | -4.26 | -9.53 | 2.87 |
| | Nove Scotia | 0.20 | 0.13 | 0.30 | -2.13 | -6.95 | 4.11 | 0.28 | 0.18 | 0.46 | -3.67 | -8.33 | 1.41 |
| | Prince Edward Island | 0.19 | 0.13 | 0.30 | -1.43 | -6.21 | 4.29 | 0.28 | 0.17 | 0.42 | -2.73 | -7.30 | 2.34 |
| | Maritime Provinces | 0.20 | 0.12 | 0.33 | -2.80 | -9.48 | 4.30 | 0.27 | 0.16 | 0.74 | -3.92 | -9.14 | 2.32 |
| Northern Saw-whet Owl | New Brunswick | 0.30 | 0.20 | 0.50 | -2.98 | -10.37 | 4.70 | 0.62 | 0.40 | 1.24 | -1.83 | -7.45 | 5.52 |
| | Nove Scotia | 0.31 | 0.21 | 0.42 | -1.39 | -7.16 | 5.60 | 0.63 | 0.44 | 0.92 | -0.37 | -4.53 | 4.14 |
| | Prince Edward Island | 0.33 | 0.23 | 0.43 | -2.65 | -8.47 | 3.95 | 0.69 | 0.47 | 1.02 | -1.12 | -5.88 | 3.81 |
| | Maritime Provinces | 0.30 | 0.20 | 0.46 | -2.39 | -9.60 | 4.99 | 0.63 | 0.41 | 1.04 | -1.19 | -6.83 | 4.66 |

period only. Specifically, when total counts from the full listening period were used as the response variable, the number of occupied routes increased by 18% for Barred Owl, 21% for Great Horned Owl, and 10% for Northern Saw-whet Owl, and the number of occupied grid cells increased by 16% for Barred Owl, 18% for Great Horned Owl, and 4% for Northern Saw-whet Owl.

Inspection of the PIT histogram indicated satisfactory model fit for both count methods, i.e., counts during 2-minute silent listening only and total counts during full listening period with playback. The posterior median estimate for Φ , the dispersion parameter, was < 1 for each species and count method (range = 0.41–0.71), suggesting counts were not overdispersed relative to a Poisson distribution, except for Barred Owl ($\Phi_{2\text{-minute silent}} = 1.21$; $\Phi_{\text{total}} = 1.23$).

The posterior median of cell-specific estimates of α_i indicated that, in 2019, Barred Owl were the most abundant, followed by Northern Saw-whet Owl and Great Horned Owl. On average, Barred Owl were found in the highest abundance in New Brunswick, whereas Northern Saw-whet and Great Horned Owl were more evenly distributed (Table 1; Fig. 2). Posterior median values for τ_i , the temporal trend from 2001–2019 transformed to annual percent change, varied spatially for each species. Barred Owl generally experienced negative cell-specific trends in Nova Scotia and positive trends in New Brunswick and PEI (Fig. 3A). Trends were significantly positive in a few grid cells in PEI (number cell; $n = 2_{2\text{-minute silent}}, n = 3_{\text{total}}$) and New Brunswick ($n = 2_{\text{total}}$) and significantly negative in upwards of two cells in Nova Scotia. Great Horned Owl had more negative and spatially variable trends, which shifted substantially with count method. On average, Great Horned Owl had stable trends in northwestern New Brunswick and southern Nova Scotia (Fig. 3B). There were 14 cells reporting significant negative trends using counts from

the 2-minute silent listening period compared to 48 cells using total counts. Northern Saw-whet Owl displayed more negative trends in the east but with moderate spatial variability depending on count method (Fig. 3C). Significant negative trends for Northern Saw-whet Owl were detected in PEI ($n = 1_{2\text{-minute silent}}, n = 2_{\text{total}}$) and parts of Nova Scotia ($n = 5_{2\text{-minute silent}}, n = 7_{\text{total}}$).

The parameters α_i and τ_i were significantly negatively correlated across space for Barred Owl ($\rho_{2\text{-minute silent}} = -0.64$, $p < 0.001$; $\rho_{\text{total}} = -0.36$, $p < 0.001$) and Great Horned Owl, ($\rho_{2\text{-minute silent}} = -0.54$, $p < 0.001$; $\rho_{\text{total}} = -0.37$, $p < 0.001$ outliers removed), indicating that negative trends generally overlapped areas of high abundance and visa versa. The relationship between these parameters was positively significant for Northern Saw-whet Owl using total counts ($\rho_{2\text{-minute silent}} = -0.01$, $p = 0.91$; $\rho_{\text{total}} = 0.24$, $p = 0.01$ outliers removed; Fig. 4).

Rank correlation of cell-specific τ_i estimates between count methods indicated significant positive correlations for all species (Fig. 5). There was evidence of negative bias in trend estimates when using total counts for Great Horned Owl (Fig. 5B) and a positive bias when using total counts for Northern Saw-whet Owl (Fig. 5C). In other words, total count estimates of τ_i are generally more negative for Great Horned Owl and slightly more positive for Northern Saw-whet Owl compared to those derived from the silent listening period counts. There was significantly less uncertainty around estimates of τ_i for total counts when compared to counts collected during the silent listening period only, as follows: Barred Owl ($t = -9.25$, $df = 88$, $p < 0.001$), Great Horned Owl ($t = -5.33$, $df = 78$, $p < 0.001$), and Northern Saw-whet Owl ($t = -7.13$, $df = 97$, $p < 0.001$).

Posterior median trends aggregated to the provincial scale, and for the entire Maritimes region, were consistent in direction,

Fig. 2. Posterior median of cell-specific estimates of α , representing the index of relative abundance in 2019 for three species of owls in the Maritimes region of Canada. Maps on the left were derived using counts from the 2-minute silent listening period, whereas maps on the right were derived using the full listening period, including call playback.

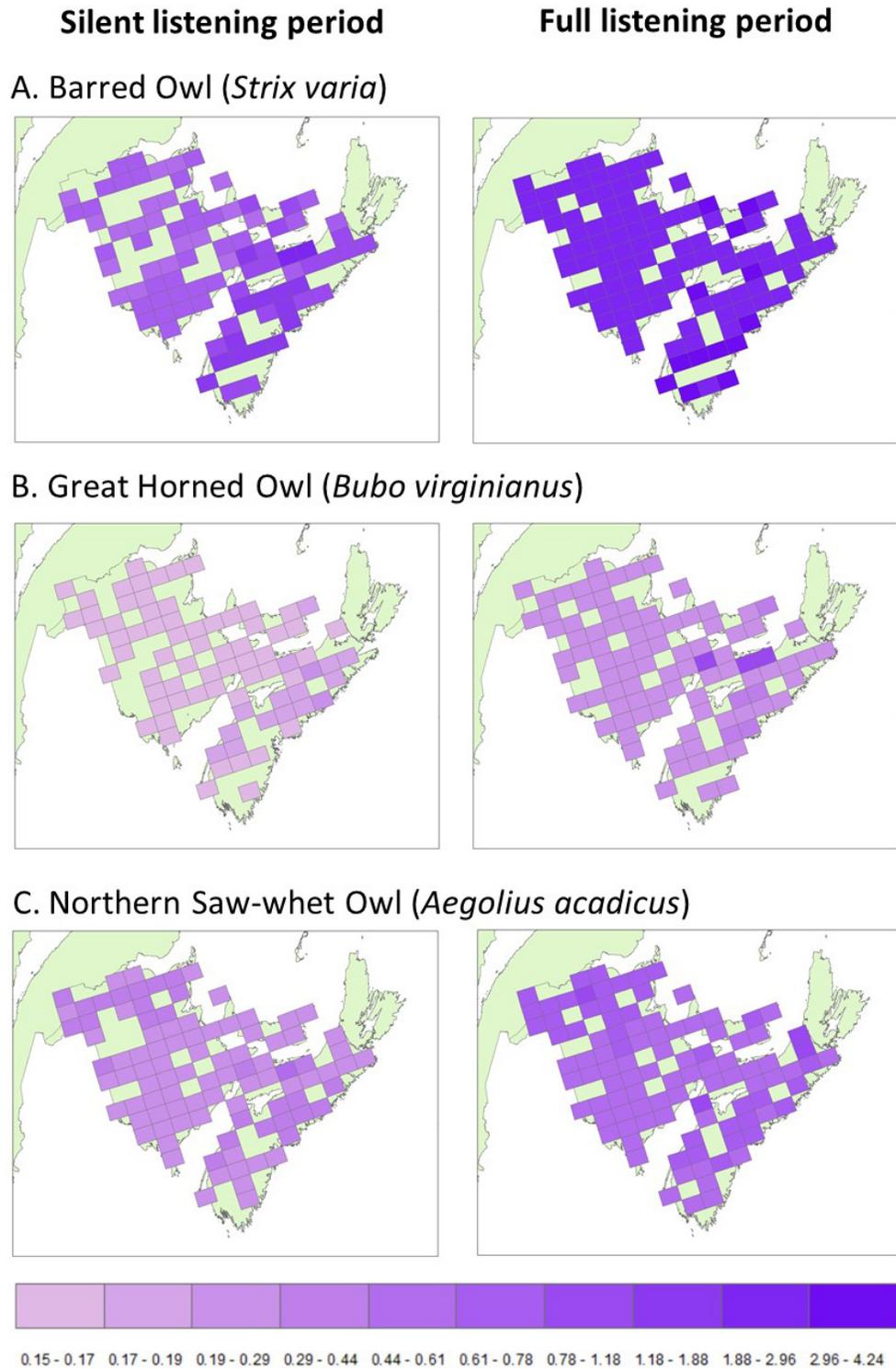


Fig. 3. Posterior median of cell-specific estimates of τ_1 representing trends in relative abundance from 2001–2019 for three species of owls in the Maritimes region of Canada. Maps on the left were derived using counts from the 2-minute silent listening period, whereas maps on the right were derived using the full listening period, including call playback. Credibility intervals that did not include zero were considered significant and are indicated with an asterisk (positive = white; negative = black).

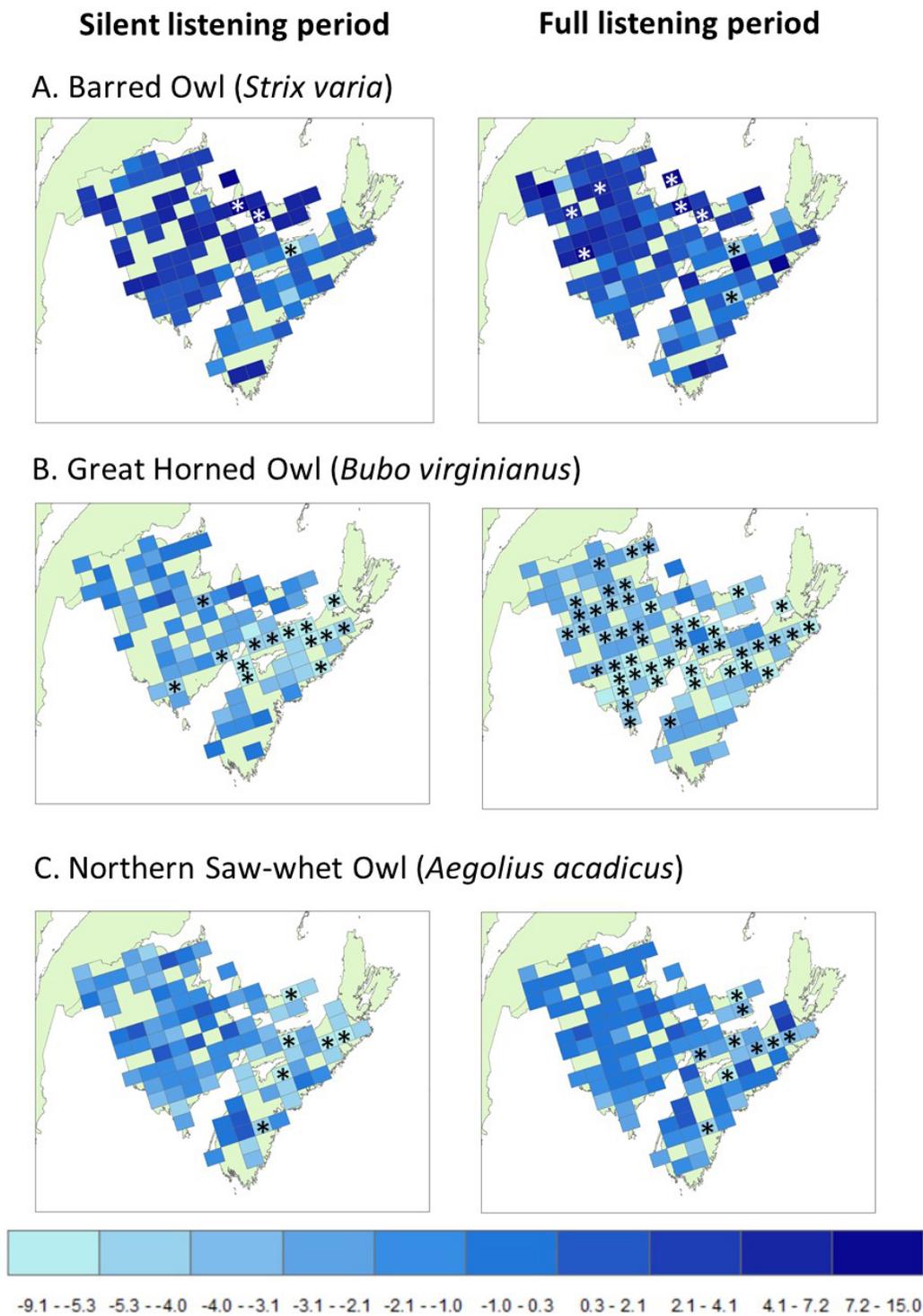


Fig. 4. Plots comparing cell-specific trends (τ_i) estimates to indices of relative abundance (α_i) for nocturnal owl survey counts collected during the 2-minute silent listening period and full listening period, including call playback, in the Maritimes region of Canada. Significantly negative trends (i.e., credibility intervals that did not include zero) are shown in red.

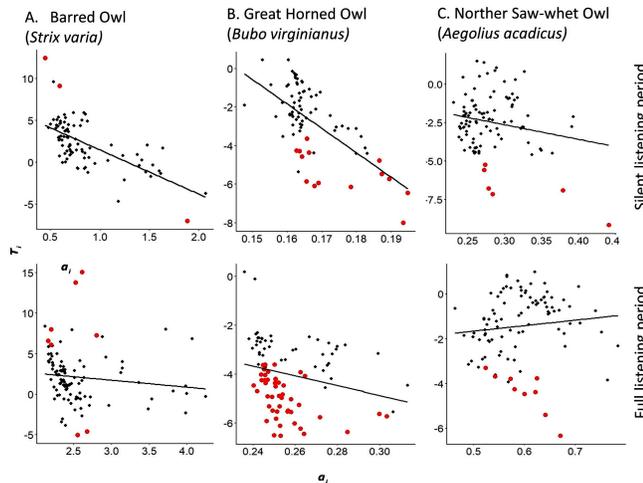
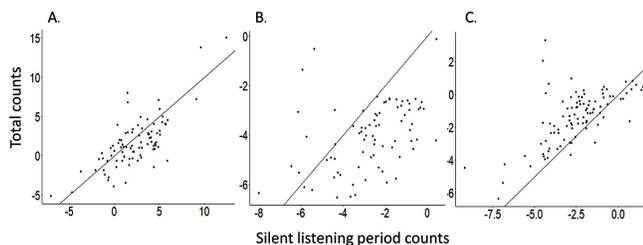


Fig. 5. Plots comparing cell-specific trend τ_i estimates of nocturnal owl survey counts collected during the 2-minute silent listening period and full listening period, including call playback, in the Maritimes region of Canada. Results of a rank correlation analysis indicated significant positive correlations for (A) Barred Owl (*Strix varia*; rho = 0.65, p-value < 0.001), (B) Great Horned Owls (*Bubo virginianus*; rho = 0.43, p-value < 0.001), and (C) Northern Saw-whet Owl (*Aegolius acadicus*; rho = 0.62, p-value < 0.001). The solid line indicates one-to-one correspondence between trend estimates.



magnitude, and significance (Table 1). Generally, owl populations in the Maritimes region of Canada appear to have remained stable over the past 19 years. This result was unaffected by the count method used.

DISCUSSION

Results at the provincial and regional scales suggest that the focal owl species included in this analysis have had stable abundance trends over the duration of the study period. However, analysis at finer scales revealed trends that may have important implications for conservation and management of these

populations. For example, Great Horned Owl had a relatively large number of grid cells displaying significant negative trends; this result is not apparent at broader scales. Further, we found that cell-specific trend estimates for Great Horned Owl were negatively correlated with abundance, i.e., negative trends in areas of high abundance and vice versa (Fig. 4). A high proportion of significantly negative cell-specific trends in areas of relative high abundance could have a disproportionate impact on the local population and may warrant further investigation if this pattern persists.

Cell-specific trend estimates τ_i derived from counts collected during the silent listening period and counts collected over the full listening period corresponded well for Barred Owl but showed bias for both Great Horned Owl and Northern Saw-whet Owl. Although it is known that systematic changes in effort (Dunn et al. 2004) or observer skill (Link and Sauer 2002) can bias trends, we would expect those processes to influence both response variables equally and in the same direction. A systematic change in detection probability, due to continuous improvement in playback technology (Conway and Gibbs 2005), may have led to the observed differential changes in the response of Great Horned Owl and Northern Saw-whet Owl to playback. It is also possible that landscape changes, such as forest clearing, could have systematically affected the attenuation distance of call playback (Yip et al. 2017) and thus the detection of owls during the full listening period. Regardless of the mechanism causing the bias, it appears that there are species-specific differences in the response, with decreasing detections of Great Horned Owl and increasing detections of Northern Saw-whet Owl following the use of call playback over time. Identifying the cause of the species-specific biases would require field trials to understand how different playback technologies and landscape changes, for example, affect the response of these species to call playback (for example, see Lima et al. 2020).

Depending on the survey objective, passive surveys (i.e., silent listening) may provide less biased results than call-playback surveys, which may prompt individual owls to move toward the surveyor and influence assessments of habitat association or detection probability based on distance sampling techniques (Conway and Gibbs 2005). However, the reduced probability of detecting an owl using passive surveys is an important consideration because the failure to detect an owl when present can also lead to biased estimates and misleading results (Shonfield et al. 2018). Although we cannot say with absolute certainty which method (if either) represents the true population trend of owls in the Maritimes, reduced uncertainty associated with using total counts lends support to using this response variable. However, consideration ought to be given to the potential for species-specific biases in trends caused by call playback. Until the source of these biases can be resolved, counts collected during the silent listening period should be used for finer-scale assessments of change in relative abundance and distribution. At broader spatial scales, the magnitude, direction, and uncertainty in trend estimates were largely unaffected by which count method was used as the response variable, which suggests status designation would not be impacted by the choice of response variable. If a status assessment was conducted across regions with different call-playback protocols (e.g., central and northern Ontario; Badzinski 2006), counts collected during the silent listening period would

need to be used as the standardized response, or a means to correct for the differences in detection probability that result from different call-playback protocols would need to be developed.

Deriving finer-scale trends in abundance creates opportunities to test alternative hypotheses about drivers of population change and the effects of management actions at scales amenable to conservation action (Ethier and Nudds 2015, Ethier et al. 2017). Our work provides a framework from which correlation analysis on precomputed annual abundance indices or trends (as opposed to the original count data) can be easily developed by regional resource managers, enabling the investigation of the spatially varying ecological processes influencing trends. For example, hypotheses that assess changes in owl distribution and abundance due to climate or land-use change associated with logging, urban development, and agriculture could be tested with precomputed trends. These variables could be measured by way of remote sensing across the region including land-use composition and configuration, climate, terrain, and human influences. Other drivers of population change, such as resource availability, would require alternate data sources. Although using precomputed trends may be considered less elegant, they are far more accessible to land managers who may not have the resources or expertise to run spatially explicit hierarchical Bayesian models on the original count data (Meehan et al. 2019). Further, we anticipate that, by making precomputed trends and indices publicly available through Birds Canada's NatureCounts web platform, they will be more broadly used by the scientific community for independent research (Dunn et al. 2005), as has been demonstrated with the BBS (Sauer et al. 2003) and CBC (Soykan et al. 2016) results.

In addition to informing the status of owls in the Maritimes, our study demonstrates the utility of hierarchical Bayesian models that incorporate spatial dependencies to obtain high-resolution trend estimates for geographic areas that are better suited to conservation planning and management (Thogmartin et al. 2004, Bled et al. 2013, Ethier and Nudds 2015, Smith et al. 2015). Including autocorrelation in our models not only allowed for statistical assumptions to be satisfied, but also improved the predictive power by allowing the borrowing of information from neighbourhood locations (Bled et al. 2013). It is anticipated that the statistical analysis presented here will form the national framework for multi-scale status assessments of owls in Canada and, through open-source data portals like NatureCounts, provide resource managers with a basis from which to assess the influence of various land management practices on owl populations across the nation.

Responses to this article can be read online at:
<https://www.ace-eco.org/issues/responses.php/2075>

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