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QUANTIFYING VOCAL ACTIVITY AND DETECTION PROBABILITY TO INFORM SURVEY METHODS FOR BARRED OWLS (*STRIX VARIA*)

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ABSTRACT.—Owls can be difficult to detect due to their secretive behavior, typically low calling rate, and low density on the landscape. Low detection probability during surveys can result in an underestimation of the presence and abundance of a species. Thus, optimizing detection probability of surveys targeting owls is necessary to accurately address ecological questions. We used datasets collected in South Carolina, USA, and Alberta, Canada, to investigate how survey detection can be optimized for Barred Owls (*Strix varia*). We examined seasonal effects on the detection probability of Barred Owls as determined by playback surveys and autonomous recording unit (ARU) surveys, and whether daily patterns of Barred Owl vocal activity could be used to improve the efficiency of ARU surveys. For each survey method, we estimated the number of survey days needed to obtain a seasonal detection probability $\geq$ 90% of Barred Owls. We found detection probability with playbacks increased as the breeding season progressed. The effect of seasonality on detection probability with ARUs was dependent on the way encounter history was defined. Barred Owl vocal activity peaked twice per night, with one vocalization peak occurring immediately after sunset and another 7–9 hr after sunset. By targeting these vocalization peaks during surveys, we found that we could reduce ARU survey time by 50% and still retain >82% of the original site detections, thereby reducing survey processing time. Although playback surveys were more efficient than ARU surveys at detecting Barred Owls, ARUs have numerous advantages, such as reducing survey effort and disturbance to the target animal. Ultimately, survey designs are dictated by the budget, personnel capacity, study region, and research objectives, but our findings will help researchers plan studies that optimize detection probability and minimize survey cost and effort.

KEY WORDS: *Barred Owl*; Strix varia; *autonomous recording units*; *call playback*; *detection probability*; *survey methods.*

CUANTIFICACIÓN DE LA ACTIVIDAD VOCAL Y LA PROBABILIDAD DE DETECCIÓN PARA ASESORAR LOS MÉTODOS DE MUESTREO DE *STRIX VARIA*

RESUMEN.—Las rapaces nocturnas pueden ser difíciles de detectar debido a su comportamiento reservado, su tasa de vocalizaciones típicamente baja y su baja densidad en el paisaje. La baja probabilidad de detección durante los muestreos puede ocasionar una subestimación de la presencia y abundancia de una especie. Por ende, es necesario optimizar la probabilidad de detección de los muestreos de rapaces nocturnas para responder con precisión preguntas ecológicas. Usamos bases de datos recogidos en Carolina del Sur, EEUU, y en Alberta, Canadá, para investigar cómo la detección en los muestreos puede ser optimizada para *Strix varia*. Examinamos los efectos de la probabilidad de detección de *S. varia* determinada por la reproducción de sonidos previamente grabados y muestreos con unidades autónomas de grabación (UAG), y si los patrones diarios de actividad vocal de *S. varia* podrían ser usados para mejorar la eficiencia de los muestreos con UAG. Para cada método de muestreo, estimamos el número necesario de días de muestreo para poder

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obtener una probabilidad de detección estacional de *S. varia* ≥ 90%. Encontramos que la probabilidad de detección mediante la reproducción de reclamos aumentó a medida que avanzó la estación reproductiva. El efecto de la estacionalidad en la probabilidad de detección con UAG dependió del modo en el que se definió el historial de encuentros. La actividad vocal de *S. varia* tuvo dos picos por noche, con un pico de vocalización inmediatamente después del anochecer y otro 7–9 h después del anochecer. Al apuntar a estos picos de vocalización durante los muestreos, encontramos que podíamos reducir el tiempo de los muestreos con UAG en un 50% y aún retener >82% de las detecciones de los sitios originales, reduciendo por ende el tiempo de procesamiento de los muestreos. Aunque los muestreos mediante la reproducción de reclamos fueron más eficientes que los muestreos con UAG para detectar a *S. varia*, las UAG tienen muchas ventajas, como la reducción del esfuerzo de muestreo y de la perturbación del animal objetivo. En última instancia, los diseños de muestreo están determinados por el presupuesto, la capacidad del personal, la región de estudio y los objetivos de investigación, pero nuestros resultados ayudarán a los investigadores a planear estudios que optimicen la probabilidad de detección y minimicen el coste y el esfuerzo de muestreo.

[Traducción del equipo editorial]

INTRODUCTION

Owls are well-adapted for stealth. In addition to being typically nocturnal, owls are equipped with camouflaged plumage and silent flight, all of which make visual detection a challenge, even for the experienced surveyor. The frequency and duration of vocalizations for owls is variable, and individuals can go for extended periods without providing an acoustic signal that surveyors can detect (Duchac et al. 2020). As tertiary consumers, owls often occur in low densities and over large territories (McGarigal and Fraser 1985, Johnsgard 2002). As a result, owl surveys may yield low detection probabilities (Kissling et al. 2010, Rognan et al. 2012), which can result in the underestimation of the presence and abundance of a species if detection probability is not accounted for (MacKenzie et al. 2006). Low detection probability will result in lower precision when estimating the proportion of sites occupied (MacKenzie et al. 2006) and reduced statistical power to detect population change over time (Wood et al. 2019). Thus, maximizing detection probability is important for accurately addressing ecological questions ranging from habitat selection to population dynamics. Increasing detection probability should be a goal for owl researchers and conservation managers to better understand owl distribution and habitat use.

Survey efforts targeting owls often employ active surveys using conspecific broadcasts (playbacks) to increase detection rates relative to passive point count surveys (Fuller and Mosher 1981, Hardy and Morrison 2000, Kissling et al. 2010). As most owls are territorial annually or during the breeding season (as reviewed in Johnsgard 2002), playbacks work by eliciting vocalizations or defensive behavior from territorial birds. Although they increase likelihood of detecting the target species (Zuberogoitia et. al 2020), playbacks may affect results by altering natural vocalization patterns or by luring owls over long distances (Zuberogoitia and Martínez 2011). With playbacks, detection rates of owls are often low and vary seasonally (Kissling et al. 2010, Cooke et al. 2017, Clement et al. 2019). Thus, additional repeated surveys are often needed to obtain greater confidence in occupancy status or abundance estimates. Costs of survey effort when using repeated playback surveys can quickly accrue, particularly when surveying remote sites with multiple surveyors.

Passive surveys using autonomous recording units (ARUs) are an alternative method to detect owls (Rognan et al. 2012, Shonfield and Bayne 2017a). ARUs are audio recording devices that are programmed to passively record on a set temporal schedule and duration. Vocalizations of the target species in ARU recordings can be used to estimate presence or abundance (e.g., Rognan et al. 2012, Shonfield and Bayne 2017b). After unit retrieval, calls are identified by acoustic, visual, or computer-based inspection of the recording and its spectrogram. Depending on the number and length of recordings, this can be a time-intensive process, but automated species recognition is emerging as a valuable tool to efficiently process a large volume of recordings within a manageable timeframe (Knight et al. 2017, Shonfield et al. 2018). ARU surveys based on visual scanning of spectrograms and/or automated computer recognition are effective for nocturnal owls (e.g., Shonfield et al. 2018, Clement et al. 2019) as few other avian species vocalize at night, making the signal detection processes easier. In addition, ARUs reduce survey effort as they can be left to record for an extended period of time, increasing the number of sampling occasions while only requiring two visits by field personnel for the deployment and retrieval of the unit. However, as ARU surveys depend on unsolicited vocalizations, the use of ARUs can result in lower detection probability of a species per unit time compared to playbacks (Sidie-Slettedahl et al. 2015, Shonfield and Bayne 2017b). Knowledge of circadian vocal patterns, call duration and frequency, as well as seasonal variation in calling behavior is needed in order to increase confidence of site-specific occupancy status using ARUs.

Barred Owls (*Strix varia*) have been surveyed with playbacks (e.g., Kelly et al. 2003, Grossman et al. 2008) and ARUs (e.g., Shonfield et al. 2018, Duchac et al. 2020), but we did not find any published evidence that these methods have been used simultaneously to survey this species. Comparison of the detection probability of Barred Owls using playbacks and ARU surveys and the effects of survey variables for these survey methods could aid surveyors to increase confidence in occupancy status and survey efficiency. Survey variables (i.e., detection covariates) in occupancy modeling are often considered nuisance parameters, but these can be used to optimize survey efficiency (Hardy and Morrison 2000, Kissling et al. 2010). Circadian and seasonal factors drive phenology and behavior, which influence response to playbacks and calling rates and therefore influence survey detection (Kissling et al. 2010, Zuberogoitia and Martínez 2011). For example, Clement et al. (2019) found that seasonal effects on detection probability of Barred Owls were opposite for playbacks and ARU surveys. Playbacks were more effective later in the breeding season and ARUs were more effective earlier in the season. Thus, seasonality is an important factor when considering which survey method to employ. Although the types of vocalizations made by Barred Owls have been well described (Odom and Mennill 2010), the circadian vocalization patterns of unsolicited Barred Owl calls are not well understood, and identification of vocal activity peaks could increase the efficiency of ARU surveys.

To compare survey methods for Barred Owls, we collected detection/non-detection data using both playbacks and ARUs during a single breeding season in the Piedmont of South Carolina, USA. We used an occupancy framework to estimate detection probability of Barred Owls and its variance with season for each survey method. In addition, we used both the ARU data from South Carolina and an ARU dataset from Alberta, Canada (Shonfield and Bayne 2018) to examine whether Barred Owl circadian vocalization patterns can be used to increase ARU survey efficiency. We used the peaks in vocal activity in both datasets to develop a recommended ARU recording schedule that maximizes detections while reducing recording time and thereby processing time. We validated this optimized ARU schedule on both datasets by comparing the site detections before and after targeting vocal activity peaks. In order to make concrete recommendations for future study designs, we estimated the number of survey occasions needed to obtain a 90% seasonal detection probability of Barred Owls (i.e., probability of detecting owls at least once during the survey season at an occupied site) using (1) 15-min playbacks, (2) 11.5-hr ARU recordings, and (3) 6-hr ARU recordings targeting vocal activity peaks based on South Carolina data. Finally, we discuss advantages and caveats of playback and ARU surveys. The results of this study are intended to aid researchers to improve study design and survey efficiency in the context of study region, season, budget, and personnel constraints.

Methods

Study Areas. Data for this study are from two previously published occupancy studies that took place in South Carolina, USA (Clement et al. 2019), and in Alberta, Canada (Shonfield and Bayne 2017b). The South Carolina study was located within a 300-km^2 area in the Piedmont ecoregion, at the foothills of the southern Appalachian range. This study region consists mainly of oak-hickory (*Quercus* spp., *Carya* spp.) and pine (*Pinus* spp.) mixed forests situated in rolling topography, and the climate is characterized by mild winters, high humidity, and frequent precipitation. The Alberta study was located in upland forested sites spread across a large area in northeastern Alberta covering roughly 16,000 km^2, south of Fort McMurray and north of Lac la Biche (Shonfield and Bayne 2017b, Shonfield et al. 2018). This study region in the boreal forest region of Alberta is relatively flat and consists of forests primarily composed of trembling aspen (*Populus tremuloides*), white spruce (*Picea glauca*), and black spruce (*Picea mariana*) trees. The climate in northeastern Alberta is characterized by cold winters, warm summers, and low humidity.

South Carolina Owl Surveys. In South Carolina, a total of 48 sampling points (hereafter referred to as "sites") were randomly selected for a separate study of Barred Owl habitat selection along an urban-to-rural gradient. For a complete description of the site selection process, see Clement et al. (2019). We used a minimum distance of 800 m between survey sites to avoid drawing owls from neighboring sites during sampling (Clement et al. 2019). Sites were surveyed using both an audio lure (playback) and autonomous recording units (ARUs) during the breeding season to increase probability of detecting owls (Bosakowski 1987, Kissling et al. 2010). We began surveys in mid-January (17 January 2018) after courtship had begun (R. Bierregaard pers. comm.); playback surveys were completed on 9 April 2018 and ARU surveys on 1 April 2018. Day length during the survey season varied from 11.42 to 12.91 hr.

Playback surveys consisted of a 15-min broadcast of conspecific calls (McGarigal and Fraser 1985) and were conducted on three separate occasions at each site. Surveys began 1 hr past sunset and ended around 0300 H EST. Sites were surveyed by two or more surveyors during calm, clear nights in random order using cluster sampling (see Clement et al. 2019).

We conducted ARU surveys using three SM2+ Song Meters (Wildlife Acoustics Inc., Maynard, MA, USA). We programmed ARUs to record continuously for 11.5 hr starting at 1900 H EST at 8 kHz in the wav format. We deployed a single ARU at each site by securing the unit to a tree approximately 1.5 m high; ARUs recorded for three consecutive nights at a site before rotation to another site. If a period of heavy rain occurred during a recording, we recorded an extra day and discarded the rain date. Deployment order was determined randomly without replacement. To ensure independence between playback and ARU detections, we did not survey using playbacks at sites with deployed ARUs. Two of the 48 sites were not surveyed with ARUs due to logistical constraints. We manually searched recordings for owl calls using SongScope 4.1.5a (Wildlife Acoustics Inc., Maynard, MA, USA) to visualize spectrograms of the recordings and identify owl calls (see Clement et al. 2019). Only territorial vocalizations were classified as owl detections (this included variations on the two-phrased "who-cooks-for-you" and ascending hoots; McGarigal and Fraser 1985, Odom and Mennill 2010). We chose manual scanning of spectrograms instead of automated acoustic recognition ("recognizers"), as we found Barred Owl recognizers had low precision amid the anthropogenic soundscape in this region.

Alberta Owl Surveys. In Alberta, we conducted passive acoustic surveys for owls using SM2+ Song Meters. We programmed each ARU to turn on and record for 10 min at the start of every hour on a 24-hr basis in stereo format at 44.1 kHz with a 16-bit resolution. We attached ARUs to trees at a height of approximately 1.5 m from the ground; ARUs were spaced a minimum of 1.2 km apart. We installed one ARU at each of 238 sites for a minimum of nine nights between 21 March and 6 May 2014. During the survey season, day length varied from 12.67 to 16.33 hr. One site's ARU failed to record, and six sites had ARUs that did not record for the full nine nights, so we removed these sites from our sample and retained a total of 231 sites.

To compile detection data of Barred Owls, we removed the daytime recordings (i.e., recordings after sunrise and before sunset) and compiled hourly detections for each of our surveyed sites. We used the program Song Scope 4.1.3A to build a recognizer (a template for automated acoustic recognition) to scan the recordings and detect the two-phrased hoot of the Barred Owl (Odom and Mennill 2010); see Shonfield et al. (2018) for additional details on the recognizer and its performance. The results output from the recognizer had a number of false positives (i.e., hits that were not Barred Owl calls), so five trained technicians verified all hits generated by the recognizer before compiling the data. The recognizer was trained to detect two-phrased hoots but also detected one-phrased hoots and ascending hoots (Odom and Mennill 2010), and these were also scored as true positive detections. Detections that technicians could not confidently identify were checked by JS, who also conducted random checks to ensure accuracy.

Detection Probability Analysis. Data were analyzed using occupancy models to estimate detection probability and the effect of survey covariates on Barred Owl detections for each survey method. Occupancy models determine detection probability using repeated observations (MacKenzie et al. 2006). Using R version 3.5.0 (R Core Team 2018) within R Studio (RStudio Team 2016), we ran single-season occupancy models with the package *unmarked* (Fiske and Chandler 2011). Detection and occupancy estimates are presented as mean ± SE; parameters are reported as beta coefficients with confidence intervals.

Survey method comparison and seasonal effects. To compare the effectiveness of playback and ARU surveys and to determine how detection probability of Barred Owls could be improved for these methods, we used the South Carolina surveys to evaluate methods within the same time frame and

Table 1. Model-ranking results for South Carolina data investigating the influence of seasonality and survey method on Barred Owl detection probability. Models with substantial support ($\Delta AIC_c < 2$) included both an additive model and an interactive model with variables date (Julian day) and method (ARU or playback). In the additive model, both date and survey method had significant effect on Barred Owl detection probability (Fig. 1). Support for the interactive model was driven by the main effect of the survey method, as the interaction term and the main effect of date both had 85% confidence intervals that crossed zero.

Model	K	AIC_C	ΔAIC_C	Model Weight
Date + Method	4	262.37	0.00	0.48
Date × Method	5	263.15	0.78	0.32
Date	3	264.81	2.43	0.14
Date^2	4	267.16	4.79	0.04
Intercept-only	2	269.18	6.80	0.02

region. We summarized owl detections for both methods in a daily encounter history dataset. The daily dataset consisted of six sampling occasions: three playback surveys and three ARU surveys summarizing owl detections by night. Sites surveyed with playbacks but not ARUs ($n=2$) were kept in our daily dataset, as occupancy modeling allows for missing sampling occasions. We ran and ranked a total of five different occupancy models using Akaike's Information Criterion for small sample sizes (AIC_c), including a null or intercept-only model with no covariates (Table 1). As we were primarily interested in modelling detection probability, the other four models included survey-specific covariates for the detection parameter and did not include any site-specific covariates for the occupancy parameter. We expected seasonality to influence the detection probability of our study species for both survey methods, so we included Julian date in a univariate model, as well as its quadratic function in another model to determine whether a peak in vocal activity occurred within our survey season (Table 1). We also speculated that the effect of seasonality on the detection probability of Barred Owls could differ by survey method (Clement et al. 2019), so we modeled Julian date along with a categorical variable representing the survey method in an additive and an interactive model (Table 1). Previous research on the same dataset investigated the relationship of Julian date and survey method (Clement et al. 2019); however, in that study ARU detections were summarized as a single encounter occasion, comprised of three consecutive nights. Here we summarize ARU detections instead as daily sampling occasions ($n = 3$) to generate estimates of daily detection probability.

Barred Owl circadian vocalization patterns. To investigate whether Barred Owls exhibit circadian vocalization patterns that could be used to optimize detection rates of passive surveys, we used the ARU data collected both in South Carolina and Alberta. These two datasets were analyzed separately using the same models in order to reduce variation caused by different sampling survey season and design. Detections from ARU surveys were summarized to create a dataset that represented encounter history summarized by hour. We obtained sunset and sunrise times for each ARU survey date using the *suncalc* R package (Agafonkin and Thieurmel 2018) and we calculated two circadian variables for each hour sampled: the time past sunset and the minimum time from daylight (i.e., time past sunset or time to sunrise). After a preliminary inspection of the ARU hourly detections, we included a model with a third-order function of time past sunset to account for two vocal activity peaks throughout the night, as well as a quadratic function of time from daylight to account for a single vocal dip during the darkest hours of the night (Table 2). We scaled and centered continuous survey variables to mean = 0 and variance = 1 prior to analysis, and we checked that variables included in the same model set were not correlated (Pearson's coefficient < 0.70). We used AIC_c within a multiple working hypotheses framework to compare relative support among our models (Burnham and Anderson 2002). We interpreted models with substantial empirical support ($\Delta AIC_c < 2$, Burnham and Anderson 2002) and we considered model parameters to be significant when 85% confidence intervals of the estimates did not overlap zero (Arnold 2010).

Optimizing ARU surveys using vocal activity peaks. Using the findings from our circadian vocalization analysis, we investigated whether Barred Owl calling patterns could be used to improve survey efficiency and minimize recording time by targeting periods of high vocal activity. We subset our ARU hourly data to target vocal activity peaks and reduced our daily ARU recording time by half (from 12 to 6 hr surveyed). After pooling hourly data into a daily sample dataset, we compared both the naive occupancy (the number of sites where owls were detected) and the occupancy probability (Ψ) of this

Table 2. Ranked results for models examining the circadian patterns of Barred Owl vocalizations, South Carolina, USA, and Alberta, Canada. Detection probability was best predicted by a third-order polynomial function of time past sunset (Past sunset)^3, suggesting that Barred Owls exhibit two distinct vocal activity peaks during the night. Aside from the intercept-only model in Alberta data, no other models were substantially supported (ΔAIC < 2)

South Carolina, USA					Alberta, CA				
Model	K	AIC_C	ΔAIC_C	Weight	Model	K	AIC_C	ΔAIC_C	Weight
(Past sunset)^3	5	298.84	0.00	0.96	(Past sunset)^3	5	712.23	0.00	0.59
(To light)^2	4	305.12	6.28	0.04	Intercept-only	2	715.86	1.93	0.22
Intercept-only	2	328.05	29.20	0.00	(To light)^2	4	714.16	3.63	0.10
Global	4	332.21	33.36	0.00	Global	4	715.95	3.72	0.09

optimized survey to our original sampling scheme to determine efficacy of targeting vocalization peaks in ARU surveys.

Survey recommendations. In order to make survey recommendations to future researchers studying Barred Owls, we determined the number of survey days required to obtain a 90% seasonal detection probability of this species using either 15-min playbacks, continuous 11.5-hr ARU surveys, or targeted 6-hr ARU surveys. We estimated seasonal detection probability (p^*), or the probability of detecting the species at least once at an occupied site during K surveys when survey detection probability (p) is assumed constant, using the following function (Stauffer et al. 2002, MacKenzie and Royle 2005):

$$p^* = 1 - (1 - p)^K$$

RESULTS

In South Carolina, we detected Barred Owls at 27 of the 48 sites using both ARU and playback methods. Playback surveys detected owls at 22 sites, ARUs detected owls at 14 sites. Of 25 occupied sites that were surveyed using both methods, 11 sites had owl detections from playbacks but not from ARUs, 5 sites had detections from ARU surveys but not from playbacks, and 9 sites had detections from both methods. In Alberta, we detected Barred Owls at 28 of the 231 sites surveyed using ARUs and automated species recognition.

Survey Methods Comparison and Seasonal Effects. In South Carolina, survey detection probability of Barred Owls averaged 0.39 ± 0.06 for 15-min playbacks and 0.23 ± 0.05 for 11.5-hr ARU surveys throughout the survey season. Although both the additive model (date + method) and the interactive model (date × method) had substantial support in our model-ranking set (ΔAIC_c <2, Table 1), support for the interactive model was driven by a positive main effect of survey method; the confidence intervals of date as a single variable and the interactive term in this model crossed zero. Thus, we chose to interpret the additive model only. In this model, detection probability for both survey methods increased throughout the survey season (β = 0.43, 85% CI = 0.18, 0.69; Fig. 1) and detection probability of owls with playbacks was higher than with ARU surveys (β = 0.74, 85% CI = 0.25, 1.23).

Barred Owl Circadian Vocalization Patterns. In both South Carolina and Alberta, hourly detection probability of Barred Owls using ARU surveys was best described by a third-order polynomial function of hours past sunset (Tables 2, 3). This model suggests that Barred Owls exhibit two distinct peaks in vocal activity; the first peak occurred immediately following sunset, and the second peak occurred between 7–9 hr past sunset (Fig. 2). Based on these results, we determined an optimal survey timeframe that targeted vocal activity peaks by surveying two sampling windows per night: 0–2 hr past sunset, and 6–10 hr past sunset. This optimized survey timeframe reduced the original South Carolina and Alberta ARU survey time by half, resulting in 6 hr of total recording time for South Carolina and 1 hr of total recording time for Alberta (consisting of six 10-min recording segments). To test the effectiveness of this optimized sampling scheme, we subset our original hourly datasets and we removed any samples outside of this timeframe. Using this reduced sampling frame, we found that we retained >82% of sites where we originally confirmed Barred Owl presence based on vocalizations. In South Carolina, the daily detection probability of the 6-hr optimized sampling scheme averaged 0.20 ± 0.05 across the survey season; this sampling scheme resulted in owl detections at 13 of the original 14 sites found to be

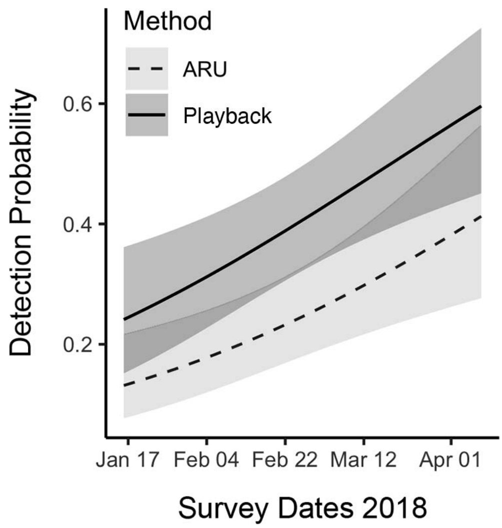

Figure 1. Effect of date on Barred Owl detection probability of playback and autonomous recording units (ARU) surveys in South Carolina, USA. Effects were estimated from an additive model that was best supported among our candidate set (Table 1). Detection probability of Barred Owls was higher with 15-min playbacks than with continuous 11.5-hr passive ARU recordings. The detection probability of Barred Owls using both playback and ARU surveys increased as the breeding season progressed, but the positive effect of date on ARU detection probability may be biased in our study because sites were surveyed with ARUs on consecutive days (see Discussion). Shaded areas represent 85% confidence intervals.

occupied. Occupancy estimates varied little between the 6-hr survey (0.40 ± 0.11) and the 11.5-hr continuous survey (0.43 ± 0.12) in South Carolina. In Alberta, the daily detection probability of Barred Owls using the optimized sampling scheme averaged 0.08 across the survey season and resulted in owl detections at 23 of the original 28 sites found to be occupied. Occupancy estimates were similar between the optimized 6-hr sampling scheme consisting of six 10-min recordings (0.19 ± 0.06) and the full sampling scheme (0.10 ± 0.04). To assess changes in daily detection probability of Barred Owls across survey methods, we collapsed hourly encounter histories into daily encounter histories using occupancy models. In South Carolina, the average ARU daily detection probability throughout the survey period decreased from 0.23 in the 11.5-hr recordings to 0.20 in the optimized 6-hr sampling scheme. In Alberta, average daily detection probability of Barred Owls decreased from 0.09 to 0.08 with the optimized ARU sampling scheme.

Survey Recommendations. To guide future research on Barred Owls, we used the average daily detection probability for each survey method used in South Carolina to estimate the number of days needed to obtain a 90% seasonal detection probability (i.e., 10% probability of false site absence). We found that when using 15-min playback surveys, a high detection probability sampling design to study Barred Owls should include a minimum of five repeated visits, and ARUs recording for 11.5 hr continuously should be left at sites for at least 9 d. The optimized ARU sampling targeting vocal activity peaks required 10 d (Fig. 3) to reach 90% seasonal detection probability of this species.

Discussion

Our results demonstrated that both survey timing and survey design can influence the detection probability of Barred Owls. Previous studies have also found that playback detection probability increase later in the breeding season for Barred

Table 3. Estimated coefficients (Coef) from parameters in the best model describing Barred Owl circadian vocal activity—a third-order polynomial function of time past sunset (Table 2). Parameters were considered to be significant (Sig = *) when values between the 85% lower and upper confidence intervals (LCI, UCI) excluded zero (Arnold 2010). Both the main effect and the cubed effect of hours past sunset were significant, suggesting that vocalizations increased later in the night and that Barred Owls called more frequently during two distinct vocal activity peaks throughout the night (Fig. 2).

	South Carolina, USA				Alberta, CA			
Parameters	Coef	LCI	UCI	Sig	Coef	LCI	UCI	Sig
Intercept-only	–2.77	–3.20	–2.34	*	–4.12	–4.46	–3.78	*
Past sunset	1.39	0.68	2.10	*	0.94	0.39	1.49	*
(Past sunset)^2	–0.16	–0.50	0.17		–0.19	–0.44	0.07	
(Past sunset)^3	–0.77	–1.16	–0.39	*	–0.53	–0.85	–0.22	*

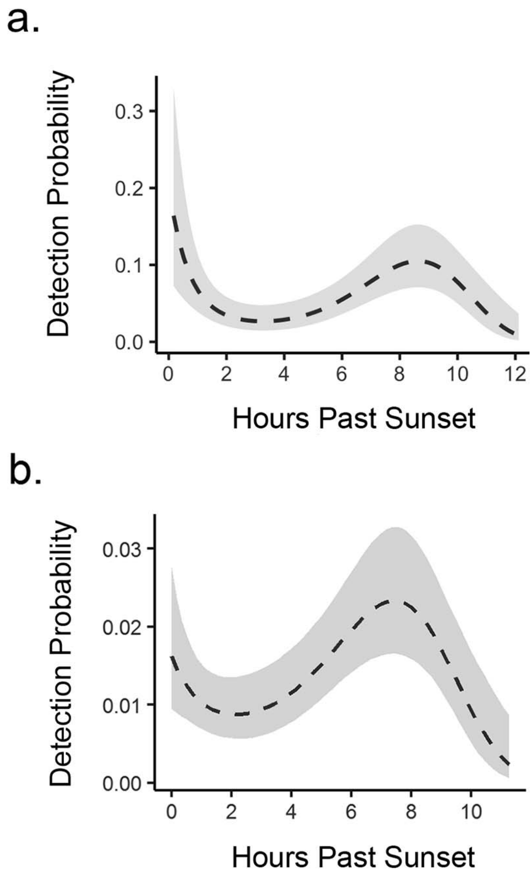

Figure 2. Barred Owls demonstrated two similar vocal activity peaks in both the ARU data collected in (a) South Carolina, USA, and in (b) Alberta, Canada. Calling peaked right after sunset, dropped 2–3 hr later and began to peak again around 7–9 hr past sunset. Plot values were predicted using a third-order polynomial model of time past sunset (Table 2). Shaded areas represent 85% confidence intervals. Detection probability is reported as hourly in South Carolina and as 10-min recordings on the hour in Alberta.

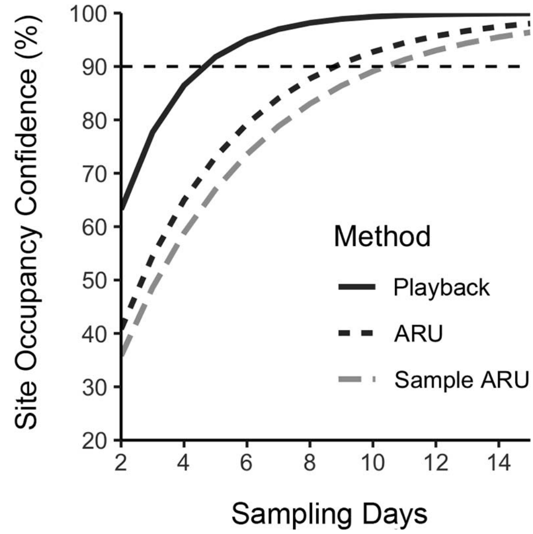

Figure 3. Estimated number of days of nocturnal surveys required to obtain a 90% probability of detecting Barred Owls at occupied sites during the breeding season. Seasonal probability of detection was estimated using each survey method's average daily detection probability in South Carolina data. Methods include 15-min broadcast surveys (playbacks), passive surveys using 11.5-hr recordings from autonomous recording units (ARUs) and optimized 6-hr ARU recordings targeting Barred Owl circadian vocalization peaks (sample ARU, Fig. 2).

Owls (McGarigal and Fraser 1985, Kissling et al. 2010) and for other raptors (Mosher et al. 1990), likely because responsiveness to playbacks increases as the breeding effort intensifies.

Although the effect of date on playback detections was similar in this analysis as in a previous study on the same data in South Carolina (Clement et al. 2019), the effect of date on ARU detection probability of Barred Owls differed between these two studies and was dependent on how detections were summarized. For the purposes of this analysis, we summarized ARU detections of owls by night in order to report daily ARU detection probability (e.g., encounter history = three ARU samples and three playback samples) and our model results indicated that ARU detection probability increased throughout the survey season. However, this sampling design was confounded as ARU recordings consisted of three consecutive nights rather than being conducted over the entire breeding season at each site or conducted randomly each night across all sites. Recording on consecutive days is typically how ARU surveys are conducted (Goyette et al. 2011, Rognan et al. 2012, Shonfield et al. 2018), as it reduces the effort of deploying and retrieving units. In contrast, Clement et al. (2019) compiled ARU samples consisting of three consecutive nights at each site into a single sampling occasion (e.g., encounter history consisted of four sampling occasions, one ARU sample and three playback samples) in order to avoid bias created from temporal clustering of ARU surveys. Using the same detection data and detection-only models, Clement et al. (2019) found that ARU detection probability of

Barred Owls decreased as the breeding season progressed. The cumulative 3-d ARU detection probability of owls throughout the survey season (i.e., seasonal detection probability) did not change substantially between both analyses (0.49 in Clement et al. 2019; 0.54 in this paper), nor did occupancy estimates differ (0.62 in both papers). However, this case demonstrates the importance of correctly summarizing detection data to avoid introducing biases in survey design. Failure to do this may cause researchers to find erroneous model estimates of detection covariates, such as the effect of date, which has the potential to influence occupancy estimates. To avoid bias due to temporal clustering of surveys with ARUs, we recommend (1) additional unit rotation (e.g., surveying sites during more than one consecutive period), or (2) additional recording devices (e.g., deploying one unit per site with all sites sampled during the same period). Depending on the study design, either of these recommendations could increase survey effort and financial cost enough to render these approaches unfeasible. If such costs are prohibitive, a more efficient strategy may be to incorporate random effects in occupancy models to account for clustered detection covariates within sites using a Bayesian framework (Royle and Kéry 2007).

Barred Owl circadian vocalization patterns in South Carolina, USA, and Alberta, Canada, were very similar relative to the time past sunset, despite large differences in day length and time of sunset between the survey seasons and within the survey periods. The predictability of Barred Owl vocalization behavior relative to sunset offers a means to maximize survey efficiency for studies across the distribution of Barred Owls when scheduling ARU recordings. By targeting two peaks of Barred Owl vocalizations throughout the night, we cut our survey time in half and retained >82% of sites with owl detections from our original recordings. Reducing survey time using the optimized sampling scheme had minimal effect on occupancy estimates in both regions. This minimized ARU survey processing time, such as listening, scanning spectrograms, or checking audio clips from the output of recognizers. The Barred Owl vocal activity peaks we described are similar to those described for time of day in Takats et al. (2001) and Odom and Mennill (2010). Describing vocalization patterns in relation to circadian variables (such as hours past sunset) may be a better tool than time of the day to predict vocal activity, as it is more biologically relevant to owls and can be generalized across time zones and seasons. We suggest researchers use peaks of vocalizations described here to increase detection rates and to reduce recording length and processing time for surveys using ARUs.

In South Carolina, playback surveys were overall more effective at detecting Barred Owls than ARU surveys. Playbacks had higher detection probability and detected owls at sites without ARU detections ($n = 11$). Broadcasting conspecific calls has been shown to increase detection rates for several other nocturnal birds (Zuberogoitia et al. 2020). Detection probability for playbacks was similar to those reported by other studies targeting Barred Owls (Bailey et al. 2009, Kissling et al. 2010), but was substantially influenced by seasonality. Although playback surveys may detect more owls per unit time than ARUs, playbacks are also more likely to lure birds from a distance (Zuberogoitia and Martínez 2011) and may influence response of heterospecifics targeted by multi-species surveys (Crozier et al. 2006). Higher detections of owls using playbacks vs. ARUs in South Carolina may have been caused by detection of neighboring owls, as home ranges were small in this region (average of 1.37 km^2, Clément et al. 2020). ARUs avoid this issue as they detect owls passively using natural vocalizations. Passive surveys also reduce the risk of disturbing birds during the critical nesting period, as playbacks may draw breeding birds away from a nest site during a territorial response (Rognan et al. 2012, Duchac et al. 2020). ARUs can be particularly advantageous for studies in remote regions where field access is difficult and nocturnal work may cause safety concerns (Shonfield et al. 2018). In addition, sound analysis of vocalizations in ARU recordings could be used to assign sex for Barred Owls (Odom and Mennill 2010) and to distinguish individuals (Freeman 2000).

Despite these advantages, ARUs can be costly to purchase, and processing time can be extensive (Rognan et al. 2012, Shonfield et al. 2018). In South Carolina, we used manual scanning to find owl calls in ARU recordings, resulting in a large investment of time and effort. Each 11.5-hr recording took an average of 1.3 hr to process detections manually. In Alberta, automated recognizers reduced processing time but produced numerous false positives, which reviewers had to manually check (Shonfield et al. 2018). These manual checks took 5 min or less (depending on the number of audio clips to check) per day of recording. The use of recognizers (templates to match specific vocalizations and automate species recognition) introduces detection error through false negatives. Although this should not be much of an issue for occupancy studies (models account for imperfect detection), it could be an issue for a different analysis approach. Both playbacks and ARUs have cost, time, and effort requirements that should be carefully considered along with survey goals when designing a study. In South Carolina, we combined survey methods and obtained an average of 90% seasonal detection probability of Barred Owls using three playback surveys and three 11.5-hr ARU recordings. The combination of multiple survey methods may optimize effort time and detection probability, as visual surveys in South Carolina detected some owls that were not detected by ARUs, and vice versa (e.g., Rognan et al. 2012).

Although detection covariates are typically considered nuisance parameters, we recommend that additional studies quantify their effect so as to guide the design and duration of similar sampling efforts (Kissling et al. 2010, Hardy and Morrison 2000). Increasing detection probability and modeling for covariates that account for detection heterogeneity is key to increase the strength and credibility of ecological models (MacKenzie et al. 2006). Better model generation that requires the investment of fewer resources will help conservation and management personnel more efficiently advance institutional goals.

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