J. Field Ornithol. 89(4):384–392, 2018 DOI: 10.1111/jofo.12274

Use of autonomous recording units increased detection of a secretive marsh bird

Lucas R. Bobay,[1] Paul J. Taillie, and Christopher E. Moorman

Fisheries, Wildlife, and Conservation Biology, College of Natural Resources, North Carolina State University, Raleigh, North Carolina 27607, USA

Received 5 July 2018; accepted 3 November 2018

ABSTRACT. Obtaining sufficient numbers of detections during point counts to make inferences concerning the presence and abundance of secretive species, such as many species of marsh birds, can be difficult. However, autonomous recording units (ARUs) can provide extended survey windows, potentially allowing for more effective detection of elusive species. We assessed the feasibility of using both ARUs and point-count surveys to monitor Black Rails (*Laterallus jamaicensis*) and Least Bitterns (*Ixobrychus exilis*), two secretive marsh birds of conservation concern. We identified vocalizations in ARU recordings using acoustic analysis software, and combined these observations with those from point counts to model occupancy of both species in coastal marshes of eastern North Carolina in 2016 and 2017 while accounting for variation in detection. Use of ARUs doubled the number of points where we detected Black Rails; thus, the combined point count-ARU model yielded a greater occupancy probability for this species. However, the ARUs recorded few Least Bittern vocalizations, suggesting that successful application of ARUs may depend on the vocal complexity of focal species. Although the appropriateness of integrating ARUs with in-person monitoring varies among species, our results illustrate that this integration increased detections of an elusive species of conservation concern.

RESUMEN. **Uso de Unidades Autónomas de Grabación incrementa la detección de un ave de pantano sigilosa**

La obtención de una cantidad suficiente de detecciones durante conteos por puntos, que permita hacer inferencias sobre la presencia y abundancia de especies sigilosas, como muchas especies de aves de pantano, puede ser difícil. Sin embargo, el uso de unidades autónomas de grabación (ARUs) puede ampliar estas oportunidades durante reconocimientos de campo, permitiendo potencialmente una detección más efectiva de especies elusivas. Determinamos la factibilidad de uso de ARUs y reconocimientos por medio de conteos por puntos para registrar rascones (*Laterallus jamaicensis*) y avetoros (*Ixobrychus exilis*), dos aves de pantano sigilosas con estatus de conservación preocupante. Identificamos vocalizaciones en grabaciones con ARUs utilizando software de análisis acústico y combinamos estas observaciones con aquellas de conteos por puntos para modelar la ocupación de ambas especies en los pantanos costeros del este de North Carolina en 2016 y 2017 mientras contabilizábamos la variación de su detección. El uso de las ARUs duplicó el número de puntos donde detectamos a *Laterallus jamaicensis*, con lo que el modelo conteo por punto-ARU generó una probabilidad de ocupación mayor para esta especie. Sin embargo, las ARUs grabaron pocas vocalizaciones de *Ixobrychus exilis*, lo que sugiere que el uso exitoso de ARUs podría depender de la complejidad vocal de la especie focal. Aunque la pertinencia de integrar ARUs con registros hechos en persona varía entre especies, nuestros resultados ilustran que dicha integración incrementa las detecciones de una especie elusiva cuya conservación es preocupante.

Key words: acoustic monitoring, Black Rail, elusive species, Least Bittern, occupancy, point count

Many species of birds are difficult to detect because of their scarcity, reluctance to vocalize, secretive behavior, or occurrence in areas where human access is impractical. For researchers, obtaining sufficient numbers of detections to make inferences about these elusive species can be especially difficult. Accurate estimates of detection probability are critical to improve estimates of occupancy and abundance from count data, but require a sufficient number of observations (Nichols et al. 2000, Thompson 2002, Royle and Nichols 2003, MacKenzie 2006, Simons et al. 2007). As a result, the large sampling effort needed to detect elusive species can be logistically prohibitive (MacKenzie et al. 2006, Durso et al. 2011). Because effective management strategies require accurate monitoring (Ralph et al. 1993), developing effective methods for detecting elusive birds is essential for informing conservation decisions.

[1]Corresponding author. Email: lrbobay@ncsu.edu

Autonomous Recording Units (ARUs) have emerged as a method for monitoring wildlife vocalizations, and can potentially ameliorate some of the challenges associated with detecting elusive species. An ARU is a contained, weatherproof recording device equipped with a microphone that can be left in the field and set to record for days at a time. ARUs can be programmed to record scheduled time windows to increase battery life and extend their functional time in the field. This extensive survey window includes the night hours when in-person surveys are difficult and some species are most detectable (Hutto and Stutzman 2009, Goyette et al. 2011, Sidie-Slettedahl et al. 2015). Compared to point counts, ARUs may also be better able to detect elusive or threatened species that seldom vocalize because they can be left in the field for long periods (Celis-Murillo et al. 2009, Venier et al. 2012, Holmes et al. 2015, Campos-Cerqueira and Aide 2016, Drake et al. 2016). Additionally, recording units provide a verifiable, permanent record of the species vocalizing at a particular site, potentially reducing observer error (Brandes 2008, Drake et al. 2016, Shonfield and Bayne 2017). Despite these potential benefits, use of ARUs can still present challenges (Hutto and Stutzman 2009, Sidie-Slettedahl et al. 2015). For example, determining relative abundance of a species is difficult with an ARU, whereas the relative locations of vocalizations determined during point counts can be used to more accurately determine the number of individuals present at a site (Sidie-Slettedahl et al. 2015). Direct comparisons of recording units to human observers have revealed mixed results, with some authors suggesting that detection rates were superior with ARUs (Acevedo and Villanueva-Rivera 2006, Celis-Murillo et al. 2009) and others reporting them as either inferior to (Hutto and Stutzman 2009, Sidie-Slettedahl et al. 2015) or equal to human observers (Holmes et al. 2014, Alquezar and Machado 2015, Van Wilgenburg et al. 2017).

Perhaps most importantly, ARU monitoring requires significant effort to locate and identify the vocalizations of species of interest in the recordings (Hutto and Stutzman 2009). Two methods have been used to detect vocalizations in ARU recordings: (1) manual listening, including visual verification of spectrograms, and (2) use of automated analysis programs such as SongScope, Kaleidoscope, RavenPro, and MonitoR (Knight et al. 2017, Shonfield and Bayne 2017). Although reducing analysis time when compared to manual review (Knight et al. 2017), these programs can yield high rates of false positives and false negatives, making manual analysis a preferred alternative for some studies (Sidie-Slettedahl et al. 2015, Stiffler et al. 2018). Additionally, the high number of false positives detected by automated analysis necessitates manual validations of detections (Knight et al. 2017). Despite these disadvantages, automated detection can provide enough data to draw inferences on species presence (Knight et al. 2017, Shonfield and Bayne 2017). New acoustic analysis methods that automate identification of vocalizations continue to emerge, but require substantial effort and may yield low accuracy of detection, especially for less complex vocalizations (Duke and Ripper 2013, Sidie-Slettedahl et al. 2015, Knight et al. 2017).

Marsh birds, particularly rails and bitterns, are notoriously elusive and occur in densely vegetated areas where access can be difficult; thus, studies of marsh birds could potentially benefit from the monitoring approach offered by ARUs. For example, Least Bitterns (*Ixobrychus exilis*) and Black Rails (*Laterallus jamaicensis*) vocalize irregularly and are difficult to monitor (Eddleman et al. 1994, LeGare et al. 1999, Bogner and Baldassarre 2002). ARUs, however, can sample continuously for long periods, making detection more likely for birds that vocalize infrequently and nocturnal species that vocalize when human access can be difficult (Hutto and Stutzman 2009, Goyette et al. 2011).

To account for the imperfect detection bias inherent to surveying birds, the Standardized North American Marsh Bird Monitoring Protocol accommodates several designs for estimating detection probability, including repeated visits, distance estimation, and time-of-detection (Conway 2011). Regardless, detecting enough individuals to make valuable inferences about distribution and habitat associations remains difficult for species that vocalize infrequently and at night, such as Black Rails, Least Bitterns, and other species of marsh birds (DeLuca et al. 2004, Correll et al. 2016, Wiest et al. 2016). Such detection issues can lead to elusive focal species being dropped from analyses due to a lack of data (Baschuk et al. 2012). As such, monitoring efforts for these secretive species may require higher-resolution detection histories to inform the detection process. This may be resolved by using ARUs to detect elusive species, including Black Rails and Least Bitterns. The extended recording window of ARUs also offers valuable information on temporal variation in bird vocalizations across both day and night hours, which can be difficult to obtain using in-person surveys because they are seldom conducted at night (Sidie-Slettedahl et al. 2015).

To better understand the utility of ARUs for monitoring elusive marsh birds, our primary goal was to examine how estimates of occupancy are influenced by augmenting traditional in-person marsh-bird monitoring with ARU recordings. Our objectives were to determine (1) if ARUs in combination with point-count surveys are more effective than point-count surveys alone at detecting elusive species, and (2) if Least Bitterns and Black Rails are well-suited for automated detection.

METHODS

Study area. Our study was conducted in the herbaceous marshes of the Albemarle-Pamlico Estuary System in eastern North Carolina. The adjacent land masses were comprised of extensive wetlands, including over 9000 ha of non-estuarine freshwater marsh and over 23,000 ha of brackish marsh (Moorhead and Brinson 1995). Marshes in the study area covered a gradient of salinity, with freshwater wetlands comprised mostly of sawgrass (*Cladium jamaicense*), cattail (*Typha* spp.), and common reed (*Phragmites australis*), and more saline marshes comprised of black needlerush (*Juncus roemarianus*), bulrush (*Schoenoplectus* spp.), salt hay (*Spartina patens*), and saltgrass (*Distichlis spicata*). At higher elevations, the marshes transitioned to forest with a small component of wax myrtle (*Myrica cerifera*) and other shrubs.

Site selection. We identified candidate marshes to survey for marsh birds using a combination of aerial photography and National Wetlands Inventory (USFWS 2010). For marshes that we had permission to access, we further limited our scope to areas accessible within 30 min walking from a road, or 1 h of paddling a canoe from a launch site. In these accessible areas, we randomly selected points with a minimum between-point distance of 400 m, as suggested by Conway (2011). The original sample included 127 points, but 35 were dropped because dense shrubs at the upper end of the transition to forest impeded foot travel. As such, the final set of survey locations included 92 points.

Point-count surveys. We conducted point-count surveys during April, May, and June 2016 and 2017, and ARU surveys during the same months in 2017. Point counts were conducted between 30 min before sunrise and 2 h after sunrise, in accordance with the Standardized North American Marsh Bird Monitoring Protocol (Conway 2011). In each year, we surveyed each site between one and four times except two points that were not visited in 2017. One survey consisted of an unlimited-radius point count with a 5-min passive period followed by a second 5-min period during which vocalizations of target species were broadcast for 1 min each. We used the same recording used by the Saltmarsh Habitat and Avian Research Program in Region Nine, which includes vocalizations of a Black Rail, Least Bittern, Virginia Rail (*Rallus limicola*), King Rail (*R. elegans*), and Clapper Rail (*R. longirostris*). We did not include the vocalization of Common Gallinules (*Gallinula galeata*) because we were primarily interested in species associated with herbaceous cover. All of the marsh–obligate species listed above were recorded because point counts were conducted to investigate several research questions, but, for the purposes of this study, we focus only on detections of Black Rails and Least Bitterns.

ARU surveys. We deployed two recording units (SongMeter SM4, Wildlife Acoustics, Maynard, MA) at a random sample of 23 of the 92 total points between 1 April and 30 June 2017. ARUs were mounted ~ 1.5 m above the marsh using PVC pipes inserted into the substrate. We programmed the units to record continuously from 2 h before sunset to 2 h after sunrise to capture the times when most marsh birds are most active (Conway 2011) and the overnight period when species such as Eastern Black Rails (*L. j. jamaicensis*) are known to vocalize (Eddleman et al. 1994) and ambient noise is at a minimum (Goyette et al. 2011). Each deployment lasted two to three nights at a given point. Each of the 23 points where an ARU was deployed received only one deployment.

Acoustic analysis. We used Kaleidoscope software (version 4.3.1) from Wildlife Acoustics to analyze raw recordings. We followed the three-stage analysis procedure described in the Kaleidoscope user's manual (Wildlife Acoustics 2017). In the first stage, we used a set of training recordings to generate "clusters" of similar vocalizations based on the structure of their visual signature, or spectrogram. Our training recordings were a set of preliminary ARU recordings collected in 2016 from nearby Cedar Island National Wildlife Refuge, where Least Bitterns are common and Black Rails are suspected to breed (Watts 2016). However, initial analysis revealed that Kaleidoscope identified too few Black Rail and Least Bittern vocalizations from these training recordings to be useful in the successive analysis stages. As such, we added high-quality recordings of both the song and growl calls of Black Rails and typical song vocalizations of Least Bitterns obtained from the Macaulay Library (www.macaulaylibrary.org) and Xeno-Canto (www.xeno-canto.org) to the training data. In general, we included as much vocalization variability as possible in training data for both focal species to minimize false negatives, acknowledging this may come at the cost of more false positives. After reclustering the training data with these augmented vocalizations, we manually labeled over 60% of the 6684 total vocalizations detected by the program as a specific species or as "non-focal" either by listening or by visually confirming spectrograms. We labeled vocalizations in all of the 77 identified clusters to ensure we provided Kaleidoscope with information for the full diversity of vocalizations in training data. In stage two, we reclustered the training data, this time using the labeled vocalizations. This stage allowed us to refine Kaleidoscope's ability to categorize vocalizations based on the vocalizations we identified. As in stage 1, Kaleidoscope reclustered the vocalizations in the training data, but only those vocalizations assigned to one of the species categories with labels we provided. We then investigated those vocalizations identified by Kaleidoscope as Black Rails or Least Bitterns to either confirm that Kaleidoscope identified it correctly, or to change the label to "non-focal" when it identified the vocalization incorrectly. We changed 13 of the 1536 Black Rail vocalizations to "non-focal" and 45 of the 187 Least Bittern vocalizations to "non-focal." Finally, we used this refined set of vocalizations to cluster the full set of field recordings from 2017. In this third stage, we manually investigated all vocalizations from the field recordings identified by Kaleidoscope to be verified as either Black Rails or Least Bitterns.

Statistical analysis. We used single-season occupancy models to investigate the relationship between detection probability and occupancy for Least Bitterns and Black Rails using the R package Unmarked (Fiske and Chandler 2011). This model framework assumes that whether a given site is occupied or does not change across the duration of the study. We acknowledge that the occupancy state may have changed between the 2016 and 2017 breeding seasons, so we included year as a covariate on occupancy to account for this variation. For each species, we fit one model to the observations from the point-count surveys only, then an analogous model to the combined observations from the point counts and the ARUs.

We estimated detection probability using the detection history across several repeated sampling occasions. We treated the passive and active survey periods of a given visit as independent sampling occasions. Detections during the passive survey period can potentially bias the subsequent active survey period, but, given that we never detected Black Rails during the passive survey period, we believe this dependence had a negligible effect on results. We included a categorical variable of method as a covariate on detection to distinguish between the passive and active survey periods. For the models with both point-count and ARU data, this method covariate included an additional category for ARU sampling occasions. Each ARU deployment was separated into 1-h independent sampling occasions. As such, we used the confirmed Black Rail and Least Bittern vocalizations identified by Kaleidoscope to determine if each species was detected or not for each 1-h sampling occasion, regardless of how many vocalizations occurred in a given sampling occasion. We did not have an equal number of 1-h sampling occasions per point. Although we did not account for uneven sampling, we believe that the sites sampled more were not systematically different from those sampled less, and thus should not bias our estimates of detection. Finally, we included linear and quadratic effects of time of day and ordinal date as covariates on detection.

To evaluate the improved model performance between the two sets of observations (in-person only and combined in-person and ARU), we built a suite of occupancy models with different covariates on detection. For each set of observations, we fit five models with different combinations of linear and quadratic effects of both date and time (Table 1). In all models, we included a covariate of method on detection and a covariate of year on occupancy. We then ranked the five models for each dataset and evaluated model diagnostics.

RESULTS

Kaleidoscope identified 11,872 Black Rail detections in the 2017 ARU recording data. Of these, we confirmed 91 vocalizations of Black Rails, including 79 songs and 12 growl calls. However, all confirmed growl calls were identified by Kaleidoscope as the more typical "keekeedrrr" vocalization. The remaining 11,781 detections were false positives, and included background noise, human voices, and vocalizations of other species of birds. The presence of Black Rails was confirmed at 11 points, including eight of 23 points (34.8%) with ARUs, four of 92 points (4.4%) with in-person surveys, and one point where both methods were used (Table S1). Kaleidoscope identified 3920 Least Bittern detections in the same ARU recording data using our clusters, but only five were true positives at three different sites. As with Black Rails, most detections were false positives.

We observed greater occupancy probabilities for Black Rails using ARUs than with point counts alone (Fig. 1). Detection probability for Black Rails was 0.05 based on point counts and 0.08 with the addition of ARU data. Mean occupancy probability increased from 0.17 for point counts to 0.38 with the addition of ARU data. The addition of ARU data made it possible to incorporate more covariates on both occupancy and detection (Table 1). Models fit only to point counts did not converge when the number of estimated parameters was greater than five, whereas we could estimate at least nine parameters with models fit to the combined point-count and ARU observations.

The amount of temporal variation we observed in the detection probability for Black Rails and Least Bitterns depended on whether ARU data were included. We were most likely to detect Black Rails between

Table 1. Model comparisons of hierarchical occupancy models with linear and quadratic covariate effects on detection of Black Rails fit to observations from both point-count surveys and point-count surveys augmented with ARUs in eastern North Carolina, 2016–2017.

Data	Detection model	Con	−log (lik)	K	AIC	ΔAIC	ω	Cum Wt
Point count	~ type[a] + time[b] + date[c] + date^2	No	16.4	7	46.7	0.0	0.5	0.48
Point count	~ type + time + date	No	17.7	6	47.4	0.7	0.3	0.81
Point count	~ type + time + time^2 + date + date^2	No	16.3	8	48.7	1.9	0.2	0.99
Point count	~ type + time	Yes	22.8	5	55.6	8.9	0.0	1.00
Point count	~ type	Yes	25.2	4	58.4	11.7	0.0	1.00
All	~ type + time + time^2 + date + date^2	Yes	88.1	9	194.2	0.0	0.6	0.59
All	~ type + time + date	Yes	91.2	7	196.3	2.1	0.2	0.80
All	~ type + time + date + date^2	Yes	90.7	8	197.3	3.1	0.1	0.93
All	~ type	Yes	94.6	5	199.2	4.9	.01	0.98
All	~ type + time	Yes	94.3	6	200.7	6.4	0.0	1.00

Model diagnostics include convergence (Con), negative log-likelihood (−log(lik)), the number of parameters (K), Akaike's Information Criterion (AIC), the difference in AIC from the top-ranked model (ΔAIC), the model weight (ω), and the cumulative model weight (CumWt).
[a]Categorical variable for active, passive, and ARU survey methods.
[b]Time of day in minutes after midnight.
[c]Ordinal date.

midnight and 04:00, although point counts were never conducted before 05:00. The probability of detecting Black Rails was close to zero at all other times (Fig. 2). The paucity of observations in the point-count data led to drastically different relationships between Black Rail detection probability and date and time than when ARU data were added (Fig. 2). The effects of date and time on detection were significant for Black Rails when ARU data were incorporated (Table 2). However, date was the only significant predictor of detection probability for the point-count model (Table 2).

DISCUSSION

Augmenting point-count surveys with ARU surveys increased the possibility of making statistical inferences about both occupancy and detection of Black Rails, but this worked less well for Least Bitterns. We increased the number of Black Rail detections and were able to incorporate more parameters into models using a combined ARU-point count dataset. Estimated detection probability for Black Rails was low even after incorporating ARU data, but ARUs provided a better time window to compensate for the secrecy of Black Rails. As a result, Black Rails were detected at more points using ARUs than by point counts alone, despite unwieldy rates of false positives during the automated vocalization detection process. In contrast, the addition of ARU data for Least Bitterns did little to improve estimates because we detected few additional Least Bittern vocalizations using ARUs.

The increased sampling window is a big advantage of ARUs over point-count surveys (Shonfield and Bayne 2017, Stiffler et al. 2018). Dense vegetation, uneven terrain, deep mud, and other obstacles make navigating tidal marshes both difficult and time-consuming. As a result, one field technician was only able to complete counts at four to five points within the recommended survey time

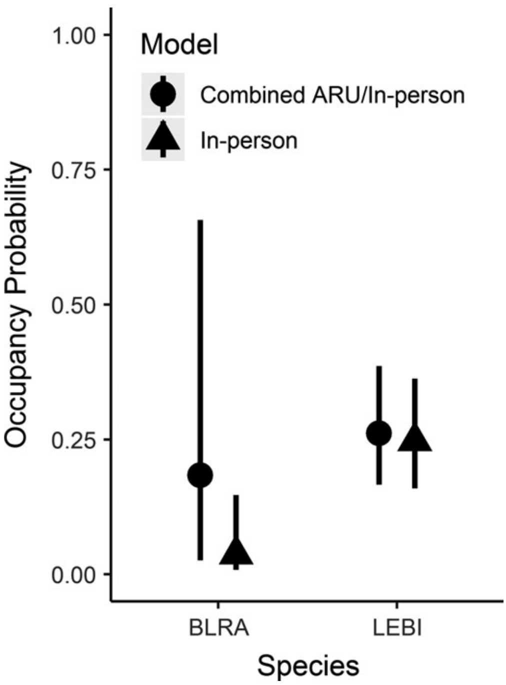

Fig. 1. Mean occupancy probability with 95% confidence intervals for Black Rails (BLRA) and Least Bitterns (LEBI) estimated using both point-count and autonomous recording unit surveys (circle) and point-count surveys only (triangles) in coastal wetlands in eastern North Carolina, 2016–2017.

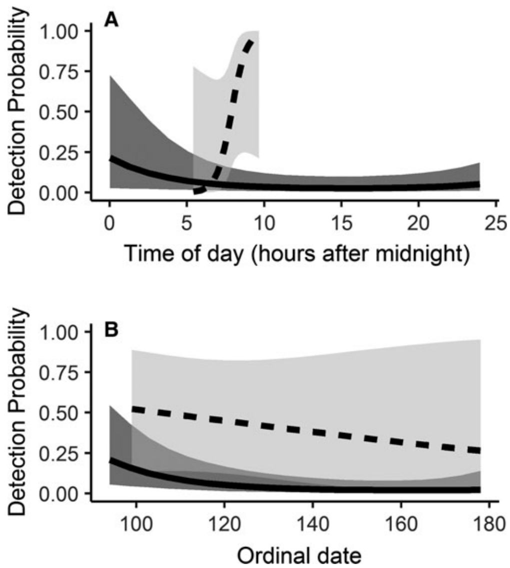

Fig. 2. Detection probability for Black Rails predicted using a combination of point-count surveys and autonomous recording units (solid line with 95% confidence interval in dark-shaded region) compared to the detection probability predicted from just point-count surveys (dashed line with 95% confidence interval in light-shaded region) in eastern North Carolina, 2016–2017. Detection probabilities are given in relation to (A) time in hours after midnight and (B) ordinal date beginning with 10 April (day 100).

Table 2. Means (± SE) for the detection covariate effects for Black Rails and Least Bitterns estimated using observations from point counts and ARU surveys combined, as well as observations from only point counts.

Parameter	Black Rails All	Least Bitterns All	Least Bitterns Point count only
Intercept	−3.49* (0.69)	−1.05* (0.35)	−0.21 (0.36)
Method - ARU	−0.64 (0.85)	−1.78* (0.86)	NA
Method - passive	−11.78 (140.56)	−0.40 (0.34)	−0.43 (0.35)
Time	−0.51 (0.32)	−0.30 (0.43)	−0.15 (0.23)
Date	−0.75* (0.29)	0.82* (0.31)	0.68* (0.27)
Time^2	0.54* (0.24)	−0.09 (0.38)	−0.42 (0.22)
Date^2	0.37 (0.27)	−0.23 (0.23)	−0.21 (0.25)

The point-count-only model for Black Rails did not converge when more than two covariate were included due to lack of detections and, therefore, is not included. An asterisk (*) indicates a significant effect ($P < 0.05$).

window. Additionally, the temporal distribution of Black Rail vocalizations documented in our study suggests that point counts conducted after sunrise do not adequately capture all vocalization times for this species. Although conducting point counts at night is possible, negotiating wetland terrain in the dark is difficult, and nocturnal surveys could overlook other, more diurnal species. ARUs could also be employed to determine the extent of Black Rail movements in response to their dynamic habitat conditions during the breeding season, which could potentially violate our assumption of population closure within a season. For scarce or elusive species such as Black Rails, ARUs may be the most feasible method of detection.

Acoustic analysis using Kaleidoscope was much less effective for Least Bitterns. The Least Bittern vocalization is low in frequency and not unique or complex (i.e., a simple note repeated 3–5 times in succession), making it difficult for search algorithms to distinguish it from other noise, such as cars and wind. Other studies have encountered similar detection issues with simple calls. Swiston and Mennill (2009) documented more false positives when using automated detection for the one- or two-note calls of Pale-billed (*Campephilus guatemalensis*) and Ivory-billed (*C. principalis*) woodpeckers than when scanning for the more complex calls of Pileated Woodpeckers (*Dryocopus pileatus*). Additionally, Sidie-Slettedahl et al. (2015) were unable to use automated software to distinguish the "click" vocalizations of Yellow Rails (*Coturnicops noveboracensis*) from the calls of Sedge Wrens (*Cistothorus platensis*) and *Pseudacris* frogs, sounds that a human observer can easily distinguish. Knight et al. (2017) reported that, of five acoustic recognizer programs, Kaleidoscope was the least effective at detecting the calls of Common Nighthawks (*Chordeiles minor*) that are also relatively simple vocalizations. Therefore, further development of automated detection programs are needed to accommodate vocalizations of some species, especially those with less complex calls.

Additional disadvantages of using the automated detection process include high rates of false positives and an unknown number of false negatives. For Black Rails, we had thousands of false positives compared to only 91 verified vocalizations, making manual verification of Kaleidoscope detections both mandatory and time-consuming. Varying levels of background noise may create uneven rates of false negatives when using automated analysis of ARU recordings. Although ARUs are potentially more effective at night when there are fewer vocalizing species and less background noise (Goyette et al. 2011), we found that loud anuran choruses in the hours immediately after sunset rendered parts of some recordings useless, as did wind and heavy rain. This noise is problematic because increased background noise and overlapping vocalizations will increase the rate of false negatives in recognizer output (Buxton and Jones 2012). Because of the unknown rate of false negatives, we were unable to determine if the nocturnal peak in Black Rail detections represented an actual increase in vocalization rate or just an artifact of a reduction in background noise late at night. The number of false positives and negatives, as well as the time required to create detectors, can lead researchers to abandon use of automated detection in favor of manually listening to recordings (Sidie-Slettedahl et al. 2015, Stiffler et al. 2018). These complexities of the verification process highlight why species that can be easily surveyed with point counts should not be the focus of ARU surveys.

Despite the aforementioned drawbacks, ARUs can be a valuable component of sampling for certain focal species and provide a way to increase detection rates of secretive species such as Black Rails. We detected Black Rails at three times as many points by combining ARU and point-count surveys than we did with point counts alone, demonstrating that use of ARUs can provide more information about the population trends and biology of this imperiled species. Little additional effort was required to place ARUs in the field because we were conducting in-person surveys at the same points. In cases similar to ours, ARUs can be added to a point-count survey protocol to improve detection of elusive species.

ACKNOWLEDGMENTS

We thank the North Carolina State University College of Natural Resources and Office of Undergraduate Research and the Department of the Interior Southeast Climate Adaptation Science Center for financial support. We also thank the biologists, managers, and personnel who assisted with access and provided invaluable information at Alligator River National Wildlife Refuge, Swanquarter National Wildlife Refuge, Gull Rock State Game Land, Alligator State Game Land, and Palmetto Peartree Preserve. We are grateful to C. Bland, A. Bledsoe, G. Loia, and A. VanVorst for their data collection effort, and to the four anonymous reviewers whose comments significantly improved our manuscript. The following audio recordings from the Macaulay Library at the Cornell Lab of Ornithology were referenced: 213729, 186584, 148345, 52874, 515850, 130911, 120420, 31525, 81800, 105742, 120298, and 164846. The following audio recordings from Xeno-canto (www.xeno-canto.org) were referenced: Furrow, R. XC232922; Hough, E. XC256611; Jones, D. XC1145; Lane, D. XC132473; Lane, D. XC142896; Lees, A. XC119783; and Spencer, A. XC109203.

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SUPPORTING INFORMATION

Additional Supporting Information may be found in the online version of this article at the publisher's website.

Table S1. Number of detections of Black Rails and Least Bitterns during in-person surveys (passive and active) and using Autonomous Recording Units.