Illinois Natural History Survey Bulletin

International • Peer-Reviewed • Open-Access
Published continuously since 1876

Estimating ability to detect secretive marsh birds over distance using autonomous recording units

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Research Article

Cite This Article:
Holiman H., J. C. Kitaif, A. M. V. Fournier, R. B. Iglay, and M. S. Woodrey. 2022. Estimating ability to detect secretive marsh birds over distance using autonomous recording units. Illinois Natural History Survey Bulletin 43:2022002. DOI: 10.21900/j.inhs.v43.866

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Data Accessibility Statement
Associated data set is available from the Illinois Data Bank (https://doi.org/10.13012/B2IDB-4450613_V1)

Keywords:
ARUs, Clapper Rail, Seaside Sparrow, Least Bittern, detection probability

Received: June 7, 2021

Accepted: August 5, 2022

Editor in Chief:
Maximilian L. Allen

Abstract

Marsh birds are highly elusive and select wetland habitats that are difficult to navigate and easily damaged by human observers. Autonomous recording units (ARUs) have been used to determine presence or absence of marsh bird species; however, distance effects on observer ability to detect a call or song vary based on study location, species of interest, and ARU product. Therefore, our objectives were to (1) evaluate if ARUs can be used to accurately count three marsh bird species (e.g., Clapper Rail *Rallus crepitans*, Least Bittern *Ixobrychus exilis*, Seaside Sparrow *Ammospiza maritima*), (2) evaluate how ability to detect a call or song changes over distance from the ARU, and (3) determine the straight-line distance surveyed by the ARU for the three species. We arranged ARUs to record calls from our marsh bird species broadcasted from Bluetooth speakers at fixed distances. We replicated possible calling scenarios by playing calls in different number combinations of individuals, ranging from 1 to 10 birds. To reduce interference from real bird vocalizations, we conducted our experiment in a recently burned pine savanna habitat that had similar herbaceous vegetation structure to the coastal emergent wetland habitats preferred by these species in southern Mississippi. We used Raven Pro bioacoustics software to produce sonogram images of the broadcasted calls in order to count individuals for each recording. We modeled ability to detect the call or song for each species at different distances from the ARU. Results showed that ARUs may be useful for counting individuals at close distances for some species (<100 m), but most counts were biased low. In Clapper Rails and Least Bitterns, count accuracy decreased between 100 and 125 m from the ARU, and count accuracy decreased 50–100 m for Seaside Sparrows. There was also a significant decline in count accuracy with increasing chorus size (Beta = −0.01, SE = 0.005). With further study and advancing technology, ARUs may be able to supplement marsh bird surveys and limit logistical issues.

Introduction

Marsh birds (rails, gallinules, bitterns, and some passerines) inhabit dense wetlands, infrequently vocalize, and are otherwise elusive and difficult to detect in the field. Traditional methods of surveying marsh birds, such as call-broadcast surveys to increase detection rates, require large investments of personnel time and can be logistically challenging to undertake (Conway 2011). Due to the challenges of gathering long-term spatial and temporal monitoring data on secretive marsh birds, there is a lack of sufficient count data for many species (Lehnert 2019; Lévêque et al. 2021). Marsh habitats can be logistically challenging to access, require resource-intensive survey methods, and can also be very fragile. Hence, repeated visits needed for call-broadcast can harm marsh habitat. If these challenges can be overcome, marsh bird species could be monitored effectively across large spatial scales, providing important information for understanding management impacts on marsh birds, as well as their population status and trends.

Autonomous recording units (ARUs) could complement current marsh bird survey techniques to study population trends. ARUs can be deployed for weeks to months at a time and record at specific times of day or continuously depending on their programming. ARUs have proven useful for avian studies, as many species can be detected by vocalization across diverse habitats (Haselmayer and Quinn 2000; Nadeau et al. 2008). Once deployed, ARUs can record data in remote areas, such as wetland habitats, causing little disturbance across prolonged time periods. ARUs have been successfully used to detect species and identify populations in previously unrecorded areas (Thompson et al. 2017; Pérez-Granados et al. 2018).

ARUs can produce similar results in rates of species detection compared to point count surveys in some situations (Venier et al. 2012) but not in others (Hutto and Stutzman 2009). Combining ARUs with point count surveys can provide better data than when either is used alone (Holmes et al. 2014; Alquezar and Machado 2015). Combining ARUS with point count surveys can also alleviate limitations of in-person counts, such as the need for adequately trained personnel and extensive travel time between points (Tegeler et al. 2012; Venier et al. 2012; Alquezar and Machado 2015; Sidie-Slettedahl et al. 2015; Perez-Granados et al. 2018). For marsh birds, which seldom call other than during crepuscular or nocturnal periods and are hard to detect when calling, ARUs can be a valuable tool for increasing detections. Frommolt and Tauchert (2013) used ARUs to determine the presence of Eurasian Bitterns (Botaurus stellaris) and detect separate individuals by their calls in a newly restored wetland area. Individual Yellow Rails (*Coturnicops noveboracensis*) were also counted from ARU recordings and sonograms (Drake et al. 2016).

Challenges of interpreting ARU data include positively identifying species calls by observers listening to recordings, and/or through computational methods. Additionally, it is difficult to determine how long an ARU can detect a call or song from a straight-line distance. For Yellow Rails, the most effective broadcasting radius for ARUs was 150–175 m (Drake et al. 2017). A similar study assessing ARUs and forest birds estimated a broadcasting radius of 50 m (Furnas and Callas 2015). These studies highlight the necessity of examining the distance an ARU can detect each species in concert with surrounding habitat type, as both call/song type and vegetation structure will impact the distance of detection and thus the inference of species occupancy/abundance determined by each ARU.

Recently, there has been an increase in the number of studies using ARUs for surveying marsh birds. Results have varied by species; detection probability of Black Rails (*Laterallus jamaicensis*) increased when counts from ARUs were used in conjunction with in-person point counts with no adverse effects on rail presences (Bobay et al. 2018). Manual listening of ARU recordings was found to be reliable for detecting King Rails (*Rallus elegans*) and Clapper Rails (*Rallus crepitans*), but error rates increased when using automated recognition software (Stiffler et al. 2018). As the ability of automated recognition software to detect species in a variety of conditions and to deal with sources of electromagnetic noises improves, computational methods may become more efficient at recognizing specific species (Schroeder and McRae 2020). Machine learning algorithms have been used to analyze ARU recordings, such as those used by Znidersic et al. (2020) to identify Least Bitterns (*Ixobrychus exilis*). Pairing ARUs with point count surveys could work best for improving detection rates and associated detection probability of secretive marsh birds

For this study, we focused on three common salt marsh species found in coastal Mississippi, USA, the Clapper Rail, Least Bittern, and Seaside Sparrow (*Ammospiza maritima*). Our objectives were to (1) evaluate if ARUs can be used to accurately count our focal marsh bird species, (2) evaluate how ability to detect a call or song changes over distance from the ARU, and (3) determine the straight-line distance surveyed by the ARU for each species.

Methods

Recordings

Our study area was located at Grand Bay National Estuarine Research Reserve in Moss Point, Mississippi, USA (30.431152, −88.426941). We chose a recently burned wet pine savanna composed of horizontal and vertical vegetation structure and density similar to Mississippi tidal salt marshes. These pine savannas included infrequent trees and were often dominated by waist-high annual grasses, with some smaller woody vegetation mixed among them. While plant species differed from tidal marsh species, the pine savanna was structurally similar to tidal marsh. Both habitat types rarely have trees and are often dominated by non-woody vegetation of a similar height, with occasional smaller woody plants interspersed between herbaceous species. In addition to habitat similarity, we chose to conduct our study in a pine savanna upland from adjacent marsh in order to remove any chance of accidentally detecting our focal species. Additionally, conducting our experiment in pine savanna avoided disturbing marsh birds during their nest-

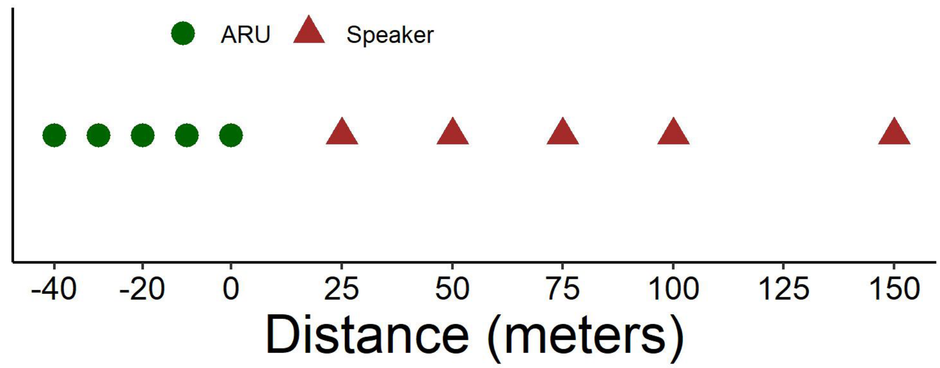

FIGURE 1 Diagram of automated recording unit (ARU) and speaker setup for trials.

ing season with broadcasted calls. We conducted all trials on a single sunny summer afternoon with light winds (≤20 km/h), high summer humidity (>70%), and temperatures in the high 20s C. We chose to test the ability of ARUs to detect three focal species of marsh birds that are common in the area. Clapper Rails and Seaside Sparrows were year-round residents and known to vocalize year-round. Least Bitterns were primarily present in winter.

We downloaded single calls for all three species from the Xeno-canto database of bird songs (https://xeno-canto.org/). Unfortunately, we did not record which specific calls we downloaded so we are unable to cite those recordings. The audio editing program Audacity was used to combine and mix different vocalizations of the same species into different chorus sizes (Audacity Team 2019). These were done in combinations of 1, 2, 3, 5, or 10 individual birds calling intermittently. The larger choruses were created from combinations of the same recording multiple times and different recordings combined together. Each completed audio file was one minute long. We used one Bluetooth speaker to act as our artificial bird and played recordings from set interval distances (25, 50, 75, 100, and 150 m) from our ARUs (Figure 1). The speaker had a broadcast rate of 100 dB at 1 m. We set Song Meter SM4 (Wildlife Acoustics, Inc., Maynard, Massachusetts, USA) autonomous recording units to continuously record each broadcasted chorus. We used a total of five ARUs, placed 10

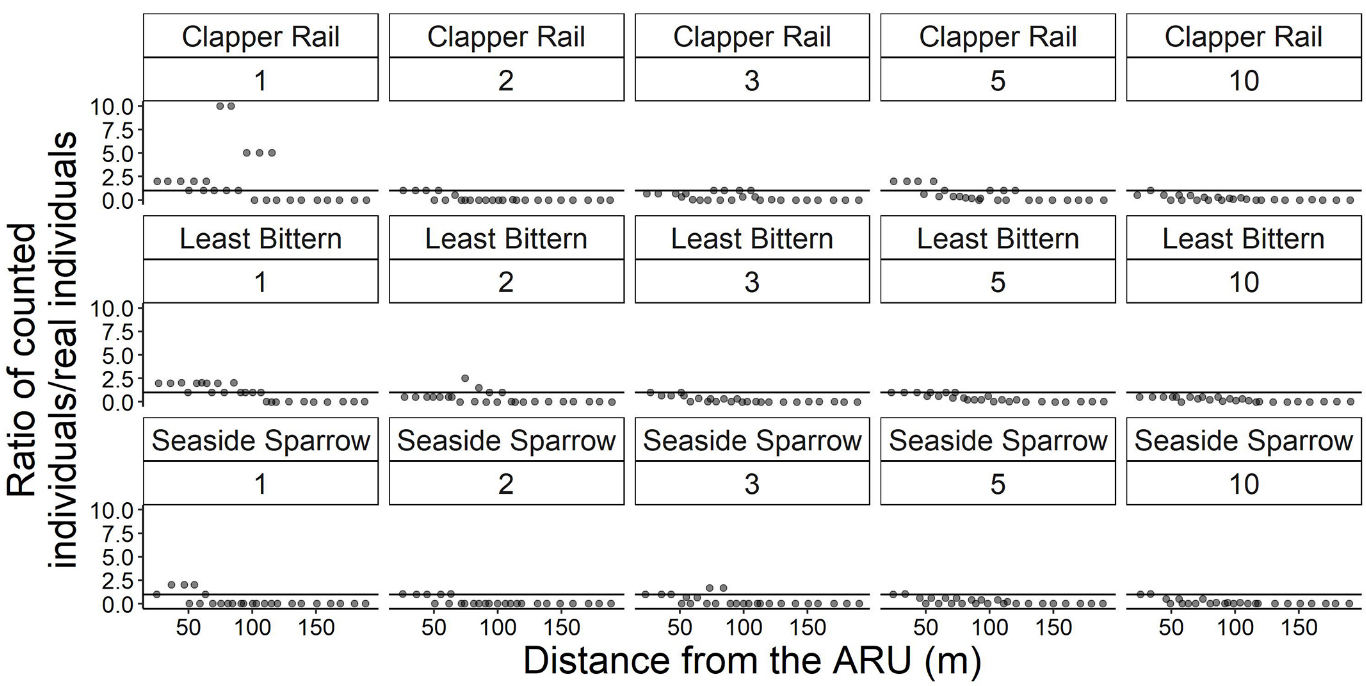

FIGURE 2 Ratio of counted individuals versus real individuals. Points above the horizontal line are overcounts, points below the horizontal line are undercounts..

m apart in a vertical line. At each distance, we played each combination of individual birds for one minute. This resulted in 25 trials for each possible chorus size, leading to a total of 375 trials for all three target species. Individual trials were assigned a random number, which was read aloud near the ARU prior to the trial, so that recordings could be identified independent of their true number of individuals. All trials were completed in the same afternoon in the same weather conditions.

Sonograms

We manually split ARU recordings among individual trials. Each trial's file was loaded into Cornell's Raven: Interactive Sound Analysis Software (Bioacoustics Research Program 2014), and the sonogram image and sound were analyzed by one observer who was familiar with the focal species calls but had no prior knowledge of the actual chorus size or distances of each file because of each file's random number identifier. The observer estimated the number of individuals of each species on the recording using the audio recording and sonogram image.

Counting accuracy

We graphically examined count bias over distance by calculating the ratio of estimated birds versus true number of birds in each recording (a ratio of 1 = unbiased estimate, a ratio <1 = underbiased, a ratio >1 = overbiased) at each distance away from the ARU. We tested for a difference in estimate bias with chorus size using a linear model with a binary response variable (correct or not) and a continuous predictor (real chorus size).

Detection of calls and songs

We examined changes in ability to detect songs and calls over distance from the ARU separately for each species. We counted a species as detected in a recording when at least one individual could be clearly heard, or its call seen on the sonogram, regardless of chorus size. A trial received a score of "no detection" when there was outside noise interference or no individuals could clearly be detected. We evaluated changes in ability to detect calls and songs among distances from the ARUs using a logistic regression with linear, quadratic, and cubic functions on the impact of distance on detection. We compared the linear, quadratic, and cubic models for each species using AIC (Burnham and Anderson 2002). We considered all models with delta AIC < 2 as probable, and among the probable models chose the simplest one (linear chosen over quadratic, chosen over cubic). We used R v.4.0.5 to perform our statistical analysis (R Core Team 2021).

Results

Counting accuracy

For each species, most counts were incorrect (Clapper Rail 107 of 125, Least Bittern 108 of 125, Seaside Sparrow 111 of 125; Figure 2), with most incorrect counts being undercounts (i.e., counting fewer individuals then were broadcast; Figure 2). For Clapper Rail and Least Bittern, count accuracy suddenly decreased between 100 and 125 m from the ARU, but ability to detect Seaside Sparrow calls and songs decreased closer to the ARU (between 50 and 100 m; Figure 2). Count accuracy also decreased with increasing chorus size (Beta = −0.01, SE = 0.005, P = 0.011).

Detection of calls and songs

A decrease in ability to detect calls and songs as distance increased between the ARU and speaker was best described by a linear model for Clapper Rail and Seaside Sparrow and a cubic model for Least Bittern (Table 1, Figure 3). For Clapper Rail, ability to detect calls and songs decreased from 0.42 (SE 0.06) at 25 m to 0.18 (SE 0.02) at 75 m. Least Bittern detection probability decreased from 0.32 (SE 0.04) at 75 m to 0.23 (SE

TABLE 1 AIC tables for species-specific models of detection over distance from the ARU (automated recording unit).

Species	Model	AIC	Delta AIC
Clapper Rail	Cubic	281.1	0
Clapper Rail	Quadratic	283.2	2.1
Clapper Rail	Linear	286.8	5.7
Least Bittern	Cubic	309.7	0
Least Bittern	Quadratic	312.5	2.8
Leat Bittern	Linear	324.4	14.7
Seaside Sparrow	Linear	200.2	0
Seaside Sparrow	Quadratic	201.3	1.1
Seaside Sparrow	Cubic	202.4	2.2

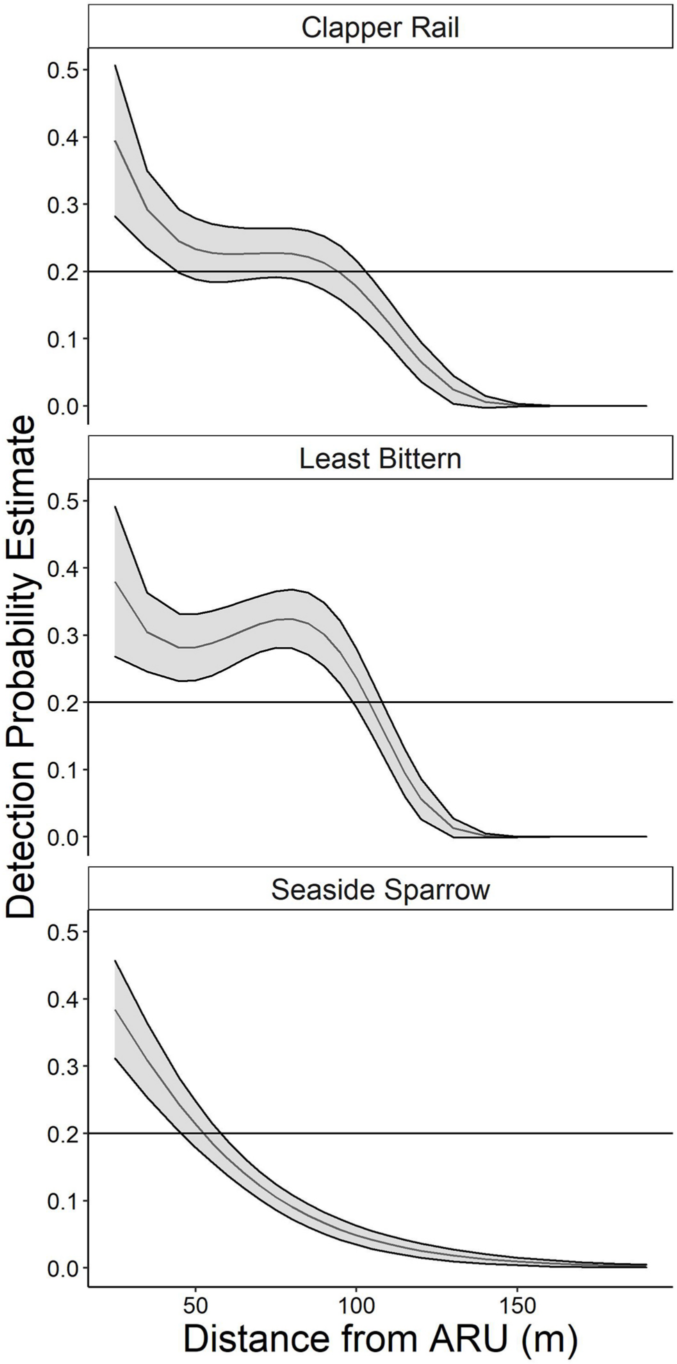

FIGURE 3 Predicted detection probabilities and their 95% confidence intervals from the best model for each species over distance from ARU (automated recording unit).

0.04) at 100 m. Ability to detect Seaside Sparrow calls and songs decreased from 0.38 (SE 0.07) at 25 m to 0.21 (SE 0.03) at 50 m.

Discussion

Our results showed that using ARUs to determine our ability to detect calls and songs can lead to variable results among call distances from the ARU and bird chorus sizes. However, ARUs still have potential to standardize marsh bird sampling with respect to presence/absence data. Effective sampling radii remain questionable and can vary by species. Hence, more research on effective sampling radii among species and surrounding ARUs is merited. For example, to avoid scenarios where our ability to detect calls and songs is below 20%, species-specific distance cutoffs of 50 m for Seaside Sparrows, 75 m for Clapper Rails, and 100 m for Least Bitterns should be considered based on this study (Figure 3). However, all sound recordings were based on straight-line distances from the omnidirectional microphone. Alternative sound angles may cause deviations in song detection and impact effective sampling distances.

Audio recordings have the benefit of being stored and played repeatedly. Unlike point count surveys, second opinions on a species identification can be gathered from other listeners and the observer effect more accurately quantified. In contrast, double observer methods still rely on each observer's ability to detect and identify calls in real time. Using multiple observers and observation methods can increase accurate detection of calls and decrease bias (Drake et al. 2016). Drake et al. (2016) used multiple observers and sampling methods to obtain Yellow Rail counts from sonograms and found that the average counts from observers were correct 83% of the time when detecting chorus sizes of 1–6 birds. Counting errors increased as the chorus sized increased, similar to our results. Due to project constraints, we had a single observer identifying individual birds. However, future research could expand upon our process by adding multiple observers to account for variation in counting accuracies and observer biases.

Data collected solely from ARUs will not be sufficient for answering all questions regarding marsh bird occupancy and abundances. However, ARU data can supplement other survey techniques. In addition to providing a digital, archivable recording for comparison among observers, point count sound files can be accessed many years after recording to assess long-term monitoring trends. Furthermore, recordings can be used to improve deep learning algorithms for automating and standardizing point count assessments similar to computer vision approaches for camera trapping or aerial image repositories (see Christin et al. 2019 for an overview) and for bioacoustic bird species classification (Salamon et al. 2017). Recordings may also contain information about other environmental processes, such as calls from bats, frogs, and insects, which could be of value to future studies and provide baseline information for unanticipated questions. Recorded traffic noise can be used as an index of site development as well. Furthermore, a long-term, historical audio data set based on repeated visits would provide valuable insights about temporal site changes including occupancy shifts among species of interest.

For the purpose of this study, we were unable to look at outside factors that could affect the reliability of audio recordings. Wind was present in all recordings, and in some cases the noise interference made it impossible to hear or see any vocalizations on the sonogram images. We suggest that future studies should look more into the effects of various wind speeds on ARU detection. Other natural and artificial made sounds, such as nontarget bird species and distant automobiles, also appeared on the sonogram images. In some cases, these outside noises were significantly louder than the marsh bird vocalizations and impeded their detection on the sonograms, making it impossible to count individual birds. During unfavorable conditions, sampling efforts may be removed from the dataset, similar to researchers not conducting point count surveys during high wind or excessive noise (Robbins et al. 1986; Ralph et al. 1995).

Some other potential concerns about using ARUs are the costs of the recording equipment, the possibility of device failure, and the processing time of audio data (Alquezar and Machado 2015; Colbert et al. 2015). Turgeon et al. (2017) assessed the variability in ARU microphones and the effects of microphone degradation over time and recommended that microphones should be tested and replaced when sensitivity loss was apparent. Audio recognition software has been developed for some species, but studies have found that automated methods can be inaccurate when compared to field identification of vocalizations by experienced observers (Hutto and Stutzman 2009). Device failure in the field should also be considered when assessing trade-offs among methods. While the use of ARUs can reduce the amount of field personnel hours, there is still considerable personnel time needed to review and process the audio files by hand, making the development of accurate automated methods to process audio files vital to using ARUs at large scales.

Recently, there has been an increase in the availability of automatic recognition programs for various bird species. Many have been programmed to detect only a specific species of interest, such as the Black Rail or Least Bittern (Bobay et al. 2018; Znidersic et al. 2020). These programs have become necessary for the massive amounts of data produced by ARUs and associated time investment for observers to manually sort through and evaluate recording data (Venier et al. 2012). A study compared the differences between human listeners and machines when detecting nocturnal forest birds in New Zealand and found similar listening ability but higher detection probability for automatic machine detectors (Castro et al. 2018). In contrast, Bobay et al. (2018) found that most detections from automatic machine recorders were false positives when targeting secretive marsh bird species. However, these recognition devices have recently been used successfully for detecting Least Bitterns (Znidersic et al. 2020). With the rise of new technology and improvements being made to existing automatic recognition software, using ARUs with automatic recognition programs could be used to supplement traditional point count and playback survey methods for surveying secretive marsh birds and increase their overall detection probability.

Our project adds to a growing body of literature on the utility and interpretation of automated recording units for the study of secretive marsh birds. We have shown that effective survey distances vary by species and that accurately counting individuals can be quite challenging in large chorus situations. With the increasing use of audio recognition software and ever-improving technology, automated recording units could be a useful tool for management of secretive marsh birds. Secretive marsh birds present a wide variety of monitoring and management challenges. Careful combination and analysis of automated recordings alongside point count and playback surveys can meet these challenges and help contribute to marsh bird conservation.

Acknowledgments

We would like the thank Mississippi State University's College of Forest Resources' Undergraduate Research Scholars Program and the Mississippi Department of Environmental Quality for sponsoring this research. This publication is a contribution of the Forest Wildlife Research Center, Mississippi State University, and the Mississippi Agricultural and Forestry Experiment Station and Coastal Research and Extension Center.

Literature Cited

Alquezar, R. D., and R. B. Machado. 2015. Comparisons between autonomous acoustic recording units and avian point counts in open woodland savanna. Wilson Journal of Ornithology 127:712–723.

Audacity Team. 2019. Audacity: Free audio editor and recorder [Computer application]. Version 2.3.1.

Bioacoustics Research Program. 2014. Raven Pro: Interactive Sound Analysis Software (Version 1.5) [Computer software]. Cornell Lab of Ornithology, Ithaca, NY, USA. Available from http://www.birds.cornell.edu/raven.

Bobay, L., P. Taillie, and C. Moorman. 2018. Use of autonomous recording units increased detection of a secretive marsh bird. Journal of Field Ornithology 89:384–392.

Burnham, K. P., and D. R. Anderson. 2002. Model selection and multimodel inference: a practical information-theoretic approach. Second edition. Springer-Verlag, New York, NY, USA.

Castro I., A. De Rosa, N. Priyadarshani, L. Bradbury, and S. Marsland. 2018. Experimental test of birdcall detection by autonomous recorder units and by human observers using broadcast. Ecology and Evolution 9:2376–2397.

Christin, S., E. Hervert, and N. Lecomte. 2019. Applications for deep learning in ecology. Methods in Ecology and Evolution 10:1632–1644.

Colbert, D. S., J. A. Ruttinger, M. Streich, M. Chamberlain, L. M. Conner, and R. J. Warren. 2015. Application of autonomous recording units to monitor gobbling activity by Wild Turkey. Wildlife Society Bulletin 39:757–763.

Conway, C. J. 2011. Standardized North American marsh bird monitoring protocol. Waterbirds 34:319–346.

Drake, K. L., M. Frey, D. Hogan, and R. Hedley. 2016. Using digital recordings and sonogram analysis to obtain counts of Yellow Rails. Wildlife Society Bulletin 40:346–354.

Frommolt, K., and K. Tauchert. 2013. Applying bioacoustic methods for long-term monitoring of a nocturnal wetland

bird. Ecological Informatics 21:4–12.
Furnas, B. J., and R. L. Callas. 2015. Using automated recorders and occupancy models to monitor common forest birds across a large geographic region. Journal of Wildlife Management 79:325–337.
Haselmayer, J., and J. Quinn. 2000. A comparison of point counts and sound recording as bird survey methods in Amazonian Southeast Peru. Condor 102:877–893.
Holmes, S. B., K. A. Mcilwrick, and L. A. Venier. 2014. Using automated sound recording and analysis to detect bird species-at-risk in southwestern Ontario woodlands. Wildlife Society Bulletin 38:591–598.
Hutto, R. L., and R. J. Stutzman. 2009. Humans versus autonomous recording units: a comparison of point-count results. Journal of Field Ornithology 80:387–398.
Lehnert, E. R. 2019. Conservation status and threats of Rallidae: a global assessment. Thesis, University of Central Oklahoma, Edmund, OK, USA.
Lévêque, L., J. C. Buettel, S. Carver, and B. W. Brook. 2021. Characterising the spatio-temporal threats, conservation hotspots, and conservation gaps for the most extinction-prone bird family (Aves: Rallidae). Royal Society Open Science 8:210262.
Nadeau, C. P., C. J. Conway, B. S. Smith, and T. E. Lewis. 2008. Maximizing detection probability of wetland-dependent birds during point-count surveys in northwestern Florida. Wilson Journal of Ornithology 120:513–518.
Pérez-Granados, C., D. Bustillo-de la Rosa, J. Gómez-Catasús, A. Barrero, I. Abril-Colón, and J. Traba. 2018. Autonomous recording units as effective tools for monitoring rare and patchily distributed Dupont’s Lark *Chersophilus duponti*. Ardea 106:139–146.
Ralph, C., S. Droege, and J. Sauer. 1995. Managing and monitoring birds using point counts: standards and applications. USDA Forest Service General Technical Report PSW-GTR-149:161–168.
R Core Team. R: a language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. Available at http://www.r-project.org/.
Robbins, C. S., D. Bystrak, and P. H. Geissler. 1986. The Breeding Bird Survey: its first fifteen years, 1965-1979. U.S. Fish and Wildlife Service, Washington, D.C., USA.
Salamon, J., J. P. Bello, A. Farnsworth, and S. Kelling. 2017. Fusing shallow and deep learning for bioacoustic bird species classification. IEEE International Conference on Acoustics, Speech and Signal Processing 2017:141–145.
Schroeder, K., and S. McRae. 2020. Automated auditory detection of a rare, secretive marsh bird with infrequent and acoustically indistinct vocalizations. Ibis 162:1033–1046.
Sidie-Slettedahl, A. M., K. C. Jensen, R. R. Johnson, T. W. Arnold, J. E. Austin, and J. D. Stafford. 2015. Evaluation of autonomous recording units for detecting 3 species of secretive marsh birds. Wildlife Society Bulletin 39:626–634.
Stiffler, L. L., J. T. Anderson, and T. E. Katzner. 2018. Occupancy modeling of autonomously recorded vocalizations to predict distribution of rallids in tidal wetlands. Wetlands 2018:605–612.
Tegeler, A. K., M. L. Morrison, and J. M. Szewczak. 2012. Using extended-duration audio recordings to survey avian species. Wildlife Society Bulletin 36:21–29.
Thompson, S. J., C. M. Handel, and L. B. Mcnew. 2017. Autonomous acoustic recorders reveal complex patterns in avian detection probability. Journal of Wildlife Management 81:1228–1241.
Turgeon, P. J., S. L. Wilgenburg, and K. L. Drake. 2017. Microphone variability and degradation: implications for monitoring programs employing autonomous recording units. Avian Conservation and Ecology 12:9.
Venier, L. A., S. B. Holmes, G. W. Holborn, K. A. Mcilwrick, and G. Brown. 2012. Evaluation of an automated recording device for monitoring forest birds. Wildlife Society Bulletin 36:30–39.
Znidersic, E., M. Towsey, W. K. Roy, S. E. Darling, A. Truskinger, P. Roe, and D. M. Watson. 2020. Using visualization and machine learning methods to monitor low detectability species—the Least Bittern as a case study. Ecological Informatics 55:101014.

SUPPLEMENTAL TABLE 1 Predicted detection probabilities for species and distance from the automated recording unit.

Species	Distance	Beta	SE
Clapper Rail	25	0.42	0.06
Clapper Rail	50	0.28	0.03
Clapper Rail	75	0.18	0.02
Clapper Rail	100	0.11	0.01
Clapper Rail	125	0.06	0.01
Clapper Rail	150	0.03	0.01
Clapper Rail	175	0.02	0.01
Clapper Rail	190	0.01	0.008
Least Bittern	25	0.37	0.11
Least Bittern	50	0.28	0.04
Least Bittern	75	0.32	0.04
Least Bittern	100	0.23	0.04
Least Bittern	125	0.02	0.02
Least Bittern	150	0.0001	0.0003
Least Bittern	175	<0.0001	<0.001
Least Bittern	190	<0.0011	<0.001
Seaside Sparrow	25	0.38	0.07
Seaside Sparrow	50	0.21	0.03
Seaside Sparrow	75	0.10	0.01
Seaside Sparrow	100	0.04	0.01
Seaside Sparrow	125	0.02	0.009
Seaside Sparrow	150	0.009	0.005
Seaside Sparrow	175	0.004	0.003
Seaside Sparrow	190	0.002	0.002