Variation in Detection Distance of Eastern Black Rail (*Laterallus jamaicensis jamaicensis*) Vocalizations by Autonomous Recording Units

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Abstract.—Autonomous recording units (ARUs) are an emerging technology that allows for passive monitoring of soniferous animals and soundscapes. Over the past decade, ARUs have become a popular tool for monitoring birds for their potential to reduce the labor and costs of traditional in-person sampling procedures. However, uncertainty surrounding factors affecting detection of avian taxa using ARUs can inhibit their monitoring efficacy. Eastern Black Rails (*Laterallus jamaicensis jamaicensis*) are a secretive marsh bird listed as a federally threatened species in the U.S.A. Eastern Black Rail vocalizations are difficult to detect by field personnel, and numerous in-person surveys can be required to confirm their presence at a site. While ARUs are an alternative for detecting Eastern Black Rails, it is unknown at what maximum distance an ARU can detect their vocalizations. We evaluated factors affecting the detection distance of simulated vocalizations for ARUs in four marsh vegetation types under a range of environmental conditions. Detection distances varied across models, vocalization and vegetation types, and call volume. *Kickeedo* vocalizations were detected at greater distances, and detection distances increased for all vocalization types in open vegetation. High relative humidity increased detection distances, while louder background noise decreased detection distances. High wind speeds in cordgrass (*Spartina spp.*) decreased detection probability disproportionately relative to other vegetation types. Based on these results, considerations of survey area, vegetation type, and site condition can allow land managers and researchers to optimize Eastern Black Rail monitoring using ARUs. Given the substantial staff time needed to monitor this species, ARUs may increase the likelihood of detection and provide an efficient alternative to in-person monitoring. *Received 28 Apr 2025, accepted 9 Sept 2025.*

Key words.—Autonomous recording units, call-broadcast simulation, detection distance, Eastern Black Rail, *Laterallus jamaicensis jamaicensis*, salt marsh, secretive marsh birds, avian monitoring, detection probability, conservation.

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The development of autonomous recording units (ARUs) and other passive monitoring technologies offers an alternative or supplemental approach to overcome the expense and logistical challenges of traditional in-person wildlife monitoring. This technology has rapidly become a popular tool for studying animals and soundscapes (Farina 2019). As a result, interest in better understanding the effective use of ARUs for monitoring animals that generate sounds has also increased (Klingbeil and Willig 2015; Drake *et al.* 2016; Bobay *et al.* 2018), especially for species that are difficult to detect (Bobay *et al.* 2018; Schroeder and McRae 2020).

Recent studies have illustrated the advantages of ARUs and identified knowledge gaps in areas related to their effective deployment. Compared to traditional in-person methods, benefits of ARUs include the ability for long, uninterrupted field deployments (Ciira 2016; Stowell and Sueur 2020), the ability to fine-tune recording time windows to match the varied activity patterns that different species exhibit, and prolonged use in remote locations (Roark and Gaul 2021). These features provide the possibility of extended sampling bouts (Celis-Murillo *et al.* 2009) and increased detection probability of target species (Bobay *et al.* 2018; Taillie and Moorman 2019). Cost-effective ways to implement monitoring programs for biologists may be provided by ARUs as they reduce the amount and duration of in-person surveys (Hill *et al.* 2018; Darras *et al.* 2019). Recordings can also be reviewed via automated call recognition software (Kogan and Margoliash 1998; Wolfgang and Haines 2016), reducing the effort needed for manual review of recordings, furthering the potential for cost savings and increased efficiency.

Despite these benefits, ARUs also have limitations because they only detect auditory signals (Klingbeil and Willig 2015); thus, their detection capability is limited to species that vocalize or make otherwise distinguishable sounds. Vocalizations within ARU recordings may be masked by environmental conditions (e.g., wind, rain, anthropogenic noise, etc.), whereas field technicians are able to use a suite of sensory information to detect animals. Relative abundance and density also cannot yet be reliably estimated from sound recordings alone (Klingbeil and Willig 2015; Shonfield and Bayne 2017), limiting the use of ARUs to determining presence or occupancy only. Additionally, ARUs rapidly generate large datasets. While automated detection software reduces user effort, some level of effort is still needed to address potentially high rates of misclassifications that are either false positives (Waddle et al. 2009; Sidie-Slettedahl *et al.* 2015; Johnson *et al.* 2023) or false negatives (Zwart *et al.* 2014). ARUs are further constrained by having limited battery life when solar panels are not used, and limited data storage (Alldredge *et al.* 2007a; Stiffler 2017). Units are also subject to substantial data loss from failed units and theft (Hutto and Stutzman 2009). Because of the relatively recent application of ARUs in monitoring avian species, there are still considerable limitations and knowledge gaps in their performance compared to traditional in-person survey methods (Hutto and Stutzman 2009; Shonfield and Bayne 2017; Darras *et al.* 2018).

Studies have reported varying results on detection distances and detection rates of wildlife vocalizations by ARUs due to differences in target species, habitat characteristics, and ARU and microphone models (Drake *et al.* 2016; Stiffler 2017; Yip *et al.* 2017). For example, some species vocalize louder than others; thus, certain species can be detected by ARUs at farther distances (Holiman *et al.* 2022), and the maximum distance at which an individual can be detected may change depending on factors such as vegetation density and equipment quality. To integrate these technologies into monitoring programs, researchers will need to understand how ARU models perform in specific ecosystems, under a variety of environmental conditions for their target species.

The Eastern Black Rail (*Laterallus jamaicensis jamaicensis*) is a small secretive marsh bird that inhabits high marsh, as well as estuarine and palustrine emergent wetlands and adjacent uplands, along the Atlantic Coast, Gulf Coast of the southern United States (hereafter, Gulf Coast), and a few interior locations between the eastern slopes of the Rocky Mountains and these coastal areas (Watts 2016). Due to range-wide declines and local extirpation caused by habitat loss and alteration, Eastern Black Rails are listed as threatened in the United States under the Endangered Species Act (U.S. Fish and Wildlife Service 2020). Eastern Black Rails are difficult to detect because they vocalize infrequently, mainly during crepuscular hours, rarely fly, and inhabit densely vegetated and remote wetlands that can be difficult for field personnel to access. Due to their low detection rates, point count survey protocols for Eastern Black Rails require many repeat visits (3–15 times; Conway 2011; Smith *et al.* 2018; Tolliver *et al.* 2019). Previous work has successfully used ARUs to detect Eastern Black

Rails (Bobay *et al.* 2018). The behavioral traits and habitats of the Eastern Black Rail make it an ideal species for surveys using ARUs because ARUs can minimize the time spent conducting in-person surveys at a sampling location, allow sampling of multiple locations simultaneously, and allow field staff to prioritize additional data needs (e.g., vegetation, topographic, or forage food base surveys), as they relate to Eastern Black Rails.

The objectives of this study were to: (1) evaluate the capabilities of ARUs in their detection of simulated Eastern Black Rail vocalizations across a range of distances, vegetation types, and environmental conditions and (2) provide guidance for biologists considering using ARUs to monitor Eastern Black Rails. We simulated vocalizations using a call-broadcast speaker to investigate the potential effects of distance, sampling equipment, vocalization characteristics, vegetation, and environmental conditions on the detection of Eastern Black Rails using ARUs. Our results may support deployment planning and research by providing information to help practitioners increase the likelihood of detecting Eastern Black Rails. Additionally, these results can increase our understanding of the amount of space effectively surveyed by an ARU under a specific set of circumstances, which may be useful for developing guidelines to minimize the survey effort required to establish Eastern Black Rail presence.

Methods

Study Sites

Study sites were located along the Gulf Coast on St. Marks National Wildlife Refuge (SMNWR), Florida (30.14°, −84.14°), Grand Bay National Estuarine Research Reserve (GBNERR), Mississippi (30.33°, −88.47°), Singing River Island marsh complex (SRI), Mississippi (30.36°, −88.53°), Brazoria National Wildlife Refuge (BNWR), Texas (29.02°, −95.29°), and San Bernard National Wildlife Refuge (SBNWR), Texas (28.88°, −95.58°). To minimize potential disturbance to nesting Eastern Black Rails, we collected data in November 2022 and March 2023, which does not overlap with the breeding season. Sampling was conducted between the hours of 0800–1700 central standard time (CST). Elevation at all sites was between sea level and 1 m.

Sound Library

We conducted detection trials (i.e., independent sets of samples across the full range of distances) by broadcasting a sequence of recordings of three different Eastern Black Rail vocalization types using FoxPro NX4 wildlife call-broadcast speakers (FOXPRO Inc., Lewistown, Pennsylvania, U.S.A.). The call-broadcast sequence consisted of the *kickeedo* (KKR) vocalization type, followed by the *churt* (CHR) vocalization type, and the *growl* (GRR) vocalization type. Since we are not aware of any studies investigating the sound pressure levels in Eastern Black Rails, we first broadcast vocalizations at a low sound pressure level (45 dBA) and then at a high sound pressure level (90 dBA). Sound pressure level settings were calibrated at 1 m using Meterk, Risepro, and XRClif sound level meters. Call types were selected because these are the most frequently detected calls for this species during marsh bird surveys along the northern Gulf Coast (J.K. Wilson, U.S. Fish and Wildlife Service, written commun., 2019). We selected the high call volume level based on the recommended sound pressure level in the Standardized North American Marsh Bird Monitoring Protocol (Conway 2011) and halved this level to establish the low call decibel level.

Call broadcast recordings of Eastern Black Rail vocalizations were downloaded from the Florida Museum (KKR; floridamuseum.ufl.edu/wp content/uploads/sites/52/2017/04/hardy12sh.mp3), Macaulay Library (GGR; https://macaulaylibrary.org/asset/22615671), and Xeno-canto (CHR; https://xeno-canto.org/783430) audio-file databases and were normalized to -23 LUFS (loudness units relative to full scale) and a peak amplitude of zero using the recording software Audacity version 3.0.4 (https://www.audacityteam.org/). Each vocalization in the broadcast sequence began with 5 seconds of silence to allow the observer standing by the ARUs to announce the vocalization type, distance, start and stop times, and decibel setting, after which the vocalization was broadcast continuously for 25 seconds.

Field Sampling

The sequence of recordings was broadcast at 25 m intervals along a 500 m transect with the speaker placed at ground level, to mimic the calling behavior of an Eastern Black Rail. The unit was placed on a wooden platform roughly the same dimensions as the base of the broadcast speaker to protect the unit from moisture, and oriented toward the stationary ARU array. High volume calls were broadcast from a maximum distance of 500 m and low volume calls were broadcast from a maximum distance of 250 m because they were not detected past 150 m during preliminary trials. We sampled three transects at SBNWR and one transect at BNWR in Texas, four transects at GBNERR and three transects at SRI in Mississippi, and seven transects at SMNWR in Florida. In Texas, where overwintering Eastern Black Rail density is higher, individuals responded infrequently to call broadcasts, and their locations and time of vocalization were recorded to avoid false positive detections of simulated calls. No Eastern Black Rails responded to call broadcasts in Mississippi or Florida.

We evaluated detection probability between three models of Wildlife Acoustics (Wildlife Acoustics, Inc. Maynard, Massachusetts, U.S.A.) SongMeter (SM) ARUs: (1) SM2 + GPS-enabled ARU equipped with SMX-II weatherproof microphones; (2) SM3 ARU; and (3) SM4 ARU. Factory microphones were used for all SM3 and SM4 units. The ARUs were set for 2-channel stereo recordings at a sampling rate of 24 kHz and 16-bit waveform audio file (wav) format. Our sampling array consisted of six ARUs including two units of each model for every detection trial (Fig. 1). One ARU of each model was equipped with YOUSHARES Furry Outdoor Windscreen Muffs to determine if the reduction of wind interference affected detection probability (Blake-Bradshaw *et al.* 2023). The order of the ARU models and wind mufflers in each array was standardized (Fig. 1) and spacing between units was ~0.5 m.

For each detection trial, we attached the six ARUs to t-posts using zip ties, which allowed us to orient the microphones perpendicular to the ground at a height of 120 cm (Fig.1). During trials, one observer remained near the ARUs while the other observer walked the 500 m transect. For each 25 m distance interval, the stationary observer recorded the distance, start and end time of each broadcast, wind direction, and background noise level. The stationary observer also recorded temperature (°C), percent relative humidity, and average wind speed (km/hr) for each sampling distance using a Kestrel 3000 portable weather station (Kestrel Instruments, Boothwyn, Pennsylvania, U.S.A.). Wind direction was recorded as a categorical variable based on the direction of the wind relative to the call-broadcast speaker: no wind, with wind (i.e., parallel winds from sound source to ARU arrays), against wind (i.e., parallel winds from ARU arrays to sound source), and perpendicular wind (i.e., winds angled 45–90° between ARU arrays and sound source). Following Conway (2011), background noise was quantified using a 0–4 scale: 0 = no noise, 1 = faint noise, 2 = moderate noise (observer unlikely to hear a bird calling beyond 100 m for > 30 seconds of a survey), 3 = loud noise (observer unlikely to hear a bird calling beyond 50m for > 30 seconds of a survey), and 4 = intense noise (observer unlikely to hear a bird calling beyond 25m for > 30 seconds of a survey). These metrics were recorded by the same observer at each distance to limit inter-observer differences in the data.

Figure 1. An example of an ARU distance sampling array. ARU units pictured from left to right are the SM2 (without wind mufflers), SM3 (with wind mufflers), SM4 (without wind mufflers), SM2 (with wind mufflers), SM3 (without wind mufflers), and SM4 (with wind mufflers).

Detection trials were conducted in four distinct marsh vegetation types (i.e., cordgrass-dominated, needlegrass rush-dominated, mixed woody & herbaceous, and salt panne) known to be used by Eastern Black Rails during the breeding season along the Gulf Coast. In cordgrass sites, the primary plant species included salt meadow cordgrass (*Spartina patens*), gulf cordgrass (*S. spartinae*), sand cordgrass (*S. bakeri*), or a combination of the three. Needlegrass rush sites were dominated by needlegrass rush (*Juncus roemerianus*). Salt panne sites consisted of patches of exposed soil interspersed with a mix of herbaceous species including saltgrass (*Distichlis spicata*), bushy seaside tansy (*Borrichia frutescens*), saltwort (*Batis maritima*), glasswort (*Salicornia* spp.), and other halophiles. Mixed woody & herbaceous sites consisted of a mix of woody shrubs (e.g., wax myrtle [*Morella cerifera*], Jesuit's bark [*Iva frutescens*], or *Baccharis* spp.) and cordgrass species listed above, such that woody vegetation comprised 35–50% of the vegetation cover.

To evaluate the influence of vegetation on detection probability, we performed five trials for most of the vegetation types and three trials in mixed woody & herbaceous vegetation (n = 18 trials). Transect locations were selected based on available vegetation types within our study sites. For a vegetation type to be sampled within a site, the site needed to contain a reasonably accessible 500 m contiguous plot of the specified vegetation type. In Florida, four trials were conducted in needlegrass rush and three were conducted in salt pannes. In Mississippi, two trials were conducted each in salt pannes, mixed woody & herbaceous, and cordgrass while one trial was conducted in needlegrass rush. In Texas, three trials were conducted in cordgrass and one was conducted in mixed woody & herbaceous.

Sound files from ARUs were uploaded to Windows Media Player (Microsoft Corporation, Inc. Redmond, Washington, U.S.A.) from secure digital (SD) cards in wav format and manually reviewed by a team of nine listeners consisting of field technicians and co-authors familiar with Eastern Black Rail vocalizations. Recordings were reviewed in a quiet room, using over-the-ear style headphones, to determine detections for each combination of ARU model, distance, vegetation type, and wind muffler status.

Statistical Analysis

We developed a series of binomial generalized linear mixed models (GLMMs; Table 1) to assess detections using the R package "glmmTMB" (Brooks *et al.* 2017). We explored single variable and multivariate models with a response variable of "yes (1)" if the vocalization was detected or "no (0)" if the vocalization was not detected.

Table 1. Top three candidate binomial generalized linear mixed models ordered by increasing corrected Akaike's Information Criterion. All models included a nested random effect of trial within site and a stand-alone random effect of listener. Variables included in our models were distance (D), ARU model (MDL), microphone wind muffler (MFL), vegetation type (VT), vocalization type (CT), call volume (CV), wind direction (WD), wind speed (WS), temperature (T), relative humidity (RH), and background noise (BN). All models had a cumulative weight value of one.

Model Name	Model Structure	K	AICc	Δ AICc	Model Likelihood	AICc Wt.	Log Likelihood
All Variables: Veg by Windspeed	D + CT + CV + WD + VT*WS + T + RH + BN + MDL + MFL	24	4181.1	0	1	1	−2066.5
All Variables: Wind Direction by Windspeed	D + CT + CV + VT + WD*WS + T + RH + BN + MDL + MFL	23	4210.9	29.83	3.34E−07	3.34E−07	−2082.4
All Variables	D + CT + CV + VT + WD + WS + T + RH + BN + MDL MFL	21	4215.1	33.99	4.17E−08	4.17E−08	−2086.5
Null	–	5	9392.8	5211.66	0	0	−4691.4

The candidate models were based on sets of variables considered to be biologically relevant (distance, vegetation type, vocalization type, and call volume), relating to sampling equipment (ARU model and wind mufflers), and environmental factors (temperature, relative humidity, wind speed, wind direction, and background noise). To account for pseudoreplication, we included a nested random effect of trial within site. Each candidate model also included a random effect of listener (individual reviewers; Roach and Barrett 2015). Correlations between numerical variables were assessed to account for potential collinearity, but no correlations were noted above our set threshold ($r > 0.5$). All analyses were performed using R v. 4.4.1 (R Core Team 2024) in R Studio v. 2024.12.0.467 (Posit Team 2024).

Models were ranked by comparing Akaike's Information Criterion corrected for small sample size (AIC_C; Burnham and Anderson 2002; Table 1). The model with the lowest AIC_C was used in the final analysis, but we also considered models within two Δ AIC_C to be competitive. Model fit was evaluated by simulating residuals using the "DHARMa" package (Hartig 2022) and examining QQ plots. Important factors were identified using an 85% confidence interval that did not overlap zero (Arnold 2010; Sutherland *et al.* 2023). Regression plots were generated using R packages "ggplot2" (Wickham 2016) and "sjPlot" (Lüdecke 2024).

Lastly, we determined the distances needed for a minimum detection probability of 50% (hereafter; 50% detection distance). We calculated the 50% detection distance for all combinations of ARU model, vegetation type, and vocalization type (Table 2). We generated predicted detection probabilities between our minimum and maximum sampling distances from the top model using the 'ggpredict' function from the package "ggeffects" (Lüdecke 2018).

Results

We conducted 18 detection trials representing 8,297 data points in marshes across Florida (n = 3,192), Mississippi (n = 3,089), and Texas (n = 2,016). Our top model for Eastern Black Rail detections was the full model with an interaction of wind speed and vegetation type (Table 1). There were no competing models within two Δ AIC_C of the top model (Table 1).

Detection probability reached 50% for the SM2 between 82.5–495 m, for the SM3 between 142.5–>500 m, and for the SM4 between 170–>500 m (Table 2). Setting the reference levels of categorical covariates to the SM2, cordgrass vegetation, KKR vocalization type, high call volume, 'against wind' wind direction, and no wind mufflers, detection probabilities reached 50% at 227.5 m for the SM3 (β = 1.04, SE = 0.1, 85% CIs: 0.89–1.19) and 257.5 m for the SM4 (β = 1.47, SE = 0.1, 85% CIs: 1.32–1.62; Fig. 2). Wind mufflers were not an important factor affecting detection probabilities (β = 0.11, SE = 0.08, 85% CIs: −0.00–0.23).

For vegetation types, vocalizations could be detected over greater distances in salt pannes. The probability of detecting a vocalization was higher in needlegrass rush (β = 3.1, SE = 1.67, 85% CIs: 0.7–5.51) and salt pannes (β = 5.24, SE = 1.68, 85% CIs: 2.82–7.66) than in cordgrass. However, at the maximum sampling distance, detection probability remained low at 0.1 in needlegrass rush and 0.45 in salt pannes (Fig. 3). There was no difference in detection probability between cordgrass and mixed woody & herbaceous

Table 2. Effective and average (AVG) sampling distances (m) across ARU models, vocalization types (*kickeedo* [KKR], *churt* [CHR], and *growl* [GRR]), and vegetation types. Reference levels of other categorical variables in our top model were set to high call volume, against wind, and no wind mufflers.

Unit	SM2				SM3				SM4			
Vocalization Type	GRR	CHR	KKR	Avg	GRR	CHR	KKR	Avg	GRR	CHR	KKR	Avg
Cordgrass	82.5	110	165	119.17	142.5	175	227.5	181.67	170	202.5	257.5	210.00
Mixed Woody & Herbaceous	95	122.5	177.5	131.67	162.5	190	242.5	198.33	187.5	215	270	224.17
Needlegrass Rush	277.5	305	360	314.17	342.5	372.5	420	378.33	365	397.5	452.5	405.00
Salt Panne	412.5	440	495	449.17	477.5	> 500	> 500	492.50	> 500	> 500	> 500	500.00
Avg	216.88	244.38	299.38	–	281.25	309.38	347.50	–	305.63	328.75	370.00	–

vegetation (β = 0.21, SE = 1.53, 85% CIs: −1.98–2.42).

Relative to KKR vocalizations, detection probabilities averaged lower for both the GRR (β = −1.31, SE = 0.1, 85% CIs: −1.46–−1.16) and CHR (β = −0.87, SE = 0.1, 85% CIs: −1.01−0.72) vocalization types and KKR vocalizations were detected over farther distances than CHR and GRR vocalizations (Fig. 4A). Additionally, ARUs were significantly less likely to detect quiet vocalizations relative to loud ones (β = −8.93, SE = 0.2, 85% CIs: −9.28–−8.59; Fig. 4B) and fewer than 10% of low volume vocalizations were detected.

Vocalizations were more likely to be detected when relative humidity was higher (β = 0.53, SE = 0.1, 85% CIs: 0.28–0.77), while vocalizations were less likely to be detected during periods of louder background noise (β = −0.35, SE = 0.06, 85% CIs: −0.44–−0.26). For wind direction, detection probabilities were reduced when wind direction was perpendicular between the speaker and ARU array (β = −0.97, SE = 0.20, 85% CIs: −1.30–−0.65) relative to when wind direction was parallel and blowing toward the sound source. While there was no main effect of wind speed, we found that higher wind speeds reduced detection probabilities in cordgrass vegetation (β = −0.33, SE = 0.20, 85% CIs: −0.65–−0.01; Fig. 5). Lastly, detection probabilities decreased with increased distance from the ARU (β = −2.32, SE = 0.07, 85% CIs: −2.43–−2.22). The intercept of the model was −1.58 (SE = 1.21) and the standard deviations of the random intercepts were 1.92 (Trial ID within Site; 85% CIs: 1.27–2.90), 1.45 (Site; 85% CIs: 0.65–3.23), and 0.45 (Listener; 85% CIs: 0.23–0.86).

50% Detection Distances

We considered each vocalization type within each vegetation type separately when comparing variation in 50% detection distances between ARU models. Across ARU models and vegetation types, 50% detection distances were shortest for the GRR vocalization type (82.5 – >500 m) and farthest for the KKR (165–>500 m; Table 2). Across ARU models and vocalization types, 50% detection distances were shortest for cordgrass vegetation (82.5–257.5 m) and farthest for salt pannes (412.5–>500 m; Table 2). Lastly, 50% detection distances of CHR and KKR vocalizations detected by SM3s and all vocalizations detected by SM4s exceeded the maximum sampling distance in salt panne vegetation (Table 2).

DISCUSSION

We investigated factors affecting detection of Eastern Black Rail vocalizations by ARUs in Gulf Coast marshes. Our main findings show that detection distance was farthest when detecting KKR vocalizations, and surveying salt panne vegetation. As in previous studies, results varied between ARU models, vocalization characteristics, and environmental conditions (Rempel *et al.* 2013; Pérez-Granados *et al.* 2019; Thomas *et al.* 2020; Haupert *et al.* 2023; Heath *et al.* 2024). Using our 50% detection distance results, end-users wanting to conduct some preliminary monitoring using ARUs could benefit from a maximum spacing of 170 m to maximize the probability that they detect the three Eastern Black Rail vocalization types across a variety of coastal vegetation

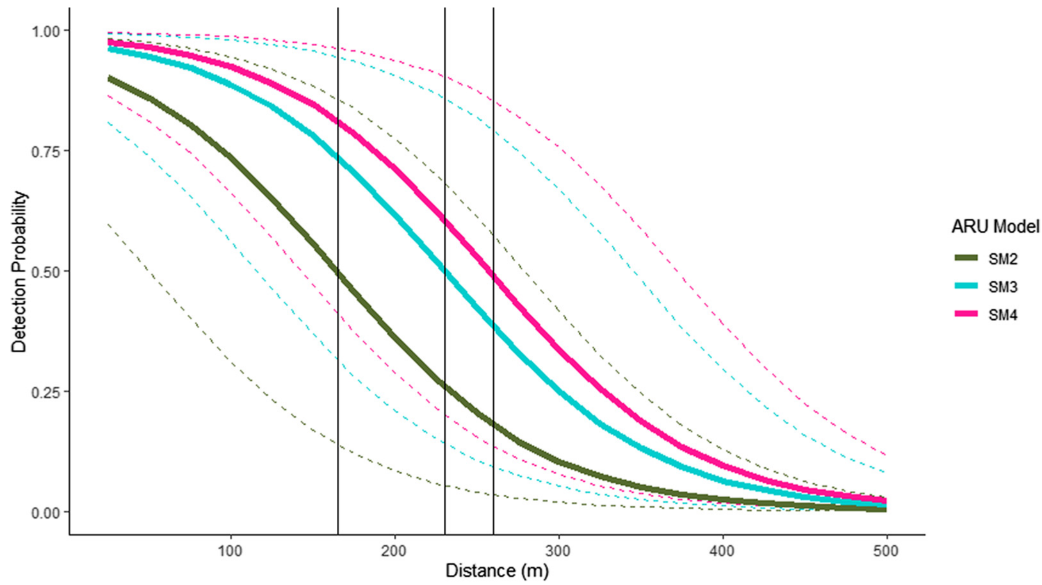

Figure 2. Detection probability slopes as a function of increasing distance for each ARU model. Reference levels in our model were set to cordgrass vegetation, KKR vocalization type, high call volume, 'against wind' wind direction, and no wind mufflers. Dotted lines represent 85% confidence intervals. Solid vertical lines mark the distance at which detection probability reaches 50% for each ARU model.

communities. If an end-user is interested in an area where the KKR vocalization type is commonly heard, the maximum spacing suggested by our results regardless of vegetation community is 250 m.

When considering ARUs for detecting Eastern Black Rails across large areas, vocalization distance is one criterion for evaluation (Thomas et al. 2020). However, monitoring needs may also depend on the size and

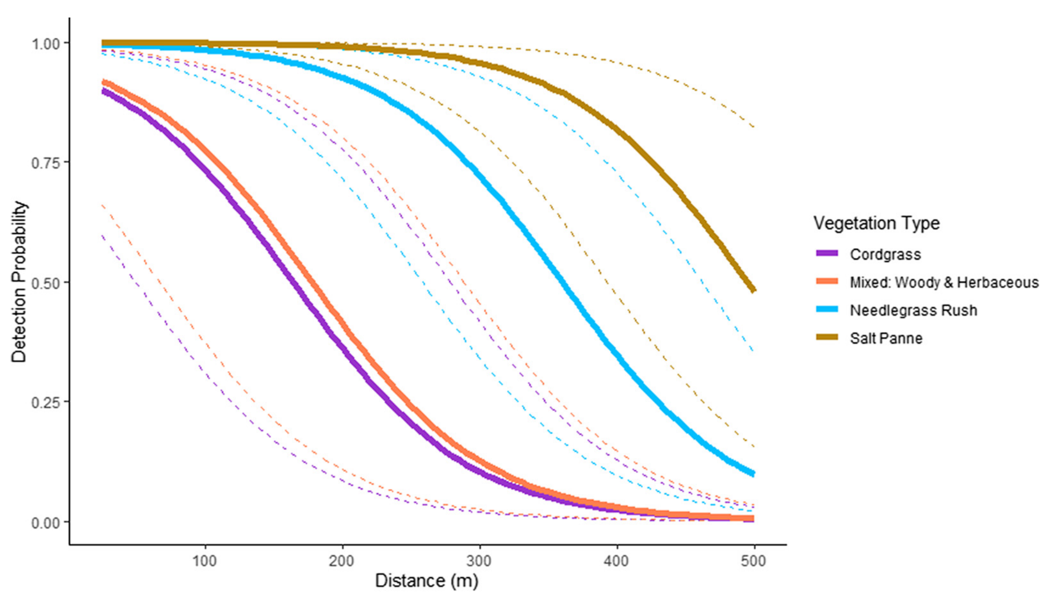

Figure 3. Detection probability slopes as a function of increasing distance for each vegetation type. Reference levels in our model were set to SM2 ARU model, KKR vocalization type, high call volume, 'against wind' wind direction, and no wind mufflers. Dotted lines represent 85% confidence intervals.

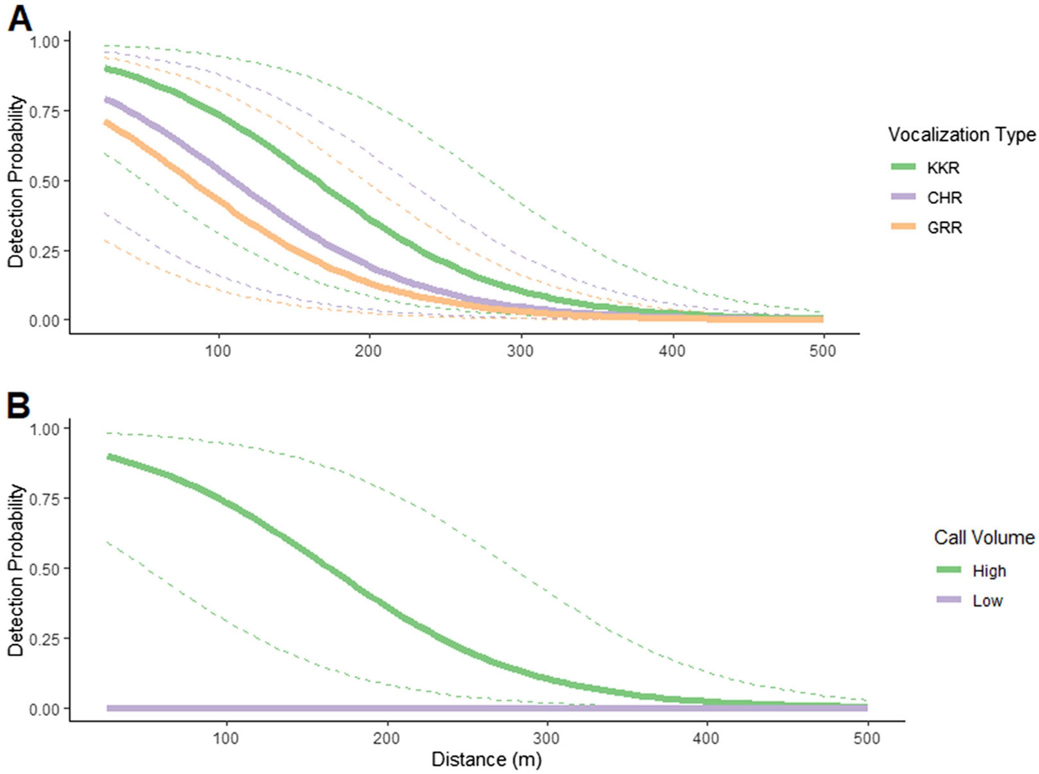

Figure 4. Detection probability slopes as a function of increasing distance for vocalization characteristics, vocalization type (A) and call volume (B). Reference levels in our model were set to SM2 ARU models, cordgrass vegetation, high call volume (A), KKR vocalization type (B), 'against wind' wind direction, and no wind mufflers. Dotted lines represent 85% confidence intervals.

vegetation characteristics of the monitored area. Microphone degradation over time may be another evaluation criterion, but was outside of the scope of this study.

Covariation was also noted across vegetation types. The greatest source of variation in 50% detection distance was vegetation type, with the largest increases observed for cordgrass with salt pannes across all ARU models and vocalization types. This is comparable to previous work finding greater ARU detection distances in open habitats compared to forested habitats (Yip *et al.* 2017) as salt pannes typically contain large expanses of bare soil and are not heavily vegetated.

The spacing of ARUs used to monitor Eastern Black Rails may vary considerably based on environmental conditions, technology, and financial resources available for monitoring. For example, to detect GRR vocalizations in cordgrass using SM2s, units could be spaced 82.5 m apart, while SM4 units detecting KKR vocalizations in a salt panne could be spaced 500 m apart. In general, monitoring open-canopy (i.e., vegetation that does not form canopies in relation to an Eastern Black Rail [e.g., salt pannes and needlegrass rush]) habitats with newer ARU models, units may be spaced farther to achieve the same detection probability as older ARU models monitoring cordgrass and shrub dominated habitats, based on our data. Thus, the same area can be surveyed with fewer units.

Optimization of ARU arrays might also be improved for Eastern Black Rails by monitoring weather and other environmental characteristics during the breeding season. Eastern Black Rails occupy parts of the mid and south Atlantic coast, Gulf Coast, and interior of the United States; hence, environmental conditions vary across these regions. Regions with higher humidity and areas with minimal background

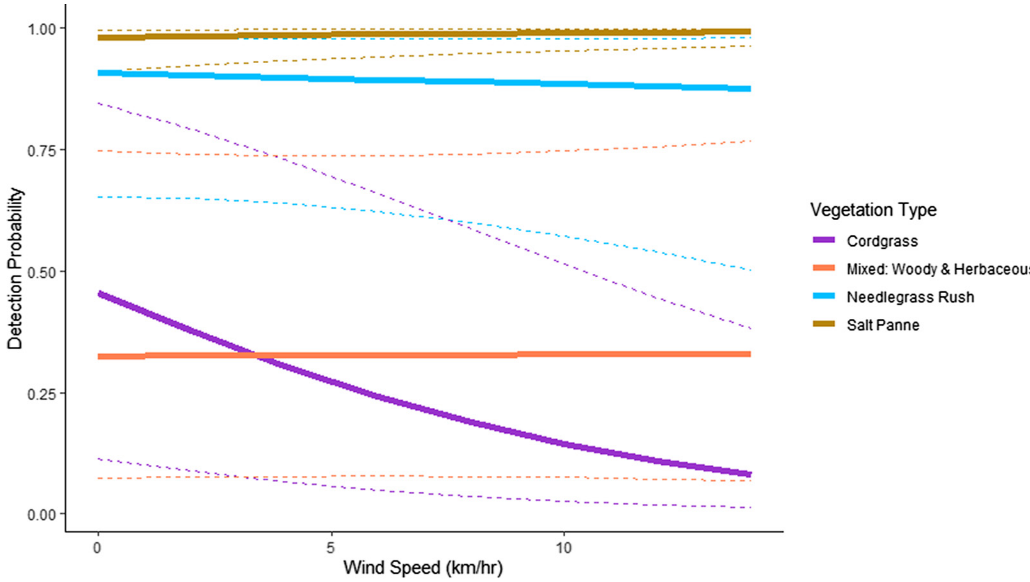

Figure 5. Detection probability slopes as a function of wind speed for each vegetation type at mean sampling distance (223.45 m). Reference levels in our model were set to SM2 ARU models, high call volume, KKR vocalization type, 'against wind' wind direction, and no wind mufflers. An interactive effect between wind speed and vegetation type was detected as detection probability decreases with increasing wind speeds in cordgrass vegetation but not in other vegetation types. Dotted lines represent 85% confidence intervals.

noise may allow for farther spacing of ARUs. Measurements of background noise and humidity may be warranted before conducting surveys at a site as these variables affect detection distance, and changes in spacing within ARU arrays may require consideration as a result. Along the Gulf Coast, Eastern Black Rails are often associated with dense stands of cordgrass species (Watts 2016). This study found that high wind speeds reduced detection probability in this vegetation type. Users should consider wind conditions for their respective geographies when spacing ARU sample points in cordgrass or vegetation of similar structure.

We found call volume to be the most important variable influencing ARU detection. However, similar experimental studies have been criticized in the past for relying upon call-playback volumes with limited variation (Van Wilgenburg *et al.* 2017). Bird calling volumes can be highly variable and are also unknown for many species (Brackenbury 1979). Detection probability can also be influenced by song directionality (Alldredge *et al.* 2007b) which did not vary in our study. While the low call volume (45 dBA) used in our study was half the numerical decibel level of our high call volume (90 dBA), it represents a raw sound pressure level that is reduced by over 99% from the high call volume (since dBA is on a log-scale). This low sound pressure level yielded minimal detection events, likely due to these broadcasts being obscured by ambient noise. The uncertainty in the decibel range of true Eastern Black Rail calling volume may affect the application of ARUs for this species as our results were produced using only two volume levels. Obtaining better estimates on calling volume, directionality, and decibel ranges of true Eastern Black Rails, could improve future assessments.

Our study was specific to Eastern Black Rails and associated vegetation types. Future studies conducted in vegetation types used by other Black Rail populations may illustrate the applicability of our results beyond the Gulf Coast and improve monitoring programs across the full range of the species. For example, verifying our results for California Black Rails (*Laterallus jamaicensis coturniculus*) using marshes dominated by bulrushes (*Schoenoplectus* spp.; Tsao *et al.* 2015; Watts 2016) and Black Rails in Colorado using cattail (*Typha* spp.) marshes (Hargett 2024) could provide validation while also improving monitoring efforts in those geographies.

Although ARUs are still a developing technology for monitoring wildlife populations (Shonefield and Bayne 2017), the advantages of ARUs continue to make them desirable research tools. Archived recordings can be reviewed by many individuals to determine the presence of a target species, providing value unable to be replicated by a single technician collecting data in the field. Additionally, for projects where staff are trained to survey one or a few focal species, the use of ARUs would record all soniferous animals and these data could be used in future projects. Having these data files archived provides a baseline that can be used to detect trends over time for both target and non-target species. Compared to field technicians, ARUs are also more effective for estimating species richness for projects where field technicians are trained to document all vocalizing birds (Darras *et al.* 2019). Although ARUs amass large amounts of data in a relatively short amount of time, automated detection software continues to improve (Ruff *et al.* 2021) and may become more beneficial for evaluating stored recordings in the future. Lastly, ARUs allow for less disturbance to target species (Darras *et al.* 2019), allowing data collection without the influence of human presence on animal behavior.

The results of our study can be used to provide general guidelines for optimizing the configuration of ARU arrays for monitoring Eastern Black Rail habitat. By considering the effects of the factors tested in this study, ARUs can be spaced depending on the characteristics of the monitored habitat and available ARU models to increase the efficiency of monitoring programs. We refer end-users to the 50% detection distances and associated information provided in this study to gauge the spacing of ARU arrays in specific monitoring scenarios as habitats and agency budgets vary.

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