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ORIGINAL RESEARCH

Occupancy Modeling of Autonomously Recorded Vocalizations to Predict Distribution of Rallids in Tidal Wetlands

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Abstract

Conservation and management for a species requires reliable information on its status, distribution, and habitat use. We identified occupancy and distributions of king (*Rallus elegans*) and clapper (*R. crepitans*) rail populations in marsh complexes along the Pamunkey and Mattaponi Rivers in Virginia, USA by modeling data on vocalizations recorded from autonomous recording units (ARUs). Occupancy probability for both species combined was 0.64 (95% CI: 0.53, 0.75) in marshes along the Pamunkey and 0.59 (0.45, 0.72) in marshes along the Mattaponi. Occupancy probability along the Pamunkey was strongly influenced by salinity, increasing logistically by a factor of 1.62 (0.6, 2.65) per parts per thousand of salinity. In contrast, there was not a strong salinity gradient on the Mattaponi and therefore vegetative community structure determined occupancy probability on that river. Estimated detection probability across both marshes was 0.63 (0.62, 0.65), but detection rates decreased as the season progressed. Monitoring wildlife within wetlands presents unique challenges for conservation managers. Our findings provide insight not only into how rails responded to environmental variation but also into the general utility of ARUs for occupancy modeling of the distribution and habitat associations of rails within tidal marsh systems.

Keywords Autonomous recording unit · Distribution · Occupancy · *Rallus elegans* · *Rallus crepitans* · Virginia

Introduction

Within marshes of the Atlantic and Gulf Coasts of the United States, two of the most prevalent rallids are the king (*Rallus elegans*) and clapper (*R. crepitans*) rail. In those regions, these species are said to exist along a salinity gradient. King rails inhabit brackish and fresh tidal marshes, whereas clapper rails reside in tidal salt marshes (Eddleman and Conway 1994; Reid et al. 1994). However, both species can occur within intermediate brackish-salt marshes (Meanley and Wetherbee 1962; Meanley 1985; Bledsoe 1988). In these areas, differentiating between species can be challenging due to similarities in phenotypes, morphometrics, and vocalizations (Massey and Zembal 1987; Graves 2001; Perkins et al. 2009; Maley and Brumfield 2013). In such instances, these birds have been classified as king-clapper rails (Conway 2011).

Although prominent within tidal marshes, these two species are poorly monitored. Large-scale monitoring programs such as the Breeding Bird Survey underrepresent tidal marsh habitat and provide unreliable estimates of current population status of marsh birds (Sauer et al. 2014). As an alternative, the standardization of monitoring protocols for secretive marsh birds has provided a targeted sampling framework to estimate occupancy and abundance and to track population trends of these species (Johnson et al. 2009; Conway 2011).

Recently, the use of autonomous recording units (ARUs) has emerged as another method for surveying marsh birds. ARUs may be especially useful for rallids because of their secretive nature, their use of inaccessible habitats, and the high rate at which they can be detected by their vocalizations (Sidie-Slettedahl et al. 2015). The use of ARUs is also sometimes favored because it provides a permanent recording of surveys that can be independently verified and it allows for reduction in observer, detection, temporal, and spatial bias

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(Haselmayer and Quinn 2000; Rempel et al. 2005; Acevedo and Villanueva-Rivera 2006; Tegeler et al. 2012).

A number of studies have assessed ARU performance in avian surveys; however, many species and systems remain unevaluated. Nevertheless, there are several studies that have compared the performance of human-observer point counts with acoustic recordings from ARUs in assessing species richness and relative abundance (Haselmayer and Quinn 2000; Acevedo and Villanueva-Rivera 2006; Hutto and Stutzman 2009; Venier et al. 2012). In many of these cases, because of the sensitivity, robustness, and accuracy of ARUs, their performance was similar to, or better than, traditional human observer point counts (Haselmayer and Quinn 2000; Hobson et al. 2002; Acevedo and Villanueva-Rivera 2006; Digby et al. 2013; Wimmer et al. 2013; Klingbeil and Willig 2015). However, other studies have reported drawbacks to ARUs including the high cost and the effort required for computer analysis (Hutto and Stutzman 2009; Swiston and Mennill 2009; Venier et al. 2012). Additionally, the high level of species-, habitat-, and ARU-specific variability in the detectable range of the particular electronics used can result in a failure to capture species that vocalize infrequently (Acevedo and Villanueva-Rivera 2006; Wimmer et al. 2013; Drake et al. 2016).

Monitoring efforts have shown significant range-wide population declines for king rails and, to a lesser extent, for clapper rails, due to wetland loss, habitat fragmentation, and saltwater infiltration (Kushlan et al. 2006; Cooper 2008; Sauer et al. 2014; Correll et al. 2016). Although these species are similar, they differ with regard to how they are managed and their conservation statuses. The king rail has been listed in over thirty state wildlife action plans as a "Species of Greatest Conservation Need" (Cooper 2008). In contrast, clapper rails are rarely given this status. For example, the Virginia Wildlife Action Plan lists the king rail as a Tier II species (very high conservation need), while the putatively more abundant clapper rail is listed as a Tier IV species (moderate conservation need; Virginia Department of Game and Inland Fisheries 2015). Conservation efforts towards these species rely primarily upon habitat management to maintain the structure and function of their habitat (Meanley 1985). Because both are of conservation concern at some level, there is an important need to generate reliable information on their status, distribution, and habitat use.

Although coastal populations of clapper rails within Virginia have been recently assessed, limited information exists for intracoastal populations within the state's tidewaters (Correll et al. 2016). The goal of this study was to determine the distribution and habitat association of king-clapper rail populations in two intracoastal marsh complexes in Virginia. Specifically, we assessed the effects of salinity and emergent vegetative community structure on rail occupancy and quantified the detection probability of rail vocalizations using ARUs.

Field-Site Description

We conducted research in tidal marsh systems along the Pamunkey and Mattaponi Rivers near West Point, Virginia. These rivers are situated at the confluence of the York River and are two of the major riverways feeding into the Chesapeake Bay. The marshes where we worked occur along a salinity gradient from mesohaline (7.2 per parts per thousand of salinity; ppt) to fresh (0.1 ppt), although high salinity waters extend farther up the Pamunkey River than the Mattaponi River (Fig. 1). The marshes along the Pamunkey River range in size from ~287–579 ha, while the marshes along the Mattaponi River range from ~125–209 ha.

The marshes themselves are flooded by daily tides and as a result are occupied by a mosaic of emergent vegetative community types whose composition is determined by tidal flood frequency and duration (Wilson et al. 2007). The marshes in this study can be classified into four dominant vegetative community types: low marsh, high marsh, salt marsh terrestrial border, and brackish marsh terrestrial border. Low marsh zones flooded regularly by daily tides are dominated by short smooth cordgrass (*Spartina alterniflora*) and black needlerush (*Juncus roemerianus)*. High marsh areas that are flooded at average tidal height are dominated by saltmeadow cordgrass (*S. patens*), big cordgrass (*S. cynosuroides*), and tall smooth cordgrass. Salt marsh terrestrial border zones are infrequently flooded by spring and storm tides and can include areas of higher elevation. These areas tend to have vegetation dominated by marsh elder (*Iva fructescens*), groundsel tree (*Baccharis halimifolia*), and Olney's three-square (*Scirpus americanus*). Brackish terrestrial border zones have vegetation characteristics of both brackish and fresh water systems. These marshes are dominated by broad-leaved plants such as arrow arum (*Peltandra virginica*) and pickerelweed (*Pontederia cordata*), and contain dense colonies of narrow-leaved cattail (*Typha angustifolia*), marsh mallow (*Kosteletzkya virginica*), southern wild rice (*Zizania aquatica*), and various sedges (*Carex* spp.).

Marshes within these river systems have previously been surveyed for secretive marsh birds by both the Virginia Department of Game and Inland Fisheries (VDGIF) and the Center for Conservation Biology (CCB). In 2002, king rails were detected within two marshes along the Pamunkey River (Paxton and Watts 2003). During 2006–2007, VDGIF reported the presence of king rails within marshes of the Mattaponi River during broadcast point count surveys (VDGIF, unpubl. data). However, recent trapping and lethal sampling found evidence of clapper rails only in both marsh systems (VDGIF, unpubl. Data 2014–2016).

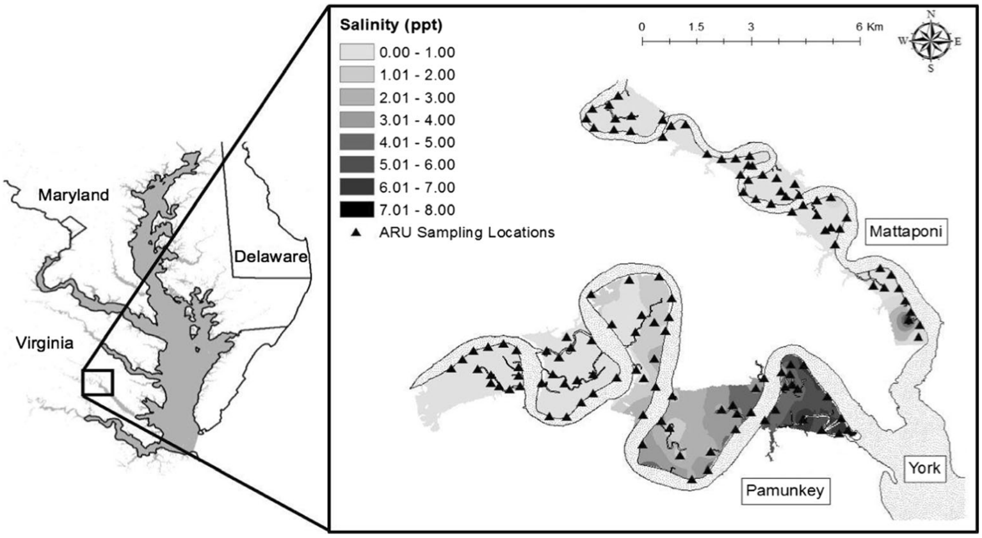

Fig. 1 Map of the study site showing marshes along Pamunkey and Mattaponi Rivers, near West Point, VA. Maps also show salinity gradients, extrapolated from salinity measurements taken at Autonomous Recording Unit (ARU) sampling locations throughout each marsh. Inset shows the location of these rivers in the Chesapeake Bay

Methods

Data Collection & Acoustic Classification

We sampled rails acoustically from May 19 to July 20 2015 in five tidal marshes along the Pamunkey River, and, from May 18 to June 29 2016, in five tidal marshes along the Mattaponi River. We used ArcMap 10.0 (Environmental Systems Research Institute (ESRI) 2011) to select 75 sampling sites in the marsh complex along the Pamunkey River and 50 sampling sites in the marsh complex along the Mattaponi River. Fewer sites were selected along the Mattaponi River because the marshes were smaller in area. We constrained sample site selection so that each location was at least 400 m from every other survey location (Conway 2011), at least 50 m from marsh edge, and easily accessible by boat from the rivers.

We deployed 5 Song Meter SM3 (Wildlife Acoustics, Maynard, Massachusetts, USA) ARUs, one per marsh, along the marsh systems. The ARUs were mounted onto t-posts, which were staked into the ground such that the ARUs were approximately 1.5 m above the substrate. We deployed the ARUs for a period of two consecutive days and then moved them to the next randomized location within that same marsh and repeated the two-day protocol. If the water level was too low to access a location, we selected the next sampling location from the randomized order and rescheduled the inaccessible location for the following high tide placement. If, upon visiting a location, we determined the location did not meet the original selection constraints, we selected a new randomized replacement site.

This approach allowed for concurrent sampling across the marsh systems. Each recording started at midnight and lasted exactly 48 h. Digital recordings were made at 24 kHz, 16-bit and stored into hourly files. We delayed sampling for a day during rainy weather or when wind speeds exceeded 20 km/h (Gibbs and Melvin 1993). In total, we sampled for 30 days in marshes along the Pamunkey River and for 20 days in marshes along the Mattaponi River.

We conducted rapid assessment vegetative surveys within a 50-m radius circular survey plot centered at each sampling location. Within each survey plot we identified the following vegetative communities and open-water features: low marsh, high marsh, salt marsh terrestrial border, brackish terrestrial border, invasive, creeks, open water, and upland (Wilson et al. 2007). We estimated the percent cover for each of the community types, categorizing cover classes as: 0 (0–<1%), 1 (1–5%), 2 (6–10%), 3 (11–25%), 4 (26–50%), 5 (51–75%), and 6 (76–100%). We also measured salinity in parts per thousand (ppt) at the water's edge using a Pro30 Conductivity and Salinity Meter (YSI, Yellow Springs, Ohio, USA).

In the laboratory, we used the interactive sound analysis software Raven Pro 1.5 (Bioacoustics Research Program 2014) to interpret the 6000 h of recordings we collected. Since both rail species have been reported in these marsh systems, we pooled all rail vocalizations as king-clapper rails. Initially, we investigated the use of an automated spectrographic detector for rail vocalizations. However, we found that using the detector resulted in a high percentage of false positives and negatives. Automated detectors tend to require large training datasets to aptly capture the variability within the call structure of a vocalization and their classifications are generally of low precision and accuracy (Swiston and Mennill 2009;Waddle et al. 2009; Sidie-Slettedahl et al. 2015).

Manual analysis of spectrograms can be more accurate and precise, but they are time and effort consuming (Swiston and Mennill 2009). Because of the high error rate of the detector, we instead choose to analyze recordings manually. To do this, we first visually scanned spectrograms for potential rail vocalizations and subsequently we aurally confirmed that they were, in fact, rails. For each hourly recording file, we documented the presence or absence of rails and recorded the start time, end time, and duration of vocalizations. Although we had 6000 h of audio to analyze, manually scanning spectrograms provided a faster and more accurate method for detection and identification of species than just listening to recordings (Sidie-Slettedahl 2013). In this study, it took about 3 min (range: 1–14 min) for an experienced observer to visually scan and aurally confirm the presence and absence of king-clapper rails in one hour of a single ARU recording.

Model Development

We estimated occupancy and detection probabilities for each river using the package "unmarked" within Program R (Fiske and Chandler 2011; R Development Core Team 2012). We considered the Pamunkey River and Mattaponi River independently in our statistical analyses due to variation in sampling year, salinity gradients, and density of rails. For our models, we created encounter histories for each sampling location by evaluating presence-absence of rails during 6-h intervals across the 48-h sampling period. As a consequence, we were able to obtain and analyze 8 repeated visits at each sampling location. Our models assessed whether occupancy probability (Ψ) was constant or dependent on salinity, or on the dominant vegetative community type. We also evaluated the influence of two potentially important covariates, day of the year and time of day, on detection probability (p). The assumptions of these occupancy models are as follows (MacKenzie et al. 2006): (a) occupancy status at each site does not change over the survey season; (b) Ψ is constant, or differences in occupancy probability are modeled using covariates; (c) p are constant across all sites and surveys or is a function of site-survey covariates; and (d) detection of species and detection histories are independent.

Model Selection

For each river system, we estimated Ψ and p using likelihood-based methods (MacKenzie et al. 2002). We ran all possible combinations of covariates of Ψ and p ($n = 16$ models) to achieve variable balance within our model set. We assessed model fit using corrected Akaike's Information Criterion (AICc) to compare models based on log-likelihood values (Akaike 1973; Burnham and Anderson 2002). We ranked and compared models based on AICc relative differences between the top ranked model and each other model (ΔAICc) and AICc weights (w_i) using the R package AICcmodavg (Burnham and Anderson 2002; Burnham et al. 2011; Mazerolle 2012). We considered models with ΔAICc <2 to be equally supported (Burnham and Anderson 2002). We calculated the relative importance of each variable based on the sum of w_i of the models that included the variable (Burnham and Anderson 2002; MacKenzie et al. 2002). We applied model averaging to estimate occupancy and detection on the set of models with ΔAICc <2. Parameter estimates were weighted by the associated w_i of the model and we calculated mean parameter estimates and unconditional variance estimates (Burnham and Anderson 2002). For each parameter, we report 95% CIs based on the unconditional variance.

Results

We detected rails at 48 of 75 survey locations (64%) along the Pamunkey River and at 29 of 50 (58%) locations surveyed along the Mattaponi River. We found no rails in the marshes on either river at sites that were farthest from the confluence of the York River.

We detected differences in probability of occupancy between the river systems. The best model for the Pamunkey River included salinity as an important site covariate (Table 1 and Fig. 2), such that as salinity increased within a marsh, the probability of occupancy by rails increased logistically by a factor of 1.62 (95% CI: 0.6, 2.65) per ppt (Fig. 3a). However, the top model for the Mattaponi River did not include a salinity term, but did include an effect of vegetative community type on occupancy probability (Table 1). While a combined effect of vegetative community type and salinity was present in another supported model with ΔAICc <2, vegetative community type was the only covariate with a relative importance >0.5 (Fig. 2). Finally, although the probability of occupancy of rails was higher in low marsh and salt marsh terrestrial border communities than in high marsh and brackish terrestrial borders, the model estimates for these parameters were never significantly different from zero (Fig. 4). The overall estimated model average probability of rail occupancy was 0.64 (95% CI: 0.53, 0.75) for the Pamunkey River and 0.59 (95% CI: 0.45, 0.72) for the Mattaponi River.

Detection probability was similar between river systems even though different models described each system (Table 1). Day of the year was the most important factor influencing probability of detecting rails along the Pamunkey River. As the sampling season progressed, the probability of detection of rails changed logistically by a factor of −0.02 (95% CI: -0.03, 0) per day (Fig. 3b). There were two additional models with ΔAICc <2; these incorporated the combined effects of date + survey and survey + time (Table 1). However, while survey and time were included within these additional models, neither parameter had relative importance value >0.50 (Fig. 2). Along the Mattaponi River, detection probability was constant within the top model. There were two additional models with ΔAICc <2. While day of the year was included in one of the models, it had an overall relative importance value of <0.5 (Fig. 2). The overall estimated probability of detecting a rail was 0.63 (95% CI: 0.62, 0.65) for the

Table 1 Model selection results for the occupancy and detection of king-clapper rails in marshes in Virginia along (A) the Pamunkey River, May–July 2015; and (B) the Mattaponi River, May – June 2016

River	Model	K	ΔAICc[a]	w_i
(A) Pamunkey	Ψ(salinity), p (date)	4	0	0.28
	Ψ (salinity), p (date + survey)	5	0.3	0.24
	Ψ (salinity), p (date + time)	5	1.4	0.14
(B) Mattaponi	Ψ (veg), p (.)	5	0	0.22
	Ψ (veg), p (date)	6	1.17	0.12
	Ψ (salinity + veg), p (.)	6	1.38	0.11

The model name shows effects on occupancy probability (Ψ) and detection probability (p); models are ranked based on AICc relative differences between the top ranked model and each other model (ΔAICc), AICc model weights (w_i), and number of parameters (K). Parameters included salinity and dominant emergent marsh community (veg) for occupancy probability and day of the year (date), time of day (time), and survey number (survey) for detection probability. Only models with ΔAICc <2 are shown; each model set contained 16 models

[a] The AIC$_c$ value of the best model was 558.48 for model set (A) and 378.63 for (B)

Pamunkey River and 0.63 (95% CI: 0.63, 0.64) for the Mattaponi River.

Discussion

Monitoring wildlife within wetlands presents unique challenges for conservation managers. We observed similarities in the occupancy and distribution of rails by river, with rails occupying 64% of the sites along the Pamunkey River and 59% of the sites along the Mattaponi River. Within both marshes, the probability of detecting a rail with an ARU also was similar (0.63).

Salinity may be the driving mechanism for patterns in rail occupancy. Salinity is known to determine the distribution of some species within wetlands, such that those with the highest salt tolerance are situated closest to the shoreline (Odum 1988; Graves 2001; Wilson et al. 2007). The high occupancy probabilities we observed at relatively high salinities may reflect the species composition along the Pamunkey River. Although

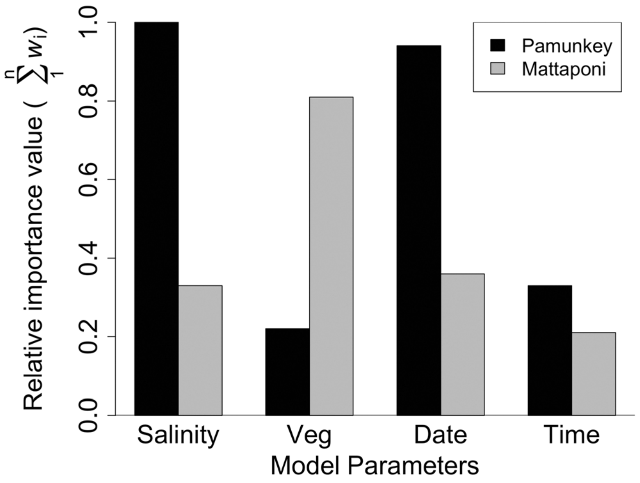

Fig. 2 Relative importance of model covariates to the probability of occupancy and detection of king-clapper rails in marshes along the Pamunkey and Mattaponi Rivers, VA. Importance values are the sum of the Akaike weight of each model containing a particular variable. Covariates represent salinity (salinity), dominant vegetative community type (veg), day of the year (date), and time of day (time)

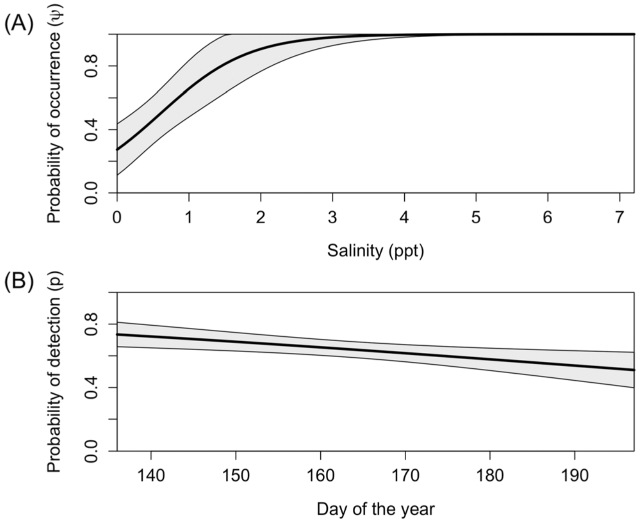

Fig. 3 Predicted model estimates of (**a**) occupancy and (**b**) detection probabilities for king-clapper rails in marshes along the Pamunkey River, Virginia May – July 2015. Estimate means and 95% CI of model-averaged predictions from models with ΔAICc <2 shown. The probability of occupancy is plotted against salinity and probability of detection is plotted against day of the year

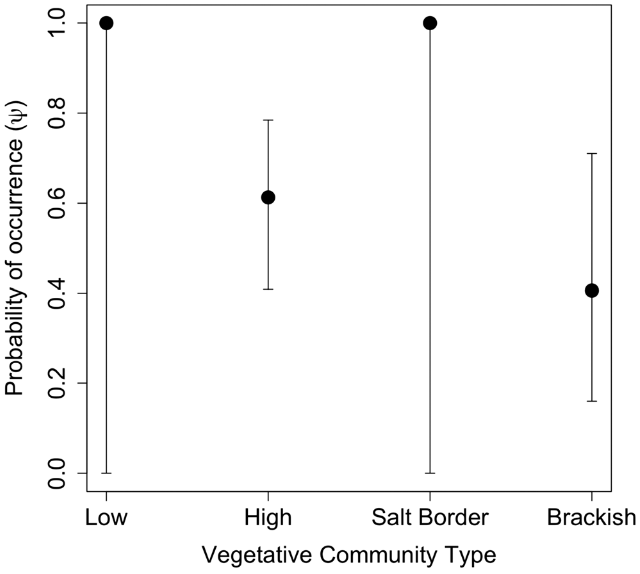

Fig. 4 Predicted model estimates of occupancy probability based on dominant vegetative community type for king-clapper rails in marshes along the Mattaponi River, Virginia May – June 2016. Estimate means and 95% CI of model-averaged predictions from models with ΔAICc <2 shown

we could not spectrographically differentiate between species, during the breeding season Clapper Rails are known to exhibit a higher preference for saline environments than do King Rails and, thus we suspect that most of the rails detected along the Pamunkey River are Clapper Rails (Meanley 1969; Eddleman and Conway 1994; Reid et al. 1994). Although this logic works for the Pamunkey River, it may not apply for the Mattaponi, where salinity was not influential in determining patterns of rail occupancy. This may be because the Pamunkey River has a wider salinity gradient than the mostly freshwater Mattaponi River.

It appeared that due to the lack of a strong salinity gradient in the Mattaponi River, the vegetative community became an influential factor determining the probability of occupancy of rails. We found greater occupancy of rails in both low marsh and salt marsh terrestrial border zones, although this was not a particularly strong effect. Within the Chesapeake Bay, both species associate predominantly, but not exclusively, with low elevational marshes (Wilson et al. 2007). Selection for these areas may be driven by habitat requirements of rallids during the breeding season. Low marsh communities are dominated by *Spartina*, a genus of plants that is associated with rail nesting habitat because it provides structural diversity that rails need to avoid nest loss from tides (Oney 1954; Storey et al. 1988; Eddleman and Conway 1994; Erwin et al. 2006). Salt marsh terrestrial border zones provide rails both with areas of higher elevation to escape tide waters and with diverse vegetation for nesting materials and protection during brood-rearing (Stone 1965; Reid et al. 1994). While high marsh zones also provide a similar tidal escape function, these areas are often dominated by dense monoculture stands of big cordgrass thought to be more appropriate for escape cover from predators than nesting habitat (Meanley 1969).

Detection probability is a function of both vocalization probability and observer detection probability, or, in our case, ARU detection probability (Conway and Gibbs 2001; Conway and Simon 2003). Vocalization rates of rails vary due to age-, sex-, breeding status-, time of day-, and seasonally-driven variation (Tacha 1975; Johnson and Dinsmore 1986; Conway and Gibbs 2001; Conway and Gibbs 2011). Due to the cryptic nature of rails and our use of ARUs, we were unable to account for age-and sex-specific variation in vocalization rates. However, to account for temporal variability, we sampled over a relatively short period of time during the breeding season and we accounted for diel variation in our statistical models. Nevertheless, and as has been observed in other studies, along both of our rivers, the probability of detecting rails decreased as the season progressed (Conway and Gibbs 2005; Conway and Nadeau 2010; Wiest and Shriver 2016). However, we found no influence of time of day on the probability of detecting rails. This may have been due in part to the day-long survey period ARUs allow and the lack of diel variation in vocalization behavior of rails within our marsh systems (Stiffler et al. 2017).

We estimated that the probability the ARU-based system would detect a rail was 0.63 (95% CI: 0.62, 0.65). Previous studies using traditional survey methods found similar or lower detectability of king rails (0.03–0.76; Budd 2007; Pierluissi and King 2008; Darrah and Krementz 2009; Rogers 2011) and of clapper rails (0.13–0.70; Lehmicke et al. 2013; Wiest and Shriver 2016). Traditional marsh bird survey methods use short durations surveys (5–15 min) and call-broadcast surveys that increase the vocalization frequency of birds (Gibbs and Melvin 1993; Conway and Gibbs 2005; Conway and Nadeau 2010). Passive surveying of secretive marsh birds by humans results in inherently low detection probabilities (Conway and Gibbs 2011). However, ARUs can potentially circumvent this low detectability by surveying for longer periods over which the mechanized "observer" does not grow tired. Additionally, traditional marsh bird surveying requires repeated visits to sites across the sampling season in order to assess detection probabilities. The timespan between site visitations may result in violation of the assumption that detection probability remains constant across the surveys and sites. In contrast, the use of ARUs makes meeting this assumption easier by allowing for repeated back-to-back surveys within short timespans (e.g., in our study, we had eight six-hour survey periods over a 48-h timespan). Furthermore, using ARUs allows simultaneous surveys at multiple locations over extended periods of time. Thus, ARUs can provide a broader spatial distribution and a greater number of survey replicates, both of which should improve occupancy and detection estimates (MacKenzie et al. 2006).

A shortcoming of our study was that we were unable to differentiate between king and clapper rail vocalizations. The vocalizations produced by both species are similar in structure and highly variable among individuals, making qualitative and quantitative differentiation difficult (Graves 2001; Conway 2011). Developing a mechanism to differentiate between species will require a large database of vocalization recordings from known individuals. This would most likely require either extensive trapping of king and clapper rails followed by targeted recording of those individuals' vocalizations or sampling in sites where extensive sampling documents presence of only one of the two species.

Counterintuitively, this shortcoming also highlights one of the benefits of using ARUs. At some point, it is highly likely that developments in technology will allow effective differentiation of recordings of these two species. Likewise, although we were unable to implement or develop an automated spectrographic detector to identify rails, effective automated scanning systems will eventually be developed. When both automated detectors and species identifiers are in place, we can easily re-evaluate our recordings to identify these two species, thereby improving our understanding of each species distribution within our study site.

Our study demonstrates the suitability of ARUs to estimate the distribution and habitat associations of rails along the Pamunkey and Mattaponi Rivers in Virginia. The development and implementation of new technologies such as ARUs provides alternative and improved methodologies for conducting long-term continuous monitoring over large spatial scales. As such, the adoption of these and other novel technologies may be an important component of understanding the effects of both short- and long-term environmental and anthropogenic threats to tidal marsh habitats.

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