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Methodology Comparison Using Occupancy Modeling for Six Species of Rails Native to the Texas Gulf Coast

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Methodology Comparison Using Occupancy Modeling for Six Species of Rails Native to the Texas Gulf Coast

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Abstract

Rails are a group of marsh birds which are traditionally difficult to monitor due to low and variable detection estimates. Many species of rail in the United States are experiencing population declines and are species of special conservation concern with added state and federal protection. However, the secrecy of rails creates inefficient and expensive survey conditions that hinder the ability to conserve and monitor populations. Black Rails, for example, are federally listed as Threatened but have very low detection probabilities that require extensive revisits to locations. Determining survey methodology that would maximize the detection probabilities for rails would minimize long-term monitoring costs by reducing the amount of field hours required to revisit survey areas.

From February-July of 2022, I utilized four survey methods (autonomous recording units, call-playback, forward-looking-infrared camera equipped drone, and trail cameras) to monitor six species of rail (King Rail [*Rallus elegans*], Clapper Rail [*R. crepitans*], Virginia Rail [*R. limicola*], Sora [*Porzana carolina*], Eastern Black Rail [*Laterallus jamaicensis*] and Yellow Rail [*Coturnicops noveboracensis*]) that winter and/or breed on the Texas Gulf Coast. Vegetation

sampling conducted from June-July was used to determine the influence of micro-habitat features on the occupancy of the six target rail species to calculate occupancy estimates for each survey site. Using occupancy modeling I calculated and compared detection estimates generated for each survey method in order to determine the methods which maximized detection probability at a species level. Advanced cluster analyses were trained, developed, and then subsequently used to sort out known vocalizations of each study species to reduce the required time spent sorting acoustic data. Additionally, I conducted a general cost analysis of the three most common survey techniques (call-playback, passive acoustic monitoring, and passive visual monitoring survey methods) to assess the expenses generated for theoretical long-term survey implementation.

Average above-ground biomass was a significant factor influencing occupancy for both Black Rail as well as Yellow Rail. Black rail detection probability ($\hat{p}$) was highest in the spring/summer using autonomous recording units ($\hat{p}$=0.279) and was low in the winter using call-playback ($\hat{p}$=0.041). Yellow Rail detection probability was highest with winter call-playback ($\hat{p}$=0.043). King/Clapper rail detection probability was influenced strongly by wind speed in the winter and water levels in the spring/summer and standing water levels influenced both winter and spring/summer occupancy. Call-playback had the highest detection probability in winter for King/Clapper Rail ($\hat{p}$=0.733) and Virginia Rail ($\hat{p}$=0.326) and autonomous recording units were best in the spring/summer for King/Clapper Rail ($\hat{p}$=0.706) and Sora ($\hat{p}$=0.474). Drone thermal imaging work revealed the possibility of finding rails as small as Black

Rail and Yellow Rail, as 27 total rail detections included 12 Black/Yellow Rails, 12 Sora, 1 Virginia, and 2 King/Clappers. Behavioral response to the drone of targeted rails was minimal, with preliminary data showing 81% of birds exhibiting no visual response to the drone although behavioral intensity would increase with increased duration of hovering over individuals. Our Gaussian kernel regression results revealed that wind speed (p=0.04) and percent cloud cover (p=0.01*)* influenced the number of rails detected on a given survey.

By establishing the methods that display the highest detection probabilities for each species, we were able to weigh the monetary cost of the methods against the potential loss/gain of detection probability. Passive acoustic monitoring reduced costs for multiple species including Black Rail, Sora, and King/Clapper Rail, as this method is far cheaper annually than traditional call-playback methods and maintains adequate detection probabilities for these species. Monitoring for Black Rail, Sora, and King/Clapper Rail may be more attainable for agencies with limited funding or resources. The potential of using drone thermal imagery also may further reduce costs while maintaining adequate detection probability for these secretive species. Future research should focus on estimating the detection probability using drone thermal imaging for each of these species, especially the smallest and most difficult to detect such as Black and Yellow Rail.

CHAPTER 1:
Introduction

Wetlands, in the most generic sense, are classified as areas regularly inundated by water that strongly influence the surrounding biota and hydrologic structure of the soil they contain (Tiner 2017). Although wetlands constitute a small portion of the global land area, 87% of the world's natural wetlands have been lost since the 18th century with up to 50% of this loss attributed to the disappearance of coastal wetlands (Davidson 2014). The drainage and removal of wetland ecosystems is largely driven by attempts to transform the land to facilitate anthropogenic growth through pest elimination, re-routing for irrigation, agricultural conversion, and direct urbanization (Dugan 1990, Lee et al. 2006). This fragmentation leads to the degradation of small, but ecologically relevant, patches that reside within the wider wetland matrix and places additional stress on taxa reliant on broad-scale connectivity (Haig et al. 1998, Naugle et al. 2000). While widespread efforts to conserve wetlands are enacted in some regions, the global rate of wetland loss from the 20th through the 21st century continued to increase relative to early records (Davidson 2014). Coastal wetlands are particularly vulnerable to the influence of human-induced climate change due to their unique transitional position between land and sea (Adam 2002, Morris et al. 2002, McKee et al. 2012, Osland et al. 2016) and this vulnerability is highlighted by a projected global loss of up to 30% by 2100 (Schuerch et al. 2018).

Estuarine emergent wetlands (hereafter, saltmarshes) are essential for reducing coastal erosion, buffering periods of flooding, and capturing stores of

CO_2 (Costanza et al. 1997, Gedan et al. 2009, Engle 2011) and their widespread loss would be detrimental to the biodiversity that they support. Saltmarsh ecosystems facilitate high plant diversity (Greenburg et al. 2006, Teixeira et al. 2014) and support an array of avian taxa that rely heavily on this system to satisfy breeding, wintering, and or migratory conditions (Huges 2004, Spencer et al. 2009). Many marshland obligate species, such as the Least Bittern (*Ixobrychus exilis*), Seaside Sparrow (*Ammodramus maritimus*), and Saltmarsh Sparrow (*A. caudacutus*), require areas with relatively stable water levels (Bayard and Elphick 2011, Chabot et al. 2014), spatially diverse interspersion of water and vegetation (Weller and Spatcher 1965, Gibbs et al. 1991, Rehm and Baldassarre 2007, Darrah and Krementz 2010) and habitat continuity (Marshall et al. 2020) to persist. The presence of marshland obligates on the landscape can thus act as an extrapolation of saltmarsh quality (Benoit and Askins 1999, Novak et al. 2006, Glisson et al. 2015). Some saltmarsh obligate species are categorized as 'secretive' as they infrequently vocalize, infrequently expose themselves visually, occupy dense or otherwise challenging to access habitat, and often exhibit cryptic plumage that allows them to easily blend into marshland environments (e.g., Bolenbaugh et al. 2011, Steidl et al. 2013, Schroeder and McRae 2019). Inconspicuous behavior leads to higher instances of Type II (false-negative) error when establishing presence/absence (MacKenzie et al. 2002, MacKenzie et al. 2006) leading to the necessity of multiple surveys and revisits which can create unfeasible and costly conditions for long-term systematic surveys of rails, bitterns, and similarly secretive groups (Sauer 1999).

An obligate wetland group of birds, rails (Rallidae), is experiencing population declines worldwide (Taylor 1998). King Rail (*Rallus elegans*) and Yellow Rail (*Coturnicops noveboracensis*) are classified as species of conservation concern within the United States (U.S. Fish and Wildlife Service 2021) and Sora (*Porzana carolina*), King, Yellow, Black (*Laterallus jamaicensis*), Clapper (*R. crepitans*), and Virginia Rails (*R. limicola*) are all considered birds of management concern (U.S. Fish and Wildlife Service 2011). The Eastern Black Rail (*L. j. jamaicensis*) is federally listed by the U.S. Fish and Wildlife Service as Threatened as of 2020 (U.S. Fish and Wildlife Service 2020). As secretive marsh birds, these species' detection probabilities are typically low and the birds themselves are challenging to consistently find (Conway and Gibbs 2011). These six rail species rely on saltmarshes to varying degrees throughout their range (Robert and Laporte 1994, Pickens and Meanley 2020, Eddleman et al. 2020) with some species such as Clapper Rail and Black Rail residing almost exclusively within coastal saltmarshes (Rush et al. 2020). In order to improve marshland habitat management decisions, population monitoring efforts, and the ability to conduct assessments of long-term species persistence, there remains a critical need to establish methodology that consistently maximizes the detection probabilities for each of these rail species.

Current marsh bird survey efforts utilize call-playback, a method in which the songs of the focal species are broadcast using a speaker in a sequential order to invoke a response by target birds occupying an area (Conway 2011). It is recommended that sites are visited at least three times per season with call-

playback methods (Conway 2011), but this can present issues when species detection is low (Mackenzie et al. 2002, Butler et al. 2015). Black Rails show a particularly low detection probability even when under optimal survey conditions (Butler et al 2015, Tolliver et al. 2019), necessitating repeated visits that range up to 15+ times per season to obtain a 90% detection probability (Conway et al. 2004, Butler et al. 2015, Tolliver et al. 2019). King Rail also show low detection probabilities ($\hat{p}$ =0.35-0.45; Darrah and Krementz 2009) compared to other species such as Yellow Rail ($\hat{p}$ =0.63; Martin et al. 2014). These species-specific differences are further complicated with differences in seasonality (Waddle et al. 2022). Thus, surveying multiple rail species would require an increased survey effort in order to account for these differences in detection probability.

Much of our understanding of rails is biased towards their breeding grounds where predicted vocalization response rates are highest (Conway 2011). Yellow Rail are migratory, residing along the Gulf Coast and portions of the interior U.S. during winter (Butler et al. 2010, Leston and Brookhout 2020) and are reported as having low response rates in the winter (Butler et al. 2023). The primary vocalization used for surveys is their breeding song (e.g., Martin et al. 2014), which does not elicit consistent detections in the winter (Butler et al. 2023). Sora, Virginia Rails, and Yellow Rails all have migratory populations in the United States and thus discerning wintering habitat preferences on both a micro- and macro-scale would allow for a comprehensive understanding of occupancy across their range (McClure et al. 2012). Eastern Black Rails also have migratory populations that winter along the Gulf and Atlantic Coasts (Watts 2016,

Eddleman et al. 2020) and may display different habitat preferences during this period than what is known on their breeding territory. The key to long-term species conservation and management resides in the ability to connect all aspects of these birds' life history, including the migratory and wintering habitat that these birds utilize for a significant portion of the year (Martin et al. 2007). Implementing survey techniques that increase the detection rates of rails, especially outside of the breeding season, would lead to stronger occupancy estimates and improved inferences on long-term population trends.

Passive acoustic surveys using autonomous recording units (hereafter, ARUs) remains a viable and efficient survey method for a variety of avian surveys (Tegeler et al. 2012, Shonfield and Bane 2017, Pérez-Granados and Traba 2021). These devices allow audio to be recorded without a human observer present in the field and can be left to continuously record for an extended period of time. This greatly reduces the number of personnel field hours required, reduces observer bias, generates an accessible dataset that can be saved and reviewed, and is a great option for sensitive species or sensitive situations (e.g., active nesting) where repeated disturbance can be detrimental (Tremblay and Ellison 1979, Stien and Ims 2015, Shonfield and Bane 2017). Passive acoustic monitoring has been used in conjunction with occupancy modeling for rails with variable success (e.g., Stiffler et al. 2018, Waddle et al. 2022), and may be useful for rails with low vocalization rates that would normally require multiple revisits with call-playback. Yellow Rails surveyed with ARUs displayed a lower detection probability compared to traditional call-playback surveys (Sidie-

Slettedahl et al. 2015) during the breeding season while the detection probability of Black Rail increased with ARU usage (Bobay et al. 2018). A recently described Yellow Rail vocalization may be used to search for passive vocalizations in the winter when the breeding song is unlikely to be passively emitted (see: Butler et al. 2023). Trail cameras for passive visual monitoring of rails also displays viable survey applications for rails, although often within limited context. Camera traps successfully captured previously undescribed Lewin's Rail (*Lewinia pectoralis*) behavior (Znidersic 2017), revealed Black Rail nesting attempts in South Carolina (Hand et al. 2019), and acted as a noninvasive method to study highly sensitive flufftails (*Sarothrura ayresi*) and rails within Africa (Colyn et al. 2017, Colyn et al. 2019). While passive visual and passive acoustic monitoring methods possess limitations, their combined use with other monitoring methods may prove invaluable to long-term survey efforts for secretive rails.

Remote sensing tools, such as unoccupied aerial vehicles (hereafter, UAVs or drones), are an emerging resource for a variety of wildlife surveying objectives. Drones can access locations that may be sensitive to human disturbance or that are impracticable for on-the-ground personnel (López and Mulero-Pázmány 2019, Monks et al. 2022), improving safety for both the study subjects and their surveyors. The exploration of the impact of drone usage on avifauna is still in its infancy as of this publication, but early literature displays that adverse reactions of birds to drone presence can be minimized or are otherwise short-term (Weimerskirch et al. 2017, Geldart et al. 2022), although

impacts remain highly species specific (Weimerskirch et al. 2017, Wilson et al. 2022). Drones can even be used to census nesting birds with reduced nest abandonment relative to human-based approaches that require repeated habitat entry (Bushaw et al. 2020). Drones combine the passive element of finding target individuals without intentionally invoking a response, with the active element of searching, counting, and/or identifying individuals with a surveyor present.

Using infrared imaging to capitalize on rail nocturnal movement may provide insights that other monitoring efforts could fail to produce. Theoretically, thermal signatures of living organisms (such as birds) would contrast against the cooler surrounding environment, revealing individuals within the vegetation (McCafferty 2013, Beaver et al. 2020). For example, infrared imaging successfully facilitated the trapping of Clapper Rails in South Carolina and increased trapping success rate when compared to acoustic playback (Mills et al. 2011). Studies implementing UAV technology combined with infrared imaging is gradually increasing within wildlife ecology (Ward et al. 2016, Fust and Loos 2020) and may be used to survey large swaths of marshland habitat in search of rails within a short period of time. Similar to the traditional use of pointing-dogs and flushing-dogs for rails in the field (e.g., Stenzel 1982, Bookhout and Stenzel 1987, Robert and Laporte 1997), drones can be used to find and 'point' to a thermal signature of interest, while a ground observer confirms the identification. This may be less disruptive than using trained dogs and potentially more effective, as dog-based searches resulted in high effort for low return when searching for Yellow Rails (Stenzel 1982). The range of UAV tools that can be

used to survey for secretive marsh birds is increasing in both affordability and practicality and the exploration of how these tools can benefit rail monitoring warrants evaluation.

Call-playback surveys for marsh birds can be an efficient approach (Conway 2011), however the time required in the field can be substantial depending on the number of repeated visits required to adequately determine occupancy (Darras et al. 2019). Methods that reduce the time required in the field can help to minimize seasonal costs associated with field work. Passive methods such as acoustic monitoring and trail cameras allow the area to be sampled and re-sampled continuously without constant human presence (Shonfield and Bane 2017, Darras et al. 2019). Drone surveys, while a 'hybrid' of the passive and active approaches, can theoretically sample a much larger area in a shorter time period compared to traditional surveys (Valle and Scarton 2020). Non-invasive equipment (i.e., drones) can also be beneficial to sensitive species or situations where human presence alters avian behavioral responses (Klein 1993). UAVs can have variable startup costs and may require additional technical training to successfully utilize (Watts et al. 2010). For facilities with limited funding, this aspect can hinder the widespread use or exploration of this technology. By assessing the costs and benefits of each survey approach as it relates to analysis-time, field-time, monetary costs, and monitoring effectiveness we can determine how each of these survey approaches can be realistically applied to secretive marsh bird management schemes.

The Texas Gulf Coast shoreline is dominated by saltmarsh and tidal ecosystems (Mendelssohn et al. 2017). These wetlands support year-round populations of Black Rail, Clapper Rail, and King Rail as well as wintering populations of Yellow Rail, Virginia Rail, and Sora (Peterson 1960). To maintain the functionality of these ecosystems, management strategies such as prescribed fire are implemented throughout the region (Rosen et al. 2014). This region is predicted to decrease in resilience if temperature and rainfall regimes change as predicted in long-term climate change scenarios (Osland 2016). Degradation would be further exacerbated by large-scale shifts in dominant plant composition that would drastically alter the system's structure (Armitage et al. 2015). The long-term monitoring of obligate marsh birds, such as rails, would develop a stronger understanding of the impacts of habitat management (and lack thereof) on species occupancy (Tozer 2016), especially in the context of added strain on the ecosystem caused by anthropogenic climate change. By exploring methods to improve rail detection rates, especially for the federally threatened Eastern Black Rail, we can shape land management to support these sensitive species while also achieving other management priories such as maintaining saltmarsh structural integrity. The primary goals of this thesis project are to: 1.) assess the utility of ARUs, trail cameras, infrared equipped UAVs, and call-playback surveys for monitoring rails, 2.) compare the detection probability estimates for each survey technique, 3.) create a multi-species occupancy model for each survey technique and each species of interest, and 4.) provide recommendations for management and survey strategies for rail species along the Texas Gulf Coast.

APPENDIX

A.1: Definitions of variables and covariates used in occupancy modeling, alphabetized.

Variable/Covariate/Term	Definition	Procurement
Average Apparent Magnitude; Moonlight; Moon	A logarithmic scale that represents moon-light; averaged over 24-hr period	Program: Quick Phase Pro (v4.1.10)
Biomass; AGB	Above ground biomass; average of 6 samples taken per point during vegetation sampling	Physical samples clipped, dried, and weighed
Cloud; Cloud Cover	Percentage of visible cloud cover	In-field estimation by observer (call-playback) and/or estimation from nearest weather station (e.g., drone surveys)
Cordgrass Cover	Amount of space covered by cordgrass (*Spartina* spp.) on the Daubenmire Scale; average of 8 samples per point conducted during vegetation sampling	Visible estimation within 20x50cm quadrat
Detection/s	Binary classification defined as either 1 (detection) or 0 (no detection), and are not necessarily indicative of separate individual observations	
Day-of-year	Conversion of calendar date to numeric format (1=January 1st, 365=December 31st)	R package 'lubridate'
Saltgrass cover	Amount of space covered by saltgrass (*Distichlis* spp.) on the Daubenmire Scale; average of 8 samples per point conducted during vegetation sampling	Visible estimation within 20x50cm quadrat
Short emergent cover; Short_EM	Amount of space covered by vegetation <1m in height (e.g., *Salicornia bigelovii, Batis maritima, Monanthochloë littoralis*) on the Daubenmire Scale; average of 8 samples per point conducted during vegetation sampling	Visible estimation within 20x50cm quadrat
Shrub Cover	Amount of space covered by woody, shrub-like vegetation (e.g., *Iva frutescens*, *Baccharis*	Visible estimation within 20x50cm quadrat

	halimifolia, Lycium carolinianumm) on the Daubenmire Scale; average of 8 samples per point conducted during vegetation sampling	
Site	Location where survey points are nested within. Sites include the following: Justin Hurst Wildlife Management Area, Mad Island WMA, Guadalupe Delta WMA, Galveston Island State Park, Mustang Island State Park	
Standing Water	Average of 4 water measurements taken 50m at each cardinal direction during vegetation sampling	Ruler in centimeters
Surface Water; Water	Individual surface-water measurement taken during a call-playback survey	Ruler in centimeters
Surveyor	Refers to the individual observer conducting surveys (e.g., call-playback surveyor)	
Tall emergent cover; Tall_EM	Amount of space covered by vegetation ≥1m in height (e.g., *Typha* spp., *Juncus* spp.) on the Daubenmire Scale; average of 8 samples per point conducted during vegetation sampling	Visible estimation within 20x50cm quadrat
Temperature	Ambient temperature in Celsius	In-field measurements via Kestrel 2000
Time	AM/PM surveys; AM surveys are 30-minutes prior to civil-sunrise to 3-hours after civil sunrise; PM surveys are 2-hours prior to civil-sunset to 30-minutes after civil-sunset.	
Water Cover	Amount of space covered by visible water on the Daubenmire Scale; average of 8 samples per point conducted during vegetation sampling	Visible estimation within 20x50cm quadrat
Wind Speed	Average wind speed in kilometers-per-hour (kph)	In-field measurements via Kestrel 2000
Woody Cover	Amount of space covered by woody vegetation <1m in height (e.g., *Borrichia frutescens*) on the	Visible estimation within 20x50cm quadrat

	Daubenmire Scale; average of 8 samples per point conducted during vegetation sampling

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CHAPTER 2:

Estimating Detection Probability Using Passive and Active Survey Methodology for Six Species of Rail

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Abstract

Rails are a secretive group of marshland birds that are challenging to detect relative to other species. Detection probabilities are variable depending on the species, time of year, and methodology used. We targeted six species of rails that reside along the Texas Gulf Coast; Sora (*Porzana carolina*), Yellow Rail (*Coturnicops noveboracensis*), and Virginia Rail (*Rallus limicola*), which are present during the winter, and King Rail (*R. elegans*), Clapper Rail (*R. crepitans*), and Black Rail (*Laterallus jamaicensis*), which are present year-round. We conducted call-playback surveys at 90 points along the Texas Gulf Coast during February-June 2022 and revisited points a minimum of 12 times. At these same points, we deployed 20 autonomous recording units (AudioMoths) and 20 Reconyx trail cameras rotated every 14-days to passively detect rails. Vegetation sampling for above-ground biomass, percent cover for select vegetative categories, and stem densities were conducted in June-July 2022. Occupancy modeling results show that call-playback generates the highest detection estimates for Yellow Rail ($\hat{p}$=0.043) and Virginia Rail ($\hat{p}$=0.326), relative to other methods, while passive acoustic monitoring is comparable and feasible for King/Clapper Rail ($\hat{p}$=0.706), Sora ($\hat{p}$=0.474), and Black Rail ($\hat{p}$=0.279) during the later portion of the survey season.

INTRODUCTION

Determining accurate abundance estimates for species with low and variable detection probability remains an issue for secretive species (species with low detection probability; Couturier et al. 2013, Dénes et al. 2015). Establishing presence, however, allows wildlife biologists to determine the minimum fine-scale habitat associations required for occupancy that may influence abundance in the long-term (Buckland and Elston 1993, MacKenzie 2005). Occupancy modeling, as described and refined by MacKenzie et al. (2018), is a valuable tool for addressing a variety of research and management objectives within the context of secretive marsh bird monitoring in lieu of more intensive techniques required to obtain true abundance estimates. Occupancy modeling can be used to establish connections between species occupancy and detection probability in order to create a more accurate representation of species presence and absence (MacKenzie et al. 2018).

Numerous passive and active survey techniques can be implemented within the framework of occupancy modeling, making this approach flexible for a range of budgets and management objectives. Call-playback remains a wide-spread and easily-standardized approach to marsh bird monitoring (Lor and Malecki 2002, Conway 2011), however it can be challenging for agencies with limited funding, time, and personnel to dedicate to high frequency systematic surveys that are required for exceptionally secretive species (Conway 2004, Steidl et al. 2013). The advent of autonomous recording units (hereafter, ARUs) allows for systematic surveys to be conducted without the need of an in-person observer

to be present (e.g., Towsey et al. 2014). The number of personnel hours required to sort through large audio files for relevant detections can be significantly reduced by creating automated classifiers which can be refined and distributed amongst individuals or agencies for added standardization or convenience (e.g., BirdNet: Cole et al. 2022; Kaleidoscope Pro/BirdNet: Manzano-Rubio et al. 2022). Visual passive monitoring approaches, such as trail cameras, are also a viable and widely available tool that requires minimal training to deploy and to sort photos post-deployment. While historically their predominant use was related to mammal-based studies (Kucera and Barret 2011), their modern application extends to an array of taxa (e.g., Collett and Fisher 2017, Boehm et al. 2022, Naqvi et al. 2022) and monitoring purposes (e.g., Jansen et al. 2014, Williams et al. 2014, Suwanrat et al. 2015), that can determine occupancy at both an individual and species scale.

The widespread use of occupancy modeling for rallids in the current literature provides a baseline of detection estimates ($\hat{p}$) for a variety of species, methodologies, and locations. Eastern Black Rail (*Laterallus jamaicensis jamaicensis*) typically have the lowest detection estimates relative to other North American rail species. Tolliver et al. (2019) calculated a $\hat{p}$=0.19 for Black Rail using a call-playback approach; Butler et al (2015) determined a similar estimate ($\hat{p}$=0.094) with call-playback, as did Legare et al. (1999) for female Black Rails. Bobay et al. (2018) found equally low detection estimates for Black Rail when combining ARUs with call-playback surveys ($\hat{p}$=0.08). These estimates differ from mean detection estimates for Sora (*Porzana carolina*) using ARUs ($\hat{p}$=

~0.34; Waddle et al. 2022), King Rail (*Rallus elegans*) and Clapper Rail (*R. crepitans*) using ARUs (~63%; Stiffler et al. 2018[a]), and when using call-playback for breeding Yellow Rail ([*Coturnicops noveboracensis*]; $\hat{p}$=0.63; Martin et al. 2014). Similarly, response probabilities of Sora and Virginia Rail (*R. limicola)* to call-playback were 0.51 and 0.73, respectively, (Robertson and Olsen 2014) although this metric differs slightly from detection probability.

Many of the non-invasive survey techniques (methods which exclude rope-drags [e.g., Soehren et al. 2018], ATV flushing [e.g., Perkins et al. 2010, Fournier and Krementz 2017], or the use of dogs [e.g., Stenzel 1982, Robert and Laporte 1997]) used for rallids are conducted within the spring or summer seasons as the detection probability is expected to be maximized during these periods. This can be problematic for species that are migratory (e.g., Yellow Rail, Sora, Virginia Rail) or that have partially migratory populations (e.g., Black Rail, King Rail) as this may bias our perceptions of their ecology and habitat associations to assumptions garnered within a small period of their life history. This refined focus on the breeding grounds for these species may lead to short-term management success, but the long-term population viability of migratory avifauna is reliant upon the connectivity and protection of their entire range including wintering and migratory habitat (Marra et al. 2018). Thus, studies that incorporate these often-overlooked aspects of rallid ecology will remain strikingly relevant as it relates to the range-wide conservation and management of these secretive species.

The overarching purpose of our study is to inform both habitat management and long-term winter and spring survey protocol for six target rail

species: Eastern Black Rail, Yellow Rail, Virginia Rail, Sora, King Rail, and Clapper Rail, with the latter two combined due to difficulties in discerning species and hybridization (Stiffler et al. 2018[b]; hereafter, King/Clapper Rail). Our project objectives meet this goal are as follows: 1.) Compare and contrast the detection estimates of each survey method used for each target rail species, 2.) Determine environmental variables that influence occupancy and detection probability for each target rail species, 3.) Estimate the cost (both in terms of time & monetarily) of each survey method utilized. In doing so we intend to contribute to the cohesive understanding of the wintering, migratory, and early breeding season habits for these six rail species residing on the Texas Gulf Coast.

METHODS

We randomly selected 90 points constrained within U.S. Fish and Wildlife Service National Wetlands Inventory wetland categories in ArcGIS Pro (v. 2.8.2). All points were set to be ≥400m apart from each other and ≥50m from main road systems in order to establish independence and to reduce edge effects. Any points determined to be inaccessible (e.g., requiring an airboat to reach) or otherwise unsafe (e.g., excessive American alligator [*Alligator mississippiensis*] activity) were re-sampled. Points were distributed between five study sites along the Texas Gulf Coast as follows: 5 at Galveston Island State Park (SP), 36 at Justin Hurst Wildlife Management Area (WMA), 19 at Mad Island WMA, 19 at Guadalupe Delta WMA, and 11 at Mustang Island SP.

Galveston Island State Park

Galveston Island SP is a coastal site with public access located within Galveston County, Texas (Fig. 1). Our points were exclusively located on the 'marsh-side' of the park, primarily within Deep Sand Shrubland, Deep Sand Grassland Swale Marsh, and Deep Sand Grassland (Elliott et al. 2014). Some of these areas bordered Brackish Low Tidal Marsh and Brackish High Tidal Marsh (Elliott et al. 2014), which directly abutted to open water. Vegetation at these points varied considerably, but shrubs consisted of *Baccharis* spp.; *Spartina* composition was largely *S. patens* and *S. spartinae*; emergent composition varied from *Typha* spp. and *Juncus gerardii*, to patches of *Salicornia bigelovii* and *Batis maritima*. Total precipitation for Galveston County in 2022 was 97.33cm with mean temperatures of 23.0°C and an average relative humidity of 69% (National Weather Service [hereafter, NWS]: Galveston Station).

Justin Hurst Wildlife Management Area

Justin Hurst WMA is located within Brazoria County, Texas (Fig. 1). Total precipitation for 2022 was 95.27cm, with lows in precipitation in April (1.72cm) and June (0.55cm; NWS: Freeport Station). Average annual temperature for the region was 21.8°C (NWS: Angleton/Lake Jackson Station). Active habitat management for game species (Mourning Dove [*Zenaida macroura*], white-tailed deer [*Odocoileus virginianus*], and waterfowl) occurs year-round and includes prescribed burns, mechanical treatment (e.g., disking, mowing, planting), and impoundment regulation. Cattle (*Bos taurus*) grazing is prevalent and widespread at the property, including within saltmarshes. Public access is restricted except for

regulated waterfowl hunts, feral hog (*Sus scrofa*) hunts, dove hunts, and white-tailed deer hunts.

Our survey points were located primarily within Brackish Low Tidal Marsh, Brackish High Tidal Marsh, and Gulf Coast Salty Prairie (Elliott et al. 2014), but we did have a few points within Baccharis Shrubland and Gulf Coast Salty Prairie Shrubland. Vegetation composition varied considerably and includes various compositions of the following: *Spartina spartinae, S. patens, S. alterniflora, Baccharis* spp.*, Borrichia frutescens, Salicornia bigelovii, Batis maritima*, *Distichlis spicata, D. littoralis, Lycium berlandieri, L. carolinianum*, and *Typha* spp. Vegetation composition varied based on proximity to water, frequency of tidal/impoundment fluctuations, and frequency of disturbance.

Mad Island Wildlife Management Area

Mad Island WMA is located within Matagorda County, Texas (Fig. 1). Average annual temperature for 2022 was 22.1°C (NWS: Palacios Station) and was the 10th warmest year on record. Total precipitation in 2022 for the region was 86.56cm, with drought conditions that increased in severity in April (0.12cm) and peaked in late July (2.36cm; NWS: Palacios Station). Active habitat management occurs year-round and includes prescribed burns, mechanical treatments, and impoundment regulation. Cattle grazing occurs on the property, although can be considered low intensity in locations where rail surveys were conducted. Public access is restricted except for regulated waterfowl, feral hog, and white-tailed deer hunts.

Our points were primarily within Brackish High Tidal Marsh and Brackish Low Tidal Marsh which held *Spartina spartinae, S. alterniflora, Distichlis spicata, Batis maritima, and Salicornia bigelovii*, although some points were on the edge of freshwater ponds/impoundments with *Typha* spp., and various freshwater emergents. <50% of points were located within periodically burned wet-prairies (*Andropogon* spp. and similar graminoids and wild-flowers, with various pockets for water accumulation). Wet-prairie systems were completely dry during our 2022 survey season and contained no ephemeral pools or moist substrate.

Guadalupe Delta Wildlife Management Area

Our study area within Guadalupe Delta WMA was split across two counties: Calhoun County, Texas and Refugio County, Texas (Fig.1). The total precipitation in 2022 was 83.99 cm, with precipitation lows occurring April (0.10cm) and July (1.09cm); average annual temperature reached 21.8°C (NWS: Point Comfort Weather Station). Active habitat and marshland management occurs year-round, including mechanical treatments, impoundment management, and prescribed burns where appropriate. Public access is restricted except for regulated American alligator, feral hog, white-tailed deer, and waterfowl hunts.

We scattered the survey points within Brackish High Tidal Marsh, Brackish Low Tidal Marsh, and Floodplain Herbaceous Wetland, with some points located within Floodplain Evergreen Shrubland, Sea-Ox-eye Daisy Flats, Floodplain Grassland, and Salty Prairie (Elliott et al. 2014). Vegetation composition within locations influenced by freshwater contained a mixture of

Typha spp., *Cyperus articulates*, *Echinodorus berteroi, Schoenoplectus pungens*, *Panicum* spp., and various grasses and freshwater emergents. Brackish locations contained semi-homogenous stands of *Spartina spartinae*, *Borrichia frutescens*, and/or *Distichlis spicata*.

Mustang Island State Park

Mustang Island SP was our southern-most coastal site and is located within Nueces County, Texas (Fig. 1). The state park is open to the public. The average annual temperature for 2022 was 22.5°C with a total precipitation of 65.60cm (NWS: Corpus Christi Station).

Our rail survey points were within Deep Sand Grassland, Brackish Low Tidal Marsh, Brackish High Tidal Marsh, and Salty Prairie, with a few points within Deep Sand Grassland Swale Marsh and along South Texas Algal Flats (Elliott et al. 2014). Vegetation composition at these points was comprised of dense mixed graminoid and forb stands of *Andropogon glomeratus, Panicum virgatum, Borrichia frutescens, Rhynchospora colorata, Hydrocotyle bonariensis,* and *Schoenoplectus pungens* with clumped patches of *Spartina spartinae.* Within dry, sand-substrate dominated areas, *Opuntia engelmannii var. lindheimeri*, *Distichlis littoralis*, *D. spicata*, *Salicornia bigelovii,* and *Batis maritima* persisted in patchy distributions. Very little standing water was present except for two points that were on the edge of deep, brackish, open water.

Call-playback Surveys

Call-playback surveys loosely followed recommendations by Conway (2011) and Butler et al. (2015) and were thus separated into two separate sampling periods: morning surveys (hereafter, AM surveys), which were conducted 30 minutes prior to civil sunrise to three hours after civil sunrise; evening surveys (hereafter, PM surveys), which were conducted two hours prior to civil sunset to 30 minutes after civil sunset. Surveys were not conducted during precipitation events nor during periods of excessive high wind (constant speeds >17kph). All 90 points were visited a minimum of 12 times from February-June 2022 with six surveys during the AM and six during the PM per point for a total of 1,080 surveys. Although some points were visited as many as 13 times, these additional revisits were removed from statistical analyses. AM/PM sampling occurred per site every ≥14-days to ensure independence. Surveyors conducted surveys independently and survey points were rotated amongst surveyors, however 'surveyor' was included as a detection variable during occupancy modeling to account for potential surveyor-specific differences.

At the start of each survey, surveyors would record the following variables: survey start-time, visual estimation of percent cloud cover, average wind speed (Kestrel 2000), temperature (Kestrel 2000), standing water (handheld ruler). If a surveyor detected a target rail species (Sora, King/Clapper Rail, Yellow Rail, Black Rail, or Virginia Rail), they wrote the species, time of the detection, whether the individual was heard or seen, and an approximate compass bearing of the detection. We combined King Rail and Clapper Rail detections as 'King/Clapper,' as both species occur at these sites and vocalizations are

challenging to decipher both by human and automated observers (Stiffler et. al 2018[b]).

We conducted call-playback surveys using a FoxPro Patriot Speaker set to ~80dB with a custom rail vocalization sequence uploaded to the unit. The call-playback sequence was 11.5-minutes long, beginning with a 5-minute period of passive listening followed by 6.5 minutes of rail playback interspersed with silence. We used standardized vocalization descriptions for rail songs and calls from Pieplow et al. (2017) and used Butler et al. (2023) in the case of the Yellow Rail "bugle" call. We structured the species order from least intrusive to most intrusive (Conway 2011) in the following order:

- 5-minute passive period
- 15- seconds of **Black Rail** "*Kee-kee-JERR"* (song)
    - 5-seconds silence
- 15-seconds of Black Rail Chatter Duet (call)
- 30-seconds silence (Transition)
- 15-seconds of **Yellow Rail** "*Tick-tick, tick-tick-tick"* (song)
    - 5-seconds silence
- 15-seconds of Yellow Rail Bugle (call)
- 30-seconds of silence (Transition)
- 15-seconds of **Sora** Whinny (song)
    - 5-seconds of silence
- 15-seconds of Sora "*Ooit"* (call)
- 30-seconds silence (Transition)
- 15-seconds of **Virginia Rail** Grunt Series (song)
    - 5-seconds of silence
- 15-seconds of Virginia Rail "*Kee-kee-burr*" (female advertising call)
- 30-seconds of silence (Transition)
- 15-seconds of **King Rail** Grunt Series (song)
    - 5-seconds of silence
- 15-seconds of King Rail *"Kek-churr"* (call)
- 30-seconds of silence (Transition)
- 15-seconds of **Clapper Rail** Grunt Series (song)
    - 5-seconds of silence
- 15-seconds of Clapper Rail *"Kek-churr"* (call)
- 30-seconds of silence (Transition)

End of Survey (Total time: **11.5** minutes)

We incorporated the recently described “bugle” vocalization (see Butler et al. 2023) within the Yellow Rail vocalization sequence and organized the bugle recording to mimic the sound of two separate individuals responding to one another.

Autonomous Monitoring

We paired 20 AudioMoth units (v. 1.2.0) together with 20 Reconyx HyperFire 2 Professional Covert IR trail cameras at our designated call-playback points for 14-day sampling periods. Each AudioMoth was enclosed within a waterproof case (IPX7) and then secured to the top of a 1.5m Powder Coated Steel U-post using 16-gauge galvanized steel wire cut to length. Trail cameras were mounted onto handmade wooden stands for stability which were then secured ~0.15-0.3m from the bottom of each U-post. AudioMoths were programmed to record continuously from 30-minutes prior to civil-sunrise to 3-hours after civil sunrise and then again at 2-hours prior to civil-sunset to 30-minutes after civil-sunset. Cameras were programmed to remain ‘active’ 24-hours a day and when triggered would capture a rapid burst of 4 photos followed by a quiet period of 15-seconds. Camera sensitivity was set to high and they were custom modified to focus at 0.6m. Joint ARU/trail camera units were rotated after ≥14-day sampling period for an intended total of 80 points sampled during the season. Points were randomly selected with replacement, so that points could have the opportunity to be re-sampled during a later portion of the survey season when occupancy may have changed. Sampling periods that extended beyond 14-days were truncated to only examine the first 14 sampling dates for analyses.

Units were distributed at sites as follows: eight at Justin Hurst WMA, four at Mad Island WMA, four at Guadalupe Delta WMA, three at Mustang Island SP, and one at Galveston Island SP.

Vegetation Sampling

At each point, we created 50m transects in each cardinal direction extending from the approximate point 'center' for a total of four transects per point (Fig. 2). Using Daubenmire cover classes (Daubenmire 1959), we placed a 20x50cm quadrat constructed with PVC pipes was placed every 25m along each transect for a total of 8 cover-class measurements (Fig. 2). We recorded the percent cover of the following variables within each 20x50cm quadrat: standing water, bare ground, detritus, and 'vegetation'. Vegetation was further split into the following categories: cordgrass (*Spartina alterniflora, S. spartinae, S. patens*), saltgrass (*Distichlis spicata*), tall emergent (non-woody cover ≥1m in height; e.g., *Typha spp., Juncus spp.*), short emergent (non-woody cover <1m in height; e.g., *Salicornia bigelovii, Batis maritima*), woody vegetative (woody plants <1m in height or otherwise considered non-shrubs; e.g., *Borrichia frutescens*), and shrub (e.g., *Iva frutescens, Baccharis halimifolia, Lycium carolinianumm*).

We measured stem density of cordgrass (*Spartina* spp.), saltgrass, and shrubs within $1m^2$ quadrats created with PVC pipes that were randomly placed eight times using a coordinate system related to the 50m transects. Stems were individually counted and averaged for each category for each point sampled. Plants were only included if the individual was fully rooted within the quadrat. In order to measure standing crop (hereafter, above ground biomass or AGB), we

conducted clip plots within $1m^2$ quadrats created with PVC pipes that were randomly placed six times. We clipped all vegetation within the quadrat to 1cm of the ground (USDI National Park Service 2003). Material was then transported and dried at ~50-60°C in a drying cabinet for a minimum of 96-hours, or until sample weight ceased fluctuating. We weighed the dried material and averaged samples to obtain a point-specific average AGB value (g/m^2). Random selection for stem density and clip plots was determined using a random number generator (-50 to 50), where negative coordinate values (-50 to 0) were associated with transects directly south and west, and positive values (0 to 50) were associated with the north and east transects (Fig. 2). Any values that caused overlap with other quadrats were re-generated.

Occasionally, rails would be detected beyond a 50m radius of the point within a drastically different habitat type than what was represented by the point. In these instances, the vegetation survey was conducted beyond the original 50m radius and within the representative area where the birds were identified. For example, if the point was in a dry upland spot, but surveyors detected Clapper Rails consistently just beyond the point and within the high salt marsh, the vegetation survey would be conducted in the high salt marsh. The vegetation survey would be 50m within this habitat type or far enough so that all four cardinal directions represented this habitat-type.

Statistical Analyses

We utilized single-season, single-species occupancy modeling as described by MacKenzie et al. (2018) for call-playback surveys, trail camera

captures, and passive acoustic monitoring. All occupancy modeling was conducted in program R (v. 4.1.1; R Core Team 2021) with the package 'unmarked' (Fiske and Chandler 2011). Due to very high overdispersion displayed by our data, we split the 12 call-playback visits into two sets of six-visits. We labeled and separately analyzed these sets as 'early-season' (First six visits from February to early-April) and 'late-season' (Last six visits from mid-April to June). Late-season modeling for migratory species (Sora, Yellow Rail, and Virginia Rail) was not conducted in this thesis, as their gradual exit from the system violates the assumption of population closure and requires special consideration; The late-season detections of these three wintering species will be analyzed separately outside of this thesis with relaxed assumptions of closed occupancy. To account for any residual over/under-dispersion issues, we ranked and assessed our final complex models QAICc values when $\hat{c}$ >1. All occupancy models (including complex models) utilize call-playback survey data, unless otherwise explicitly stated, as these have the most revisits and the most survey points sampled.

We processed our ARU data with Kaleidoscope Pro (v. 5.4.2; Wildlife Acoustics) by creating advanced classifiers for each target rail species. Training files for each species were acquired with permission from Cornell's Macaulay Library. We supplemented training with additional files of commonly encountered species (e.g., Red-winged Blackbird [*Agelaius phoeniceus*], Willet [*Tringa semipalmata semipalmata*], Black-necked Stilt [*Himantopus mexicanus*]) and background noise (e.g., wind, human voices) included from personal files or

modified files from Xeno-Canto. We used 2027 training files for the Sora classifier, 1798 training files for the King/Clapper Rail classifier, 1005 training files for the Black Rail classifier, 610 training files for the Yellow Rail classifier, and 271 training files for our Virginia Rail classifier. We trained classifiers to sort audio by species-specific vocalizations, with each vocalization being clustered separately. Our Black Rail classifier searched for "*Kee-kee-JERR,"* Churr series, and "*kew*" calls and separated them into separate clusters. Our Sora classifier searched for *"Ooit"* calls and the descending Whinny song. The Yellow Rail classifier searched for the "*Tick-tick, tick-tick-tick"* song and the 'bugle' call. The Virginia Rail classifier searched for the grunt series, "*Kiddik kiddik*" song, and "*Kee-kee-burr*" calls. We combined King Rail and Clapper Rail training vocalizations and created an advanced classifier to search for single note 'kek'-series and the grunt-series. Final advanced classifier settings are provided within Table 1.

Covariates analyzed for call-playback occupancy estimates included: average above ground biomass (AGB), site, average standing water, average tall-emergent cover, average short-emergent cover, average saltgrass cover, average cordgrass cover, average water cover, average bareground cover, average woody cover, and average shrub cover. Covariates were selected based on results from correlation matrixes as well as ecological relevancy to the species and environments studied. We used call-playback survey results to calculate occupancy estimates, as we had the most revisits and points for this method. Variables analyzed for call-playback detection estimates included: temperature,

survey time (AM/PM), day-of-year (0-365), surveyor, water level, average wind speed, percent cloud cover, and apparent magnitude (i.e., moonlight). For trail camera surveys we examined day-of-year data and moonlight; For passive acoustic monitoring, we included day-of-year, moonlight, and average daily windspeed. Moonlight or moon phase is occasionally noted as impacting rail detection (Yellow Rail: Prescott et al. 2002; Virginia Rail: Prescott et al. 2002; Tango et al. 1997; Black Rail: Tolliver et al. 2019, Spear et al. 1999; Rouget's Rail [*Rougetius rougetii*]*:* Ripley 1977) and may impact general activity levels for nocturnal species (e.g., Whip-poor-will [*Antrostomus vociferus*]: Wilson and Watts 2006). To see how this variable may impact trail camera capture and passive acoustic vocalizations of rails, we used QuickPhase Pro4 to calculate average daily magnitude in a 24hr period for each day sampled. Average daily windspeed was calculated using data generated from the closest weather station to each site, which we then used to average the continuous wind speeds in a 24hr period for each date sampled during the 14-day ARU sampling window.

RESULTS

Vegetation Sampling

We conducted vegetation surveys at 87 of the 90 survey points from 1 June- 30 June 2022. Three survey points were not sampled for vegetation as the water levels attracted active American alligators and the vegetation height and density prevented safe visibility. These three points were excluded from occupancy modeling analyses. Stem density data displayed high correlation with other vegetation variables and was thus discarded from analyses.

Call-playback

During the 2022 season we recorded a total of 96 Black Rail detections, where detections are a binary classification of either 1 (detection) or 0 (no detection): 35 detections within the early-season with 14 points containing ≥1 detection; 61 detections within the late-season with 27 points containing ≥1 detection. Ranking occupancy variables by AICc scores resulted in significance for site-specific differences (AICcWt=0.59) and average biomass (AICcWt=0.22) for early-season Black Rail and average tall-emergent cover (AICcWt=0.18), site-specific differences (AICcWt=0.15), and average biomass (AICcWt =0.13) for late-season Black Rail (Table 2). For detection variables, day-of-year (AICcWt=0.51) and percent cloud cover (AICcWt=0.12) were impactful for early-season detection, while surveyor-specific differences (AICcWt =0.77) were very significant (ΔAICc >2) during the late-season (Table 3). Surveyor differences indicate a difference in detection probability for each surveyor, with surveyor one showing lower detection probability for Black Rail ($\hat{p}$=0.45) than surveyor two ($\hat{p}$=0.67). Early-season complex models including both detection and occupancy variables resulted in top models containing average above-ground biomass, site, and day-of-year, although QAICc scores are close to one another (Table 4). Late-season complex models resulted in the top model that included average biomass, average tall-emergent cover, and surveyor, however top models are close in QAICc ranking (Table 5). Both early-season and late-season occupancy estimates for Black Rail were highest at Galveston Island SP (early-season: ψ=0.84; late-season: ψ=0.65) relative to other sites (Table 6). Proportion

of the area occupied was 0.16 during early-season and 0.31 during the late-season (Table 6).

We only recorded 19 total Yellow Rail detections throughout the 2022 field season: 10 during the early-season with 8 points containing ≥1 detection; 9 during late-season with 8 points containing ≥1 detection. Due to this very limited sample size of Yellow Rail detections, the analyses presented are included to examine general trends and are provisional until a larger sample size can be obtained. For these reasons, we also refrained from conducting additive variable and covariate ranking. The top ranked detection variable that held the greatest weight was 'time' (AICcWt=0.26), closely followed by average wind speed, survey water level, and surveyor differences (Table 7). The highest ranked occupancy variable was average above ground biomass (AICcWt=0.92), which held >90% of the model weight (Table 8). The proportion of area occupied was 0.13 for early-season Yellow Rail (Table 6).

We recorded a total of 135 Sora detections in 2022: 53 early-season detections with 24 points containing ≥1 detection; 82 late-season detections with 32 points containing ≥1 detection. Early-season Sora detection variable AICc ranking resulted in surveyor-specific differences and wind speed as the highest ranked (Table 9), while early-season covariate AICc ranking resulted in average cordgrass cover, average tall-emergent cover, and the survey site holding most of the weight (Table 10). Complex QAICc model ranking resulted in the null-model ranking the highest (Table 11).

Detection estimates for early-season Sora are $\hat{p}$=0.34 when examining the null model (Table 12), however when tall-emergent cover and surveyor detection differences are included, the detection estimate decreases to $\hat{p}$=0.19. Surveyor differences indicate a difference in detection probability for each surveyor, with surveyor one showing lower detection probability for Sora ($\hat{p}$=0.45) than surveyor two ($\hat{p}$=0.72). The next best complex model is closely ranked with the null, and thus both are included. The proportion of area occupied was 0.29 for early-season Sora, with the highest occupancy at Guadalupe Delta WMA (Table 6).

We recorded a total of 38 Virginia Rail detections, with 21 detections occurring during the early-season and 10 points containing a minimum of 1 detection. During the late-season, we recorded 17 Virginia Rail detections with 10 points containing a minimum of 1 detection. AICc ranking of early-season Virginia Rail detection variables resulted in survey time, water levels, and cloud cover being the top-ranked variables (Table 13). Due to very close AICc values (Table 13), we chose to include all three variables for complex model ranking. AICc ranking of early-season Virginia Rail occupancy variables resulted in average above ground biomass and average tall emergent cover as being the top ranked covariates (Table 14), although both are very close in AICc ranking. Complex models for early-season Virginia Rail displays biomass, water, and time as being the best model, however this model is ranked very close to the other models created and is only slightly higher-ranked than the next best model with less variables (Table 15). Using time as a detection estimate variable, detection

estimates are at $\hat{p}$=0.21 (SE 0.08) for AM surveys and $\hat{p}$=0.09 (SE 0.08) for PM surveys. The proportion of area occupied by Virginia Rail was 0.11 (Table 6).

We recorded a total of 396 detections of King/Clapper Rail during the 2022 season: 195 early-season detections and 64 points with ≥1 detection; 201 late-season detections and 57 points with ≥1 detection. Covariate ranking for occupancy estimates for early-season King/Clapper Rail resulted in the following top-ranked covariates: site-specific differences, average saltgrass cover, average bareground, and average standing water (Table 16). Variable ranking for detection estimates for early-season King/Clapper Rail resulted in wind speed holding the majority of the weight when compared to other variables (Table 17). Complex occupancy models for early-season King/Clapper Rail resulted in the model including site and wind speed, however close QAICc values shows that the second best-ranked model including average standing water is close in importance (Table 18). Covariate ranking for late-season King/Clapper Rail resulted in site and average standing water ranking the highest and holding the majority of the weight (Table 16), while variable ranking resulted in water being ranked highest and holding the most weight compared to other variables. The detection variable that ranked highest in importance for late-season King/Clapper Rail was standing water (Table 17). Complex occupancy models for late-season King/Clapper Rail resulted in the best model also including average standing water (Table 19). The proportion of area occupied was 0.73 for early-season and 0.65 for late-season, with Justin Hurst WMA having the highest estimated occupancy during early-

season (96%; Table 6) and Mad Island WMA having the highest estimated occupancy during late-season (79%; Table 6).

Passive Visual Monitoring (Trail Cameras)

We deployed trail cameras starting 14 February and achieved 139 deployments. Due to supply chain issues impacting AudioMoth distribution, we had to redeploy trail cameras at points already sampled once we obtained the ARUs. AudioMoths and trail cameras were then simultaneously deployed on the same posts. We captured a total of 114,553 photos in 2022: 52,064 at Justin Hurst, 29,183 at Mustang Island, 21,417 at Guadalupe Delta, 11,261 at Mad Island, and 628 at Galveston Island. Of these photos, we captured a total of 1786 rail photos: 711 at Justin Hurst WMA, 644 at Guadalupe Delta WMA, 379 at Mad Island WMA, 28 at Galveston Island SP, and 24 at Mustang Island SP. The majority of the rail photos were of Sora (1,251), followed by Virginia Rail (256), King/Clapper Rail (255), and Black Rail (24). We captured 0 photos of Yellow Rail during the 2022 season. False triggers often occurred due to vegetation swaying in the wind, rodents (*Oryzomys spp., Sigmodon spp., Peromyscus spp.*), and non-target bird species (including but not limited to: Boat-tailed Grackles [*Quiscalus major*], Great-tailed Grackles [*Q. mexicanus*], LeConte's Sparrows [*Ammodramus leconteii*], Swamp Sparrows [*Melospiza georgiana*], Savannah Sparrows [*Passerculus sandwichensis*], Sedge Wrens [*Cistothorus stellaris*], Marsh Wrens [*C. palustris*], Purple Gallinule [*Porphyrio martinicus*], and Red-winged Blackbirds).

We used naïve detection estimates for model ranking due to our small sample size of rail detections. We did explore the effects of moonlight and day-of-year on detection for all species and included them in separate ranking tables (Table 20), however naïve detection estimates are compared against other survey methods (Table 12).

Passive Acoustic Monitoring (Autonomous Recording Units)

Due to supply-chain issues, we were forced to delay the majority of 2022 ARU deployment until mid-April (Late-season). We were able to implement 56 successful ARU deployments and generated a total of 2061.29 GB of audio data. Red-winged Blackbirds and Eastern Meadowlarks (*Sturnella magna*) often perched on top of the ARUs to sing, especially early morning and late afternoons. Relevant rail detections may have overlapped with the very loud vocalizations of these species individuals of whom would often sing for extended periods at a time. False positives generated by the classifiers included Red-winged Blackbirds, Eastern Meadowlarks, Seaside Sparrows (*Ammodramus maritimus*), and various shorebirds (*Calidris* spp.), but varied considerably depending on the individual classifier, location of the ARU, and season. Of the 56 successful ARU deployments, we detected Black Rail at least once at 18 deployment points, Yellow Rail at 2, Sora at 14, Virginia Rail at 0, and King/Clapper Rail at 27.

Detection estimates generated from passive acoustic surveys for all species are the naïve detection estimates (Table 12), however we also explored the effect of moonlight, day-of-year, and average daily continuous wind speed on detection (Table 21). None of the models indicate strong relationships between the variables

and detection for Sora, Black Rail, or King/Clapper Rails (Table 21). Moonlight is an important variable for detecting Sora (Table 21), although the relationship is not strong (ΔAICc <2).

DISCUSSION

Black Rail & Yellow Rail

Our call-playback detection estimate for Black Rail during the late-season ($\hat{p}$=0.23) is comparable to spring/breeding season mean call-playback estimates for Black Rail along the Gulf Coast reported in the literature (≥3 visits, $\hat{p}$=0.19, Tolliver et al. 2019; 6 visits, $\hat{p}$= 0.094, Butler et al. 2015), even though our mean occupancy estimates are generally lower than these studies (Proportion of area occupied: ψ=0.16). The discrepancy of detection estimates may be due to differences in the call-playback sequence and the exact vocalizations used. Since our study encompasses multiple species, we must include these species' vocalizations regardless of whether they are expected to be present at a given point or not. Many rail species show an increase in detection probability when heterospecific vocalizations are included in the call-playback sequence (Nadeau et al. 2013). Black Rail are known to respond to heterospecific rail vocalizations (Todd 1980), and this may have inadvertently increased our Black Rail detection probability relative to studies only utilizing Black Rail vocalizations. Our late-season passive acoustic monitoring detection estimate for Black Rail ($\hat{p}$=0.27) is similar to our late-season call-playback estimate ($\hat{p}$=0.23), which indicates that there are additional factors influencing late-season vocalization rates besides the call-playback sequence or the number of revisits.

Our detection variables selected in our top models for Black Rail slightly differ from that of the literature. We did not find significance of average daily apparent magnitude (Table 3), although moon-phase significantly impacted Black Rail detection for some studies (e.g., Tolliver et al. 2019). Additionally, we saw no significant impact of the timing of surveys (AM vs. PM) on detection probability (Table 3). Since we only surveyed during dawn and dusk, which are similar in detection probability estimates (Butler et al. 2015), the effect of time was likely minimized. We may have found a stronger effect of time if we had surveyed later in the night prior to midnight when Black Rail are predicted to peak in vocalization rates during the late-season (Butler et al. 2015). In contrast, while our Yellow Rail sample size was small, we found that survey time (AM vs. PM) was an influential variable on detection probability (Table 7). Detection estimates are predicted to be higher during the evening compared to the morning (AM: $\hat{p}$=0.15 vs. PM: $\hat{p}$=0.45) which matches reported vocal activity determined from ARU detections of wintering Yellow Rail reported by Butler et al. (2023). Breeding Yellow Rails are reported to frequently vocalize during the crepuscular period just prior to sunrise and sunset (Bazin and Baldwin 2007) and passively sing prior to call-playback elicitation during this period (Martin et al. 2014), which supports our observations on Yellow Rail wintering grounds. Anecdotally, we noticeably flushed more individual Yellow Rails when we would walk out to our call-playback points during the dusk and evening periods and we heard more passive bugles prior to call-playback elicitation during this period as well. Yellow

Rail activity, such as foraging and daily movement, may be highest during the crepuscular time frames regardless of seasonality.

Day-of-year was the most influential variable on early-season Black Rail detection probability, while surveyor differences were the highest ranked for late-season detection probability. Surveyor differences indicated that one surveyor was more likely to detect Black Rail ($\hat{p}$=0.45 vs $\hat{p}$=0.67) and Sora ($\hat{p}$=0.45 vs. $\hat{p}$=0.72) than the other. While both surveyors were trained to detect all target species, ability to detect rails may be influenced by other factors besides skill or experience. Surveyors may have overestimated rail detections by confusing one species' vocalizations with another; surveyors may have underestimated detections by being more hesitant to record distant and hard to hear rail vocalizations, individuals that only called once, or those that vocalized an a-typical vocalization. These results reflect the importance of including surveyors as a detection variable, regardless of training or skill, as individual surveyor variation may lead to differences in detection estimates that should be accounted for. The detection probability and standard error between surveyors was moderately consistent between both Black Rail and Sora, indicating that the differences present were likely the same regardless of species.

The significance of AGB for Eastern Black Rail echoes the significance of 10-20cm stem density found by Butler et al. (2015) and the preference of California Black Rail (*L. j. coturniculus*) to areas with high stem densities and canopy coverage (Flore and Eddleman 1995). The importance of AGB for early season Yellow Rail occupancy (Table 8; Fig. 3) mirrors that of results for Black

Rail (Table 2; Table 4; Fig. 4). Black Rail and Yellow Rail are commonly reported as wintering together along the Texas Gulf Coast (Butler et al. 2022; *Pers. Communication, Chris Butler)*, primarily in drier *Spartina spartinae* dominated high-marsh (Anderson 1977). We frequently recorded both species on the same surveys during call-playback and we consistently encountered Yellow Rail during drone surveys when searching for Black Rail (*Chapter 3, Olsen*). In 2023, we captured both Yellow Rail and Black Rail on the same trail camera trapping period (results from 2023 not included) within dry *S. spartinae* high-marsh. If both species winter together and have similar winter-habitat requirements, then habitat management (e.g., prescribed fire) for one species may actively facilitate the management of the other. Some areas that were burned during our 2023 field season held Yellow Rail as early as 1-month post-burn, especially when the burn was patchy and left random portions of standing vegetation. Yellow Rail are generally more tolerant of wet prairie and sedgeland systems compared to Black Rail (Leston and Brookhout 2020), even during the winter. These wetter areas visually have less AGB biomass and canopy cover compared to *S. spartinae* dominated high-marsh and were uncommon at our study sites. Other variables that showed importance for Yellow Rail occupancy included standing water levels and average cordgrass cover (Table 7) and the true significance of these covariates may be better distinguished with a larger wintering Yellow Rail sample size.

Yellow Rail are not reported as being vocally active during their winter and migratory periods, although they will occasionally sing their *Tick-tick, tick-*

tick-tick song during migration (Reynard 1974). We incorporated the bugle vocalization (Butler et al. 2023) into our call-playback study design as well as the breeding song in order to explicitly determine if responses could be elicited from wintering Yellow Rail. Our preliminary call-playback results utilized within the Butler et al. (2023) study displayed a significant difference in the number of Yellow Rail responses elicited by broadcasting the bugle call compared to passive listening, broadcasting the *Tick-tick, tick-tick-tick* song, and from broadcasting heterospecific vocalizations of Black Rail, Virginia Rail, King Rail, Clapper Rail, and Sora. The ability to elicit Yellow Rail vocalizations allowed us to incorporate occupancy modeling for this species in this thesis, and while our sample size of early-season call-playback detections is small (early-season n=10, late-season n=9*)*, there remains an observable difference in the 2022 detection estimates of call-playback (n=19; $\hat{p}$=0.043) compared to passive acoustic monitoring (n=2*;* $\hat{p}$=0.002) and trail cameras (n=0; $\hat{p}$=0). The purpose of this vocalization on the wintering grounds is uncertain, however we suggest that it may be used as a contact call amongst individuals (Butler et al. 2023). Rail vocalization frequency often displays density dependence: Sora and Virginia Rail have density-based detectability differences for call-playback (Robertson and Olsen 2014) and the rate of the King Rail grunt series (Pieplow 2017), a vocalization which acts as a 'roll call' amongst individuals, is also shown to be correlated with density (Schroeder and McRae 2020). Under this pretense, passive acoustic monitoring efforts for non-breeding Yellow Rail that incorporate the bugle vocalization may experience difficulties due to spatial variability in wintering Yellow Rail densities

(Butler et al. 2021). If the bugle vocalization is functionally reliant upon Yellow Rail density, then the detection probability and frequency of passive bugle vocalizations will be influential on ARU detection rates. While Butler et al. (2023) recorded a higher proportion of bugles during their ARU surveys than our study, an ARU array may have facilitated a better representation of passively vocalizing Yellow Rail within appropriate habitat compared to our single ARU set-up, especially with the limited detection range of the bugle call (Butler et al. 2023). Future studies that aim to explain the effect of Yellow Rail densities on detection estimates as well as exploring the potential use of ARU arrays may lead to improved passive acoustic monitoring methods that maximize the detection of non-breeding Yellow Rail. Winter surveying for Yellow Rail traditionally consists of rope-drags, where a rope weighted with noise makers (e.g., bottles full of pebbles or jingle bells) is drug through an area where Yellow Rail are suspected to be occupying in order to flush birds for identification (e.g., Butler et al. 2010). The effective use of the bugle vocalization would reduce the need for resource intensive and invasive surveys for determining occupancy of this very secretive species of rail.

In densely vegetated areas dominated by semi-homogenous stands of *S. spartinae*, trail camera placement was reliant on either human-created or naturally established 'tunnels' underneath the vegetation. These natural gaps underneath the canopy of vegetation are navigable by Black Rail (Weske 1969) and could be modified to attempt to lead rails towards triggering distance of the trail camera. We modified these tunnels to either funnel multiple pathways to one central area

where the camera would be placed, or by creating new tunnels in instances where dense vegetation otherwise precluded camera visibility. We infrequently captured Black Rails by trail cameras, but their capture may be more predictable in situations where a camera array is utilized or in areas where occupancy is already established and the monitoring of expected individuals is the focus (e.g., Hand et al. 2021). We failed to capture any Yellow Rails during camera trapping in 2022, but when conducting drone surveys or walking to call-playback points we often observed individual Yellow Rail walking on top of the *S. spartinae* canopy rather than underneath it. While they do utilize tunnel systems like Black Rail (Pers. Obs.), they may do so infrequently. A different approach for capturing Yellow Rail detections using trail cameras should be refined and we suggest that an array be used to maximize potential detections for both species.

Sora & Virginia Rail

While our highest ranked occupancy model for early-season Sora was the null model (Table 11), average tall-emergent cover was selected as one of the most influential variables on occupancy (Table 10). The influence of this variable is consistent with previous studies on migratory and wintering Sora, which report a preference to sites containing tall-emergent vegetation (Sayre and Rundle 1984, Conway 1990, Crowley 1994;) interspersed with seed-bearing plants (Rundle and Fredrickson 1981, Sayre and Rundle 1984). Predicted occupancy probability increased as tall emergent coverage class increased, further supporting that tall emergent cover is an important variable for wintering Sora. The influence of cordgrass presence on Sora occupancy did not show an obvious trend. This may

be due to differences in cordgrass species, which were lumped into a single classification class. The cordgrass species recorded at our sites largely consisted of *S. spartinae*, a species that often establishes on drier substrates. Sora on migration prefer wet areas with <15cm of water (Rundle and Fredrickson 1981, Sayre and Rundle 1984), where this cordgrass species is not found in great proportions. Sora show an avoidance of dry emergent stands during the breeding season (Johnson and Dinsmore 1986), and thus it is likely that avoidance of drier stands dominated by *S. spartinae* occurs during the migratory and wintering period is contributing to the decline in occupancy probability as cordgrass cover increases. However, in many wetter areas *S. patens* and *S. alterniflora* were present and interspersed with areas of deeper water. *S. spartinae* provide both seeds and general cover in these wetter areas, potentially facilitating the occupancy of Sora until a certain point. Alternatively, the presence of these plant species may be representative of ideal water and substrate conditions that influence Sora occupancy, acting more as an indicator of preferred conditions rather than being the source of sustained occupancy. While water was not a top-ranked variable for Sora in our study, this may be representative of how we obtained our water measurements rather than a true interpretation of lack of significance. Water cover and average water depth were taken late-season during vegetation surveys when Texas was in a severe drought, revealing bare-ground/mud as opposed to measurable water.

Trail cameras were very effective in capturing Sora and Virginia Rail (Table 12) compared to other species. This may be explained by inter-specific

differences in daily movements and home range size, as species such Clapper Rails have wider variation in home range size (home range=1.37 to 11.51 ha; Overton 2007, Rush et al. 2010) and seasonality in home range (Meanley 1985), while Black Rail (home range=1.57-2.30ha; Haverland et al. 2021) and Yellow Rail (home range=1.6ha; Grace et al. 2005) both have arguably more restrictive winter home ranges. Sora migratory and wintering territoriality is noted to be minimal (Melvin and Gibbs 2020) and their daily movement may dependent upon optimal forage conditions and general food availability (Sayre and Rundle 1984, Fournier et al. 2018). Cameras placed in areas that contain ideal foraging characteristics (e.g., ideal water levels) may attract higher densities of Sora and thus increase the likelihood of capturing a Sora on a given camera-trap day. Under these circumstances, a shorter camera-trap time-window may still capture Sora while reducing the influence of shifting environmental conditions (e.g., changes in water levels) on occupancy. Additionally, the emergent habitat favored by migratory Sora and Virginia Rail is arguably easier for optimal camera setup, as there are often distinct mammal trails that can be exploited. Both species were also noted to semi-frequently expose themselves at the very edge of emergent habitat, allowing cameras to be successfully triggered when placed on muddy banks where deeper water and emergent vegetation met. This ease in camera placement may have disproportionately skewed the number of Sora and Virginia Rail triggers relative to our other target species.

We detected zero Virginia Rail on ARUs (Table 21), even at locations where occupancy was known due to responses on call-playback surveys. The

reduction of the detection probability of passive surveying for this species is similar to results by Conway and Gibbs (2001) which displayed a >500% increase in the number of Virginia Rail detections with the use of call-playback compared to passive detections. Sora acoustic monitoring in the early-season showed slight influence of moonlight on detection probability (AIC weight=0.50), however more variables should be analyzed in order to determine environmental influences on ARU detection. The use of ARUs for late season Sora, however, was very effective as detection estimates were higher than call-playback for early season (Table 12). This method may be a feasible survey strategy for detecting wintering Sora prior to migration and exit from the system.

King Rail & Clapper Rail

The gradual decline in the number of King/Clapper Rails detected per call-playback survey as the season progressed (Fig. 5) further supports our reduced late-season call-playback detection probability (Table 12) compared to early-season results. Waddle et al. (2022) found that King Rail detection probability gradually increased from February to June while Clapper Rail detection probabilities gradually declined as the season progressed. Stiffler et al. (2018[a]) found a gradual decline in detection probability for combined King/Clapper Rails as a function of date, which is similar to the reduction in detection probability from early to late-season that we determined as well (Table 12). While we combined King/Clapper Rail detections, it is likely that most birds we detected were Clapper Rail, as 80% of our study sites and associated points can be considered predominantly brackish, tidally influenced saltmarsh. The decline in

the number of King/Clapper Rails detected per survey (Fig. 5) as a function of survey date also displays this trend. This is likely explained by the period of nesting and brood rearing by King/Clapper Rails which occurs within this timeframe (Rush et al. 2020).

We did find that late-season ARUs produced a similar detection probability to early-season call-playback (Table 12), potentially indicating a viable alternative even as detection probability declines. Using ARUs, Stiffler et al. (2018[a]) determined an average detection estimate for King/Clapper Rails as 0.63; Waddle et al. (2022) determined an average detection estimate for Clapper Rails as 0.604 and 0.476 for King Rails when using ARUs. Our estimate of 0.706 is similar to these studies, though is slightly higher which may be due to differences in ARU recording-duration or the ARU model used (Song Meters vs. AudioMoths). Our recording duration was tailored to initiate during the predicted period of peak vocalization activity in both the morning and evening (Conway 2011) and recorded for the entire 3.5-hour period morning/evening period. Since ARUs were recording continuously for a total of seven hours per day, the likelihood of a unit capturing a passively vocalizing King/Clapper Rail may be higher than the likelihood of a call-playback surveyor recording an individual within the 11.5-minute survey timeframe, especially when vocalization response rates decline later in the season (Waddle et al. 2022). The constant recording period produced a greater number of audio files, but the use of an automated classifier reduced both the processing time of raw files (~10 minutes per 30GB) as well as the time required by a surveyor to scour for target species. The 14-day

consecutive sampling period that we implemented may have also contributed to the increase in our detection estimates relative to other studies.

Water levels, both at the individual survey level and the landscape level from vegetation surveys, played an important role for both early and late-season King/Clapper Rail. King/Clapper Rail tend to occupy areas with deeper water compared to other rail species, especially in areas where vegetation can be interspersed with channels of water (Rehm and Baldassarre 2007). We measured surface water each survey to capture revisit variation in water levels as many of our points were tidally influenced or are within impoundments that change based on seasonal management objectives. Rails may be pushed around the landscape into wetter areas when points are dry, influencing surveyor detection of occupying individuals. Predicted late-season occupancy increased as standing water depths increased, until eventually leveling off at a depth of ~5cm (Fig. 6). Early-season King/Clapper rail detection was less influenced by standing water than late-season, which may be representative of the drought that the Texas Gulf Coast experienced in 2022. This drought rapidly altered water levels, making changes in water availability more prevalent than during the early-season. Wind as an influence on detection may be due to a combination of reduced surveyor ability to detect rails (Yip et al. 2017) and reduced King/Clapper Rail vocalization activity during periods of high wind (Robbins 1981, Carr and Lima 2010), and supports the recommendations to conduct surveys during periods of low wind speeds (Robbins 1981, Conway 2011) to increase detection probabilities for King/Clapper Rails as well as other species.

MONITORING & MANAGEMENT RECOMMENDATIONS

Yellow Rail & Black Rail

The amount of above ground biomass (AGB) in an area that is suspected to have Black or Yellow Rail should be considered prior to major habitat modifications, such as prescribed burns or mechanical disturbance. Although our results do not show a plateau for AGB (Fig. 4), there is likely a maximum threshold of AGB that facilitates Black Rail occupancy prior to becoming exclusionary. Specific impacts of prescribed fire on Eastern Black Rail are less clear, but in some portions of this species' range individuals return to burned sites as early as 2.5 months post-burn (Hand et al. 2021) and low-intensity semi-frequent landscape disturbance is shown to facilitate occupancy for other rail species (Conway et al. 2010, Austin and Buhl 2013, Rogers et al. 2013, Johnson and Lehman 2021). The rate of AGB accumulation of saltmarshes is largely influenced by precipitation (De Leeuw 1990, Dunton et al. 2001), and the precipitation gradient along the Gulf Coast would lead to differences in return intervals of rails post-burn. Yellow Rail may be more sensitive to biomass accumulation (Fig.3) as well as woody encroachment as shown by their negative relationship between time since fire and occupancy on the breeding grounds (Burkman 1993, Austin and Buhl 2013). While frequent fire intervals (<3 years) are shown to potentially facilitate Yellow Rail occupancy in wet prairie and pine savanna habitat types (Soehren et al. 2018, Morris et al. 2020), in high/low saltmarsh where AGB per square meter is projected to be higher, fire interval should instead be modified based on AGB estimates where feasible. We

recommend that large-scale habitat modifications within dry, *S. Spartinae* dominated high-marsh should follow a 3–5-year disturbance interval and wet prairie or similar systems maintain a frequent disturbance interval (<3 years) in order to actively facilitate the occupancy of both rail species on the Gulf Coast of Texas Additional consideration for locations with active cattle grazing is recommended. The combination of cattle grazing with prescribed fire facilitates Yellow Rail persistence in some instances (Mizell 1998), but we did observe that areas with high frequency and high intensity cattle activity had widespread vegetation compaction and surface drainage issues. High intensity grazing may severely alter the vegetation structure through a reduction of height and cover (Robert 1997), detracting from otherwise inhabitable areas for Black Rail. This may be further exacerbated in locations without irrigation or that are otherwise dry, especially in the early-season (Richmond et al. 2012). Low intensity grazing, however, may maintain AGB at appropriate levels when other disturbance methods are not feasible, as shown with Virginia Rail and Sora (Cent 2019). The joint impacts of grazing intensity combined with other habitat disturbance mechanisms, like prescribed fire frequency/intensity, should be explored further in future studies.

In areas managed for waterfowl (e.g., impoundments), it should be noted that deep-water marshes and partial marshes (50% open water to 50% emergent vegetative cover) used by waterfowl are not conducive to Yellow Rail habitat preferences (Brookhout 1995, Alvo and Robert 1999). This aspect of Yellow Rail wintering ecology requires further examination, but we predict that impoundment

manipulation that allows for a transition of moist ground with semi-dense AGB cover that then leads into deeper water would allow for the simultaneous management of waterfowl and Black and Yellow Rails (Goldade et. al. 2002). A larger sample size of wintering Yellow Rail is required to further extrapolate on the relationship of microhabitat-scale hydrology and occupancy.

We recommend surveying for wintering Yellow Rail using call-playback methods that incorporate the bugle vocalization. Future studies using passive acoustic monitoring and advanced classifiers may increase the detection probability for Yellow Rail, but current work indicates that passive vocalization by Yellow Rail may require increased survey effort for effective detection (Table 12). Surveys with an ARU array placed within viable habitat (e.g., Butler et al. 2023) may increase the detection probability for Yellow Rail compared to our results from late-season ARU placement. Additionally, early-season ARU placement may reveal higher detection estimates than late-season, which will be explored outside of this thesis in 2023.

We recommend surveying for wintering Black Rail using ARUs, rather than call-playback. Even though we do not have early-season ARU data from our 2022 season, the low call-playback detection estimates (Table 12) make call-playback surveys very costly to implement during the winter (Table 23). Per additional-hour rates for call playback are significantly higher than that of passive acoustic monitoring (Table 23) and low winter detection estimates will inherently require additional survey hours to determine occupancy regardless of method. For late-season Black Rail, we also recommend the use of ARUs, as the detection

estimates are comparable between passive acoustic monitoring and call-playback, while being significantly higher than passive visual monitoring (Table 12). ARU cost-efficiency is largely determined by assumed classifier success, and we argue that training a classifier with adequate target and non-target vocalization files will be necessary to maximize efficiency. We provide access to our advanced classifier files used in this thesis and recommend that interested users continue to train/modify these files to reduce location-specific variation that may increase false positive rates and reduce detection efficiency.

Sora & Virginia Rail

While we did detect both Virginia Rail and Sora in brackish marshes, freshwater impoundment management may be the most feasible method of allowing habitat managers to achieve waterfowl management goals while creating additional habitat for wintering Sora and Virginia Rail. Sora and Virginia Rail occupancy are both influenced by the presence of emergent vegetation (Table 10, Table 14) and thus impoundment management for waterfowl may inadvertently create optimal habitat and foraging conditions for these species. We recommend that management include adequate interspersion near deep-water impoundments, which would allow for tall-emergent vegetation and short-succulents to establish on the banks that would provide adequate cover for Sora and Virginia Rail to forage and occupy (Rehm and Baldassarre 2007). We predict that a gradual transition of water levels from bank to center would provide the most optimal conditions for these species. The implementation of discing followed by gradual

fall flooding (<15cm) can stimulate seed-producing annual-plant growth and provide additional forage for migratory Sora (Fredrickson and Reid 1986).

Call-playback for wintering Sora should be considered for long-term, early-season surveys. Vocalization rates are predicted to increase upon the approach of the breeding season (Lor and Malecki 2002, Conway 2011) which increases the viability of passive acoustic surveying methods to alleviate costs for late-season surveying. We recommend that surveys for late-season Sora be conducted starting in early-April when vocalization activity is predicted to increase; habitat usage assumptions garnered from surveys within the pre-spring migratory period may differ than that of wintering Sora, and both may be required depending on specific management and monitoring objectives.

We recommend call-playback for both winter and late-season monitoring of Virginia Rail. Reliance on passive vocalizations of this species may inaccurately underrepresent Virginia Rail occupancy, especially in the early-season prior to migratory movement (Marion et al. 1981). Trail cameras may be a more affordable long-term option for monitoring than call-playback, with the consequence of reduced detection probability compared to call-playback (Table?). However, trail camera detection probability may be increased with an array of trail cameras and with careful placement consideration.

King Rail & Clapper Rail

Our results indicate that water levels appear to strongly influence King/Clapper Rail presence (Table 18, Table 19, Fig 6). Many of the low-marshes

where we often detected high proportions of King/Clapper Rail contained deep water (2cm-12cm) with mixed proportions of *S. alterniflora* clumps, patches of emergent succulents, and bare-round (mud). The presence of deeper water interspersed with vegetation facilitates optimal foraging conditions by providing cover for both the rails themselves as well as their prey items. Management that promotes marshland vegetative regeneration (e.g., prescribed fire) and maintains adequate water levels will likely promote occupancy for King/Clapper Rail. Population monitoring in areas where rail hunting is common and reducing vegetation and exposed-mud degradation caused by human entry into the habitat would be beneficial for maintaining occupied areas during hunting seasons when pressure on populations is highest. Freshwater and/or brackish impoundment regulation, as described in the "MONITORING & MANAGEMENT RECOMMENDATIONS: *Sora & Virginia Rail*" subsection would also benefit King/Clapper Rail persistence.

The detection estimates generated from passive acoustic monitoring of King/Clapper Rails is comparable to call-playback detection estimates and we highly recommend the use of ARUs for year-round monitoring. While we do not currently have estimates for early-season ARUs, we predict that passive acoustic monitoring will remain comparable if early-season placement is the only viable option, as the number of King/Clapper Rails detected per survey is highest during the early-season (Fig 6). The efficiency and cost-effectiveness of AudioMoths compared to in-person call-playback (Table 23) make wide-scale, multi-year implementation feasible for areas with limited budgets. If implementing passive

acoustic monitoring, we recommend the use of an automated classifier such as Kaleidoscope Pro's (Wildlife Acoustics) advanced classifier option in order to further reduce the time required to detect King/Clapper Rails. The classifier utilized within this study is available for use and modification and we recommend additional training of this classifier to further reduce false-positive rates. Long-term monitoring of Clapper Rail and King Rail populations may allow wildlife biologists and habitat managers to detect shifts in occupancy over time, facilitating the large-scale visualization of patterns and trends relating to area usage. This may become increasingly important in areas where rail hunting is popular or where biologists want to know the impact of certain management regimes on marshland species.

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Tables and Figures

Table 1. Specifications used when creating 'advanced classifiers' in Kaleidoscope Pro (v. 5.4.2; Wildlife Acoustics) for Black Rail (*Laterallus jamaicensis*), Yellow Rail (*Coturnicops noveboracensis*), Sora (*Porzana carolina*), Virginia Rail (*Rallus limicola*), King/Clapper Rail (*R. elegans/R. limicola*).

Species	Frequency Minimum	Frequency Maximum	Duration (sec)	Max Gap	Max States	Max Clusters
Black Rail	1000	5000	0.25-1.2	0.35	12	500
Yellow Rail	1000	9000	0.25-1.2	0.35	12	500
Sora	1000	8000	0.25-0.70	0.35	12	500
Virginia Rail	1000	5000	0.25-3.0	0.35	12	500
King/Clapper Rail	1000	8000	0.25-0.70	0.35	12	500

Table 2. Ranked occupancy (ψ) models with naïve detection ($\hat{p}$) for early-season and late-season Black Rail (*Laterallus jamaicensis)* call-playback surveys. Ranking is based on corrected Akaike's Information Criteria (AICc).

Early-season Black Rail					Late-season Black Rail				
Occupancy Model	K	AICc	ΔAICc	AICcWt	Occupancy Model	K	AICc	ΔAICc	AICcWt
ψ(Site)$\hat{p}$(.)	6	188.40	0.00	0.59	ψ(Avg_TallEMCover)$\hat{p}$(.)	4	321.63	0.00	0.18
ψ(Biomass)$\hat{p}$(.)	3	190.38	1.98	0.22	ψ(Site)$\hat{p}$(.)	6	322.00	0.37	0.15
ψ(Avg_CordgrassCover)$\hat{p}$(.)	7	193.16	4.76	0.05	ψ(Biomass)$\hat{p}$(.)	3	322.33	0.70	0.13
ψ(.)$\hat{p}$(.)	2	193.77	5.37	0.04	ψ(.)$\hat{p}$(.)	2	322.77	1.15	0.10
ψ(Avg_TallEMCover)$\hat{p}$(.)	4	194.37	5.97	0.03	ψ(Avg_SaltgrassCover)$\hat{p}$(.)	5	322.88	1.25	0.10
ψ(Avg_StandingWater)$\hat{p}$(.)	3	195.74	7.34	0.02	ψ(Avg_ShortEMCover)$\hat{p}$(.)	7	323.08	1.46	0.09
ψ(Avg_WaterCover)$\hat{p}$(.)	5	195.80	7.40	0.01	ψ(Avg_WaterCover)$\hat{p}$(.)	5	323.18	1.55	0.08
ψ(Avg_ShrubCover)$\hat{p}$(.)	4	196.51	8.11	0.01	ψ(Avg_CordgrassCover)$\hat{p}$(.)	7	323.75	2.13	0.06
ψ(Avg_BareGCover)$\hat{p}$(.)	6	196.62	8.22	0.01	ψ(Avg_ShrubCover)$\hat{p}$(.)	4	324.84	3.22	0.04
ψ(Avg_WoodyCover)$\hat{p}$(.)	5	198.06	9.66	0.00	ψ(Avg_StandingWater)$\hat{p}$(.)	3	324.90	3.27	0.04
ψ(Avg_SaltgrassCover)$\hat{p}$(.)	5	198.81	10.41	0.00	ψ(Avg_Bareground)$\hat{p}$(.)	6	325.18	3.55	0.03
ψ(Avg_ShortEMCover)$\hat{p}$(.)	7	198.93	10.53	0.00	ψ(Avg_WoodyCover)$\hat{p}$(.)	5	326.94	5.31	0.01

Table 3. Ranked occupancy models with naïve occupancy (ψ) and detection ($\hat{p}$) variables for early-season and late-season Black Rail (*Laterallus jamaicensis*) call-playback surveys. Ranking is based on corrected Akaike's Information Criteria (AICc).

Early-season Black Rail					Late-season Black Rail				
Detection Model	K	AICc	ΔAICc	AICcWt	Detection Model	K	AICc	ΔAICc	AICcWt
ψ(.)$\hat{p}$(day-of-year)	3	190.12	0.00	0.51	ψ(.)$\hat{p}$(surveyor)	3	317.51	0.00	0.77
ψ(.)$\hat{p}$(cloud)	3	193.08	2.96	0.12	ψ(.)$\hat{p}$(.)	2	322.77	5.26	0.06
ψ(.)$\hat{p}$(.)	2	193.77	3.65	0.08	ψ(.)$\hat{p}$(water)	3	323.51	6.00	0.04
ψ(.)$\hat{p}$(surveyor)	3	193.80	3.68	0.08	ψ(.)$\hat{p}$(temperature)	3	323.97	6.46	0.03
ψ(.)$\hat{p}$(temperature)	3	194.43	4.31	0.06	ψ(.)$\hat{p}$(wind)	3	324.14	6.63	0.03
ψ(.)$\hat{p}$(moonlight)	3	194.87	4.75	0.05	ψ(.)$\hat{p}$(moonlight)	3	324.58	7.06	0.02
ψ(.)$\hat{p}$(time)	3	195.49	5.37	0.04	ψ(.)$\hat{p}$(time)	3	324.69	7.18	0.02
ψ(.)$\hat{p}$(water)	3	195.66	5.54	0.03	ψ(.)$\hat{p}$(cloud)	3	324.81	7.30	0.02
ψ(.)$\hat{p}$(wind)	3	195.78	5.66	0.03	ψ(.)$\hat{p}$(day-of-year)	3	324.89	7.38	0.02

Table 4. Complex occupancy model ranking for early-season Black Rail (*Laterallus jamaicensis*) using call-playback data. Ranking is corrected Quasi-Akaike information criterion (QAICc) to compensate for minor bouts of over-dispersion ($\hat{c}$ >1) displayed by the dataset.

Early-season Black Rail									
Detection Model	K	QAICc	ΔQAICc	QAICcWt	Occupancy Model	K	QAICc	ΔQAICc	QAICcWt
ψ(.)$\hat{p}$(day-of-year)	4	128.64	0.00	0.40	ψ(Site)$\hat{p}$(.)	7	166.58	0.00	0.46
ψ(.)$\hat{p}$(.)	3	130.23	1.59	0.18	ψ(Biomass)$\hat{p}$(.)	4	167.19	0.61	0.34
ψ(.)$\hat{p}$(day-of-year+cloud+surveyor)	6	130.57	1.93	0.15	ψ(.)$\hat{p}$(.)	3	169.76	3.18	0.09
ψ(.)$\hat{p}$(cloud)	4	130.57	1.94	0.15	ψ(Biomass+Site+Avg_Cordgrass) $\hat{p}$(.)	13	170.82	4.24	0.06
ψ(.)$\hat{p}$(surveyor)	4	131.05	2.41	0.12	ψ(Avg_Cordgrass)$\hat{p}$(.)	8	171.08	4.49	0.05
Final Complex Models									
ψ(Biomass+Site)$\hat{p}$(day-of-year)	**9**	**140.71**	**0.00**	**0.38**					
ψ(Biomass)$\hat{p}$(day-of-year)	5	140.97	0.27	0.33					
ψ(Site)$\hat{p}$(day-of-year)	8	141.65	0.94	0.24					
ψ(.)$\hat{p}$(.)	3	144.70	3.99	0.05					

Table 5. Complex occupancy model ranking for late-season Black Rail (*Laterallus jamaicensis*) using call-playback data. Ranking is corrected Quasi-Akaike information criterion (QAICc) to compensate for minor bouts of over-dispersion ($\hat{c}$ >1) displayed by the dataset.

Late-season Black Rail

Detection Model	K	QAICc	ΔQAICc	QAICcWt
ψ(.)$\hat{p}$(surveyor)	4	276.78	0.00	0.89
ψ(.)$\hat{p}$(.)	3	280.97	4.19	0.11
Final Complex Models				
ψ(Biomass+TallEMCover)$\hat{p}$(surveyor)	**7**	**285.82**	**0.00**	**0.34**
ψ(Biomass+TallEMCover+Site)$\hat{p}$(surveyor)	11	286.49	0.66	0.24
ψ(Site+TallEMCover)$\hat{p}$(surveyor)	10	288.20	2.38	0.10
ψ(TallEMCover)$\hat{p}$(surveyor)	6	288.39	2.56	0.09
ψ(Biomass+Site)$\hat{p}$(surveyor)	9	288.53	2.71	0.09
ψ(Biomass)$\hat{p}$(surveyor)	5	288.64	2.81	0.08
ψ(Site)$\hat{p}$(surveyor)	8	289.53	3.71	0.05
ψ(.)$\hat{p}$(.)	3	293.34	7.52	0.01

Occupancy Model	K	QAICc	ΔQAICc	QAICcWt
ψ(TallEMCover+Site+Biomass)$\hat{p}$(.)	10	165.47	0.00	1
ψ(TallEMCover)$\hat{p}$(.)	5	283.03	117.57	0
ψ(Biomass)$\hat{p}$(.)	4	283.31	117.84	0
ψ(.)$\hat{p}$(.)	3	283.36	117.89	0
ψ(Site)$\hat{p}$(.)	7	284.07	118.60	0

Table 6. Occupancy estimates for King Rail/Clapper Rail (*Rallus elegans/R. crepitans*), Black Rail (*Laterallus jamaicensis)*, Sora (*Porzana carolina*), Yellow Rail (*Coturnicops noveboracensis*), and Virginia Rail (*R. limicola*) using call-playback data. King/Clapper and Black Rail are both split into 'early-season' and 'late-season' estimates. Estimates for Yellow Rail, Sora, and Virginia Rail are for early-season, as they are migratory and exit the system during late-season.

Occupancy Estimates (ψ)						
Species	Proportion of Area Occupied	Galveston Island	Justin Hurst WMA	Mad Island WMA	Guadalupe Delta WMA	Mustang Island
(Early-season) King Rail/ Clapper Rail	0.73	0.81	0.96	0.70	0.51	0.45
(Late-season) King Rail/ Clapper Rail	0.65	0.60	0.75	0.79	0.69	0.09
(Early-season) Black Rail	0.16	0.84	0.20	0.05	0.06	0.09
(Late-season) Black Rail	0.31	0.65	0.45	0.34	0.13	0.09
Yellow Rail	0.13	0.00	0.39	0.00	0.15	0.21
Virginia Rail	0.11	0.00	0.12	0.12	0.28	0.00
Sora	0.29	0.22	0.30	0.30	0.48	0.00

Table 7. Ranked occupancy models with naïve occupancy (ψ) and detection ($\hat{p}$) variables for early-season Yellow Rail (*Coturnicops noveboracensis)* call-playback surveys. Ranking is based on corrected Akaike's Information Criteria (AICc).

Early-season Yellow Rail				
Detection Model	K	AICc	ΔAICc	AICcWt
ψ(.)$\hat{p}$(time)	3	97.39	0.00	0.26
ψ(.)$\hat{p}$(wind)	3	97.99	0.60	0.19
ψ(.)$\hat{p}$(water)	3	98.22	0.83	0.17
ψ(.)$\hat{p}$(surveyor)	3	98.35	0.96	0.16
ψ(.)$\hat{p}$(.)	2	99.47	2.08	0.09
ψ(.)$\hat{p}$(cloud)	3	101.45	4.06	0.03
ψ(.)$\hat{p}$(moonlight)	3	101.50	4.11	0.03
ψ(.)$\hat{p}$(temperature)	3	101.58	4.19	0.03
ψ(.)$\hat{p}$(day-of-year)	3	101.61	4.33	0.03

Table 8. Ranked occupancy (ψ) models with naïve detection ($\hat{p}$) for early-season Yellow Rail (*Coturnicops noveboracensis)* call-playback surveys. Ranking is based on corrected Akaike's Information Criteria (AICc).

Early-season Yellow Rail				
Occupancy Model	K	AICc	ΔAICc	AICcWt
ψ(Biomass)$\hat{p}$(.)	3	90.50	0.00	0.92
ψ(Avg_CordgrassCover)$\hat{p}$(.)	7	97.57	7.07	0.03
ψ(Avg_StandingWater)$\hat{p}$(.)	3	97.96	7.46	0.02
ψ(.)$\hat{p}$(.)	2	99.47	8.97	0.01
ψ(Avg_WoodyCover)$\hat{p}$(.)	5	100.65	10.15	0.01
ψ(Avg_SaltgrassCover)$\hat{p}$(.)	5	101.23	10.73	0.00
ψ(Site)$\hat{p}$(.)	6	101.58	11.08	0.00
ψ(Avg_TallEMCover)$\hat{p}$(.)	4	102.31	11.81	0.00
ψ(Avg_ShrubCover)$\hat{p}$(.)	4	103.23	12.73	0.00
ψ(Avg_ShortEMCover)$\hat{p}$(.)	7	103.25	12.75	0.00
ψ(Avg_WaterCover)$\hat{p}$(.)	5	103.57	13.07	0.00
ψ(Avg_Bareground)$\hat{p}$(.)	6	104.16	13.66	0.00

Table 9. Ranked occupancy models with naïve occupancy (ψ) and detection ($\hat{p}$) variables for early-season Sora (*Porzana carolinensis)* call-playback surveys. Ranking is based on corrected Akaike's Information Criteria (AICc).

Early-season Sora				
Detection Model	K	AICc	ΔAICc	AICcWt
ψ(.)$\hat{p}$(surveyor)	3	283.64	0.00	0.88
ψ(.)$\hat{p}$(wind)	3	288.77	5.13	0.07
ψ(.)$\hat{p}$(day-of-year)	3	291.73	8.09	0.02
ψ(.)$\hat{p}$(.)	2	292.46	8.82	0.01
ψ(.)$\hat{p}$(water)	3	293.62	9.98	0.01
ψ(.)$\hat{p}$(temperature)	3	293.80	10.16	0.01
ψ(.)$\hat{p}$(time)	3	293.89	10.26	0.01
ψ(.)$\hat{p}$(cloud)	3	294.31	10.67	0.00
ψ(.)$\hat{p}$(moonlight)	3	294.58	10.94	0.00

Table 10. Ranked occupancy (ψ) models with naïve detection ($\hat{p}$) for early-season Sora (*Porzana carolinensis)* call-playback surveys. Ranking is based on corrected Akaike's Information Criteria (AICc).

Early-season Sora				
Occupancy Model	K	AICc	ΔAICc	AICcWt
ψ(Avg_Cordgrass)$\hat{p}$(.)	7	288.24	0.00	0.51
ψ(Avg_TallEMCover)$\hat{p}$(.)	4	288.80	1.55	0.23
ψ(Site)$\hat{p}$(.)	6	292.06	3.81	0.08
ψ(.)$\hat{p}$(.)	2	292.46	4.22	0.06
ψ(Biomass)$\hat{p}$(.)	3	293.90	5.66	0.03
ψ(StandingWater)$\hat{p}$(.)	3	294.46	6.22	0.02
ψ(Avg_WoodyCover)$\hat{p}$(.)	5	294.48	6.24	0.02
ψ(Avg_BareGround)$\hat{p}$(.)	6	295.48	7.24	0.01
ψ(Avg_ShrubCover)$\hat{p}$(.)	4	295.71	7.47	0.01
ψ(Avg_WaterCover)$\hat{p}$(.)	5	295.87	7.63	0.01
ψ(Avg_Saltgrass)$\hat{p}$(.)	5	296.56	8.32	0.01
ψ(Avg_ShortEMCover)$\hat{p}$(.)	7	299.49	11.25	0.00

Table 11. Complex occupancy model ranking for early-season Sora (*Porzana carolinensis*) using call-playback data. Ranking is corrected Quasi-Akaike information criterion (QAICc) to compensate for minor bouts of over-dispersion ($\hat{c}$ >1) displayed by the dataset.

Early-season Sora									
Detection Model	K	QAICc	ΔQAICc	QAICcWt	Occupancy Model	K	QAICc	ΔQAICc	QAICcWt
ψ(.)$\hat{p}$(surveyor)	4	80.53	0.00	0.34	ψ(.)$\hat{p}$(.)	3	140.39	0.00	0.55
ψ(.)$\hat{p}$(surveyor+wind)	5	81.17	0.65	0.24	ψ(Avg_TallEMCover)$\hat{p}$(.)	5	141.58	1.19	0.30
ψ(.)$\hat{p}$(.)	3	81.18	0.65	0.24	ψ(Avg_Cordgrass)$\hat{p}$(.)	8	144.74	4.35	0.06
ψ(.)$\hat{p}$(wind)	4	81.86	1.33	0.17	ψ(Site)$\hat{p}$(.)	7	145.19	4.80	0.05
Final Complex Models					ψ(Avg_TallEMCover+Avg_Cordgrass)$\hat{p}$(.)	10	147.23	6.84	0.02
ψ(.)$\hat{p}$(.)	**3**	**96.39**	**0.00**	**0.43**	ψ(Avg_TallEMCover+Site)$\hat{p}$(.)	9	147.45	7.06	0.02
ψ(Avg_TallEMCover)$\hat{p}$(surveyor)	6	97.41	1.02	0.26	ψ(Avg_Cordgrass+Site)$\hat{p}$(.)	12	150.67	10.28	0.00
ψ(Avg_TallEMCover)$\hat{p}$(surveyor+wind)	7	97.93	1.54	0.20	ψ(Avg_TallEMCover+Avg_Cordgrassr+Site)$\hat{p}$(.)	14	154.01	13.62	0.00
ψ(Avg_TallEMCover)$\hat{p}$(wind)	6	99.27	2.88	0.10					

Table 12. Detection estimates ($\hat{p}$) for Yellow Rail (*Coturnicops noveboracensis*), Eastern Black Rail (*Laterallus jamaicensis jamaicensis*), King/Clapper Rail (*R. elegans*/*R. crepitans*), Sora (*Porzana carolina*), Virginia Rail (*R. limicola*). Early-season represents surveys conducted from February through early-April. Late season represents surveys conducted from Mid-April to June. All-season represents surveys conducted throughout the entire survey season from February-June.

Rail Species	Survey Method	Season	Detection Estimate ($\hat{p}$)
Yellow Rail	Call-playback	Early	0.043
	Autonomous Recording Units	Late	0.003
	Trail Camera	All-season	0.000
Black Rail	Call-playback	Early	0.041
	- - - -	Late	0.232
	Autonomous Recording Units	Late	0.279
	Trail Camera	All-season	0.002
King Rail/Clapper Rail	Call-playback	Early	0.733
	- - - -	Late	0.514
	Autonomous Recording Units	Late	0.706
	Trail Camera	All-season	0.128
Sora	Call-playback	Early	0.337
	Autonomous Recording Units	Late	0.474
	Trail Camera	All-season	0.291
Virginia Rail	Call-playback	Early	0.326
	Autonomous Recording Units	Late	0.000
	Trail Camera	All-season	0.178

Table 13. Ranked occupancy models with naïve occupancy (ψ) and detection ($\hat{p}$) variables for early-season Virginia Rail (*Rallus limicola)* call-playback surveys. Ranking is based on corrected Akaike's Information Criteria (AICc).

Early-season Virginia Rail				
Detection Model	K	AICc	ΔAICc	AICcWt
ψ(.)$\hat{p}$(time)	3	140.75	0.00	0.23
ψ(.)$\hat{p}$(water)	3	140.99	0.24	0.21
ψ(.)$\hat{p}$(cloud)	3	141.98	1.23	0.13
ψ(.)$\hat{p}$(.)	2	142.06	1.31	0.12
ψ(.)$\hat{p}$(day-of-year)	3	142.12	1.37	0.12
ψ(.)$\hat{p}$(temperature)	3	143.73	2.98	0.05
ψ(.)$\hat{p}$(surveyor)	3	143.87	3.13	0.05
ψ(.)$\hat{p}$(moonlight)	3	143.92	3.17	0.05
ψ(.)$\hat{p}$(wind)	3	144.18	3.43	0.04

Table 14. Ranked occupancy (ψ) models with naïve detection ($\hat{p}$) for early-season Virginia Rail (*Rallus limicola)* call-playback surveys. Ranking is based on corrected Akaike's Information Criteria (AICc).

Early-season Virginia Rail				
Occupancy Model	K	AICc	ΔAICc	AICcWt
ψ(Biomass)$\hat{p}$(.)	3	139.72	0.00	0.37
ψ(Avg_TallEM_Cover)$\hat{p}$(.)	4	139.94	0.22	0.33
ψ(.)$\hat{p}$(.)	2	142.06	2.34	0.11
ψ(Bareground)$\hat{p}$(.)	6	143.92	4.20	0.04
ψ(Avg_StandingWater)$\hat{p}$(.)	3	144.20	4.48	0.04
ψ(Avg_WoodyCover)$\hat{p}$(.)	5	144.31	4.59	0.04
ψ(Site)$\hat{p}$(.)	6	144.79	5.08	0.03
ψ(Avg_ShrubCover)$\hat{p}$(.)	4	145.66	5.94	0.02
ψ(Avg_WaterCover)$\hat{p}$(.)	5	147.66	7.94	0.01
ψ(Avg_SaltgrassCover)$\hat{p}$(.)	5	147.79	8.07	0.01
ψ(Avg_CordgrassCover)$\hat{p}$(.)	7	148.26	8.54	0.01
Ψ(Avg_ShortEMCover)$\hat{p}$(.)	7	149.44	9.72	0.00

Table 15. Complex occupancy model ranking for early-season Virginia Rail (*Rallus limicola)* using call-playback data. Ranking is corrected Quasi-Akaike information criterion (QAICc) to compensate for minor bouts of over-dispersion ($\hat{c}$ >1) displayed by the dataset.

Early-season Virginia Rail				
Detection Model	K	QAICc	ΔQAICc	QAICcWt
ψ(.)$\hat{p}$(time+water)	5	111.76	0.00	0.17
ψ(.)$\hat{p}$(time)	4	111.92	0.16	0.16
ψ(.)$\hat{p}$(water)	4	112.10	0.34	0.15
ψ(.)$\hat{p}$(.)	3	112.38	0.62	0.13
ψ(.)$\hat{p}$(time+cloud)	6	112.49	0.73	0.12
ψ(.)$\hat{p}$(cloud)	4	112.86	1.10	0.10
ψ(.)$\hat{p}$(water+cloud)	7	113.01	1.25	0.09
ψ(.)$\hat{p}$(time+water+cloud)	6	113.20	1.43	0.08
Final Complex Models				
ψ(Biomass)$\hat{p}$(water+time)	**6**	**101.58**	**0.00**	**0.16**
ψ(Biomass)$\hat{p}$(water)	5	101.66	0.08	0.15
ψ(Biomass)$\hat{p}$(time)	5	101.68	0.10	0.15
ψ(Avg_TallEMCover)$\hat{p}$(time)	6	102.56	0.98	0.10
ψ(Avg_TallEMCover)$\hat{p}$(water +time)	7	102.68	1.10	0.09
ψ(.)$\hat{p}$(.)	3	102.73	1.15	0.09
ψ(Avg_TallEMCover)$\hat{p}$(water)	6	102.75	1.17	0.09

Occupancy Model	K	QAICc	ΔQAICc	QAICcWt
ψ(Biomass)$\hat{p}$(.)	4	114.38	0.00	0.36
ψ(Avg_TallEMCover)$\hat{p}$(.)	5	115.07	0.68	0.26
ψ(Biomass+Avg_TallEMCover)$\hat{p}$(.)	6	115.55	1.17	0.20
ψ(.)$\hat{p}$(.)	3	115.75	1.36	0.18

ψ(Avg_TallEMCover+Biomass)$\hat{p}$(time)	7	103.32	1.74	0.07
ψ(Biomass+Avg_TallEMCover)$\hat{p}$(time+water)	8	103.43	1.85	0.06
ψ(Avg_TallEMCover+Biomass)$\hat{p}$(water)	7	103.44	1.86	0.06

Table 16. Ranked occupancy (ψ) models with naïve detection ($\hat{p}$) for early-season and late-season King/Clapper Rail (*Rallus elegans/R. crepitans)* call-playback surveys. Ranking is based on corrected Akaike's Information Criteria (AICc).

Early-season King/Clapper Rail					Late-season King/Clapper Rail				
Occupancy Model	K	AICc	ΔAICc	AICcWt	Occupancy Model	K	AICc	ΔAICc	AICcWt
ψ(Site)$\hat{p}$(.)	6	624.86	0.00	0.80	ψ(Site)$\hat{p}$(.)	6	569.36	0.00	0.89
ψ(Avg_SaltgrassCover)$\hat{p}$(.)	5	628.46	3.60	0.13	ψ(Avg_StandingWater)$\hat{p}$(.)	3	574.37	5.01	0.07
ψ(Avg_Bareground)$\hat{p}$(.)	6	630.94	6.08	0.04	ψ(Avg_ShrubCover)$\hat{p}$(.)	4	578.39	9.03	0.01
ψ(Avg_StandingWater)$\hat{p}$(.)	3	632.96	8.10	0.01	ψ(Avg_SaltgrassCover)$\hat{p}$(.)	5	578.40	9.04	0.01
ψ(Biomass)$\hat{p}$(.)	3	633.67	8.81	0.01	ψ(.)$\hat{p}$(.)	2	579.19	9.83	0.01
ψ(.)$\hat{p}$(.)	2	634.96	10.10	0.01	ψ(Biomass)$\hat{p}$(.)	3	581.20	11.84	0.00
ψ(Avg_CordgrassCover)$\hat{p}$(.)	7	636.09	11.23	0.00	ψ(Avg_WaterCover)$\hat{p}$(.)	5	581.85	12.49	0.00
ψ(Avg_WoodyCover)$\hat{p}$(.)	5	638.20	13.34	0.00	ψ(Avg_WoodyCover)$\hat{p}$(.)	5	582.21	12.85	0.00
ψ(Avg_ShrubCover)$\hat{p}$(.)	4	638.22	13.36	0.00	ψ(Avg_ShortEMCover)$\hat{p}$(.)	7	582.51	13.15	0.00
ψ(Avg_WaterCover)$\hat{p}$(.)	5	638.77	13.91	0.00	ψ(Avg_TallEMCover)$\hat{p}$(.)	4	582.95	13.59	0.00
ψ(Avg_TallEMCover)$\hat{p}$(.)	4	639.05	14.19	0.00	ψ(Avg_Bareground)$\hat{p}$(.)	6	584.01	14.65	0.00
ψ(Avg_ShortEMCover)$\hat{p}$(.)	7	640.56	15.70	0.00	ψ(Avg_CordCover)$\hat{p}$(.)	7	584.98	15.62	0.00

Table 17. Ranked occupancy models with naïve occupancy (ψ) and detection ($\hat{p}$) variables for early-season and late-season King/Clapper Rail (*Rallus elegans/Rallus crepitans)* call-playback surveys. Ranking is based on corrected Akaike's Information Criteria (AICc).

Early-season King/Clapper Rail					Late-season King/Clapper Rail				
Detection Model	K	AICc	ΔAICc	AICcWt	Detection Model	K	AICc	ΔAICc	AICcWt
ψ(.)$\hat{p}$(wind)	3	598.67	0.00	1	ψ(.)$\hat{p}$(water)	3	564.54	0.00	1
ψ(.)$\hat{p}$(surveyor)	3	629.63	30.95	0	ψ(.)$\hat{p}$(.)	2	579.19	14.65	0
ψ(.)$\hat{p}$(time)	4	634.00	35.33	0	ψ(.)$\hat{p}$(day-of-year)	3	580.56	16.03	0
ψ(.)$\hat{p}$(.)	2	634.96	36.29	0	ψ(.)$\hat{p}$(moonlight)	3	580.71	16.17	0
ψ(.)$\hat{p}$(cloud)	3	635.21	36.53	0	ψ(.)$\hat{p}$(wind)	3	580.84	16.30	0
ψ(.)$\hat{p}$(temperature)	3	636.19	37.51	0	ψ(.)$\hat{p}$(surveyor)	3	580.87	16.33	0
ψ(.)$\hat{p}$(water)	3	636.32	37.64	0	ψ(.)$\hat{p}$(cloud)	3	581.26	16.72	0
ψ(.)$\hat{p}$(moonlight)	3	636.56	37.89	0	ψ(.)$\hat{p}$(time)	3	581.32	16.78	0
ψ(.)$\hat{p}$(day-of-year)	3	637.10	38.42	0	ψ(.)$\hat{p}$(temperature)	3	581.33	16.79	0

Table 18. Complex occupancy model ranking for early-season King/Clapper Rail (*Rallus elegans/Rallus crepitans)* based on call-playback. Ranking is corrected Quasi-Akaike information criterion (QAICc) to compensate for minor bouts of over-dispersion (ĉ >1).

Early-season King/Clapper Rail									
Detection Model	K	QAICc	ΔQAICc	QAICcWt	Occupancy Model	K	QAICc	ΔQAICc	QAICcWt
ψ(.)$\hat{p}$(wind)	4	323.59	0.00	1	ψ(Site)$\hat{p}$(.)	7	325.98	0.00	0.18
ψ(.)$\hat{p}$(.)	3	341.83	18.25	0	ψ(Site+Avg_StandingWater)$\hat{p}$(.)	8	326.32	0.34	0.15
					ψ(.)$\hat{p}$(.)	3	326.50	0.52	0.14
Final Complex Models									
ψ(Site)$\hat{p}$(wind)	8	328.92	0.00	0.43	ψ(Avg_Bareground+Avg_StandingWater)$\hat{p}$(.)	8	326.53	0.55	0.14
ψ(Site+Avg_StandingWater)$\hat{p}$(wind)	**9**	**329.23**	**0.31**	**0.80**	ψ(Avg_StandingWater)$\hat{p}$(.)	4	326.60	0.61	0.13
ψ(Avg_StandingWater)$\hat{p}$(wind)	5	330.51	1.59	1.00	ψ(Avg_SaltgrassCover)$\hat{p}$(.)	6	326.61	0.63	0.13
ψ(.)$\hat{p}$(.)	3	349.13	20.21	1.00	ψ(Site+Avg_SaltgrassCover)$\hat{p}$(.)	10	328.63	2.65	0.05
					ψ(Avg_Bareground)$\hat{p}$(.)	7	329.07	3.08	0.04
					ψ(Site+Avg_StandingWater+Avg_Saltgrass)$\hat{p}$(.)	11	329.94	3.96	0.02
					ψ(Site+Avg_Bareground)$\hat{p}$(.)	11	332.13	6.15	0.01

ψ(Site+Avg_StandingWater+Avg_Bare ground)$\hat{p}$(.)	12	333.26	7.28	0.00
ψ(Site+Avg_StandingWater+Avg_Bare ground+Avg_SaltgrassCover)$\hat{p}$(.)	15	338.05	12.07	0.00

Table 19. Complex occupancy model ranking for late-season King/Clapper Rail (*Rallus elegans/Rallus crepitans)* using call-playback data. Ranking is corrected Quasi-Akaike information criterion (QAICc) to compensate for minor bouts of over-dispersion (ĉ >1).

Late-season King/Clapper Rail

Detection Model	K	QAICc	ΔQAICc	QAICcWt
ψ(.)$\hat{p}$(water)	4	207.15	0.00	0.87
ψ(.)$\hat{p}$(.)	3	210.93	3.78	0.13
Final Complex Models				
ψ(Avg_StandingWater)$\hat{p}$(water)	**5**	**207.64**	**0.00**	**0.66**
ψ(Site)$\hat{p}$(water)	8	210.53	2.89	0.15
ψ(Avg_StandingWater+Site)$\hat{p}$(water)	9	211.44	3.80	0.10
ψ(.)$\hat{p}$(.)	3	211.66	4.02	0.09

Occupancy Model	K	QAICc	ΔQAICc	QAICcWt
ψ(Site+Avg_StandingWater)$\hat{p}$(.)	7	567.22	0.00	0.73
ψ(Site)$\hat{p}$(.)	6	569.36	2.13	0.25
ψ(Avg_StandingWater)$\hat{p}$(.)	3	574.37	7.15	0.02
ψ(.)$\hat{p}$(.)	2	579.19	11.96	0.00

Table 20. AICc ranking for Eastern Black Rail (*Laterallus jamaicensis jamaicensis*), Virginia Rail (*Rallus limicola*), King/Clapper Rail (*R. elegans*/ *R. crepitans*), and Sora (*Porzana carolina*) trail camera detection models. Moonlight and day-of-year (0-365) are included as potential variables for influencing detection probability on trail camera captures.

Black Rail Trail Camera Detection Models

Detection Model	K	AICc	ΔAICc	AICcWt
$\psi(.)\hat{p}$(day-of-year)	3	57.26	0.00	0.62
$\psi(.)\hat{p}$(moonlight)	3	58.71	1.45	0.30
$\psi(.)\hat{p}(.)$	2	61.23	3.96	0.08

King/Clapper Trail Camera Detection Models

Detection Model	K	AICc	ΔAICc	AICcWt
$\psi(.)\hat{p}$(day-of-year)	3	188.96	0.00	0.52
$\psi(.)\hat{p}$(moonlight)	3	190.16	1.20	0.28
$\psi(.)\hat{p}(.)$	2	190.84	1.88	0.20

Virginia Rail Trail Camera Detection Models

Detection Model	K	AICc	ΔAICc	AICcWt
$\psi(.)\hat{p}$(moonlight)	3	190.97	0.00	0.43
$\psi(.)\hat{p}(.)$	2	191.58	0.61	0.32
$\psi(.)\hat{p}$(day-of-year)	3	192.01	1.04	0.26

Sora Trail Camera Detection Models

Detection Model	K	AICc	ΔAICc	AICcWt
$\psi(.)\hat{p}$(moonlight)	3	434.60	0.00	0.40
$\psi(.)\hat{p}(.)$	2	434.75	0.16	0.37
$\psi(.)\hat{p}$(day-of-year)	3	435.64	1.05	0.24

Table 21. AICc Ranking for Black Rail (*Laterallus jamaicensis*), King/Clapper Rail (*Rallus elegans/R. crepitans*), and Sora (*Porzana carolina*), for passive acoustic monitoring models. Yellow Rail is omitted due to low detections; Virginia Rail (*R. limicola*) is omitted due to zero detections.

Early-season Black Rail AudioMoth Detection Models

Detection Model	K	AICc	ΔAICc	AICcWt
$\psi(.)\hat{p}(.)$	2	353.85	0.00	0.41
$\psi(.)\hat{p}$(wind)	3	354.72	0.87	0.26
$\psi(.)\hat{p}$(moonlight)	2	355.52	1.67	0.18
$\psi(.)\hat{p}$(day-of-year)	3	355.85	2.00	0.15

King/Clapper Rail AudioMoth Detection Models

Detection Model	K	AICc	ΔAICc	AICcWt
$\psi(.)\hat{p}(.)$	2	519.70	0.00	0.39
$\psi(.)\hat{p}$(day-of-year)	3	520.27	0.56	0.30
$\psi(.)\hat{p}$(wind)	3	521.44	1.74	0.16
$\psi(.)\hat{p}$(moonlight)	3	521.70	2.00	0.14

Sora AudioMoth Detection Models

Detection Model	K	AICc	ΔAICc	AICcWt
$\psi(.)\hat{p}$(moonlight)	3	335.68	0.00	0.50
$\psi(.)\hat{p}(.)$	2	337.01	1.33	0.26
$\psi(.)\hat{p}$(wind)	3	338.18	2.51	0.14
$\psi(.)\hat{p}$(day-of-year)	3	338.89	3.21	0.10

Table 22. Cost analysis for 3 survey techniques for rails: call-playback, passive acoustic monitoring with the use of autonomous recording units, and passive visual monitoring with the use of trail cameras. Analysis does not include the additional cost and time for conducting vegetation surveys, as this aspect is highly dependent on the goals of the project itself and is subject to change in order to fit the objectives of the proposed monitoring effort.

Survey Method	Equipment/Personnel	Monetary Costs ($USD)/unit	Personnel Hours	Approx. 1st Season Costs	Approx. 2nd Season Costs
Call-playback	Minimum of one trained[a1] surveyor	$12-18/hr	8hrs/survey day[a2]	~$14,400[a3]	~$14,400
	Broadcast speaker (e.g., FoxPro Patriot)	$150/unit		$150	
	Kestrel 2000 Unit	$100/unit		$100	
	Minor costs: Batteries, datasheets, annual repairs to speaker, surveyor safety (e.g., snake gaiters, first aid kits) etc.	$500 (variable)		$500	$500
TOTAL Call-playback Season Cost				**$15,150**	**$14,900**
TOTAL Cost/Hr				**$252.20/hr**	**$248.33/hr**
Passive Acoustic Monitoring	ARUs: AudioMoth v. 1.2.0 w/ waterproof case	$254/unit	≥30min per one ARU deployment	$5080 (20 units)	
	Additional personnel to place ARUs and analyze data (optional)	$12-18/hr	15min-60min per top detection cluster analysis per ~98hr[b1] of audio	$900[b2]	$900

	Data-logger (optional)	$170/unit		$170	
	Kaleidoscope Pro (or similar software)	$400/year	8-40hr to train one advanced classifier (highly variable)	Analysis: $144 -$720 ($18/hr rate) Software: $400/yr	$400
	Minor costs: AA-batteries for ARUs, u-posts, annual repairs, microSD cards	$400 (variable)		$400	$400
TOTAL Passive Acoustic Monitoring Season Cost				**$7,094-$7,670**	**$1,700**
TOTAL Cost/Hr				**$118.23-$127.83/hr**	**$28.33/hr**
Passive Visual Monitoring	Trail cameras (Reconyx HyperFire 2 Professional Covert IR)	$460/camera	≥30min per one trail camera deployment	$9,200 (20 cameras)	
	Additional personnel to place trail cameras and analyze photos (optional)	$12-18/hr	10 min per 500 photos	~$600[c1]	~$600
	Minor costs: batteries, microSD cards, replacement of damaged cameras	$600 (variable)		$600	$600
TOTAL Passive Visual Monitoring Season Cost				**$10,400**	**$1,200**
TOTAL Cost/Hr				**$173.33/hr**	**$20/hr**

a1: Surveyor must be trained to effectively detect auditory vocalizations of all target species (in this study, this includes: King/Clapper Rail, Sora, Black Rail, Yellow Rail, and Virginia Rail); Training hours not included.
a2: 8hrs per day split into two survey periods (3.5hrs of AM surveys, 3.5hrs of PM surveys) and 1 additional hour of data entry.
a3: Salary based on $18/hr at 40/hr per week, for 20 total weeks
b1: 98hrs of audio is based on ~7hrs (3.5hrs AM, 3.5hrs PM) of audio recordings per day, for 14-days.
b2: Cost determined at $18/hr for an average of 37.5 min per analysis for 80 points.
c1: Cost determined at $18/hr multiplied by 33.33hr per 100,000 photos analyzed.

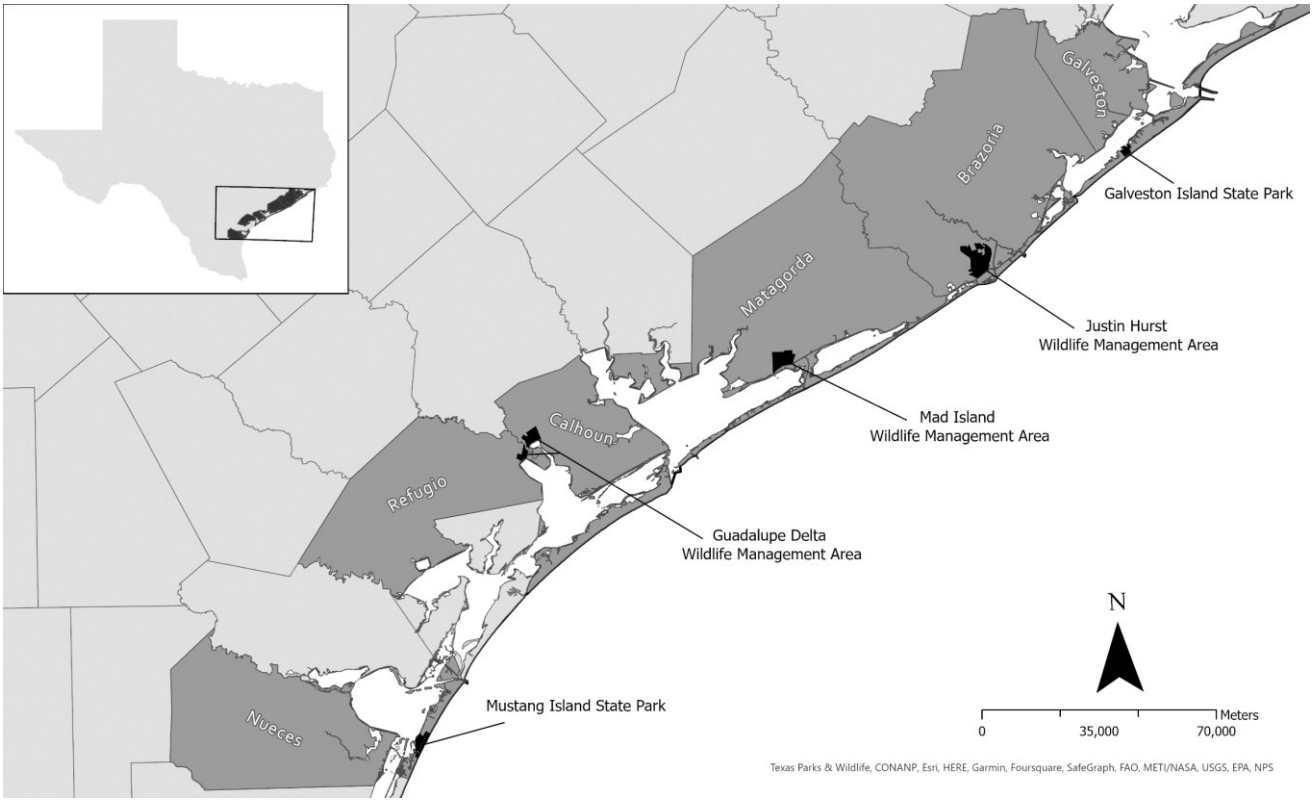

Figure 1. Map of the Texas, USA highlighting 5 study sites incorporated within this study: Galveston Island State Park (Galveston County), Justin Hurst Wildlife Management Area (Brazoria County), Mad Island Wildlife Management Area (Matagorda County), Guadalupe Delta Wildlife Management Area (Calhoun County and Refugio County), and Mustang Island State Park (Nueces County).

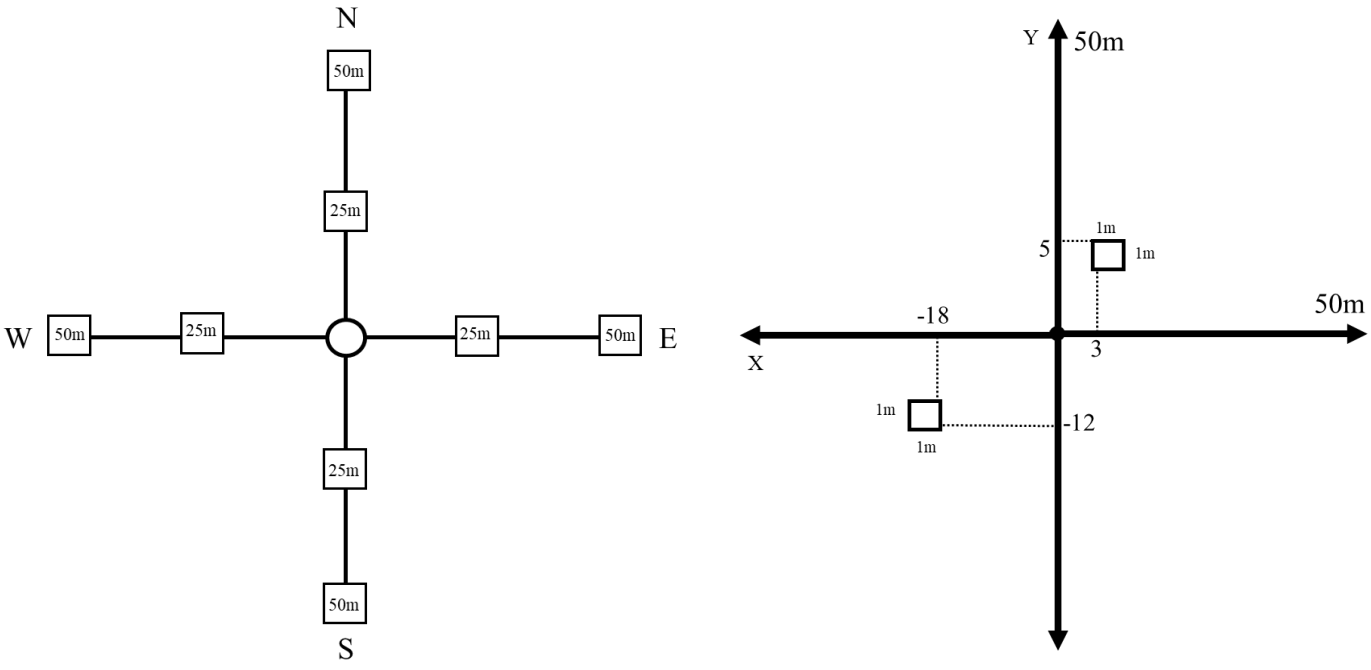

Figure 2. Representation (not to scale) of vegetation transects used for above ground biomass collection, stem density measurements, and percent cover estimates. Transect A shows the 25m-spaced quadrats used for percent cover in four cardinal directions. Transect B shows two examples of the X, Y coordinate system utilized for randomly placing the 1m x 1m quadrats.

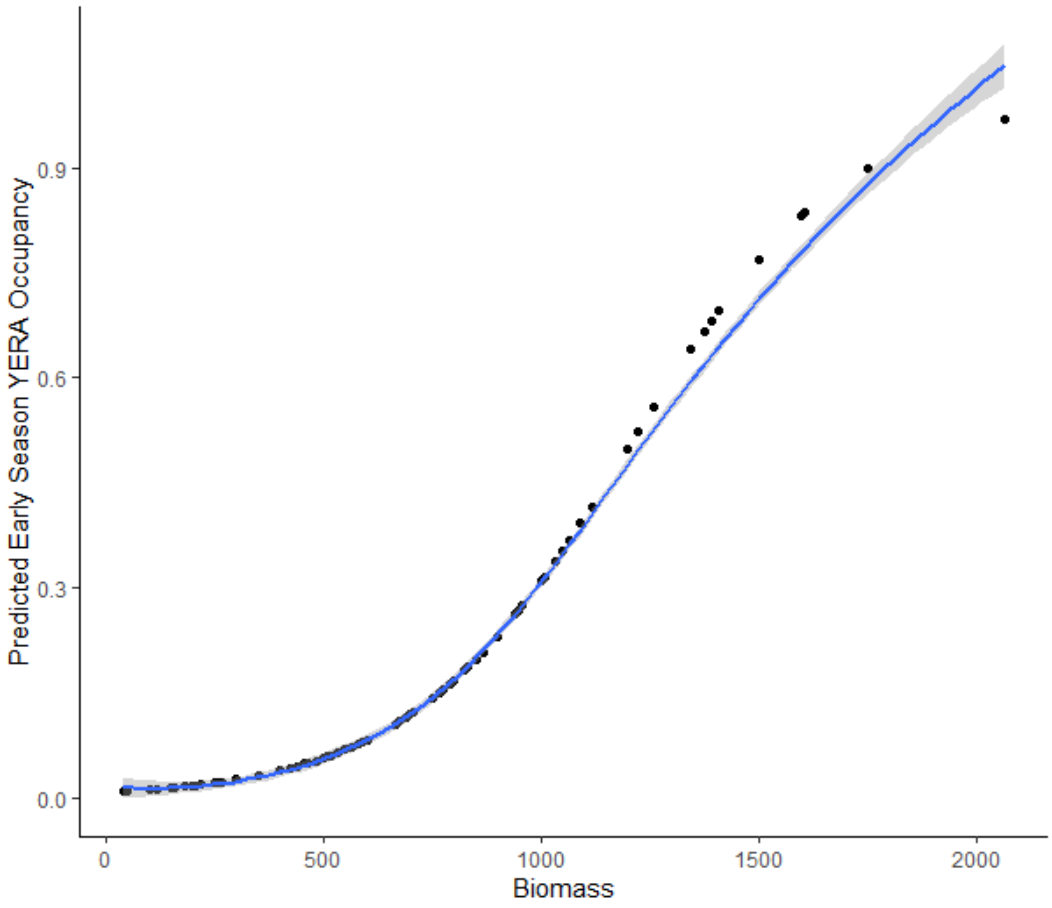

Figure 3. Average biomass (g) as it relates to estimated Yellow Rail (*Coturnicops noveboracensis*; YERA) occupancy.

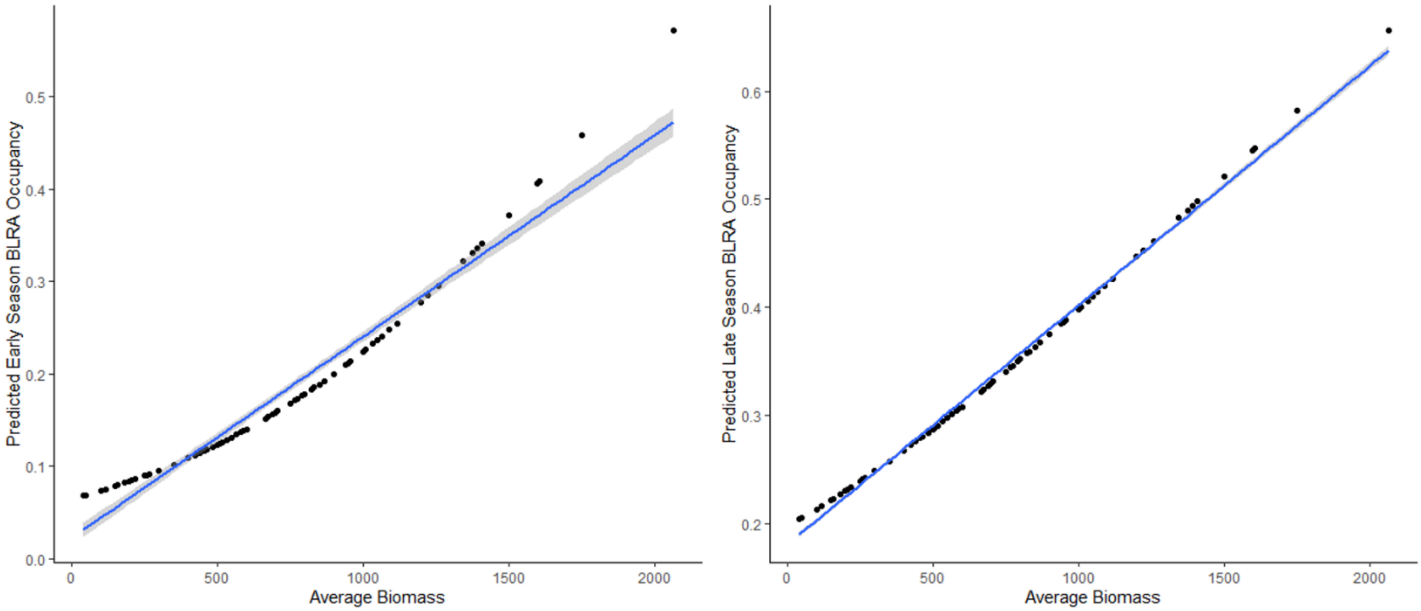

Figure 4. Average biomass (g) as it relates to estimated Black Rail (*Laterallus jamaicensis*; BLRA) occupancy for early-season (Left) and late-season (Right).

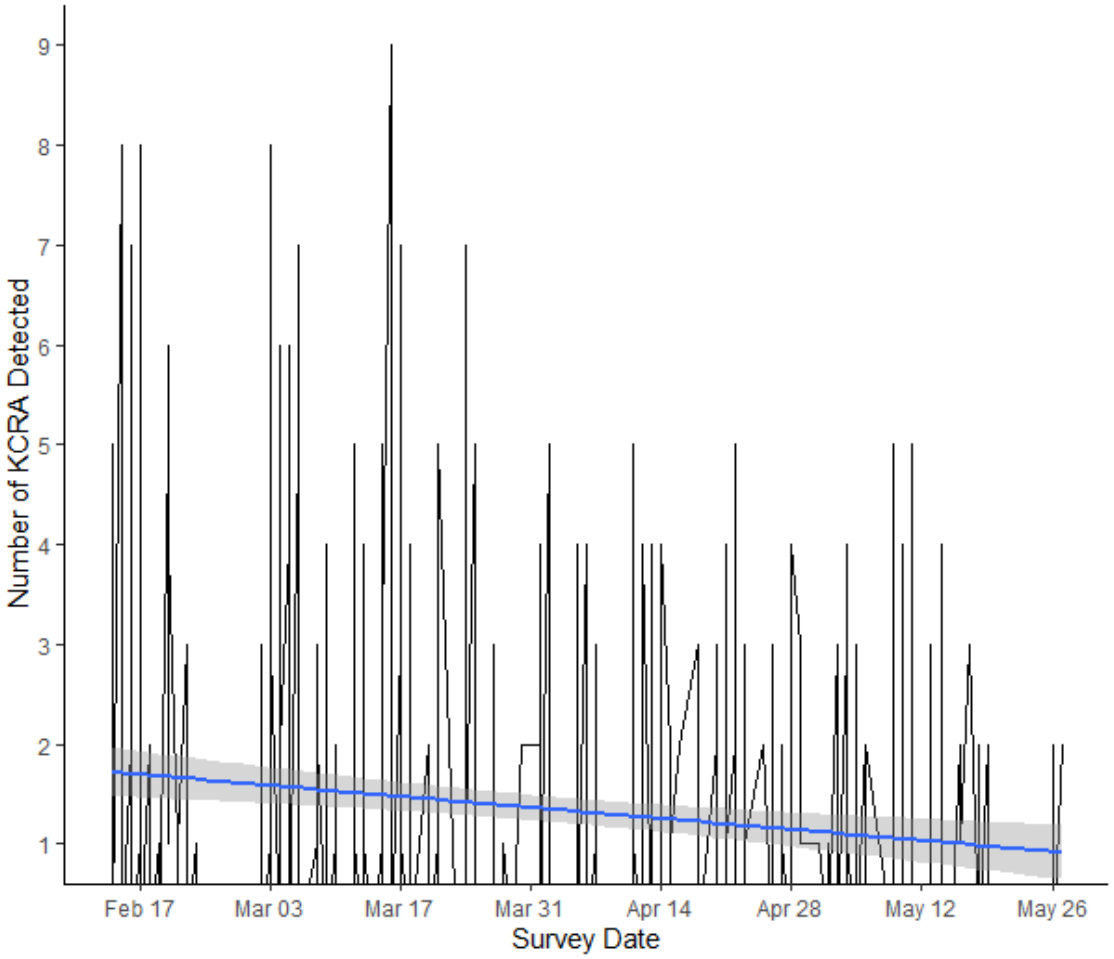

Figure 5. The number of King/Clapper Rail (*Rallus elegans/R. crepitans*), combined as 'KCRA', detected per survey as a function of the survey date. Blue line is the trend line, showing a gradual decline in the number of KCRA as date progresses.

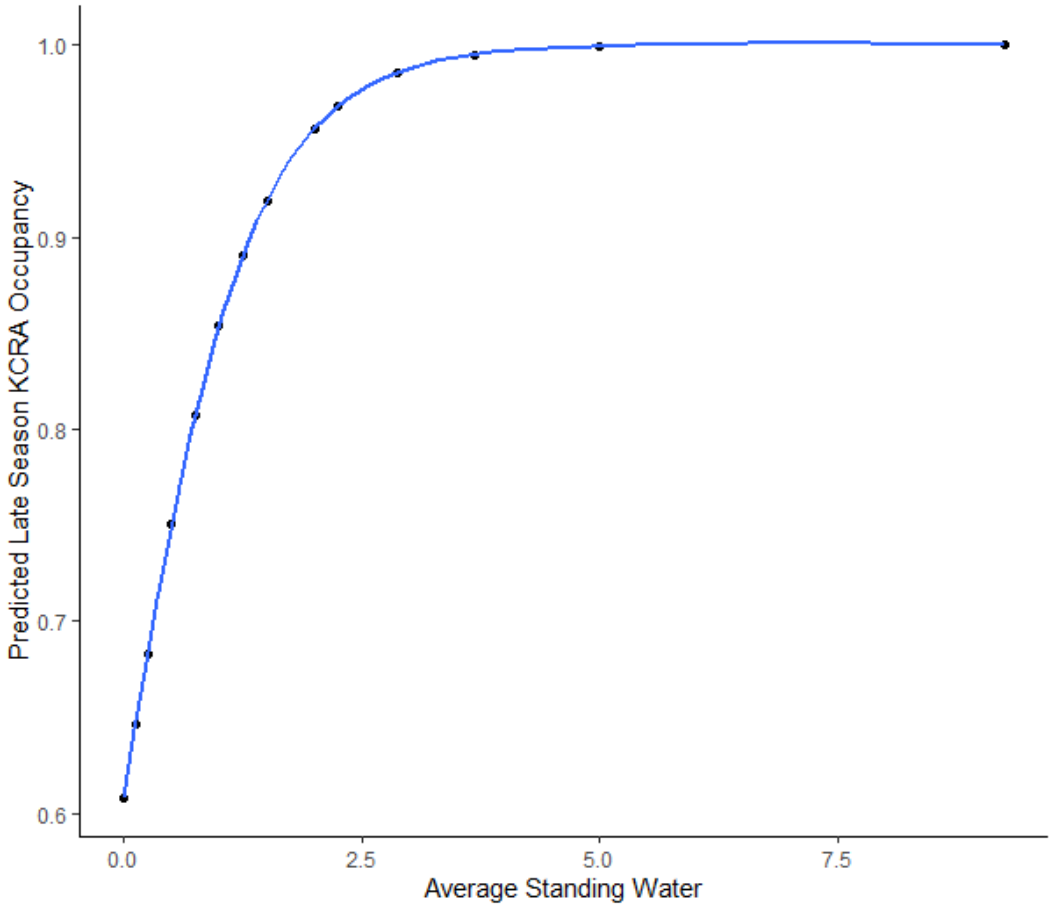

Figure 6. The predicted detection probability of late-season King/Clapper Rail (Rallus elegans/R. crepitans), combined as 'KCRA', detected per call-playback survey as a function of average standing water measurements (cm).

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CHAPTER 3:

Preliminary Assessment of Thermal Imaging Equipped Aerial Drones for Secretive Marsh Bird Detection

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ABSTRACT

Rails are a highly secretive group of marshland obligate species that are difficult to consistently survey and detect. Current survey efforts utilize either call–playback or autonomous recording devices, but the low detection probabilities for rails create challenges for long-term systematic monitoring. Between 8 April and 16 May 2022, we flew a small aerial drone equipped with a thermal camera to survey for six species of rail (Black Rail (*Laterallus jamaicensis*), Yellow Rail (*Coturnicops noveboracensis*), Sora (*Porzana carolina*), Virginia Rail (*Rallus limicola*), Clapper Rail (*Rallus crepitans*), and King Rail (*Rallus elegans*)) along the Gulf Coast of Texas to assess the feasibility of long-term drone monitoring.

We successfully conducted 33 flights at 15 m above ground level and detected rails on the first visit at 42% of known occupied points. We achieved 27 total rail detections, including 12 Black Rail/Yellow Rail detections. Of the birds detected, 81% exhibited no response to the drone's first approach. We intend for this preliminary data to shape future survey protocol for secretive species occupying difficult to navigate terrain.

Key words: black rail, thermal, Texas, nocturnal survey, disturbance

Introduction

The practicality of small (<55lbs) unoccupied aerial systems (hereafter, 'drone' or 'sUAS') to survey for a variety of wildlife species is increasing (Chabot and Bird 2015, Christie et al. 2016). As sUAS technology becomes increasingly accessible for a range of budgets (Crutsinger et al. 2016), the integration of remote sensing units further amplifies their utility for field biologists. Thermal imaging allows for precise and reliable estimates of large species (e.g., Beaver et al. 2020), however surveys for smaller targets present mixed results (e.g., Scholten et al. 2019, Stander et al. 2021). Targets with a small body size at relatively low population densities require further investigation to determine appropriate survey procedures.

Rails are an understudied group of marshland obligate birds. In Texas, we targeted six species of rail that reside along the Gulf Coast during the winter, three of which (Sora [*Porzana carolina*], Virginia Rail [*Rallus limicola*], and Yellow Rail [*Coturnicops noveboracensis*]) use this area as overwintering habitat while the remainder (King [*R. elegans*], Clapper [*R. crepitans*], and Eastern Black

Rail [*Laterallus jamaicensis jamaicensis*]) are present year-round (Rappole and Blacklock 1994). Rail populations on the Gulf Coast, compared to interior populations, may be particularly vulnerable to changes in ecosystem functionality caused by anthropogenic climate change (Mulholland et al. 1998). Yellow Rail are listed as a species of Special Concern within the Canadian portion of their range (COSEWIC 2009) and are classified as a Species of Conservation Concern in the United States (USFWS 2021). King Rail are classified as a Species of Management Concern across their range (USFWS 2011), even though many U.S. states have a legal hunting season for them. Eastern Black Rail are considered Threatened under the Endangered Species Act and are suspected to be declining throughout their contracted range (Watts 2016, USFWS 2020, Watts et al. 2021). Despite these concerns, systematic long-term population monitoring remains limited for most species.

Rails typically exhibit 'secretive' behavior (Ripley 1977), making them difficult to study. The majority of rail species can be found within densely vegetated marshlands where they forage, raise young, and otherwise traverse mostly unseen (Ripley 1977, Brookhout and Stenzel 1987). These marshlands can be either emergent or estuarine, depending on the species, and both present logistical challenges to adequately sample (Gallant 2015). Additionally, many species are crepuscular or nocturnal, constraining maximum survey productivity to specific timeframes (Conway and Gibbs 2011, Butler et al. 2015). As a result, most traditional surveys for rails involve call-playback methods during mornings and evenings, where a species' call or song is broadcast in order to elicit a response

(Conway 2011). Response-rate is variable across species, with Eastern Black Rail, for example, having particularly low response-rates (e.g., Butler et al. 2015, $\hat{p}$ =0.10) which require ≥10 revisits for an adequate estimate of occupancy (Butler et al. 2015, Tolliver et al. 2019). Seasonality presents additional challenges, with guidelines recommending surveys during the breeding season (Conway 2011), as winter response-rates are expected to be comparably low. This limits the ability to systematically survey wintering populations, with surveyors often resorting to exceedingly labor-intensive draglines (e.g., Morris et al. 2017, Soehren et al. 2017) for highly unresponsive birds such as Yellow Rail (Butler et al. 2016, Butler et al. 2022).

Drone surveys of bird populations in difficult to traverse areas shows both remarkable accuracy and logistical utility. For example, McClelland et al. (2016) successfully surveyed endangered Tristan Albatross (*Diomedea dabbenena*) populations on Inaccessible Island in the South Atlantic Ocean and Junda et al. (2015) showed that drones could be operated safely and efficiently to survey raptor nests. The behavioral response of birds towards drones is impacted by a variety of factors such as the species involved (Junda et al. 2016, Blackwell et al. 2019), sUAS-type (fixed vs. multi-rotor; McEvoy et al. 2016, Lyons et al. 2018, Egan et al. 2020), launch distance, and angle-of-attack (Vas et al. 2015). Many studies show few visual behavioral changes in surveyed birds (e.g., Vas et al. 2015, Ellis-Felege et al. 2022) suggesting versatility for future applications. The difficulties associated with navigating wetland ecosystems and finding secretive marsh birds, such as rails, may be alleviated with sUAS usage.

The primary objectives of this proof-of-concept were: 1.) To determine if thermal imagery could be used to find both small and large sized rails, 2.) to measure the visual behavioral response of rails detected during sUAS flights, and 3.) to assess the effect of certain environmental variables that may influence survey conditions. We qualitatively assessed our first two objectives in order to provide a baseline for future surveys of secretive marsh birds that incorporate similar remote sensing technology.

METHODS

The University of Central Oklahoma Institutional Animal Care and Use Committee approved all procedures (IACUC #20014). All applicable ethical guidelines for the use of birds in research have been followed, including those presented in the Ornithological Council's "Guidelines to the Use of Wild Birds in Research" (Fair et al. 2010) and the appropriate permits were obtained (aerial wildlife management permit M-3585 and scientific permit SPR-0121-009).

Study Area

Drone survey points were randomly selected from a set of 90 call-playback points that were broadly constrained to estuarine and freshwater marshland habitat in order to target six study species (Sora, Eastern Black Rail, Yellow Rail, Virginia Rail, King Rail, and Clapper Rail) within the following areas of the Texas Gulf Coast: Justin Hurst Wildlife Management Area (WMA; Brazoria, TX), Mad Island WMA (Matagorda, TX), Guadalupe Delta WMA (Calhoun, Victoria, and Refugio, TX), and Mustang Island State Park (Nueces, TX). The drone survey

points were within Brackish High Tidal Marsh, Brackish Low Tidal Marsh, Salty Prairie, Riparian Grassland, and Floodplain Herbaceous Wetland ecological systems (Elliot et al. 2014). Proportions of *Spartina spartinae*, *S. alterniflora*, *S. patens*, *Salicornia bigelovii*, *Borrichia frutescens, Baccharis* spp., *Batis maritima*, *Distichlis spicata*, *Lycium carolinianumm* (var. *quadrifidum*), *Typha* spp., and *Juncus* spp. are present within these ecological systems, but the exact species composition at the point-level was dependent on salinity and standing-water conditions. Mustang Island State Park uniquely contained points within areas of Deep Sand Grassland classification (Elliot et al. 2014) harboring additional plant species such as *Schizachyrium scoparium* (var. *littorale*), and *Aristida* spp.

Drone System and Operation

We used an IF750 black quadcopter built by Inspired Flight (San Luis Obispo, CA). The unit is W965 x L965x H415 mm when fully operational. It uses two 6S 7000mAh lithium-ion polymer batteries and has a flight time of ~25 minutes. It operates on the PX4 system (Modified Quadrotor 4001) and utilizes a Modal AI Flight Core. We did not utilize any specialized launching equipment, but when required to launch in dense vegetation we would flatten out a stable area to act as a launch point. At 4.5m, the drone is ~75dB, and ~68dB at 15m.

The infrared (IR) camera used in this study was a WIRIS Pro SC with a base IR camera resolution of 640 x 512 pixels and the ability to take super resolution pictures of 1,266 x 1010 pixels. The camera's spectral range is 7.5 – 13.5µm for long-wave infrared detection with focal plane array active sensor size of 1.088 x 0.8705cm. The temperature range has capabilities of -40 °C up to >1000 °C.

Temperature accuracy is within ± 2 °C. We saved photos as super resolution radiometric images and videos using radiometric full-frame IR recording for analyses post-flight. This camera also has digital visual capabilities, however we refrained from utilizing this feature as all of our flights were at night. The WIRIS OS was linked to a handheld controller for real-time data streaming and manual camera control during flights.

Drone Surveys

We conducted drone flights from 8 April – 16 May 2022 at 21 points distributed throughout our study areas: Justin Hurst WMA (*n*=10), Mustang Island State Park (*n*=5), Mad Island WMA (*n*=3), and Guadalupe Delta WMA (*n*=3). The 21 points utilized for drone surveys were randomly selected from 90 pre-established call-playback points from an ongoing study on wintering rail species. Early preliminary data of 12 call-playback visits from the concurrent study indicated rail detections at 19 of these 21 points. The 2 points assumed to be unoccupied were included in order to assess if drone flights could reveal previously undetected individuals from call-playback.

Using the program QGroundControl, we downloaded Google Satellite maps for offline use and created survey polygons for all of our designated points for repeatability (Fig 1). Transects within the survey polygons were spaced with 80% front and side overlap. We sized polygons to 6967 m^2 – 7246 m^2 with the survey point approximately centered within the polygon. We chose to avoid flying over extensive swaths of deep, open water, such as the middle of a lake or pond and as a result the shape of the polygons were often irregular. When conducting surveys,

we launched and landed the drone ≥ 100m from the survey starting point in order to reduce potential disturbance (Weston et al. 2020).

We conducted surveys between 24:00hr- 06:30hr at an altitude of 15.24m above ground level at ~3.2-6.4 km/h; nights with poorer thermal resolution (e.g., nights where the ambient temperature was warmest) resulted in flight speeds closer to ~3.2 km/h. At this height, we had a horizontal field of view (FOV) of 20.9m, vertical FOV of 16.2m, and diagonal FOV of 26.5m. We conducted all flights with a minimum of two surveyors: one as the designated pilot-in-command (PIC) and one as the designated visual observer. The remote PIC manually flew transects in a lawnmower pattern to allow for abrupt stops if a heat-signature of interest was detected. All photos and videos were manually taken by the PIC. The visual observer maintained a line of sight with the drone during surveys and recorded data in order to allow the PIC to examine the camera interface, maintain transects, and monitor aspects of the drone's health (e.g., battery life, altitude, etc.). The drone's lights were colored to allow for orientation, with the front-left light colored red, the front-right light colored green, and the rear left and right lights colored white. Prior to the start of the surveys, the visual observer would record the survey start time, estimated % cloud cover, and temperature and wind speed using a hand-held Kestrel 2000 unit. Estimates of cloud cover were determined based on star visibility or using data from the closest weather station to the survey area. Measures of relative humidity were gathered post survey using hourly data generated by the closest weather station to the survey. Moonlight values at the start of the survey were determined post survey using hourly

measures generated in the program QuickPhasePro 4. During each survey, if a rail was detected by the pilot-in-command (Fig 2), the visual observer would record the size class (Table 1), behavior (Table 2), time of detection, and any additional notes as relayed by the pilot-in-command viewing the real-time camera stream. Behavioral classifications (Type I, II, or III) were based on Vas et al. (2015) and were ranked from increasing intensity of behavioral change: Type I behavior was defined as no visible behavioral change upon first approach; Type II as slight behavioral changes, such as a switch to vigilance or slow movement away from where the drone approached; Type III was an extreme change in behavior upon first approach, such as flushing or rapid movement away from the drone. We flew the drone as low as 4.5m above at least one rail of each size class during test flights to provide baselines for our classifications.

We identified heat signatures as rails using their size, shape, and behavior based on PIC practice flights prior to official data collection. During surveys, the PIC would frequently hover the drone over heat signatures of interest in order to better assess these features. Similarly sized passerines (e.g., Eastern Meadowlarks [*Sturnella magna*], Boat-tailed Grackles [*Quiscalus major*]) were distinguished from rails as they would flush almost immediately upon the approach of the drone during practice flights. Additionally, these species were often found roosting in shrubs or short trees, or on nests that could be identified to species, while all rail identifications were strictly on the ground or within emergent vegetation. Occasionally, the thermal signature of rodents (e.g., *Sigmodon hispidus*) mimicked that of 'small' rails (Fig 3). Rodents typically reacted abruptly and

would initiate a running escape in response to the drone's presence. During instances of general uncertainty, the visual observer would be instructed to walk to where the signature was located to make an accurate visual identification. The drone would be lowered to better assess the subject when the identification of thermal signatures was uncertain but observer-access to the point of interest was restricted (e.g., feral hog [*Sus scrofa*] activity). We recorded all behavior of potential rails at initial detection prior to lowering or hovering the drone for extended periods.

Statistics

All statistical analyses conducted pertain to environmental variables in relation to rail detection during surveys (Objective 3) and were not used to evaluate Objective 1 or Objective 2. We conducted a Gaussian kernel regression with a fixed bandwidth in order to determine the influence of relative humidity, temperature, and wind speed on the total number of rails detected and whether rails on the ground were detected on drone surveys (0, 1) during a given survey period. Due to a limited sample size, we refrained from examinations relating to specific size-class. We tested for linearity using basic plotting, which lead to our use of a non-parametric approach. Models were created in R (R Core Team 2022) version 4.1.1 with the package "np" (Hayfield and Racine 2008). Due to our small sample size, we ranked variable influence using the cross-validation bootstrapping Method II as described by Racine et al. (2006) for nonparametric regression models.

RESULTS

Surveys

We successfully conducted 33 flights at our 21 points: 16 flights at Justin Hurst WMA, eight at Mustang Island State Park, five at Mad Island WMA, and four at Guadalupe Delta WMA. Flight times averaged 43 minutes per survey (including time for battery swaps). We detected rails on 14 of the 33 flights (42%). We attempted to revisit points up to 3 times, however due to weather conditions and drone malfunctions during the season we were unable to meet this objective. We were able to revisit three points three times, five points two times, and all other points a maximum of once during the season. At the 19 known-occupied points, 42% of first-time detections of rails occurred on the first visit at points. At points where visits were >1, 63% of first-time detections occurred in the first visit and 25% of first-time detections occurred in the second visit. At the two points predicted to be unoccupied, we did not detect any rails during drone surveys. We achieved 27 total detections across all 4 size classes (Fig 2): 12 small, 12 medium short-billed, one medium long-billed, and two large. We ground-confirmed five of these individuals: two Black Rail, two Sora, and one Yellow Rail. We also attempted to ground-confirm a presumed Clapper Rail (Fig 2), but the individual ran past the visual observer precluding ID confirmation. Of the individuals detected, 81.48% exhibited Type I behavior when first approached by the drone, 1.48% exhibited Type III behavior, and only one rail was recorded exhibiting Type II behavior. When examining two rails (one medium short-billed rail and one long-billed rail) for ≥60 seconds, individuals exhibiting Type I behavior switched to increased vigilance by remaining still and moving the head back and

forth or slowly moved away (Type II). Two medium short-billed rails flushed (Type III) when we hovered the drone low for >180 seconds. On two occasions, we noticed rails resuming prior behavior when we re-flew the drone over individuals.

Statistics

We removed one data point, a night that we detected a total of nine rails, from the statistical analyses due to it acting as an outlier. Additionally, we chose to remove moonlight from analyses due to a limited sample size and potential inaccuracies with in-field visible moonlight compared to the calculated values post-survey. Plotting our data for both the total number of rails detected as well as whether a rail was or was not detected (hereafter, rail detection) revealed violations of linearity and thus non-parametric modeling was utilized for all models. Our model for rail detection performed slightly poorer (R^2=0.40) compared to our model for the number of rails detected on given survey (R^2=0.47). When examining influences on rail detection, we found no statistical significance in wind speed (p=0.07), relative humidity (p=0.11), percent cloud cover (p=0.12), or temperature (p=0.58). We did find significance of wind speed (p=0.04) and the percent cloud cover (p=0.01) in relation to the total number of rails detected during a survey period, but we found no significance for relative humidity (p=0.78) nor temperature (p=0.89).

DISCUSSION

We successfully used thermal imagery to detect small, medium, and large-sized target rails. For species such as Black Rail, call-playback requires as many as 10 revisits in order to have an adequate detection probability for individuals (Butler et al. 2015, Tolliver et al. 2019). Wintering Yellow Rail display similar detection issues, requiring rope-drags for systematic surveys (e.g., Butler et al. 2016). We were able to detect 12 small-sized rails within 1-3 drone visits, displaying potential for the use of drone surveys to acquire occupancy estimates for Black Rails and Yellow Rails with a less intensive revisit requirement. A more detailed comparison between the number of drone revisits necessary to generate adequate detection estimates for these species would reveal a stronger assessment of feasibility, but is beyond the scope of our available data.

We were able to detect more small and medium-sized rails than large species such as Clapper Rail. Clapper Rail were consistently recorded at multiple drone points during the call-playback surveys conducted as part of a simultaneous study, however we failed to yield consistent Clapper Rail detections via drone. Clapper Rail vocalizations can be detected by an observer a substantial distance away from a singing individual (per. obs.), which may artificially inflate the number of successful detections during call-playback surveys. Additionally, depending on the time of year, Clapper Rail may increase their movement and range size (Meanly 1985). While our polygons are seemingly large, they may not encompass the daily movements of Clapper Rail in the area. We predict that consistent repeated sUAS surveys at points may yield increased detection of large-sized rails. Surveys that specifically focus on large-sized rails may benefit from the

manipulation of polygon size and shape to better reflect potential Clapper Rail/King Rail habitat usage to further increase the detection probability of these species.

The majority of surveys resulted in 0-3 rail detections in a single survey, however we did experience a night in late April where we detected nine individuals. Of these individuals, we identified one Yellow Rail (ground-confirmed), one medium long-billed rail, and seven medium short-billed individuals. All individuals displayed Type I behavior upon approach and were found spatially separated from one another. This point was revisited again in May and only two rails were identified (one ground-confirmed Sora and one large rail). We predict that migratory Sora may have been congregated in the area due to ideal environmental conditions (e.g., food availability, cover) prior to the start of spring migratory movement. Pospichal and Marshall (1954) noted that Sora congregate in locations abundant in food prior to peak fall migration. This specific survey location is within a wet transition zone that lies between drier high marsh dominated by *Spartina spartinae* and deep brackish water. This area contains saturated substrate sustaining succulent vegetation (e.g., *Batis maritima*) interspersed with emergent vegetation. These ecological and hydrological characteristics may facilitate ideal foraging conditions prior to spring migration (Webster 1964, Rundle and Sayre 1983, Sayer and Rundle 1984). Although many of our survey areas displayed similar environmental conditions, additional microhabitat features influencing presence as well as unexplored survey conditions influencing thermal detection may be further driving this irregular instance of numerous detections.

We measured the initial behavioral response of each rail detected in order to assess visual disturbance and shape future survey protocol. Over half of the rails detected exhibited no behavioral change in relation to the drone's first approach, even when vertically descending and hovering as low as 4.5m. The ability to fly close to individuals with rarely any escape-response is similar to the results demonstrated by Vas et al. (2015) and by Weimerskirch et al.'s (2018) study on adult King Penguins (*Aptenodytes patagonicus*). Rails are more likely to run or sulk away from a perceived threat rather than flush (Lima 1993). However, only one rail exhibited Type II behavior when first approached by the drone. Multirotor drones also tend to elicit fewer escape responses by birds than fixed wing models (Lyons et al. 2018, Blackwell et al. 2019, Egan et al. 2020). Although we do not have an accurate means of measuring rail response to ambient volume compared to visual perceived threat in this study, we predict that the majority of the Type II and Type III behavioral responses we recorded were due to the noise generated by the drone at low altitudes rather than it acting as a visual threat. At 15m, the drone is ~68dB in volume, which may be disturbing when hovering directly over an individual for extended periods (Weston et al. 2020, Duporge et al. 2021). Additional studies should account for rail response to auditory disturbance by flying at the highest altitude possible while still allowing for quick and accurate thermal identification.

Our statistical results show that the two primary factors influencing the number of rails detected on a given night are wind speed and cloud cover. Clouds can absorb some of the incoming infrared radiation, making it difficult to detect individuals

when cloud cover is thick (McCafferty et al. 2011). Wind velocity can impact both the surface temperature of an organism's plumage (McCafferty et al. 2011) as well as the surrounding vegetated environment (Bakken and Gates 1975), altering the heat loss of organisms that are particularly low to the ground (Bakken and Gates 1975) such as rails. We predict that there may be other environmental variables influencing the number of rails detected during a survey period and argue that additional data from a wider range of environmental conditions may reveal stronger inferences. Other factors besides the weather-related variables tested in this study may be influencing if a rail was detected on a given survey, such as surveyor experience or vegetation density and composition (Prosser et al. 2020), and may partially explain the lack of significance of environmental variables shown in our model.

FUTURE CONSIDERATIONS

Although the majority (81%) of our flights did not result in adverse behavior, we suggest that future studies experiment with thermal visibility of rails starting at a minimum of 30m. While we show in this study that visual behavioral responses by rails were low, we did not measure heart-rate or other internal responses. Results by Weimerskirch et al. (2018) show that physiological stress responses may not mirror visible behavioral responses, as adult King Penguins experienced an increase in heart rate in response to drone flights even though little behavioral response was exhibited. These impacts were shown to be short term (Weimerskirch et al. 2018), but care should be taken when surveying for sensitive species of rail (e.g., Eastern Black Rail) and especially during the breeding

season. Our flights were primarily conducted in the winter and early spring prior to major nesting and brood rearing. Changes in visible behavior appeared to be short term as we witnessed rails resuming prior behavior after drone engagement. Thus, we recommend hovering over a potential rail for ≤60seconds and taking photos or videos that can be scrutinized post-flight if identification cannot be accurately confirmed within that timeframe.

Anti-predator responses of rails to humans directly entering habitat are likely more frequent than is known. The majority of surveys for secretive marsh species utilize call-playback, requiring surveyors to enter feasible habitat and survey within that habitat for extended periods of time (≥10 minutes; e.g., Martin et al. 2014). This is often during the breeding season when call-response rates are highest (Conway 2011) and requires repeated entry due to low detection probabilities (Darrah and Krementz 2009, Conway 2011, Butler et al. 2015). Human presence increases the physiological and the behavioral stress responses of multiple avian families (Burger 1994, Carney and Sydeman 1999, Ellenberg et al. 2013). Additionally, on the few occasions that we ground-confirmed rails, all attempts resulted in either the rails rapidly moving away from the direction of the surveyor or flushing before the observer was ~30m away from the individual. This behavior was only visible due to the thermal imaging capabilities of the drone, as the rails were not yet detected by the in-field observer prior to these behavioral changes. We predict that this adverse behavioral response to human presence occurs when surveyors enter sites for call-playback surveys as well as during rope-drag surveys. The use of sUAS technology may be a less disruptive

option for both rails and their surrounding habitat during the winter or spring, especially for less vocal or sensitive species.

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Data availability: Data are not publicly posted due to the sensitivity of the species involved. Thermal video and images of rodents [https://doi.org/10.7910/DVN/6V4HUC] and Sora [https://doi.org/10.7910/DVN/TRTLXZ] are available via Harvard DataVerse with all relevant metadata removed or altered.

Figures and Tables

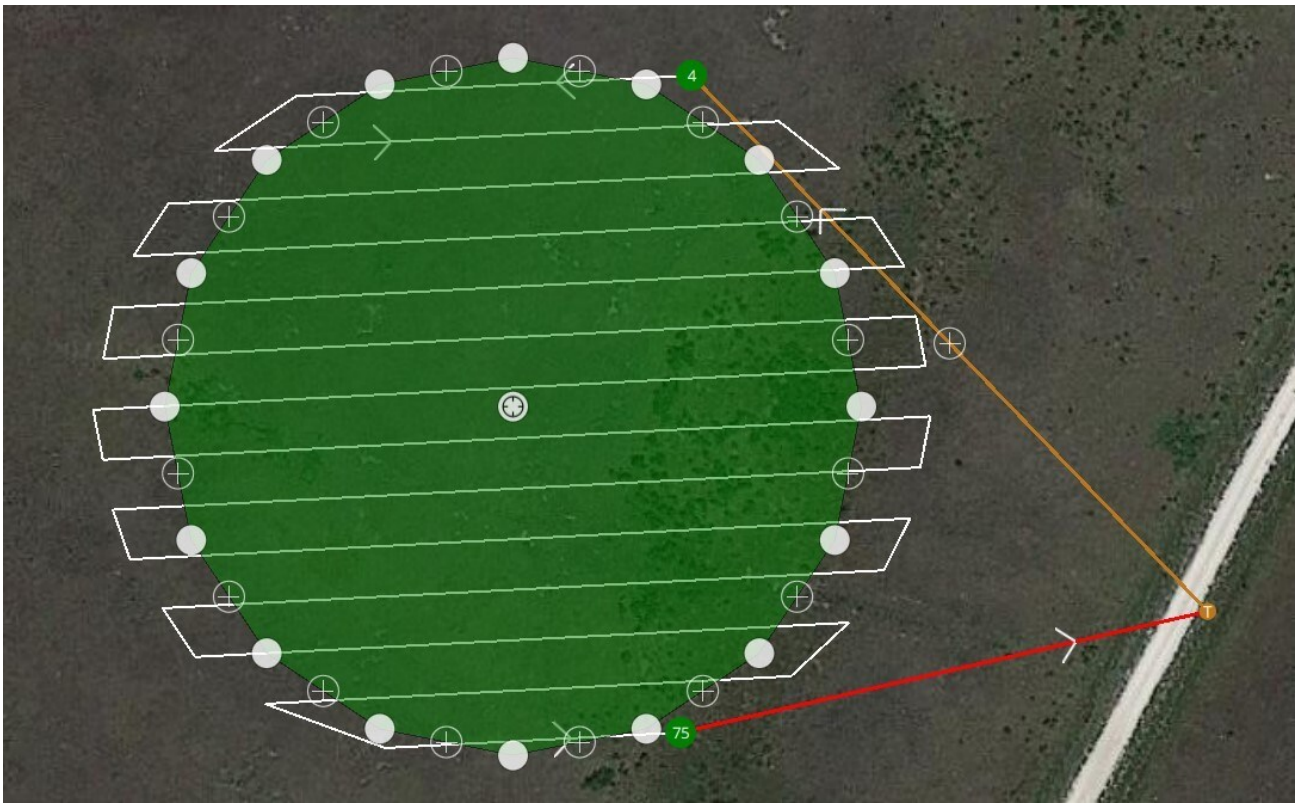

Fig. 1. Example of a survey area within QGroundControl using a Google Satellite base map (©2022 CNES/Airbus, Houston-Galveston Area Council, Maxar Technologies, Texas General Land Office, U.S. Geological Survey, Map data ©2022). The "T" represents the takeoff point of the drone, which is on a gravel road in this example (~100 m from survey start). The white lines represent the transects the drone will fly to survey the polygon area.

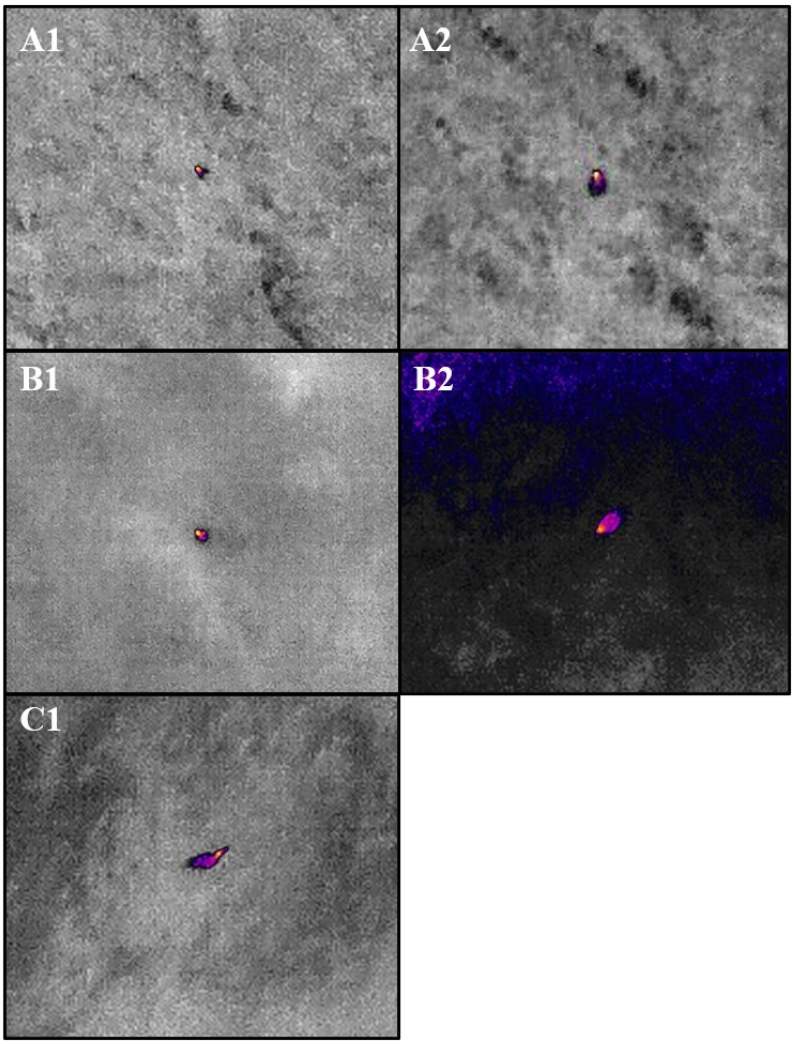

Figure 2. Thermal images (1,266 x 1010 pixels) of the three size classes of rail ranked from smallest (A) to largest (C). Row A is a ground-confirmed Black Rail (*Laterallus jamaicensis jamaicensis*) at 15m (A1) and 9m (A2). Row B is of a ground-confirmed Sora (*Porzana carolina*) at 18m (B1) and 9m (B2). Row C is of an assumed Clapper Rail (*Rallus crepitans*) at 15m (C1). Medium-long-billed rails (not shown) are of a similar size as row B, but with the addition of a longer visible bill. Images examined using ThermoLab.

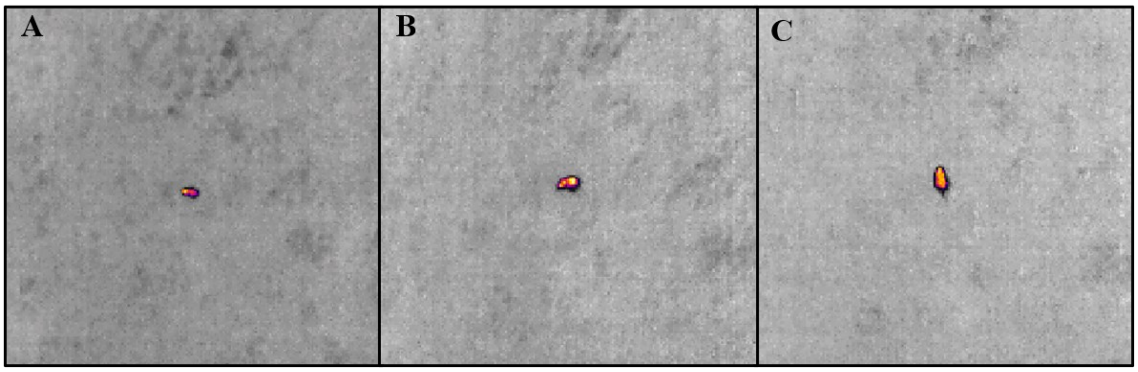

Figure 3. Thermal images (640 x 512 pixels) from a thermal video taken with a multirotor quadcopter at 15.24m (A) and between 6-9.1m (B; C). Panels A and B are of the rodent facing left. Panel C is of the rodent facing forward. Identified via thermal images and behavior, as the individual was rapidly moving and 'digging' at the vegetation. Images examined using ThermoLab.

Table 1. Table with size designations for each rail species examined in this study. 'Approximate Body Size' is in reference to the approximate body length (cm) of birds within each size class. The smallest size class, 'small,' represents Yellow Rail (*Coturnicops noveboracensis*) and Black Rail (*Laterallus jamaicensis jamaicensis*) as both species look very similar on the thermal camera. Black Rail average 10-15cm (Eddleman et al. 2020); Yellow Rail average slightly larger between 15-18cm (Ridgway and Friedmann 1941). Sora (*Porzana carolina*) and Virginia Rail (*Rallus limicola*) are larger than species within the 'small' class, and are designated as medium-sized at 20-25cm (Melvin and Gibbs 2020) and 22-27cm (Conway 2020), respectively. The largest species are Clapper Rail (*R. crepitans*) and King Rail (*R. elegans*) at 32-41cm (Rush et al. 2020), with King Rail averaging slightly larger than Clapper Rail (Perkins et al. 2009).

Species	Approximate Body Size (cm)	Designated Size Class
Yellow Rail[a], Black Rail	10-18	Small
Sora[a]	20-25	Medium (Short bill)
Virginia Rail[a]	22-27	Medium (Long bill)
King Rail, Clapper Rail	32-41	Large

[a] Winter residents

Table 2. Behavioral classifications used when a rail is detected by the drone. Response intensity gradually increases from Type I through Type III, with the latter being the most extreme response.

Response Type	Definition
Type I	No response; no visible change in behavior from when first seen and approached
Type II	Slight change in behavior in response to drone presence; gradual movement away from drone, examining drone (repeated head movement), sustained pause of feeding/movement
Type III	Extensive change in behavior; rapid running away, flushing

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