Predictive Mapping of Yellow Rail (*Coturnicops noveboracensis*) Density and Abundance in the Western Boreal Forest via Ground and Satellite Remote Sensors

by

Logan James Thomas McLeod

A thesis submitted in partial fulfillment of the requirements for the degree of

Master of Science
in
Ecology

Department of Biological Sciences
University of Alberta

Abstract

The Yellow Rail (*Coturnicops noveboracensis*) is a small, secretive, wetland bird, which is apparently rare throughout most of its range. Almost nothing is known about its abundance and density in the wetlands of the western boreal forest. Emerging technologies have enabled us to effectively survey for Yellow Rail in remote wetlands by using ground-based remote sensors (autonomous recording units; ARUs) to conduct passive acoustic monitoring. This technique was employed to survey Yellow Rail populations across two large study areas: one in the taiga plains of the Northwest Territories, and the other in the boreal plains of Alberta, Canada.

For the Edéhzhíe Indigenous Protected Area (NWT), a predictive map of Yellow Rail density was developed based on data obtained from a systematic avian survey conducted in 2016, using 205 ARUs. Counts of Yellow Rail were converted to density estimates using habitat specific effective detection radii obtained via call-playback experiments. Generalized linear models and covariates from a detailed landcover classification effort were used to develop the spatial model. Yellow Rail appeared to breed at relatively high densities (0.07 males/ha compared to average densities of 0.04-0.05 males/ha) in Edéhzhíe and they were strongly associated with marsh wetlands. The Mills Lake wetland complex was identified as an important breeding area for Yellow Rail in the Northwest Territories based on a population estimate of ca. 560 breeding pairs.

For the Alberta Oilsands Region, a predictive map of Yellow Rail breeding abundance was developed using acoustic data compiled from the first five years (2013-2017) of an ongoing bioacoustic monitoring program. Recent developments in open-access satellite data, cloud computing

(Google Earth Engine), and data science were leveraged to secure large-scale, high-resolution (10 m) landcover data. Multiple satellite remote sensors were used to derive fifteen predictor variables: Sentinel-1 synthetic aperture radar, Sentinel-2 optical imagery, and Advanced Land Observation Satellite digital elevation maps. Gradient boosted regression was used to develop the spatial model. Six remote sensing predictors (DPOL, ΔVH, REIP, ARI, VH, and SWI), were identified as having strong predictive capacity. Several predictors had complex non-linear responses and multiple important interactions were identified. Approximately 1.5% of available wetland habitat in the region was predicted to be highly suitable for Yellow Rail.

Preface

Author Contributions

This thesis is an original work by Logan McLeod.

Chapter 2 of this thesis is an unpublished manuscript: L.J.T. McLeod, S. Haché, and E.M. Bayne, “High density populations of Yellow Rail (*Coturnicops noveboracensis*) revealed by audio recordings at the northern edge of their breeding range”. I was responsible for concept formation, data analysis, and writing the manuscript. S. Haché provided the data and contributed to concept formation and writing of the manuscript. E. Bayne provided input and feedback on concept formation and writing of the manuscript.

Chapter 3 of this thesis is an unpublished manuscript: L.J.T. McLeod, E.R. DeLancey, and E.M. Bayne, “Spatially explicit abundance modelling of a highly specialized wetland bird using satellite remote sensing.” I was responsible for concept formation, data collection, data analysis, and writing the manuscript. E.R. DeLancey provided data and contributed to concept formation, data analysis, and writing of the manuscript. E. Bayne provided input and feedback on concept formation, analysis, and writing of the manuscript.

Project Funding

Funding for Chapter 2 was provided by: Environment and Climate Change Canada – Canadian Wildlife Service (Northern Region)

Funding for Chapter 3 was provided by: The Environmental Monitoring Committee for the Lower Athabasca (EMCLA), Oilsands Monitoring (OSM), Canada’s Oil Sands Innovation Alliance (COSIA), the Alberta Biodiversity Monitoring Institute (ABMI), Suncor Energy, Imperial Oil Resources, Shell Canada, and the Natural Sciences and Engineering Research Council of Canada (NSERC).

Acknowledgements

I give special thanks to Alex MacPhail, Michelle Knaggs, Natasha Annich, Daniel Yip, Julia Shonfield, Michael Foisy, Nicole Boucher, Hedwig Lankau, and Monica Kohler for their contributions to the Yellow Rail project. In addition to these key personnel I sincerely acknowledge all the many people that hiked, quadded, and trudged many wet kilometers to deploy ARUs and collect field data for the project. I would also like to acknowledge the contributions from the many groups who deployed recorders on our behalf, including: Parks Canada at Wood Buffalo National Park, the Athabasca Chipewyan and Mikisew Cree community-based monitoring program, and the Canadian Wildlife Service in Yellowknife.

I would like to thank my supervisor Dr. Erin Bayne for giving me the chance to be able to pursue this MSc and for giving me so many opportunities to explore my curiosity about birds. I would also like to thank Dr. Jim Schieck and Dr. Cynthia Paszkowski for serving as members of my committee. I met many inspiring people over the course of my project and would not be where I am today, in life, and as a scientist, without their influence. To my colleagues who didn't work with me in the boreal: Anjolene Hunt, Jesse Watson, Cameron Nordell, Justine Kummer, Easwar Vasi, Scott Wilson, and others, thank you for your tremendous friendship and encouragement. I thank Evan DeLancey for numerous helpful discussions, constructive feedback, and for inspiring me to explore Yellow Rail analyses with remote sensing data, Richard Hedley for reviewing parts of my work, and Samuel Haché for providing me with a great deal of constructive feedback and always reminding me to "finish your goddamn thesis."

I thank my parents, Gordon and Diana, to whom I've no doubt caused a great deal of stress over the years. They will be very relieved that I've finished, and I hope now they can worry about me a bit less. Finally, I thank Caitlin Willier for her love and support, and for listening to me complain.

“As yet the Yellow Rail lives not complete in any literature. For above all other North American birds, his is an unwritten life.” - N.N.

Photo: Jamie Baker

Table of Contents

List of Tables

List of Figures

Chapter 1 Introduction

Accurately monitoring the status of rare species is a fundamental challenge in conservation biology. Many researchers avoid studying rare species because of the increased time and cost involved, and the added risk their project might fail (McDonald, 2004). At the core of this challenge is that a species may be perceived as ‘rare’ for several different reasons. The definition of rarity varies widely but most often refers to factors such as abundance, range size, or habitat specificity (Gaston, 1997). While a rare population is often defined by low overall numbers, large populations can also appear rare because they are sparsely distributed throughout a broad range or because the individuals are difficult to find (i.e. they are elusive). In some cases, ineffective survey methods can create an illusion of rarity (McDonald, 2004). Effective monitoring of rare species requires a firm understanding of why a species is rare, and the optimal study design for a species that is common within a specific habitat (i.e. locally abundant), but uses a habitat that itself is rare, is very different than for a species with small populations spread widely across different habitats. Similarly, if a species is elusive (i.e. difficult to detect) it has significant implications for how one approaches monitoring.

Advances in bioacoustics methods have shown great promise for improving our ability to monitor rare species. A new approach to surveying bird populations is to deploy acoustic recording units (ARUs), a type of ground-based remote sensor, to collect large amounts of acoustic data from the same location (see: Shonfield and Bayne 2017). This allows for the collection of large numbers of repeat visits with only two physical visits by an observer (to deploy and to retrieve the unit). To date, most work with ARUs has relied on humans to listen to the data generated to estimate which species are present. By listening to data in specific subsets, humans can estimate calling rates within a single “visit” (e.g. sequential listening to 1-minute segments in a 3-minute period) and detection rates between visits (i.e. listen for species on different days or at different times of day). These types of data allow for more detailed models to be created than is possible with observers conducting repeated surveys in the field. Other benefits of using ARUs in this way include the ability to repeat point counts, compare observers, and validate identifications for difficult species. Automated methods for identifying birds from audio recordings are emerging alongside advances in the disciplines of machine learning and artificial intelligence. Automated song recognition can be used to determine the absolute probability of a species being present over an extended period.

The Yellow Rail (*Coturnicops noveboracensis*) is a secretive wetland bird that is assumed to be very rare. In Canada, it is widely distributed from northeast British Columbia and the southern Northwest Territories to the coast of New Brunswick (Leston & Bookhout, 2015). Much of its range is in remote areas and over 50% of the Yellow Rail breeding population is in the boreal zone (Wells & Blancher, 2011). There is a great deal of concern over the conservation status of Yellow Rail and it has been listed on Schedule 1 of the federal *Species at Risk Act* (S.C. 2002, c.29; *SARA*) as a species of Special Concern in Canada. Several studies have identified Yellow Rail breeding habitat as areas of wetland dominated by graminoid vegetation like sedges with little to no standing water (Leston & Bookhout, 2015; Robert & Laporte, 1999; Stalheim, 1974; Stenzel, 1982). These habitat requirements make them very specialized.

In the western boreal forest, we know very little about the state of Yellow Rail populations. Targeted surveys can reveal some details about the species occurrence in specific wetlands (Prescott et al., 2002), but it is also necessary to predict both where rails will occur, and how many there are, across broader regions. Given the narrow breadth of habitat conditions suitable for breeding Yellow Rail, modelling and mapping this species could be highly effective for identifying breeding areas. Building a spatial model for a species requires input variables that characterize the study area and provide an accurate description of the environment. When classified landcover products are available these can be used for this purpose, but characterization of wetland ecosystems with Geographic Information Systems remains a challenge. Open-access satellite data is creating new opportunities for ecologists because large amounts of large-scale, high-resolution landcover data are now available to be freely used.

The core objective of my thesis is to use passive acoustic monitoring datasets to improve our understanding of Yellow Rail populations across the western boreal forest. In chapter 2, I use new techniques for estimating densities from audio recordings and build a spatial model of Yellow Rail density to produce a predictive map for the Edéhzhíe Indigenous Protected Area, Northwest Territories. In chapter 3, I test the utility of satellite remote sensing covariates for predicting Yellow Rail abundance in northeast Alberta. I assess the performance of 15 predictors and produce a high-resolution predictive map which will aid conservation management. In chapter 4, I synthesize the results and ideas from the preceding chapters and provide suggestions for future research.

Chapter 2 High density populations of Yellow Rail (Coturnicops noveboracensis) revealed by audio recordings at the northern edge of their breeding range

2.1 INTRODUCTION

The boreal zone of North America represents one of the largest and most intact forest ecosystems on the planet (Brandt et al., 2013; Potapov et al., 2008). It supports over 300 breeding bird species including an estimated 47 million waterbirds, making it a globally important biodiversity region (Wells & Blancher, 2011). However, these ecosystems are being threatened by rapid anthropogenic changes associated with agriculture, forestry, energy development, and climate change (Schindler & Lee, 2010). Anthropogenic disturbances are concentrated in southern boreal regions where ~70% of bird species show numerical responses to cumulative impacts (Wells, 2011), but more data is needed for northern boreal regions. In Canada, moderate to high reliability monitoring data are available for 84% of waterfowl species (32/38) and 61% of shorebirds (28/46), but only 54% of 'other waterbirds' (53/98; i.e. marsh birds, inland colonial waterbirds, and seabirds), the lowest of any bird group (North American Bird Conservation Initiative 2012). Kushlan et al. (2002), identified "… developing a better understanding of populations, particularly the least abundant and most poorly understood" as the main priority for boreal waterbird conservation.

The North American Breeding Bird Survey (BBS) currently provides the only continental long-term abundance data for many species during the breeding season (Pardieck, Ziolkowski, Lutmerding, & Hudson, 2018; Sauer, Link, Fallon, Pardieck, & Ziolkowski, 2013). However, low sample sizes owing to the limited number of roads in northern regions result in imprecise estimates of abundance and population trends for many boreal species (Pankratz, Haché, Sólymos, & Bayne, 2017; Sauer et al., 2013; Sauer, Niven, Pardieck, Ziolkowski, & Link, 2017). There are also biases in habitat representation implicit to road-side surveys, which results in wetlands being generally underrepresented (Gibbs & Melvin, 1993; Herkert, 1995; Sauer et al., 2017). Marsh bird monitoring programs proffer to fill this gap, but these programs do not extend into the boreal region (Bird Studies Canada, 2019; Tozer, Drake, & Falconer, 2016). As such, major gaps exist in our understanding of species' distributions, abundances, and population sizes of boreal breeding waterbirds, which limits our ability to determine their status (Cumming et al., 2010).

The Yellow Rail (*Coturnicops noveboracensis*) is a secretive marsh bird that primarily vocalizes at night and often breeds in remote wetlands (Leston & Bookhout, 2015). These traits make it a challenging species to survey. Over 50% of the Yellow Rail breeding population is in the boreal zone (Wells & Blancher, 2011), where it is widely distributed in Canada from northeast British Columbia and the southern Northwest Territories to the coast of New Brunswick (Leston & Bookhout, 2015). There is concern over the status of the Yellow Rail because it is assumed to have a small population size (estimated 10,000 – 25,000; Wetlands International 2019), compressed wintering range, ongoing threats to wetland habitats, and evidence of local population declines (i.e. historical sites now unoccupied; COSEWIC 2009). As a result, it is listed on Schedule 1 of the federal *Species at Risk Act* (S.C. 2002, c.29; *SARA*) as a Species of Special Concern in Canada.

Development of effective survey techniques for Yellow Rail and other secretive marsh birds has been an active research topic since the 1980s (Bart et al., 1984; Bazin and Baldwin, 2007; Martin et al., 2014). The current standard approach, described in the North American marsh bird monitoring protocol (Conway, 2011), combines a passive observation period with a period of call broadcast to elicit territorial responses from individuals in order to improve detection probability (Conway & Nadeau, 2010; Gibbs & Melvin, 1993). This technique has been somewhat effective for Yellow Rail. Prescott et al. (2002) and Martin et al. (2014) detected ~20% and ~10% more individuals, respectively, after employing playbacks. However, Tozer et al. (2016) reported no significant differences in detectability of Yellow Rail between passive listening and call broadcast survey periods. This protocol has additional limitations: 1) it requires human observers to be physically present at survey locations during the night, and 2) attracting birds using call broadcast surveys could result in a positive bias in density estimates or erroneous fine-scale habitat associations. An alternative survey method, passive acoustic monitoring (PAM), has been widely applied in avian research in recent years (reviewed by Shonfield and Bayne, 2017). This approach involves the deployment of audio recorders to record animal sounds, and the subsequent interpretation of the recordings by trained observers. Yellow Rail produce readily detectable and distinguishable sounds, which can be used to estimate abundance and density (K. L. Drake et al., 2016; Marques et al., 2013).

Macroecological theory predicts that the average population density of a species is typically highest at the centre of its range and declines gradually towards the range margins, i.e. the ‘abundant-centre assumption’ (Brown, 1984; Guo, Taper, Schoenberger, & Brandle, 2005; Lawton, 1993). The mechanistic explanation for this pattern is that local population density reflects the suitability of a site, and spatial autocorrelation of favourable conditions results in reduced site quality at increasing distance from the centre (Brown, 1984). Environmental factors are often considered most important for determining the northern edge of a species range but life history traits, such as dispersal ability or interspecific competition, are also known to play a role. Many ecological hypotheses have been derived from the abundant-centre assumption (see Sagarin et al., 2006). For example, edge populations are often considered to be marginal and maintained only by immigration from core populations (Kawecki, 2008; Pulliam, 1988), and it has been speculated that edge populations may be more genetically distinct or have traits that make them more resistant to environmental change. Abundance data are needed from across a species range to test many of the predictions generated by these hypotheses (Sagarin et al., 2006).

Our objective was to provide density estimates of Yellow Rail within Edéhzhíe, an Indigenous Protected Area in the Dehcho region of the Northwest Territories, Canada. We used data collected in a systematic avian survey using PAM conducted by the Canadian Wildlife Survey in 2016. We converted counts to densities by deriving an effective detection radius for the species' vocalizations and, subsequently, built a spatial density model for Yellow Rail based on generalized linear models (GLMs). We hypothesized that our covariates associated with wetland habitat features would be strongly associated with Yellow Rail density. Specifically, areas which are covered by fen or marsh classes with open vegetation and graminoids are predicted support the highest densities of Yellow Rail. Based on the 'abundant-centre' assumption, we predict low density estimates for Yellow Rail. They had not been observed in Edéhzhíe prior to the survey and there were fewer than 20 records across the entire Northwest Territories (NWT/NU Checklist, 2018).

2.2 METHODS

2.2.1 Study Area and Sampling Design

The study was conducted in the Edéhzhíe Indigenous Protected Area situated west of Great Slave Lake in the Dehcho region of the Northwest Territories, Canada (Dehcho Land Use Planning Committee, 2006). It is a large (14,218 km^2) and relatively undisturbed tract of northern boreal forest located in the Taiga Plains ecozone, overlapping three ecoregions: the Hay River Lowland, Horn Plateau, and Great Slave Lake Plain (Ecological Stratification Working Group, 1995). A prominent feature of the area is the Horn Plateau, an area of highland (500-825 m above sea level) rising above the surrounding lowland plains (125-300 m above sea level). A transition is seen from a mid-boreal climate in areas south of the plateau to a low subarctic climate on the plateau and to the north (Ecosystem Classification Group, 2007). Wetlands are very abundant and cover 39% of the overall land area. These wetlands can be divided into two broad groups with five main classes: peatlands which consist of bogs and fens, and mineral wetlands which consist of marshes, swamps, and shallow open water; AESRD 2015). Wetlands in Edéhzhíe are characterized by extensive peatlands which typically form in cool, flat, low-lying areas with poorly drained soils. These contain mainly zonal boreal wetland vegetation (i.e. determined by climate variables) and make up 96% of the wetland area. Conversely, mineral wetlands classes (4% by area) have predominately azonal vegetation (i.e. determined by non-climatic variables).

Throughout the study area, a systematic grid of 33 study sites spaced evenly 20 km apart was established in 2016. An additional eight non-systematic study sites were assigned randomly within an 800 m buffer around Mills Lake and Willow Lake (four study sites per lake). Each study site was comprised of five sampling stations: four in a 2 x 2 grid (spaced 600 m apart) and a fifth at the grid centroid. This sampling design resulted in 205 sampling stations, but four were not surveyed due to safety considerations and data could not be retrieved from two additional recorders. Thus, the total number of sampling stations was 199.

At each station, PAM was conducted using autonomous recording units (ARUs; model SM3 & SM4, Wildlife Acoustics Inc., Maynard, Massachusetts, USA) with built-in omnidirectional microphones (frequency response: 20–20,000 Hz). The ARUs were deployed, one per station, between May 9-15 and July 23-28 and were programmed to record in stereo format at 44.1 kHz (SM4 units) or 48 kHz (SM3 units) with a 16-bit resolution. Microphone gain was set at 48 dB for both channels. The recording schedule was ten minutes at the beginning of each hour starting one hour before sunset until the fifth hour after sunrise every day. Three additional ten-minute recordings were scheduled at sunrise, midnight, and 15:00 for a total of nine recordings daily. Recorders were secured to a small diameter tree (<18 cm diameter) or stand ~1.5 m above the ground.

2.2.2 Audio Processing

The number of Yellow Rails per sampling station was determined from a combination of automatic processing and human listening. A subset of recordings was processed using a standard interpretation and data entry protocol (Lankau, Macphail, Knaggs, & Bayne, 2017) by five experienced observers as part of a preliminary analysis. Specifically, two three-minute recordings were interpreted for 152 sampling stations at sunrise (June 10 and on a day randomly selected in June; see Haché et al. in prep), and ten three-minute recordings in June were interpreted for 49 sampling stations across all sites (see Bayne et al. 2017 for details).

A Yellow Rail 'recognizer' was used to process all the audio recordings to detect vocalizing rails with the software program Song Scope (Wildlife Acoustics, 2011). A recognizer is a machine-learning algorithm which facilitates rapid processing of recordings to locate target vocalizations. The recognizer was trained on annotated clips of Yellow Rail calls and the settings were chosen based on the unique characteristics of the vocalization. The call of the Yellow Rail is a distinctive 'ticking' which is unique to the species (Figure 2.1). The usual rhythmic form of the call is: --, ---/--, ---/--, --- (Peabody, 1922). Calls detected by the recognizer were validated by a human observer to confirm positive identification. To derive abundance estimates from our recognizer detections, human observers processed eight additional recordings for each sampling station where a Yellow Rail was detected: 12:00 AM and 2:00 AM on four random dates (June 7, 14, 18, and 21) following the same listening protocol (Lankau et al. 2017).

2.2.3 Effective Detection Radius

To determine the area sampled by the ARUs, we estimated an effective detection radius (EDR), i.e. the distance from the recorder at which as many calling Yellow Rail are detected beyond the EDR as remain undetected within the EDR (Burnham et al., 2004; Matsuoka et al., 2012). By calculating habitat-specific EDR, we accounted for variation in sound transmission and did not have to assume perfect detection (Yip, Leston, Bayne, Sólymos, & Grover, 2017). EDR can be represented as the parameter, τ, in a half-normal detection function: $p(d) = exp(-d^2/\tau^2)$. Following the methods presented by Yip et al. (2017), we calculated an EDR for Yellow Rail calling in open graminoid habitats using the equation: $\tau = (1/\beta)^{0.5}$. A series of call playback experiments (Yip et al., unpublished data) were conducted, where Yellow Rail calls were broadcast at 90 dB (measured 1m from source) which is similar to the 'loudness' (sound power measured in dB) of Yellow Rail vocalizations (95 dB at 30 cm from source) reported *in situ* by Drake et al. (2016). The detection function was modeled using GLMs with an intercept fixed at 0, a complementary-log-log link function, and binomial distribution. Models included an interaction effect between distance and the parameters (wind, temperature, barometric pressure) but main effects were excluded to accommodate a fixed intercept. To make distance a linear predictor, it was transformed $x = -d^2$ before modelling. The EDR was estimated by summing the beta coefficients (β) of variables related to distance in the top-ranked model. The resulting EDR was 256 m (Lower 95 % C.I.= 204 m and Upper 95% C.I.= 301 m).

2.2.4 Landcover Data

A detailed vegetation and landscape classification of Edéhzhíe was conducted between 2014 and 2016 (JWRL Geomatics, 2017). This was achieved by photo interpretation and digital image-capture conducted according to Northwest Territories forest vegetation inventory standards (NWT-ENR, 2012). Wetlands were classified according to the 4-letter codes used by Halsey et al. (2003) consistent with the Alberta Wetland Classification System (AESRD, 2015). We used each of the letters in the 4-letter code as a categorical wetland covariate: wetland class, wetland vegetation, wetland structure, and local vegetation. The study area was classified into 48755 polygons and these polygons were subsampled to create 30 m pixel rasters for each wetland covariate, to be used for spatial modelling.

2.2.5 Statistical Analyses

We estimated densities (D) for each sampling station using the canonical density estimator: $D = n/a$ the number of birds counted (n) divided by the area sampled (a) (Buckland, 2001; Marques et al., 2013). We then used GLMs to fit a spatial model for Yellow Rail density using the package dismo (Hijmans & Elith, 2013) in R version 3.4.4 (R Core Team, 2018). We tested a series of candidate models incorporating all combinations of the four wetland covariates. Model selection was based on Akaike's Information Criterion (AIC^c ; Burnham and Anderson, 2002). The top-ranked model was used to generate a predictive map.

2.3 RESULTS

Yellow Rails were detected at 21 stations by human listening, and a further ten stations by recognizers, for a total of 31 sampling stations (15.6%). The species was detected at 18 of the 20 sampling stations at Mills Lake (90%). Several other detections came from wetlands adjacent to large lakes: Willow Lake (three stations), and Bulmer Lake (five stations). Mean abundance per occupied sampling station was (1.3 ± 0.27 SE). Our top ranked model included only the wetland class covariate. Models including wetland vegetation, wetland structure, and local vegetation had higher AIC^c scores. A summary of the model outputs is shown in (Table 1). Two levels of wetland class were significant: fen ($p < 0.01$) and marsh ($p < 0.001$). The largest positive beta value for predicting variation in yellow rail density was the wetland class, marsh. Alternatively, the wetland classes bog, and swamp had non-significant negative beta values.

2.4 DISCUSSION

Yellow Rail appear to breed at relatively high densities in appropriate habitat throughout Edéhzhíe. They were detected at 15.5% of the sampling stations. Notably, a relatively large number of detections ($n = 13$) were made at latitudes north of 61.75°N, which are beyond the northern limit of the most recent breeding distribution map for this species (Canadian Wildlife Service, 2011). In our study area, there were also multiple detections at the most northerly sites near Bulmer Lake at 62.72°N. In 2018, a calling male was detected using similar survey methods near Fort Good Hope (66.36°N) approximately 500 km northwest of Bulmer Lake, but Yellow Rail density in this area appeared very low (Haché and Pankratz, unpublished data). This supports a growing body of evidence suggesting that the species is more wide-spread throughout the western boreal than previously reported (NWT/NU Checklist, 2018; Phinney, 2015; Prescott et al., 2002).

Yellow Rail may have eluded detection in the region due to the bird's secretive nature and the remoteness of the sites. Alternatively, it is possible that this represents a relatively recent breeding range expansion for the species. Northern range shifts have been observed in the breeding and wintering ranges of many bird species (Brommer, 2004; La Sorte & Thompson III, 2007; Thomas & Lennon, 1999). However, the accuracy of range delineations is dependent on sampling effort and the actual position of a range boundary is often underestimated when sampling effort is low (Shoo, Williams, & Hero, 2006). This is frequently the case for birds breeding in boreal ecosystems where large areas are undersampled (Barker, Cumming, & Darveau, 2014; Cumming et al., 2010). Increased monitoring coverage for waterbirds in the boreal zone will be essential for accurately assessing changes to these species' distributions in response to climate change.

Our results show that Yellow Rail have a strong association with marshes that are open (non-treed) and dominated by graminoids (<25% shrubs). The predicted density for this combination of covariate levels was 0.07/ha. We also documented densities at individual survey stations as high as 0.15/ha. Across all other combinations of covariate levels, the highest density observed at any survey station was 0.05/ha with modelled densities ranging between 0.0004 and 0.01/ha. Reported estimates from other areas across the species' range are generally between 0.04 to 0.06 males/ha (Leston & Bookhout, 2015; Robert, Jobin, Shaffer, Robillard, & Gagnon, 2004; Robert & Laporte, 1999; H. F. Wilson, 2005). However, densities between 0.18 – 0.43/ha have been reported from Saskatchewan (K. Drake & Latremouille, 2016; McMaster, 2007). Drake and Latremouille (2016) used two estimates of ARU detection radius (175m and 200m), which were both lower than even the lower bound of our EDR 95% credible interval. Thus, it is unclear to what degree these high density estimates from other areas are valid or are reflecting a potential bias due to a considerably smaller EDR. Robert et al. (2004) also reported high densities of 0.08/ha from a transect survey along James Bay in Quebec. In Alberta, observed densities from acoustic data have ranged from 0.05-0.19/ha, but these are considered conservative estimates because there were too many Yellow Rail to count at several sampling stations (McLeod et al., unpublished data).

There are 549 marsh, open, and graminoid wetlands in Edéhzhíe with a total area of 14,626 ha (median patch size = 6.4 ha). These would support an estimated population size of ~900 breeding males (906 ± 146). More than half of this high-quality Yellow Rail habitat, 8,311ha, is situated in the Mills Lake wetland complex located at the southeastern boundary of Edéhzhíe. It is known for extensive marsh vegetation: floating sedge mats, emergent and submergent aquatic vegetation (Trottier & Kemper, 1974). These marsh communities, particularly the shallow-water areas, attract thousands of migrating waterfowl in spring and fall each year (Latour, 2003; Salter, 1974). It is considered a globally significant Important Bird Area (IBA, 2004) and a key terrestrial migratory bird habitat site (Latour et al., 2008). We detected Yellow Rail at 90% of our ARU stations within this complex, a total of 28 individuals, and a predicted abundance of ca. 560 breeding males. This wetland complex should be considered an important breeding area for Yellow Rail in the Northwest Territories. In their surveys in Alberta, Prescott et al. (2002) had the highest counts of Yellow Rail (21 males) at Hay-Zama lake, a large wetland complex in the extreme northwest of the province, which is in the same ecoregion as Mills Lake, the Hay River Lowlands.

Our model makes a single prediction for all marsh wetlands but there might be significant variation within this classification not characterized by our wetland covariates. Yellow Rail have been detected in wetlands as small as 0.5 ha but it has been speculated that they favour large wetland complexes (Alvo & Robert, 1999). Smaller wetlands may become unsuitable due to interannual variation in water level while larger complexes may have a buffering effect on this variation. The vegetation found in the Mills Lake wetland complex is quite distinct from typical boreal wetlands because the plant community is adapted to the physiological demands of growing in permanent standing water on rich alluvial soils (Trottier & Kemper, 1974). It is dominated by *Carex atheroides*, a robust sedge more typical of prairie wetlands (Trottier & Kemper, 1974). However, this wetland complex may also experience more pronounced flooding and drying events as it is adjacent to the Mackenzie River, which is a fast, northward-flowing, river which could create important interannual variations in the suitability of the habitat for Yellow Rail.

Yellow Rail are known to prefer shallow (0-15 cm) wetlands (Austin & Buhl, 2013; Bookhout & Stenzel, 1987; Robert & Laporte, 1999; Stenzel, 1982). They also nest in areas where senescent vegetation accumulates. However, this information was not available for our study and future work should explore how much of the unexplained variation in the model could be explained by variation in water depth. Moreover, our sampling locations were aggregated in drier margins of the wetlands, while increased depth would likely correspond with lower densities of rails. Thus, extrapolating density estimates from sampling locations located mainly in shallow portions of Mills Lake to the entire wetland complex might have produced overestimates of population sizes. Tozer (2007) speculated that high concentrations of rail at sites along the St. Lawrence River were the result of a population being concentrated in a smaller area due to flooding in the outer margins of the wetland.

The core (i.e. centre of abundance) of the breeding Yellow Rail population is assumed to be located within the Hudson Bay and James Bay coastal wetlands (COSEWIC, 2009). It was estimated "a few thousand pairs" (ca. 6,000-8,000) breed in that region and another roughly 2,000 pairs throughout the rest of Canada (Alvo & Robert, 1999; COSEWIC, 2009). In this study, we estimated that between 750 and 1052 pairs might breed in Edéhzhíe alone. While Mills Lake may a unique area in NWT, there is no reason to believe this pattern is isolated to Edéhzhíe. Similar habitat areas exist beyond Edéhzhíe and throughout the taiga plains. Increasing geographic coverage of monitoring programs throughout the NWT could contribute to a greater understanding of distribution and population size for this and other species breeding in northern boreal regions. This baseline information is required to inform species status assessments and set appropriate distribution and population objectives to allow species at risk to recover.

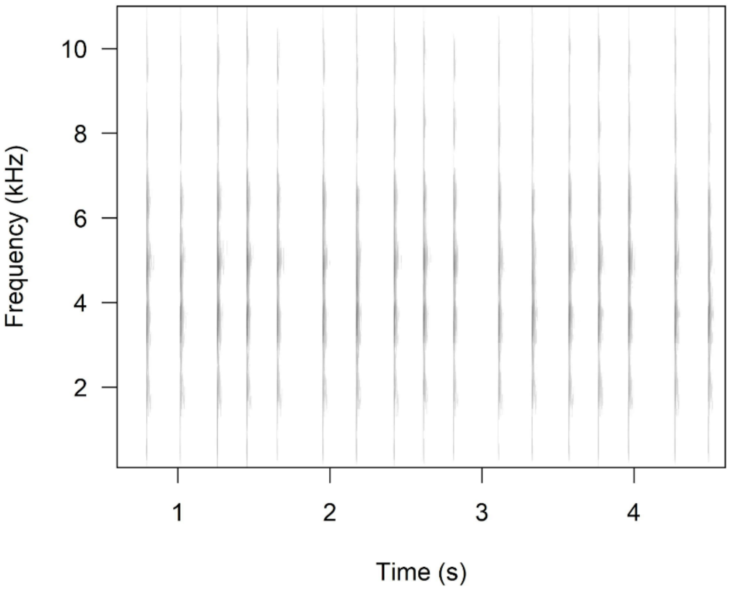

Figure 2.1: Sonogram of the Yellow Rail call.

Table 2.1: Beta (β) coefficients and standard error (SE) for the top-ranked model. The level withheld for contrast is wetland class – Fen.

Variable	**β**	**SE**	
(Intercept) - Fen	0.006	0.002	**
Wetland class – Bog	-0.004	0.003	
Wetland class – Marsh	0.062	0.005	***
Wetland class – Swamp	-0.006	0.013	

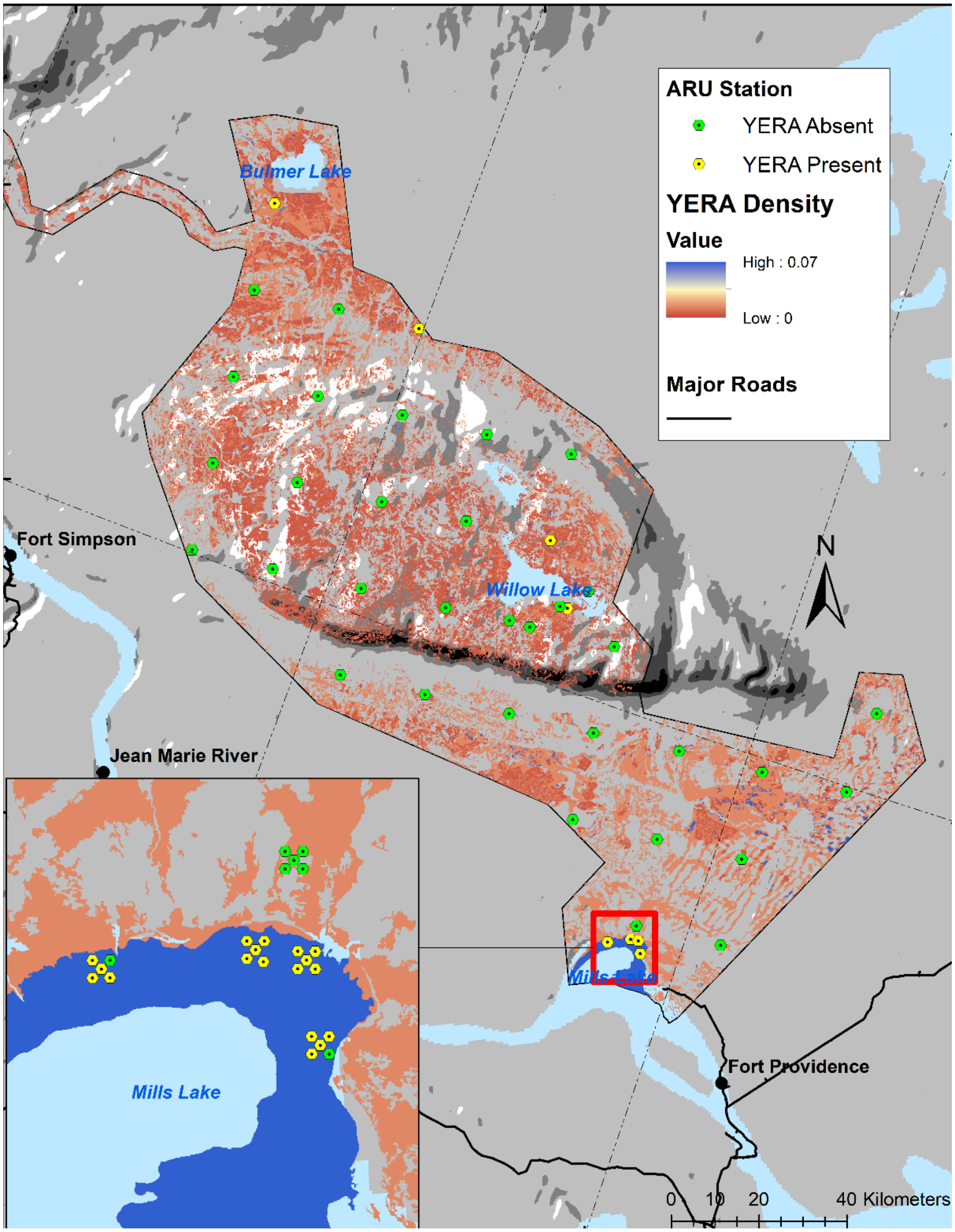

Figure 2.2: Predicted density (number of territorial males/ha) of Yellow Rail in Edéhzhíe, Northwest Territories, Canada.

2.5 LITERATURE CITED

AESRD. (2015). *Alberta wetland classification system*. Edmonton.

Alvo, R., & Robert, M. (1999). *COSEWIC Assessment and status report on the Yellow Rail (Coturnicops noveboracensis) in Canada*. Ottawa.

Austin, J. E., & Buhl, D. A. (2013). Relating Yellow Rail (Coturnicops noveboracensis) occupancy to habitat and landscape features in the context of fire. *Waterbirds*, *36*(2), 199–213. https://doi.org/10.1675/063.036.0209

Barker, N. K. S., Cumming, S. G., & Darveau, M. (2014). Models to predict the distribution and abundance of breeding ducks in Canada. *Avian Conservation and Ecology*, *9*(2), 41–82. https://doi.org/10.5751/ACE-00699-090207

Bart, J., Stehn, R. A., Herrick, J. A., Heaslip, N. A., Bookhout, T. A., & Stenzel, J. R. (1984). Survey methods for breeding Yellow Rails. *The Journal of Wildlife Management*, *48*(4), 1382–1386.

Bazin, R., & Baldwin, F. B. (2007). *Canadian Wildlife Service standardized protocol for the survey of Yellow Rails (Coturnicops noveboracensis) in prairie and northern region*. Winnipeg.

Bird Studies Canada. (2019). Marsh monitoring program. Retrieved 28 January 2019, from https://www.birdscanada.org/volunteer/natmmp/

Bookhout, T. A., & Stenzel, J. R. (1987). Habitat and movements of breeding Yellow Rails. *The Wilson Bulletin*, *99*(3), 441–447.

Brandt, J., Flannigan, M., Maynard, D., Thompson, I., & Volney, W. (2013). An introduction to Canada's boreal zone: ecosystem processes, health, sustainability, and environmental issues. *Environmental Reviews*, *21*(4), 207–226. https://doi.org/Doi 10.1139/Er-2013-0040

Brommer, J. E. (2004). The range margins of northern birds shift polewards. *Annales Zoologici Fennici*, *41*, 391–397.

Brown, J. H. (1984). On the relationship between abundance and distribution of species. *The American Naturalist*, *124*(2), 255–279. https://doi.org/10.1086/284267

Buckland, S. T. (2001). *Introduction to distance sampling: Estimating abundance of biological populations*. Oxford: Oxford University Press.

Burnham, K. P., & Anderson, D. R. (2002). *Model selection and multimodel inference* (2nd ed.). New York: Springer - Verlag New York. https://doi.org/10.1016/j.ecolmodel.2003.11.004

Burnham, K. P., Buckland, S. T., Laake, J. L., Borchers, D. L., Marques, T. A., Bishop, J. R., & Thomas, L. (2004). Further topics in distance sampling. In *Advanced Distance Sampling: Estimating abundance of biological populations* (pp. 326–408). Oxford: Oxford University Press.

Canadian Wildlife Service. (2011). Yellow rail range in Northwest Territories and Nunavut. Yellowknife, Northwest Territories: Environment and Climate Change Canada.

Conway, C. J. (2011). Standardized North American marsh bird monitoring protocol. *Waterbirds*, *34*(3), 319–346. https://doi.org/10.1675/063.034.0307

Conway, C. J., & Nadeau, C. P. (2010). Effects of broadcasting conspecific and heterospecific calls on detection of marsh birds in North America. *Wetlands*, *30*(2), 358–368. https://doi.org/10.1007/s13157-010-0030-1

COSEWIC. (2009). *COSEWIC assessment and status report on the Yellow Rail Coturnicops noveboracensis in Canada*. Ottawa.

Cumming, S. G., Lefevre, K. L., Bayne, E. M., Fontaine, T., Schmiegelow, F. K., & Song, S. J. (2010). Toward conservation of Canada’s boreal forest avifauna: Design and application of ecological models at continental extents. *Avian Conservation and Ecology*, *5*(2), art8.

Dehcho Land Use Planning Committee. (2006). *Respect for the land: The Dehcho land use plan (Ndéh Ts’edîîchá: Dehcho Ndéh T’áh Ats’et’î K’eh Eghálats’ênda)*.

Drake, K. L., Frey, M., Hogan, D., & Hedley, R. (2016). Using digital recordings and sonogram analysis to obtain counts of Yellow Rails. *Wildlife Society Bulletin*, *40*(2), 346–354. https://doi.org/10.1002/wsb.658

Drake, K., & Latremouille, L. (2016). *Fishing Lake conveyance channel wildlife assessment: final report 2011-2015*. Saskatoon.

Ecological Stratification Working Group. (1995). *A national ecological framework for Canada*. Ottawa/Hull. Report and national map at 1:7500 000 scale.

Ecosystem Classification Group. (2007). *Ecological regions of the Northwest Territories - taiga plains*. Yellowknife.

Elith, J., & Leathwick, J. R. (2009). Species distribution models: Ecological explanation and prediction across space and time. *Annual Review of Ecology, Evolution, and Systematics*, *40*(1), 677–697. https://doi.org/10.1146/annurev.ecolsys.110308.120159

Gibbs, J. P., & Melvin, S. M. (1993). Call-response surveys for monitoring breeding waterbirds. *The Journal of Wildlife Management*, *57*(1), 27–34. https://doi.org/10.1183/09031936.00167908

Guisan, A., & Zimmermann, N. E. (2000). Predictive habitat distribution models in ecology. *Ecological Modelling*, *135*, 147–186. https://doi.org/10.1016/S0304-3800(00)00354-9

Guo, Q., Taper, M., Schoenberger, M. M., & Brandle, J. R. (2005). Spatial-temporal population dynamics across species range: from centre to margin. *Oikos*, *108*(1), 47–57. https://doi.org/10.1111/j.0030-1299.2005.13149.x

Halsey, L. A., Vitt, D. H., Beilman, D., Crow, S., Mehelcic, S., & Wells, R. (2003). *Alberta wetland inventory standards version 2.0*. Edmonton: Alberta Sustainable Resource Development.

Herkert, J. R. (1995). An analysis of Midwestern breeding bird population trends: 1966-1993. *American Midland Naturalist*, *134*(1), 41. https://doi.org/10.2307/2426481

Hijmans, R. J., & Elith, J. (2013). *Species distribution modeling with R Introduction*. https://doi.org/10.1016/S0550-3213(02)00216-X

IBA. (2004). Mills Lake IBA site summary. Retrieved 1 February 2019, from https://www.ibacanada.com/site.jsp?siteID=NT083

JWRL Geomatics. (2017). *Vegetation and landscape classification of Edéhzhíe candidate national wildlife area*.

Kawecki, T. J. (2008). Adaptation to marginal habitats. *Annual Review of Ecology, Evolution, and Systematics*, *39*(1), 321–342. https://doi.org/10.1146/annurev.ecolsys.38.091206.095622

Kushlan, J. A., Steinkamp, M. J., Parsons, K. C., Capp, J., Acosta Cruz, M., Coulter, M., … Wohl, K. (2002). *Waterbird conservation for the Americas: The North American waterbird conservation plan, Version 1*. Washington D.C.

La Sorte, F. A., & Thompson III, F. R. (2007). Poleward shifts in winter ranges of North American birds. *Ecology*, *88*(7), 1803–1812.

Lankau, H., Macphail, A., Knaggs, M., & Bayne, E. M. (2017). *Bioacoustic Unit: Acoustic recording analysis protocol*. Edmonton.

Latour, P. B. (2003). *Aerial surveys of geese, swans, and shore-birds at Mills Lake, NWT during the spring and fall migration period: 1994-1997*.

Latour, P. B., Leger, J., Hines, J. E., Mallory, M. L., Mulders, D. L., Gilchrist, H. G., … Dickson, D. L. (2008).

Key migratory bird terrestrial habitat sites in the Northwest territories and nunavut. *Occasional Paper of the Canadian Wildlife Service*.

Lawton, J. H. (1993). Range, population abundance and conservation. *Oikos*, *8*(7), 409–413.

Leston, L., & Bookhout, T. A. (2015). Yellow Rail (*Coturnicops noveboracensis*), version 2.0. https://doi.org/10.2173/bna.139

Marques, T. A., Thomas, L., Martin, S. W., Mellinger, D. K., Ward, J. A., Moretti, D. J., … Tyack, P. L. (2013). Estimating animal population density using passive acoustics. *Biological Reviews*, *88*(2), 287–309. https://doi.org/10.1111/brv.12001

Martin, K., Koper, N., & Bazin, R. (2014). Optimizing repeat-visit, call-broadcast nocturnal surveys for Yellow Rails (*Coturnicops noveboracensis*). *Waterbirds*, *37*(1), 68–78. https://doi.org/10.1675/063.037.0109

Matsuoka, S. M., Bayne, E. M., Sólymos, P., Fontaine, P. C., Cumming, S. G., Schmiegelow, F. K., & Song, S. J. (2012). Using binomial distance-sampling models to estimate the effective detection radius of point-count surveys across boreal Canada. *The Auk*, *129*(2), 268–282. https://doi.org/10.1525/auk.2012.11190

McMaster, G. (2007). *Addendum to 'Assessment of potential impacts of the East and West Fishing Lake conveyance options on habitat and historic resources'*. Regina.

North American Bird Conservation Initiative. (2012). The state of Canada's birds. https://doi.org/978-1-100-20674-5

NWT-ENR. (2012). *Northwest Territories forest vegetation inventory standards with softcopy supplement, V4.4*. Yellowknife.

NWT/NU Checklist. (2018). Northwest Territories/Nunavut (NWT/NU) bird checklist survey. Retrieved 11 February 2019, from https://www.canada.ca/en/environment-climate-change/services/bird-surveys/landbird/ebird-northwest-territories-nunavut.html

Pankratz, R. F., Haché, S., Sólymos, P., & Bayne, E. M. (2017). Potential benefits of augmenting road-based breeding bird surveys with autonomous recordings. *Avian Conservation and Ecology*, *12*(2), art18. https://doi.org/10.5751/ACE-01087-120218

Pardieck, K. L., Ziolkowski, D. J. J., Lutmerding, M., & Hudson, M.-A. R. (2018). 2018. North American breeding bird survey dataset 1966 - 2017, version 2017.0. U.S. Geological Survey, Patuxent Wildlife Research Center. U.S. Geological Survey: Patuxent Wildlife Research Center. https://doi.org/https://doi.org/10.5066/F76972V8

Peabody, P. (1922). Haunts and breeding habits of the Yellow Rail. *Journal of the Museum of Comparative Oology*, *2*, 33–44.

Phinney, M. (2015). Yellow Rail (Coturnicops noveboracensis). In P. Davidson, R. Cannings, A. Couturier, D. Lepage, & C. Di Corrado (Eds.), *The Atlas of the Breeding Birds of British Columbia, 2008-2012* (p. 2). Delta: Bird Studies Canada.

Potapov, P., Yaroshenko, A., Turubanova, S., Dubinin, M., Laestadius, L., Thies, C., … Zhuravleva, I. (2008). Mapping the world's intact forest landscapes by remote sensing. *Ecology and Society*, *13*(2), art51. https://doi.org/10.5751/ES-02670-130251

Prescott, D. R. C., Norton, M. R., & Michaud, I. M. G. (2002). A survey of Yellow and Virginia Rails in Alberta using nocturnal call playbacks. *Canadian Field-Naturalist*, *116*(3), 408–415.

Pulliam, H. R. (1988). Sources, sinks, and population regulation. *The American Naturalist*, *132*(5), 652–661.

R Core Team. (2018). *R: A language and environment for statistical computing*. Vienna, Austria.

Robert, M., Jobin, B., Shaffer, F., Robillard, L., & Gagnon, B. (2004). Yellow Rail distribution and numbers in Southern James Bay, Québec, Canada. *Waterbirds*, *27*(3), 282–288. https://doi.org/10.1675/1524-4695(2004)027[0282:YRDANI]2.0.CO;2

Robert, M., & Laporte, P. (1999). Numbers and movements of Yellow Rails along the St. Lawrence River, Québec. *The Condor*, *101*(3), 667–671. https://doi.org/10.2307/1370197

Sagarin, R. D., Gaines, S. D., & Gaylord, B. (2006). Moving beyond assumptions to understand abundance distributions across the ranges of species. *Trends in Ecology and Evolution*, *21*(9), 524–530. https://doi.org/10.1016/j.tree.2006.06.008

Salter, R. (1974). *Autumn migration of birds through the central and upper Mackenzie Valley region, 1972*. *Arctic Gas Biological Report Series* (Vol. 13). Calgary.

Sauer, J. R., Link, W. A., Fallon, J. E., Pardieck, K. L., & Ziolkowski, D. J. J. (2013). The North American Breeding Bird Survey 1966-2011: Summary analysis and species accounts. *North American Fauna*, *79*(1). https://doi.org/10.3996/nafa.79.0001

Sauer, J. R., Niven, D. K., Pardieck, K. L., Ziolkowski, D. J. J., & Link, W. A. (2017). Expanding the North American breeding bird survey analysis to include additional species and regions. *Journal of Fish and Wildlife Management*, *8*(1), 154–172. https://doi.org/10.3996/102015-JFWM-109

Schindler, D. W., & Lee, P. G. (2010). Comprehensive conservation planning to protect biodiversity and ecosystem services in Canadian boreal regions under a warming climate and increasing exploitation. *Biological Conservation*, *143*(7), 1571–1586. https://doi.org/10.1016/j.biocon.2010.04.003

Shonfield, J., & Bayne, E. M. (2017). Autonomous recording units in avian ecological research: current use and future applications. *Avian Conservation and Ecology*, *12*(1), art14. https://doi.org/10.5751/ACE-00974-120114

Shoo, L. P., Williams, S. E., & Hero, J. M. (2006). Detecting climate change induced range shifts: where and how should we be looking? *Austral Ecology*, *31*(1), 22–29. https://doi.org/10.1111/j.1442-9993.2006.01539.x

Stenzel, J. R. (1982). *Ecology of breeding Yellow Rails at Seney National Wildlife Refuge*. Master's thesis, Ohio

State University, Columbus.

Thomas, C. D., & Lennon, J. J. (1999). Birds extend their ranges northwards. *Nature*, *399*, 213. https://doi.org/10.1039/b301690k

Tozer, D. C. (2007). Yellow Rail. In M. Cadman, D. Sutherland, B. GG, D. Lapage, & A. Couturier (Eds.), *The Atlas of the Breeding Birds of Ontario* (pp. 196–197). Bird Studies Canada.

Tozer, D. C., Drake, K. L., & Falconer, C. M. (2016). Modeling detection probability to improve marsh bird surveys in Southern Canada and the Great Lakes states. *Avian Conservation and Ecology*, *11*(2). https://doi.org/10.5751/ACE-00875-110203

Trottier, G., & Kemper, J. (1974). *A reconnaissance vegetation survey, Mills Lake, Northwest Territories*. Edmonton.

Wells, J. V. (2011). Boreal forest threats and conservation status. In J. V Wells (Ed.), *Boreal birds in North America: A hemispheric view of their conservation links and significance. Studies in Avian Biology (no. 41)* (pp. 1–6). Berkeley, CA: University of California Press.

Wells, J. V, & Blancher, P. J. (2011). Global role for sustaining bird populations. In J. V Wells (Ed.), *Boreal birds in North America: A hemispheric view of their conservation links and significance. Studies in Avian Biology (no. 41)* (pp. 7–22). Berkeley, CA: University of California Press.

Wetlands International. (2019). Waterbird Population Estimates. Retrieved 10 January 2019, from http://wpe.wetlands.org/

Wildlife Acoustics. (2011). *Song Scope: Bioacoustics software version 4.0 documentation*. Maynard.

Wilson, H. F. (2005). *Habitat use patterns of Yellow Rails (Coturnicops noveboracensis) at Douglas Marsh, Manitoba*. Undergraduate thesis, Brandon University.

Yip, D. A., Leston, L., Bayne, E. M., Sólymos, P., & Grover, A. (2017). Experimentally derived detection distances from audio recordings and human observers enable integrated analysis of point count data. *Avian Conservation and Ecology*, *12*(1), art11. https://doi.org/10.5751/ACE-00997-120111

Chapter 3 Spatially explicit abundance modelling of a highly specialized wetland bird using satellite remote sensing

3.1 INTRODUCTION

Understanding patterns of species distribution and abundance is fundamental to modern wildlife biology. Species distribution models (SDMs), and their derivatives, are powerful and popular tools used by ecologists to quantitatively describe these patterns using landscape and environmental characteristics (Elith and Leathwick, 2009; Guisan and Zimmermann, 2000). SDMs rely on spatially explicit descriptions of habitat to model species occurrence and can reveal which variables best predict where a species occurs (e.g. Jarnevich et al., 2016; McFarland et al., 2015). Geographic Information Systems (GIS) and remote sensing technologies have revolutionized the field in terms of the breadth and resolution of datasets available for describing habitat (Cord, Meentemeyer, Leitao, & Vaclavik, 2013; Gottschalk et al., 2005). Recent developments in open-access satellite data (Landsat, Sentinel-1, Sentinel-2), cloud computing (Google Earth Engine), and data science have made large-scale, high-resolution landcover data available for scientists conducting applied research (Drusch et al., 2012; Gorelick et al., 2017; Hird et al., 2017). However, the integration of remote sensing data into ecological models has not yet reached its full potential.

The Yellow Rail (*Coturnicops noveboracensis*) is a secretive marsh bird that is assumed to be very rare. It is widely distributed in Canada from northeast British Columbia and the southern Northwest Territories to the coast of New Brunswick (Leston & Bookhout, 2015). Much of its range is in remote areas and over 50% of the Yellow Rail breeding population is in the boreal zone (Wells & Blancher, 2011). As a result, very little is known about its population status across much of its range and large populations have gone undetected until recently. There is significant concern over the conservation status of the Yellow Rail because of very small population size estimates (10,000 – 25,000; Wetlands International 2019), a compressed wintering range, ongoing threats to wetland habitats (e.g. due to resource development; Willier, 2017), and evidence of local population declines (COSEWIC, 2009). This has led to its listing on Schedule 1 of the federal *Species at Risk Act* (S.C. 2002, c.29; *SARA*) as a species of Special Concern in Canada. Several studies have identified its breeding habitat as areas of wetland dominated by graminoid vegetation, like sedges (Cyperaceae) with little to no standing water (Leston & Bookhout, 2015; Robert & Laporte, 1999; Stalheim, 1974; Stenzel, 1982). It has been described as the 'goldilocks' of the Rallidae due to its apparent highly specific habitat associations (Austin & Buhl, 2013). Given this narrow breadth of suitable habitat conditions, modelling and mapping this species could be highly effective for conservation planning but our ability to locate suitable wetlands has been a challenge to date.

Characterization of wetland ecosystems with GIS and remote sensing remains challenging because of the dynamic nature of some wetland types, and the influence of subsurface hydrology which cannot be measured by remote sensing. In Canada, there have been several efforts to map and classify wetlands. Traditionally, this is accomplished either through: (1) photo-interpreted or modeled, vector-based inventories (ABMI, 2018a; AESRD, 2015; Tarnocai, Kettles, & Lacelle, 2011), or, (2) remotely sensed landcover classification (Amani et al., 2019; Ducks Unlimited Canada, 2015; Hird et al., 2017; Mahdianpari et al., 2018). However, these approaches have downsides. The accuracy of photo interpretation is limited by the quality and timing of the source imagery (e.g. leaf-off colour infrared photography is best for wetland mapping; Tiner, 1999), and remotely sensed landcover classification (e.g. using MODIS, Landsat, or Sentinel data) often ignores the underlying hydrology that drives wetland formation, structure, and function (Ozesmi & Bauer, 2002). Even the best wetland-mapping products suffer from the fact that they represent snapshots or single-state views of ecosystems which cannot account for dynamic changes often seen in vegetation, hydrology, short-term climate, and landscape disturbance. For this reason, the predictive ability of many remote-sensing landcover classifications decreases over time and performance may decline after only a few years (McFarland et al., 2015).

For an SDM to be useful, the environmental variables used in the model need to be appropriate for the scale of study and available with sufficient quality, coverage, and resolution. Additionally, it is advantageous if they can be linked as directly as possible to some known or hypothesized biological mechanism. Given that SDMs are, by their nature, only as good as the environmental covariates upon which they are built, ecologists often seek out the most accurate descriptions, with the highest resolution, of the environment available. Typically, this involves some form of classification using a single remote sensor. However, hybrid approaches to landcover mapping, that use ensembles of optical remote sensing, radar, and digital elevation model (DEM) derivatives, have emerged with more promising results. For wetlands, products that rely on DEM derivatives may better reflect important wetland hydrological patterns than standard classifications (DeLancey et al., 2019; Difebo, Richardson, & Price, 2015; Dvorett, Davis, & Papeş, 2016; Hird et al., 2017; Jiang et al., 2015; Lang, McCarty, Oesterling, & Yeo, 2013). Many of these hybrid approaches are made possible by Google Earth Engine (GEE), which is a cloud-based platform that allows users to access a multi-petabyte catalogue of remote sensing satellite data. GEE makes these data available online through its parallel computation service and facilitates the analysis and processing of datasets through a built-in application programming interface (Gorelick et al., 2017). These capabilities have been used to develop the Advanced Landcover Prediction and Habitat Assessment (ALPHA) program, an active framework for wetland mapping and monitoring across Alberta (ABMI, 2019; DeLancey et al., 2019; Hird et al., 2017).

The GEE platform and mapping products like ALPHA have enabled development of SDMs using large amounts of remotely sensed data, from a variety of sources, to classify species distribution and model species abundance of wetland birds like the Yellow Rail at both high-resolution (10 m) and large spatial extents. Using satellite data for building SDMs enables us to skip the landcover classification step frequently involved in generating SDM inputs. This allows us to avoid building models based on prior models (landcover classifications), a practice which compounds error rates. By modelling directly with continuous variables derived from earth observation satellite data, we propose that it becomes possible to dynamically update SDMs with annual, or seasonal, remote sensing inputs to better reflect changes within dynamic wetland ecosystems. This framework for building SDMs may be very promising for conserving highly specialized species like the Yellow Rail.

3.2 METHODS

3.2.1 Study Area

The study was conducted over a large region of northeastern Alberta, Canada (Figure 3.1) defined by the boundaries of the Athabasca oilsands area (93,260 km^2) and the Cold Lake oilsands area (17,834 km^2). This area is notable for its high resource potential, vast deposits of oil-infused sand or bitumen, and for an abundance of wetlands. It falls within the Boreal Plains ecozone and Boreal Forest natural region (Ecological Stratification Working Group, 1995; Natural Regions Committee, 2006). There are four component ecoregions: the Boreal Transition, Mid-boreal Uplands, Slave River Lowlands, and Wabasca Lowlands.

The climate of the boreal forest natural region is characterized by short summers and long, cold winters (Natural Regions Committee, 2006). In our study area there is a gradual transition from a subhumid low-boreal climate in the Boreal Transition to a subhumid mid-boreal climate across the rest of the study area (Strong, Zoltai, & Ironside, 1989). Therefore, the mean summer temperature (MST) is slightly warmer and the mean annual precipitation (MAP) is higher in the southern portions of the study area (MST: 14˚C, MAP: 450-550 mm in the

Boreal Transition; MST: 13˚C, MAP: 300-400 mm in the Slave River lowlands). Typical vegetation communities include deciduous, coniferous, and mixedwood forests, interspersed with extensive wetland complexes (Natural Regions Committee, 2006). The primary human disturbances are forestry and extensive oil and gas development, especially in the areas around Fort McMurray and Fort MacKay, while agriculture is limited to the south of the study area in the vicinity of Cold Lake and Lac La Biche (ABMI, 2017).

Wetland habitat is very abundant in the Boreal Plains where it covers 30.3% of the overall land area (Environment and Climate Change Canada, 2016). Wetlands are even more prominent on the landscape within our study area where approximately 47,864 km^2 (43%) can be classified as wetland habitat (ABMI, 2019). The Government of Alberta recognizes five main wetland classes across the province: bog, fen, marsh, swamp, and shallow open water (AESRD, 2015). These can be divided into two broad groups: peatlands (bogs, fens, and some swamps) and mineral wetlands (marshes, swamps, and shallow open water; AESRD 2015). Wetlands in northeastern Alberta are characterized by extensive peatlands which typically form in cool, flat, low-lying areas with poorly drained soils. Due to the climate of northern Alberta, most peatlands are forested, typically with black spruce (*Picea mariana*) but in more nutrient-rich fens, with surface and groundwater flow, tamarack (*Larix laricina*) dominates (Waddington et al., 2015). Peatlands with less vegetation structure also occur and these may be dominated by shrubs or graminoids (AESRD, 2015; Vitt & Chee, 1990). Our sample locations were originally identified using the Ducks Unlimited Enhanced Wetland Classification (DU-EWC; Ducks Unlimited Canada, 2015) which helped us to target low-structure wetland areas potentially suitable for Yellow Rail. In general, our surveys covered the breadth of wetland classes within our study area; however, our 2013 and 2014 surveys did sample from a broader range of wetland habitats than in subsequent years because program priorities shifted from finding new populations of Yellow Rail to trend-monitoring at known breeding sites.

3.2.2 Yellow Rail Abundance Data

Acoustic surveys for Yellow Rail were conducted using autonomous recording units (ARUs) (Models: SM2+, SM3, and SM4; Wildlife Acoustics, Inc., Maynard, Massachusetts, USA). The ARUs have built-in omnidirectional microphones (frequency response: 20–20,000 Hz) and record in stereo format at 44.1 kHz with a 16-bit resolution. Microphone gain was set at 48 dB for both channels. The ARUs were scheduled to record the first 10 min of every hour daily for the duration of their deployment.

We used the data from acoustic surveys conducted over 4 years (2013 – 2016) as part of a long-term monitoring effort. ARUs were deployed at 1016 different sampling sites throughout the study area. Sites were clustered into groups of five: four ARUs in a 2 x 2 grid (spaced 600m apart) and a fifth at the grid centroid. This spacing was chosen to approximate the home range size of Yellow Rail reported in the literature (Leston and Bookhout 2015). New sites were added each year, and some previous sites where Yellow Rail were detected continued to be sampled in the subsequent years. ARUs were deployed and retrieved between: 09 May 2013 – 02 August 2013 (n = 427); 24 April 2014 – 06 July 2014 (n = 365); 03 May 2015 – 30 June 2015 (n = 489); and 10 March 2016 – 25 July 2016 (n = 259). At each sampling location, one ARU was attached to a tree or stand ~1.5m above the ground. Trees >18cm diameter were not used to avoid interference with the directionality of the microphones. Some ARUs were deployed ahead of the typical Yellow Rail breeding season and left in place until early June. Subsequently, ARUs were moved on an approximately bi-weekly rotation to new sample sites to increase the number of sites that could be sampled with a limited inventory of recorders.

Counts of Yellow Rail were determined from a combination of automatic processing and human listening. A Yellow Rail ‘recognizer’ was used to process all the audio recordings collected to detect vocalizing rails. A recognizer is a machine-learning algorithm which facilitates rapid processing of recordings to locate target vocalizations. The software program Song Scope (Wildlife Acoustics, 2011) uses digital signal processing algorithms to compare and identify target vocalizations in recordings. The recognizer was trained on annotated clips of Yellow Rail calls and the settings were chosen based on the unique characteristics of the vocalization. Calls detected from the recognizer were validated by a human observer to confirm positive identification. A subset of recordings was processed by human observers using standardized listening and data entry protocols (Lankau et al., 2017). Recordings targeted for human listening were randomly selected, spanning across the dates that ARUs were deployed. A minimum of four nocturnal recordings were processed at every site and the maximum number of individual Yellow Rail heard during an individual recording was taken as the final count.

3.2.3 Effective Detection Radius

To estimate the area sampled by the ARUs, we estimated an effective detection radius (EDR), i.e. the distance from the recorder at which the detection probability for a calling Yellow Rail reaches 50% (Burnham et al., 2004; Matsuoka et al., 2012). By calculating habitat-specific EDR, we accounted for variation in sound transmission and could relax an assumption of perfect detection (Yip et al., 2017). EDR can be represented as the parameter, τ, in a half-normal detection function: $p(d) = exp(-d^2/\tau^2)$. Following the methods presented by Yip et al. (2017), we calculated an EDR for Yellow Rail calling in wetland habitats using the equation $\tau = (1/\beta)^{0.5}$. A series of call playback experiments (Yip et al., unpublished data) were conducted, where Yellow Rail calls were broadcast at 90 dB (measured 1 m from source) which is similar to the 'loudness' (sound power measured in dB) of Yellow Rail vocalizations (95 dB at 30 cm from source) reported *in situ* by Drake et al. (2016). For subsequent modelling, landscape input values were averaged under a buffer to reflect the uncertainty in the point source of a detected Yellow Rail vocalization.

3.2.4 Remote Sensing Data

Sentinel-1, Sentinel-2 (Copernicus Programme, 2016, 2017) and the Advanced Land Observing Satellite (ALOS) Digital Elevation Model (DEM) (JAXA, 2019) data were used as inputs to the yellow rail abundance model. All Sentinel and ALOS data were acquired, processed, and downloaded through GEE (Gorelick *et al.,* 2017). GEE stores Sentinel-1 (Synthetic Aperture Radar – SAR – imagery) ground range detected scenes which have been pre-processed with the Sentinel-1 Toolbox (Sentinel Application Platform – Sentinel-1 Toolbox). These pre-processing steps include thermal noise removal, radiometric calibration, and terrain correction. Dual polarization (VV VH) Sentinel-1 images were further processed in the GEE environment by performing an incidence angle correction (Gauthier *et al.,* 1998) and smoothing with a 3x3 Sigma Lee filter (Lee et al., 2009; credit to Guido Lemoine for GEE code). Once all Sentinel-1 images were processed, a difference of polarization (DPOL) was calculated (see Table 1) and added to the available bands. To generate a single composite image for the Sentinel-1 inputs, the per-pixel mean of the VH and DPOL bands were calculated. A total of 478 Sentinel-1 images were used in the calculation of the VH and DPOL variables. ΔVH was calculated by taking the per-pixel mean of summer/spring images and subtracting the per pixel mean of winter images.

Sentinel-2 (optical imagery) top of atmosphere data was acquired through GEE. Clouds, shadows, snow, and ice were removed with the QA60 band (a quality control band used to identify bad pixels) and further cloud masking was done using bands 1 (aerosols) and 11 (cloud). Sentinel-2 images intersecting with the study area during 2017-2018 leaf-on season (May 15 – August 31) were used to extract the 10m bands and generate vegetation indices. The merged Sentinel-2 data was generated using a median composting algorithm where the median time series value for each pixel was selected as the most representative pixel. A total of 3,148 Sentinel-2 images were used in the calculation of the 10m bands and vegetation indices. ΔNDVI was calculated by subtracting the median pixel leaf-off values (fall) from the median pixel of leaf-on (spring / summer) values.

The ALOS DEM data was turned into a floating-point raster, then resampled to 10m resolution using cubic convolution and then subsequently smoothed using a 7x7 pixel mean filter. Three topographic indices – SAGA Wetness Index (SWI), Topographic Position Index (TPI), and Valley Bottom Flatness (VBF) – were then calculated in SAGA version 5.0.0 (Conrad et al., 2015). All the input variables can be seen in Figure 3.2 and the equations and description can be seen in Table 1.

3.2.5 Statistical Analyses

Yellow Rail are wetland obligates so it would not be meaningful to predict their abundance over upland areas. To narrow our sampling frame appropriately, we applied a binary wetland / upland classification with a threshold probability ≥ 0.35 using the ALPHA wetland probability (ABMI, 2019; DeLancey et al., 2019) data set. This threshold had the highest overall accuracy in cross-validation accuracy assessment (overall accuracy = 83.4%, kappa statistic = 0.667, and AUC = 0.910; ABMI, 2019).

Sampling sites which were in locations within known human footprint features, or in areas with open water based on spatial delineations from the ABMI Human Footprint Inventory (ABMI, 2017) and Boreal Surface Water Inventory (ABMI, 2018b) were removed at this stage (n = 15). For the remaining sample sites (n = 1001) a buffer based on our EDR’s lower 95 C.I. (204 m) was established and the values for each remote sensing input were averaged over this space to account for the spatial uncertainty in our aural observations.

SDMs based on count data can be used to predict spatial variation in abundance or density (Elith & Leathwick, 2009). We used boosted regression trees (BRTs) to fit SDMs for Yellow Rail abundance using the package dismo (Hijmans & Elith, 2013) in R version 3.4.4 (R Core Team, 2018). BRT is an ensemble method (i.e. combining multiple learning algorithms) that builds and averages many individual classification trees using a boosting algorithm (Breiman, 2001). BRTs, in general, have good predictive performance relative to other commonly used methods and can also model nonlinear response curves and complex interactions (Elith et al., 2008, 2006; De'ath, 2007). Machine learning approaches have a tendency toward model overfitting and are often seen as a ‘black-box’ with limited model interpretability. In this regard, BRTs compare favourably to neural networks or support vector machines providing both excellent predictive ability and allowing ecological relationships to be quantified and explored (De'ath, 2007).

Three model parameters are user-defined: learning rate sets the shrinkage applied to each tree (ie. the rate at which the contribution of subsequent trees to the overall model is decreased); tree complexity which specifies the number of nodes per tree thereby regulating the depth of interaction between predictors; and bag fraction which determines the proportion of observed data randomly selected for each tree. Parameters were generally set according to recommendations in Elith et al. (2008). For the models, we used a bag fraction = 0.5. We varied tree complexity (tc = 1,2,3,5,10) and learning rate (lr = 0.5, 0.1, 0.05, 0.01) using a grid search technique to find appropriate settings. The learning rate was adjusted until the optimal number of trees exceeded 1000 as calculated through the 10-fold cross validation procedure implemented with gbm.step in dismo. Our selected settings were: tree complexity = 5 and learning rate = 0.04.

To quantify the relationships, between the predictors and response, the relative influence (RI) of each predictor was calculated using the method of Friedman (2001), implemented with dismo. This is a stagewise approach where, each time a predictor is selected for splitting, the squared improvement on the model is summed and averaged across all trees. The values are then normalized so the RI scores sum to 100 where higher RI scores indicate more influential predictors (Elith et al., 2008). To illustrate the relationships, between the predictors and response, we used partial dependence plots to show the effect each predictor had on the response while the other predictors were held at their mean (Elith et al., 2008). Interactions were assessed using the dismo function gbm.interactions which tests whether interactions have been detected and modelled, and reports the relative strength of the interactions (Hijmans & Elith, 2013). To illustrate strong interactions, we plotted perspective plots showing predicted values for two selected predictors while all the other variables were held to their mean.

We used the dismo function gbm.simplify to test for and remove predictors that were relatively uninformative in the final model (Hijmans & Elith, 2013). To illustrate our predictions, we used the base model to generate a predictive map.

3.3 RESULTS

At least one Yellow Rail was detected at 18% (185/1016) of our sample sites between 2013 and 2016. The year by year breakdown was 13.5% in 2013 (58/427), 12% in 2014 (43/365), 15% in 2015 (73/489), and 27% in 2016 (70/259). The use of recognizers improved our detectability as we found 10 sample sites where Yellow Rail went undetected after our standard listening effort of four nocturnal 10-minute recordings. At 49 sites the maximum count was assessed as “Too Many to Count” and was adjusted to a value of three. At minimum, 287 calling Yellow Rail were detected at our sample sites. The frequency of each observed abundance before and after the "Too Many to Count" adjustment is shown in Figure 3.3.

3.3.1 Predictive Model

All variables were tested for independence. Table 2 contains the results of pairwise Spearman's correlation coefficients, which assess monotonic relationships. Correlation values greater than 0.7 or less than -0.7 are bolded. A value close to 1 or -1 indicates the variables are highly correlated. Highly correlated variables within our study were B2 and B3; B2 and B4; B3 and B4; B4 and ∆NDVI; B8 and NDWI; and SWI and VBF and these were removed from the simplified model.

The optimal number of trees as determined by the 10-fold cross-validation from gbm.step was 1850 the deviance in the base model was 0.7706 ± 0.06. The predictor with the greatest relative influence on the model was difference of polarization (DPOL; RI = 26.9%). It was followed by ΔVH, the winter to summer change in VH SAR backscatter (ΔVH; RI = 19.17%), Red Edge Inflection Point (REIP; RI = 10.1%), Anthocyanin Reflectance Index (ARI; RI = 9.2%), VH SAR backscatter (VH; RI = 5.2%), and Saga Wetness Index (SWI; RI = 4.5%). Six predictors were retained after model simplification: DPOL, ∆VH, REIP, ARI, VH, and SWI (Table 2). The other nine predictors (TPI, ∆NDVI, VBF, B2, B8, B3, NDVI, B4, NDWI) all had RI > 4.3% (Table 2). The average change in deviance when these variables were removed did not exceed the standard error of the deviance for the initial model (Figure 3.4).

Predicted abundance ranged from 0 to 25. There were 478639589 10x10 m pixels in our study area. The breakdown of the abundance prediction was: 98.52% less than one, 1.09% between one and two, 0.25% between two and three, 0.08% between three and four, 0.03% between four and five, 0.01% between five and six, and 0.01% greater than six.

3.3.2 Variable Responses

Partial dependence plots for the top 12 variables in the base model are shown (Figure 3.5). Several of the response curves were not smooth, indicating complex non-linear relationships. Yellow rail abundance decreased at higher values of DPOL (specifically > 1.6) and peaked between 1.4-1.6. Abundance tended to decrease with larger variations in VH polarization between winter and summer (i.e. lower ΔVH values) and positive abundance values were seen only at ΔVH values < -6. Abundance tended to increase with higher values of REIP and were positive at REIP > 722. For ARI and VH abundance increased gradually with higher values for these predictors.

Our analysis of interaction effects revealed 11 important interactions, although most of these were relatively weak. The four strongest interactions are illustrated with perspective plots (Figure 3.6). Our model showed a particularly strong interaction between ΔVH and REIP (interaction size = 581.3), an order of magnitude larger than other interactions in the model. REIP values > 722 corresponded with the highest predicted abundances but only where ΔVH was low (< -6). Two other strong interactions included the predictor ΔVH: ΔVH * DPOL and ΔVH * VH. Another supported interaction in our model is between REIP and ARI. In the interaction plots we see a peak at REIP values ca. 721 and ARI ca. -0.1.

3.4 DISCUSSION

3.4.1 Interpretation of Predictive Map

The final product of this study was a mapping tool which shows the predicted abundance of breeding Yellow Rail at 10 m resolution across our study area in northeastern Alberta. Predicted abundance is on a continuous scale and ranges from 0 to 25. One and on-half percent of the study area had a predicted abundance of at least one Yellow Rail. Extreme predictions (i.e. > six) were likely the result of outlying values in the unprocessed input rasters, but these occur in only 0.01% of all pixels. The predicted abundance deviates from a prediction of the true count of individuals because the abundance of Yellow Rail was not measured accurately when the number of individuals exceeded three. The human interpreter of the audio indicated 'Too Many to Count' when the birds were too numerous to distinguish their vocalizations with certainty and these observations were adjusted to an assumed count of three, artificially constraining the upper limit of our input abundances. Therefore, our predicted abundances should be interpreted as an ordered ranking where higher predicted abundance corresponds to an increased likelihood that more individual Yellow Rails are present during breeding season. It can also provide information about the probability of Yellow Rail occurrence, by means of a threshold, although this would result in a loss of resolution (Guillera-Arroita et al., 2015). Several authors have noted that different thresholds can maximize variable aspects of model performance, therefore the choice of a threshold should be tailored to the specific application (Dalgarno et al., 2017; Lawson et al., 2014; Liu et al. , 2005).

3.4.2 Important Variables for Yellow Rail Prediction

The selection of suitable environmental predictor variables in SDMs is essential for ensuring high predictive accuracy and realistic results. We examined 15 predictors derived from multiple sources of satellite remote sensing.

Optical Predictors (Sentinel-2):

The nine predictors from the Sentinel-2 optical imagery (Copernicus Programme, 2017) together accounted for 36.3% relative influence. However, individually, seven of them were not large contributors to the predictions. The four colour bands B2 - blue, B3 - green, B4 - red, B8 – near infra-red were all among the weakest predictors. This was expected since individual bands values are often a function of brightness rather than vegetation attributes. Vegetation indices (as also used in this study) are generally more appropriate proxies for vegetation structure and productivity.

NDVI and NDWI were relatively weak predictors of Yellow Rail abundance while ΔNDVI had a slightly greater influence. The response of ΔNDVI indicates a small peak between 0 and 0.1 reflecting a positive change in NDVI between winter and summer. The literature description of Yellow Rail habitat indicates they prefer graminoid dominated wetlands without evergreen vegetation; therefore, we would expect a pronounced change in NDVI between seasons. The modelled response was quite muted, however, likely due to the better fit to other vegetation and time-series indices (below).

ARI and REIP, two derived optical predictors, were the most influential optical predicters and both were retained in the simplified model. The model also supported an interaction between REIP and ARI. ARI increases with the amount of vegetation expressing red coloured foliage from anthocyanin pigments. Plants express anthocyanin for optical masking of chlorophyll to reduce risk of photo-oxidative damage to leaf cells (Feild, Lee, & Holbrook, 2001). This can be a seasonal change associated with vegetation senescence but also certain plants and mosses express anthocyanins when growing in open canopies. We can potentially link our model support to open canopy areas where the anthocyanin pigments would be expressed in plants due to UV stress responses

(Schaefer & Rolshausen, 2006). In the perspective plot of the interaction there is a peak at REIP values of 721 and ARI values of -0.1. This could be indicative of a specific vegetation type associated with higher Yellow Rail abundance. For example, peat mosses (e.g. *Sphagnum magellanicum*), pitcher plants (*Sarracenia purpurea*), and small bog cranberry (*Vaccinium oxycoccos*) express anthocyanin pigments when exposed to UV radiation, and these fen species occur in many of the wetlands with high predicted abundance of Yellow Rail in our study area.

Issues of scale are well known in SDMs where predictors are only important at the correct resolution (Cord et al., 2013; Graham et al., 2019). This is likely important for optical predictors and therefore issues may have arisen from our method of aggregating the values for our predictors over a buffer to account for the uncertainty in the location of a detected bird. Finer resolution information about the location of the birds on the landscape would likely be of great benefit (i.e. matching the resolution at which plant species are differentiable).

Synthetic Aperture Radar predictors (Sentinel-1):

The three predictors from the Sentinel-1 SAR data (Copernicus Programme, 2016) were all among the most important predictors. They accounted for 51.8% relative influence and all of them were retained in the simplified model. Yellow Rail abundance responded to the most influential predictor, DPOL, peaking at low values (specifically DPOL < 1.6). This predictor can be used as an indicator for surface vegetation structure, as well as soil moisture content and wetness. Areas that have even vegetation height and/or standing water, such as a lake or a grassland, have low DPOL, whereas areas with uneven vegetation height (e.g. forests) have higher DPOL. This predictor could be identifying relatively open wetland habitats, such as graminoid fen, which are preferred by Yellow Rail (Leston & Bookhout, 2015). This type of fen is also often associated with areas of low relief terrain (Halsey et al., 2003).

Higher Yellow Rail abundances were also associated with low values of VH. VH polarization is the vertical polarization sending horizontal polarization receiving synthetic aperture radar backscatter. It provides an indication of volume scattering (e.g. vegetation cover) as opposed to direct or double bounce polarization which have different properties. This means either vegetation is detected (high VH) or bare ground/surface water is present (low VH). The relationship between this predictor and Yellow Rail abundance is very logical because VH should help characterize low-structure wetlands.

Predicted Yellow Rail abundance also tended to decrease with larger variations in VH polarization between winter and summer. ∆VH roughly relates to the change in volume scatter between winter and summer, so areas with standing water in the summer and open canopy with snow cover in the winter would have low ∆VH, whereas areas with deciduous shrub or tree cover would have high ∆VH. Not only was ∆VH a strong predictor, our model found several strong interactions incorporating this variable. For example, the peak abundances predicted by REIP, DPOL, and VH were all maximized when ∆VH was low. The interaction between ∆VH and REIP was the most important interaction in the model and the highest Yellow Rail abundances were seen in wetlands that were highly productive (high REIP) and also had low VH variation between summer and winter (low ∆VH). Similarly, wetlands with high VH and low DPOL values (less than 1.6; indicative of even vegetation), contribute most to the model when associated with low seasonal variation in VH (i.e. low ∆VH). Intuitively, these findings may indicate that certain wetland types, specifically productive graminoid wetlands, with seasonally consistent or persistent uniform vegetation, are favourable habitat for Yellow Rail, which is consistent with the literature (Leston & Bookhout, 2015).

Digital Elevation Map derivatives (Advanced Land Observation Satellite):

The three predictors from the ALOS DEM accounted for 11.9% relative influence. While this contribution is relatively small, one variable SWI was retained in the simplified model. Topographic Position Index (TPI) is used to identify topographic highs and lows such as ridges and valleys. It was removed during model simplification but contributed 4.3% relative importance to the model when included. This variable is an important component of models that classify wetlands from uplands (Hird et al., 2017; Lang et al., 2013). Our approach involved masking out upland areas before modelling, however, so the variability seen in TPI was significantly reduced in our constrained sampling frame. TPI could be an important variable where topographic relief is more variable or if uplands are included in the analysis. Multi-resolution Valley Bottom Flatness (VBF) is an index used to identify depositional portions of the landscape. It provides a visual portrayal of low relief areas and identification of valley bottom constrictions (Gallant & Dowling, 2003). Low values indicate steep areas and high values are flat areas in large valleys. Larger wetland complexes tend to occur in these areas and there was a positive abundance response to high VBF values (up to 7); however, the relative influence of the predictor was low. Of the ALOS predictors SWI was the most important. It was retained after model simplification and in the reduced model had a relative influence of 8.7%. High SWI values roughly indicate areas with high drainage or connectivity where water is less likely to be stagnant. This is a feature common to marshes and fens while bogs are known to have less water flow. The response for this predictor suggests Yellow Rail abundance is somewhat higher in these wetlands which might help identify these features.

3.4.3 Key Takeaways

Conventional SDMs incorporate a variety of coarse multivariate environmental predictors such as classifications with discrete values for environmental variables or data that is measured by hand or interpreted from photographs. Remotely sensed data can provide a finer and more continuous representation of geospatial variables. Machine learning algorithms like BRT help facilitate ecologists to quantify relationships that cannot be described linearly or without additional dimensionality (Cord et al., 2013; Fern & Morrison, 2017; Gottschalk et al., 2005). While many of the predictors we explored do not directly relate to distinct environmental features they indirectly capture characteristics expressed by various environmental conditions. Additionally, all the inputs used can be computed from the direct measurements of the satellite sensors (i.e. they do not have to be modelled and validated) and they can be recalculated annually or sub-annually (e.g. the repeat cycle for Sentinel-1 and Sentinel-2 are 12-days and 10-days, respectively). These attributes would allow you to create new models for a given year and predict dynamic change in a way that no static landcover product could.

We developed this model with the intention of providing a modeling framework for predicting Yellow Rail breeding habitat in Northeastern Alberta, Canada. We also aimed to test a set of predictors that may be used in other regions, or at broader extents. Of the predictors retained in the final model, all the layers are available at a Canada-wide coverage south of 60N. However, using methods developed here, and given good quality satellite data, our approach could be applied to broader extents and to other species with strong habitat associations. We strongly recommend using satellite data to create SDMs for other species, especially for species at risk which require accurate and highly specific habitat maps for industry.

Our framework requires species detections with abundance, an understanding of species habitat associations, and accurate satellite data. There are several challenges associated with these requirements. First, it will be necessary to ensure that occurrence data adequately cover the geographic and environmental extent of the prediction area. Deriving abundance data from ARU recordings can be difficult depending on the species. Although we show that the model's predictive performance on independent data was reasonably good, model transferability may be an issue, especially for species that are more generalized regarding habitat use and have different environmental responses.

Table 3.1: List of 15 input variables used in the yellow rail abundance model

Variable	Data source	Description	Equation	Biological Indication
ARI	Sentinel-2	Anthocyanin Reflectance Index. An index sensitive to anthocyanin pigments in plant foliage (Gitelson, Merzlyak, & Chivkunova, 2001).	$\left(\frac{Band\ 8}{Band\ 2}\right) - \left(\frac{Band\ 8}{Band\ 3}\right)$	High values indicate more anthocyanin (i.e. plants with red pigment)
B2	Sentinel-2	The Sentinel-2 10m resolution blue band (central wavelength - 490nm).	-	Sensitive to vegetation senescing, carotenoid pigments, browning, and soil background (Jaramaz, Simic, & Saljnikov, 2013)
B3	Sentinel-2	The Sentinel-2 10m resolution green band (central wavelength - 560nm).	-	Sensitive to total chlorophyll in vegetation (Jaramaz et al., 2013)
B4	Sentinel-2	The Sentinel-2 10m resolution red band (central wavelength - 665nm).	-	Maximum chlorophyll absorption (Jaramaz et al., 2013)
B8	Sentinel-2	The Sentinel-2 10m resolution near infrared band (central wavelength - 842nm).	-	Sensitive to total chlorophyll, biomass, and leaf area index (Jaramaz et al., 2013)
NDVI	Sentinel-2	Normalized Difference Vegetation Index. Index for estimating photosynthetic activity, and leaf area (Rouse, Haas, Schell, & Deering, 1974).	$\frac{(Band\ 8\ -\ Band\ 4)}{(Band\ 8\ +\ Band\ 4)}$	High values indicate low photosynthetic activity and leaf area
ΔNDVI	Sentinel-2	Winter to summer seasonal change in NDVI index		Winter - summer photosynthetic activity
NDWI	Sentinel-2	Normalized difference Water Index from (Mcfeeters, 1999)	$\frac{(Band\ 3\ -\ Band\ 8)}{(Band\ 3\ +\ Band\ 8)}$	Low values indicate high water content
DPOL	Sentinel-1	Normalized Difference of Polarization.	$\frac{(VH\ -\ VV)}{(VH\ +\ VV)}$	Low DPOL indicates smooth vegetation or surface water. High DPOL indicates rough or undulating vegetation.
REIP	Sentinel-2	Red Edge Inflection Point. An approximation on a hyperspectral index for estimating the position (in nm) of the NIR/red inflection point in vegetation spectra (Herrmann et al., 2011).	$702 + 40\left(\frac{\left(\frac{Band\ 4\ +\ Band\ 7}{2}\right) - Band\ 5}{(Band\ 6 - Band\ 5)}\right)$	High REIP indicates more productive wetland vegetation
TPI	ALOS, SRTM DEMs	Topographic Position Index (TPI) generated in SAGA (Conrad et al., 2015). An index describing the relative position of a pixel within a valley, ridge top continuum calculated in a given window size. TPI was calculated with a 500m moving window for this purpose (Weiss, 2001).	-	High values indicate topographic highs such as a ridge top
SWI	ALOS, SRTM DEMs	Saga Wetness Index. A SAGA (Conrad et al., 2015) version of the Topographic Wetness Index. Potential wetness of the ground based on topography (Böhner et al., 2002).	-	High values indicate potential for water pooling and low values indicate well drained areas
VBF	ALOS, SRTM DEMs	Multi-resolution Valley Bottom Flatness (VBF). An index to identify depositional parts of the landscape. It provides a	-	Low values indicate steep areas and high values are flat areas in large valleys

		visual portrayal of low relief areas and identification of valley bottom constrictions (Gallant & Dowling, 2003).		
VH	Sentinel-1	Vertical polarization sending horizontal polarization receiving SAR backscatter in decibels.	-	VH provides an indication of vegetation roughness
ΔVH	Sentinel-1	Winter to summer change in VH	-	High negative values represent high vegetation seasonality.

Table 3.2: *Pairwise Spearman correlation coefficients (rho) for the 15 possible predictors. Strong correlations, rho > 0.7, are indicated in bold.*

	ARI	*B2*	*B3*	*B4*	*B8*	*DPOL*	*NDVI*	*ΔNDVI*	*NDWI*	*REIP*	*SWI*	*TPI*	*VBF*	*VH*	*ΔVH*
ARI	------														
B2	0.20	------													
B3	0.63	**0.84**	------												
B4	0.35	**0.89**	**0.84**	------											
B8	0.68	0.00	0.43	0.07	------										
DPOL	0.01	-0.51	-0.38	-0.42	0.10	------									
NDVI	0.21	-0.65	-0.29	-0.67	0.63	0.37	------								
ΔNDVI	0.07	0.67	0.50	**0.70**	-0.21	-0.28	-0.67	------							
NDWI	-0.40	0.42	0.02	0.35	**-0.86**	-0.30	**-0.90**	0.50	------						
REIP	-0.22	0.34	0.18	0.28	-0.10	-0.43	-0.30	0.28	0.22	------					
SWI	0.16	0.34	0.34	0.36	0.14	-0.21	-0.15	0.22	-0.01	0.07	------				
TPI	-0.08	0.27	0.16	0.23	-0.10	-0.15	-0.20	0.22	0.16	0.01	0.53	------			
VBF	0.14	0.38	0.36	0.40	0.12	-0.24	-0.18	0.29	0.03	0.10	**0.79**	0.57	------		
VH	-0.28	-0.48	-0.48	-0.66	-0.06	0.07	0.50	-0.57	-0.24	-0.07	-0.24	-0.06	-0.22	------	
ΔVH	-0.20	0.05	-0.05	-0.10	-0.18	-0.32	-0.09	-0.04	0.20	0.14	-0.23	-0.06	-0.22	0.29	------

Table 3.3: Summary of the relative contributions (%) of the 15 possible input variables in the boosted regression tree Yellow Rail abundance models with cross-validation on data from 1001 sample sites. Full model included all 15 predictors and 6 were retained after model simplification.

Predictor	**Base Model**	**Simplified Model**	**Drop Order**
DPOL	26.9	31.8	-
ΔVH	19.7	22.5	-
REIP	10.1	15.1	-
ARI	9.2	13.2	-
VH	5.2	8.7	-
SWI	4.5	8.7	-
TPI	4.3		7
ΔNDVI	4.0		8
VBF	3.1		6
B2	3.0		9
B8	2.5		4
B3	2.4		3
NDVI	2.1		5
B4	1.6		2
NDWI	1.4		1

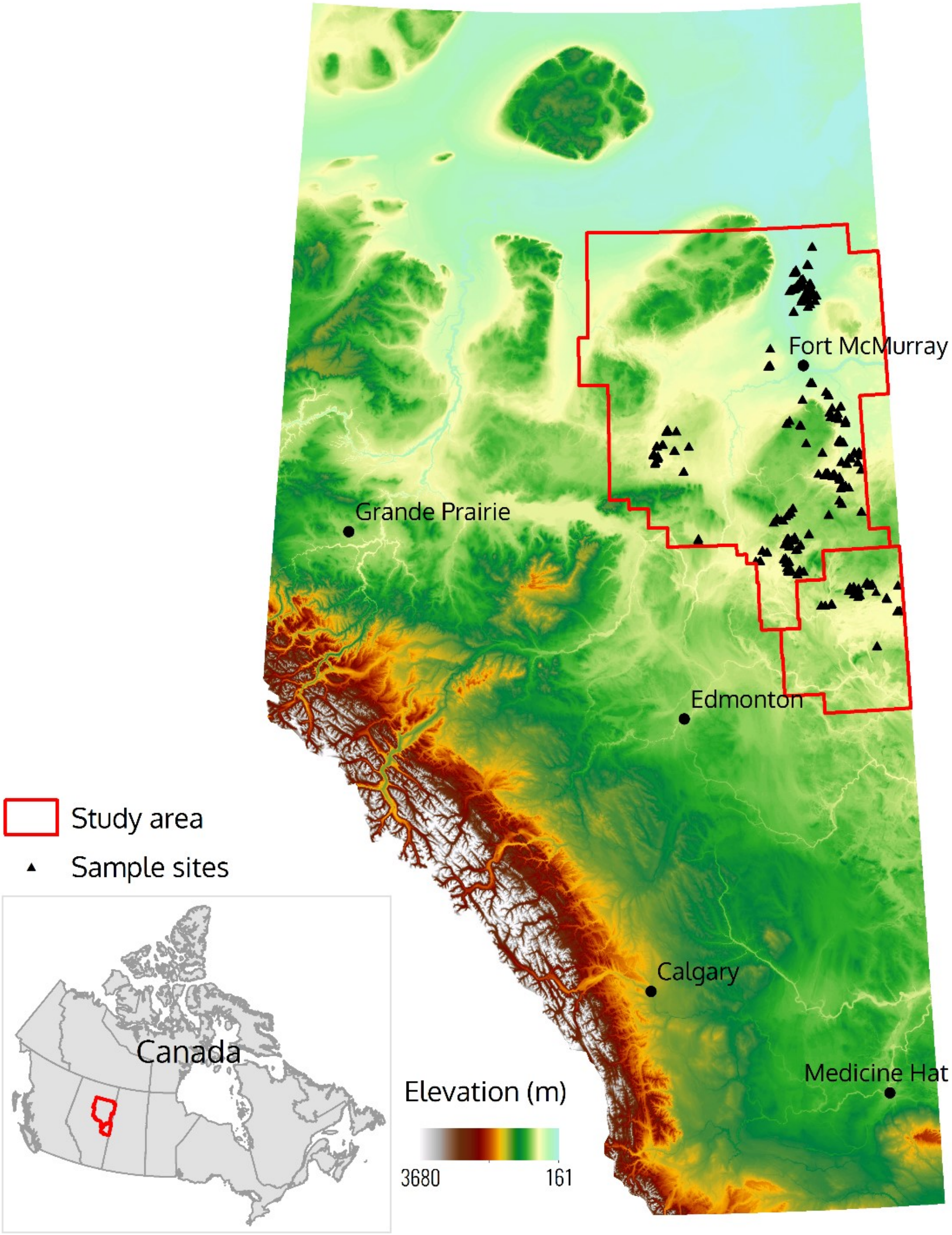

Figure 3.1: Location of the study area and sample sites within Alberta.

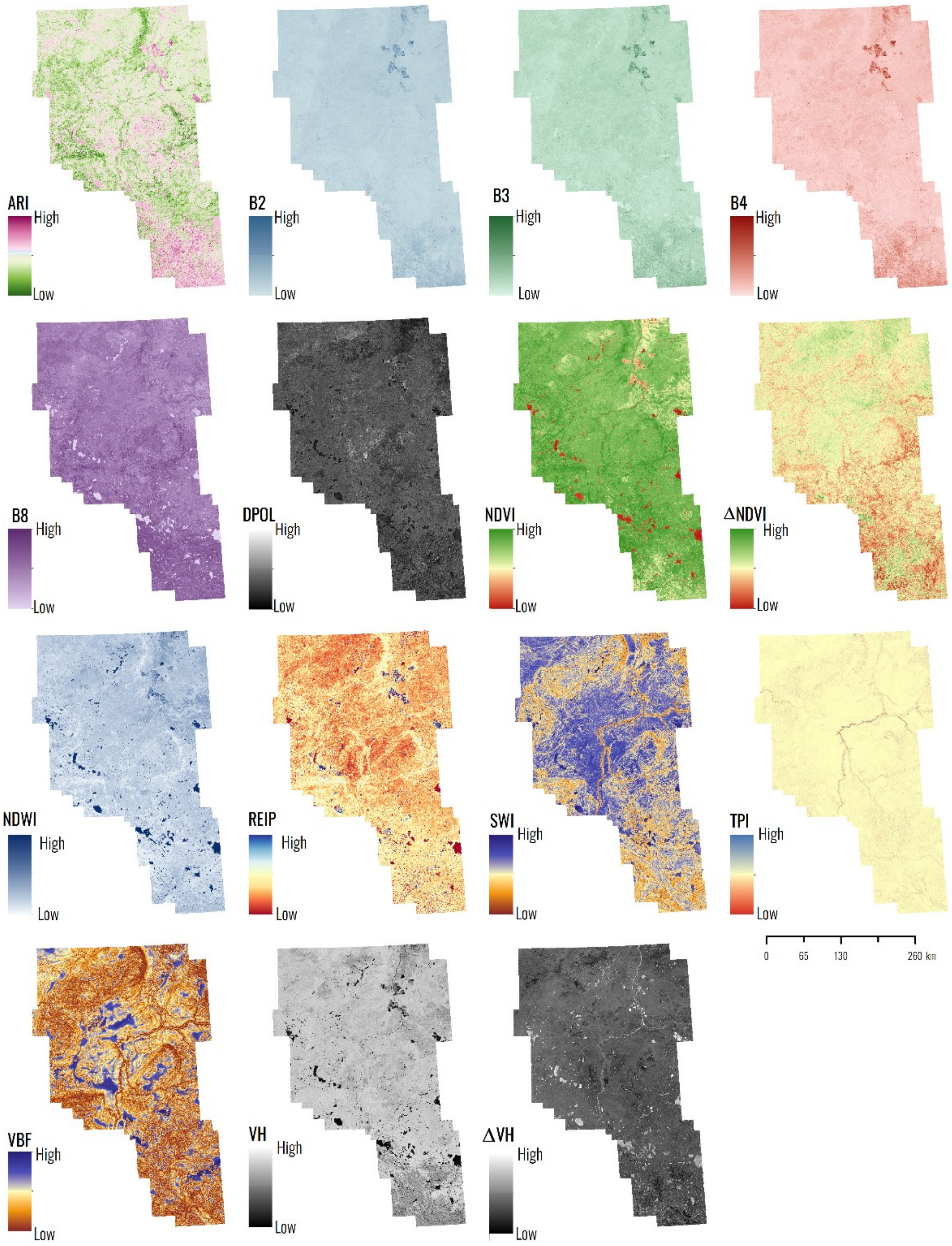

Figure 3.2: All 15 possible input variables across the study area.

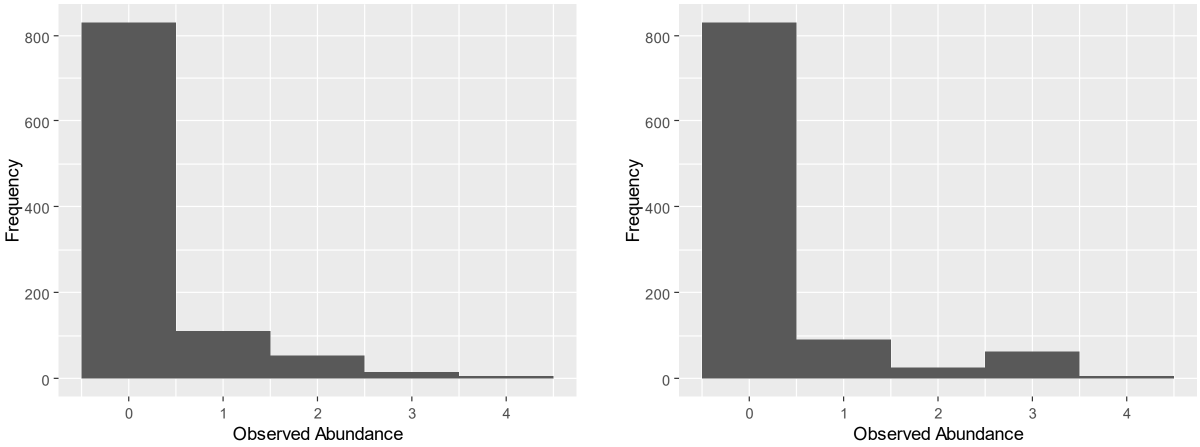

Figure 3.3: Histogram of the frequency of observed abundances before (left) and after adjustment for "Too Many to Count" (right).

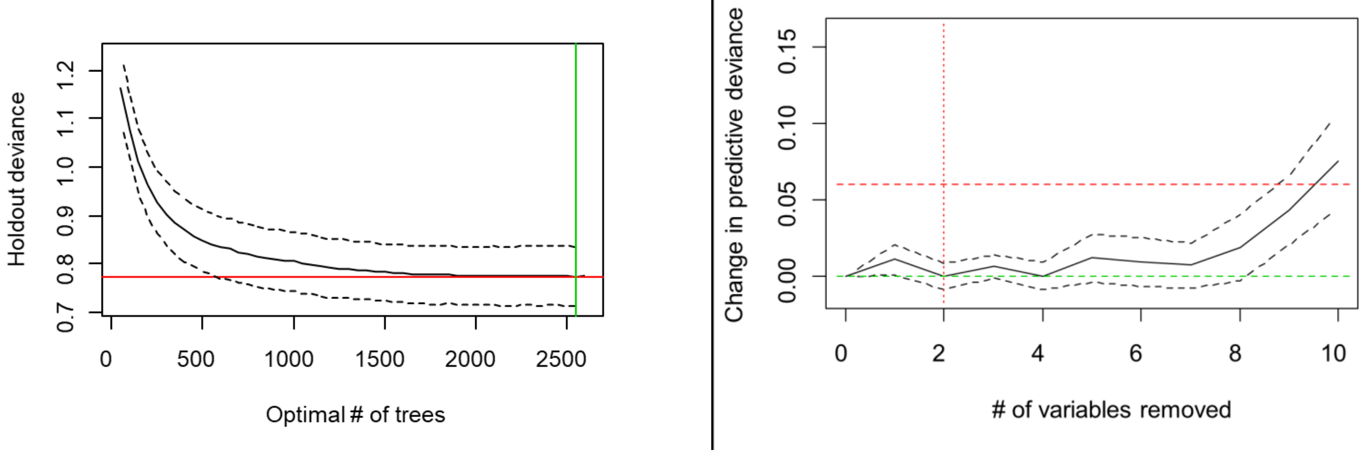

Figure 3.4: Plot of the optimal number of trees for the model with learning rate = 0.04, tree depth = 5, and bag fraction = 0.5. The holdout deviance for the model is 0.74. (Left) and plot of the change in deviance with the step-wise removal of variables for model simplification (Right). Variables are dropped sequentially until the change in predictive deviance exceeds the original SE (0.06). In total 9 variables were dropped at this threshold and 6 were retained.

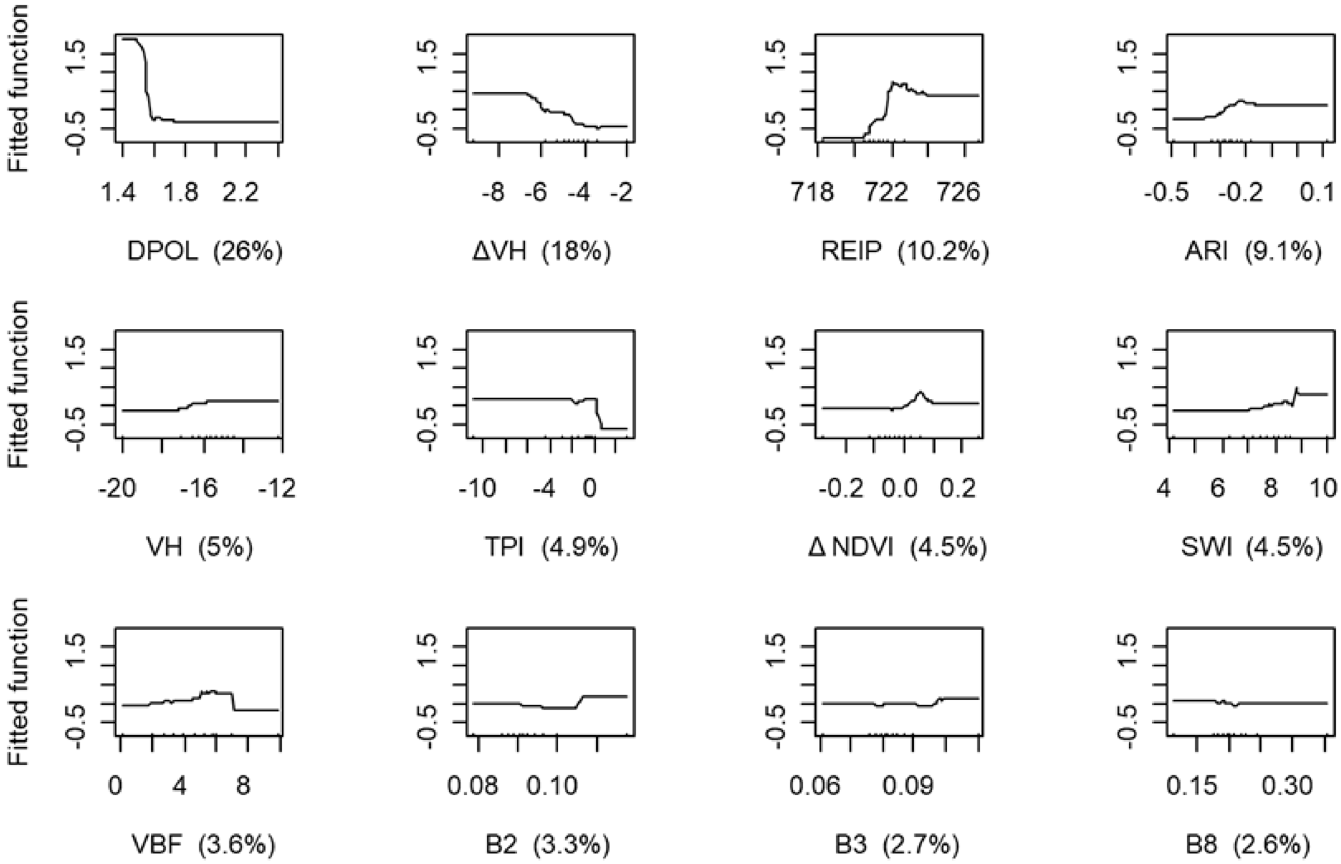

Figure 3.5: Partial dependence plots for the top 12 predictors by relative importance from the full Yellow Rail abundance model. Partial dependence plots show the effect of each predictor on abundance with all other predictors held to their mean. Rug plots, shown along the X-axis, indicate the distribution of input data for each predictor.

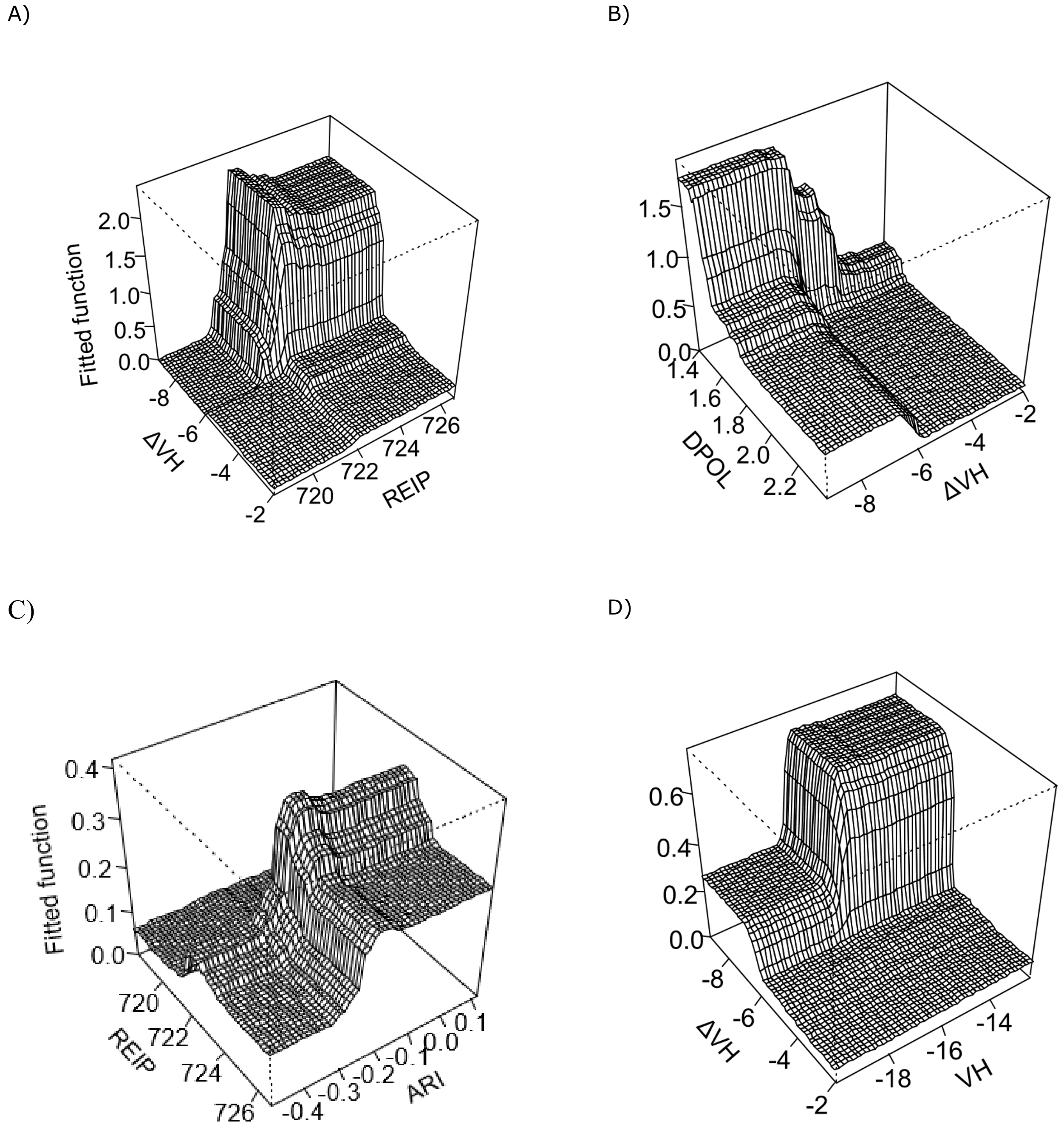

Figure 3.6: Perspective plots for the four strongest pairwise interactions. Panel A) ΔVH x REIP, interaction size: 581.3; panel B) ΔVH x DPOL, interaction size: 48.9; panel C) ΔVH x VH, interaction size: 35.4; panel D) REIP x ARI, interaction size 32.0

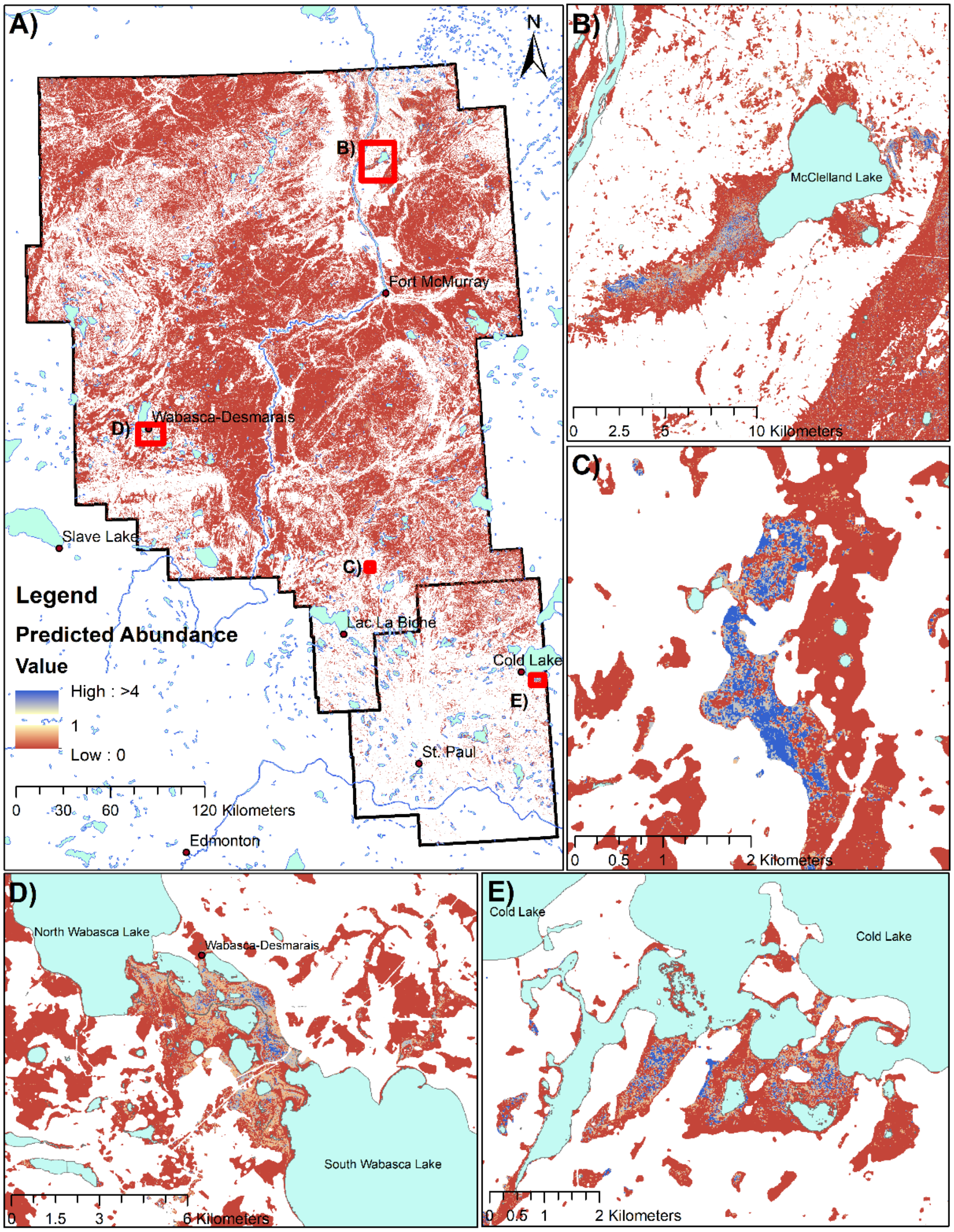

Figure 3.7: An overview of the full predictive map for Yellow Rail breeding abundance with values generated from the final model is shown (Panel A). Four interesting wetlands are highlighted: the McClelland Lake wetland complex near Fort McKay (Panel B), a fen / meadow marsh near Philomena (Panel C), the Wabasca lakes wetland complex (Panel D), and the Cold Lake wetland complex (Panel E). From these enlarged areas, it was observed that the model had both high sensitivity and specificity in predicting Yellow Rail abundance within these wetland complexes.

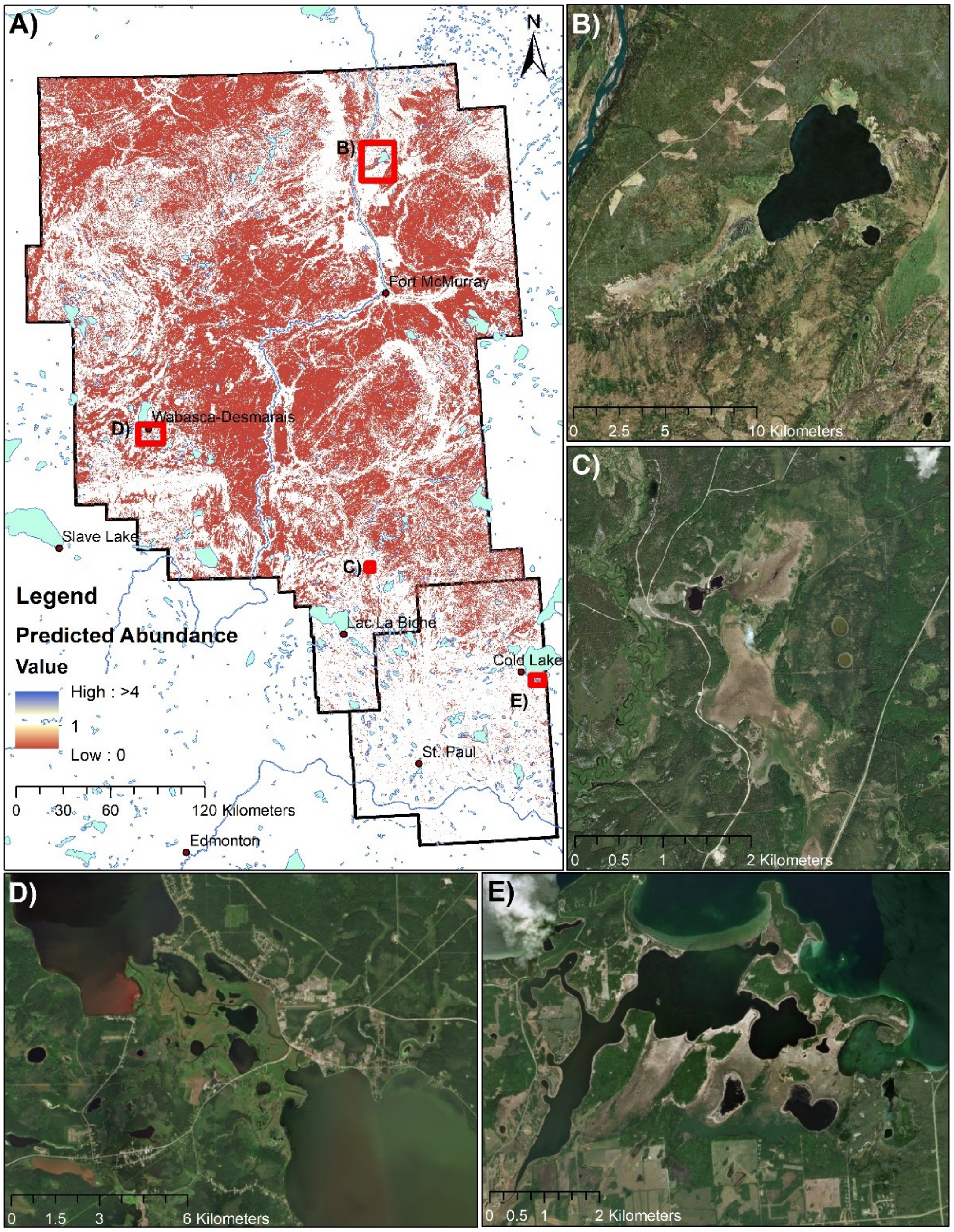

Figure 3.8: An overview of the full predictive map for Yellow Rail breeding abundance with values generated from the final model is shown (Panel A)with satellite views. Four interesting wetlands are highlighted: the McClelland Lake wetland complex near Fort McKay (Panel B), a fen / meadow marsh near Philomena (Panel C), the Wabasca lakes wetland complex (Panel D), and the Cold Lake wetland complex (Panel E).

3.5 LITERATURE CITED

ABMI. (2017). The status of human footprint in Alberta. Retrieved from https://abmi.ca/home/data-analytics/da-top/da-product-overview/GIS-Land-Surface/HF-inventory.html

ABMI. (2018). Boreal surface water inventory. Retrieved from https://www.abmi.ca/home/data-analytics/da-top/da-product-overview/GIS-Land-Surface/Boreal-Surface-Water-Inventory.html?scroll=true

ABMI. (2019). Boreal wetland probability data. Retrieved from https://www.abmi.ca/home/data-analytics/da-top/da-product-overview/GIS-Land-Surface/Boreal-Wetland-Probability-Data.html?scroll=true

AESRD. (2015). *Alberta wetland classification system*. Edmonton.

Austin, J. E., & Buhl, D. A. (2013). Relating Yellow Rail (Coturnicops noveboracensis) occupancy to habitat and landscape features in the context of fire. *Waterbirds*, *36*(2), 199–213. https://doi.org/10.1675/063.036.0209

Böhner, J., Köthe, R., Conrad, O., Gross, J., Ringeler, A., & Selige, T. (2002). *Soil regionalisation by means of terrain analysis and process parameterisation*.

Breiman, L. (2001). Statistical modeling : the two cultures. *Statistical Science*, *16*(3), 199–231.

Burnham, K. P., Buckland, S. T., Laake, J. L., Borchers, D. L., Marques, T. A., Bishop, J. R., & Thomas, L. (2004). Further topics in distance sampling. In *Advanced Distance Sampling: Estimating abundance of biological populations* (pp. 326–408). Oxford: Oxford University Press.

Conrad, O., Bechtel, B., Bock, M., Dietrich, H., Fisher, E., Gerlitz, L., … Bohner, J. (2015). System for automated geoscientific analyses (SAGA) v. 2.1.4. *Geoscientific Model Development*

Discussions, *8*(2), 2271–2312.

Copernicus Programme. (2016). Sentinel-1 SAR technical guide. Retrieved from https://sentinels.copernicus.eu/web/sentinel/missions/sentinel-1

Copernicus Programme. (2017). Sentinel-2 User Handbook. Retrieved from https://sentinels.copernicus.eu/web/sentinel/user-guides/document-library/-/asset_publisher/xlslt4309D5h/content/sentinel-2-user-handbook

Cord, A. R., Meentemeyer, R. K., Leitao, P. J., & Vaclavik, T. (2013). Modelling species distributions with remote sensing data: bridging disciplinary perspectives. *Journal of Biogeography*, *40*, 2226–2227. https://doi.org/10.1111/jbi.12199

COSEWIC. (2009). *COSEWIC assessment and status report on the Yellow Rail Coturnicops noveboracensis in Canada*. Ottawa.

Dalgarno, S., Mersey, J. E., Gedalof, Z., & Lemon, M. (2017). Species-environment associations and predicted distribution of Black Oystercatcher breeding pairs in Haida Gwaii , British Columbia, Canada. *Avian Conservation and Ecology*, *12*(2), Art9.

DeLancey, E. R., Kariyeva, J., Bried, J. T., & Hird, J. N. (2019). Large-scale probabilistic identification of peatlands in the boreal natural region of Alberta, Canada using Google Earth Engine, open-access satellite data, and machine learning. Manuscript in preparation.

Difebo, A., Richardson, M., & Price, J. (2015). Fusion of multispectral imagery and LiDAR digital terrain derivatives for ecosystem mapping and morphological characterization of a northern peatland complex. In R. W. Tiner, M. Lang, & V. V Klemas (Eds.), *Remote Sensing of Wetlands: Applications and Advances* (pp. 399–412). Boca Raton, Florida: Taylor & Francis.

Drake, K. L., Frey, M., Hogan, D., & Hedley, R. (2016). Using digital recordings and sonogram analysis to obtain counts of Yellow Rails. *Wildlife Society Bulletin*, *40*(2), 346–354. https://doi.org/10.1002/wsb.658

Drusch, M., Del Bello, U., Carlier, S., Colin, O., Fernandez, V., Gascon, F., … Bargellini, P. (2012). Sentinel-2: ESA's optical high-resolution mission for GMES operational services. *Remote Sensing of Environment*, *120*, 25–36. https://doi.org/10.1016/j.rse.2011.11.026

Ducks Unlimited Canada. (2011). *Enhanced wetland classification inferred products user guide version 1.0*. Stonewall, Manitoba, Canada.

Dvorett, D., Davis, C., & Papeş, M. (2016). Mapping and hydrologic attribution of temporary wetlands using recurrent landsat imagery. *Wetlands*, *36*(3), 431–443. https://doi.org/10.1007/s13157-016-0752-9

Ecological Stratification Working Group. (1995). *A national ecological framework for Canada*. Ottawa/Hull. Report and national map at 1:7500 000 scale.

Elith, J, Leathwick, J. R., & Hastie, T. (2008). A working guide to boosted regression trees. *Journal of Animal Ecology*, *77*, 802–813. https://doi.org/10.1111/j.1365-2656.2008.01390.x

Elith, Jane, Graham, C. H., Anderson, R. P., Dudık, M., Ferrier, S., Guisan, A., … Zimmermann, N. E. (2006). Novel methods improve prediction of species ' distributions from occurrence data. *Ecography*, *2*, 129–151.

Elith, Jane, & Leathwick, J. R. (2009). Species distribution models: Ecological explanation and prediction across space and time. *Annual Review of Ecology, Evolution, and Systematics*, *40*(1), 677–697. https://doi.org/10.1146/annurev.ecolsys.110308.120159

Environment and Climate Change Canada. (2016). *Canadian environmental sustainability indicators: Extent of Canada's wetlands*. Gatineau.

Feild, T. S., Lee, D. W., & Holbrook, N. M. (2001). Why leaves turn red in autumn. The role of anthocyanins in senescing leaves of Red-Osier Dogwood. *Plant Physiology*, *127*, 566–574. https://doi.org/10.1104/pp.010063.566

Fern, R. R., & Morrison, M. L. (2017). Mapping critical areas for migratory songbirds using a fusion of remote sensing and distributional modeling techniques. *Ecological Informatics*, *42*(August), 55–60. https://doi.org/10.1016/j.ecoinf.2017.09.007

Fox, J. (2017). Don't force your regression through zero just because you know the true intercept has to be zero. Retrieved from https://dynamicecology.wordpress.com/2017/04/13/dont-force-your-regression-through-zero-just-because-you-know-the-true-intercept-has-to-be-zero/

Friedman, J. H. (2001). Greedy function approximation: a gradient boosting machine. *The Annals of Statistics*, *29*(5), 1189–1232.

Gallant, J. C., & Dowling, T. I. (2003). A multiresolution index of valley bottom flatness for mapping depositional areas. *Water Resources Research*, *39*(12), 1347. https://doi.org/10.1029/2002WR001426

Gitelson, A. A., Merzlyak, M. N., & Chivkunova, O. B. (2001). Optical properties and nondestructive estimation of anthocyanin content in plant leaves. *Photochemistry and Photobiology*, *74*(1), 38–45.

Glenn, D. (2007). Boosted trees for ecological modeling and prediction. *Ecology*, *88*(1), 243–251.

Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D., & Moore, R. (2017). Google Earth Engine: Planetary-scale geospatial analysis for everyone. *Remote Sensing of Environment*, *202*, 18–27. https://doi.org/10.1016/j.rse.2017.06.031

Gottschalk, T. K., Huettmann, F., & Ehlers, M. (2005). Thirty years of analysing and modelling avian habitat relationships using satellite imagery data: A review. *International Journal of Remote Sensing*, *26*(12), 2631–2656. https://doi.org/10.1080/01431160512331338041

Government of Canada. (2002). Species at risk act / Loi sur les espèces en péril. Ottawa: Minister of Justice.

Graham, L. J., Eigenbrod, F., Spake, R., Gillings, S., Watts, K., & Graham, L. J. (2019). Incorporating fine-scale environmental heterogeneity into broad-extent models. *Methods in Ecology and Evolution*, 1–12. https://doi.org/10.1111/2041-210X.13177

Guillera-Arroita, G., Lahoz-Monfort, J. J., Elith, J., Gordon, A., Kujala, H., Lentini, P. E., … Wintle, B. A. (2015). Is my species distribution model fit for purpose? Matching data and models to applications. *Global Ecology and Biogreography*, *24*, 276–292. https://doi.org/10.1111/geb.12268

Guisan, A., & Zimmermann, N. E. (2000). Predictive habitat distribution models in ecology. *Ecological Modelling*, *135*, 147–186. https://doi.org/10.1016/S0304-3800(00)00354-9

Halsey, L. A., Vitt, D. H., Beilman, D., Crow, S., Mehelcic, S., & Wells, R. (2003). *Alberta wetland inventory standards version 2.0*. Edmonton: Alberta Sustainable Resource Development.

Herrmann, I., Pimstein, A., Karnieli, A., Cohen, Y., Alchanatis, V., & Bonfil, D. (2011). LAI assessment of wheat and potato crops by VENuS and Sentinel-2 bands. *Remote Sensing of Environment*, *115*, 2141–2151. https://doi.org/10.1016/j.rse.2011.04.018

Hijmans, R. J., & Elith, J. (2013). *Species distribution modeling with R Introduction*. https://doi.org/10.1016/S0550-3213(02)00216-X

Hird, J. N., DeLancey, E. R., McDermid, G. J., & Kariyeva, J. (2017). Google earth engine, open-access satellite data, and machine learning in support of large-area probabilistic wetland mapping. *Remote Sensing*, *9*(12). https://doi.org/10.3390/rs9121315

Jaramaz, D., Simic, S. B., & Saljnikov, E. R. (2013). The ESA Sentinel-2 mission vegetation variables for remote sensing of plant monitoring. In *Conference Proceedings 2nd International Scientific Conference* (pp. 950–961).

Jarnevich, C. S., Holcombe, T. R., Grisham, B. A., Timmer, J., Boal, C. W., Butler, M. J., … Pelt, W. E. Van. (2016). Assessing range-wide habitat suitability for the Lesser Prairie- Chicken. *Avian Conservation and Ecology*, *11*(1), 1–18. https://doi.org/10.5751/ACE-00807-110102

Jiang, H., Liu, C., Sun, X., Lu, J., Zou, C., Hou, Y., & Lu, X. (2015). Remote sensing reversion of water depths and water management for the stopover site of siberian cranes at Momoge, China. *Wetlands*, *35*(2), 369–379. https://doi.org/10.1007/s13157-015-0626-6

Lang, M., McCarty, G., Oesterling, R., & Yeo, I.-Y. (2013). Topographic metrics for improved mapping of forested wetlands. *Wetlands*, *33*(1), 141–155. https://doi.org/10.1007/s13157-012-0359-8

Lankau, H., Macphail, A., Knaggs, M., & Bayne, E. M. (2017). *Bioacoustic Unit: Acoustic recording analysis protocol*. Edmonton.

Lawson, C. R., Hodgson, J. A., Wilson, R. J., & Richards, S. A. (2014). Prevalence , thresholds and the performance of presence - absence models. *Methods in Ecology and Evolution*, *5*, 54–64. https://doi.org/10.1111/2041-210X.12123

Lee, J.-S., Wen, J.-H., Ainsworth, T. L., Chen, K.-S., & Chen, A. J. (2009). Improved sigma filter for speckle filtering of SAR imagery. *IEEE Transactions on Geoscience and Remote Sensing*, *47*(1), 202–213.

Leston, L., & Bookhout, T. A. (2015). Yellow Rail (*Coturnicops noveboracensis*), version 2.0.

https://doi.org/10.2173/bna.139

Liu, C., Berry, P. M., Dawson, T. P., & Pearson, R. G. (2005). Selecting thresholds of occurrence in the prediction of species distributions. *Ecography*, *28*, 385–393.

Matsuoka, S. M., Bayne, E. M., Sólymos, P., Fontaine, P. C., Cumming, S. G., Schmiegelow, F. K., & Song, S. J. (2012). Using binomial distance-sampling models to estimate the effective detection radius of point-count surveys across boreal Canada. *The Auk*, *129*(2), 268–282. https://doi.org/10.1525/auk.2012.11190

McFarland, T. M., Grzybowski, J. A., Mathewson, H. A., & Morrison, M. L. (2015). Presence-only species distribution models to predict suitability over a long-term study for a species with a growing population. *Wildlife Society Bulletin*, *39*(1), 218–224. https://doi.org/10.1002/wsb.497

Mcfeeters, S. K. (1999). The use of the normalized difference water index (NDWI) in the delineation of open water features. *International Journal of Remote Sensing*, *17*(7), 1425–1432. https://doi.org/10.1080/01431169608948714

Natural Regions Committee. (2006). *Natural regions and subregions of Alberta*. Edmonton.

Ozesmi, S. L., & Bauer, M. E. (2002). Satellite remote sensing of wetlands. *Wetlands Ecology and Management*, *10*(5), 381–402. https://doi.org/10.1023/A:1020908432489

Persson, M., Lindberg, E., & Reese, H. (2018). Tree species classification with multi-temporal Sentinel-2 data. *Remote Sensing*, *10*, 1–17. https://doi.org/10.3390/rs10111794

R Core Team. (2018). *R: A language and environment for statistical computing*. Vienna, Austria.

Robert, M., & Laporte, P. (1999). Numbers and movements of Yellow Rails along the St. Lawrence River, Québec. *The Condor*, *101*(3), 667–671. https://doi.org/10.2307/1370197

Rouse, J. J., Haas, R., Schell, J., & Deering, W. (1974). Monitoring vegetation systems in the great plains with ERTS. In *NASA. Goddard Space Flight Center 3d ERTS-1 Symposium* (pp. 309–317).

Schaefer, H., & Rolshausen, G. (2006). Plants on red alert: do insects pay attention? *Bioessays*, *28*(1), 65–71. https://doi.org/10.1002/bies.20340

Stalheim, P. S. (1974). *Behavior and ecology of the Yellow Rail (Coturnicops noveboracensis)*. Master's thesis, University of Minneasota, Minneapolis.

Stenzel, J. R. (1982). *Ecology of breeding Yellow Rails at Seney National Wildlife Refuge*. Master's thesis, Ohio State University, Columbus.

Strong, W., Zoltai, S. C., & Ironside, G. (1989). *Ecoclimatic regions of canada*. Ottawa: Canadian Wildlife Service.

Tarnocai, C., Kettles, I., & Lacelle, B. (2011). *Peatlands of Canada database and maps version 3*. Ottawa, Ontario, Canada.

Thompson, D. K., Simpson, B. N., & Beaudoin, A. (2016). Using forest structure to predict the distribution of treed boreal peatlands in Canada. *Forest Ecology and Management*, *372*, 19–27. https://doi.org/10.1016/j.foreco.2016.03.056

Tiner, R. W. (1999). *Wetland indicators: A guide to wetland identification, delineation, classification, and mapping*. Boca Raton, Florida: Taylor & Francis.

Weiss, A. D. (2001). Topographic position and landforms analysis. In *Poster Presentation, ESRI User Conference*. San Diego.

Wells, J. V, & Blancher, P. J. (2011). Global role for sustaining bird populations. In J. V Wells (Ed.), *Boreal birds in North America: A hemispheric view of their conservation links and significance.*

Studies in Avian Biology (no. 41) (pp. 7–22). Berkeley, CA: University of California Press.

Wetlands International. (2019). Waterbird Population Estimates. Retrieved 10 January 2019, from http://wpe.wetlands.org/

Wildlife Acoustics. (2011). *Song Scope: Bioacoustics software version 4.0 documentation*. Maynard.

Yip, D. A., Leston, L., Bayne, E. M., Sólymos, P., & Grover, A. (2017). Experimentally derived detection distances from audio recordings and human observers enable integrated analysis of point count data. *Avian Conservation and Ecology*, *12*(1), art11. https://doi.org/10.5751/ACE-00997-120111

Chapter 4 Conclusion

4.1 Summary of Key Findings

Yellow Rail populations have long been poorly known throughout the western boreal forest. Since the species had only infrequently been detected, it was assumed that it was very rare. Our findings strongly suggest that Yellow Rail are more common than previously thought in this region.

In chapter 2, I presented the findings from a survey of the Edéhzhíe indigenous protected area in NWT and modelled Yellow Rail density across that study area.

A surprisingly large number of Yellow Rail were detected (n = 41) and the species was present at 15.5% of the sampling stations. This was unexpected because the previously delineated range of Yellow Rail only reached the southern portion of the study area (61.75°N) while I detected rails north to 62.72°. This highlights the need for increased monitoring for waterbirds in the boreal zone. The best predictor for high densities of Yellow Rail was coverage by the wetland class, marsh, which distinguished itself as the most important habitat. In Edéhzhíe, much of the marsh habitat occurs within the Mills Lake wetland complex which should be recognized as a regionally significant breeding area assuming the 2016 numbers are representative of a typical year.

In chapter 3, I presented the findings from a long-term survey program in the oilsands area of Northeastern Alberta and modelled Yellow Rail abundance across the study area with a novel approach using continuous predictors accessed from satellite remote sensors.

The final product of this study was a predictive mapping tool which shows the predicted abundance of breeding Yellow Rail at 10m resolution across the study area. This map is a significant improvement over existing spatial tools because it allows us to accurately differentiate areas of preferred habitat within wetlands that would otherwise be seen as homogenous in a typical wetland classification system. Using a BRT modelling framework helped quantify relationships between our predictors that could not have been described with GLMs because the responses were not linear and we were able to test for important interactions. We identified several predictors that should be useful for modelling the distribution of Yellow Rail or other wetland birds in other areas. Sentinel-1 SAR predictors had the highest relative influence and these variables helped characterize the specific habitat requirements of Yellow Rail.

4.2 Conservation Implications

Finding large numbers of Yellow Rail within Edéhzhíe is good news for conservation because these populations are located within a newly established protected area. In the Northwest Territories, habitat is generally intact and is largely free from anthropogenic threats. However, the sedge meadow habitats upon which Yellow Rail rely are very sensitive. One concern for the long-term viability of these populations is the effects of climate change. Notably, there has been a long-term trend in the southern Northwest Territories for wetlands to become more wet. Satellite imagery of the area between 1986 and 2011 showed the proportion land covered by water has gone from 5.7% to 11% over that period (Korosi et al., 2017). This resulted in sedge meadows, especially along lake margins, becoming inundated with consequences for wildlife that rely on them (e.g. bison being displaced). These are precisely the areas our model predicts are most suitable for Yellow Rail.

Northern, or ‘cold-edge’ range limits are often associated with limits in the physiological tolerance of a species or corresponding changes in food plant communities due to climate regulation on the distributions of those species (Calosi et al., 2010; Gaston, 2009; Lynch et al., 2014). For migratory birds, another factor in determining northern range boundaries is the cost associated with dispersing a longer distance. These costs include increased energy expenditure and increased risk of mortality which may each limit a species ability to disperse beyond a certain extent. However, it has been shown that these costs can be compensated by lower predation risk on the breeding ground and increased availability of food (Mckinnon et al., 2010). Changes to the distribution of Yellow Rail would have significant conservation implications. Optimistically, a warming climate might ‘unlock’ additional suitable breeding habitat beyond their current distribution and into areas with relatively little human footprint. However, it is not clear, to what extent this could compensate for lost or degraded habitat elsewhere, or whether they have a limit to their dispersal ability. Yellow Rail are projected to lose 100% of their climatically suitable winter range and are among the species assessed as climate endangered (Langham et al., 2015).

In our Alberta study area, resource development is expected to increase substantially (Alberta Energy Regulator, 2016) and human footprint will also continue to increase. To ensure the conservation of Yellow Rail in the region it will be beneficial to have a better understanding of its distribution and abundance on the landscape to facilitate conservation planning and mitigation of development impacts. Maps can provide information about areas that should be protected and can inform industry proponents about highly sensitive areas within their leases that should be targeted for mitigation efforts. High-impact developments should avoid areas with high predicted Yellow Rail abundance and these wetlands should have their hydrological function preserved.

4.3 Recommendations for Future Research

The studies conducted in this thesis benefited tremendously from the application of new technologies. ARUs were integral to our ability to survey for Yellow Rail effectively, but bioacoustics methodology is still developing.

Estimating density from audio recordings is an active area of research and there is likely to be continued improvement in methods for estimating and standardizing animal density using passive acoustics (Darras, Furnas, Fitriawan, Mulyani, & Tscharntke, 2018; Yip et al., 2019, 2017). It is inherently challenging to accurately estimate density from audio recordings and this is an important source of error for the studies presented in this thesis. Novel approaches using sound-level measurements may be useful for providing the most objective distance estimates (Yip et al., 2019). To address the uncertainty in the point source of a vocalization, sound localization techniques could be used (S. J. Wilson & Bayne, 2018). This would allow us to relate the breeding locations of the birds more directly to model inputs. However, the intensity of sampling, and the associated costs, would have to increase as arrays of recorders are required.

The application of automatic song recognition tools improved our ability to detect Yellow Rail on audio recordings. The Yellow Rail call is relatively simple which makes it an ideal candidate for automated recognition. There are a number of obstacles to perfecting automated recognition but in the future it may be possible to derive counts automatically from audio recordings (Priyadarshani, Marsland, & Castro, 2018). A combination of deep learning and image processing of sonograms to detect peaks corresponding to the characteristic ‘tiks’ of the call could be converted to objective counts.

In chapter 3, we outlined a framework for modelling the abundance of Yellow Rail across a region with satellite remote sensing inputs. One of the key advantages of this approach is that remotely sensed data can provide a finer and more continuous representation of geospatial variables. Additional habitat characterization measures could be used to improve these models, such as LiDAR which has been shown to be very useful as a tool for measuring height and density of surface vegetation conditions, but such data may be prohibitively costly to acquire. All of the inputs we used are freely available and can be computed directly from the measurements of satellite sensors (i.e. they do not have to be modelled and validated) and they can be recalculated annually or sub-annually (e.g. the repeat cycle for Sentinel-1 and Sentinel-2 are 12-days and 10-days, respectively). These attributes would allow the creation of new models for a given year and predict dynamic change in a way that no static landcover product can. This would be a leap forward for spatial modelling of species because it becomes possible to update models dynamically with annual, or seasonal, inputs that would improve our ability to characterize changing wetland conditions. It should be a priority to develop and validate models that account for annual variation in Yellow Rail abundance because it could increase our understanding of what constitutes critical habitat for the species under different short-term environmental conditions (i.e. a wet season vs. a dry season).

One future goal would be to create a national abundance map for the species. To achieve this, would require abundance data and landscape information from all parts of the Yellow Rail range across Canada. Earth Observation satellite data is uniquely suited to this because our data sources provide coverage for the whole globe (below 60˚N) and the various data streams can be used as predictors and correlates for environmental attributes. It will be a challenge to account for the increased variation that results from populations in markedly different environmental contexts (i.e.

coastal vs. inland wetlands) and it is expected that different predictors may be more or less influential regionally.

Literature Cited

ABMI. (2017). The status of human footprint in Alberta. Retrieved from https://abmi.ca/home/data-analytics/da-top/da-product-overview/GIS-Land-Surface/HF-inventory.html

ABMI. (2018a). 3 x 7 - km photoplot land cover data. Retrieved from https://www.abmi.ca/home/data-analytics/da-top/da-product-overview/GIS-Land-Surface/Photoplot-Land-Cover-Dataset.html

ABMI. (2018b). Boreal surface water inventory. Retrieved from https://www.abmi.ca/home/data-analytics/da-top/da-product-overview/GIS-Land-Surface/Boreal-Surface-Water-Inventory.html?scroll=true

ABMI. (2019). Boreal wetland probability data. Retrieved from https://www.abmi.ca/home/data-analytics/da-top/da-product-overview/GIS-Land-Surface/Boreal-Wetland-Probability-Data.html?scroll=true

AESRD. (2015). *Alberta wetland classification system*. Edmonton.

Alvo, R., & Robert, M. (1999). *COSEWIC Assessment and status report on the Yellow Rail (Coturnicops noveboracensis) in Canada*. Ottawa.

Amani, M., Mahdavi, S., Afshar, M., Brisco, B., Huang, W., Mirzadeh, S. M. J., … Hopkinson, C. (2019). Canadian wetland inventory using google earth engine: the first map and preliminary results. *Remote Sensing*, *11*(7), 842. https://doi.org/10.3390/rs11070842

Austin, J. E., & Buhl, D. A. (2013). Relating Yellow Rail (Coturnicops noveboracensis) occupancy to habitat and landscape features in the context of fire. *Waterbirds*, *36*(2), 199–213.

https://doi.org/10.1675/063.036.0209

Barker, N. K. S., Cumming, S. G., & Darveau, M. (2014). Models to predict the distribution and abundance of breeding ducks in Canada. *Avian Conservation and Ecology*, *9*(2), 41–82. https://doi.org/10.5751/ACE-00699-090207

Bart, J., Stehn, R. A., Herrick, J. A., Heaslip, N. A., Bookhout, T. A., & Stenzel, J. R. (1984). Survey methods for breeding Yellow Rails. *The Journal of Wildlife Management*, *48*(4), 1382–1386.

Bazin, R., & Baldwin, F. B. (2007). *Canadian Wildlife Service standardized protocol for the survey of Yellow Rails (Coturnicops noveboracensis) in prairie and northern region*. Winnipeg.

Bird Studies Canada. (2019). Marsh monitoring program. Retrieved 28 January 2019, from https://www.birdscanada.org/volunteer/natmmp/

Böhner, J., Köthe, R., Conrad, O., Gross, J., Ringeler, A., & Selige, T. (2002). *Soil regionalisation by means of terrain analysis and process parameterisation*.

Bookhout, T. A., & Stenzel, J. R. (1987). Habitat and movements of breeding Yellow Rails. *The Wilson Bulletin*, *99*(3), 441–447.

Brandt, J., Flannigan, M., Maynard, D., Thompson, I., & Volney, W. (2013). An introduction to Canada's boreal zone: ecosystem processes, health, sustainability, and environmental issues. *Environmental Reviews*, *21*(4), 207–226. https://doi.org/Doi 10.1139/Er-2013-0040

Breiman, L. (2001). Statistical modeling : the two cultures. *Statistical Science*, *16*(3), 199–231.

Brommer, J. E. (2004). The range margins of northern birds shift polewards. *Annales Zoologici Fennici*, *41*, 391–397.

Brown, J. H. (1984). On the relationship between abundance and distribution of species. *The*

American Naturalist, *124*(2), 255–279. https://doi.org/10.1086/284267

Buckland, S. T. (2001). *Introduction to distance sampling: Estimating abundance of biological populations*. Oxford: Oxford University Press.

Burnham, K. P., & Anderson, D. R. (2002). *Model selection and multimodel inference* (2nd ed.). New York: Springer - Verlag New York. https://doi.org/10.1016/j.ecolmodel.2003.11.004

Burnham, K. P., Buckland, S. T., Laake, J. L., Borchers, D. L., Marques, T. A., Bishop, J. R., & Thomas, L. (2004). Further topics in distance sampling. In *Advanced Distance Sampling: Estimating abundance of biological populations* (pp. 326–408). Oxford: Oxford University Press.

Calosi, P., Bilton, D. T., Spicer, J. I., Votier, S. C., & Atfield, A. (2010). What determines a species' geographical range? Thermal biology and latitudinal range size relationships in European diving beetles (Coleoptera: Dytiscidae). *Journal of Animal Ecology*, *79*(1), 194–204. https://doi.org/10.1111/j.1365-2656.2009.01611.x

Canadian Wildlife Service. (2011). Yellow rail range in Northwest Territories and Nunavut. Yellowknife, Northwest Territories: Environment and Climate Change Canada.

Conrad, O., Bechtel, B., Bock, M., Dietrich, H., Fisher, E., Gerlitz, L., … Bohner, J. (2015). System for automated geoscientific analyses (SAGA) v. 2.1.4. *Geoscientific Model Development Discussions*, *8*(2), 2271–2312.

Conway, C. J. (2011). Standardized North American marsh bird monitoring protocol. *Waterbirds*, *34*(3), 319–346. https://doi.org/10.1675/063.034.0307

Conway, C. J., & Nadeau, C. P. (2010). Effects of broadcasting conspecific and heterospecific calls on detection of marsh birds in North America. *Wetlands*, *30(2)*, 358–368.

https://doi.org/10.1007/s13157-010-0030-1

Copernicus Programme. (2016). Sentinel-1 SAR technical guide. Retrieved from https://sentinels.copernicus.eu/web/sentinel/missions/sentinel-1

Copernicus Programme. (2017). Sentinel-2 User Handbook. Retrieved from https://sentinels.copernicus.eu/web/sentinel/user-guides/document-library/-/asset_publisher/xlslt4309D5h/content/sentinel-2-user-handbook

Cord, A. R., Meentemeyer, R. K., Leitao, P. J., & Vaclavik, T. (2013). Modelling species distributions with remote sensing data: bridging disciplinary perspectives. *Journal of Biogeography*, *40*, 2226–2227. https://doi.org/10.1111/jbi.12199

COSEWIC. (2009). *COSEWIC assessment and status report on the Yellow Rail Coturnicops noveboracensis in Canada*. Ottawa.

Cumming, S. G., Lefevre, K. L., Bayne, E. M., Fontaine, T., Schmiegelow, F. K., & Song, S. J. (2010). Toward conservation of Canada's boreal forest avifauna: Design and application of ecological models at continental extents. *Avian Conservation and Ecology*, *5*(2), art8.

Dalgarno, S., Mersey, J. E., Gedalof, Z., & Lemon, M. (2017). Species-environment associations and predicted distribution of Black Oystercatcher breeding pairs in Haida Gwaii , British Columbia, Canada. *Avian Conservation and Ecology*, *12*(2), Art9.

Darras, K., Furnas, B., Fitriawan, I., Mulyani, Y., & Tscharntke, T. (2018). Estimating bird detection distances in sound recordings for standardizing detection ranges and distance sampling. *Methods in Ecology and Evolution*, *9*(9), 1928–1938. https://doi.org/10.1111/2041-210X.13031

Dehcho Land Use Planning Committee. (2006). *Respect for the land: The Dehcho land use plan (Ndéh Ts'edîîchá: Dehcho Ndéh T'áh Ats'et'î K'eh Eghálats'ênda)*.

DeLancey, E. R., Kariyeva, J., Bried, J. T., & Hird, J. N. (2019). Large-scale probabilistic identification of peatlands in the boreal natural region of Alberta, Canada using Google Earth Engine, open-access satellite data, and machine learning. Manuscript in preparation.

Difebo, A., Richardson, M., & Price, J. (2015). Fusion of multispectral imagery and LiDAR digital terrain derivatives for ecosystem mapping and morphological characterization of a northern peatland complex. In R. W. Tiner, M. Lang, & V. V Klemas (Eds.), *Remote Sensing of Wetlands: Applications and Advances* (pp. 399–412). Boca Raton, Florida: Taylor & Francis.

Drake, K. L., Frey, M., Hogan, D., & Hedley, R. (2016). Using digital recordings and sonogram analysis to obtain counts of Yellow Rails. *Wildlife Society Bulletin*, *40*(2), 346–354. https://doi.org/10.1002/wsb.658

Drake, K., & Latremouille, L. (2016). *Fishing Lake conveyance channel wildlife assessment: final report 2011-2015*. Saskatoon.

Drusch, M., Del Bello, U., Carlier, S., Colin, O., Fernandez, V., Gascon, F., … Bargellini, P. (2012). Sentinel-2: ESA's optical high-resolution mission for GMES operational services. *Remote Sensing of Environment*, *120*, 25–36. https://doi.org/10.1016/j.rse.2011.11.026

Ducks Unlimited Canada. (2015). *Enhanced wetland classification inferred products user guide version 1.0*. Stonewall, Manitoba, Canada.

Dvorett, D., Davis, C., & Papeş, M. (2016). Mapping and hydrologic attribution of temporary wetlands using recurrent landsat imagery. *Wetlands*, *36*(3), 431–443. https://doi.org/10.1007/s13157-016-0752-9

Ecological Stratification Working Group. (1995). *A national ecological framework for Canada*. Ottawa/Hull. Report and national map at 1:7500 000 scale.

Ecosystem Classification Group. (2007). *Ecological regions of the Northwest Territories - taiga plains*. Yellowknife.

Elith, J., Graham, C. H., Anderson, R. P., Dudık, M., Ferrier, S., Guisan, A., … Zimmermann, N. E. (2006). Novel methods improve prediction of species ’ distributions from occurrence data. *Ecography*, *2*(January), 129–151.

Elith, J., & Leathwick, J. R. (2009). Species distribution models: Ecological explanation and prediction across space and time. *Annual Review of Ecology, Evolution, and Systematics*, *40*(1), 677–697. https://doi.org/10.1146/annurev.ecolsys.110308.120159

Elith, J., Leathwick, J. R., & Hastie, T. (2008). A working guide to boosted regression trees. *Journal of Animal Ecology*, *77*, 802–813. https://doi.org/10.1111/j.1365-2656.2008.01390.x

Environment and Climate Change Canada. (2016). *Canadian environmental sustainability indicators: Extent of Canada’s wetlands*. Gatineau.

Feild, T. S., Lee, D. W., & Holbrook, N. M. (2001). Why leaves turn red in autumn. The role of anthocyanins in senescing leaves of Red-Osier Dogwood. *Plant Physiology*, *127*, 566–574. https://doi.org/10.1104/pp.010063.566

Fern, R. R., & Morrison, M. L. (2017). Mapping critical areas for migratory songbirds using a fusion of remote sensing and distributional modeling techniques. *Ecological Informatics*, *42*(August), 55–60. https://doi.org/10.1016/j.ecoinf.2017.09.007

Friedman, J. H. (2001). Greedy function approximation: a gradient boosting machine. *The Annals of Statistics*, *29*(5), 1189–1232.

Gallant, J. C., & Dowling, T. I. (2003). A multiresolution index of valley bottom flatness for mapping depositional areas. *Water Resources Research*, *39*(12), 1347.

https://doi.org/10.1029/2002WR001426

Gaston, K. J. (1997). What is rarity? In W. E. Kunin & K. J. Gaston (Eds.), *The biology of rarity: Causes and consequences of rare-common differences* (pp. 30–47). London: Chapman and Hall.

Gaston, K. J. (2009). Geographic range limits of species. *Proceedings of the Royal Society B: Biological Sciences*, *276*(1661), 1391–1393. https://doi.org/10.1098/rspb.2009.0100

Gibbs, J. P., & Melvin, S. M. (1993). Call-response surveys for monitoring breeding waterbirds. *The Journal of Wildlife Management*, *57*(1), 27–34. https://doi.org/10.1183/09031936.00167908

Gitelson, A. A., Merzlyak, M. N., & Chivkunova, O. B. (2001). Optical properties and nondestructive estimation of anthocyanin content in plant leaves. *Photochemistry and Photobiology*, *74*(1), 38–45.

Glenn, D. (2007). Boosted trees for ecological modeling and prediction. *Ecology*, *88*(1), 243–251.

Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D., & Moore, R. (2017). Google Earth Engine: Planetary-scale geospatial analysis for everyone. *Remote Sensing of Environment*, *202*, 18–27. https://doi.org/10.1016/j.rse.2017.06.031

Gottschalk, T. K., Huettmann, F., & Ehlers, M. (2005). Thirty years of analysing and modelling avian habitat relationships using satellite imagery data: A review. *International Journal of Remote Sensing*, *26*(12), 2631–2656. https://doi.org/10.1080/01431160512331338041

Government of Canada. (2002). Species at risk act / Loi sur les espèces en péril. Ottawa: Minister of Justice.

Graham, L. J., Eigenbrod, F., Spake, R., Gillings, S., Watts, K., & Graham, L. J. (2019). Incorporating fine-scale environmental heterogeneity into broad-extent models. *Methods in Ecology and Evolution*, 1–12. https://doi.org/10.1111/2041-210X.13177

Guillera-Arroita, G., Lahoz-Monfort, J. J., Elith, J., Gordon, A., Kujala, H., Lentini, P. E., … Wintle, B. A. (2015). Is my species distribution model fit for purpose? Matching data and models to applications. *Global Ecology and Biogreography*, *24*, 276–292. https://doi.org/10.1111/geb.12268

Guisan, A., & Zimmermann, N. E. (2000). Predictive habitat distribution models in ecology. *Ecological Modelling*, *135*, 147–186. https://doi.org/10.1016/S0304-3800(00)00354-9

Guo, Q., Taper, M., Schoenberger, M. M., & Brandle, J. R. (2005). Spatial-temporal population dynamics across species range: from centre to margin. *Oikos*, *108*(1), 47–57. https://doi.org/10.1111/j.0030-1299.2005.13149.x

Halsey, L. A., Vitt, D. H., Beilman, D., Crow, S., Mehelcic, S., & Wells, R. (2003). *Alberta wetland inventory standards version 2.0*. Edmonton: Alberta Sustainable Resource Development.

Herkert, J. R. (1995). An analysis of Midwestern breeding bird population trends: 1966-1993. *American Midland Naturalist*, *134*(1), 41. https://doi.org/10.2307/2426481

Herrmann, I., Pimstein, A., Karnieli, A., Cohen, Y., Alchanatis, V., & Bonfil, D. (2011). LAI assessment of wheat and potato crops by VENuS and Sentinel-2 bands. *Remote Sensing of Environment*, *115*, 2141–2151. https://doi.org/10.1016/j.rse.2011.04.018

Hijmans, R. J., & Elith, J. (2013). *Species distribution modeling with R Introduction*. https://doi.org/10.1016/S0550-3213(02)00216-X

Hird, J. N., DeLancey, E. R., McDermid, G. J., & Kariyeva, J. (2017). Google earth engine, open-access satellite data, and machine learning in support of large-area probabilistic wetland mapping. *Remote Sensing*, *9*(12). https://doi.org/10.3390/rs9121315

IBA. (2004). Mills Lake IBA site summary. Retrieved 1 February 2019, from https://www.ibacanada.com/site.jsp?siteID=NT083

Jaramaz, D., Simic, S. B., & Saljnikov, E. R. (2013). The ESA Sentinel-2 mission vegetation variables for remote sensing of plant monitoring. In *Conference Proceedings 2nd International Scientific Conference* (pp. 950–961).

Jarnevich, C. S., Holcombe, T. R., Grisham, B. A., Timmer, J., Boal, C. W., Butler, M. J., … Pelt, W. E. Van. (2016). Assessing range-wide habitat suitability for the Lesser Prairie- Chicken. *Avian Conservation and Ecology*, *11*(1), 1–18. https://doi.org/10.5751/ACE-00807-110102

Jiang, H., Liu, C., Sun, X., Lu, J., Zou, C., Hou, Y., & Lu, X. (2015). Remote sensing reversion of water depths and water management for the stopover site of siberian cranes at Momoge, China. *Wetlands*, *35*(2), 369–379. https://doi.org/10.1007/s13157-015-0626-6

JWRL Geomatics. (2017). *Vegetation and landscape classification of Edéhzhíe candidate national wildlife area*.

Kawecki, T. J. (2008). Adaptation to marginal habitats. *Annual Review of Ecology, Evolution, and Systematics*, *39*(1), 321–342. https://doi.org/10.1146/annurev.ecolsys.38.091206.095622

Korosi, J. B., Thienpont, J. R., Pisaric, M. F., Demontigny, P., Perreault, J. T., McDonald, J., … Blais, J. M. (2017). Broad-scale lake expansion and flooding inundates essential wood bison habitat. *Nature Communications*, *8*, 1–8. https://doi.org/10.1038/ncomms14510

Kushlan, J. A., Steinkamp, M. J., Parsons, K. C., Capp, J., Acosta Cruz, M., Coulter, M., … Wohl, K. (2002). *Waterbird conservation for the Americas: The North American waterbird conservation plan, Version 1*. Washington D.C.

La Sorte, F. A., & Thompson III, F. R. (2007). Poleward shifts in winter ranges of North American birds. *Ecology*, *88*(7), 1803–1812.

Lang, M., McCarty, G., Oesterling, R., & Yeo, I.-Y. (2013). Topographic metrics for improved mapping of forested wetlands. *Wetlands*, *33*(1), 141–155. https://doi.org/10.1007/s13157-012-0359-8

Langham, G., Scheutz, J., Soykan, C., Wilsey, C., Auer, T., LeBaron, G., … Distler, T. (2015). *Audubon's birds and climate change Report*. https://doi.org/10.1037/0022-0663.96.1.130

Lankau, H., Macphail, A., Knaggs, M., & Bayne, E. M. (2017). *Bioacoustic Unit: Acoustic recording analysis protocol*. Edmonton.

Latour, P. B. (2003). *Aerial surveys of geese, swans, and shore-birds at Mills Lake, NWT during the spring and fall migration period: 1994-1997*.

Latour, P. B., Leger, J., Hines, J. E., Mallory, M. L., Mulders, D. L., Gilchrist, H. G., … Dickson, D. L. (2008). *Key migratory bird terrestrial habitat sites in the Northwest territories and nunavut*. *Occasional Paper of the Canadian Wildlife Service*.

Lawson, C. R., Hodgson, J. A., Wilson, R. J., & Richards, S. A. (2014). Prevalence , thresholds and the performance of presence - absence models. *Methods in Ecology and Evolution*, *5*, 54–64. https://doi.org/10.1111/2041-210X.12123

Lawton, J. H. (1993). Range, population abundance and conservation. *Oikos*, *8*(7), 409–413.

Lee, J.-S., Wen, J.-H., Ainsworth, T. L., Chen, K.-S., & Chen, A. J. (2009). Improved sigma filter for speckle filtering of SAR imagery. *IEEE Transactions on Geoscience and Remote Sensing*, *47*(1), 202–213.

Leston, L., & Bookhout, T. A. (2015). Yellow Rail (Coturnicops noveboracensis), version 2.0. https://doi.org/10.2173/bna.139

Liu, C., Berry, P. M., Dawson, T. P., & Pearson, R. G. (2005). Selecting thresholds of occurrence in the prediction of species distributions. *Ecography*, *28*, 385–393.

Lynch, H. J., Rhainds, M., Calabrese, J. M., Cantrell, S., Fagan, W. F., Lynch, H. J., … Fagan, W. F. (2014). How climate extremes — not means — define a species ' geographic range boundary. *Ecological Monographs*, *84*(1), 131–149.

Mahdianpari, M., Salehi, B., Mohammadimanesh, F., Homayouni, S., Gill, E., Mahdianpari, M., … Gill, E. (2018). The first wetland inventory map of Newfoundland at a spatial resolution of 10m using Sentinel-1 and Sentinel-2 data on the Google Earth Engine cloud computing platform. *Remote Sensing*, *11*(1), 43. https://doi.org/10.3390/rs11010043

Marques, T. A., Thomas, L., Martin, S. W., Mellinger, D. K., Ward, J. A., Moretti, D. J., … Tyack, P. L. (2013). Estimating animal population density using passive acoustics. *Biological Reviews*, *88*(2), 287–309. https://doi.org/10.1111/brv.12001

Martin, K., Koper, N., & Bazin, R. (2014). Optimizing repeat-visit, call-broadcast nocturnal surveys for Yellow Rails (Coturnicops noveboracensis). *Waterbirds*, *37*(1), 68–78. https://doi.org/10.1675/063.037.0109

Matsuoka, S. M., Bayne, E. M., Sólymos, P., Fontaine, P. C., Cumming, S. G., Schmiegelow, F. K., & Song, S. J. (2012). Using binomial distance-sampling models to estimate the effective detection radius of point-count surveys across boreal Canada. *The Auk*, *129*(2), 268–282. https://doi.org/10.1525/auk.2012.11190

McDonald, L. L. (2004). Sampling rare populations. In W. L. Thompson (Ed.), *Sampling rare or elusive species, concepts, designs, and techniques for estimating population parameters* (pp. 11–43). Washington D.C.: Island Press.

McFarland, T. M., Grzybowski, J. A., Mathewson, H. A., & Morrison, M. L. (2015). Presence-only species distribution models to predict suitability over a long-term study for a species with a growing population. *Wildlife Society Bulletin*, *39*(1), 218–224. https://doi.org/10.1002/wsb.497

Mcfeeters, S. K. (1999). The use of the normalized difference water index (NDWI) in the delineation of open water features. *International Journal of Remote Sensing*, *17*(7), 1425–1432. https://doi.org/10.1080/01431169608948714

Mckinnon, L., Smith, P. A., Nol, E., Martin, J. L., Doyle, F. I., Abraham, K. F., … Bêty, J. (2010). Lower predation risk for migratory birds at high latitudes. *Science*, *327*(5963), 326–327. https://doi.org/10.1126/science.1183010

McLeod, L. J., Hache, S., & Bayne, E. M. (2019). High density populations of Yellow Rail (Coturnicops noveboracensis) revealed by audio recordings at the northern edge of their breeding range. *In Prep*.

McMaster, G. (2007). *Addendum to 'Assessment of potential impacts of the East and West Fishing Lake conveyance options on habitat and historic resources'*. Regina.

Natural Regions Committee. (2006). *Natural regions and subregions of Alberta*. Edmonton.

North American Bird Conservation Initiative. (2012). The state of Canada's birds. https://doi.org/978-1-100-20674-5

NWT-ENR. (2012). *Northwest Territories forest vegetation inventory standards with softcopy supplement, V4.4*. Yellowknife.

NWT/NU Checklist. (2018). Northwest Territories/Nunavut (NWT/NU) bird checklist survey. Retrieved 11 February 2019, from https://www.canada.ca/en/environment-climate-change/services/bird-surveys/landbird/ebird-northwest-territories-nunavut.html

Ozesmi, S. L., & Bauer, M. E. (2002). Satellite remote sensing of wetlands. *Wetlands Ecology and*

Management, *10*(5), 381–402. https://doi.org/10.1023/A:1020908432489

Pankratz, R. F., Hache, S., Sólymos, P., & Bayne, E. M. (2017). Potential benefits of augmenting road-based breeding bird surveys with autonomous recordings. *Avian Conservation and Ecology*, *12*(2), art18. https://doi.org/10.5751/ACE-01087-120218

Pardieck, K. L., Ziolkowski, D. J. J., Lutmerding, M., & Hudson, M.-A. R. (2018). 2018. North American breeding bird survey dataset 1966 - 2017, version 2017.0. U.S. Geological Survey, Patuxent Wildlife Research Center. U.S. Geological Survey: Patuxent Wildlife Research Center. https://doi.org/https://doi.org/10.5066/F76972V8

Peabody, P. (1922). Haunts and breeding habits of the Yellow Rail. *Journal of the Museum of Comparative Oology*, *2*, 33–44.

Phinney, M. (2015). Yellow Rail (Coturnicops noveboracensis). In P. Davidson, R. Cannings, A. Couturier, D. Lepage, & C. Di Corrado (Eds.), *The Atlas of the Breeding Birds of British Columbia, 2008-2012* (p. 2). Delta: Bird Studies Canada.

Potapov, P., Yaroshenko, A., Turubanova, S., Dubinin, M., Laestadius, L., Thies, C., … Zhuravleva, I. (2008). Mapping the world's intact forest landscapes by remote sensing. *Ecology and Society*, *13*(2), art51. https://doi.org/10.5751/ES-02670-130251

Prescott, D. R. C., Norton, M. R., & Michaud, I. M. G. (2002). A survey of Yellow and Virginia Rails in Alberta using nocturnal call playbacks. *Canadian Field-Naturalist*, *116*(3), 408–415.

Priyadarshani, N., Marsland, S., & Castro, I. (2018). Automated birdsong recognition in complex acoustic environments: a review. *Journal of Avian Biology*, *49*(5), 1–27. https://doi.org/10.1111/jav.01447

Pulliam, H. R. (1988). Sources, sinks, and population regulation. *The American Naturalist*, *132*(5), 652–661.

R Core Team. (2018). *R: A language and environment for statistical computing*. Vienna, Austria.

Robert, M., Jobin, B., Shaffer, F., Robillard, L., & Gagnon, B. (2004). Yellow Rail distribution and numbers in Southern James Bay, Québec, Canada. *Waterbirds*, *27*(3), 282–288. https://doi.org/10.1675/1524-4695(2004)027[0282:YRDANI]2.0.CO;2

Robert, M., & Laporte, P. (1999). Numbers and movements of Yellow Rails along the St. Lawrence River, Québec. *The Condor*, *101*(3), 667–671. https://doi.org/10.2307/1370197

Rouse, J. J., Haas, R., Schell, J., & Deering, W. (1974). Monitoring vegetation systems in the great plains with ERTS. In *NASA. Goddard Space Flight Center 3d ERTS-1 Symposium* (pp. 309–317).

Sagarin, R. D., Gaines, S. D., & Gaylord, B. (2006). Moving beyond assumptions to understand abundance distributions across the ranges of species. *Trends in Ecology and Evolution*, *21*(9), 524–530. https://doi.org/10.1016/j.tree.2006.06.008

Salter, R. (1974). *Autumn migration of birds through the central and upper Mackenzie Valley region, 1972*. *Arctic Gas Biological Report Series* (Vol. 13). Calgary.

Sauer, J. R., Link, W. A., Fallon, J. E., Pardieck, K. L., & Ziolkowski, D. J. J. (2013). The North American Breeding Bird Survey 1966-2011: Summary analysis and species accounts. *North American Fauna*, *79*(1). https://doi.org/10.3996/nafa.79.0001

Sauer, J. R., Niven, D. K., Pardieck, K. L., Ziolkowski, D. J. J., & Link, W. A. (2017). Expanding the North American breeding bird survey analysis to include additional species and regions. *Journal of Fish and Wildlife Management*, *8*(1), 154–172. https://doi.org/10.3996/102015-JFWM-109

Schaefer, H., & Rolshausen, G. (2006). Plants on red alert: do insects pay attention? *Bioessays*, *28*(1), 65–71. https://doi.org/10.1002/bies.20340

Schindler, D. W., & Lee, P. G. (2010). Comprehensive conservation planning to protect biodiversity and ecosystem services in Canadian boreal regions under a warming climate and increasing exploitation. *Biological Conservation*, *143*(7), 1571–1586. https://doi.org/10.1016/j.biocon.2010.04.003

Shonfield, J., & Bayne, E. M. (2017). Autonomous recording units in avian ecological research: current use and future applications. *Avian Conservation and Ecology*, *12*(1), art14. https://doi.org/10.5751/ACE-00974-120114

Shoo, L. P., Williams, S. E., & Hero, J. M. (2006). Detecting climate change induced range shifts: where and how should we be looking? *Austral Ecology*, *31*(1), 22–29. https://doi.org/10.1111/j.1442-9993.2006.01539.x

Stalheim, P. S. (1974). *Behavior and ecology of the Yellow Rail (Coturnicops noveboracensis)*. Master's thesis, University of Minneasota, Minneapolis.

Stenzel, J. R. (1982). *Ecology of breeding Yellow Rails at Seney National Wildlife Refuge*. Master's thesis, Ohio State University, Columbus.

Strong, W., Zoltai, S. C., & Ironside, G. (1989). *Ecoclimatic regions of canada*. Ottawa: Canadian Wildlife Service.

Tarnocai, C., Kettles, I., & Lacelle, B. (2011). *Peatlands of Canada database and maps version 3*. Ottawa, Ontario, Canada.

Thomas, C. D., & Lennon, J. J. (1999). Birds extend their ranges northwards. *Nature*, *399*, 213. https://doi.org/10.1039/b301690k

Tiner, R. W. (1999). *Wetland indicators: A guide to wetland identification, delineation, classification, and mapping*. Boca Raton, Florida: Taylor & Francis.

Tozer, D. C. (2007). Yellow Rail. In M. Cadman, D. Sutherland, B. GG, D. Lapage, & A. Couturier (Eds.), *The Atlas of the Breeding Birds of Ontario* (pp. 196–197). Bird Studies Canada.

Tozer, D. C., Drake, K. L., & Falconer, C. M. (2016). Modeling detection probability to improve marsh bird surveys in Southern Canada and the Great Lakes states. *Avian Conservation and Ecology*, *11*(2). https://doi.org/10.5751/ACE-00875-110203

Trottier, G., & Kemper, J. (1974). *A reconnaissance vegetation survey, Mills Lake, Northwest Territories*. Edmonton.

Vitt, D. H., & Chee, W. L. (1990). The relationships of vegetation to surface water chemistry and peat chemistry in fens of Alberta, Canada. *Vegetatio*, *89*(2), 87–106. https://doi.org/10.1007/BF00032163

Waddington, J., Morris, P., Kettridge, N., Granath, G., Thompson, D., & Moore, P. (2015). Hydrological feedbacks in northern peatlands. *Ecohydrology*, *8*(1), 113–127. https://doi.org/10.1002/eco.1493

Weiss, A. D. (2001). Topographic position and landforms analysis. In *Poster Presentation, ESRI User Conference*. San Diego.

Wells, J. V. (2011). Boreal forest threats and conservation status. In J. V Wells (Ed.), *Boreal birds in North America: A hemispheric view of their conservation links and significance. Studies in Avian Biology (no. 41)* (pp. 1–6). Berkeley, CA: University of California Press.

Wells, J. V, & Blancher, P. J. (2011). Global role for sustaining bird populations. In J. V Wells (Ed.), *Boreal birds in North America: A hemispheric view of their conservation links and significance.*

Studies in Avian Biology (no. 41) (pp. 7–22). Berkeley, CA: University of California Press.

Wetlands International. (2019). Waterbird Population Estimates. Retrieved 10 January 2019, from http://wpe.wetlands.org/

Wildlife Acoustics. (2011). *Song Scope: Bioacoustics software version 4.0 documentation*. Maynard.

Wilson, H. F. (2005). *Habitat use patterns of Yellow Rails (Coturnicops noveboracensis) at Douglas Marsh, Manitoba*. Undergraduate thesis, Brandon University.

Wilson, S. J., & Bayne, E. M. (2018). Use of an acoustic location system to understand how presence of conspecifics and canopy cover influence ovenbird (Seiurus aurocapilla) space use near reclaimed wellsites in the boreal forest of Alberta. *Avian Conservation and Ecology*, *13*(2). https://doi.org/10.5751/ACE-01248-130204

Yip, D. A., Knight, E. C., Haave-Audet, E., Wilson, S. J., Charchuk, C., Scott, C. D., … Bayne, E. M. (2019). Sound level measurements from audio recordings provide objective distance estimates for distance sampling wildlife populations. *Remote Sensing in Ecology and Conservation*, Advance online publication. rse2.118. https://doi.org/10.1002/rse2.118

Yip, D. A., Leston, L., Bayne, E. M., Sólymos, P., & Grover, A. (2017). Experimentally derived detection distances from audio recordings and human observers enable integrated analysis of point count data. *Avian Conservation and Ecology*, *12*(1), art11. https://doi.org/10.5751/ACE-00997-120111