Incorporating Multi-Spectral Imaging Into Long-Term Upland Breeding Bird Monitoring

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INCORPORATING MULTI-SPECTRAL IMAGING INTO LONG-TERM
UPLAND BREEDING BIRD MONITORING

being

A Thesis Presented to the Graduate Faculty
of the Fort Hays State University in
Partial Fulfillment of the Requirements for
the Degree of Master of Science

by

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B.S., University of Nebraska—Lincoln

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The Master of Science Degree
By
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PREFACE

This thesis consists of two overall components. Chapter 1 is the summary of three years of upland breeding bird surveys and vegetation assessments designed to establish a long-term monitoring protocol for Quivira National Wildlife Refuge in central Kansas. One of the primary goals of the project was to develop a standardized protocol that could be used at Quivira and other wildlife refuges across the country. The breeding bird surveys were just one component of a multi-faceted project, and the breakthroughs discovered by our research team have provided the best opportunity to establish a standardized method of long-term ecosystem monitoring across the National Wildlife Refuge System. My thesis is a portion of that project and thus chapter one is written in the format required by the US Fish and Wildlife Service (USFWS) for final report submission as part of the finalization process of the Cooperative Agreement that funded the research.

Based on the results of the initial research, Appendix A is written in a USFWS approved proposal format to request continued research funding that would allow testing of my vegetation analysis technique at Crescent Lake National Wildlife Refuge in western Nebraska. After completion of the remaining facets of the research project at Quivira, this thesis composed of the final report and research proposal will be the primary information presented to USFWS administrators and personnel.
ABSTRACT

Quivira National Wildlife Refuge in Kansas, United States partnered with Fort Hays State University Hays, KS in 2014 to begin a collaborative research project that aimed to develop a long-term monitoring protocol guided by the Comprehensive Conservation Plan for the refuge published in 2013. This plan identified specific wildlife taxa underrepresented in management impact assessments throughout the property. As a result of this plan, surveys were established to monitor interactions between upland breeding birds and the vegetation community. I conducted point count surveys in 2016, 2017, and 2018 for 122 observation points across four transects. I measured seventeen vegetation variables at each observation point between 13-26 July 2016, 5-13 June 2017, 24-27 July 2017, and 18-22 June 2018. I obtained multi-spectral imagery for June 2017 from GeoEye-1 satellite operated by Satellite Imaging Corporation to compare the 17 vegetation variables with remotely-sensed vegetation data. I used reflectance signatures of five unique vegetation classes to generate five vegetation cover types by using supervised Maximum Likelihood Classification in ArcGIS. I modelled single-season occupancy by using traditional and remote-sensed vegetation variables as covariates for Bell’s vireo (Vireo bellii), grasshopper sparrow (Ammodramus savannarum), upland sandpiper (Bartramia longicauda), warbling vireo (Vireo gilvus), and western kingbird (Tyrannus verticalis). Covariates derived from multi-spectral imagery consistently performed equal to or better than comparable field-measured covariates for four of the five species. I then applied the multi-spectral imagery classification technique to imagery of proposed wilderness area at Crescent Lake National Wildlife Refuge in Nebraska,
United States captured 27 June 2018 to assess translatability of these methods. I identified five habitat classes sensitive to vegetative productivity and exposed bare ground that potentially could be reassessed multiple times through the 15 year lifespan of the Comprehensive Conservation Plan to determine vegetation changes across the 9,915 hectares. These assessments promote an adaptive management approach to plant community dynamics on federal properties by allowing for annual assessments that better mimic real world dynamics but require a fraction of the resources.
ACKNOWLEDGMENTS

I thank the Department of Biological Sciences at Fort Hays State for bringing me on to this research project. I think that being able to join the “Quivira Crew” in the middle of this project allowed me the greatest opportunity to learn the methods and motivation for the work being done down at Quivira National Wildlife Refuge. I came into graduate school with a relatively sound understanding of how to perform habitat work on areas similar to Quivira. However, I only had a limited understanding of why the work was being done and how it affected grasslands at a landscape scale. I wanted to learn to think critically like a scientist and become a well-rounded biologist, and I believe that in my time at Fort Hays State University I have accomplished exactly that. While I am far from the scientist I want to be at the end of my career, the steps I have taken toward that end product can be directly attributed to the faculty in the Biology Department. I especially thank Dr. William Stark and Dr. Rob Channell for the time and knowledge that they devoted to me and the Quivira project. Also, thank you to Dr. Elmer J. Finck and Mr. Curtis Schmidt for serving on my thesis committee and adding to the long list of phenomenal people I had the privilege of working with during graduate school.

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Ordination plot of bird survey observation points at Quivira National Wildlife Refuge after nonmetric multidimensional scaling using Bray distance measurements of presence/absence of bird species for A) 2016 (Stress = 0.221), B) 2017 (Stress = 0.202), and C) 2018 (Stress = 0.210). Points are colored by four habitat classes defined by the refuge’s comprehensive conservation planning using the National Vegetation Classification Standard. Strong disagreement between the ordinations and NVCS habitat classifications indicate that bird community structure is not reflective of NVCS based management practices.

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Ordination plot of bird survey observation points at Quivira National Wildlife Refuge after nonmetric multidimensional scaling using Euclidian distance measurements of eight standardized vegetation measurement variables for A) July 2016 (Stress = 0.233), B) June 2017 (Stress = 0.222), and C) June 2018 (Stress =
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Ordination plot of bird survey observation points at Quivira National Wildlife Refuge after nonmetric multidimensional scaling using Bray distance measurements of presence/absence of bird species for species for A) 2016 (Stress = 0.221), B) 2017 (Stress = 0.202), and C) 2018 (Stress = 0.210). Points are colored by the five groups defined by hierarchical cluster analysis of eight standardized vegetation measurement variables for A) July 2016, B) June 2017, and C) June 2018. Bird communities were unresponsive to vegetation classes derived from field-measured measurements for any season.

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CHAPTER 1: DEVELOPMENT OF LONG-TERM MONITORING PROTOCOLS

INTRODUCTION

Background of Comprehensive Conservation Plans

The National Wildlife Refuge System Improvement Act of 1997 (US Congress, 1997) requires the US Fish and Wildlife Service (USFWS) to develop a Comprehensive Conservation Plan (CCP) for each property within the national wildlife refuge system. The goal of a CCP is to maintain the biological integrity, diversity, and environmental health of a refuge and facilitate compatible wildlife-dependent recreation such as hunting, fishing, wildlife viewing, and environmental education (U.S. Fish & Wildlife Service, 2000). These plans outline management for a 15-year period and they define objectives for each refuge to fulfill its obligation to meet the mission of the National Wildlife Refuge System.

Each CCP contains a chapter that describes the refuge, its geography, and the ecological communities present. This chapter often highlights the refuge’s role (breeding habitat, migratory stop over, etc.) in conserving each of these communities and categorizes species by conservation status. These categories can include species in need of additional conservation measures, species of greatest conservation need, and/or species that need additional research on their status on the refuge. This chapter also contains a detailed description of the vegetation communities present throughout the refuge. These vegetation communities have been defined by a number of techniques since the inception of the CCPs and have most recently used the National Vegetation Classification Standard (NVCS; Cummins & Allen, 2015; McPeak, 2014; U.S. Geological Survey, 2006;
Grossman et al., 1998). This system currently consists of an eight-level vegetation hierarchy that results in fine-scaled maps of vegetation classifications that uses plant species alliance and association to define vegetation classes (Jennings et al., 2009). These classifications, while applicable in the year surveyed, could pose issues for long term planning. The maps generated from the data during the drafting process of CCPs might be outdated by the beginning of the 15-year lifespan of the finalized CCP document and potentially even more so by the end of the document’s life. Plant communities in both grassland and wetland ecosystems have demonstrated rapid transition along similar or shorter timelines than CCP lifespans as the result of disturbances such as eastern redcedar (Juniperus virginiana L.) encroachment (Wang et al., 2018) and exotic plant invasion (Wester et al., 2018; Lathrop, Windham, & Montesano, 2003). Also, active management practices like brush removal, prescribed burning, and water impoundment are strategically conducted to rapidly modify the plant communities present on the refuge. Temporally inaccurate vegetation maps could misguide refuge management and result in detrimental management practices for at-risk species. Another issue with NVCS mapping is it requires substantial investments of time and resources precluding efforts to update in appropriate timeframes for effective adaptive management. However, these maps continue to be the basic structure for the development of management plans for National Wildlife Refuges.

Comprehensive Conservation Plans provide the framework for identifying species and refuge management practices that need to be researched. They are a catalyst driving the development and implementation of monitoring protocols for refuges to assess
species responses to active management practices and long-term environmental changes. Given the longevity of these plans and their use of vegetation as the basic structure for the management plan, assessment of these plant communities must be shifted toward more frequent sampling, as these plant communities and the species that rely on them are dynamic in nature (Skagen, Augustine, & Derner, 2018). A new vegetation assessment protocol based on research at Quivira National Wildlife Refuge could provide a standardized method that is responsive to shifts in habitat quality and quantity on relatively short time frames. This protocol could then be implemented across all refuges in the USFWS’s Mountain-Prairie Region and provide the foundation for assessments of upland breeding bird populations’ response to vegetation changes. This protocol also would allow CCPs to be more responsive the entirety of their 15-year lifespans.

**Background of Quivira National Wildlife Refuge Study**

In 2009 the US Fish and Wildlife Service began a planning process to draft a CCP for Quivira National Wildlife Refuge. Quivira National Wildlife Refuge (QNWR), located in central Kansas, is an 8,957-hectare property composed of an interior saline wetland complex intermixed within uplands of sand prairie, cottonwood savannas, and shrub thickets (U.S. Fish & Wildlife Service, 2013; Figure 1). Historically, the refuge has been managed for migratory shorebirds and waterfowl as well as other game species. However, the refuge hosts numerous other non-game wildlife species (upland breeding songbirds, amphibians, reptiles, etc.). From an international perspective, Quivira National Wildlife Refuge plays a major role in bird conservation due to the amount of habitat it provides in a highly fragmented landscape and its location as a major stopover
point along the Central Flyway for North American migratory birds (Andersson et al., 2018; Gil-Weir et al., 2012; Skagen, 1997).

Managers at QNWR must account for both migrating and summer resident birds that use the central flyway (U.S. Fish and Wildlife Service, 2013). Many species of songbirds use the refuge for breeding, and the property could provide significant amounts of suitable habitat within some species breeding ranges. Because of this, an understanding of what habitats breeding birds are selecting for on the refuge and how bird populations trends could guide decisions about type and timing of active management practices made by refuge managers (Koper & Schmiegelow, 2006; Dale et al., 2005; Vickery et al., 1995). Many of the breeding birds (grassland, shrubland, waterfowl, and shorebirds) that use the refuge as habitat are recognized at various levels of conservation need across the Great Plains and Central Flyway (U.S. Fish & Wildlife Service, 2008).

In accordance with the National Wildlife Refuge System Improvement Act of 1997, the CCP drafted for QNWR would create a foundation for management decisions and projects to be implemented over a 15-year period (U.S. Fish & Wildlife Service, 2013). The objectives defined in the CCP establish QNWR’s role within the National Wildlife Refuge System. Upon completion of the finalized Comprehensive Conservation Plan in 2013, refuge personnel identified knowledge voids on how management decisions impacted non-game species. To address this, the refuge entered into a research partnership with Fort Hays State University (FHSU) in 2014 to conduct small-scale surveys of herpetofauna. These surveys expanded in 2015 to include terrestrial
herpetofauna, upland breeding birds, and aquatic turtles. Each survey component was designed to help address needs for ecological data on non-game species identified in the newly released CCP. These surveys provided valuable insight for each of these groups, and suggested that methods for monitoring each focus group needed to be investigated individually. A study design suitable for upland breeding birds was developed in 2016, and herpetofauna surveys were added in 2017. The upland breeding bird study design developed for 2016 was then continued through the 2017 and 2018 active seasons.

The objectives for my thesis is to investigate effectiveness of long-term monitoring protocol of upland breeding birds at QNWR to determine if methods were able to:

- Detect breeding bird species associations with specific vegetation characteristics on the refuge
- Detect breeding bird communities and vegetation communities occurring on the refuge
- Determine relationships between breeding bird communities and vegetation communities on the refuge
- Determine if remote sensing is a viable option for collecting vegetation data to be used for the above listed objectives listed above
METHODS

Bird Surveys

Beginning in May 2016, I conducted surveys focused on upland breeding birds on four transects totaling 116 observation points distributed across the refuge. I based observation point locations on habitat classifications as defined by the NVCS. This was designed to assess avian responses to management decisions that were guided by plant communities defined by the NVCS. I uniformly distributed observation points among four major habitat classifications: native tallgrass, native midgrass, native shortgrass, and wetland. The CCP defined these habitat types as containing the following dominant vegetation:

- **Native midgrass**: little bluestem, *Schizachyrium scoparium* (Michx.) Nash
- **Native shortgrass**: saltgrass, *Distichlis spicata* (L.) Greene; prairie dog town, buffalograss, *Bouteloua dactyloides* (Nutt.) J.T. Columbus
- **Wetland**: prairie cordgrass *Spartina pectinate* Bosc ex Link; cattail *Typha* L.; water; spikerush *Eleocharis* R. Br.; phragmites *Phragmites australis* (Cav.) Trin. Ex Steud.

The CCP management goals were based on the plant community composition defined by the NVCS, because understanding the relationship between the avian communities and vegetation communities was a priority.
I conducted surveys from 28 May to 5 July 2016. I expanded the survey season in 2017 to begin earlier in the breeding season (18 May) and extended it to 14 July to identify initiation and conclusion of the breeding season. Based on the 2017 results, I further refined the survey season to start 15 May and end 27 June in 2018 since breeding activity in the previous sampling seasons diminished after 1 July.

I used modified surveys procedure from the Landbird Monitoring Protocol (Knutson et al. 2008) and began surveys approximately 20 minutes before sunrise each morning. I recorded start time, maximum wind speed (kilometers per hour) and beginning atmospheric temperature (Degrees Celsius) at the initiation of each survey. At each observation point, I recorded visual and auditory observations for five minutes. I documented abundance of each upland breeding bird species and categorized observations into two distance categories: 0-50 meters from observation point and >50-200 meters from observation point (Diefenbach, Brauning, & Mattice, 2003). After the survey, I again recorded maximum wind speed and atmospheric temperature in addition to survey stop time and whether precipitation occurred during the survey. I stopped or postponed surveys if heavy rainfall or thunderstorms were present, or maximum wind gusts were above 24 kilometers per hour (Ralph et al., 1993; Mikol, 1980).

**Vegetation Sampling**

I collected habitat measurements consisting of seventeen vegetation variables at each bird observation point (Table 1). I measured these from 13-26 July 2016, 5-13 June and 24-27 July 2017, and 18-22 June 2018. I modified timing of vegetation sampling each year in order to capture vegetation characteristics when they would have the greatest
influence on breeding birds at QNWR with the ultimate goal of improving the occupancy models.

**Multi-spectral Imagery**

I used multi-spectral imagery captured on 10 June 2017 from the GeoEye-1 Satellite to explore other methods of quantifying vegetation cover. The satellite captured 1.84-meter resolution within four spectral ranges: Blue (450-510nm), Green (510-580nm), Red (655-690nm), and Near Infra-Red (780-920nm). I performed supervised classification of the raster image by using the Maximum Likelihood Classification function in “ArcMAP” (ESRI, 2017) to categorize the imagery into five cover classes: deciduous tree, native shrub, herbaceous vegetation, wetland vegetation, and water. These five general vegetation categories presented a simpler approach to classification than the 40 classifications distinguished by the NVCS classification system from 2011. This generalized approach might also permit refuge staff to inventory vegetation communities on a more frequent basis with reduced effort compared to NVCS mapping, allowing this remote-sensing imagery to guide adaptive management practices.

Using polygons established from the new classification system, I extracted percent cover of each category within a 50-meter buffer around each bird observation point. This method essentially provides 4,268 replicates (1.84 square meter) of cover class estimates compared to the four replicates of the 1 square meter modified Daubenmire frame used in the “on the ground” methods listed in Table 1.
Statistical Analysis

Occupancy Modeling

I built single-season occupancy models by using the software program “Presence” (Hines, 2006) to investigate bird species’ response to vegetation characteristics. This program estimates patch occupancy rates by incorporating imperfect detection of individuals across multiple sample periods within a season (MacKenzie et al., 2017); and is capable of including site covariates that might affect occupancy probability (Mackenzie et al., 2002). Program Presence ranks models using Akaike’s Information Criterion (AIC; Bozdogan, 1987; Akaike, 1974), and provides an AIC weight for comparing adequacy of multiple models (Burnham, Anderson, & Huyvaert, 2010; Wagenmakers & Farrell, 2004). Initially, I generated occupancy models for every species encountered within the 50-meter buffer during each survey season with two conditions: constant probability of occupancy with constant probability of detection and constant probability of occupancy with variable probability of detection between sampling periods. I deemed species in each year amenable to further occupancy analysis when they had estimated occupancies between 30 percent and 80 percent. I then built occupancy models with variable probability of species occupancy influenced by vegetation covariates measured for that year. I considered species with lower than 30 percent estimated occupancy too rare to properly associate them with vegetation characteristics and their low occupancy might have been caused by other factors that I did not include in models. I assumed species with greater than 80 percent estimated occupancy were too ubiquitous to determine preferred habitat characteristics and would
not provide any insight for management decisions. Additionally, I deemed species within that estimated occupancy range across multiple survey years amenable for multi-season occupancy analysis. The multi-season occupancy analysis allowed me to investigate probabilities of colonization and extinction across observation points between years. These models provided insight into temporal changes to species use of the refuge.

I built advanced occupancy models of species amenable to further analysis for the 2016, 2017, and 2018 survey seasons. I initially used traditional field-measured vegetation covariate measurements described in Table 1. However, some results did not agree with the well-documented life histories of many of the species amenable for further analysis. For example, the percent of the surveyed areas composed of shrubs and deciduous trees appeared to be underrepresented in the established vegetation survey protocol. Measurements of these variables on the refuge provided evidence of how critical these components are to species like Bell’s vireo (*Vireo bellii*) and northern bobwhite (*Colinus virginianus*) life histories. Because of the underrepresentation of woody habitat components, I also incorporated vegetation percent cover determined from remotely sensed satellite imagery into the vegetation data from June 2017. I used these new covariates to build occupancy models for five bird species encountered in 2017 (Bell’s vireo; grasshopper sparrow, *Ammodramus savannarum*; upland sandpiper, *Bartramia longicauda*; warbling vireo, *Vireo gilvus*; western kingbird, *Tyrannus verticalis*). I chose these species because they were amenable to further analysis using vegetation covariates, showed notable probabilities of colonization or extinction from
2016 to 2017, and were associated with unique habitat types according to their life histories.

**Bird and Vegetation Community Analysis**

In order to assess bird community structure, vegetation community structure, and bird community response to vegetation community structure, I performed nonmetric multidimensional scaling (NMDS) and hierarchical cluster analysis in the software program “R” (R Development Core Team, 2008) using the “vegan” package (Oksanen et al., 2013). I assessed each year’s bird communities by using presence/absence data from all incidences closer than 50 meters across the 116 observation points. I assessed each year’s plant communities by using values for the top eight vegetation measurements. I selected these measurements because they had the highest mean model rank in the advanced single-season occupancy analysis discussed previously. These variables were standardized to have a mean of 0 and standard deviation of 1.0 using “ade4” package (Bougeard & Dray, 2018; Chessel, Dufour, & Thioulouse, 2004; Dray, Dufour, & Chessel, 2007; Dray & Dufour, 2007) in “R.”

By performing two types of cluster analysis, I was able compare how communities were structured with two different methods and determine whether both techniques agreed with each other. Similar results between the two techniques might provide evidence of established communities in any given year. In order to determine whether the two techniques agreed with each other, I first generated a plot of the NMDS ordination coordinates for each observation point. I then constructed a dendrogram from the hierarchical cluster analysis technique. I cut the dendrogram to assign observation
points into one of a number of communities determined a posteriori. I assigned a shape and color to each community and subsequently gave that shape and color value to each observation point found within the respective community. I then graphed the observation points by using the coordinates from the NMDS analysis, and I made the marker for each point to be its assigned shape and color from the hierarchical cluster analysis technique.

If communities existed within the observation points, then points with the same shape and color designation would be structured around each other on the NMDS plot. If the plot of the observation points had noticeable overlap between clusters, no defined areas for clusters, seemingly random distribution among clusters, or any other easily identified issues among clusters, then the results would suggest that there is no structure to the community being assessed.

I performed this assessment on the upland breeding bird communities for each year and for the plant communities for each year. Similarly, I then assigned a color and shape to each observation point based on its NVCS classification and marked the graphed points of each year’s bird community NMDS and vegetation community NMDS accordingly to determine whether structure for either of the community types was linked to the NVCS habitat categories.

Finally, I marked the observation point site scores from the bird community NMDS analysis with the shape and color of the vegetation groups identified in the previous cluster analysis for each year. Agreement between these techniques would suggest bird community were based on vegetation characteristics around the observation points.
RESULTS

Bird Surveys

Survey results for 2016 included 14,061 observations of 48 species over 10 sample periods and included 614 observations of six species listed as Species in Need of Conservation (SINC) at either the state or federal level. Survey efforts for 2017 yielded 26,708 observations of 57 species over 16 sample periods, and also produced 931 observations among eight species designated as SINC. The 2018 results included 10,797 observations of 53 species over 10 sample periods, including 836 observations of six species designated as SINC.

Species Response to Vegetation

The number of species potentially amenable to further single season occupancy analysis were 16 for 2016, 17 for 2017, and 18 for 2018. The model ranking analysis revealed that eight vegetation covariates had the greatest influence on variable site occupancy among species. These covariates were: “distance to nearest shrub”, “distance to nearest tree”, “litter depth”, “percent bare ground”, “percent forb cover”, “percent grass cover”, “percent litter cover”, and “visual obstruction” (this list is not indicative of performance rank). Cumulatively, 27 species were amenable to development of multi-season occupancy models to investigate probabilities of colonization and extinction among the three years.

For the five species selected for comparison between remotely sensed and field-measured vegetation covariate performance, the models of remotely sensed percent cover supported the capabilities of multi-spectral imagery to monitor breeding bird response to
vegetation characteristics. For Bell’s vireo, percent cover of shrubs derived from the multi-spectral imagery had an AIC model weight of 0.96, and scored 6.92 points lower than the best performing traditional measurement of “visual obstruction”, 15.2 points lower than “percent shrub cover” estimated using the Daubenmire frame, 102.97 points lower than the “tallest shrub” measurement, and 169.15 points lower than the “distance to nearest shrub” measurement (Table 2). For grasshopper sparrow, five models scored similarly (within 2.00 AIC points of the lowest scoring model; Table 3). This included three traditional field-measured variables and two variables derived from the multi-spectral imagery. For upland sandpiper, remotely sensed deciduous tree percent cover was the lowest scoring model and had an AIC weight of 0.76 (Table 4). Remotely sensed shrub percent cover was the next lowest scoring model for upland sandpiper with an AIC weight of 0.16. The lowest scoring model for warbling vireo was “distance to nearest tree” which had an AIC weight of 0.997 (Table 5). Models of remotely sensed vegetation cover did not rank well compared to traditional methods for this species. The western kingbird occupancy model that scored lowest was remotely sensed percent shrub cover (Table 6). This model had an AIC weight of 0.947 and scored 7.22 points lower than the second best model.

**Community Response to Vegetation**

Assessment of the hierarchical cluster analyses for each year suggested that there were five major bird communities occurring across the observation points within a year (Figures 2-4). The color-coded clusters in each year’s ordination were shown to strongly agree for each year meaning that structure exists within the bird communities (Figure 5).
However, when the same NMDS values were plotted as points colored by NVCS classification, all three years strongly suggested that the bird communities were not associated with the NVCS habitat classifications (Figure 6). Based on these results, grassland bird communities did exist each year, but were not related to NVCS classification.

Although less clear than the bird communities, five clusters indicative of structured vegetation communities emerged for each year (Figure 7). When these NMDS scores were plotted and colored by NVCS habitat classes, these vegetation communities offered little evidence of spatial association (Figure 8). Based on these results, vegetation communities also existed each year but did not reflect NVCS classification either. Finally, clusters did not appear when bird community NMDS graphs were marked by the vegetation communities in each year for any of the three survey seasons (Figure 9).

Due to the initial success of extracting vegetative characteristics from remote-sensed multi-spectral imagery and incorporating them into species level analysis, I combined the top ranking vegetation variables from the field-measured measurements with the variables measured with the multi-spectral imagery to determine if I could improve the vegetation NMDS ordination for 2017. Using the standardized vegetation variables measured in June 2017, an NMDS and cluster analysis were combined to produce a graph that identified seven habitat clusters and three isolated observation points (Figure 10).
DISCUSSION

The single-season occupancy model scores supported continued investigation into the potential for remote-sensing as a path forward in development of long-term monitoring protocol that use annual vegetation assessments for QNWR and other wildlife refuges. This is because results from the multi-spectral imaging approach showed similar, if not better, explanatory capability of refuge vegetation characteristics than the traditional field-measured techniques. When considering the model weights for Bell’s vireo, upland sandpiper, and western kingbird, species occupancy was explained better with multi-spectral determined cover classes compared to any of the traditional measurements. These results support the implementation of multi-spectral imagery into refuge monitoring and planning considerations. The multi-spectral analysis also required a fraction of the time to complete (20 working hours) compared to the vegetation data from the field (384 working hours in 2016, 1060 working hours in 2017, and 445 working hours in 2018). The amount of time and resources required to collect and enter the data for 17 vegetation variables is not realistic as a long-term protocol for refuge staff due to funding and personnel constraints. Analysis using multi-spectral imagery gives a more cost-effective and feasible technique for incorporating vegetation characteristics into monitoring of bird communities at a refuge scale.

However, these results do not preclude the necessity of some level of analysis using field-based measurements. For example, the most informative models for warbling vireo were field-measured measurements i.e., “distance to nearest tree.” Additionally, the supervised classifications required a knowledge of the refuge and its vegetation that could
only be obtained by spending time on the refuge. The effectiveness of the multi-spectral analysis and the importance of understanding the refuge at the ground level resulted in a combined approach to vegetation sampling that uses multi-spectral imagery and the eight highest ranking field-measured vegetation measurements as the best path forward to develop long-term monitoring of refuge resources.

Originally, one of the primary goals of the study was to investigate avian community structure in response to vegetation variability across the refuge. Ideally, a refuge of this size with the number of unique habitats identified by the NVCS would have dynamic bird and vegetative communities supported and manipulated by applied management practices. However, there is no evidence from this analysis that supports continued use of NVCS classifications because no structure was identified in any of the community analyses.

There are possible explanations as to why bird communities might not have been structured around specific vegetation communities. First, many of the upland areas on the refuge contain fossil fuel extraction sites, are dissected by roads and water diversions, and/or have areas of “go back” land that was once used for production agriculture. Both remnant and active substantial modifications to habitats on the refuge might be significantly influencing bird communities instead of vegetation qualities. Also, extreme manipulations of production agriculture fields and encroachment of woody plant species on properties surrounding the refuge might have decreased bird selectiveness for habitat qualities within the refuge as seen in other studies (Cunningham & Johnson, 2006; Greer et al., 2016). In other words, birds might have been selecting uplands on the refuge
because this might be the only available habitat in the surrounding landscape.

Additionally, plant community classifications as described by the NVCS that are used to guide management and develop FHSU’s research protocol were created four years before bird surveys were conducted. This could mean that bird community associations that might have occurred with vegetation at the time vegetation classifications were made was already undetectable at less than one-third of the way through the lifespan of the current CCP. This suggests a change in how management objectives are defined in the CCPs might be necessary. The management practices conducted to meet these objectives must be more adaptable to changing vegetative conditions on the refuge, and a shift to more frequent monitoring that is sensitive to those changes promotes that adaptability.

The use of remotely-sensed imagery alone or the combined technique that uses remotely-sensed imagery with a select number of field-measured vegetation measurements is more realistic for long-term monitoring protocol of grassland bird species. The combined monitoring approach could:

1. Provide QNWR with the opportunity to progress forward with the survey design set up by FHSU.
2. Permit for more frequent analysis of the habitats that exist on the refuge.
3. Identify changes in habitat characteristics due to disturbances and management practices.

These applications could allow for adaptation of habitat management practices to changing conditions on the refuge through the remainder of QNWR’s current CCP. This increased sampling frequency using the remotely-sensed or combined approach could
support more effective and strategic refuge management. Because my results indicated that breeding birds were responsive to remotely sensed vegetation variables, future studies should investigate how to incorporate multispectral imagery into assessments of breeding bird response to applied management practices. Finally, the recommended protocol could be adapted for vegetation monitoring at other National Wildlife Refuges, but it should be tested at another location before being considered for wide-spread application (Appendix A).
APPENDIX A: INITIATION OF LONG-TERM MONITORING протокол AT CRESCENT LAKE NATIONAL WILDLIFE REFUGE, NE, USA

BACKGROUND AND JUSTIFICATION

The methods developed for long-term monitoring of upland breeding birds at Quivira National Wildlife Refuge (QNWR) might be able to be replicated at other National Wildlife Refuges across the Great Plains. A standardized monitoring format implemented across those refuges would improve communication between US Fish and Wildlife Service (USFWS) personnel and promote a more cohesive approach to wildlife refuge management across the region. However, prior to installation across the entire national wildlife refuge complex, a study to confirm protocol capabilities and further develop and refine methods would be indispensable to the success of such protocol.

Crescent Lake National Wildlife Refuge (CLNWR) is an 18,541-hectare property located in western Nebraska (Figure 11) that is suitable for the USFWS to test the protocol developed by FHSU. The refuge is a unique complex of rolling sandhills intermixed with natural lakes and wetlands sustained by a shallow aquifer. While CLNWR and QNWR have markedly different habitats and breeding bird compositions, both face similar challenges (e.g., water rights, habitat for federally endangered species, and refuge management under a reduced staff and budget). Cooperators from Fort Hays State University’s Department of Biological Sciences have working knowledge of the protocol and would be an effective partner for finalizing the assessment protocol.

FHSU acquired imagery for CLNWR so that the design and testing process of the proposed monitoring protocol could begin. Observation point selection for breeding bird
surveys at QNWR was based on National Vegetation Classification Standard (NVCS) classes and made prior to development of habitat classes based on multi-spectral imagery. The bird communities identified from those surveys were not reflective of NVCS classifications, and the structuring of points by using the NVCS might have masked any response to the vegetation communities present. Thus, a bird survey protocol built around habitat classification determined from multi-spectral imagery could be more effective at identifying initial bird communities. The imagery could then be collected and assessed in subsequent years to update habitat classifications as vegetation qualities change. A protocol that is sensitive to vegetation community changes and breeding bird community changes among seasons would provide refuge managers with evidence of responsiveness of these communities to applied management practices.

A monitoring protocol based on remotely-sensed or combined habitat assessment protocol were both shown to be sufficient at identifying vegetative communities in a heavily altered system. However, the most pressing issue is its ability to perform equally, if not better, in a relatively intact system. Crescent Lake National Wildlife Refuge, with its 9,915 hectares of proposed wilderness area, would be a suitable site to continue with the development of long-term monitoring protocol adaptable to any property within the refuge system. A successful protocol would thus be able to accomplish the following:

1. Detect bird species responses to vegetation characteristics in each survey season. In addition, protocol would detect species level responses to changes of vegetation characteristics among survey seasons.
2. Identify vegetation communities present on the refuge and their changes in meaningful timeframes.

3. Provide data capable of identifying bird communities that exist according to each habitat classification and detect changes in habitat classifications through time.

Surveys at QNWR demonstrated the ability of the protocol for that refuge to detect species response to vegetation characteristics and identify breeding bird and vegetation communities. However, the protocol was not in place long enough to effectively investigate community dynamics and how breeding bird communities were associated with vegetation communities.

Crescent Lake National Wildlife Refuges most recent comprehensive conservation plan (CCP) was approved in 2002 (U.S. Fish and Wildlife Service, 2002). Accordingly, an evaluation of this CCP will soon be scheduled. A new CCP could be drafted that includes managing the refuge with this long-term monitoring protocol. The following remotely sensed habitat mapping provides the cornerstone of a long-term monitoring protocol that can be accomplished by the current very limited staff.
METHODS

Vegetation Classification - Completed

I obtained satellite imagery from the Digital Globe satellite WorldView2. The satellite carries a multi-spectral sensor that captures eight bands of radiation reflectance (Table 7). Images captured on 27 June 2018 were uploaded to “ArcMAP” (ESRI, 2017) and projected as a raster layer. I then clipped the raster layer to contain only the proposed wilderness area of CLNWR (Figure 12). Similar to the processes at QNWR, I identified signatures for five general vegetation reflectance types by searching for areas with unique colors that would distinguish major vegetation functional groups. Ideally, I would verify these classes with on-the-ground sampling prior to data gathering, but time and travel constraints did not allow for this during the preliminary investigation. Instead, I used ArcMAP to visualize and search for vegetation classes by using knowledge of the refuge’s habitats from prior visits and the vegetation map from the refuge’s 2002 CCP for guidance. With that guidance, I determined that reflectances correspond with the following land cover types: water, bare sand, vegetation in sub-irrigated meadows, emergent aquatic vegetation, and upland herbaceous vegetation. While the focus of the study would be upland breeding birds, I identified water and emergent aquatic vegetation so that they could be distinguished from the other habitats. I constructed polygons around areas identified as one of the five reflectances. I then used these polygons as training samples to conduct Maximum Likelihood Classification of the multi-spectral image. The classification resulted in placement of each pixel into one of the five
vegetation categories (water, sand, emergent aquatic vegetation, sub-irrigated meadow vegetation, and upland herbaceous vegetation).

The output resulted in two new raster datasets. The first was a conversion of each raster point from the clipped multi-spectral image of the refuge to a raster point classified as one of the five reflectance categories (Figure 13). The second dataset was a raster that categorized the grid cells into 14 confidence interval ranges based on the function having correctly identified the reflectance class of the grid cell. Using these confidence raster datasets, I identified areas with confidence probabilities lower than 0.25, I constructed additional training polygons, I created a new signature file, and I conducted the supervised classification function again.

For the initial investigation, I decided a dataset with over 0.60 of the pixels containing greater than 0.25 confidence of correct classification would be suitable for analysis. I then overlaid a grid of 200 meter by 200 meter square polygons onto the proposed wilderness area to create a habitat classification map that would be determined empirically by values from the supervised classification. This polygon size would allow for a 100-meter detection radius around bird observation points if they were placed in the center of the polygon. Observations within 100 meters might be more suitable compared to 200 meters from survey protocol at Quiviran National Wildlife Refuge, given effective distances for bird detectability and comparison to other breeding bird surveys (Sutherland, Newton, & Green, 2004; Diefenbach, Brauning, & Mattice, 2003).

I calculated the number of pixels from each vegetation class of the supervised classification raster by using the Tabulate Area function in ARC GIS. I then graphed for
each class, percent cover on the “x” axis and frequency on the “y” axis to detect breaks in the dataset that could then be used to classify the polygons as a habitat class based on percent cover ranges of vegetation classifications. I defined habitat classes as either aquatic, sub-irrigated meadow, choppy sands, broken upland, or stable upland based on how habitat was mapped in the 2002 CCP. I specifically investigated breaks for percent of each polygon covered with sand and percent of each polygon covered by vegetation in sub-irrigated meadows.

**Establishing Bird Survey Transects – Not Complete**

Based on the completed classification, four 20-point transects surveyed by two researchers could be distributed equally across the four focal habitat classes identified by the remote sensing analysis. This survey design would allow observers to document the number of species present across the surveyed area, and it would allow for the ability to distinguish common from rare species (Ralph, Sauer, & Droege, 1995). Based on the results from QNWR, surveys would be conducted from 15 May through June 30 (Fort Hays State University, 2018). This time frame would also allow for comparison of breeding season lengths between CLNWR and QNWR. Observers would document all visual and audio observations of upland breeding birds within a 100-meter radius of the observation point. These observation points would be placed a minimum of 150 meters from each other in order to meet the assumptions of observation point independence and closed within-year populations required in order to perform occupancy analysis (Bailey & Adams, 2005). The distance between and number of observation points for each survey route would also permit for efficient time to complete surveys while breeding
behavior is still elevated during the morning hours. Surveys would begin at point 1 and continue to point 20 in the odd-numbered sampling periods, then the order would be reversed for the even-numbered sampling period (Fort Hays State University, 2017).

**Measuring Vegetation Covariates – Not Complete**

Vegetation measurements would be conducted using the recommended combined approach at each site. These measurements would be conducted in early June (Fort Hays State University, 2018) and would include field-measured measurements of distance to nearest shrub, distance to nearest tree, litter depth, percent bare ground, percent forb cover, percent grass cover, percent litter cover, and visual obstruction (Table 1). Multispectral imagery would be used to calculate the percent cover of herbaceous vegetation, sub-irrigated meadow vegetation, and bare sand within a 100 meter buffer around each observation point. The field-measured measurements would still require both a Robel pole and Daubenmire frame to complete and, consequentially, would not substantially reduce the effort required to complete field-measured assessments. However, one of the main goals of my study would be to continue to refine these methods in order to develop a suitable template for numerous refuges to implement. Continuing these measurements would allow for comparison between CLNWR and QNWR, with the objective of eventually eliminating the need for either the Robel pole or the Daubenmire frame or reducing need of use to only ground truthing remotely sensed data to check for accuracy.
RESULTS OF VEGETATION CLASSIFICATION

The process of building a training sample, creating a signature file, then performing the Maximum Likelihood Classification with an acceptable confidence raster took three iterations. The confidence raster data point indicated that the analysis was able to classify 41.3 percent of the points with an estimated probability of correct identification at greater than 50 percent (Table 8). This analysis was complemented by a visual assessment after each iteration to determine whether points with low confidences still appeared to be correctly assigned to a classification.

The calculated area values extracted to each tessellation polygon indicated separations at 17 percent cover for vegetation in sub-irrigated meadows and at 5 and 25 percent cover for sparcely vegetated sand. Percent cover of water and percent cover of emergent vegetation were not considered in any further analysis. The breaks were then used to assign each polygon to a habitat class based on the following criteria:

- Aquatic: polygons with >10 percent of their area covered by raster points classified as aquatic emergent vegetation and/or >1 percent of their area covered by raster points classified as water. These polygons were then removed from further classification to establish clearly defined aquatic areas for 2018.
- Sub-Irrigated Meadow: polygons with >17 percent of their area covered by raster points classified as vegetation in sub-irrigated meadow.
- Choppy Sands: polygons with <17 percent of its area covered by raster points classified as vegetation in sub-irrigated meadow, and >25 percent of raster points classified as sand.
- Broken Upland: polygons with <17 percent of their area covered by raster points classified as vegetation in sub-irrigated meadow, and 5 to 25 percent of their raster points classified as sand.

- Stable Upland: polygons with <17 percent of their area covered by raster points classified as vegetation is sub-irrigated meadow, and <5 percent of their raster points classified as sand.

The resulting classification resulted in 79 polygons classified as aquatic, 314 polygons classified as sub-irrigated meadow, 74 polygons classified as choppy sands, 334 classified as broken upland, and 2325 polygons classified as stable upland (Figure 14).
DISCUSSION, OUTCOMES, and BENEFITS

A primary issue with the habitat classification from multi-spectral imagery was the low confidence of accurately predicting the reflectance class for each pixel. Over 58 percent of the pixels had a less than 50 percent confidence of being correctly classified. However, the training samples were constructed with essentially no field based data, so this percent was acceptable for an initial investigation and could be greatly improved with time spent on the refuge. A combined method of vegetation assessments accompanied by empirical data from the refuge could potentially improve confidence in the Maximum Likelihood Classification analysis. With that being said, the proposed classifications were congruent with the classifications in the 2002 CCP. This demonstrates the capabilities of our remote-sensing technique to be quickly applied to any refuge. By obtaining this imagery on an annual basis, yearly assessments could greatly assist refuge personnel with adaptations to management plans, as well as provide justification for practices that occur on the refuge.

The identified vegetation categories at CLNWR were different from the categories identified at QNWR. This translatability from QNWR to CLNWR provides evidence for application to other refuges. These standardized methods are broad enough for communication among managers and assessment of entire refuge complexes, while still being fundamentally applicable to the day-to-day habitat management practices of each individual refuge. While initial analysis has only addressed the vegetation assessment component to establishment of long-term monitoring protocol, it could provide insight into bird communities on the refuge. By placing bird survey observation
points based on the initial habitat classification, refuge personnel could monitor changes to bird species presence and community composition as vegetation changes. These shifts could be detected by the combined vegetation assessment protocol across the observation points as habitat changes occur.

There are logistical constraints that need to be considered before finalizing bird survey observation points. First, there is limited accessibility to the proposed wilderness area, and these entrances might require up to one hour of travel to access and return from. Survey routes and locations need to be established with this consideration of travel time to survey start points since survey would begin well before 5:00 a.m. through most of the summer. Safety of the researchers is also a restricting factor because of individual proximity to assistance on the refuge and proximity of the refuge itself to emergency resources. Finally, the protocol should begin to reflect the capabilities of a refuge with limited staffing if these monitoring efforts are expected to be continued after the conclusion of this phase of research collaborations between the USFWS and FHSU.

This protocol would provide the best opportunity to conduct long-term monitoring that accomplishes the previously mentioned objectives:

- Identifying bird species responses to vegetation qualities in each survey season,
- Identify vegetation communities present on the refuge and be able to detect habitat changes on the refuge.
- Identifying bird communities that exist according to each habitat classification and how they respond should habitat classes change during the study.
If the proposed protocol successfully accomplishes these objectives, then it would provide a clear path forward for establishing standardized monitoring of upland breeding birds that could be implemented across many of the refuges within the Great Plains.

**Additional Benefits of Imagery**

The remote-sensing imagery could be used opportunistically used to inform other management decisions on refuges. In two examples from visual inspection of the 27 June 2018 imagery from CLNWR, I showed the potential of the imagery to perform counts of muskrat huts (Figure 15) and identify areas of potential heavy livestock use or downy brome (*Bromus tectorum*) invasion (Figure 16). In the case of muskrat hut counts, not only would biologists be able to monitor furbearing mammal population dynamics, but they could also meet other major refuge management goals by assessing the quality and availability of potential nesting sites for Canada goose populations. The potential areas of heavy use/exotic species invasion could provide refuge managers with the evidence needed to defer grazing into an area, set up temporary fencing until range conditions in the over-utilized area were improved, or guide targeted herbicide application efforts. Imagery captured at other times of the year might have sufficient resolution to relative abundance of waterfowl (Laliberte & Ripple, 2003; LaRue et al., 2014). Other possibilities could include water availability assessments for migrating shorebirds, and evidence of unlawful activity occurring within refuge boundaries (Liu, 2006).

**Conclusions**

In conclusion, a study of protocol for long-term monitoring assessments at CLNWR is the ideal next step in FHSU’s collaborative research with the USFWS. This
study would beta test the effectiveness of procedures refined through the research completed at QNWR. It would ultimately provide the most valuable insight for incorporating remote-sensing of properties within the National Wildlife Refuge System into long-term monitoring of their existing and changing ecological communities. The capabilities of remote-sensing imagery, while not limited to long-term grassland bird monitoring, are a feasible tool to develop standardized refuge assessment protocol across the region. Most importantly, my study could help refuge personnel continue to improve Comprehensive Conservation Plans and refuge management practices to more appropriately manage the flora and fauna that use the refuge system, even under shrinking budgets and staff.


Table 1: Explanation of vegetation covariates measured at each observation point for sampling conducted 13-26 July 2016, 5-13 June 2017, 24-27 July 2017, and 18-22 June 2018.

<table>
<thead>
<tr>
<th>Covariate</th>
<th>Units</th>
<th>Tool</th>
<th>Measurement Proximity to Observation Point</th>
<th>Classification</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nearest Tree</td>
<td>Meters</td>
<td>Range Finder</td>
<td>At point</td>
<td>Distance to nearest single stemmed woody vegetation greater than 25 decimeters in height out to 250 meters</td>
</tr>
<tr>
<td>Nearest Shrub</td>
<td>Meters</td>
<td>Range Finder</td>
<td>At point</td>
<td>Distance to woody vegetation less than 25 decimeters in height out to 250 meters</td>
</tr>
<tr>
<td>Mean Percent Grass Cover</td>
<td>Cover Class Midpoint*</td>
<td>1x1 meter Daubenmire Frame</td>
<td>50 meters in each Cardinal direction</td>
<td>Mean of cover class midpoints for percent cover of all live grasses</td>
</tr>
<tr>
<td>Mean Percent Forb Cover</td>
<td>Cover Class Midpoint*</td>
<td>1x1 meter Daubenmire Frame</td>
<td>50 meters in each Cardinal direction</td>
<td>Mean of cover class midpoints for percent cover of all live forbs</td>
</tr>
<tr>
<td>Mean Percent Shrub Cover</td>
<td>Cover Class Midpoint*</td>
<td>1x1 meter Daubenmire Frame</td>
<td>50 meters in each Cardinal direction</td>
<td>Mean of cover class midpoints for percent cover of all live shrubs</td>
</tr>
<tr>
<td>Mean Percent Litter Cover</td>
<td>Cover Class Midpoint*</td>
<td>1x1 meter Daubenmire Frame</td>
<td>50 meters in each Cardinal direction</td>
<td>Mean of cover class midpoints for percent cover of non-free-standing dead vegetation from previous growing seasons</td>
</tr>
<tr>
<td>Mean Percent Standing Dead Vegetation Cover</td>
<td>Cover Class Midpoint*</td>
<td>1x1 meter Daubenmire Frame</td>
<td>50 meters in each Cardinal direction</td>
<td>Mean of cover class midpoints for percent cover of free-standing dead vegetation from previous growing seasons</td>
</tr>
<tr>
<td>Mean Percent Bare Ground</td>
<td>Cover Class Midpoint*</td>
<td>1x1 meter Daubenmire Frame</td>
<td>50 meters in each Cardinal direction</td>
<td>Mean of the lowest visible band at a distance of four meters from the pole and one meter above the substrate in each Cardinal direction</td>
</tr>
<tr>
<td>Visual Obstruction</td>
<td>0.25 Decimeters</td>
<td>Robel Pole</td>
<td>50 meters in each Cardinal direction</td>
<td>Mean of the tallest observed litter material at four meters from the Robel pole in each Cardinal direction</td>
</tr>
<tr>
<td>Litter Depth</td>
<td>Millimeters</td>
<td>Metric Ruler</td>
<td>50 meters in each Cardinal direction</td>
<td>Mean of the tallest observed grass plant within a four-meter radius of the Robel pole in each Cardinal direction</td>
</tr>
<tr>
<td>Tallest Grass</td>
<td>0.25 Decimeters</td>
<td>Metric Ruler</td>
<td>50 meters in each Cardinal direction</td>
<td>Mean of the tallest observed forb plant within a four-meter radius of the Robel pole in each Cardinal direction</td>
</tr>
<tr>
<td>Tallest Forb</td>
<td>0.25 Decimeters</td>
<td>Metric Ruler</td>
<td>50 meters in each Cardinal direction</td>
<td>Mean of the tallest observed forb plant within a four-meter radius of the Robel pole in each Cardinal direction</td>
</tr>
</tbody>
</table>
Table 1 continued:

<table>
<thead>
<tr>
<th>Covariate</th>
<th>Units</th>
<th>Tool</th>
<th>Measurement Proximity to Observation Point</th>
<th>Classification</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tallest Shrub</td>
<td>0.25 Decimeters</td>
<td>Metric Ruler</td>
<td>50 meters in each Cardinal direction</td>
<td>Mean of the tallest observed shrub plant within a four-meter radius of the Robel pole in each Cardinal direction</td>
</tr>
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<td>Water Presence</td>
<td>Presences/Absence</td>
<td>1x1 meter Daubenmire Frame</td>
<td>50 meters in each Cardinal direction</td>
<td>Occurrence of standing water within any of the frame placements</td>
</tr>
<tr>
<td>Mean Percent Native Vegetation Cover</td>
<td>Cover Class Midpoint*</td>
<td>1x1 meter Daubenmire Frame</td>
<td>50 meters in each Cardinal direction</td>
<td>Mean of cover class midpoints for percent cover of plants historically present in the region</td>
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<tr>
<td>Mean Percent Exotic Vegetation Cover</td>
<td>Cover Class Midpoint*</td>
<td>1x1 meter Daubenmire Frame</td>
<td>50 meters in each Cardinal direction</td>
<td>Mean of cover class midpoints for percent cover of plants introduced to the region through anthropogenic means</td>
</tr>
<tr>
<td>Mean Percent Cover Other Matter</td>
<td>Cover Class Midpoint*</td>
<td>1x1 meter Daubenmire Frame</td>
<td>50 meters in each Cardinal direction</td>
<td>Mean of cover class midpoints for percent cover of other matter occurring within the frame (ex: fecal excrement, course woody debris)</td>
</tr>
</tbody>
</table>

*: cover classes with their respective midpoints: 0.1-4.9%, 2.5%; 5.0-24.9%, 15%; 25.0-49.9%, 37.5%; 50.0-74.9%, 62.5%; 75.0%-94.9%, 85%; 95.0-100%, 97.5%.
Table 2: Comparison of selected single-covariate occupancy model results for the best performing field-measured covariates collected 5-12 June 2017 and derived covariates from remote-sensed multi-spectral imagery captured 10 June 2017 for Bell’s vireo (*Vireo bellii*).  

<table>
<thead>
<tr>
<th>Vegetation Covariate</th>
<th>delta AIC</th>
<th>AIC Weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>Remote-Sensed Shrub Cover</td>
<td>-</td>
<td>0.9644</td>
</tr>
<tr>
<td>Visual Obstruction</td>
<td>6.92</td>
<td>0.0303</td>
</tr>
<tr>
<td>Remote-Sensed Herbaceous Cover</td>
<td>12.22</td>
<td>0.002</td>
</tr>
<tr>
<td>Percent Bare Ground</td>
<td>12.28</td>
<td>0.002</td>
</tr>
<tr>
<td>Percent Shrub</td>
<td>15.2</td>
<td>0</td>
</tr>
<tr>
<td>Remote-Sensed Deciduous Tree Cover</td>
<td>27.59</td>
<td>0</td>
</tr>
<tr>
<td>Remote-Sensed Wetland Vegetation Cover</td>
<td>35.9</td>
<td>0</td>
</tr>
<tr>
<td>Remote-Sensed Water Cover</td>
<td>40.89</td>
<td>0</td>
</tr>
<tr>
<td>Tallest Shrub</td>
<td>102.97</td>
<td>0</td>
</tr>
<tr>
<td>Distance to Nearest Shrub</td>
<td>169.15</td>
<td>0</td>
</tr>
</tbody>
</table>
Table 3: Comparison of selected single-covariate occupancy model results for the best performing field-measured covariates collected 5-12 June 2017 and derived covariates from remote-sensed multi-spectral imagery captured 10 June 2017 for grasshopper sparrow (*Ammodramus savannarum*).

<table>
<thead>
<tr>
<th>Vegetation Covariate</th>
<th>delta AIC</th>
<th>AIC Weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>Litter Depth</td>
<td>-</td>
<td>0.167</td>
</tr>
<tr>
<td>Remote-Sensed Shrub Cover</td>
<td>0.6</td>
<td>0.123</td>
</tr>
<tr>
<td>Tallest Grass</td>
<td>0.7</td>
<td>0.117</td>
</tr>
<tr>
<td>Tallest Forb</td>
<td>1.87</td>
<td>0.065</td>
</tr>
<tr>
<td>Remote-Sensed Deciduous Tree Cover</td>
<td>1.9</td>
<td>0.064</td>
</tr>
<tr>
<td>Remote-Sensed Herbaceous Cover</td>
<td>2.51</td>
<td>0.047</td>
</tr>
<tr>
<td>Percent Grass Cover</td>
<td>2.52</td>
<td>0.047</td>
</tr>
<tr>
<td>Remote-Sensed Water Cover</td>
<td>4.45</td>
<td>0.018</td>
</tr>
<tr>
<td>Remote-Sensed Wetland Vegetation Cover</td>
<td>4.77</td>
<td>0.015</td>
</tr>
</tbody>
</table>
Table 4: Comparison of selected single-covariate occupancy model results for the best performing field-measured covariates collected 5-12 June 2017 and derived covariates from remote-sensed multi-spectral imagery captured 10 June 2017 for upland sandpiper (*Bartramia longicauda*).

<table>
<thead>
<tr>
<th>Vegetation Covariate</th>
<th>delta AIC</th>
<th>AIC Weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>Remote-Sensed Deciduous Tree Cover</td>
<td>-</td>
<td>0.760</td>
</tr>
<tr>
<td>Remote-Sensed Shrub Cover</td>
<td>3.09</td>
<td>0.162</td>
</tr>
<tr>
<td>Percent Bare Ground</td>
<td>7.13</td>
<td>0.021</td>
</tr>
<tr>
<td>Water Presence/Absence</td>
<td>7.24</td>
<td>0.020</td>
</tr>
<tr>
<td>Percent Forb Cover</td>
<td>8.26</td>
<td>0.012</td>
</tr>
<tr>
<td>Distance to Nearest Tree</td>
<td>9.44</td>
<td>0.007</td>
</tr>
<tr>
<td>Distance to Nearest Shrub</td>
<td>9.57</td>
<td>0.006</td>
</tr>
<tr>
<td>Remote Sensed Water Cover</td>
<td>10.15</td>
<td>0.005</td>
</tr>
<tr>
<td>Remote-Sensed Wetland Vegetation Cover</td>
<td>11.82</td>
<td>0.002</td>
</tr>
<tr>
<td>Remote-Sensed Herbaceous Cover</td>
<td>12.47</td>
<td>0.002</td>
</tr>
<tr>
<td>Percent Shrub Cover</td>
<td>12.57</td>
<td>0.001</td>
</tr>
</tbody>
</table>
Table 5: Comparison of selected single-covariate occupancy model results for the best performing field-measured covariates collected 5-12 June 2017 and derived covariates from remote-sensed multi-spectral imagery captured 10 June 2017 for warbling vireo (*Vireo gilvus*).

<table>
<thead>
<tr>
<th>Vegetation Covariate</th>
<th>delta AIC</th>
<th>AIC Weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>Distance to Nearest Tree</td>
<td>-</td>
<td>0.997</td>
</tr>
<tr>
<td>Distance to Nearest Shrub</td>
<td>11.87</td>
<td>0.003</td>
</tr>
<tr>
<td>Remote-Sensed Wetland Vegetation Cover</td>
<td>15.99</td>
<td>0</td>
</tr>
<tr>
<td>Tallest Forb</td>
<td>22.2</td>
<td>0</td>
</tr>
<tr>
<td>Remote-Sensed Herbaceous Cover</td>
<td>22.54</td>
<td>0</td>
</tr>
<tr>
<td>Remote-Sensed Water Cover</td>
<td>32</td>
<td>0</td>
</tr>
<tr>
<td>Remote-Sensed Deciduous Tree Cover</td>
<td>32.66</td>
<td>0</td>
</tr>
<tr>
<td>Remote Sensed Shrub Cover</td>
<td>34.04</td>
<td>0</td>
</tr>
</tbody>
</table>
Table 6: Comparison of selected single-covariate occupancy model results for the best performing field-measured covariates collected 5-12 June 2017 and derived covariates from remote-sensed multi-spectral imagery captured 10 June 2017 for western kingbird (*Tyrannus verticalis*).

<table>
<thead>
<tr>
<th>Vegetation Covariate</th>
<th>delta AIC</th>
<th>AIC Weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>Remote-Sensed Shrub Cover</td>
<td>-</td>
<td>0.947</td>
</tr>
<tr>
<td>Percent Bare Ground</td>
<td>7.22</td>
<td>0.026</td>
</tr>
<tr>
<td>Remote-Sensed Deciduous Tree Cover</td>
<td>9.74</td>
<td>0.007</td>
</tr>
<tr>
<td>Remote-Sensed Herbaceous Cover</td>
<td>9.78</td>
<td>0.007</td>
</tr>
<tr>
<td>Tallest Shrub</td>
<td>9.84</td>
<td>0.007</td>
</tr>
<tr>
<td>Visual Obstruction</td>
<td>11.65</td>
<td>0.003</td>
</tr>
<tr>
<td>Tallest Forb</td>
<td>12.66</td>
<td>0.002</td>
</tr>
<tr>
<td>Remote-Sensed Wetland Vegetation Cover</td>
<td>13.48</td>
<td>0.001</td>
</tr>
<tr>
<td>Remote-Sensed Water Cover</td>
<td>14.20</td>
<td>0.001</td>
</tr>
</tbody>
</table>
Table 7: Reflectance ranges of the eight spectral bands captured by Worlview2 satellite’s multi-spectral lens.

<table>
<thead>
<tr>
<th>Band Name</th>
<th>Center Wavelength (nm)</th>
<th>Minimum Lower Band Edge (nm)</th>
<th>Maximum Upper Band Edge (nm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>MS1 (NIR1)</td>
<td>835</td>
<td>770</td>
<td>895</td>
</tr>
<tr>
<td>MS2 (Red)</td>
<td>660</td>
<td>630</td>
<td>690</td>
</tr>
<tr>
<td>MS3 (Green)</td>
<td>545</td>
<td>510</td>
<td>580</td>
</tr>
<tr>
<td>MS4 (Blue)</td>
<td>480</td>
<td>450</td>
<td>510</td>
</tr>
<tr>
<td>MS5 (Red Edge)</td>
<td>725</td>
<td>705</td>
<td>745</td>
</tr>
<tr>
<td>MS6 (Yellow)</td>
<td>605</td>
<td>585</td>
<td>625</td>
</tr>
<tr>
<td>MS7 (Coastal)</td>
<td>425</td>
<td>400</td>
<td>450</td>
</tr>
<tr>
<td>MS8 (NIR 2)</td>
<td>950</td>
<td>860</td>
<td>1040</td>
</tr>
</tbody>
</table>
Table 8: Proportion of raster points assigned to each raster confidence class after Maximum Likelihood Classification was performed on multi-spectral imagery captured 27 June 2018 at Crescent Lake National Wildlife Refuge.

<table>
<thead>
<tr>
<th>Confidence Range of Correct Classification</th>
<th>Number of Raster Points</th>
<th>Proportion of Raster Points</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.999-1.00</td>
<td>221308</td>
<td>0.008</td>
</tr>
<tr>
<td>0.995-0.998</td>
<td>199022</td>
<td>0.007</td>
</tr>
<tr>
<td>0.975-0.994</td>
<td>516992</td>
<td>0.018</td>
</tr>
<tr>
<td>0.95-0.974</td>
<td>786267</td>
<td>0.027</td>
</tr>
<tr>
<td>0.9-0.94</td>
<td>1422459</td>
<td>0.049</td>
</tr>
<tr>
<td>0.75-0.89</td>
<td>3578601</td>
<td>0.124</td>
</tr>
<tr>
<td>0.5-0.74</td>
<td>5232169</td>
<td>0.181</td>
</tr>
<tr>
<td>0.25-0.49</td>
<td>5397887</td>
<td>0.187</td>
</tr>
<tr>
<td>0.1-0.24</td>
<td>4337079</td>
<td>0.150</td>
</tr>
<tr>
<td>0.05-0.09</td>
<td>2002022</td>
<td>0.069</td>
</tr>
<tr>
<td>0.025-0.04</td>
<td>1407894</td>
<td>0.049</td>
</tr>
<tr>
<td>0.01-0.024</td>
<td>1274095</td>
<td>0.044</td>
</tr>
<tr>
<td>0.005-0.9</td>
<td>641363</td>
<td>0.022</td>
</tr>
<tr>
<td>0-0.004</td>
<td>1900226</td>
<td>0.066</td>
</tr>
</tbody>
</table>
Figure 1: Quivira National Wildlife Refuge, the location for initial development of long-term monitoring protocol, in central Kansas, United States.
Figure 2: Hierarchical cluster analysis dendrogram of bird survey observation points at Quivira National Wildlife Refuge using complete Bray distance measurements for bird presence/absence in 2016. The dendrogram was cut into five clusters for further comparisons.
Figure 3: Hierarchical cluster analysis dendrogram of bird survey observation points at Quivira National Wildlife Refuge using complete Bray distance measurements for bird presence/absence in 2017. The dendrogram was cut into five clusters for further comparisons.
Figure 4: Hierarchical cluster analysis dendrogram of bird survey observation points at Quivira National Wildlife Refuge using complete Bray distance measurements for bird presence/absence in 2018. The dendrogram was cut into five clusters for further comparisons.
Figure 5: Ordination plot of bird survey observation points at Quivira National Wildlife Refuge after nonmetric multidimensional scaling using Bray distance measurements of presence/absence of bird species for A) 2016 (Stress = 0.221), B) 2017 (Stress = 0.202), and C) 2018 (Stress = 0.210). Points are colored by five groups defined by hierarchical cluster analysis for the same data from each year. Agreements between the ordination and cluster analysis for each year indicate structure to the bird communities on the refuge for all three survey seasons.
Figure 6: Ordination plot of bird survey observation points at Quivira National Wildlife Refuge after nonmetric multidimensional scaling using Bray distance measurements of presence/absence of bird species for A) 2016 (Stress = 0.221), B) 2017 (Stress = 0.202), and C) 2018 (Stress = 0.210). Points are colored by four habitat classes defined by the refuge’s comprehensive conservation planning using the National Vegetation Classification Standard. Strong disagreement between the ordinations and NVCS habitat classifications indicate that bird community structure is not reflective of NVCS based management practices.
Figure 7: Ordination plot of bird survey observation points at Quivira National Wildlife Refuge after nonmetric multidimensional scaling using Euclidian distance measurements of eight standardized field-measured vegetation measurement variables for A) July 2016 (Stress = 0.233), B) June 2017 (Stress = 0.222), and C) June 2018 (Stress = 0.181). Points are colored by five groups defined by hierarchical cluster analysis for the same data (Stress = 0.233). Groups for each year were relatively muted compared to the clarity of the bird communities in Figure 5 but still easily distinguishable.
Figure 8: Ordination plot of bird survey observation points at Quivira National Wildlife Refuge after nonmetric multidimensional scaling using Euclidian distance measurements of eight standardized vegetation measurement variables for A) July 2016 (Stress = 0.233), B) June 2017 (Stress = 0.222), and C) June 2018 (Stress = 0.181). Points are colored by four habitat classes defined by the refuge’s comprehensive conservation planning using the National Vegetation Classification Standard. Strong disagreement between the ordinations and NVCS habitat classifications indicate that NVCS classes do not depict the actual vegetation communities occurring on the refuge.
Figure 9: Ordination plot of bird survey observation points at Quivira National Wildlife Refuge after nonmetric multidimensional scaling using Bray distance measurements of presence/absence of bird species for species for A) 2016 (Stress = 0.221), B) 2017 (Stress = 0.202), and C) 2018 (Stress = 0.210). Points are colored by the five groups defined by hierarchical cluster analysis of eight standardized vegetation measurement variables for A) July 2016, B) June 2017, and C) June 2018. Bird communities were unresponsive to vegetation classes derived from field-measured measurements for any season.
Figure 10: Ordination plot of bird survey observation points at Quivira National Wildlife Refuge after nonmetric multidimensional scaling using Euclidian distance measurements with standardized values of vegetation measurement variables included in the combined sampling model for June 2017. Points were colored by the eight clusters identified using hierarchical cluster analysis for the same data (Stress = 0.177).
Figure 11: Crescent Lake National Wildlife Refuge in western Nebraska. The focus area for the proposed study consists primarily of proposed wilderness area.
Figure 12: Multi-spectral image captured by Worldview2 satellite on 27 June 2018 of the proposed focus area for development of long-term monitoring protocol at Crescent Lake National Wildlife Refuge in western Nebraska.
Figure 13: Maximum Likelihood supervised classification into five reflectance signatures for multi-spectral imagery captured 27 June 2018 at Crescent Lake National Wildlife Refuge.
Figure 14: Map of 200-meter by 200-meter tessellation polygons designated into five habitat classes based on analysis of Maximum Likelihood Classification of multi-spectral imagery captured 27 June 2018 at Crescent Lake National Wildlife Refuge.
Figure 15: Map of muskrat huts in and around Deer Lake at Crescent Lake National Wildlife Refuge using multi-spectral imagery of the refuge captured 27 June 2018 that demonstrates the multiple potential capabilities of multi-spectral imaging for the US Fish and Wildlife Service.
Figure 16: Areas of suspected overgrazing or exotic species invasion identified using multi-spectral imagery of Crescent Lake National Wildlife Refuge captured 27 June 2018 that demonstrate the expanded potential capabilities of multi-spectral imaging for the US Fish and Wildlife Service (i = 8.2 hectares, ii = 8.6 hectares, iii = 5.1 hectares). Polygons i and iii are areas within the refuge that appear to have potentially problematic vegetation. Polygon ii is on private land adjacent to the refuge that might be a potential source of invasion of exotic plants on the refuge.
I, Kyle William Schumacher, agree to license Fort Hays State University to electronically disseminate my thesis/field study entitled

Incorporating Multispectral Imaging Into Long-Term Upland Breeding Bird Monitoring

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Printed Name

Signature