Application of Thermal and Ultraviolet Sensors in Remote Sensing of Upland Ducks

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Application of Thermal and Ultraviolet Sensors in Remote Sensing of Upland Ducks

by

Matthew W. Helvey

B.S. Clemson University, 2015

A thesis submitted in partial fulfillment of the requirements for the degree of Master of Science in the Chester F. Carlson Center for Imaging Science College of Science Rochester Institute of Technology

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the Remote Sensing of Upland Ducks

by

Matthew W. Helvey

Submitted to the
Chester F. Carlson Center for Imaging Science
in partial fulfillment of the requirements
for the Master of Science Degree
at the Rochester Institute of Technology

Abstract

Detection, mapping, and monitoring of wildlife populations can provide significant insight
into the health and trajectory of the ecosystems they rely on. In fact, it was not until recently that
the benefits of wetland ecosystems were fully understood. Unfortunately, by that point, the United
States had removed more than 50% of its native wetlands. The Prairie Pothole Region in North
America is the premier breeding location for ducks; responsible for producing more than 50% of
the North American ducks annually. The current survey methods for obtaining duck population
counts are accomplished primarily using manned flights with observers manually identifying and
counting the ducks below with coordinated ground surveys at a subset of these areas to obtain
breeding pair estimates. The current industry standard for in situ assessment of nest locations for
reproductive effort estimates is known as the “chain drag method”, a manually intensive ground
survey technique. However, recent improvements to small unmanned aerial systems (sUAS),
coupled with the increased performance of lightweight sensors provide the potential for an
alternative survey method. Our objective for this study was to assess the feasibility of utilizing
sUAS based thermal longwave infrared (LWIR) imagery for detecting duck nests and ultraviolet
(UV) imagery to classify breeding pairs in the Prairie Pothole Region. Our team deployed a DRS
Tamarisk 640 LWIR sensor aboard a DJI Matrice 600 hexa-copter at Ducks Unlimited’s Coteau
Ranch in Sheridan County, North Dakota, to obtain the thermal imagery. At the ranch, 24 nests
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and terrain, were varied between flights and the impact that each had on detection accuracy was examined. Each nest image was min-max normalized and contrast enhanced using a high-pass filter, prior to input into the detection algorithm. We determined that the variable with the highest impact on detection accuracies was altitude. We were able to achieve detection accuracies of 58% and 69% for the 80m and 40m flights, respectively. We also determined that flights in the early morning yielded the highest detection accuracies, which was attributed to the increased contrast between the landscape and the nests after the prairie cooled overnight. Additionally, the detection accuracies were lowest during morning flights when the hens might be off the nests on a recess break from incubation. Therefore, we determined that with increases in spatial resolution, the use of sUAS based thermal imagery is feasible for detecting nests across the prairie and that flights should occur early in the morning while the hens are on the nest, in order to maximize detection potential. To assess the feasibility of classifying breeding duck pairs using UV imagery, our team took a preliminary step in simulating UAS reflectance imagery by collecting 260 scans across nine species of upland ducks with a fixed measurement geometry using an OceanOptic’s spectroradiometer. We established baseline accuracies of 83%, 83%, and 76% for classifying age, sex, and species, respectively, by using a random forest (RF) classifier with simulated panchromatic (250-850nm) image sets. When using imagery at narrow UV bands with the same RF classifier, we were able to increase classification accuracies for age and species by 7%. Therefore, we demonstrated the potential for the use of sUAS based imagery as an alternate method for surveying nesting ducks, as well as potential improvements in age and species classification using UV imagery during breeding pair aerial surveys. Next steps should include efforts to extend these findings to airborne sensing systems, toward eventual operational implementation. Such an approach could alleviate environmental impacts associated with in situ surveys, while increasing the scale (scope and exhaustiveness) of surveys.
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Chapter 1

Introduction

1.1 CONTEXT

Wetlands are among the most endangered ecosystems in the world [1]. It was not until recently that the many benefits of wetland ecosystems were truly understood. To preserve and improve the remaining wetland ecosystems, extensive and intentional management of key areas is required. Part of proper ecosystem management is monitoring and understanding wildlife populations that use important habitats such as wetlands. By doing this, we can gain great insight into the health and trajectory of both the species themselves and the ecosystems they rely on. The Prairie Pothole Region is a major wetland area and one of the most threatened ecosystems in North America losing more than 50,000 acres of native prairie ever year that impact wetland quality [2]. It is also the primary breeding location for ducks; responsible for producing more than 50% of the North American ducks annually [3]. The current survey methods for duck populations are accomplished primarily using manned flights with two observers identifying and recording counts of the ducks below at the start of the breeding season [4]. This information is coupled with intense ground surveys at a subset of wetlands. The current industry standard for locating nest sites to estimate reproductive effort is known as the chain drag method, a manually intensive ground survey technique [3]. Recent improvements to small unmanned aerial systems (sUAS), coupled with the increased performance of lightweight sensors provide the potential for an alternative
The application of remotely sensed thermal longwave infrared imagery has already been successfully demonstrated for detecting a variety of other animals including species of panthers, livestock, insects, and birds [6][7][8]. Additionally, its feasibility for quickly and accurately identifying active nests has been demonstrated for the Northern Lapwing (*Vanellus vanellus*) and even for small songbird nests [9][10]. Based on this previous work, we hypothesized that sUAS-based thermal imagery can be utilized to identify active duck nests across the prairie. Ultraviolet reflectance (250-450nm) in avairy plumage has been demonstrated as ubiquitous across all species and is more significant than visual reflectance (450-850nm) [11][12]. Based on this, we hypothesized that ultraviolet imagery can be utilized to improve species classification of breeding duck pairs.

### 1.2 OBJECTIVES

- **Objective 1:** Assess the feasibility of utilizing sUAS based remote thermal (LWIR) imagery to detect active duck nests
- **Objective 2:** Assess the feasibility of utilizing remotely sensed ultraviolet (250-400nm) images to classify breeding duck pairs

### 1.3 THESIS LAYOUT

#### 1.3.1 Chapter 2: Background

This chapter provides a comprehensive overview of the high level problem (waterfowl population surveys), the current methods for addressing that problem and areas of improvement (mid-winter survey and waterfowl breeding population survey), and alternate survey methods utilizing UAVs that have been successfully demonstrated for other wildlife species.

#### 1.3.2 Chapter 3: Duck Nest Detection with Thermal Imagery

This chapter is an expansion of a paper that was published in the proceedings from the IEEE Geoscience and Remote Sensing Society (IGARSS) 2020 conference. It focuses on addressing Objective 1, while investigating the effects of sensor altitude, time of day, and terrain on correct nest detection rates.
1.3.3 Chapter 4: Classification of Breeding Duck Pairs with UV Imagery

This chapter explores the potential effectiveness of utilizing ultraviolet (UV) imagery with well-known algorithms to automatically classify the sex, age, and species of observed breeding duck pairs. This is written as an independent chapter to be used as a foundation for future scientific publication.

1.3.4 Chapter 5: Summary

This chapter provides a summary of the work done and conclusions of this thesis as well as provides ideas for future work and improvements moving forward.

1.4 SCIENTIFIC CONTRIBUTIONS

- Demonstrated the potential of sUAS based thermal imagery for accurately identifying duck nests and explored the impact of spatial resolution, time of day, and habitat on those accuracies.
- Demonstrated the capability of sUAS based imagery for classifying species, age, and sex of breeding duck pairs with winter plumage.
- Demonstrated the viability of utilizing ultraviolet (250-400nm) imagery for classifying breeding duck pairs during aerial surveys with higher accuracies when compared to visible (400-900nm) imagery.
- Validated the leading theory that a main biophysical purpose of ultraviolet reflectance in aviary plumage is for mate signaling and selection.
Chapter 2

Background

2.1 FOREWORD

This chapter provides a comprehensive overview of the need for waterfowl population surveys, the current survey methods for addressing that problem (mid-winter survey and waterfowl breeding population survey), the potential areas of improvement, and alternate survey methods utilizing small unmanned aircraft systems (sUAS) that have been successfully demonstrated for other wildlife species. Subsequent chapters focus on specific scientific approaches to address duck population monitoring and are intended to be stand-alone chapters for dissemination in this thesis, i.e., some overlap in background information is to be expected.

2.2 THE NEED FOR WETLANDS

Within the past 100 years, the wetlands of North America have been on both extremes of the conservation spectrum. Prior to the 1970s, the United States actively drained and removed wetlands across the country, mainly because they were only seen as a hinderance to development and a hazard to health [13]. Wetlands are home to a large variety of life. This can include diseases (e.g., diarrhea, cholera, typhoid fever, schistosomiasis, and malaria) and the creatures that carry
them, which can be harmful to humans [14]. Additionally, wetlands present barriers to transportation and require expensive development for integration into current infrastructure with development costs up to two times higher when compared to dry land [15]. However, wetlands also contain fertile soil because they contain rich biodiversity and biomass, thereby making them ideal for agricultural expansion and resulting in a desire to drain them. The United States lost over 50% of its palustrine (freshwater marsh) or estuarine (saltwater marsh) wetlands as a result of the intentional drainage efforts prior to 1970 [13]. This represents a substantial loss, when considering that 8% of the landmass in the contiguous United States is currently classified as wetlands. Many such practices were considered “conservation efforts” due to the perceived benefits that removal brought as well as the limited understanding of the benefits that the native wetlands provided. It is now known that wetlands are in fact responsible for many beneficial processes. They break down toxic chemicals, including those found in many pesticides, into useful forms, they protect neighboring ecosystems from flooding by temporarily storing the large influxes of water, and they are also responsible for filtering and recharging local ground water supplies [16]. Wetlands even have a large role in the global climate change arena. They act as carbon sinks, both from developing their own biomass as well as storing carbon that has flown in from watershed sources [17]. Finally, they are critical for supporting the growth and success of numerous and diverse species of fauna and wildlife [1].

For these reasons, wetlands in the United States have moved to a protected state with regulations like the 1985 U.S. Farm Bill (Public Law 99-198) and the Clean Water Act of 1970 (Public Law 92-500) being written to reduce the drainage and damage to the ecosystems [18] [19]. Even with all the new protections in place, wetlands are still among the most endangered ecosystems worldwide [1]. It is in this context that the monitoring and researching key species in wetlands is critically important.
2.3 BENEFITS OF MONITORING DUCK POPULATIONS

Monitoring wildlife populations and breeding patterns within an ecosystem is useful in providing part of the total picture of that ecosystem’s health [20]. The careful monitoring of duck populations is required for several reasons. Proper management of wetland areas is required to reduce and reverse the degradation of these ecosystems which, in turn, necessitates a need for timely and efficient methods for monitoring ecosystem health. For example, upland ducks are a major group of animals that rely on the habitats provided by the Prairie Pothole Region, a depressional palustrine (freshwater marsh) wetland spanning across the northern plains of the United States and Canada. The Prairie Pothole Region is the nesting grounds for more than 50% of all North American ducks and one third of all North American waterfowl, while only making up 10% of potential breeding grounds in North America [21] [3]. By monitoring the populations of breeding duck pairs, we can further our understanding of the type and the health of the various ecosystems in the Prairie Pothole Region [22]. Tracking changes among the populations also allows us to monitor the impacts of local industry, agriculture, and infrastructure development on
those ecosystems.

Individual states are legally obligated to obtain waterfowl population counts to aid in the management of migratory bird species under the Migratory Bird Treaty Act (16 U.S.C. 703–712, MBTA). The MBTA, signed by the United States, Canada, Mexico, Japan, and Russia, prohibits the “take” (including killing, capturing, selling, trading, and transport) of protected migratory bird species without prior authorization by the Department of Interior U.S. Fish and Wildlife Service [23]. Developing and understanding accurate population counts is therefore necessary to determine limits on hunting for these protected bird species.

Finally, the state of North Dakota and its local businesses rely on the proper management of bird populations to continue supporting tourism, North Dakota’s third largest industry with more than $3B in annual revenue. Many tourists in North Dakota visit for the abundant hunting, bird watching, and sightseeing in all 53 counties across the state. Additionally, tourism is the fifth largest employment sector in the state. In 2019, North Dakota saw a 6% increase in revenue from non-resident hunters while only seeing a 1.8% increase in revenue from tourism overall [24].

It thus follows that accurate monitoring of duck populations through timely surveys is essential for managing the species as well as their habitats. The successful management of ducks and their habitats will benefit the entire ecosystem, the health and diversity other wildlife species, and in turn will improve the revenue and enjoyment that those resources bring to residents and visitors alike.

2.4 DUCKS AND THEIR NESTS

The Prairie Pothole Region is the primary nesting habitat for several species of ducks including: blue-winged teal (Spatula discors), green winged teal (Anas crecca), gadwall (Mareca strepera), mallard (Anas platyrhynchos), northern pintail (Anas acuta), northern shoveler (Spatula clypeata), American wigeon (Mareca americana), ring-necked duck (Aythya collaris), canvasback (Aythya valisineria), lesser scaup (Aythya affinis), and redhead (Aythya americana) [21] [25]. The primary breeding season for these ducks begins with nest building, egg-laying, and incubation of eggs from April through July followed by raising the young from June to August. Throughout the breeding season, the female ducks are responsible for incubating and caring for the eggs and then
caring for the young chicks as they develop [26].

Most species of ducks in the region build their nests on land, typically within 200m of water, and lay clutches of between 4 and 13 eggs per nest. There is significant variety in nest location choices among duck species from wetland edges or floating vegetation to the uplands, but they all utilize local vegetation for protection and camouflage. When building the nests in the uplands, the females will scrape a bowl into the ground with their feet and then pull loose vegetation into and around the nest to construct sidewalls and covering. After the nest is completed, the females will begin laying eggs at a rate of one egg per day until the clutch of eggs is complete. While laying eggs, the female will line the nest with loose vegetation and bend tall vegetation over the nest for added concealment. After laying the eggs but prior to incubation, the female will pluck her own down and pad it around the eggs to provide protection and insulation. For ducks like the blue-winged teal and the mallard, the interior diameter of the nest bowls typically ranges between 14-22cm, the exterior diameter ranges between 26-29cm, and the depth ranges between 3-15cm [26]. In Figure 2.2(a), we can see an active clutch of eggs after vegetation has been pulled back to expose the interior. We can compare that with the other image (Figure 2.2(b)) and see how well the females camouflage the nests with surrounding vegetation.

Figure 2.2. Exposed duck nest (a) (left) and undisturbed duck nest (b) (right). When looking at the exposed nest, we can see how much larger the nest is inside when compared to the entrance. Also, note the dense cover made of vegetation and feathers that the female pulls over the nest to camouflage and protect it from predators and the elements. It is evident that these nest characteristics present a non-trivial problem when considering detection and monitoring via remote sensing.
2.5 CURRENT METHODS FOR SURVEYING DUCK POPULATIONS

Obtaining accurate and timely population counts over large areas is difficult. As the need for these data has grown, the survey methods have evolved and continue to improve. In the United States, the major duck population surveys were initially developed to provide insight into population and breeding health of various species in support of the Migratory Bird Treaty Act of 1918 [27]. While the benefits of using aircraft to assist in these surveys might seem obvious now, it wasn’t until 1931 that Frederick C. Lincoln was able to convince the U.S. Army to fly him and a photographer over the Potomac River for the first aerial survey [28]. In 1935, the first mid-winter survey (MWS) utilizing aerial crews was conducted. Still in use today, the MWS aims to obtain total population counts by monitoring the four major flyways, or migratory paths, during the mass migrations that occur between mating seasons [4]. The other major annual waterfowl survey conducted in North America is the waterfowl breeding population survey (WBPS). The WBPS occurs over the breeding habitats and aims to capture the number of breeding pairs to provide an understanding of breeding potential [29].

Both surveys are primarily conducted using aerial collection techniques and are complimented in small areas with ground reference campaigns. The aerial surveys are conducted by pairs of pilot-biologists flying over the search areas at speeds of 193km/hr and altitudes of 30-50m AGL. The biologists are each responsible for accurately counting every bird within 200m of their side of the aircraft, all while flying and navigating. They provide counts and identification verbally which is captured by a recording device and transcribed into a database through an automated system on the ground. Obtaining aerial counts is a strenuous task with several inherent sources of counting errors. First, scanning the search area while flying at the designated speed means each biologist must count every bird within a 10,000m² area the aircraft passes over every second. The birds can also be in motion or begin flying, thus leading to double counting, or missed birds. Finally, because the tasks are observationally strenuous and the flights are long, observer fatigue can impact counting accuracies [29]. Each of these sources of errors might be mitigated by using remotely sensed imagery with automated detection algorithms.

Because the nests are small and well hidden from predators, the current industry standard for locating nest sites is a ground survey technique referred to as the chain drag method [3]. This search method employs a team of two all-terrain vehicles (ATVs) driving in parallel with a 50-
60m steel chain towed between them as seen in Figure 2.3. When the chain passes over or hits the back of the nesting hens, the hens will flush, revealing the nest location. A spotter will note the flushing location, while another member searches the area for the nest location. Diagrams of the search pattern and vehicle spacing are shown in Figure 2.4. This search method is manpower- and time-intensive, hindering largescale nest count efforts and total accuracies [3]. The ability to correctly detect nest location from aerial imagery could drastically reduce time and increase search areas, as well as increasing overall nest count accuracies.

Figure 2.3. The chain drag in progress - the imprint in the vegetation of the chain being towed between the two ATVs is clearly visible. Also note the clear tracks visible from previous paths across the terrain highlighting the disruption to the habitat [30].
Figure 2.4. Diagrams of an ideal drag search pattern (left) and proper chain drag interval (right). Notice how important coordination between vehicles is while dragging to ensure proper spacing and complete area coverage. Also note how searching directly on and around ponds and wetlands is impossible with this method [3].

2.6 REMOTE SENSING IN ECOLOGY

The introduction and development of photography has benefitted many industries, including wildlife and ecological monitoring. Being able to remotely monitor and observe wildlife has several benefits. It reduces the cost for observing large areas or for conducting observations over long periods of time [31]. Using remote triggers with photography equipment can reduce the disruptions caused by repeated in-person observations, as well as allowing for the capture of rare or infrequent events [32]. By placing the imaging systems aboard aerial and orbiting platforms, large areas can be observed in a timely manner. On a large scale, utilizing space-based satellite imagers with large spatial resolutions allows for global monitoring and trending of habitats. The downside to the inherently low resolution of satellite-based remote sensing systems is that their applications to wildlife monitoring are limited to cases where observable changes to the environments are induced by the species [33] [34]. This means, for monitoring migratory waterfowl who do not drastically change their landscapes, lower altitude aerial systems with high resolution imagery are required.
Small unmanned aerial vehicles/systems (sUAV/sUAS) have several benefits over manned aerial systems. They can fly grids and patterns with higher spatial precision than their manned aircraft equivalents [35]. Additionally, autonomous flight software does not suffer from distractions and fatigue that can affect human pilots [35]. sUAS furthermore have a large flexibility in form factor, while removing unnecessary weight and space to hold and protect human passengers. Because of this, they can efficiently carry many types of sensors and can bridge the gap in spatial and temporal scales between ground and traditional aircraft surveys [5]. The utilization of sUAS with detection algorithms for wildlife surveys has been shown to reduce both time and costs while increasing detection and classification accuracies when compared to manned aerial surveys. Chrétien et al., for example, examined four different species of mammals using multispectral imagery, validating the potential for sUAS based remotely sensed imagery in wildlife monitoring and management [6]. Most importantly, the use of unmanned systems could completely eliminate the primary cause of work-related deaths for field biologists, namely aircraft crashes [5].

While the use of sUAS for monitoring ducks is still being investigated and developed, its potential has already been successfully demonstrated with other avian species. Díaz-Delgado et al. utilized sUAS based multispectral imagery to provide accurate estimates of population (colony size) and productivity (number of chicks born) for slender-billed gulls (*Chroicocephalus genei*). They obtained high resolution (pixel sizes of 0.5-0.8cm) RGB imagery of the nesting islands utilizing an Olympus EPM2 digital camera mounted aboard a sUAS. Their flight lines had 80% overlap to ensure highly accurate ortho-mosaicking. The authors manually identified and labeled nesting, standing, and flying birds to provide as training data into several classification algorithms. The classifiers they chose were a support vector machine and a random forest, both of which we will expand on in Chapter 4. Using those classifiers, they were able to achieve overall accuracies of 82% and 98% for population and productivity, respectively [8]. Israel and Reinhard demonstrated the effectiveness of using sUAS-based thermal imagery in accurately detecting northern lapwing (*Vanellus vanellus*) nests in open fields. They flew a sUAS over fields containing known nest sites in a mosaicking pattern with only 30% overlap, thus leading to a high uncertainty in identified nest locations (±5m at 40m altitude). Instead of an RGB sensor, they utilized an uncooled Vanadium Oxide microbolometer, which produces 7.5-13.5µm panchromatic imagery with 3.6cm GSD from an altitude of 40m. After mosaicking the imagery, they applied a custom
Microbolometer Optimization algorithm to enhance nest signature contrast by 10-50% before visually identifying nest locations. With their flight technique and image processing methodology, they were able to detect 93% of the known nests [9].

Based on these successful demonstrations and the reduction of error sources that are inherent to human involvement, we sought to explore specific methods and challenges of using UAS-based remote imagery to conduct duck population and nest surveys and to provide foundational work in understanding sensor, flight, and algorithm requirements for automated detection and classification of duck nests and breeding pairs.
Chapter 3

Duck Nest Detection with Thermal Imagery

3.1 FOREWORD

This chapter is an expansion of a paper that was published in the proceedings from the IEEE Geoscience and Remote Sensing Society (IGARSS) 2020 conference. It focuses on addressing Objective 1, while investigating the effects of sensor altitude, time of day, and search area on correct nest detection rates.

3.2 INTRODUCTION

Monitoring wildlife populations in an environment can provide insight into the health, stresses, and productivity of that ecosystem. Waterfowl (ducks and geese) are monitored and studied extensively, since they are important game species in North America. Given that ducks are migratory birds protected under the Migratory Bird Treaty Act, industry is also required to evaluate impacts of any development they may have on migratory bird populations and their habitat in environmental impact statements and evaluate any incidental take that occurs as a result of changes they make to the landscape (e.g., wind turbines, changes to wetlands, installation of well pads for gas and oil extraction) [27]. Therefore, it is critical to develop methods that can accurately and efficiently assess breeding duck numbers to facilitate wildlife conservation efforts.
and help companies meet compliance requirements with federal wildlife laws. More than 50% of ducks are spawned in the Prairie Pothole Region of North America, making this region particularly important for efficiently and accurately obtaining breeding population estimates [3].

Our objective was to assess the feasibility of utilizing remotely sensed infrared (8-14µm) images to detect duck nests in North Dakota within the Prairie Pothole Region and make recommendations about criteria needed for using this technique to monitor upland nesting ducks.

### 3.3 BACKGROUND

Thermal imaging has benefitted a variety of fields including biology and ornithology [7][9]. When imaging objects on Earth in the longwave infrared spectrum, we are typically measuring self-emitted electromagnetic (EM) radiation as opposed to reflected radiation originating from another source such as the sun. One way to describe a material’s ability to emit radiation is to compare it to a blackbody radiator. A blackbody radiator perfectly absorbs and emits electromagnetic radiation with a direct relationship to its temperature as seen in the following equation.

\[
L = \frac{\sigma T^4}{\pi}
\]

In this equation, \( \sigma \) represents the Stefan-Boltzmann constant: \( 5.67 \times 10^{-8} \text{W} \cdot \text{m}^{-2} \cdot \text{K}^{-4} \), \( T \) represents the material’s surface temperature in units Kelvin, and \( L \) is the resulting radiance in \( \text{W/m}^2 \) [36].

H. T. Hammel (1956) discovered that the thermal emissivity of biological and organic tissue roughly approximates that of a blackbody radiator. Bird plumage from species belonging to Galloanserinae was shown to have an emissivity of 96-98% and avian eggshells were shown to have an emissivity of 92-96% [37]. Additionally, the color of the plumage does not influence the emissivity in the thermal spectrum [38]. Prior to 1998, thermal imagery was rarely used for surveying wildlife populations. At that time, Havens and Sharp demonstrated that thermal imagery can be utilized for detecting wildlife with more accuracy than a red-green-blue (RGB) image. In their paper, they demonstrate the feasibility of utilizing remotely sensed mid-wave thermal infrared imagery (3-5 µm) to detect and identify panthers (\textit{Puma concolor coryi}) [7]. Israel and Reinhard (2017) sought to take advantage of modern thermal imagers that have been optimized to fly
onboard small unmanned aerial systems (sUAS). They flew a sUAS over several fields where northern lapwing (Vanellus vanellus) were nesting. Lapwings are small birds which nest in the open on the ground, thus making them ideal for thermal imaging. Israel and Reinhard were able to detect 93% of lapwing nests in their plots when flying at altitudes of 40m above ground level and demonstrated an increase in accuracy while the hens were off nest, which was then attributed to the hot eggs exhibiting a higher contrast than the hen’s insulating plumage [9].

When using thermal imagery for detection, having a high thermal contrast is important. Ducks’ body temperatures typically range from 38-43°C while the prairie temperatures typically ranged from around 10°C at night to 32°C during the day [16] [36]. Without any other factors, this would give us an average contrast of up to 30°C during night and 8°C during the day. This previous work led us to believe that we should be able to observe a strong thermal radiation contrast between the nests and the environment’s background temperature [40].

3.4 METHODS

3.4.1 Location

For the past 5 years, the University of North Dakota (UND) Fisheries and Wildlife Biology program, in partnership with Ducks Unlimited, Inc. (DU), has monitored nesting duck populations on DU’s ranch in Sheridan County, North Dakota. The ranch is divided into 4 search areas that we will refer to as plots (Figure 3.1). To obtain the nest locations on the ranch, the UND team used the chain drag method outlined in Chapter 2 [3]. After locating a nest, which we will refer to as sites, the team would mark it with orange flagging as well as with a flag positioned 5m north of the site. Additionally, they used the ArcCollector app with cellphone GPS for geotagging site locations [41]. This works well when operating in the field, but unfortunately for our research, the cellphone GPS has an accuracy of ±9m in any direction [42]. Therefore, we had to identify nests solely based on visual cues in a search area in each image to confirm the exact location.
Figure 3.1. The plot locations on the Coteau Ranch in Sheridan, ND. Each plot area was physically fenced off from each other area. Plot-1 had the steepest terrain features with more hills and valleys than the other two. Additionally, it had more, but smaller temporary wetlands throughout. Plot-2 had several large wetlands among shallow rolling hills and Plot-3 had minimal wetlands among a single large valley.

Flights were conducted over known nest sites in plots 1, 2, and 3 (Figure 3.1). Plot-1 consisted of several rolling hills with pockets of temporary wetlands in some of the valleys. Plot-2 had flatter terrain but larger, more permanent wetlands, while Plot-3 consisted of a single valley between two large hills with few wetlands within the plot boundaries.

3.4.2 Dates, Times, and Weather

To maximize the number of active nest sites in each plot during our flights, the team decided on a two-week window during the location’s historically peak nesting period in June. The
week of 3-7 June 2019 was selected for data collections due to favorable weather forecast. The actual weather data can be seen in Table 3.1 and the hourly wind speeds for a typical day are shown in Table 3.2.

Table 3.1. Weather data in Wing, ND from 2-8 June 2020 obtained from weather station: KNDBALDW3. Note the only precipitation during the collection period occurred on the morning of 4 June. Additionally, we can see that the temperatures all fell within the expected values for the week [39].

<table>
<thead>
<tr>
<th>Date</th>
<th>Temperature (° F)</th>
<th>Dew Point (° F)</th>
<th>Humidity (%)</th>
<th>Wind Speed (mph)</th>
<th>Pressure (Hg)</th>
<th>Precipitation (in)</th>
</tr>
</thead>
<tbody>
<tr>
<td>June</td>
<td>Max</td>
<td>Avg</td>
<td>Min</td>
<td>Max</td>
<td>Avg</td>
<td>Min</td>
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<tr>
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<td>79</td>
<td>63.8</td>
<td>49</td>
<td>56</td>
<td>47.7</td>
<td>42</td>
</tr>
<tr>
<td>3</td>
<td>89</td>
<td>72.8</td>
<td>56</td>
<td>65</td>
<td>58.2</td>
<td>51</td>
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<td>87</td>
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<td>53</td>
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<td>6</td>
<td>86</td>
<td>74.4</td>
<td>57</td>
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<td>50.9</td>
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<tr>
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<td>68</td>
<td>59.2</td>
<td>51</td>
<td>60</td>
<td>52.3</td>
<td>42</td>
</tr>
</tbody>
</table>

Table 3.2. Wind speeds (mph) in Wing, ND on June 5th, 2019. The data from this day is representative of wind activity throughout the week. Note that after 12pm, wind speeds climb to levels outside of the DJI Matrice 600 hexa-copter’s maximum operating limit of 17mph [39].

Aside from the early morning flights on June 4th, which followed significant thunderstorms, every other flight had clear skies. The flights were conducted from 0500-1300 for several reasons. First, we expected the highest thermal contrast between the warm nests and the cold background to occur after the ground cooled off overnight. Second, during that period, the nesting hens would temporarily vacate the nest for feeding, theoretically removing a layer of insulation and increasing the potential for higher contrasting temperatures [43][9]. Finally, winds were typically calm in the mornings up until 0900 where they gradually increased through the afternoon [39]. Due to hardware limitations, we were unable to collect data with winds higher than 8m/s (approximately 17mph), so flights were planned to be completed prior to 1200 each day [44].
Three main flight time blocks were selected for each plot, early morning (0400-0600), morning (0600-0800), and midday (1100-1300). We expected a higher contrast in measured thermal signal between the nesting sites and their background during the early morning. This is because the prairie will cool off overnight while the nests stay a relatively constant temperature (around 37°C) [43]. The difference in the two early flights was to capture images of the nests while the hens were nesting (early morning) and while the hens may be off the nest (morning) [45][43]. However, a dense ground fog that persisted through the morning was one weather related issue that complicated the June 5th flights (see Results).

3.4.3 Unmanned Aerial System (UAS)

RIT’s UAS research lab travelled to ND, providing the flight hardware, collection sensors, and flight expertise needed to conduct the experiment. The airframe used during this experiment was Dà-Jiāng Innovations (DJI’s) Matrice 600 Pro hexa-copter (Figure 3.2). The Matrice weighs 10kg and can carry a full payload of 6kg [44]. It has a maximum range of 5.5km but legally must remain within the pilot’s line of sight throughout the flight. This was not a problem at the ranch since the terrain, while hilly, was clear of visual obstructions to every border.

Figure 3.2. Matrice 600 with UAS Lab’s custom payload prepared for flight operations at Ducks Unlimited’s Coteau Ranch in Sheridan County, North Dakota, United States of America. The payload consists of multispectral VNIR, LiDAR, panchromatic LWIR, hyperspectral VNIR, panchromatic red-edge, and GPS/IMU sensors.
The RIT UAS lab has developed a custom payload consisting of six data collection sensors: Headwall Nano VNIR (visual-near infra-red) imager, Velodyne VLP-16 LiDAR (light detection and ranging), DRS (Diagnostic/Retrieval Systems Technologies) Tamarisk 640 LWIR (long wave infra-red) microbolometer, Mako G-419 RGB (red/green/blue) imager, MicaSense Red Edge M imager, and Applanix APX15 GPS (global positioning system) and IMU (inertial measurement unit). We utilized the Tamarisk for obtaining thermal imagery for this experiment, the Mako for collecting context images, and the GPS/IMU for precise flight location tracking.

The DRS Tamarisk 640 utilizes an uncooled vanadium oxide (VOx) microbolometer detector in a 640x480 pixel array. Unlike a CCD which measures incident photons on the detector, a microbolometer measures the change in temperature of the detector that is a result of the amount of IR radiation absorbed by the absorbing material (VOx). This temperature change is indirectly determined by measuring the change in resistance through the detector as shown (see Figure 3.3). This system operates as a panchromatic imager across the 8-14µm range with a thermal sensitivity of <50mK (NEΔT) at room temperature. A 16.7mm lens was used in flight resulting in a 1.01mrad IFOV and a F# of 1.25 and the exposure was set to 33.2ms. This system provided a ground sampling distance (GSD) of 3cm at 100ft (30.48m) [46].

Figure 3.3. The cross-section of a microbolometer sensor [47]. Note how incoming IR radiation is absorbed and the resulting thermal change is what is measured. Because of the material properties of the absorber, a direct relationship between the measured temperature difference and the actual irradiance can be determined.
The Mako G-419 is a 4.2-megapixel RGB camera built around a 2048x2048 complementary metal–oxide–semiconductor (CMOS) sensor with a pixel size of 5.5x5.5µm. The CMOS is based on measuring changes in voltage at each pixel instead of passing the charge through the array to a readout like a CCD. This results in higher readout speeds at the cost of complexity and fixed noise. At full resolution, the Mako can record up to 26.3 frames per second. At an altitude of 100ft (30.48m), the Mako has a GSD of 1cm [48]. This high resolution and frame rate paired with RGB images makes the Mako ideal for providing context to the thermal imagery during each flight.

The Applanix APX-15-UAV is a combined Global Navigation Satellite System (GNSS) inertial system that has been integrated with the lab’s DJI Matrice 600 UAS. GNSS is an umbrella term that includes all the available GPS type satellites across the globe [49]. This integrated package also provides a real-time kinematic (RTK) correction to the GNSS acquired positioning data. The APX-15 reports positional accuracies of 1.5-3.0m prior to processing but when the RTK is applied, accuracies increase to 2-5cm [50].

### 3.4.4 Flight Design

Aside from takeoff and landing, the UAS flew autonomously following a programmed flight path. The flights were planned and controlled using Universal Ground Control Software (UGCS) [51]. The maximum flight time for the DJI Matrice 600 with the full payload is 18 minutes [44]. Therefore, full plot coverage during a single flight was unfeasible. To address the flight time issue, unique flight paths were developed to optimize image collection while controlling several variables: altitude, time of day, and site location. The chosen solution was a single altitude flight that would visit each nest site individually, perform a slow pass for the thermal image collect, and then quickly move to the next site (Figure 3.4).
As mentioned previously, ducks that were the focus of this work typically have nests with bowl sizes of 15-23cm across. Therefore, our minimum GSD should be no larger than 5cm (1/3 the smallest nest size) to ensure at least one full nest pixel in the image. We chose flight altitudes of 40m and 80m, resulting in GSDs of 3.9 cm and 7.9cm respectively, so that we could obtain images with higher and lower resolutions than required. We determined a maximum velocity of 3m/s to maintain a pixel blur of less than one pixel during image capture. This was done by dividing the estimated GSD by the exposure time of the sensor. Two pools of water were used for calibrating the thermal imagery during post processing. One pool was left at ambient temperature while the other was cooled using ice. Temperatures from both pools were recorded using automated temperature loggers at regular five-minute intervals throughout the collections.

3.4.5 Data Management and Processing

Following the flights, the collected raw sensor data was processed by RIT’s UAS lab into images with timestamps and geolocations which were obtained from the Applanix APX-15. Next, we imported all the imagery into Python and converted into standardized arrays prior to inputting to the detection algorithms. Three main processing steps were used for the automated detection

Figure 3.4. Flight plan for plot-1. This flight plan was designed to optimize number of site visits per flight because of the 20-minute flight time limitation. Between sites, the drone would fly at 10m/s and over the nests, flight speed was reduced top 3 m/s to maintain a motion blur of less than 1 pixel.
algorithm. First, a minmax normalization was applied to the images, allowing for a generic threshold to be applied later. The minmax normalization was done using the following equation [52]:

\[ z_{i,j} = \frac{x_{i,j} - \min(x)}{\max(x) - \min(x)} \]

In this equation, \( z \) represents the normalized image and \( x \) represents the original image. Three normalizations to maximum and minimum values were examined: locally per image, globally per flight, and globally across all flights. Based on the success that Israel’s team had, the algorithm included a step to enhance the contrast for each image [9]. This was done by converting the images into the frequency domain using a discrete Fourier transformation, applying a 101x101 element high-pass filter, and returning to spatial domain using an inverse discrete Fourier transform. Finally, a binary decision threshold was applied to each image highlighting any pixels that were hotter than the background. This threshold was designed to highlight any pixels that were statistically high by more than one standard deviation in a local region.

3.5 RESULTS AND DISCUSSION

The UND team located and marked 24 duck nests prior to the data collection week: 15 nests in Plot-1, five nests in Plot-2, and four nests in Plot-3. Additionally, after each day of data collection, the team verified that each of the marked nests were still active and survived predation. These nests were found in a variety of terrain with variance in vegetation coverage over the nests sites, two of which can be seen in Figure 2.2. An important aspect to note in the photos is how well covered and hidden the nests were. This is an issue that we will expand on in a later section. Across the 24 sites, a total of 134 site collects were completed, but 15 of the collects on the morning of June 4th were unusable due to dense fog that covered the area. Fog is defined as a cloud that touches the ground and consists of condensed water vapor droplets suspended in the air. In addition to emitting their own thermal radiation, these individual droplets will reflect and refract the radiation that travels through the fog and when the cloud reaches a sufficient density, it completely obscures transmission across all spectral regions [53]. The effect of the fog on the images can be seen in Figure 3.6. Of note is the globally normalized image showing signals close to 0. The results from the image processing steps are shown visually in Figure 3.5.
CHAPTER 3. DUCK NEST DETECTION WITH THERMAL IMAGERY

Figure 3.5. Positive (Top) and negative (Bottom) nest detections. Top image is from 0400 on 4 June 2019, flown at 40m over Plot 1. Bottom image is from 1132 on 4 June flown at 80m over Plot 2. Note, each image should have a single clear nest visible.

Figure 3.6. Foggy morning results. It is obvious from these images that noise is obscuring the signal from the target. This is due to the low temperature and high variability of water droplets that make up the fog. Note the global normalized image showing that the entire image is close to 0 signal.

Using the detection algorithm on a dataset consisting of a 50/50 split of images containing a nest and images without a nest, we obtained an overall detection accuracy of 64%. With a kappa value of 0.28, this result is significantly better than the 50% accuracy we would expect if we had used random change to predict nest presence. It was also significantly lower than what we hypothesized based on previous work and calculated flight values.

In Table 3.3, we can see the variation in detection rates for each of the three variables in this dataset: date, time, and plot number. Of the three areas, Plot 3 demonstrated the most detection stability between collects, thus indicating that variations in the nests themselves were most important. Summaries of each variable are shown in Table 3.4.
CHAPTER 3. DUCK NEST DETECTION WITH THERMAL IMAGERY

Table 3.3. Nest detection results. The colored bands correspond to flights conducted within each of the three plots. Note the absence of data from the morning of 5 June. From these data, we can see that changes in altitude resulted in the most consistent variations in accuracy.

<table>
<thead>
<tr>
<th>Date</th>
<th>Total Nests</th>
<th>Positive ID</th>
<th>Accuracy</th>
<th>Time</th>
<th>Altitude</th>
<th>Total Nests</th>
<th>Positive ID</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
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<td>32</td>
<td>5</td>
<td>58%</td>
<td>952</td>
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<td>16</td>
<td>5</td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td>1040</td>
<td>80m</td>
<td>16</td>
<td>0</td>
<td>50%</td>
</tr>
<tr>
<td>4-Jun-19</td>
<td>67</td>
<td>19</td>
<td>64%</td>
<td>400</td>
<td>40m</td>
<td>12</td>
<td>6</td>
<td>75%</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
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<td>40m</td>
<td>15</td>
<td>4</td>
<td>63%</td>
</tr>
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<td></td>
<td></td>
<td></td>
<td>615</td>
<td>80m</td>
<td>15</td>
<td>1</td>
<td>53%</td>
</tr>
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<td></td>
<td></td>
<td></td>
<td>1110</td>
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<td>5</td>
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<tr>
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<td></td>
<td></td>
<td></td>
<td>1132</td>
<td>80m</td>
<td>5</td>
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</tr>
<tr>
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<td>75%</td>
<td>1155</td>
<td>40m</td>
<td>4</td>
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<td>75%</td>
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<td></td>
<td></td>
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</tr>
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<td></td>
<td></td>
<td></td>
<td>604</td>
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<td>4</td>
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</tbody>
</table>

Table 3.4. Variable detection rate summaries. Note the variable with the most significant impact on detection accuracy was altitude. This is due to the lower than expected thermal LWIR contrast resulting from the small nest openings, high vegetation coverage, and insulating plumage of the hen. Additionally, we can see that the morning flights yielded higher accuracies due to the higher contrast between the cooled prairie and the warm nests but we also see a decrease in accuracies during the time when hens might be on recess.

<table>
<thead>
<tr>
<th>Altitude</th>
<th>Total Nests</th>
<th>Positive ID</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>40m</td>
<td>60</td>
<td>23</td>
<td>69%</td>
</tr>
<tr>
<td>80m</td>
<td>59</td>
<td>10</td>
<td>58%</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Time</th>
<th>Total Nests</th>
<th>Positive ID</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Early Morning</td>
<td>31</td>
<td>12</td>
<td>69%</td>
</tr>
<tr>
<td>Morning</td>
<td>38</td>
<td>8</td>
<td>61%</td>
</tr>
<tr>
<td>Mid-day</td>
<td>50</td>
<td>13</td>
<td>63%</td>
</tr>
</tbody>
</table>

From these results, we can see that the variable with the highest impact on detection rate was altitude. While the 40m flights yielded a detection accuracy of 69%, the 80m flights had an accuracy of 58%. This is indicative that the strongest factor to account for when using this method is spatial resolution of the system. A potential reason for the low accuracies is if the nest contrast was being lost in the noise of the natural variance of the prairie. To assess this, we examined the variance of a uniform area by calibrating the imagery using the temperature monitored pools and computing the statistics of a uniform area in the prairie. Through our analysis, we determined the prairie’s temperature variance to be 0.5°C, an order of magnitude above the sensor’s sensitivity of 0.05°C and below the expected nest contrast of 8-30°C (day-night). To increase the accuracy using the same methods, one would need to fly at even lower altitudes or utilize a higher resolution.
imaging system. The most significant reason these results differ from our expectations is because one of our initial assumptions was incorrect. While the nests are roughly 20cm across on the inside, the hens pull vegetation and plumage around and over the nest both while they are incubating and when they leave. This means that the visible part of the nest is much smaller or nonexistent when viewed from above (see Figure 2.2). In addition to obscuring the line-of-sight, the added cover is designed to insulate the nest, thereby reducing the temperature on the outer surface of the nest.

When examining the effect that time of flight has, we can see that early flights do increase detection rates and that flights while the hen was on nest have higher accuracy than those without. When comparing the nesting process of ducks to the lapwing bird study by Israel and Reinhard, a specific difference is obvious. Lapwing birds’ nest in the open and leave the nest uncovered when the hens temporarily leave. Ducks on the other hand take care to cover and insulate the nest from predators and the elements unless they are flushed by a threat. Therefore, even though the hot eggs would provide higher contrast than the warm ducks, they are not visible in the duck nests. This led to our conclusion that when obtaining thermal imagery of duck nests, spatial resolution is the most important factor and that flights should be conducted in early morning while the hens are still incubating (sitting on) the nest to obtain the highest contrast.

3.6 CONCLUSIONS

The wetlands of the world are some of the most endangered habitats. Accurate and timely duck nest counts in the Prairie Pothole Region provides necessary data to understand the health of the population and habitat as well as the impacts from external sources. The current industry standard for nest detection, the chain drag method, is manpower intensive and can be invasive to the landscape. Therefore, the goal of our research was to determine the feasibility of utilizing remotely sensed imagery with an automated detection algorithm to detect nest locations quickly and accurately. Our team hypothesized that thermal imagery could be used due to the high expected thermal contrast between the nests and the background. To test this, our team deployed a DRS Tamarisk 640 LWIR aboard a DJI Matrice 600 hexa-copter and obtained imagery over a ranch in the Prairie Pothole Region of ND from 3-7 June 2019. By comparing imagery collected across 24 flights against four variables, we were able to determine that automated nest detection using sUAS-based longwave thermal infrared imagery is feasible if the spatial resolution can be improved,
either by flying at lower altitudes or by utilizing higher resolution imaging sensors. Additionally, when obtaining thermal infrared imagery of duck nests, the images should be captured early in the morning while the hen is on nest, to optimize longwave thermal contrast. We suggest future research explore impacts of vegetation in combination with altitude to determine limitations of thermal sensors for detecting grassland nesting birds.
Chapter 4

Classification of Breeding Duck Pairs with UV Imagery

4.1 FOREWORD

This chapter explores the potential effectiveness of utilizing ultraviolet (UV) imagery with well-known classification algorithms to automatically label sex, age, and species of observed breeding duck pairs. It is written as an independent chapter to be used as a foundation for future scientific publication. As such, several areas are repeated from the overall background that was provided in Chapter 2.

4.2 INTRODUCTION

Major habitat loss has occurred across the United States due to increases in agriculture, industry, and deforestation. In turn, this loss paired with over-harvesting pre- and early-1900s led to significant decreases in wildlife populations including waterfowl. Because this problem was larger than the state level, Congress established the Migratory Bird Act of 1913 which grew into the Migratory Bird Treaty Act (MBTA) when Canada and Mexico joined [28]. The MBTA’s goal was to manage bird populations through careful monitoring and by limiting the “take” of certain
species. Several waterfowl surveys were developed to understand and monitor population trends and overall species health [27]. These surveys provide indispensable information that is used to track and monitor waterfowl populations across the United States and provide insight into the environments they inhabit.

In 1935, the first mid-winter waterfowl survey (MWS) was conducted. This survey is conducted in each of the four flyways (a collection of migratory routes) through the contiguous United States during January and provides general population counts and distributions in wintering habitats. Additionally, the U.S. Fish & Wildlife Service has conducted waterfowl breeding population surveys during the summer months across 2 million square miles of known breeding habitats since 1955 [54]. Both surveys utilize a combination of air- and ground-based counts to efficiently develop a comprehensive population count of the entire area. Air crews comprised of a pilot and an observer fly over the landscape at speeds of around 193 km/hr and altitudes of 30-50m above ground to conduct the aerial surveys [29]. Both crew members are trained biologists and bird spotters and each member is responsible for identifying waterfowl within 200m on the left and right sides of the aircraft. The observations are made verbally during flight, recorded, and are then transcribed using software after landing. In a subset of areas, ground crews also walk through and conduct a manual survey to use for comparison and validation of the aerial surveys [29]. Several issues arise from conducting the aerial surveys when using manned fixed wing aircraft. First, it is difficult for a human observer to accurately obtain species counts from the air while flying quickly over large survey areas with wide varieties of species. This challenging process is strenuous on the aircrew who fly for hours at a time and begin to suffer from observer fatigue which further affects the count accuracy [29]. Second, birds are not always stationary and worse yet, do not remain stationary for long periods of time. They can be flying over the landscape and they often flush when the aircraft flies over, further complicating the count accuracies [29]. Finally, these low, slow flights are dangerous and are the leading cause of work-related fatalities for biologists [55]. These issues arguably can be alleviated using automated detection algorithms on remotely sensed imagery over the same collection areas.

Hong et al. (2019) investigated the feasibility of utilizing remotely sensed imagery in combination with deep learning algorithms for the automated detection of birds in various environments. Their dataset was comprised of high resolution (1cm GSD) RGB imagery of both wild birds and decoys. When using the Faster R-CNN Inception v2 neural network, they were able
to achieve average precision values of 0.95. One of the previously mentioned issues that their algorithm did not tackle was that of moving birds. They theorized that it would be possible to detect the moving objects between images and eliminate the redundant counts of flying birds. While their model was designed for bird detection, it demonstrated a distinct potential for applications in population counts and species classification [56]. With that foundation laid, we can investigate the impact of using different parts of the EM spectrum than the visible (400-700nm).

Sir John Lubbock, an accomplished scientist from England, published the book Observations on Ants, Bees, and Wasps in 1881. In this book, he is credited with the first demonstration of a living organism perceiving ultraviolet (UV) light. He specifically examined ants, who instinctively move their larva away from direct radiation to protect them. Lubbock demonstrated that action by using a prism to shine different colors of light on the larva. He discovered the ants continued to move the larva away from the apparent dark region located past the blue and violet regions of the spectral dispersion [57]. This indicated that the ants could perceive, in some manner, that there was radiation present outside the perception possible to humans. Huth and Burkhardt (1972), in turn, demonstrated UV sensitivity in hummingbirds for the first time [58]. Other scientists went on to demonstrate the same sensitivity in many species and it is now accepted as a general property of the vision of non-nocturnal birds [59]. To demonstrate the physical basis for the UV sensitivity that had been demonstrated in other experiments, Chen et al. (1984) designed an experiment to measure the spectral sensitivity of bird retinas. They demonstrated that birds contain a 4th cone class of photoreceptors that is centered around 370nm. They also demonstrated that birds have an increased sensitivity to UV radiation compared to radiation in the visible spectrum (400-700nm) [12].

In addition to their ability to see UV radiation, birds have plumage which reflects strongly in the UV region. A main function of this strong reflectance is that it adds to their color and patterning for signaling when trying to find a sexual mate [60] [61] [62]. Studying this further, Eaton and Lanyon (2003) demonstrated the ubiquity of avian UV plumage reflectance. They showed that plumage in every avian family reflects significant amounts of UV light, with 63.3% of all plumage having higher than 5% reflectance and 13.6% of plumage having UV reflectance more than 20%. When looking at specific colors, most of the brown and red plumage had less than 5% reflectance while other colors had more than 5% reflectance in the UV. Additionally, they showed that the UV plumage occurs in cryptic patches and dimorphism among birds [11]. This
previous work led us to hypothesize that utilizing UV imagery will improve species classification accuracies when compared to RGB and panchromatic imagery. Summarily, we hypothesize that sUAS based remotely sensed imagery can be utilized as an improved aerial survey method and that UV imagery will improve automated classification of upland ducks’ species, sex, and age.

Our objective thus was to assess the effectiveness of utilizing ultraviolet (250-400nm) remotely sensed imagery to classify ducks’ species, sex, and age. We hypothesized that the use of UV imagery would increase classification accuracies for age, sex, and species when compared to results from visible spectrum imagery.

4.3 METHODS

4.3.1 Overall Design

The first step in this experiment was to obtain image samples to use to build training and testing datasets and thereby provide input to the classification algorithms. Without any remotely sensed UV imagery available, we had to develop simulated image sets. Hyperspectral images were generated by utilizing a point spectrometer in a scanning fashion to obtain a coarse resolution image of a duck’s back. A point spectrometer works by collecting a single beam of light, diffracting it with either a prism or a grating, and measuring the diffracted light landing on a one-dimensional array of detector elements [63]. The point spectrometer we used was Ocean Optics’ USB4000 with a grating that evenly dispersed light into the 200-905nm spectral range across 3648 detector elements [64]. We can see in Figure 4.1 that the light enters the spectrometer through the fiber optic port (1), is diffracted with the grating (5) and captured spectrally with the detector array (8).
The birds that were scanned had all been collected during the fall/early winter and were donated by hunters after harvesting. The ducks were frozen and shipped from North Dakota, USA, to RIT. The ducks remained frozen throughout the measurements to preserve them for multiple scans and further observations as well as to avoid biohazard issues. Biologists at UND used plumage characteristics from the body and wings to identify each ducks’ species, age, and sex [65]. The species, age, sex of the scanned ducks and totals for each of those categories are shown in Table 4.1. Several scanning approaches were considered and will be discussed next.
CHAPTER 4. CLASSIFICATION OF NESTING DUCK PAIRS WITH UV IMAGERY

Table 4.1. Scanned ducks breakdown. Each duck was collected during fall/early winter in ND. Several scans of each duck were gathered in various sensor orientations. As shown, for many species, only one sex or gender was collected. This forced the formation of single large datasets to classify species, sex, and age. This ultimately leading to increased confusion, particularly in sex classification due to the similarities in juvenile birds across species.

<table>
<thead>
<tr>
<th>Species</th>
<th>Sex</th>
<th>Age</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Male</td>
<td>Female</td>
<td>Juv</td>
</tr>
<tr>
<td>American Wigeon (Mareca americana)</td>
<td>12</td>
<td>0</td>
<td>12</td>
</tr>
<tr>
<td>Blue Wing Teal (Anas discors)</td>
<td>0</td>
<td>10</td>
<td>10</td>
</tr>
<tr>
<td>Canvasback (Aythya valisineria)</td>
<td>13</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Green Winged Teal (Anas carolinensis)</td>
<td>10</td>
<td>10</td>
<td>0</td>
</tr>
<tr>
<td>Lesser Scaup (Aythya affinis)</td>
<td>0</td>
<td>14</td>
<td>0</td>
</tr>
<tr>
<td>Mallard (Anas platyrhynchos)</td>
<td>0</td>
<td>10</td>
<td>0</td>
</tr>
<tr>
<td>Northern Pintail (Anas acuta)</td>
<td>10</td>
<td>10</td>
<td>20</td>
</tr>
<tr>
<td>Northern Shoveler (Anas clypeata)</td>
<td>10</td>
<td>10</td>
<td>10</td>
</tr>
<tr>
<td>Ring Necked Duck (Aythya collaris)</td>
<td>0</td>
<td>11</td>
<td>0</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td>55</td>
<td>75</td>
<td>52</td>
</tr>
</tbody>
</table>

4.3.2 Initial Attempts

We initially designed our methodology for scanning the ducks using the sun and sky as illumination sources to mimic UAS imagery as closely as possible. The experimental set up shown in Figure 4.2, was utilized to measure the duck in a grid format with a point spectrometer while using the UV radiation from the sun and sky as the source. While the signal-to-noise ratio was not an issue, the constant changes in cloud cover in the natural environment made the conversion from digital counts to reflectance unfeasible without obtaining reference measurements for every simulated pixel location. Additionally, under the suns’ warmth, the ducks began to thaw during the scans, releasing contaminants which then had to be removed, thereby adding additional time to the scanning process.
CHAPTER 4. CLASSIFICATION OF NESTING DUCK PAIRS WITH UV IMAGERY

Figure 4.2. Outdoor measurement experimental setup. This setup attempted to simulate the imagery as closely to field conditions as possible. Ultimately, this setup proved infeasible for the number of samples required due to the variability in cloud cover/illumination and the thawing of the frozen specimen due to increased scan lengths.

Figure 4.3. Scanning bed experimental setup. This setup aimed to automate the scanning method using a modified computer numerical control (CNC) machine with a custom probe holder. The custom holder allowed for consistent adjustments in the illumination and viewing measurement geometry.
The next experiment design utilized a scanning bed with a UV lamp and a spectrometer set into a hemispherical holder to allow for angular measurements to be collected (Figure 4.3). The scanning bed allowed for consistent and automated spatial measurements while the angular holder enabled examination of the impact that changes to viewing/illumination angle may have. During testing, we determined that the experimental setup was too sensitive to small changes in distance between the probe, the light source, and the target. Changes of less than 2% in distance resulted in more than 15% changes in digital counts. Without being able to determine the measurement of distance for every pixel, we would not be able to correct for this. Instead, we decided to fix the distance between the source, spectrometer, and surface using a probe and holder. Unfortunately, this approach was incompatible with the automated scanner system.

4.3.3 Experimental Design

The final experimental setup utilized a combined illumination and measurement probe with a holder, thus ensuring a constant distance measurement of the reference and the targets. We used a DH-2000-BAL Deuterium Tungsten Halogen lamp from Ocean Optics as the illumination source. This lamp combines a deuterium source with a tungsten halogen source into a single fiber optic output. A sharp spectral feature around 655nm, known as a D-alpha line or Balmer Alpha line, is inherent to all hydrogen and deuterium sources. This feature is caused by emissions resulting from electron transitions from the 3rd to 2nd energy levels [66]. Because this feature is so strong, it produces an unbalanced output between the deuterium and the halogen sources. By reducing the deuterium output enough that the feature balances with the halogen output, UV signal is also reduced to low enough levels to compromise the spectrometer signal-to-noise performance. However, one of the filters built into the DH-2000-BAL eliminates this feature completely, resulting in a spectrally smooth and temporally stable output as shown in Figure 4.4 [67]. The USB4000 UV spectrometer was integrated with the DH-2000-BAL using a bifurcated fiber optic cable in the configuration (see Figure 4.5). The fiber optic has higher than 90% transmission across the measured spectrum of 200-905nm.
Figure 4.4. DH-2000-BAL output in absolute irradiance vs. wavelength. Note the smooth area around 655nm where the D-alpha spectral feature usually lies. Additionally, we can observe the smooth and continuous output in the UV region of interest (250-400nm).

Figure 4.5. UV-Visible Reflection/Backscatter Probe Configuration. Note the fiber optic layout with the illumination transmitting through the six outer fibers and the spectrometer reading from the single inner fiber. This configuration allowed for even illumination and consistent measurement geometry when paired with a fixed probe holder.
This experimental setup was able to produce both stable and repeatable reflectance measurements with less than 0.5% variations in measured irradiance across a two-minute period between measurements after warming up for 10 minutes. As mentioned previously, each duck was scanned in a grid pattern across its back imitating an aerial image with a 2.5cm (~1in) GSD. The scanning pattern and associated pixel numbering scheme is shown in Figure 4.6. A dark measurement was obtained prior to each scan and then subtracted from each measurement to remove any constant system noise. Following the dark measurement but before scanning the duck, a reference scan was obtained using a Spectralon reflector which has higher than 95% reflectance across the measured spectrum [68]. This reference scan was required to convert the measured radiance in digital counts to a reflectance. Each duck scan took approximately two minutes including reference and dark measurements, setup, and cleanup. In total, we obtained 260 hyperspectral reflectance cubes of ducks using this scanning method (Table 4.1).
Figure 4.6. Duck scanning procedure. On top, we can see the scanning method and direction for each bird, in the middle we have an index when the 2D array is unwrapped into a single vector, and on the bottom, we can see the 2D indexing method used. The 5x7 pixel configuration was used to simulate an image at 2.5cm (~1in) GSD from a sUAS.
4.3.4 Data Storage and Processing

Each scanned image was stored as two separate array files in a NumPy format named with a SPECIES_AGE_Sex.npy convention. The first file contained the measured 5x7x3648 spectral hypercube in digital counts (DCs) and the second file contained a similar hypercube that had been converted into reflectance. With our setup, the reflectance conversion was the simple calculation shown below with the measured reference sourced from the Spectralon reflector.

\[ \text{Reflectance} = \frac{\text{DC}_{\text{Measured Target}}}{\text{DC}_{\text{Measured Reference}}} \]

The data had to then be organized and sorted into training and testing data with labels. We used a cross-validation method based on 20% of the data as testing data per iteration, given our relatively small dataset. Cross-validation is the practice of partitioning a data set into multiple blocks, using one block as testing data and the rest as training data, and averaging the results at the end [69]. Additionally, many species only contained scans from a single sex or a single age, so all the samples for each of the categories were grouped into single datasets. With the testing and training data labeled and organized, we could begin exploring the effect of various classifiers.

The first and simplest classifier we used was K-nearest neighbors (KNN). A KNN works by comparing the Euclidean distance between the test data point and all the data points in the training dataset. Euclidean distance is simply the distance between two points in n-dimensional space and can be calculated using the following equation.

\[ D_{AB} = \sqrt{\sum_{i=1}^{n} (A_i - B_i)^2} \]

In this equation, \( \tilde{A} \) and \( \tilde{B} \) represent two points in n-dimensional space and \( D_{AB} \) represents Euclidean distance between those points. After calculating the distance from a test data point to all possible neighbors, the number (K) of nearest training data points are compared and the majority label is chosen as the solution. If there is a tie for the majority, the number (K) is reduced by one, until there is a majority winner. While there is no training time required, this classifier is computationally expensive every run and grows exponentially as a dataset grows [70]. This can be seen when looking at the computational complexity of the KNN algorithm. Using Big-O notation, the complexity is: \( O(n \times m) \) where n represents the number of data points and m represents the
dimensionality of the data (35 for our unwrapped image arrays).

The second classifier we looked at was cosine similarity (CS). The CS classifier functions similarly to the KNN but minimizes angles between point vectors instead of distances between points. To calculate the angle between each of the points we used the following equation:

\[
\text{Cosine Similarity} = \cos(\theta_{AB}) = \frac{A \cdot B}{\|A\| \times \|B\|} = \frac{\sum_{i=1}^{n} A_i B_i}{\sqrt{\sum_{i=1}^{n} A_i^2} \sqrt{\sum_{i=1}^{n} B_i^2}}
\]

By comparing the angles between point vectors instead of distance, the classifier ignores differences in magnitude when comparing two points which could be a benefit or a detriment. The changes in magnitude could be useful for helping differentiate two birds who have the same reflectance patterns but with varying strengths. Opposingly, ignoring those magnitude differences would allow us to remove uniform changes in illumination. Because our measurement method was static with no changes in illumination, we expect the CS and KNN classifiers to have similar results. It has the same computational requirements as the KNN, \(O(n \times m)\), but ignores uniform offsets in the data due to changes in illumination [71].

The third classifier examined was a Support Vector Machine (SVM). SVMs partition the data space into labelled regions using hyperplanes. It selects the optimal hyperplanes to use by maximizing the margins between each of the classes and the hyperplane while minimizing classification errors in the training data [72]. Then, it simply determines which side of the partitions the test data falls into and assigns that space’s label. Often, the data is not linearly separable. To use the SVM, we must transform the dataset using a transformation kernel. One transformation we explored was the radial basis function (RBF) kernel approximation. The equation for the kernel function is shown in the following equation where \(\gamma\) represents gamma, the width of the function:

\[
f(x) = \exp\left(\frac{1}{2\gamma^2}||x-x_i||^2\right)
\]

We compared usage of a linear model and using an RBF kernel to separate the data using an exhaustive fit and score method across several parameters. Through this optimization, we found the RBF kernel to consistently achieve accuracies 10-20% higher for all classes than the linear kernel. This is because the RBF kernel allows for a more complex partition of the dataset [73]. The RBF-SVM is trained ahead of time when the data space is partitioned, thus making it quick
and computationally cheap to use when classifying the testing data.

Finally, we explored the random decision forest (RF) classifier. The RF classifier is an ensemble of decision tree classifiers that each vote on the correct output label and a majority vote is selected. A single decision tree functions by receiving an input and flowing it through decision nodes until it reaches a solution or label known as a leaf. A simple example of a decision tree is shown in Figure 4.7. In this example, our input would start the tree at the top by evaluating whether parameter X is less than 10 or not. If it is less than 10, it would flow down the left side to the next decision. If it is not less than 10, it would flow down the right. This continues until a label “leaf” is reached, shown as the blue letters A-D in the example [74]. The trees can be designed or “grown” in several ways. With RF, each of the decision trees is grown using randomly selected inputs or combinations of inputs at each decision point in the individual trees. The randomization is toned to minimize correlation while maintaining strength [69]. Like the SVM, the RF is trained on a dataset and can then be used quickly for labelling individual test inputs.

![Example decision tree](image)

Figure 4.7. Example decision tree. We enter the tree with a decision regarding a single parameter, in this case: X. If parameter X is less than 10, we move down the true branch to the next decision. If it is not less than 10, we move down the false branch. This occurs until we reach a label “leaf” shown in blue. So, if our input had parameters X < 10, Y < 0, and Z > 5, our tree would classify it as C [74].
4.4 RESULTS AND DISCUSSION

4.4.1 Baselining the Classifiers

The goal of this experiment was to determine if using images collected over the UV spectral region will improve the ability to classify the ducks’ species, sex, and age. Our intent was to provide a proof-of-concept approach, under ideal laboratory conditions, for potential extension to sUAS platforms. We therefore needed to establish a baseline. We chose to baseline our data using the highest accuracy obtained from the previously mentioned classifiers but constrained to panchromatic images. The panchromatic images were generated by collapsing the hyperspectral reflectance image cubes and summing the values along the spectral axis from 250-850nm, as demonstrated mathematically with the equation below where Y is our two-dimensional (5x7) panchromatic image and X is our n-dimensional (5x7x3648) reflectance hypercube. This is demonstrated visually in Figure 4.8, where we can see the hypercube, the hypercube separated and summed in the spectral dimension and the resulting two-dimensional panchromatic image.

\[ Y_{i,j} = \sum_{k=1}^{n} X_{i,j,k} \]

Figure 4.8. Visualization of panchromatic image generation. We start with the hyperspectral image cube of the letter I. The spectral dimension is shown using various colors and the two spatial dimensions are shown as the front face. The cube is collapsed in the spectral dimension by summing up all the spectral slices into a single image, shown on the right.
As mentioned, the KNN and CS classifiers are not pretrained and required no prior inputs. An exhaustive fit and score optimization was done to select the best parameters for training the SVM and RF classifiers on our datasets. The RBF-SVM has two important parameters that were optimized, gamma and cost. Gamma determines the size and shape of the RBF kernel while cost influences the threshold decision points. For our optimization we restricted the gamma to a range of 0.0001-1 and restricted cost to a range of 1-1000. For our dataset, we determined an optimal gamma of 0.01 and cost of 10 for all three classifications.

The two parameters that impact Random Forest are maximum layer depth and number of trees. As we did with the SVM, we utilized an exhaustive fit and score optimization for the RF variables. We limited the depth parameter to a range of 1-20 and the number of trees to a range of 10-200. Through optimization, we found that 105 tree estimators with a depth of 10 resulted in highest performance. The optimization results for depth are shown in Figure 4.9. After training and optimization, we ran the datasets through a cross validation to obtain final accuracies for each classifier using the panchromatic images. The accuracies of each of our classifiers, along with the kappa coefficients for each of the classification categories, are shown in Table 4.2. Kappa coefficients are regularly used in remote sensing to determine if classifier accuracies are significantly different. The kappa coefficient, \( \hat{\kappa} \), is calculated with the following equation, where \( p_o \) represents proportion of correct classifications from the examined classifier and \( p_c \) represents proportion of correct classifications if using chance.

\[
\hat{\kappa} = \frac{p_o - p_c}{1 - p_c}
\]

The kappa coefficients are then compared between classifiers to determine if their accuracies are significantly different. To compare coefficients from two related samples like we have, the following equation is used, where \( z \) represents the resulting value.

\[
z = \frac{\hat{\kappa}_1 - \hat{\kappa}_2}{(\hat{\sigma}^2_{k_1} + \hat{\sigma}^2_{k_2} - 2\hat{\sigma}_{k_1k_2})}
\]

In this equation, \( \hat{\sigma}^2_{k_1} \) and \( \hat{\sigma}^2_{k_2} \) represent the estimated variances in the kappa coefficients and \( \hat{\sigma}_{k_1k_2} \) represents the estimated covariance between the two coefficients. We used the widely accepted 5% (\( |z| > 1.96 \)) difference to determine significance [75]. When examining the resulting \( z \)-values, we can see that the random forest classifier significantly outperformed KNN and CS for
age and sex and every other classifier for species classification. Therefore, we selected the Random Forest classifier and its accuracies as our baseline.

![Random Forest Optimization (species)](image)

Figure 4.9. Random Forest classifier depth parameter optimization results. Note that after a depth of 10, accuracy levels out and hovers around 75%. While the depths above 10 would yield similar results, a depth of 10 was selected for our classifiers to reduce computation complexity by minimizing the size of the decision tree.

Table 4.2. Classifier accuracy for simulated panchromatic imagery. The Random Forest and SVM classifiers outperformed the KNN and CS classifiers in all three categories, with the largest difference in accuracy in the species classification. When examining the kappa coefficients with the standard 5% significance,

<table>
<thead>
<tr>
<th>Classifier</th>
<th>Age</th>
<th>Sex</th>
<th>Species</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Accuracy</td>
<td>Kappa</td>
<td>Accuracy</td>
</tr>
<tr>
<td>K-Nearest Neighbors</td>
<td>80%</td>
<td>0.60</td>
<td>78%</td>
</tr>
<tr>
<td>Cosine Similarity</td>
<td>80%</td>
<td>0.60</td>
<td>80%</td>
</tr>
<tr>
<td>Support Vector Machine (RBF)</td>
<td>84%</td>
<td>0.68</td>
<td>83%</td>
</tr>
<tr>
<td>Random Forest</td>
<td>84%</td>
<td>0.68</td>
<td>83%</td>
</tr>
</tbody>
</table>

Table 4.3. Z values for comparing classifier accuracies. Using the standardized 5% significance ($|z| > 1.96$), we can see that the RF outperforms all the other classifiers for species classification and is the best choice for use as our baseline.

<table>
<thead>
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The main confusions arose between the Northern Pintail, the American Wigeon, and Green Winged Teal. This is mainly a result of having mostly juvenile samples obtained during fall/winter where ducks plumage is primarily camouflaged and not as unique as the bright breeding plumages defining sex and species.

The confusion matrices for the Random Forest classifier are shown in Figure 4.10. A confusion matrix is developed by taking the input images labels and comparing them to the predicted labels when the image is run through the prediction algorithm. An interesting thing to note in the confusion matrices are which species ended up being confused the most. When we look at the predictions, we can see that the green winged teals, northern pintails, and American wigeons were the most misidentified species. This was attributed to the types of each species measured and the time of year that the birds were obtained. When we refer to Table 4.1, we can see that for all three of these species, the only birds we collected were juvenile. This, combined with the knowledge that the birds were all collected in fall/early winter, means that all of the birds from that species still had visually similar plumage optimized for camouflage and none of them had begun developing the strong colorful patterning used for signaling mates [25].
4.4.2 The UV Effect

With our baseline accuracies established, we reran the classifiers with wavelength specific images. Each of these wavelength specific images are cross-sections of the reflectance hypercube along the spectral axis. An example of the scanned image at 380nm is shown in Figure 4.11 next to an image of the duck specimen (scale is in percent reflectance (0-1)).

![Figure 4.11. Scanned image (right) of a northern shoveler (left) at 380nm (scale is in percent reflectance (0-1)). Note the strong reflection (17-22%) of the blue wings as well as the dark signals of the lower body. Additionally, we can see a much stronger increase in reflectance on the patterned wings in the UV region when compared to the RGB image.](image)

Figure 4.12 shows the accuracies of each classifier plotted as a function of spectral wavelength. The highest accuracy achieved using the panchromatic images as a baseline are also shown in black. We can observe increases in accuracy for both age and species, but not for sex. For age, we see increases of 6% and 2% when using the SVM and the RF classifiers, respectively. This is a direct result of the overall changes to plumage for juvenile ducks maturing to mating age. When the ducks mature, their plumage transitions from camouflaged dark patterning to bright colorful patterns for signaling mates. Similar to Eaton and Lanyon (2003) showed, as the color of the birds plumage increases, the UV reflectance in those areas significantly increases [11]. Our results show that the increase in accuracy is strongest in the 370-430nm region, which is located...
at the ducks’ approximate UV visual response peak. These results contribute supporting evidence to the theory that a main function of UV reflectance in avian species is for selecting sexual mates [59].

Figure 4.12. Classification accuracies as functions of wavelength in the UV spectrum. The top plots are both binary classifiers where age on the left is either juvenile or adult and sex on the right is either male or female (50% accuracy with random chance). For species, the classifier would choose from nine possible labels (11% accuracy with random chance). We can see that accuracies for both age and species classification generally increased across the UV spectrum while classification accuracy for sex generally decreased.

We generally observed a decrease in sex prediction accuracy when using specific wavelength images. This is because of the way we had to construct our datasets for training and testing, due to a limited number of samples. As mentioned previously, the measured birds were collected during the fall and early winter. This implies that the juveniles still had their camouflage patterned plumage, while the adults had transitioned to a subdued version of their bright signaling patterns, also for camouflage reasons. Additionally, when we constructed the sex dataset, we
included all ages and species in the same set. When these two factors are combined, it is obvious that ducks of different sexes will look similar when compared to opposite sexes of different species, especially for the juvenile birds. We therefore recommend that an increased number of samples of both sexes for each species be acquired in future studies. Finally, when examining species accuracy using UV imagery, we observed improvements across the spectrum with a peak increase in accuracy of 7% around 300nm. These results demonstrate the feasibility for using remotely sensed UV imagery to classify ducks by age, sex, and species. Additionally, it shows the use of UV imagery will increase classification accuracies over imagery in the visible spectrum. When considering that the birds had their winter plumage, these results also lead us to expect significantly better results when examining birds with their fully developed breeding coloring and patterns.

### 4.5 Conclusion

Automated waterfowl survey methods utilizing remotely sensed imagery could significantly increase accuracy and efficiency of population counts both in local regions and globally. Our team hypothesized that utilizing UV imagery could yield higher classification accuracies than RGB or panchromatic imagery based on previous findings on the significant UV reflectance of avian plumage. To test this hypothesis, we took a preliminary step in simulating UAS reflectance imagery by collecting 260 scans across nine species of upland ducks using OceanOptic’s USB4000 point spectrometer with a fixed measurement geometry. We established baseline accuracies of 83%, 83%, and 76% for classifying age, sex, and species respectively by using a random forest classifier with the simulated panchromatic (250-850nm) datasets. When using imagery at narrow UV bands, we were able to increase classification accuracies for age and species by 7%. The increase in accuracy for age classification adds validity to the theory that a main biophysical purpose for the UV reflectance in bird plumage is for mate selection, particularly because the increase in classification accuracy was highest where a duck’s visual response peaks, i.e., at approximately 380nm [60] [61] [62]. Because the ducks measured were obtained during fall/winter, we expect classification accuracies to be even higher when measuring ducks obtained in spring and early summer when prime breeding plumage coloring is most prevalent. We recommend this study be expanded to include a larger number of specimens across different time
periods in the annual cycle of ducks to allow for assessment of within-species age and sex classifications. We expect classification for all three categories to increase when removing those extra sources of confusion.
Chapter 5

Summary

5.1 SUMMARY

This thesis is divided into three main chapters. Chapter 1 provides a brief introduction to the work accomplished and an overview to the thesis. Additionally, it presents the two main objectives of our work: 1) Assess the feasibility of utilizing UAS based remote thermal imagery to detect active duck nests and 2) Assess the feasibility of utilizing remotely sensed ultraviolet (250-400nm) images to classify breeding duck pairs.

Chapter 2 provides a comprehensive overview of the problem, current solutions, and potential alternatives. It sets the stage for our work by establishing why various sectors require accurate and timely annual waterfowl population counts. It then examines the current industry standards for waterfowl population survey techniques and the benefits and issues associated with each. Finally, we investigate potential alternate survey methods utilizing remote sensing and sUAS through previous related works.

Chapter 3 is a standalone section that encompasses our work to address objective one. The chapter was accepted into the 2020 IGARSS conference proceedings. It contains a condensed high-
level background with additional information regarding thermal (LWIR) imagery and its potential applications in duck nest detection. It then details the experiment design and the data collection trip to North Dakota accomplished by the RIT UAS lab, the University of North Dakota Fisheries and Wildlife Biology program, and Ducks Unlimited in June of 2019. A detection algorithm was then designed and implemented to examine the effects of altitude, time of day, and terrain on nest detection rates. We found that nest detection using sUAS based thermal imagery and an automated detection algorithm is feasible if spatial resolution can be improved and that the imagery should be collected in the early morning while the hen is on the nest.

Chapter 4 is also a standalone section written with the intent to submit for publication in a peer-reviewed journal. It aims to address objective two and provides detailed background on the prevalence of UV reflectance among aviary plumage and the potential that has for improving classification performance. Then, it covers several experimental designs and the data collection methods. Finally, it explores the results from several well-known classification algorithms on both panchromatic and narrowband UV imagery. We found that classification of species, age, and sex were all feasible utilizing panchromatic imagery and we demonstrated significant increases in species and age classification accuracies when utilizing imagery in the UV spectrum (250-400nm) compared to the visible spectrum (400-850nm).

5.2 CONCLUSIONS

Monitoring and understanding wildlife populations can provide great insight into the health and trajectory of the ecosystems they rely on. It was not until recently that the many benefits of wetland ecosystems were fully understood. Unfortunately, by that point, the United States had already removed more than 50% of its wetlands. The Prairie Pothole Region is a major wetland area in North America that is still losing more than 6200 acres of wetlands annually [2]. It is also the premier breeding location for ducks; responsible for producing more than 50% of the North American ducks annually [3]. The current survey methods for obtaining duck population counts are accomplished primarily using manned flights with two observers identifying and counting the ducks below [29]. The current industry standard for in situ assessments of nest locations is known as the “chain drag method”, a manually intensive ground survey technique. However, recent improvements to small unmanned aerial systems (sUAS), coupled with the increased performance
of lightweight sensors provide the potential for an alternative surveyal method. Our objective for this study was to assess the feasibility of utilizing sUAS based thermal imagery for detecting duck nests in the and UV imagery to classify breeding pairs in the Prairie Pothole Region.

To obtain the thermal imagery, our team travelled to Ducks Unlimited’s Coteau Ranch in Sheridan County, North Dakota, United States of America. At the ranch, 24 nests were located by the UND team. Each nest site was imaged at 40m and 80m altitudes during the early morning (0400-0600), morning (0600-0800), and midday (1100-1300). Then, each image was min-max normalized and contrast enhanced using a high-pass filter prior to the detection algorithm. Three parameters, altitude, time of day, and terrain, were varied between flights to determine their impacts on detection accuracies. The variable with the highest impact on detection accuracies was altitude. We were able to achieve detection accuracies of 58% and 69% for the 80m and 40m flights, respectively. We also determined that flights in the early morning yielded the highest detection accuracies due to the increased contrast between the prairie and the nests after the prairie cooled overnight. However, the detection accuracies were lowest during morning flights when the female ducks might be recessing off nest. Therefore, we determined that with an improvement to spatial resolution, the use of sUAS based thermal imagery is feasible for detecting nests across the prairie and that flights should occur early in the morning while the hens are on the nest to maximize thermal contrast and detection potential.

To assess the feasibility of classifying breeding duck pairs using ultraviolet imagery, our team took a preliminary step in simulating sUAS reflectance imagery by collecting 260 scans across nine species of upland ducks with a fixed measurement geometry. We established baseline accuracies of 83%, 83%, and 76% for classifying age, sex, and species respectively by using a random forest classifier with simulated panchromatic (250-850nm) image sets. Several classification algorithms were examined with the random forest significantly outperforming the others. When using imagery at narrow ultraviolet bands with the same random forest classifier, we were able to increase classification accuracies for age and species by 7%. Therefore, we demonstrated the potential for sUAS based imagery to be used as an alternate method for surveying breeding duck pairs as well as the potential improvements in age and species classification that the use of ultraviolet imagery might provide. We also hypothesized that significant improvements in classification performance could be achieved for age, sex, and species when examining UV imagery of ducks obtained during the breeding season as opposed to the ducks obtained in the fall.
and winter that we examined in this study.

We concluded that sUAS-based remotely sensed imagery has the potential to be utilized as an alternate survey method for both waterfowl population and nest counts. Additionally, we demonstrated the potential for ultraviolet spectrum imagery to improve duck species, sex, and age classification results when compared to visible spectrum.

5.3 FUTURE WORK AND IMPROVEMENTS

A few improvements in the research approach as well as several follow-up activities were identified throughout this study and are described below.

5.3.1 Follow-up Study on Sample Deterioration

Frozen ducks were used during the UV image set generation process for the duck classification work. One potential issue we considered, but did not fully explore, was the effects that sample deterioration had on overall plumage reflectance. During our work, we did ensure that minor thawing of fresh samples (10 minutes in direct sunlight and 80ºF) resulted in no significant changes in measured reflectance. Therefore, we recommend a future study to further explore several other specimen handling conditions and their potential effects.

The first condition to explore is that of repeated thawing and freezing of specimens. During our initial experimental design, we moved the ducks in and out of the freezer several times and noticed that after three of those rotations, the samples began to accumulate substantial frost. The first study should explore the effects that these rotations have on reflectance measurements. The samples should be measured after immediately coming out of the freezer and after thawing in 5-minute intervals up to 30 minutes. These measurements should be done after each freezing cycle, for as many as 10 cycles. Each sample should have five measurement areas clearly marked for consistent measurements. We hypothesize that as frost begins to accumulate on the samples during refreezing, the measurements will become inconsistent.

While our team measured the ducks within several days of receipt, consideration should be taken for the total length of time that the ducks have been frozen. A study should be done to explore the effects that long duration freezing has on the samples. The samples should be measured at
weekly intervals for one year while remaining frozen throughout the process. We hypothesize that if kept frozen, the sample measurements should remain consistent throughout the experiment.

5.3.2 Thermal Sensing Flight Optimization

Based on our early research, we planned on the duck nests having a diameter of 15cm, which drove our GSD requirement of 5cm to ensure at least one full pixel of the nest will be in the image. While the interior diameter of the nest bowls was the expected size, we did not take into account the fact that the ducks pull vegetation around and over the nests, thus resulting in a significantly smaller opening. Because this assumption was incorrect, the optimal spatial resolution for consistent nest detection using thermal imagery is still undetermined. Therefore, we recommend a study to assess the optimal altitude/spatial resolution to consistently obtain high contrast thermal (LWIR) imagery of duck nests in the prairie. This study should examine the impact of several flight variables in a controlled manner. Nests with a variety of vegetative cover density should be located and marked with highly reflective markers for locating the nests in imagery. An example marking method would be to place two markers at equal distances on opposite sides of the nest so that the nest can be located directly in between them in the imagery. For the marker itself, we recommend aluminum foil since it has a high reflectance (>98%) in the infrared region above 2μm. Then, image data sets should be collected directly over each nest at altitudes between 20 and 80m at intervals of 1m. The maximum altitude for positive nest detection can then be determined using a detection algorithm and results can be statistically compared between the differences in vegetative cover. With altitude better understood, the effects of motion blur can be explored.

Additional flights should be conducted where images are obtained at the highest altitude determined sufficient for nest detection in the above recommended study. Imagery should be collected over each nest site at various speeds to better understand the effects of motion blur. Speeds will vary based on the GSD (a function of altitude) and the integration time of the sensor. The flight speed to achieve a motion blur of one pixel can be calculated using the following equation. We recommend adjusting flight velocities to imagery with a motion blur between 0- and 5-pixels in 0.5-pixel increments.
Using the collected imagery with a detection algorithm, results can be generated and compared for each of the flight speeds leading to a determination of maximum acceptable motion blur.

5.3.3 Expanded UV Classification Study – Inter- vs. Intraspecies

For some of the duck species in our UV dataset, we were only able to obtain samples from a single sex (male/female) or a single age group (juvenile/adult). This forced us to perform interspecies classification for age and sex, which probably added confusion and lowered overall accuracies. We therefore recommend an expanded UV breeding pair classification study with large enough intraspecies samples to address this deficiency. To assess any potential differences of utilizing the intra- vs. the interspecies datasets, at least 30 samples of each age and sex should be gathered for several unique species. We hypothesize that classifying age and sex within each species will yield higher results than those achieved here by combining data from all nine species.

5.3.4 Expanded UV Classification Study – Winter vs. Breeding Plumage

The duck samples that comprised our UV dataset were all obtained through donations from hunters during the fall/winter season. This means that for the juvenile samples, none of the birds had matured enough to develop sex-unique markings or any mate signaling plumage. Additionally, the adult samples had transitioned back to a subdued pattern for wintering. The winter plumage is optimized for camouflage and is visually similar between species and sexes. Therefore, we recommend that this study be conducted using a large sample of ducks from the same nine species used in our work, but with the new ducks being acquired after their spring molt. We hypothesize that accuracies will be higher for age, sex, and species classification when examining ducks with mating plumage vs. winter plumage and that the improvements in classification accuracy that we saw using UV imagery will be more pronounced. The hunter harvested fall/winter samples are still relevant for mid-winter surveys, and the breeding season plumage study would be most relevant to spring breeding pair surveys conducted by the U.S. Fish and Wildlife Service and other agencies.
5.3.5 Follow-up Study on UV System Design

There are several areas that our UV work can be expanded on. First, staying in the more controlled laboratory setting, a study should be done to explore the effects that changes in spatial and spectral resolution have on classification results. We recommend starting with a study on spectral resolution after data have been gathered for the expanded plumage and interspecies studies. There are several options for UV sensors, each of which can be explored and simulated using hyperspectral data. One option would be to use a digital single-lens reflex (DSLR) camera with a UV-pass filter. Other options would be to obtain a camera designed for UV imaging such as the SCM2020-UV-TR or the “pco.edge 4.2 bi UV” from PCO-Tech Inc. The quantum efficiency for the “SCM2020-UV-TR” sensor is shown in Figure 5.1, where we can see the strong response through the UV region. This response plot includes the losses through the sensors’ optics and the detector itself.

![Figure 5.1](image)

Figure 5.1. Sensor quantum efficiency of the SCM2020-UV-TR across the UV and visible regions. This is the total quantum efficiency including losses from the optics and the detector. We can see a strong response from UV region (200-400nm) as well as in the visible (400-900nm) region. [76]

These cameras have silicon detectors that have been optimized for imaging in the UV and come with several bandpass filter options. Data for these sensors can be generated by applying the bandpass filter and the camera responses to the calibrated hyperspectral imagery and summing across the spectral dimension. This will result in an approximation of the images each sensor would
provide. After simulated imagery is generated, the random forest classifier can be trained and ran for each of the spectral resolution filters to determine the classification accuracies for each. We hypothesize that a UV-pass filter will provide sufficient classification accuracies. With the optimal sensor known, a follow-up study could explore the spatial resolution limitations.

An understanding of the sensor signal to noise ratio (SNR) is required since there is substantially less UV signal available from the sunlight than the combined UV-visible signal. This SNR will determine the integration time required as a function of spatial resolution and will determine the maximum flight speed that can be achieved during collects. To explore these effects, the chosen sensor should be used to collect new data sets with a variety of GSDs from the 3cm resolution that we used in our work to the 0.5cm pixel size that Díaz-Delgado et al. (2017) used to achieve a classification accuracy of 98% for slender billed gulls. Then, new classification accuracies can be determined using the random forest classifier. Next, an assessment of the maximum motion blur should be conducted in the same manner that we described for the expanded thermal imaging study in 5.3.2. The maximum flight speed to maintain acceptable motion blur can be now be calculated. The total viewable area can then be calculated for a single flight using the flight velocity, altitude, and sensor field of view. With that work, we now have a linked relationship between total area coverage during a single flight and expected classification accuracies that can be used in a flight planning trade study for applying this methodology on a larger scale.
Bibliography


[50] Trimble, “APX-15 UAV Data Sheet.”


