Evaluation of an unmanned aircraft system for detecting surrogate caribou targets in Labrador

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PREFACE

This is a manuscript-based thesis consisting of an introductory chapter, one original manuscript that has been prepared for submission to a refereed journal and a final concluding chapter. The Masters candidate, Charla Patterson, designed the project, collected the data, conducted all post-data collection processing, performed all the statistical analyses, and is the primary author of all chapters. Dr. David Bird acted as a research supervisor, provided financial and logistical support, and edited the thesis. Chapter 2 has been prepared for submission to the Journal of Unmanned Vehicle Systems. It is also co-authored by William Koski, who assisted with experimental design and provided feedback during the analysis, Dr. Paul Pace who assisted with study coordination and data collection, and Brian McLuckie for assisting with data collection.

Abstract

Regular, standardized population inventories have been suggested as an important component to the recovery of declining populations of boreal caribou (*Rangifer tarandus caribou*). Current survey methods typically employ manned aircraft, which can be noisy, expensive to operate, and dangerous for the people conducting the surveys. Small Unmanned Aerial Systems (sUAS) have garnered attention as a promising alternative for conducting aerial surveys in manned aircraft. Our research investigates the feasibility of using an UAS to conduct aerial surveys and determine which factors affect the detection of surrogate caribou targets, and hence might affect detection of real caribou. In the fall of 2013, we tested the capabilities of the Brican TD100e, a small, electric-powered fixed-wing UAS, to fly beyond line of sight (BLOS) near Goose Bay, Labrador. Seven surveys were done using different flight paths to collect aerial images of 26 surrogate caribou targets placed in six different habitats. Mixed effects logistic regression models were used to evaluate how habitat type, distance of the target from the image centerline, photo analysts' experience level, flight time, and the target contrast against the landscape influenced the detection of surrogate caribou targets. We found that

habitat type, target contrast, and the flight time affected target detection. Overall, 77.5% of the targets were detected; the odds of a photo analyst detecting a target in open habitat were roughly 10.5 times higher than in burned habitat and 42 times higher than in heavy forest. Target detection was influenced by the contrast of the target against the landscape, where a higher CID was associated with greater target detection. The detection of targets was 87% during evening flights and 75% for morning flights. This study was the first of its kind to successfully fly a UAS beyond line of sight over land for non-military applications in Canada and the findings of our research provide recommendations for using UAS to survey caribou in the future.

Résumé

La realization fréquente d'inventaires et d'estimations démographiques font partie des stratégies misent en oeuvre pour protéger le caribou boréal. Les outils couramment utilisés dans ce type de recherche sont les avions et les hélicoptères. Cependant, ces pratiques sont coûteuses, bruyantes et parfois même dangereuses. La mise en place de système d'aéronef sans pilote (UAS) s'impose en tant que méthode révolutionnaire pour effectuer des observations aériennes et réaliser des inventaires fauniques. Ce projet de recherche vise à déterminer la qualité des informations recueillies par l'UAS lors du ratissage de la zone d'étude et trouver les conditions qui affectent la détection de cibles ressemblant aux caribous. Nous avons testé le Brican TD1000e, un petit avion a voilure fixe et a moteur électrique ne nécessitant aucun pilote, durant l'automne 2013 près de la base militaire de Goose Bay au Labrador. L'UAS à effectuer sept vols qui ont permis de recueillir des images aériennes de 26 cibles placées dans six habitats distincts. Pour ces enquêtes, nous avons utilisé le modèle à régression à effet mixte pour déterminer dans quelles mesures le type d'habitat, la position et le contraste des cibles dans les photos, le temps de vol et le niveau d'expérience de l'observateur, pouvaient influencer la détection des cibles. En tout, 77,5% des cibles ont été détectées : les chances pour qu’un photo analyst détecte une cible dans un habitat à ciel ouvert étaient à peine 10,5 fois plus élevées que dans un habitat dévasté par le feu et 42 fois plus élevées que dans un habitat où la forêt était dense. Les résultats de notre recherche permettent, entre autre, de fournir un guide des facteurs pratiques à considérer en utilisant un UAS pour effectuer les observations aériennes des caribous boréals.

CHAPTER 1:

GENERAL INTRODUCTION AND LITERATURE REVIEW

1.1 Background on Boreal Caribou in Labrador

In Canada, the range of caribou extends from the West Coast all the way to the East Coast and the island of Newfoundland (Thomas and Gray 2002). Although there is only one species of caribou recognized worldwide, populations vary widely in their ecology, genetics, behavior, and morphology, which has led to challenges in the past when trying to classify and distinguish different groups. In Canada, caribou were previously classified into four existing subspecies including the Peary caribou (*Rangifer tarandus pearyi*), the barren-ground caribou (*R.t. groenlandicus*), Grant's caribou (*R.t. granti*) and the woodland caribou (*R.t.caribou*) based on differences in morphology, geographic occurrence and ecology (Banfield 1974). Alternatively, caribou have also been classified based on their life history strategies; Bergerud (1996) identified two broad ecotypes which included those that were sedentary and those that were migratory. Prior to calving, the migratory ecotype travel to calving grounds located above the treeline into areas with lower predator densities, forming large aggregations during the calving season (Bergerud 1988, 1996; Schaefer 2003). Conversely, the sedentary ecotype do not migrate long distances, opting instead to spatially isolate themselves from other individuals on the landscape to reduce the probably of encountering predators (Bergerud 1985; Bergerud et al. 1990; James et al. 2004). To reduce predation risk, the sedentary ecotype will also tend to avoid habitat preferred by predators and alternate prey species, such as moose (*Alces alces*) (Rettie and Messier 2000; James et al. 2004; Courtois et al. 2007). Recently, the nomenclature for distinguishing caribou populations has been changed by COSEWIC (2011) to reflect a more updated understanding of the spatial, behavioural, ecological and genetic differences between caribou populations. Based on this new classification, there are twelve discrete and ecologically significant groups of caribou in Canada, including the boreal caribou which was previously recognized as the woodland caribou subspecies and as being part of the sedentary ecotype.

Boreal caribou are found across northern Canada ranging from the western corner of the Yukon to central and eastern Labrador and on the island of Newfoundland (Thomas and Gray 2002). They inhabit large, undisturbed habitat dominated by mature coniferous stands, as well as peatland and bog complexes (Rettie and Messier 2000). In the last three decades, boreal caribou have been experiencing range contractions and steady declines in population size across Canada (Rettie and Messier 1998; Schaefer et al. 1999). The number of boreal caribou in Canada is estimated to be somewhere between 31,000 to 39,000 (excluding the island of Newfoundland)(Environment Canada, 2008) and they are listed as either threatened or endangered in six of the nine provinces and territories where they occur (COSEWIC 2011).

In Labrador, boreal caribou populations are divided into three distinct herds including the Lac Joseph, Mealy Mountain and the Red Wine Mountain herds (Schmelzer et al. 2004). All three populations are listed as *threatened* under both provincial and federal legislation (Thomas and Gray 2002). In Labrador, boreal caribou populations are declining at an estimated rate of 13-26% per year (Schaefer et al. 1999), which is faster than those estimated for populations in other provinces (Ouellet et al. 1996; Stuart-Smith et al. 1997; Rettie and Messier 1998). The decline is likely a combination of direct and indirect factors including: a reduction in the availability and quality of suitable habitat; climate change; hunting and predation; increase in land development and the creation of roads, pipelines, and other linear features; and an increase presence of human activity in previously undisturbed areas (Bergerud 2000: Schmelzer et al. 2004).

1.2 Conducting population inventories on boreal caribou

The widespread decline of caribou across Canada has raised concerns about their conservation status and the sustainability of current management practices. Conducting regular population inventories is an important step towards their recovery (Schmelzer et al. 2004). Frequent surveys are especially important since population sizes have been known to change rapidly (Gunn et al. 2006; Cuyler 2007) and the confidence intervals around most population estimates are too high to confirm changes without several surveys. A population of caribou located on three islands in Nunavut declined by 98% within a 15-year period from 6048 individuals to roughly a hundred. An absence of survey data during that time frame delayed the detection of the decline and limited our understanding of what caused it, making the recovery of these populations challenging (Gunn et al. 2006). Despite the importance of regular population inventories, there is an absence of accurate population size estimates and population trends for many boreal caribou herds (Courtois et al. 2003; Callaghan et al. 2011). The Scientific Review for the Identification of Critical Habitat for Woodland Caribou recognized 57 local populations of boreal caribou across Canada (excluding Newfoundland), of which 5.3% populations were increasing in size, 29.3% were declining, 28.1% were reportedly stable and the status of the remaining 36.8% was unknown (Environment Canada, 2008). Gathering population data on boreal caribou has been a notoriously challenging task because they occur at densities that can be as few as 1.5 caribou/km^2, they form small herds that are sparsely distributed over expansive areas (Crête 1991; Courtois et al. 2001), and they live in forested habitat that reduce detection during surveys.

The challenges associated with estimating boreal caribou population sizes have led to variation in survey techniques. Mark-recapture (resight) surveys have previously been used (Brown 1986; Schaefer 1997), but more frequently, manned aircraft surveys are preferred. Aerial surveys typically involve delimiting the survey area, dividing it into plots or transects, and then using either a fixed-wing aircraft or helicopter to fly over selected areas to conduct strip censuses, simple random sampling, stratified random sampling, or complete coverage surveys (Courtois et al. 2003). In many cases, telemetry data or past survey results are used to delimit the area that will be surveyed and to potentially classify the survey area into strata based on caribou presence from previous years. It is important to consider the annual and seasonal range of caribou as well as the environmental factors that limit their range such as snow depth, land topography, elevation and vegetation structures (Ministry of Sustainable Resource Management 2002). Based on boreal caribou life history strategies and the objectives of the survey, most are conducted between October to April during the rut, winter or pre-calving season (Schmelzer et al. 2004).

Conducting frequent aerial surveys can be expensive and time-consuming, as well as dangerous for humans aboard the manned aircraft. Monitoring overall population trends has been suggested as an alternative method for managing boreal caribou populations by, for example, using total coverage surveys in a few control areas as a proxy of overall population trends (Bourbonnais et al. 1997; Courtois et al. 2003) as well as using observations made during moose surveys conducted in hunting zones to track population sizes (Courtois et al. 1996). The first method produces population estimates that cannot be accurately extrapolated to the entire range of the population and is very expensive, and the second method fails to provide detailed information about the location of caribou herds (Courtois et al. 1996).

The lack of accurate, unbiased, standardized survey methods has resulted in an absence of reliable population estimates for boreal caribou. There have been efforts to address this issue by evaluating survey methods and identifying those that best balance between cost and effectiveness (Courtois et al. 2003; Carr et al. 2012). The method used by Courtois et al. (2003) involved a two-phase survey in which track networks were located in the first phase, and then plots from the area were randomly selected to conduct full coverage surveys in the second phase. This method had a visibility rate of caribou (i.e. proportion of collared individuals that were detected) at 0.85 and cost approximately \$4/ km^2, for a survey area of 42,539 km^2. Although their methodology proved to be more economical compared to the two surveys conducted in that area in previous years, it is important to explore alternative methods to help reduce costs, increase safety, reduce disturbance to wildlife while still maintaining accuracy and repeatability of the survey methods.

Outside of traditional survey methods, there has been a shift towards less invasive alternatives, particularly in the case of species that are sensitive to human disturbance, such as boreal caribou. Among those methods, genetic analysis of fecal samples has been shown to accurately estimate boreal caribou populations (Carr et al. 2012; Hettinga et al. 2012). Unfortunately, this method remains expensive when compared to other techniques (Carr et al. 2012). Finding an accurate, non-invasive, and inexpensive method to estimate boreal caribou populations has been very difficult, but newly emerging technologies might provide a solution. Several researchers have suggested the use of a small Unmanned Aircraft System (UAS) to conduct aerial surveys (Jones et al. 2006; Chabot and Bird 2012; Koski et al. 2013) because they are safer, less obtrusive, and more affordable compared to manned aircraft surveys. A growing number of wildlife studies have used UAS to survey a wide range of species (Soriano et al. 2009; Rodriguez et al. 2012; Hodgson et al. 2013; Vermeulen et al. 2013; Chabot et al. 2014; Kadaba 2014); however, most non-military applications of UAS have been restricted to line of sight, or about 1 km from the pilot.

1.3 Unmanned Aircraft Systems in Wildlife Research

In wildlife research and management, manned aircraft are an essential tool for counting, tracking and observing wildlife. Despite their utility, manned aircraft can be expensive, obtrusive and dangerous for individuals onboard (Wiegmann and Taneja 2003). Between 1937 and 2000, light manned aircraft crashes have caused 60% of fatalities for wildlife biologists in the United States (Sasse 2003). There has been a surge of interest in the use of UAS as a possible complementary and/or supplementary tool to manned aircraft for a number of applications because they offer a safer, more convenient and less invasive platform for collecting aerial data. Unmanned aircraft systems, which have also been referred to as Unmanned Aerial Vehicles (UAVs) or drones, are aircraft that operate without an onboard pilot and have the option to be flown autonomously. Unmanned aircraft systems consist of several components including the aircraft or UAV, a ground control station, a pilot that can operate the aircraft remotely when necessary, and a spotter who monitors the aircraft. Small UAS include models that weigh less than 25 kg with both rotary and fixed wing aircraft. Rotary wing models can be vertically launched, can hover in place and are more maneuverable, making them ideal for flying in tight spaces that might otherwise be inaccessible, whereas fixed wing planes are generally faster, have a longer range and are useful for covering larger areas (Chabot et al. 2014). A large variety of available different models come in various shapes and sizes as well as a range of sensors that can be mounted on the aircraft (Hardin and Jensen 2011; Watts et al. 2012; Nex and Remondino 2013).

The advent of a non-invasive aerial platform for remotely collecting data on wildlife and their environment is not novel (Flamm et al. 2000; Nowacek et al. 2001); one of the first platform designs entailed using a helium-filled balloon equipped with a video camera to collect images of marine mammals. Flamm et al. (2000) also used this platform to assess the life-stage structure of manatees (*Trichechus spp*.) and Nowacek et al. (2001) gathered imagery with sufficient resolution to observe prey fish behaviour as well as identify individuals. They emphasized that this platform provided more complete behavioural data when compared to observations made for a marine vessel (Nowacek et al. 2001). Despite the potential applications of these technologies, they did not generate much interest among researchers until recently, coinciding with the advent of modern UAS platforms and sensors, as well increased accessibility and affordability for non-military applications (Anderson and Gaston 2013).

In the early stages, methods for collecting data on wildlife with more modern UAS were pioneered by Abd-Elrahman et al. (2005) and Jones et al. (2006), who each used a small UAS to photograph different species of wildlife. The imagery collected was of sufficient resolution that individual animals could be distinguished and counted. Since then, the use of UAS in wildlife research has experienced a surge of interest for remotely sensing habitat and vegetation structures (e.g. Hardin and Jackson 2005; Rango et al. 2009; Breckenridge and Dakins 2011; Laliberte et al. 2011; Dunford et al. 2009; Hervouet et al. 2011; Getzin et al. 2012) as well as wildlife studies (e.g. Chabot et al. 2014; Rodriguez et al. 2012; Kabada 2014). Examples of this kind of research include work done by Rodriguez et al. (2012) who tracked the daily foraging routes of lesser kestrels (*Falco naumanni*). They used data loggers to track the routes travelled by individuals and then subsequently programmed the GPS coordinates of their movements into a UAS to visit locations visited by the kestrels to capture real-time, high-resolution imagery of selected foraging habitats. Similar habitat assessment was done by Kabada (2014) who used a UAS to study habitat selection of the desert kit fox (*Vulpes macrotis arsipus*) in the Mojave and Colorado deserts in California by collecting aerial imagery of burrows and vegetation with a small rotary wing UAS. Chabot et al. (2014) used a small fixed wing UAS to remotely sense wetland habitat occupied by breeding least bitterns (*Ixobrychus exilis*). The imagery collected was used to create a high resolution map used to assess habitat predictors of breeding density of least bitterns. They compared the water vegetation ratios obtained from UAS data to those obtained from conventional ground-based surveys and found similar results, but suggested that UAS estimates are likely closer to the actual values and that they provide superior detection of interspersed water. Unmanned aircraft systems lend themselves well for this branch of research as they can be deployed readily, can collect high resolution imagery, are maneuverable and can be programmed to repeatedly fly the same path, making it possible to capture changes occurring on both temporal and spatial scales that might otherwise go undetected by other remote sensing technologies (Whitehead and Hugenholtz 2014).

In addition to using UAS to study wildlife habitat selection, a number of studies have used UAS to survey wildlife (Chabot and Bird 2012; Sarda-Palomera et al. 2012; Grenzdorffer 2013; Hodgson et al. 2013; Vermeulen et al. 2013; van Gemert et al. 2014; Chabot et al. 2015; Ratcliffe et al. 2015). Compared to conventional aircraft surveys, there are advantages to using aerial imagery to estimate wildlife populations; it produces a permanent record which allows for repeated analysis, facilitates the application of different analysis techniques, and can be examined by multiple observers. Chabot and Bird (2012) used a small UAS to detect and quantify staging flocks of snow geese (*Chen cearulescens*) and Canada geese (*Branta canadensis*) from aerial imagery. When they compared the survey results from the UAS to those obtained from ground surveys, they found that the performance of the UAS was strongly dependent on the contrast of the species against the landscape in the captured images and in some cases, the UAS was able to detect birds that were not seen in ground surveys (Chabot and Bird 2012). In similar studies, Sarda-Palomera et al. (2012) used a small UAS to survey a breeding population of black-headed gulls (*Chroicocephalus ridibundus*) and Grenzdörffer (2013) used a UAS to perform an automatic bird count of a common gull colony (*Larus canus*). Having proven to be an efficient platform for surveying waterbirds, it has been used to survey other bird species (Watt et al. 2010, Potapov et al. 2013; Chabot et al. 2015), and generated interest as a possible platform for surveying marine wildlife (Koski et al. 2009, 2013; Martin et al. 2012). Most reported uses of UAS for surveying marine mammals have focused on breeding pinnipeds, as well as sirenians because they congregate in predictable locations where they can readily be surveyed (Jones et al. 2006; Martin et al. 2012).

Some recent studies have also explored the possibility of using UAS to survey terrestrial species such as elephants (Koh and Wich 2012; Vermeulen et al. 2013). However, studies that utilize UAS to study terrestrial wildlife are limited to flying within visual range of the pilots which has prevented their use for surveying large terrestrial ungulates such as deer, caribou or moose.

1.4 Research Purpose and Objectives

In order to assess the feasibility of using a UAS for the purpose of surveying a wide-ranging terrestrial mammal, it is first necessary to test the ability of the aircraft to conduct beyond line of sight (BLOS) missions and to assess the detectability of the target species in their natural habitat. In the fall of 2013, we obtained permission to use a small electric UAS to fly BLOS in the airspace controlled by the military near Goose Bay, Labrador, and we evaluated the capabilities of an UAS to operate BLOS safely for the purpose of wildlife surveys. The aircraft was equipped with a digital single lens reflex (DSLR) color camera, mounted to provide a nadir image (i.e. positioned to provide a direct overhead view of the ground). The primary objectives were to test the ability of the UAS to fly BLOS for the purpose of conducting wildlife surveys and to collect aerial images of surrogate caribou targets to evaluate how habitat type, photo analysts' experience level, timing of aerial surveys, the contrast of the target against the landscape in imagery, altitude and the distance of the target from the image centerline influenced the detection of surrogate caribou targets. This study was the first of its kind to successfully fly a UAS beyond line of sight over land for non-military applications in Canada and the findings of our research will undoubtedly provide an evaluation for using UAS to survey caribou in the future.

1.5 Literature Cited

Abd-Elrahman, A. 2005. Development of pattern recognition algorithm for automatic bird detection from unmanned aerial vehicle imagery. *Surveying and Land Information Science: Journal of the American Congress on Surveying and Mapping,* **65**:37-46.

Anderson, K., and Gaston, K. J. 2013. Lightweight unmanned aerial vehicles will revolutionize spatial ecology. *Frontiers in Ecology and the Environment,* **11**:138-146.

Banfield, A.W.F. 1974. Mammals of Canada. University of Toronto Press. Toronto, Ontario.

Bergerud, A.T. 1985. Antipredator strategies of caribou: Dispersion along shorelines. *Canadian Journal of Zoology*, **63**: 1324-1329.

Bergerud, A.T. 1988. Caribou, wolves, and man. *Trends in Ecology and Evolution,* **3**: 68-72.

Bergerud, A.T. 1996.Evolving perspectives on caribou population dynamics, have we got it right yet? *Rangifer, Special Issue*, **9**: 95-116.

Bergerud, A.T. 2000. Caribou. In: S. Demarais and P.R. Krausman (Eds.) Ecology and management of large mammals in North America. Prentice Hall, NJ.

Bergerud, A.T., Ferguson, R., and Butler, H. 1990. Spring migration and dispersion of woodland caribou at calving. *Animal Behaviour*, **39**: 360-368.

Bourbonnais, N., A. Gingras, and Rochette, B. 1997. Inventaire aérien du caribou dans une portion de la zone de chasse 19 sud (partie est) en mars 1993. Ministère de l'Environnement et de la Faune. Sept-Îles, Québec. 11 pp.

Breckenridge, R. P. and Dakins, M. E. 2011. Evaluation of bare ground on rangelands using unmanned aerial vehicles: A case study. *GIScience & Remote Sensing*, **48:** 74–85. doi:10.2747/1548-1603.48.1.74.

Brown, W.K. 1986. The ecology of a woodland caribou herd in central Labrador. M.Sc. Thesis, University of Waterloo, Waterloo, Ontario.

Carr, N. L., Rodgers, A. R., Kingston, S. R., Hettinga, P. N., Thompson, L. M., Renton, J. L., and Wilson, P.J. 2012. Comparative woodland caribou population surveys in Slate Islands Provincial Park, Ontario. *Rangifer*, **32**: 205-217.

Chabot, D., Bird, D.M. 2012. Evaluation of an off-the-shelf unmanned aircraft system for surveying flocks of geese. *Waterbirds,* **35**: 170-174.

Chabot, D., Carignan, V. and Bird, D.M. 2014. Measuring habitat quality for least bitterns in a created wetland with use of a small unmanned aircraft. *Wetlands*, **34**: 527-533.

Chabot, D., Craik, S.R. and Bird, D.M. 2015. Population Census of a Large Common Tern Colony with a Small Unmanned Aircraft. *PLoS one*, **10**(4): e0122588.

COSEWIC. 2011. Designatable units for Caribou (*Rangifer tarandus*) in Canada. Committee on the Status of Endangered Wildlife in Canada. Ottawa. 88 pp.

Courtois, R., F. Potvin, S. Couturier, and Gingras, A. 1996. Révision des programmes d'inventaires aériens des grands cervidés. Ministère de l'Environnement et de la Faune. Québec, Québec. 49 pp.

Courtois, R., Gingras, A., Dussault, C., Breton, L., and Ouellet, J.P. 2003. An aerial survey technique for the forest-dwelling ecotype of woodland caribou, *Rangifer tarandus* caribou. *Canadian Field-Naturalist*, **117:** 546-554.

Courtois, R., Ouellet, J.P., Gingras, A., Dussault, C. and Banville, D. 2001. La situation du caribou forestier au Québec. *Naturaliste Canadien*, **128:** 53-63.

Courtois, R., Ouellet, J. P., Breton, L., Gingras, A. and Dussault, C. 2007. Effects of forest disturbance on density, space use, and mortality of woodland caribou. *Ecoscience,* **14**: 491–498.

Crête, M. 1991. Mise au point de la technique d'inventaire du caribou dans la taïga. Ministère du Loisir, de la Chasse et de la Pêche. Québec, Québec. 20 pp.

Cuyler, C. 2007. West Greenland caribou explosion: What happened? What about the future? *Rangifer*, **27**: 219-226.

Dunford, R., K. Michel, M. Gagnage, H. Piégay, and Trémelo, M. L. 2009. Potential and constraints of unmanned aerial vehicle technology for the characterization of mediterranean riparian forest. *International Journal of Remote Sensing*, **30**: 4915–4935. doi:10.1080/01431160903023025.

Environment Canada. 2008. Scientific review for the identification of critical habitat for woodland caribou (*Rangifer tarandus caribou*), boreal population, in Canada. Environment Canada. Ottawa, ON. 72 p.

Flamm, R. O., Owen, E. C., Owen, C. F., Wells, R. S., and Nowacek, D. 2000. Aerial videogrammetry from a tethered airship to assess manatee life-stage structure. *Marine Mammal Science*, **16**: 617-630.

Getzin S., K. Wiegand and Schoning, I. 2012. Assessing biodiversity in forests using very high-resolution images and unmanned aerial vehicles. *Methods in Ecology and Evolution,* **3**: 397–404.

Grenzdörffer, G. 2013. UAS-based automatic bird count of a common gull colony *In* International Archives lf the Photogrammetry, Remote Sensing and Spatial Information Sciences Volume **XL-1/W2**:169-174.

Gunn, A. 2003. Voles, lemmings and caribou - population cycles revisited? *Rangifer*, **23***:* 105-111.

Gunn, A., Miller, F. L., Barry, S. J., and Buchan, A. 2006. A near-total decline in caribou on Prince of Wales, Somerset, and Russell Islands, Canadian Arctic. *Arctic*, **59:**1-13.

Hardin, P.J. and Jackson, M.W. 2005. An unmanned aerial vehicle for rangeland photography. *Rangeland Ecology and Management,* **58**: 439–442.

Hardin, P.J., and Jensen, R.R. 2011. Small-scale unmanned aerial vehicles in environmental remote sensing: challenges and opportunities. *GIScience & Remote Sensing*, **48:** 99-111.

Hervouet, A., R. Dunford, H. Piegay, B. Belletti and Tremelo, M.-L. 2011. Analysis of post-flood recruitment patterns in braided-channel rivers at multiple scales based on an image series collected by unmanned aerial vehicles, ultra-light aerial vehicles, and satellites. *GIScience & Remote Sensing,* **48**: 50–73.

Hettinga, P. N., Arnason, A. N., Manseau, M., Cross, D., Whaley, K., and Wilson, P.J. 2012. Estimating size and trend of the North Interlake woodland caribou population using fecal-DNA and capture–recapture models. *Journal of Wildlife Management,* **6:** 1153-1164.

Hodgson, A., Kelly, N., and Peel, D. 2013. Unmanned aerial vehicles (UAVs) for surveying marine fauna: a dugong case study. *PloS one*, **8:** e79556.

James, A. R., Boutin, S., Hebert, D. M. and Rippin, A.B. 2004. Spatial separation of caribou from moose and its relation to predation by wolves. *Journal of Wildlife Management*, **68**: 799-809.

Jones, G. P., Pearlstine, L. G., and Percival, F.H. 2006. An assessment of small unmanned aerial vehicles for wildlife research. *Wildlife Society Bulletin,* **34:** 750-758.

Kadaba, D. 2014. Ecology of the desert kit fox *(Vulpes macrotis arsipus)* in Chuckwalla Valley, California. (Doctoral dissertation, School of the Environment, Duke University).

Koh, L. P. and Wich, S.A. 2012. Dawn of drone ecology: low-cost autonomous aerial vehicles for conservation. *Tropical Conservation Science,* **5**:121–132.

Koski, W.R., Allen, T., Ireland, D., Buck, G., Smith, P.R., Macrander, A.M., Halick, M.A., Rushing, C., Sliwa, D.J., and McDonald, T.L. 2009. Evaluation of an unmanned airborne system for monitoring marine mammals. *Aquatic Mammals,* **35**: 347.

Koski, W. R., Thomas, T. A., Funk, D. W., and Macrander, A.M. 2013. Marine mammal sightings by analysts of digital imagery versus aerial surveyors: a preliminary comparison. *Journal of Unmanned Vehicle Systems*, **1:** 25-40.

Laliberte, A. S., Goforth, M. A., Steele, C. M. and Rango, A. 2011. Multispectral remote sensing from unmanned aircraft: Image processing workflows and applications for rangeland environments. *Remote Sensing* **3**: 2529–2551. doi:10.3390/rs3112529.

Martin, J., Edwards, H. H., Burgess, M. A., Percival, H. F., Fagan, D. E., Gardner, B. E., Ortega-Ortiz, J.G., Ifju, P.G., Evers, B.S. and Rambo, T. J. (2012). Estimating distribution of hidden objects with drones: From tennis balls to manatees. *PloS one,* 7: e38882.

Ministry of Sustainable Resource Management. 2002. Aerial-based inventory methods for selected ungulates: Bison, Mountain Goat, Mountain Sheep, Moose, Elk, Deer and Caribou: Standards for components of British Columbia's biodiversity No. 32. Version 2.0. Ministry of Sustainable Resource Management. Victoria, British Columbia, Canada.

Murden, S. B. and Risenhoover, K. L. 2000. A blimp system to obtain high-resolution, low-altitude aerial photography and videography. *Wildlife Society Bulletin,* **28**: 958–962.

Nex, F., and Remondino, F. 2013. UAV for 3D mapping applications: a review. *Applied Geomatics*, **6**: 1–15.

Nowacek, D. P., Tyack, P. L, and Wells, R.S. 2001. A platform for continuous behavioral and acoustic observation of free-ranging marine mammals:

Overhead video combined with underwater audio. *Marine Mammal Science,* **17**: 191-199.

Ouellet, J.-P., Ferron, J. and Sirois, L. 1996. Space and habitat use by the threatened Gaspé caribou in southeastern Quebec. *Canadian Journal of Zool*ogy, **74:** 1922-1933.

Potapov, E.R., Utekhina, I.G., McGrady, M.J. and Rimlinger, D. 2013. Usage of UAV for Surveying Steller's Sea Eagle Nests. *Raptors Conservation*, **27**:253–260.

Rango A., Laliberte, A., Herrick, J. E., Winters, C., Havstad, K., Steele C. and Browning, D. 2009. Unmanned aerial vehicle-based remote sensing for rangeland assessment, monitoring, and management. *Journal of Applied Remote Sensing*, **3**: 033542.

Ratcliffe, N., Guihen, D., Robst, J., Crofts, S., Stanworth, A., and Enderlein, P. 2015. A protocol for the aerial survey of penguin colonies using UAVs. *Journal of Unmanned Vehicle Systems in press.*

Rettie, W.J., and Messier, F. 1998. Dynamics of woodland caribou populations at the southern limit of their range in Saskatchewan. *Canadian Journal of Zoology*, **76:** 251-259.

Rettie, W.J. and Messier, F. 2000. Hierarchical habitat selection by woodland caribou: Its relationship to limiting factors. *Ecography*, **23**:466-478.

Rodríguez, A., Negro, J. J., Mulero, M., Rodríguez, C., Hernández-Pliego, J., and Bustamante, J. 2012. The eye in the sky: Combined use of unmanned aerial systems and GPS data loggers for ecological research and conservation of small birds. *PloS one,* **7:** e50336.

Sasse, D.B. 2003. Job-related mortality of wildlife workers in the United States, 1937-2000. *Wildlife Society Bulletin*, **31**: 1015-1020.

Schaefer, J. A. 1997. Red Wine aerial census, January 1997. Newfoundland-Labrador Wildlife Division, Report to Department of National Defense.

Schaefer, J. 2003. Long-term range recession and the persistence of caribou in the taiga. *Conservation Biology*, **17**: 1435-1439.

Schaefer, J.A., Veitch, A.M., Harrington, F.H., Brown, W.K., Theberge, J.B. and Luttich, S.N. 1999. Demography of decline of the Red Wine Mountains caribou herd. *Journal of Wildlife Management*, **63:** 580-587.

Schmelzer, I., Brazil, J., Chubbs, T., French, S., Hearn, B., Jeffery, R., LeDrew, L., Martin, H., McNeill, A., Nuna, R., Otto, R., Phillips, F., Mitchell, G., Pittman, G., Simon, N., and Yetman, G. 2004. Recovery strategy for three woodland caribou herds (*Rangifer tarandus caribou*; boreal population) in Labrador. Department of Environment and Conservation, Government of Newfoundland and Labrador, Corner Brook.

Soriano, P., Caballero, F., and Ollero, A. 2009. RF-based particle filter localization for wildlife tracking by using an UAV. *40th International Symposium of Robotics, 2009.* Barcelona, Spain.

Stuart-Smith, A.K., Bradshaw, C.J.A., Boutin, S. Hebert, D.M. and Rippin, A.B. 1997.Woodland caribou relative to landscape patterns in northeastern Alberta. *Journal of Wildlife Management*, **61:** 622-633.

Thomas, D.C., and Gray, D.R. 2002. Update COSEWIC status report on the woodland caribou *Rangifer tarandus caribou* in Canada. Environment Canada, Committee on the Status of Endangered Wildlife in Canada, Ottawa, Ontario pp. 1-98.

Van Gemert, J., Verschoor, C.R., Mettes, P., Epema, K., Koh, L.P. & Wich, S. 2014. Nature Conservation Drones for Automatic Localization and Counting of Animals. Computer Vision in vehicle technology with Special Session on Micro Aerial Vehicles Zurich, Switzerland

Vermeulen, C., Lejeune, P., Lisein, J., Sawadogo, P., and Bouché, P. 2013. Unmanned aerial survey of elephants. *PLoS one,* **8:** e54700.

Watts, A. C., Perry, J. H., Smith, S. E., Burgess, M. A., Wilkinson, B. E., Szantoi, Z., Ifju, P.G., and Percival, H. F. 2010. Small unmanned aircraft systems for low-altitude aerial surveys. *Journal of Wildlife Management,* **74:** 1614-1619.

Watts, A.C., Ambrosia, V.G., and Hinkley, E.A. 2012. Unmanned aircraft systems in remote sensing and scientific research: classification and considerations of use. *Remote Sensing*, **4:** 1671–1692.

Whitehead, K. and Hugenholtz, C. H. 2014. Remote sensing of the environment with small unmanned aircraft systems (UASs), part 1: a review of progress and challenges. *Journal of Unmanned Vehicle Systems*, **2**:69-85.

Wiegmann, D. A., and Taneja, N. 2003. Analysis of injuries among pilots involved in fatal general aviation airplane accidents. *Accident Analysis & Prevention,* **35**: 571-577. doi:10.1016/S0001-4575(02)00037-4.

CONNECTING STATEMENT

Unmanned aircraft systems are emerging as a useful tool for researchers and wildlife managers for a variety of applications. However, UAS might not necessarily be the best option for all purposes; their performance will depend largely on the objectives and limitations of the project. Once these are clearly defined, it is necessary to select the appropriate aircraft and payload, and then test their ability to satisfy the demands of the project prior to conducting large-scale missions.

Using UAS for the purpose of wildlife surveys has generated much interest, but there have been no studies to date that have successfully flown BLOS for terrestrial surveys of wildlife. Before these types of medium- and long-distance surveys can be done, it is important to evaluate the performance of the aircraft and the payload for this purpose. The study described in Chapter 2 evaluates the feasibility of using a small, fixed wing UAS for surveying boreal caribou by testing its ability to fly BLOS, collect aerial imagery with a DSLR camera and then by conducting a post-assessment of the factors that affect the detectability of surrogate caribou targets in a controlled study. This work provides recommendations for using UAS to survey caribou and other wildlife in the future.

CHAPTER 2:

EVALUATION OF AN UNMANNED AIRCRAFT SYSTEM FOR DETECTING SURROGATE CARIBOU TARGETS IN LABRADOR

2.1 Abstract

Regular, standardized population inventories have been suggested as an important component to the recovery of declining populations of boreal caribou (*Rangifer tarandus caribou*). Current survey methods typically employ manned aircraft, which can be noisy, expensive to operate, and dangerous for the people conducting the surveys. Small Unmanned Aerial Systems (sUAS) have garnered attention as a promising alternative for conducting aerial surveys in manned aircraft. Our research investigates the feasibility of using a UAS to conduct aerial surveys and determine which factors affect the detection of surrogate caribou targets, and hence might affect detection of real caribou. In the fall of 2013, we tested the capabilities of the Brican TD100e, a small, electric-powered fixed-wing UAS, to fly beyond line of sight (BLOS) near Goose Bay, Labrador. Seven surveys were done using different flight paths to collect aerial images of 26 surrogate caribou targets placed in six different habitats. Mixed effects logistic regression models were used to evaluate how habitat type, distance of the target from the image centerline, photo analysts' experience level, flight time, and the

target contrast against the landscape influenced the detection of surrogate caribou targets. We found that habitat type, target contrast, and the flight time affected target detection. Overall, 77.5% of the targets were detected; the odds of a photo analyst detecting a target in open habitat were roughly 10.5 times higher than in burned habitat and 42 times higher than in heavy forest. Target detection was influenced by the contrast of the target against the landscape, where higher contrast was associated with greater target detection. The detection of targets was 87% during evening flights and 75% for morning flights. This study was the first of its kind to successfully fly a UAS beyond line of sight over land for non-military applications in Canada and the findings of our research will undoubtedly provide recommendations for using UAS to survey caribou in the future.

2.2 Introduction

Boreal caribou (*Rangifer tarandus caribou*) are found across northern Canada ranging from the western corner of the Yukon to central and eastern Labrador and on the island of Newfoundland (Thomas and Gray 2002). Under the species caribou, boreal caribou are classified by COSEWIC as one of twelve distinct groups based on differences in behavior, morphology, ecology and genetics (COSEWIC, 2011). In the last three decades, boreal caribou have been experiencing range contractions and steady declines in population size across

Canada (Rettie and Messier 1998; Schaefer et al. 1999). The number of boreal caribou in Canada is estimated to be between 31,000 to 39,000 (excluding the island of Newfoundland) (Environment Canada, 2008) and they are listed as either threatened or endangered in six of the nine provinces and territories where they occur (COSEWIC 2011), including Labrador (Thomas and Gray 2002). In Labrador, boreal caribou populations are declining at an estimated rate of 13–26% per year (Schaefer et al. 1999), which is faster than those estimated for populations in other provinces (Ouellet et al. 1996; Stuart-Smith et al. 1997; Rettie and Messier 1998).

The widespread decline of caribou across Canada has raised concerns about their conservation status and the sustainability of current management practices. Conducting regular population inventories is an important step towards their recovery (Schmelzer et al. 2004). Frequent surveys are especially important since population sizes have been known to change rapidly (Gunn et al. 2006; Cuyler 2007) and the confidence intervals around most population estimates are too high to confirm changes without several surveys. A population of caribou located on three islands in Nunavut declined by 98% within a 15-year period from 6048 individuals to roughly a hundred. An absence of survey data during that time frame delayed the detection of the decline and limited our understanding of what caused it, making the recovery of these populations challenging (Gunn et al. 2006). Despite the importance of regular population inventories, there is an absence of accurate population size estimates and data on population trends for many boreal caribou herds (Courtois et al. 2003; Callaghan et al. 2011). The Scientific Review for the Identification of Critical Habitat for Woodland Caribou recognized 57 local populations of boreal caribou across Canada (excluding Newfoundland), of which 5.3% populations were increasing in size, 29.3% were declining, 28.1% were reportedly stable and the status of the remaining majority 36.8% was unknown (Environment Canada 2008). Gathering population data on boreal caribou has been a notoriously challenging task because they occur at densities as low as 1.5 caribou/km^2, they form small herds with a clustered distribution over a wide area (Crête 1991; Courtois et al. 2001), and they live in forested areas that reduce detection during surveys. Aerial surveys conducted by people have been the preferred technique for estimating caribou populations; however, manned aircraft can be expensive, their noise can disturb sensitive wildlife, and they are dangerous for individuals onboard (Wiegmann and Taneja 2003). From 1963 to 2000, a crash in manned light aircraft was the leading cause of mortality for biologists in the United States (Sasse 2003).

Finding an accurate, non-invasive and inexpensive method to estimate boreal caribou populations presents a difficult challenge, but newly emerging technologies could help address some of these difficulties. Several researchers have suggested the use of a small unmanned air vehicle system (UAS) to conduct aerial surveys (Jones et al. 2006; Chabot and Bird 2012; Grenzdorffer 2013; Koski et al. 2013; Vermeulen et al. 2013; van Gemert et al. 2014; Chabot et al. 2015; Ratcliffe et al. 2015) because they are safer, less obtrusive, and more affordable compared to manned aircraft surveys. For the purpose of conducting surveys, unmanned aircraft systems equipped with a camera can be used to gather aerial imagery or video footage that can later be analyzed to estimate the abundance of a target species.

Aerial imagery collected by manned aircraft or satellites has been used in the past to estimate wildlife populations (Boyd 2000; Udevitz et al. 2008; Buckland et al. 2012; Fretwell et al. 2012). Unmanned aircraft systems offer a more convenient platform for unobtrusively obtaining high resolution imagery or video footage of wildlife because they can fly at low altitude and can survey hard-to-reach places. Imagery obtained from UAS provides very high spatial resolution (≤10 cm/pixel) compared to satellite imagery (≥ 60 cm/pixel) (Fretwell et al. 2012). Unmanned aircraft systems have been used to detect animals including large and small terrestrial mammals, birds, reptiles and marine mammals as well as to identify evidence of wildlife such as nests and tracks (Jones et al. 2006; Koski et al. 2009, 2015; Chabot and Bird 2012; Sarda-Palomera et al. 2012; Potapov et al. 2013; Grenzdorffer 2013; Hodgson et al. 2013; Vermeulen et al.

2013; Mulero-Pazmany et al. 2014, van Gemert et al. 2014; Chabot et al. 2015; Ratcliffe et al. 2015). However, due to past regulatory restrictions involved with non-military BLOS flight of UAS in North America, most studies that utilize UAS to study terrestrial wildlife are limited to flying within visual range of the pilot which has prevented their use for surveying large terrestrial ungulates such as deer, caribou or moose. In order to assess the feasibility of using an UAS for the purpose of surveying caribou, it is first necessary to test the ability of the aircraft to conduct beyond line of sight (BLOS) missions and to assess the detectability of the target species in their natural habitats.

In both traditional aerial surveys and those that use a digital medium for data collection, the detectability of target species is dependent on several factors that are often specific to the environment and the species of interest. Previous research has shown that the detectability of ungulates is influenced by group size, canopy cover, individual activity (bedded, standing, moving), ground terrain, and light conditions (Thomas and Gray 2002; Gilbert and Moeller 2008; Patterson et al. 2014; Peters et al. 2014). Of these factors, vegetation cover, which is largely dependent on the habitat, is the most frequently reported factor known to affect the detectability of target wildlife during surveys (Gasaway 1985; Samuel et al. 1987; Gilbert and Moeller 2008; McIntosh et al. 2009; Jarding 2010; Griffin et al. 2013). For this reason we chose to focus on the effect of habitat on the detection of targets. The accuracy of wildlife population estimates generated from aerial surveys are also largely dependent on the experience level of the observers (Miller et al. 1998; Garel et al. 2005). Imagery or video footage collected by a UAS can be reviewed more slowly, which may help reduce error in detecting targets and help the photo analyst gain experience properly identifying the target species. If the photo analysts' experience level is an important predictor affecting the detection of surrogate caribou targets, then correct target detection should improve as photo analysts gain experience. Although we did not include light conditions in our analysis, the timing of flight loosely captures the effect of light conditions on target detection; the implications are discussed further in the discussion.

For surveys that use digital media for surveying wildlife, there some additional factors that we wanted to include in study, as they could affect the detection of target wildlife in aerial imagery. Chabot and Bird (2012) used a small UAS to detect and quantify staging flocks of snow geese (*Chen cearulescens*) and Canada geese (*Branta canadensis*) from aerial imagery, and they found that the detection of the target species was strongly dependent on the contrast of the species against the landscape in the captured images (Chabot and Bird 2012). The altitude at which surveys are conducted can also influence target detection, as it directly affects the swath width covered in video footage or images collected in flight. Flying at a higher altitude provides greater coverage, but the ground resolution is decreased. We also wanted to test the effect of the distance of the target from the centerline of the image to control for chromatic imperfections in photos and the obscuring effect of landscape features at the edges of images. Even with high quality lenses, there are still some chromatic aberrations caused by the inability of the lens to focus all colour wavelengths on the same focal plane or at the same position on the focal plane. This can cause blurring, or noticeably colored edges around objects in the image. We also wanted to control for the obscuring effect of landscape features at the edge of images; targets located directly beneath the aircraft when the image was captured are less likely to be obscured by trees or other objects because they are imaged from directly overhead. Targets located farther away from the centerline towards the edges of the image are more likely to be obscured by trees and other landscape features as they are photographed at an angle.

In the fall of 2013, we obtained permission to use a small electric UAS to fly BLOS in the airspace controlled by the military near Goose Bay, Labrador, and we evaluated its capabilities to safely operate BLOS for the purpose of wildlife surveys. The aircraft was equipped with a digital single lens reflex (DSLR) color camera, mounted to provide a nadir image (i.e. positioned to provide a direct overhead view of the ground). The primary objectives were to test the ability of the UAS to fly BLOS for the purpose of conducting wildlife surveys and to collect aerial images of surrogate caribou targets to evaluate how habitat type, photo analysts' experience level, timing of aerial surveys, the contrast of the target against the landscape in imagery, altitude and the distance of the target from the image centerline influenced the detection of surrogate caribou targets. This study was the first of its kind to successfully fly a UAS beyond line of sight over land for non-military applications in Canada and the findings of our research will undoubtedly provide an evaluation for using UAS to survey caribou in the future.

2.3 Methods

2.3.1 Study area

All flights were done in the Practice Target Area (PTA) in Labrador, Canada (lat: 52.297691°, long: -60.997204°), which is approximately 100 km south of Goose Bay. Brican Flight Systems Inc. and McGill University were given permission from the military authorities at 5 Wing Goose Bay and Transport Canada to conduct BLOS flights with an UAS in a restricted airspace falling within a 60 km radius of the PTA.

The landscape in the region had a very uneven terrain with small hills and cliffs that rise up to 600 m above sea level. However, the 4.1 km^2 study area where the aerial surveys were conducted had a fairly even terrain that varied only by 15-20 m. The area was characterized by varying density of forest cover, which consisted predominantly of black spruce (*Picea mariana*) as well as low herbaceous vegetation, bog-complexes, and streams. Reindeer lichen (*Cladoniaaccae spp.*) was common throughout the area and growing in patches varying in size. All targets were placed within a 4.1 km^2 study area which contained a total of six different habitat types including: i) heavy forest, ii) medium cover forest, iii) sparse cover with lichen ground-cover, iv) sparse cover with no lichen ground-cover, v) open and vi) recently burned areas (Fig. 2.1). We distinguished between sparsely forested habitat with and without lichen because the white reindeer lichen ground cover could influence how easily a target could be distinguished from the landscape. In areas where there was no lichen, the ground cover was dominated by blueberry bushes and bare soil which provided a reddish-brown backdrop with higher contrast in aerial photos.

2.3.2 Unmanned Aerial Vehicle System

The UAS used in our study was the TD100E fixed-wing, propeller-driven, aircraft (Fig. 2.2) provided by Brican Flight Systems Inc. (Brampton, ON). It consisted of a small electric-powered unmanned aerial vehicle, a pneumatic launch system, radio-controlled (RC) transmitter, antenna tracker, and ground control station.

TD-110E Specifications

The aircraft was made of carbon-epoxy composites. This small aircraft (4.978 m wingspan, 2.0 m long, 24.9 kg gross weight) was powered by an electric motor and lithium polymer batteries. This allowed flight times of about 120 minutes to loss of battery power or 80–90 minutes allowing for unexpected last-minute events. Flight speeds ranged from a minimum of 64 km/h (35 knots) to a maximum of 145 km/h (80 knots). The average flight altitude for the experiments was ~652 m and the median flight altitude was ~690 m above sea level at a flight speed of ~90 km/h. One flight was conducted at a lower altitude ~550-600 m above sea level, but for the remaining six flights, the altitude was maintained at ~690m. We did not vary the flight altitude with the terrain because the terrain of the 4.1 km^2 study area where the aerial surveys were conducted only varied by 15-20 m.

The aircraft was launched using a pneumatic catapult (Brican Flight Systems Inc.) (Fig. 2.2). Once airborne, the plane was controlled using either direct command mode or autopilot mode. The plane had no landing gear, so landing the aircraft involved floating it to the ground and skidding to a stop. This was done either manually by a trained pilot or using the autopilot mode. All flights were pre-programmed, meaning the aircraft was being operated using the autopilot mode; direct control was only used when landing the plane.

Communication Links

The UAS had multiple data control links used to communicate with the aircraft. The primary communication links included the remote control link, which used a remote controller operating in conjunction with the autopilot. It had an estimated visual range of 1.5 km and was used for manual control of the unmanned aircraft. The autopilot command and control link used a Microhard MHX910A modem and operated at 902-928 MHz within a range of up to about 35 km from the ground control station. Also, a secondary autopilot communication system utilized an Iridium 9522B satellite transceiver and operated at 1.6 GHz. The latter system was used to provide secure communications for BLOS flight, and was operative at all distances from the ground control station.

Autopilot Software

The aircraft was equipped with a Micropilot 2128g2 autopilot. This allowed the unmanned aircraft to fly autonomously using pre-programmed flight paths. The autopilot software also controlled the camera that was set to take a picture about every 300 m along the flight path.

The Payload

The UAS was equipped with a digital single lens reflex (DSLR) colour camera — the Nikon D3X with a 50 mm focal length lens and 6048 × 4032 pixel resolution. The camera was mounted to provide a nadir image (i.e. positioned to provide a direct overhead view of the ground). For most flights the camera used the following fixed settings for capturing photos: aperture set at f /4.5; ISO sensitivity 250; and a shutter speed set at either 1/1000, 1/1250, or 1/800 s. The field of view (FOV) for the lens was 38.7 degrees. The swath covered on the ground by the DLSR imagery was ~260 m which equated to ~4.3 cm/pixel. The environment was ideal for this type of sensor, especially when trying to detect a high-contrast target such as a caribou against the natural background of the Labrador landscape.

2.3.3 Data Collection

The UAS was pre-programmed to fly a grid pattern over the area where surrogate caribou targets had been randomly placed in different habitats. During all flights, the camera and flight altitude were adjusted to provide a swath width of ~ 260 m. The median flight altitude was ~690 m above sea level. The altitude was selected in order to obtain a resolution of one pixel on the ground of 0.04 m or better based on resolution tests done the previous year. A uniform distance between the center of each photograph was selected to fire the camera rather than a firing interval based on time to avoid variable overlap between successive photographs. Variable overlap would result if the same time interval between photographs were used when the UAS was flying upwind versus downwind. The DGPS position information from the GCS triggered the camera to fire whenever the UAS travelled 300 m. The camera data were stored on board the TD100 and downloaded following the flight. Conducting flights required two operators, one to monitor the flight for safety issues and a second to operate the ground control station. The UAS was pre-programmed to fly transects in a grid pattern prior to each survey. A different flight pattern was used for each survey, and was created by offsetting the pre-defined grid by random amounts up to the transect spacing. The data recorded on the Nikon camera were archived onto a portable hard drive immediately following the flight.

Surrogate Caribou Targets

We used unpainted 0.6 m × 1.2 m fir plywood boards of uniform shape and size as surrogate targets for the caribou. These targets were approximately the same colour as caribou and they were also approximately the same size when viewed from an aerial perspective. It is important to note thoughthat these plywood targets would naturally be more easily detected in aerial photographs than real caribou because of their uniform colour and rectangular shape; however, capturing aerial imagery of these targets and assessing detectability provided useful information on factors that influence their detection. A similar study by Koski et al. (2009) used kayaks to evaluate the factors that could influence the detection of whales in aerial video-footage collected by a UAS.

Target Placement

Using satellite imagery from Google Earth, we selected a total of 26 points within each of the six habitat types falling within the defined study area (Fig. 2.1). Use of Google Earth provided a coarse map of the study site which allowed for division of the site into different habitat types and random selection of locations for target placement. The GPS locations selected using Google Earth were entered into a hand-held GPS device, the Garmin Etrex Venture (Garmin International, Inc, Olathe, Kansas) with a mean error of 12.4 ± 4.36 m. The Etrex was used to navigate to the selected locations for target placement at the beginning of the study and for target recovery at the end of the study. In cases where the selected location did not match the habitat type viewed in Google Earth, we decided whether or not to move the target to a new location based on how many targets we had placed in each habitat type to ensure that each habitat type in our study was adequately represented. If we did not already have 5-6 targets placed in that habitat type, we left the target in place and recorded the habitat class. If there were already enough targets placed in that habitat type and we required more targets placed in a different habitat category, we selected a new location from Google Earth and moved the target. A fire that passed through the area after the Google Earth imagery was obtained caused the discrepancy between the habitats shown on Google Earth and those that were present. We left some of the targets in the area that had been affected by the forest fire, because this ecosystem has a natural forest fire regime, but we did have to relocate three targets to ensure adequate sample sizes for all the habitat types. Once all targets were placed in the six different habitats, their position remained unmodified for the duration of all test flights conducted during this study.

Survey Patterns

Once all targets were placed, the unmanned aircraft was programmed to fly a pre-defined grid pattern of parallel transects. We conducted multiple surveys by offsetting the pre-defined grid by random amounts up to the transect spacing. This was done to capture images of each target at different positions from the transect center-line. All flights were done in the morning from 07:00–9:30 or in the afternoon from 14:00–15:00. There were 464 individual targets captured in images during morning (AM) flights and 149 during evening (PM) flights. The overlap between adjacent transects was designed to be ~10%, so some targets were detected on adjacent transects during the same survey. The aircraft had a median flight altitude of 690 m and an average altitude of ~652 m (419–729 m) above sea level.

Image acquisition

We chose to program the autopilot to take a picture about every 300 m along the flight path to ensure there was sufficient overlap between images and that a manageable number of photos were collected. If we had programmed it to take photos more frequently, the number of images can quickly accumulate into the thousands and become difficult to process during analysis. Approximately 6100 images were collected from seven test flights conducted from 6–10 September 2013.

2.3.4 Imagery analyses

Reference Data Sheet

A total of 26 targets were placed within the study area and photographed by the UAS during each survey. All images were geo-referenced using the WGS 84 datum. The GPS data were extracted from the metadata of the photographs and converted to x-y coordinates in ArcGIS version 10.1 (Environmental Systems Research Institute, Inc., Redlands, California) using the *Geotagged Photos to Points* tool. The recorded locations for the targets were also plotted in Arcmap and the study area was defined as a rectangular polygon (area = 4.1 km^2). All aerial photos that were outside the study area were discarded. From the original 6100 images collected, only 1314 images fell within this area. A buffer of 350 m was set around each of the target locations, and all photos falling within the buffer zone were carefully examined for the presence of targets. Only 354 images had targets present and were shown to photo analysts.

In each photo that targets were located, the pixel latitude, longitude, and the distance from the center-line of each individual target were recorded using XnView (Software available at http:// www.xnview.com). The centerline was defined as the line that intersects the nadir point in the image. If every photo were taken at an exactly vertical position above the ground, the centerline would be drawn through the middle of the photograph. However, oftentimes, winds can shift the pitch and roll of the aircraft, causing the camera to tilt and capture the image at a slightly oblique angle, which displaced the centerline. In most of the photos we analyzed, the centerline fell at the center of the image. In cases where the nadir had shifted from the center of the image, it was approximated by looking at landscape features to approximate the nadir centerline. Every image was processed to extract the GPS coordinates of the photo, and the presence or absence of targets in the image.

We used Image J (software available at rsbweb.nih.gov/ij/) to calculate the corrected integrated density (CID) of the targets in the images, herein referred to as 'target contrast'. This was done by using the select feature to trace the contour of the target and then using the measure feature to extract information on the area, mean gray scale value and the integrated density of the selected pixels. A section of pixels surrounding the target was then selected and measured to extract the same information. These values were used to calculate the corrected integrated density of the target against the landscape (or its contrast) using the formula CID = Integrated Density of the target – (Area of selected target X Mean gray scale value of the selected background). This value was used as a measure of how the targets appeared against the landscape (Fig.2.3).

Target detection by human analysts

Four photo analysts were selected to examine ~300 images each. All photos were examined using the Evolution II QNIX high resolution 27” IPS monitor with 2560 x 1440 pixel display to control for image display quality. Aerial images were collected while the plane was flying pre-programmed transects, causing considerable overlap between images. To prevent continuity of the images being examined by photo analysts, the photos were divided by randomly selecting a starting point and then allocating images one at a time to each of the four photo analysts until they were all distributed. No photo was examined more than one time by the same analyst. None of the photo analysts had previous experience detecting targets from aerial imagery prior to their involvement with this study. Each photo analyst was instructed to look at approximately the same number of photos per day and given a limit of two weeks to complete the survey. They were to record the observation day, which was a measure of accumulated experience looking for targets in the images. Both photos with and without targets were examined by analysts to ensure that they were not identifying marginal targets because they anticipated a target in each photo. For each photo, analysts recorded the presence or absence of any targets, and how confident they were that their response was correct using a scale of 0-5. A rating of zero indicates they have no confidence and a rating of five indicates they are very confident. When targets were present, the photo analysts recorded the x and y pixel coordinates of the center of the target. After all photos were show to the photo analysts, their responses were evaluated for accuracy by crosschecking their responses with the known locations of targets in each photo. It was then possible to record whether the photo analyst correctly identified the presence or absence of any targets as well as false positive and false negative detections.

2.3.5 Statistical Analysis

All graphical and statistical analyses were carried out in the statistical software package R (version 3.1.2) (R Development Core Team 2013). To conduct our analysis, we used general linear mixed models (GLMMs) and followed the recommendations outlined by Grueber et al. (2011). These types of models are ideal for dealing with data that are unbalanced, non-normally distributed, or have missing data. They also provide a powerful tool for evaluating the size and direction of effects while simultaneously accounting for random effects (Bolker et al. 2009). For our analysis, we aimed to evaluate which predictors had the greatest effect on the detection of surrogate caribou targets. We only included photos where targets were present, and we also removed all false positive detections of targets as well. False positives were excluded from the analysis because there were too few false positives in our dataset to provide a useful analysis. The majority of those false positive detections were the result of an old piece of metal debris that had been left in the woods. When photo analysts correctly identified a target, it was labelled as a “success”; when they failed to find the target, it was labelled as “failure”, and these outcomes were coded as 1 and 0, respectively. Before conducting our analysis, we built a linear model that included all the fixed effects and calculated the variance-inflation factors (VIF) to assess for multicollinearity between the explanatory variables. All values were less than the cutoff of VIF <5 (O’brien 2007), suggesting that multicollinearity did not present a serious issue.

Our models were fit using the *glmer* function from the *lme4* package (Bates et al. 2014). We used Laplace approximation of maximum likelihood with a binomial error structure and a logit link function. We were primarily interested in the influence of fixed effects so the random effect of ‘photo analyst ID’ was included in all models. We included photo analyst ID as a random effect to account for the lack of independence between survey responses as well as the inherent differences in performance between individuals. The fixed effects included: ‘habitat type’, ‘photo analysts’ experience level’, ‘distance of the target from the image centerline’, ‘target contrast’, and ‘flight time’ (Table 2.1). The variable ‘Altitude’ was originally included in the analysis, but the distribution of the data collected for altitude was not normally distributed, and the majority of images were collected within a narrow altitude range between 675-715 m. For these reasons, we ultimately decided to exclude altitude from the remainder of our analysis. Interactions were not included as they were not considered relevant for the intent of our analysis. To facilitate direct comparison, we centered continuous predictors by subtracting the mean and dividing by two standard deviations (Gelman 2008) using the *standardize* function the *arm* package (Gelman et al. 2009). The categorical and binary predictors were left unchanged. We generated a model set using the *dredge* function from the MuMIn package (Barton 2012) that included all combinations of the six explanatory variables, all of which included the random effect.

To compare our models, we used the Akaike Information Criterion corrected for small sample sizes (AICc) (Aikaike 1973) and Akaike weight (wi) to rank models. The Akaike weight can be interpreted as the likelihood that a given model from within a set best fits the data with regards to fit and overall parsimony. We delineated the top model set using the top 2AICc of models (Burnham and Anderson 2002). There was only one top model, so model averaging was not used, and instead, we used this model to compute 95% confidence intervals for the fixed effects as well as the odds ratios. Tukey's HSD analysis was performed using the *glht* function from the *multcomp* package (Piepho 2004) to determine the differences in detection between different habitat types for the best fitting model.

2.4 Results

Our model set included 32 different models; the best fitting model for target detectability included the habitat type, flight time, and target contrast (Table 2.2). These three variables appeared in all three of the top candidate models, with the only difference between the three top candidate models being the inclusion of one additional predictor in the last two (either distance from the centerline or observation day) (Table 2.2). Observation day, a proxy for the photo analysts' experience level, did not appear in our top model. However, it should be noted that the results from our analysis might have been affected by the low number of photo analysts as well as the low sample sizes for some days in the 14-day period. Although participants were instructed to look through their allotted images within two weeks and to look at roughly the same number of photos per day, most of our photo analysts were consistent for the first week and then left the rest until the end of the week. Consequently, we did not acquire a true measure of photo analysts' experience level.

All inferences regarding target detectability were made using the best fitting model (Table 2.3). Overall, 77.5% of the targets were detected; the percentage of targets detected was highest in open habitat (97%), and lowest in heavy cover forest (25%) (Fig. 2.4). The odds of a photo analyst detecting a target in open habitat were roughly 42 times higher than in heavy forest and 10.5 higher than in burned habitat. When compared to open habitat, target detectability was significantly different for targets in areas with sparse cover and no lichen (B= -1.8912, SE = 0.7528 , z = -2.512, p= 0.012) , burned habitat (B= -2.3504, SE =0.7628, z = -3.081, p= 0.002), medium cover forest (B= -1.9019, SE= 0.6980, z = -2.725, p = 0.006), and heavy cover forest (B= -3.7348, SE = 0.8182 , z = -4.565, p< 0.001). There was no significant difference in target detection between open habitat and sparsely covered areas with lichen groundcover (B= -0.9786, SE= 0.7133, z= -1.372, p= 0.170). Pairwise comparisons of different habitat types using Tukey's HSD test revealed that the detection of targets was significantly lower in heavy forest compared to all other habitat types. Detection of targets was higher in open habitat compared to burned areas and heavy forest. There were no significant differences between open, sparse cover (no lichen), sparse cover (lichen), and medium cover forest. There were also no differences in detection between habitat with sparse cover (no lichen), sparse cover (lichen), burned habitat, and medium cover habitat (Fig. 2.5).

Target detectability was influenced by the contrast of the target against the landscape (B= 6.3960, SE = 0.9011, z= 7.098, $p<0.001$) as well as the timing of aircraft surveys (B= 1.1096, SE= 0.3465, z= 3.202, p= 0.00136). The detection of targets was 87% during evening flights and 75% for morning flights (Fig.2.6).

2.5 Discussion

As a platform for use in wildlife research and conservation, UAS have definitely sparked much interest (Jones et al. 2006; Koski et al. 2009,, 2013,, 2015; Soriano et al. 2009; Koh and Wich 2012; Rodriguez et al. 2012; Hodgson et al. 2013; Vermeulen et al. 2013; Chabot et al. 2014; Kadaba 2014). Our study demonstrated that a small UAS equipped with a basic payload can successfully fly BLOS for the purpose of surveying wildlife. The payload we used was a Nikon D3X, and we were able to capture imagery with a ~ 4.3 cm/pixel ground resolution. The UAS was able to survey different habitat types and collect imagery with sufficient resolution to identify targets and fine-scale habitat features, making it possible to discern targets from other objects in the environment. The imagery collected was successfully used to identify the parameters influencing target detection.

The best fitting model did not include photo analysts' experience level, measured as the number of days (from 1 to 14) that a photo analyst had previously spent looking through images. Although photo analysts' were instructed to look at approximately the same number of photos per day and given a limit of two weeks to complete the survey, most of the photo analysts looked at the same number of photos per day at the beginning of the first week, but left the rest of the images until the end of the second week. Consequently, the data might not have adequately captured the effect of photo analysts' experience level on target detection. Although positive target detection did not improve with experience level for photo analysts, we did find that some individuals were inherently better at correctly identifying targets compared to others. Therefore, using aerial imagery or video footage collected by a UAS could be advantageous, as the data can be stored and reviewed by multiple observers, which would reduce bias caused by differences in performance between analysts.

The contrast of targets in the aerial imagery was expected to influence the detection of surrogate caribou targets. For example, previous research by Chabot and Bird (2102) showed that when comparing the performance of a UAS for surveying Canada geese and snow geese, the performance was better and less variable for snow geese, a white-bodied species with a high contrast against bare ground, compared to brown-bodied Canada geese on a less contrasting background. Although we did find that target detection was positively correlated with target contrast against the landscape, we only included one measure affecting the visibility of targets in the imagery. The predictor we used was measured from the imagery post data collection, and was strongly dependent on image quality and the conditions under which the image was captured. To improve upon our results, we suggest that trials be conducted which involve several measures that affect image quality such as light intensity and cloud conditions.

We also expected that the placement of surrogate caribou targets in different habitats would affect detectability. We found that the odds of target detection were lowest in heavy forest and burned habitat. The targets placed in burned habitat were likely difficult to detect because numerous rocks and dead trees that were of similar shape, colour and size compared to the surrogate caribou targets cluttered the images. As might have been expected, the targets placed in heavy forest cover had the lowest detectability compared to other habitats. During aerial surveys, it is very difficult to see wildlife in forested areas because of direct canopy cover, and the obscuring effect of shadows. To address these issues, researchers have developed sightability models to account for visibility bias (Bodie et al. 1995; Pearse et al. 2008; Rice et al. 2009;) and have also resorted to technological solutions, e.g. thermal infrared sensing (Dunn et al. 2002; Potvin and Breton 2005). These steps are especially important for maintaining the accuracy of population estimates generated from aerial surveys, because the number of individuals missed can be very high. For example, a survey conducted in Alberta in 1993 estimated sightability of caribou to be approximately 40% based on the detection of radio-collared individuals (Stuart-Smith et al. 1997).

We also found that the time of day when surveys were conducted affected target detection; detection was higher in the evening flights compared to those done in the morning. There are likely multiple factors to consider here, including differences in morning and evening light conditions, the effect of shadows, and cloud cover. Morning flights were conducted between 07:00 to 09;30 . Within this time period, the sun's position in the sky starts at a lower angle and rises progressively as the time approaches midday. As the sun rises, the light becomes more direct and shadows become shorter. Afternoon flights were conducted between 14:30 to 15:00, so shadows were short but becoming longer as the sun was setting. It is likely that the long shadows observed earlier in the morning made it more difficult to identify targets located in habitats with trees or vegetation that can cast obscuring shadows. Also, the mornings were generally clear and afternoons were typically overcast. When cloud cover was present, it created diffuse light conditions and reduced the obscuring effect of shadows, especially in environments with trees. Previous research has shown that light intensity and time of day can influence target detection (LeResche and Rausch 1974; Allen 2005; Franke et al. 2012). LeResche and Rausch (1974) found that the detection of moose was higher in midday aerial surveys compared to those conducted in the mornings and evenings.

Although we have identified important factors affecting the detectability of surrogate caribou targets, it is important to note the limitations of our study. First, the method used to select the placement of targets could have introduced bias in our results because site selection was not truly random. Although we were unable to see the fine-scale habitat features in the satellite imagery used to select target locations within the 4.1 km^2 study site, the locations were ultimately selected by looking at a map, which could have introduced bias by avoiding the placement of targets near the edge of the study site or preferentially placing targets in areas with more cover. A truly random approach would have involved randomly choosing latitude and longitude positions within the study area for target placement, but this would have made it difficult to ensure that all habitat types were equally represented in our study. Furthermore, the sites were selected at a much smaller scale compared to that at which the imagery was collected, which would effectively reduce the effect of selection bias.

Another consideration is that we did not include group size in our study, which has also been identified as an important factor affecting the detection of ungulates (Thomas and Gray 2002; Patterson et al. 2014; Peters et al. 2014). We had set up a trial with different sized groups of surrogate caribou targets, but adverse weather conditions and time limitations restricting flying opportunities prevented adequate sampling of the different group sizes. We also removed false positives from the analysis because there were too few in our dataset to provide a useful analysis. It is likely that the low number of false positive detections is a result of the distinct shape and uniform colour of the targets. Using more life-like surrogate caribou targets arranged in different positions (standing, bedded, or grazing) could have provided a more realistic evaluation of how frequently false positive detections might occur in caribou surveys with UAS. We were also unable to compare how the detection of surrogate caribou targets compared to real caribou. We originally intended to gather aerial imagery of caribou with the UAS, but there were no collared individuals within a reasonable flying distance of the PTA. Since caribou are sparsely spaced across the landscape, and in general do not move long distances, it was not realistic to expect that they would have moved into an area we could fly over within the time frame of our study.

Lastly, the variable ‘altitude’ was removed from our analysis because there was not enough variability in altitude during flights to provide a useful analysis. The altitude at which the aircraft is flown directly affects the swath width covered in the survey as well as the pixel to ground resolution in any video or imagery collected. We tried to maintain our flight altitude at ~ 690 m above sea level, which gave a swath width of ~ 260 m and a ground resolution of approximately 4.3 cm. Flying at a higher altitude will increase the swath width, so the aircraft can survey a larger area in less time, but it must be balanced with the ground resolution to ensure adequate resolution for identifying the target species.

2.6 Summary and Conclusions

The primary objectives of this study were to test the ability of the UAS to fly BLOS for the purpose of conducting wildlife surveys and to collect aerial images to evaluate which factors influenced the detection of surrogate caribou targets. This study was the first of its kind to successfully fly a UAS BLOS over land for non-military applications in Canada. We achieved the first objective by demonstrating that a small UAS equipped with a basic payload can successfully fly BLOS to conduct aerial surveys and gather data. This is an important step towards incorporating UAS as a tool for surveying boreal caribou, as this species generally occupies large territories in remote areas that are difficult to access and thus, would require BLOS flight. The Brican TD 100e provides an ideal platform for surveying sensitive species such as caribou because it is small and silent, allowing for inconspicuous data collection and thereby minimizing the risk of disturbance to the animals (Koski et al. 2009; Chabot and Bird 2012; Sarda-Palomera et al. 2012).

We completed our second objective by using the aerial imagery collected by the UAS to evaluate the different factors affecting the detection of surrogate caribou targets. Although the results obtained from detectability studies using decoys cannot be directly applied to surveys of wild ungulates, they do provide important insight into the primary factors influencing detection of wildlife (e.g. Koski et al. 2009; Strobel and Butler 2014). The results from our study indicate that habitat type, flight timing and target contrast influenced target detectability. For the purpose of surveying wildlife, UAS are most appropriate for detecting species that are distinguishable from the surrounding landscape (have a high contrast against the ground), and for small-scale surveys in environments with minimal concealing vegetation such as heavy forests. Ideal conditions for data collection would be flying at midday when there is minimal shadow. We found that there was a difference in the performance of the photo analysts, therefore using UAS imagery or video footage could be a useful tool for reducing observer bias, as data can be stored and interpreted by multiple observers (Nowacek and Tyack 2001; Watts et al. 2010).

The disadvantage of using aerial imagery or video footage collected by a UAS to evaluate animal abundance is that it can produce large quantities of data that are difficult to process and store (Koh and Wich 2012; van Gemert et al. 2014). Our study involved processing thousands of images after only seven flights over a fairly small area. Manually processing such large quantities of data is labour-intensive, slow, and possibly very expensive. Efforts are underway to create and integrate automatic pattern recognition algorithms into data processing to help accelerate the process (Abd-Elrahman 2005), but to date, this type of software is not yet readily available to researchers.

We were able to identify the factors that limit the detection of surrogate caribou targets, but the detection of wildlife could possibly be improved by using a combination of sensors such as infrared or hyperspectral cameras. Previous studies have successfully used infrared camera surveys to detect wildlife (Garner et al. 1995; Haroldson et al. 2003; Kissell and Nimmo 2011; Israel 2011); however, species identification is not easily achieved using only infrared imagery and thermal infrared sensors can have difficulty detecting wildlife concealed by canopy cover (Garner et al. 1995; Dunn et al. 2002, Potvin et Breton 2005). Barring cost, the optimum payload would be a combination of sensors; for example, Franke et al. (2012) used a combination of infrared and natural colour imagery to survey and detect different ungulate species. They used the infrared imagery to detect the presence of the animal and then identified the species using high resolution, natural colour imagery. For our study, the size of our aircraft limited the payload capacity such that we could only include a DSLR camera, but the potential for using a UAS equipped with a multi-sensor system is possible. Based on the results from this research, it is suggested that researchers interested in using UAS should define the purpose of their study and then make an informed choice about the type of aircraft and payload they would need to use to satisfy their objectives.

2.7 Literature Cited

Abd-Elrahman, A. 2005. Development of pattern recognition algorithm for automatic bird detection from unmanned aerial vehicle imagery. Surv. Land Inf. Sci., **65**(1): 37–46.

Akaike, H. 1973. Information theory as an extension of the maximum likelihood principle. *In:* Second International Symposium on Information Theory. Edited by B.N.Petrov *and* F.Csaki. Akademiai Kiado, Budapest. *pp.* 267–281.

Allen, J. R. 2005. Use of sightability models and resource selection functions to enhance aerial population surveys of Elk (*Cervus elaphus*) in Alberta. Masters Thesis, University of Alberta, Alberta, Canada.

Anderson, K., and Gaston, K.J. 2013. Lightweight unmanned aerial vehicles will revolutionize spatial ecology. Front. Ecol. Environ., **11**(3): 138-146.

Bartoń K. 2012. MuMIn: Multi-model inference. Available: http://mumin.r-forge.r-project.org.

Bates, D., Maechler, M., Bolker B. and Walker, S. 2014. *lme4: Linear mixed-effects models using Eigen and S4*. R package version 1.1-7, http://CRAN.R-project.org/package=lme4.

Bodie, W.L., Garton, E.O., Taylor, E.R., and McCoy, M. 1995. A sightability model for Bighorn Sheep in canyon habitats. J. Wildlife Manage., **59** (4): 832-840.

Bolker, B. M., Brooks, M. E., Clark, C. J., Geange, S. W., Poulsen, J. R., Stevens, M. H. H., and White, J. S. S. 2009. Generalized linear mixed models: a practical guide for ecology and evolution. Trends Ecol. Evol., **24** (3): 127-135.

Boyd, W. S. 2000. A comparison of photo counts versus visual estimates for determining the size of snow goose flocks. J. Field Ornithol., **71** (4): 686-690.

Buckland, S. T., Burt, M. L., Rexstad, E. A., Mellor, M., Williams, A. E., and Woodward, R. 2012. Aerial surveys of seabirds: the advent of digital methods. J. Appl. Ecol., **49** (4): 960-967.

Burnham, K.P. *and* Anderson, D.R. 2002. Model Selection and Multimodel Inference: A Practical Information-Theoretic Approach, 2nd edn. *Springer, Berlin.*

Callaghan,C.,Virc, S. and Duffe, J. 2011. Woodland caribou, boreal population, trends in Canada. Canadian Biodiversity: Ecosystem Status and Trends 2010,Technical Thematic Report No. 11. Canadian Councils of Resource Ministers. Ottawa, ON. Iv + 36 p. available at: *http://www.biodivcanada.ca/default.asp?lang=En&n=137E1147-0*

Chabot, D. and Bird, D.M. 2012. Evaluation of an off-the-shelf unmanned aircraft system for surveying flocks of geese. Waterbirds, **35** (1): 170-174.

Chabot, D., Carignan, V. and Bird, D.M. 2014. Measuring habitat quality for least bitterns in a created wetland with use of a small unmanned aircraft. Wetlands, **34** (3): 527-533.

Chabot, D., Craik, S.R. and Bird, D.M. 2015. Population census of a Llarge common tern colony with a small unmanned aircraft. PLoS one, **10**(4): e0122588.

COSEWIC. 2011. Designatable units for caribou (*Rangifer tarandus*) in Canada. Committee on the Status of Endangered Wildlife in Canada. Ottawa, Canada. pp. 1-88.

Courtois, R., J.-P. Ouellet, A. Gingras, C. Dussault, and Banville, D. 2001. La situation du caribou forestier au Québec. Nat. Can., **125** (3): 53-63.

Crête, M. 1991. Mise au point de la technique d'inventaire du caribou dans la taïga. Ministère du Loisir, de la Chasse et de la Pêche. Québec, Québec. 20 pp.

Cuyler, C. 2007. West Greenland caribou explosion: What happened? What about the future? Rangifer, **27**(4): 219-226.

Dunn, W. C., Donnelly, J. P., and W. J. Krausmann. 2002. Using thermal infrared sensing to count elk in the southwestern United States. Wildlife Soc. Bull., **30** (3): 963-967.

Environment Canada. 2008. Scientific review for the identification of critical habitat for woodland caribou (*Rangifer tarandus caribou*), boreal population, in Canada. Environment Canada. Ottawa, ON. 72 p.

Franke, U., Goll, B., Hohmann, U., and Heurich, M. 2012. Aerial ungulate surveys with a combination of infrared and high–resolution natural colour images. Anim. Biodivers. Conserv., **35**(2): 285-293.

Fretwell, P. T., LaRue, M. A., Morin, P., Kooyman, G. L., Wienecke, B., Ratcliffe, N., Fox, A.J., Fleming, A.H., Porter, C. and Trathan, P. N. 2012. An emperor penguin population estimate: the first global, synoptic survey of a species from space. *PLoS One*, **7**(4): e33751.

Garel, M., Cugnasse, J. M., Gaillard, J. M., Loison, A., Santosa, Y., and Maublanc, M. L. 2005. Effect of observer experience on the monitoring of a mouflon population. *Acta theriologica*, **50**(1): 109-114.

Garner, D. L., Underwood, H. B. and Porter, W. F. 1995. Use of modern infrared thermography for wildlife population surveys. Environ. Manage., **19**(2): 233–238.

Gasaway, W. C., Dubois, S. D., and Harbo, S.J. 1985. Biases in aerial transect surveys for moose during May and June. J. Wildlife Manage., **49**(3): 777-784.

Gelman, A. 2008. Scaling regression inputs by dividing by two standard deviations. Stat. Med., **27**(15): 2865–2873.

Gelman, A., Su, Y.S., Yajima, M., Hill, J., Pittau, M.G., Kerman, J., *Zheng, T. and Dorie, V.* 2009. Arm: data analysis using regression and multilevel/ hierarchical models. R package, version 9.01. Available at: *http://CRAN.R-project.org/package=arm*

Gilbert, B. A., and Moeller, B.J. 2008. Modeling elk sightability bias of aerial surveys during winter in the central Cascades. Northwest Sci., **82**(3): 222-228.

Grenzdörffer, G. 2013. UAS-based automatic bird count of a common gull colony *In* International Archives lf the Photogrammetry, Remote Sensing and Spatial Information Sciences Volume **XL-1/W2**:169-174.

Griffin, P. C., Lubow, B. C., Jenkins, K. J., Vales, D. J., Moeller, B. J., Reid, M., Happe, P.J., Mccorquodale, S.M., Tirhi, M.J., Schaberl, J.P. and Beirne, K. 2013. A hybrid double-observer sightability model for aerial surveys. J. Wildlife Manage., **77**(8): 1532-1544.

Grueber, C. E., Nakagawa, S., Laws, R. J., and Jamieson, I. G. 2011. Multimodel inference in ecology and evolution: challenges and solutions. J. Evolution. Biol., **24**(4): 699-711.

Gunn, A., Miller, F. L., Barry, S. J., and Buchan, A. 2006. A near-total decline in caribou on Prince of Wales, Somerset, and Russell Islands, Canadian Arctic. Arctic, **59**(1): 1-13.

Haroldson, B. S., Wiggers, E. P., Beringer, J., Hansen, L. P. and McAninch, J. B. 2003. Evaluation of aerial thermal imaging for detecting white–tailed deer in a deciduous forest environment. Wildlife Soc. Bull., **31**(4): 1188–1197.

Hodgson, A., Kelly, N., and Peel, D. 2013. Unmanned aerial vehicles (UAVs) for surveying marine fauna: a dugong case study. PloS one, **8**(11): e79556.

Israel, M. 2011. A UAV-based roe deer fawn detection system. *In*: International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, Volume XXXVIII-1/C22, Zurich 2011 Workshop, 14-16 September 2011, Zurich, Switzerland. Remote Sensing Technology Institute, Experimental Methods, German Aerospace Center, Oberpfaffenhofen, Germany. pp. 51-55.

Jarding, A. R. 2010. Population estimation procedures for elk and deer in the Black Hills, South Dakota: development of a sightability model and spotlight survey. Doctoral dissertation, South Dakota State University, South Dakota, USA.

Jones, G. P., Pearlstine, L. G. and Percival, F.H. 2006. An assessment of small unmanned aerial vehicles for wildlife research. Wildlife Soc. Bull**.,** **34**(3): 750-758.

Kadaba, D. 2014. Ecology of the desert kit fox (*Vulpes macrotis arsipus*) in Chuckwalla Valley, California. Doctoral dissertation, School of the Environment, Duke University, Durham, North Carolina, USA.

Kissell Jr, R. E., and Nimmo, S. K. 2011. A technique to estimate white-tailed deer *Odocoileus virginianus* density using vertical-looking infrared imagery. Wildlife Biol., **17**(1): 85-92.

Koh, L. P. and Wich, S.A. 2012. Dawn of drone ecology: low-cost autonomous aerial vehicles for conservation. Trop. Conserv. Sci., **5**(2):121–132.

Koski, W.R., Allen, T., Ireland, D., Buck, G., Smith, P.R., Macrander, A.M., Halick, M.A., Rushing, C., Sliwa, D.J., and McDonald, T.L. 2009. Evaluation of an unmanned airborne system for monitoring marine mammals. Aquat. Mamm., **35**(3):347.

Koski, W. R., Thomas, T. A., Funk, D. W., and Macrander, A.M. 2013. Marine mammal sightings by analysts of digital imagery versus aerial surveyors: a preliminary comparison. J. Unmanned Vehicle Syst., **1**(1): 25-40.

Koski, W. R., Gamage, G., Davis, A. R., Mathews, T., LeBlanc, B., and Ferguson, S. H. 2015. Evaluation of UAS for photographic re-identification of bowhead whales, *Balaena mysticetus*. J. Unmanned Vehicle Syst., **3**(1): 22-29.

LeResche, R. E, and Rausch, R. A. 1974. Accuracy and precision of aerial moose censusing. J. Wildlife Manage., **38** (2): 175-182.

Martin, J., Edwards, H. H., Burgess, M. A., Percival, H. F., Fagan, D. E., Gardner, B. E., Ortega-Ortiz, J.G.,Ifju, P.G., Evers, B.S., and Rambo, T. J. 2012. Estimating distribution of hidden objects with drones: From tennis balls to manatees. PloS one, **7**: e38882.

McIntosh, T. E., Rosatte, R. C., Hamr, J., and Murray, D. L. 2009. Development of a sightability model for low-density elk populations in Ontario, Canada. J. Wildlife Manage., **73**(4):580-585.

Miller, K. E., Ackerman, B. B., Lefebvre, L. W., and Clifton, K. B. 1998. An evaluation of strip-transect aerial survey methods for monitoring manatee populations in Florida. Wildlife Soc. Bull., **26** (3):561-570.

Mulero-Pázmány, M., Stolper, R., Van Essen, L. D., Negro, J. J., and Sassen, T. 2014. Remotely piloted aircraft systems as a rhinoceros anti-poaching tool in Africa. PloS one, **9**(1): e83873.

Nowacek, D. P., Tyack, P. L., and Wells, R.S. 2001. A platform for continuous behavioral and acoustic observation of free-ranging marine mammals: Overhead video combined with underwater audio. Mar. Mammal Sci., **17**(1): 191-199.

O'brien, R. M. 2007. A caution regarding rules of thumb for variance inflation factors. Qual. Quant., **41**(5): 673-690.

Ouellet, J.-P., Ferron, J. and Sirois, L. 1996. Space and habitat use by the threatened Gaspé caribou in southeastern Quebec. Can. J. Zool., **74**(10): 1922-1933.

Patterson, L. D., Drake, C. C., Allen, M. L. and Parent, L. 2014. Detecting a population decline of woodland caribou (*Rangifer tarandus caribou*) from non-standardized monitoring data in Pukaskwa National Park, Ontario. Wildlife Soc. Bull., **38**(2): 348-357.

Pearse, A.T., Gerard P.D., Dinsmore, S.J., Kaminski, R.M. and Reinecke, K.J. 2008. Estimation and correction of visibility bias in aerial surveys of wintering ducks. J. Wildlife Manage., =**72** (3): 808-813.

Peters, W., Hebblewhite, M., Smith, K. G., Webb, S. M., Webb, N., Webb, N., Russell, M., Stambaugh, C. and Anderson, R. B. 2014. Contrasting aerial moose population estimation methods and evaluating sightability in west-central Alberta, Canada. Wildlife Soc. Bull., **38**(3):639-649.

Piepho, H.-P. 2004. An algorithm for a letter-based representation of all pairwise comparisons, J. Comput. Graph. Stat., **13**(2): 456–466.

Potapov, E.R., Utekhina, I.G., McGrady, M.J. and Rimlinger, D. 2013. Usage of UAV for Surveying Steller's Sea Eagle Nests. Raptors Cons., **27**:253–260.

Potvin, F., and Breton, L. 2005. Testing 2 aerial survey techniques on deer in fenced enclosures- visual double-counts and thermal infrared sensing. Wildlife Soc. Bull**., 33**(1)**:** 317-325.

Ratcliffe, N., Guihen, D., Robst, J., Crofts, S., Stanworth, A., and Enderlein, P. 2015. A protocol for the aerial survey of penguin colonies using UAVs. J. Unmanned Vehicle Syst., pp.1-7.

R Development Core Team. 2013. R: a language and environment for statistical computing. *R Foundation for Statistical Computing,* Vienna, Austria.

Rettie, W.J., and Messier, F. 1998. Dynamics of woodland caribou populations at the southern limit of their range in Saskatchewan. Can. J. Zool., **76**(2)**:** 251-259.

Rice, C.G., Jenkins, K.J., and Chang, W.Y. 2009. A sightability model for mountain goats. J. Wildlife Manage., **73**(3): 468-478.

Rodríguez, A., Negro, J. J., Mulero, M., Rodríguez, C., Hernández-Pliego, J., and Bustamante, J. 2012. The eye in the sky: Combined use of unmanned aerial systems and GPS data loggers for ecological research and conservation of small birds. PloS one**, 7**(12)**:** e50336.

Samuel, M. D., Garton, E. O., Schlegel, M. W. and Carson, R.G. 1987. Visibility bias during aerial surveys of elk in northcentral Idaho. J. Wildlife Manage., **51**(3): 622-630.

Sarda–Palomera, F., Bota, G., Vinolo, C., Pallares, O., Sazatornil, Brotons, I., Gomariz, S. and Sarda, F. 2012. Fine-scale bird monitoring from light unmanned aircraft systems. Ibis, **154**(1): 177–183.

Sasse, D.B. 2003. Job-related mortality of wildlife workers in the United States, 1937-2000. Wildlife Soc. Bull**., 31**(4): 1015-1020.

Schaefer, J.A., A.M. Veitch, F.H. Harrington, W.K. Brown, J.B. Theberge, and Luttich, S.N. 1999. Demography of decline of the Red Wine Mountains caribou herd. J. Wildlife Manage., **63**(2)**:** 580-587.

Schmelzer, I., Brazil, J., Chubbs, T., French, S., Hearn, B., Jeffery, R., LeDrew, L., Martin, H., McNeill, A., Nuna, R., Otto, R., Phillips, F., Mitchell, G., Pittman, G., Simon, N., and Yetman, G. 2004. Recovery strategy for three woodland caribou herds (*Rangifer tarandus caribou*; boreal population) in Labrador. Department of Environment and Conservation, Government of Newfoundland and Labrador, Corner Brook.

Soriano, P., Caballero, F. and Ollero, A. 2009. RF-based particle filter localization for wildlife tracking by using a UAV In Proceedings of the 40th International Symposium of Robotics, 2009, Barcelona, Spain. University of Seville, Seville, Spain. pp. 239-244.

Strobel, B. N. and Butler, M. J. 2014. Monitoring whooping crane abundance using aerial surveys: Influences on detectability. Wildlife Soc. B**., 38**(1)**:** 188-195.

Stuart-Smith, A.K., Bradshaw, C.J.A., Boutin, S., Hebert, D.M. and Rippin, A.B. 1997. Woodland caribou relative to landscape patterns in northeastern Alberta. J. Wildlife Manage., **61**(3):622-633.

Thomas, D.C. and Gray, D.R. 2002. Update COSEWIC status report on the woodland caribou *Rangifer tarandus caribou* in Canada. Environment Canada, Committee on the Status of Endangered Wildlife in Canada, Ottawa, Ontario. 1- 98 pp.

Transport Canada. 2008. Staff Instruction: The review and processing of an application for a Special Flight Operations Certificate for the Operation of an Unmanned Air Vehicle (UAV) System. Ottawa: General Aviation.

Udevitz, M. S., Burn, D. M., and Webber, M. A. 2008. Estimation of walrus populations on sea ice with infrared imagery and aerial photography. Mar. Mammal Sci., **24**(1): 57-70.

Van Gemert, J., Verschoor, C.R., Mettes, P., Epema, K., Koh, L.P. & Wich, S. 2014. Nature Conservation Drones for Automatic Localization and Counting of Animals. Computer Vision in vehicle technology with Special Session on Micro Aerial Vehicles Zurich, Switzerland

Vermeulen, C., Lejeune, P., Lisein, J., Sawadogo, P., and Bouché, P. 2013. Unmanned aerial survey of elephants. PLoS one, **8**(2): e54700.

Watts, A. C., Perry, J. H., Smith, S. E., Burgess, M. A., Wilkinson, B. E., Szantoi, Z., Ifju, P.G., and Percival, H. F. 2010. Small unmanned aircraft systems for low-altitude aerial surveys. J. Wildlife Manage., **74** (7): 1614-1619.

Wiegmann, D. A., and Taneja, N. 2003. Analysis of injuries among pilots involved in fatal general aviation airplane accidents. Accident Anal. Prev., **35**(4): 571-577.

Table 2.1. Description of all covariates included in candidate models.

No.	Variable	Definition
	Response variable	
1	Detection	Successful detection=1, No detection=0
	Predictors	
2	AM/PM	The time that the flight was conducted (morning= AM (7:00-9:30), afternoon = PM (14:30-15:00).
3	Distance from center-line	Measured distance in pixels of the target from the center-line (nadir) in the image
4	Corrected Integrated Density (Target contrast)	CID = Integrated Density of the target – (Area of selected target X Mean gray scale value of the selected background)
5	Habitat Type	Habitat where targets were placed, either i) burned, ii) open, iii) heavy forest, iv) medium forest, v) sparse forest with lichen, vi) sparse forest no lichen
6	Photo Analyst Experience Level	Number of days (from 1 to <9) that a photo analyst had previously spent looking through images
7	Photo Analyst ID	Identification number of the analyst

Table 2.2. Summary of top three mixed logistic regression models for the detection of surrogate caribou targets (n=26) from aerial images (n=613) collected by an unmanned aircraft system on the military training area near Goose Bay, Labrador, 2013. For model, we provide the number of estimated parameters (*K*), second-order Akaike's Information Criterion (AIC_c) the difference in AIC compared to lowest AICc of the model set (ΔAIC_c), log-likelihood (logLik), and AIC_c wt (w_i).

Model (fixed effects) [a]	K	AICc	Δ AIC_c	logLik	w_i
HAB + AM/PM + CID	9	439.4	0	-210.562	0.692
HAB + AM/PM+ CDIST +CID	10	441.5	2.1	-210.562	0.246
HAB +AM/PM +OBSDAY+CID	17	445.8	6.4	-205.396	0.028

[a] HAB = habitat type (Open, SNL= sparse cover without lichen, SPL= sparse cover with lichen, Burned = recently affected by forest fire, Heavy = heavy forest, Medium = medium forest); AM/PM = Flight time (AM= morning flight, PM= evening flight); CID= A measure of the contrast of target pixels compared to background pixels (CID = Integrated density of the target– (Area of selected target X Mean gray scale value of the selected background).; CDIST = the distance in pixels of the center of the target from the centerline of the photograph; OBSDAY = A proxy of the photo analysts' experience level measured as the number of days (from 1 to <9) that a photo analyst had previously spent looking through images.

Table 2.3. Summary of parameter estimates (on the logit scale) from the top mixed effects logistic regression model for the detection of surrogate caribou targets (n=26) from aerial images (n=613) collected by an unmanned aircraft system on the military training area near Goose Bay, Labrador, 2013.

Parameter [a]	Estimate	95% CI	Std. Error	Z value
Intercept	4.3066	(2.848, 5.765)	0.7441	5.788
AM /PM	1.1096	(0.4304, 1.789)	0.3465	3.202
Habitat (Open)				
SNL	-1.8912	(-3.367, -0.4158)	0.7528	-2.512
SPL	-0.9786	(-2.377, 0.4194)	0.7133	-1.372
Burned	-2.3504	(-3.845, -0.8553)	0.7628	-3.081
Heavy	-3.7348	(-5.338, -2.131)	0.8182	-4.565
Medium	-1.9019	(- 3.270, -0.5339)	0.6980	-2.725
CID	6.3960	(4.630, 8.162)	0.9011	7.098

[a] AM/PM = Flight time (AM= morning flight, PM= evening flight); Habitat= (Open = reference group, SNL= sparse cover without lichen, SPL= sparse cover with lichen, Burned = recently affected by forest fire, Heavy = heavy forest, Medium = medium forest); CID= A measure of the contrast of target pixels compared to background pixels (CID = Integrated density of the target– (Area of selected target X Mean gray scale value of the selected background).

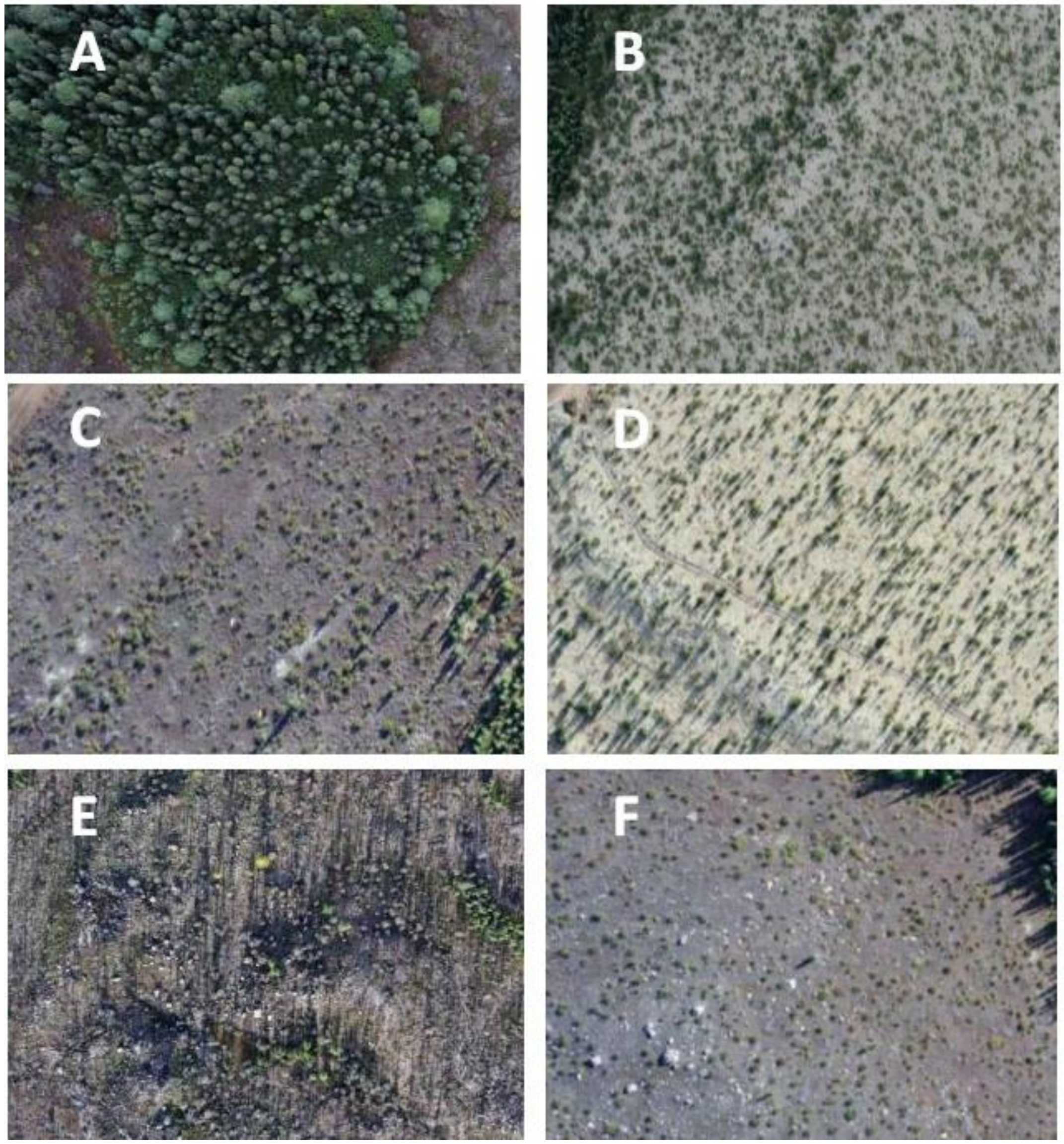

Fig. 2.1: The six different habitat types in which surrogate caribou targets were placed for aerial surveys with an unmanned aircraft system in Labrador: A) heavy forest, B) medium cover forest, C) sparse cover without lichen ground-cover, D) sparse cover with lichen ground-cover, E) recently burned areas, and F) open habitat.

Fig. 2.2. The unmanned aircraft system used in our study was the Brican TD100e model fixed-wing, propeller-driven, aircraft. Note the pneumatic launcher.

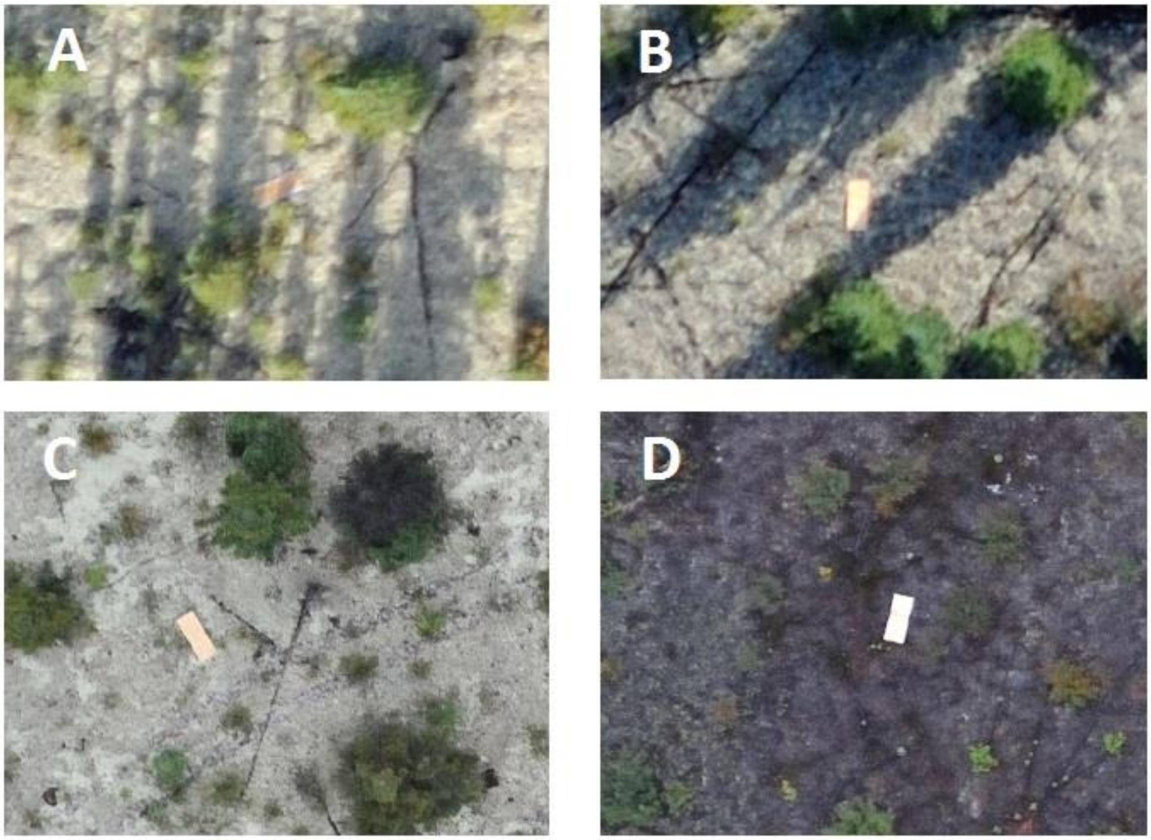

Fig.2.3 Surrogate caribou targets with Corrected Integrated Density (CID) pixel grayscale values ranging from A) 3349, B) 27689, C) 76572 and D) 20,2106 . The CID is a measure of target contrast against the landscape using the formula CID = Integrated Density of the target – (Area of selected target X Mean gray scale value of the selected background).

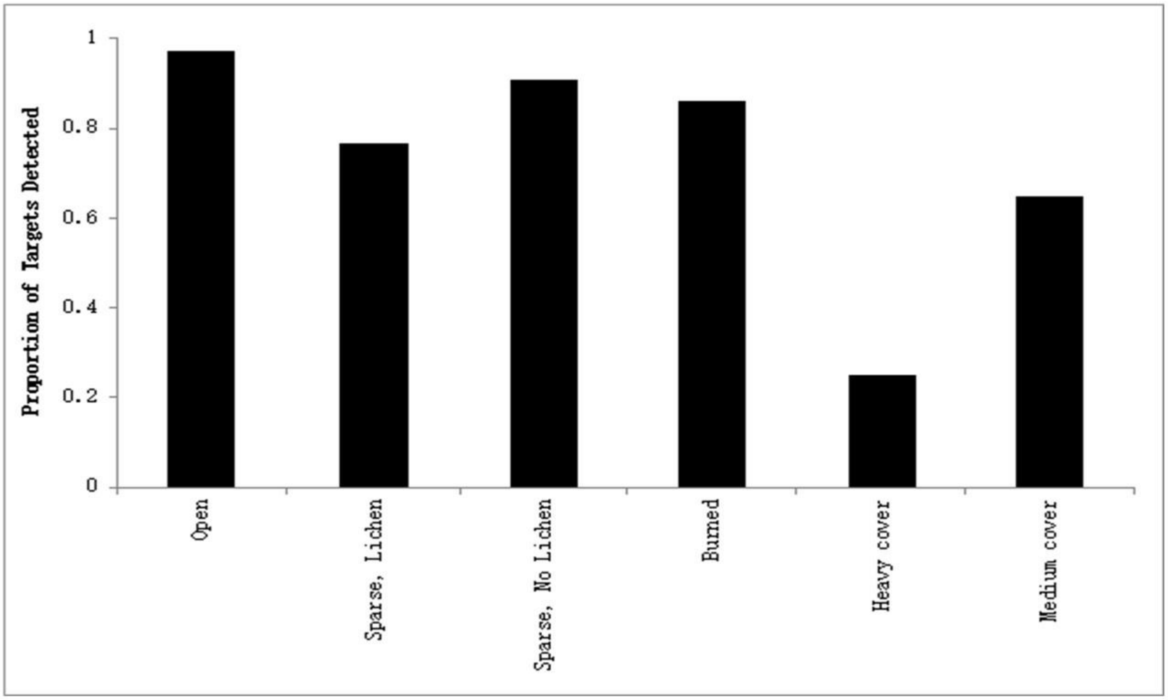

Fig.2.4 The relative proportion of surrogate caribou targets (n=26) detected from aerial images (n=613) collected by an unmanned aircraft system on the military training area near Goose Bay, Labrador, 2013. Targets were placed in six habitats including: open areas (n=100 photos), habitat characterized by sparse ground cover with lichen (n=111), sparse cover without lichen (n=130), recently burned forest (n=85), heavy forest (n=48) and medium cover forest (n=139).

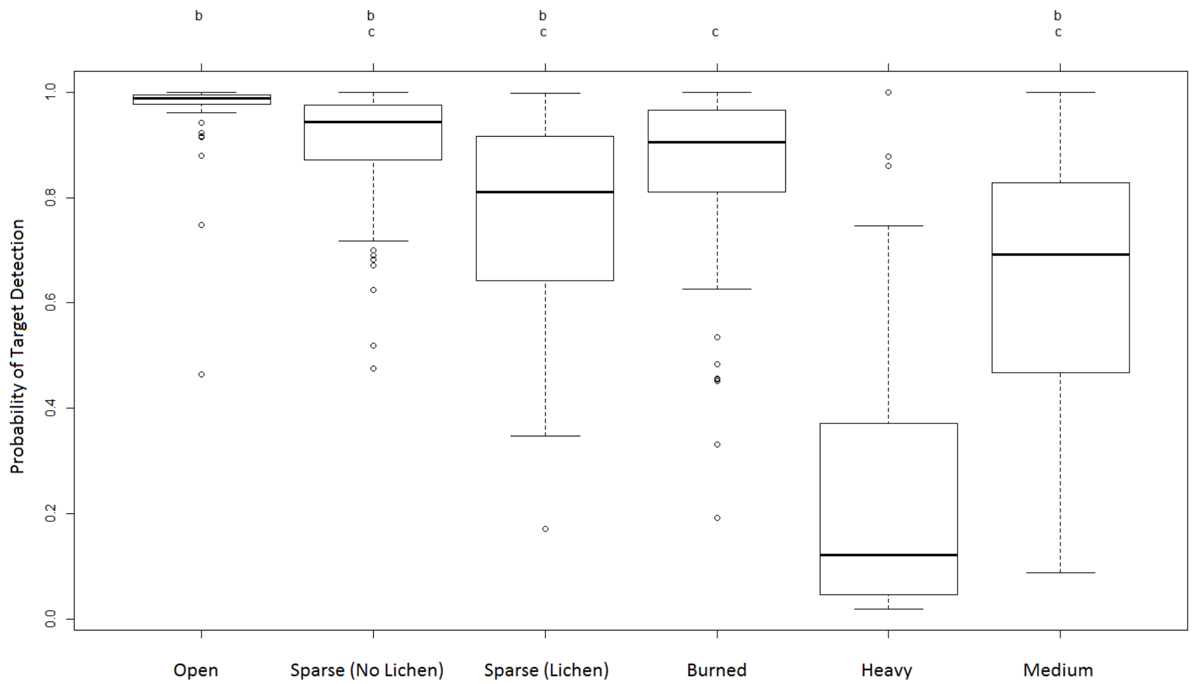

Fig.2.5. Tukey's HDS pairwise comparison of the detection of surrogate caribou targets (n=26) detected from aerial images (n=613) collected by an unmanned aircraft system on the military training area near Goose Bay, Labrador, 2013. Equal letters indicate no significant differences between groups and different letters indicate significant difference at the 0.05 level of significance. Targets were placed in six habitats including: i) open areas (n=100 photos), ii) sparse cover without lichen (n=130), iii) sparse cover with lichen ground-cover (n=111), recently burned forest (n=85), heavy forest (n=48) and medium cover forest (n=139).

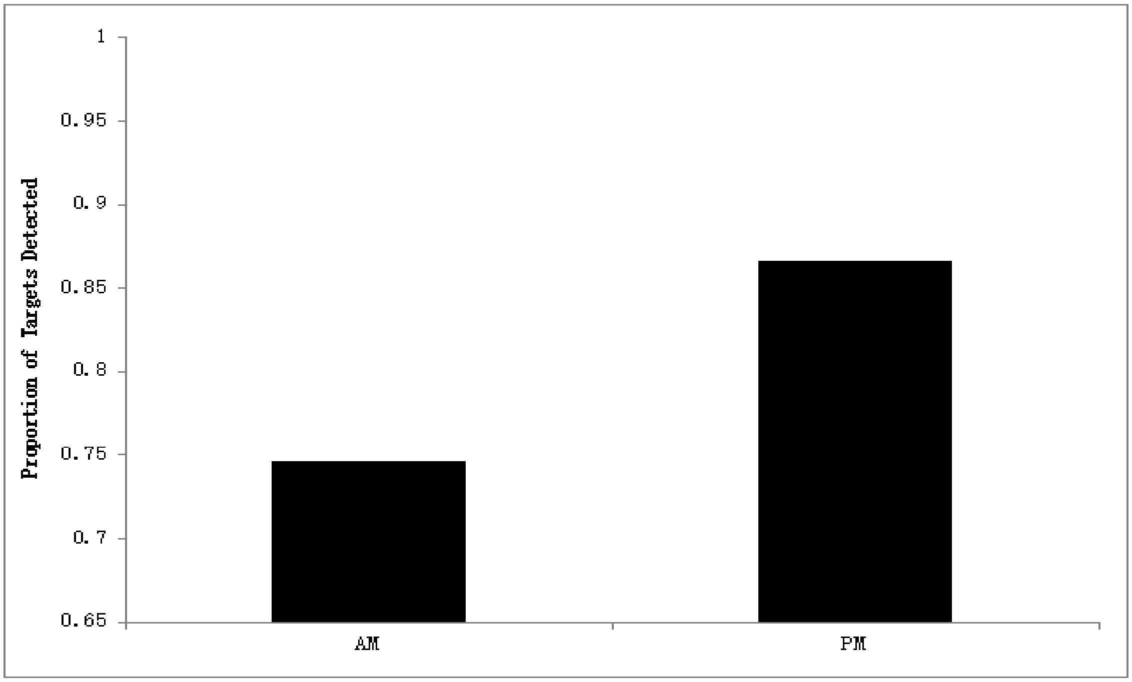

Fig. 2.6. The relative proportion of surrogate caribou targets (n=26) detected from aerial images (n=613) collected by an unmanned aircraft system on the military training area near Goose Bay, Labrador, 2013 during morning (AM) (n= 464 detections) or afternoon flights (PM) (n=149).

CHAPTER 3:

CONCLUSIONS AND FUTURE DIRECTIONS

The objective of this thesis was to evaluate the feasibility of using a UAS for the purpose of surveying boreal caribou in sub-arctic boreal forest habitat. I sought to i) test the ability of the aircraft to fly beyond line of sight ii) identify which factors influence the detectability of surrogate caribou targets and iii) provide recommendations for researchers interested in using UAS for surveying wildlife. This study was the first of its kind to successfully fly a UAS beyond line of sight over land for non-military applications in Canada. We were able to successfully demonstrate that UAS can safely fly missions autonomously outside the visual range of the pilot for the purpose of collecting aerial imagery. The UAS was able to survey different habitat types with sufficient resolution to identify targets and fine-scale habitat features, making it possible to discern targets from other objects in the environment. The imagery collected was successfully used to identify the parameters influencing target detection. It was revealed that habitat type, flight time and the brightness of the target compared to the surrounding landscape affected target detection. For the purpose of surveying wildlife, UAS are most appropriate for detecting species that are distinguishable from the surrounding landscape, and for small-scale surveys in environments with minimal concealing vegetation. Ideal conditions for data collection would be either flying at midday when there is minimal shadow or when there is cloud cover, given that other weather conditions are adequate. The detection of wildlife could possibly be improved by using a combination of sensors such as infrared or hyperspectral, but payload capacity would be a limiting factor. Additionally, there is a need for more research on the applications of hyperspectral sensors for detecting animals. Based on the results from this research, it is suggested that researchers interested in using UAS should define the purpose of their study and then make an informed choice about the type of aircraft and payload they would need to use to satisfy their objectives.