WILDLIFE MULTISPECIES REMOTE SENSING USING VISIBLE AND THERMAL INFRARED IMAGERY ACQUIRED FROM AN UNMANNED AERIAL VEHICLE (UAV)

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ABSTRACT:

Wildlife aerial surveys require time and significant resources. Multispecies detection could reduce costs to a single census for species that coexist spatially. Traditional methods are demanding for observers in terms of concentration and are not adapted to multispecies censuses. The processing of multispectral aerial imagery acquired from an unmanned aerial vehicle (UAV) represents a potential solution for multispecies detection. The method used in this study is based on a multicriteria object-based image analysis applied on visible and thermal infrared imagery acquired from a UAV. This project aimed to detect American bison, fallow deer, gray wolves, and elks located in separate enclosures with a known number of individuals. Results showed that all bison and elks were detected without errors, while for deer and wolves, 0–2 individuals per flight line were mistaken with ground elements or undetected. This approach also detected simultaneously and separately the four targeted species even in the presence of other untargeted ones. These results confirm the potential of multispectral imagery acquired from UAV for wildlife census. Its operational application remains limited to small areas related to the current regulations and available technology. Standardization of the workflow will help to reduce time and expertise requirements for such technology.

1. INTRODUCTION

Precise management of wildlife is often based on population density data (Skalski et al., 2005, Pierce et al., 2012, Williams et al., 2012). Aerial survey is generally used to census large animals over large areas; especially for remote or inaccessible areas (Siniff and Skoog, 1964; Caughley, 1977; Bodie et al., 1995). However, during aerial surveys, observers have to locate, identify, and count wildlife in a very short time (Caughley, 1974). Several methods have been developed to simplify the task for observers such as using several simultaneous observers (Bayliss and Yeomans, 1989; Marsh and Sinclair, 1989; Potvin et al., 1992 Cumberland, 2012), conducting circular flights (Floyd et al., 1979; Stoll et al., 1991; Wiggers and Beckerman, 1993; Havens and Sharp, 1998), and using aerial photography (Garner et al., 1995; Naugle et al., 1996; Haroldson et al., 2003; Israel, 2011; Chabot and Bird, 2012; Franke et al., 2012).

Terrestrial camera traps have been used for multispecies detection for several years but results are presently limited by sampling design and data processing biases (Topler et al., 2008; Ahumada et al., 2013; Burton et al., 2015). Until now, there are no standardized methods to detect several species simultaneously using aerial surveys. Multispecies detection can be useful to study species that coexist spatially in order to reduce survey costs (Bayliss and Yeomans, 1989) and to better understand ecological processes (Burton et al., 2015). However, this practice is too demanding for aerial observers who already need considerable focus to detect single species.

Multispectral aerial imagery is useful for species detection because information is permanently recorded and can be analyzed repeatedly after the census (Terletzky et al., 2012). Furthermore, the use of unmanned aerial vehicles (UAV) to acquire imagery provides very high spatial and temporal resolutions difficult to access with other acquisition platforms (e.g., satellite, airplane, helicopter, etc.) (Eisenbeiβ, 2009; Whitehead et al., 2014). Very high spatial resolution provides a high level of details which allows differences in characteristics between species to be distinguished. High temporal resolution allows to conducting censuses in favorable observation windows (i.e., weather, phenology) that can be narrow and highly inconstant.

Until now, very few studies have tested the combined use of UAV, multispectral imagery, and image processing for multispecies detection. This combination was successfully tested on one species by Chrétien et al. (2015). They developed an approach to detect and count white-tailed deer (*Odocoileus virginianus*) by applying a multicriteria object-based image analysis (MOBIA) on visible and thermal infrared imagery acquired by UAV. Thus, the main objective of the present study was to adapt and evaluate the performance of this approach for detecting and counting simultaneously several large mammal species in a controlled environment.

2. STUDY SITE

The study was conducted at the Falardeau Wildlife Observation and Agricultural Interpretive Centre (Centre d'observation de la faune et d'interprétation de l'agriculture de Falardeau) in Saint-David-de-Falardeau (Québec, Canada). This center welcomes several species of mammals, birds, and reptiles in separate enclosures with a known number of individuals (figure 1). The aim of this project was to detect 4 American bison (*Bison bison*) including 1 calf, 6 fallow deer (*Dama dama*), 5 gray wolves (*Canis lupus*), and 3 elks (*Cervus canadensis*) (figure 2). The tree vegetation within the enclosures of fallow deer and gray wolves consists mainly of birch (*Betula sp*.). No vegetation is present within the enclosures of American bison and elk, except for a few isolated trees.

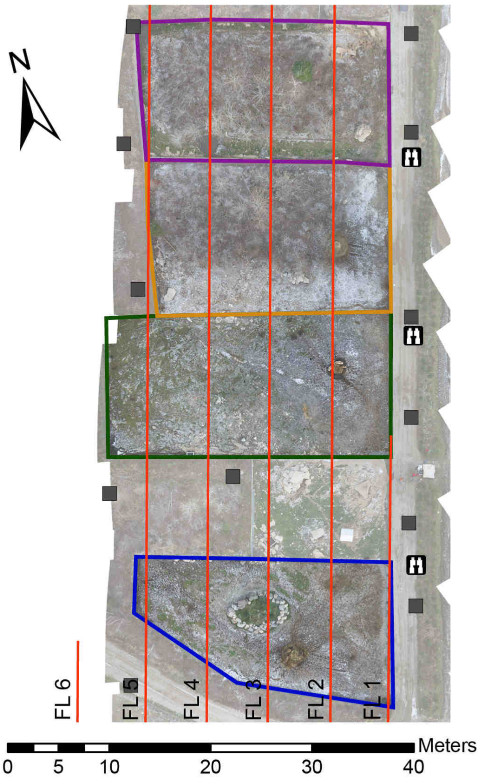

Figure 1. Study area: Enclosures at the Falardeau Wildlife Observation and Agricultural Interpretive Centre in Saint-David-de-Falardeau, Québec, Canada. **Blue enclosure**: American bison (*Bison bison*), **Green enclosure**: elks (*Cervus canadensis*), **Orange enclosure**: fallow deer (*Dama dama*) and **Purple enclosure**: grey wolves (*Canis lupus*). Flight lines (FL; red lines), ground targets (■) and observers (binocular symbol) are indicated.

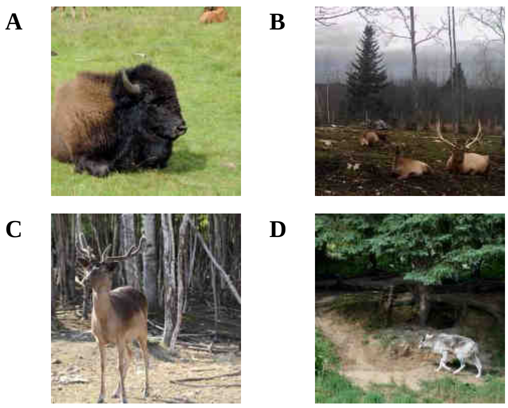

Figure 2. Studied species. **A**. American bison (*Bison bison*); **B**. elks (*Cervus canadensis*); **C**. fallow deer (*Dama dama*); and **D**. grey wolf (*Canis lupus*). © L.-P. Chrétien, E. Gavelle

3. MATERIAL AND METHODS

3.1 Data acquisition system

Data acquisition was performed using a system consisting of a VTOL (vertical take-off and landing) UAV (Responder, ING Robotic Aviation; table 1; figure 3) equipped with the Tau640 (FLIR Systems) and D7000 (Nikon Inc.) sensors (table 2). Visible and thermal infrared images were acquired simultaneously aboard the UAV. The GPS/INS data from the UAV were not available for image georeferencing considering their exclusive use by the autopilot system.

Table 1. UAV specifications and flight limitations

Specifications	
Vehicle type	VTOL helicopter
Length	1328 mm
Height	408 mm
Main blade length	690 mm
Main blade diameter	1562 mm
Tail rotor diameter	281 mm
Weight (with motor)	2.83 kg
Flying weight	Max 12 kg
Maximum forward speed	80 km/hr
Endurance	Up to 20 minutes
Battery	two 6-cell Lithium Polymer
IMU accuracy	N/A
GPS accuracy	Horizontal : ± 2 m Vertical : ± 1 m
Flight limitations	
Maximum wind speed	30 km/hr
Minimum visibility	1 600 m
Minimum ceiling	150 m AGL
Maximum flight altitude	300 m AGL

Table 2. Sensors specifications

Specifications	**Tau640**	**D7000***
Sensor type	Uncooled VOx microbolometer	Sony IMX071 CMOS
Spectral range	Thermal infrared (7.5–13.5 µm)	Visible (0.40–0.75 µm)
Processor	N/A	Expeed 2
Sensor size	10.88x8.70 mm	23.6x15.7 mm
Focal length	19 mm	38 mm
Shutter speed	N/A	1/500–1/160
ISO sensitivity	N/A	800
Aperture	*f*/1.25	*f*/6.3–*f*/11
Field of view (*FoV*)	32°x26°	35°x23°
Size	44x44x30 mm	132x105x166 mm
Weight	80 g	1270 g
Image size	640 x 480 pixels (0.3 MP)	4928 x 3264 pixels (16 MP)
Ground sampling distance (GSD) **	5.4 cm/pixel	0.8 cm/pixel
Radiometric resolution	8-bit	12-bit
Footprint**	34.42x25.82 m	37.28x24.69 m
Signal output	Analog Digital***	Digital
File format	ASF (NTSC 30Hz video) ***	NEF/RAW

* with the AF-S DX Nikkor 18-105 mm f/3.5-5.6G ED VR lens (Nikon Inc.); ** At an altitude of 60 m; *** Digital recording with an analog to digital converter PV500 EVO (Lawmate)

Figure 3. Ground control station and unmanned aerial vehicle used in this study (Responder, ING Robotic Aviation).

3.2 Data acquisition

A total of one flight including six flight lines (figure 1) was conducted between 1040 and 1055 hr on 6 November 2012 under a Special Flight Operating Certificate (SFOC) issued by Transport Canada (Reference Number: 5105-01 RDIMS 7899416). During this flight, the altitude above ground level was 60 m and cruise speeds ranged from 18 to 35 km/hr depending on the wind and UAV orientation. The resulting images had a ground sampling distance (GSD) of 0.8 cm/pixel in the visible and 5.4 cm/pixel in thermal infrared.

The day before the flight, 22 ground targets were installed in open areas close to access roads (figure 1) and were located using a GeoXH^{TM} GPS (Trimble) with an accuracy of 10 to 30 cm. These targets were used for imagery georeferencing. Different colors and materials were used for these targets based on their spectral properties in the visible and thermal infrared ranges. Among these targets, 5 of them served as control points to validate that the images were correctly georeferenced.

Ground data observations were collected to validate the detection of animals by the image processing. These data were collected by 3 observers distributed near enclosures (figure 1). Each observer noted the position of each individual during the UAV flight over the enclosure. This information was used to map the position of individuals for comparison with the elements detected by image processing so as to evaluate the performance of the classification.

3.3 Data processing

Data preprocessing of visible images and thermal infrared video was performed to obtain a georeferenced mosaic (figure 4; see Chrétien et al. (2015) for more details). A total of 3 flight lines were analyzed over the 6 lines acquired. Three flight lines were rejected due to a position outside the study area (FL1), a lack of overlapping between images (FL5), and a flight interruption due to low batteries (FL6). The other flight lines were mosaicked and analyzed separately and independently in order to reduce detection errors related to potential animal movements between lines.

For each mosaic, a multicriteria object-based image analysis (MOBIA) was performed using *e*Cognition Developer 8.7 (Trimble) according to the following steps:

- multiresolution segmentation (Trimble, 2011) with a scale parameter of 150, a color/shape and a regularity/compactness of 0.9/0.1 and 0.5/0.5 respectively;
- preclassification based primarily on spectral criteria to detect all potential animals;
- merger of these objects to create superobjets;
- sequential classification to identify each targeted species by adapting at each iteration the species-specific threshold values for the spectral, geometric, and contextual criteria. Elements that have not been assigned to a species were tagged as false positives and excluded after the end of all iterations.

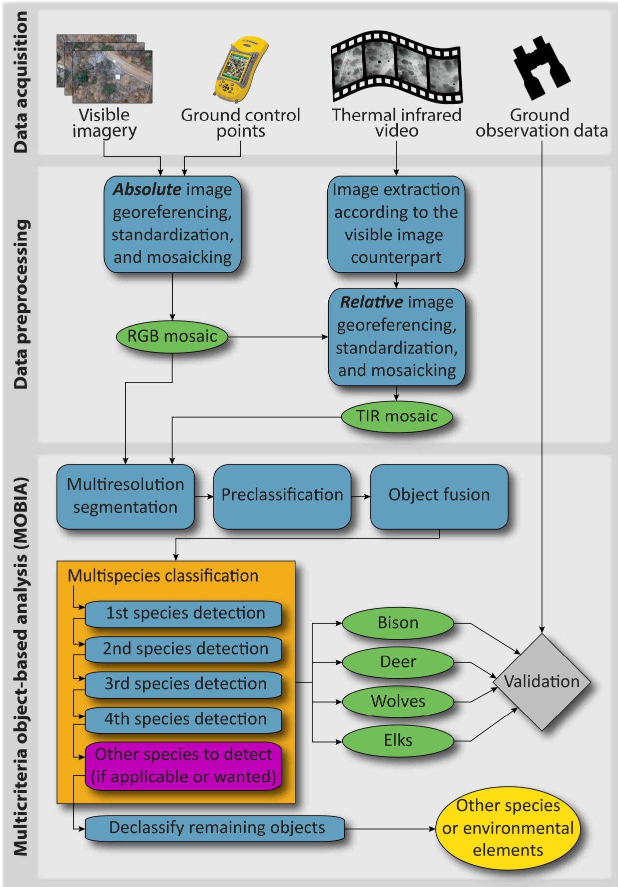

Figure 4. Multispecies detection including data acquisition, preprocessing, and multicriteria object-based image analysis (MOBIA)

Individuals were counted based on the ratio between the size of each area detected and the approximate size of the largest individual recorded in the literature for the targeted species (Nowak, 1999; Feldhamer et al., 2003).

3.4 Validation of the classification

For each classification and each species, a binary error matrix with the polygon as the minimum mapping unit was calculated (Congalton and Green, 2009). Validation polygons used for the "species" class came from ground data collected during flights. Polygons for the "non–animal" class were identified by visual interpretation of environmental elements (e.g., deciduous, coniferous, snow, ground targets, feeding troughs, etc.). The validation of the classification was carried out by comparing the dominant class in each polygon (> 50%) and the class identified in the field.

4. RESULTS

The MOBIA did not perform perfectly to detect and classify all individuals per species (figure 5). Bison and elks were all detected and classified while for fallow deer and wolves, between 0 to 1 individual per flight line was wrongly classified as landscape elements such as bare soil (table 3). Moreover, for fallow deer and wolves, between 0 and 2 individuals per flight line were not detected.

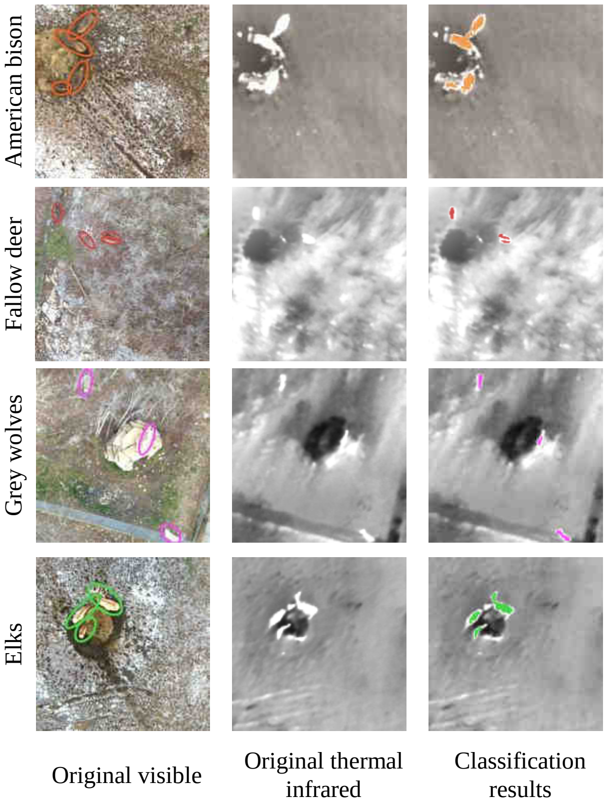

Figure 5. Examples of the classification results for the MOBIA with the visible and thermal infrared imagery. **Orange**. American bison (*Bison bison*); **Red**. fallow deer (*Dama dama*); **Magenta**. grey wolves (*Canis lupus*); and **Green**. elks (*Cervus canadensis*).

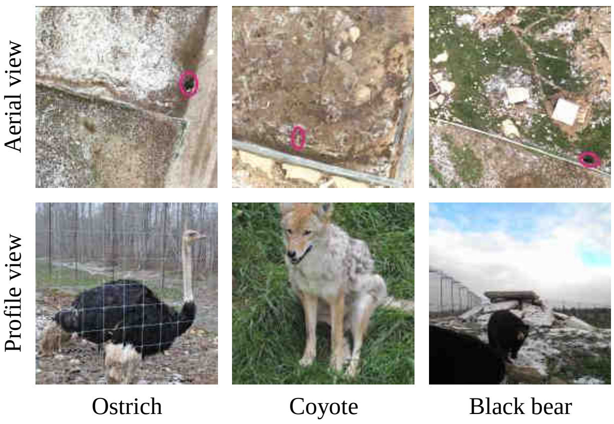

Figure 6. Other species present (magenta). **Left**. ostrich (*Struthio camelus*); **Center**. coyote (*Canis latrans*); and **Right**. Black bear (*Ursus americanus*). © L.-P. Chrétien, CGQ

The method has also simultaneously and distinctly detected and classified the four targeted species: 0–3 elks, 0–4 bison, 2–4 wolves, and 2–4 fallow deer per flight line (table 3). The results showed no confusion for interspecies identification. Furthermore, other species (i.e., non-targeted species) were present on the acquired images such as 1 ostrich (*Struthio camelus*), 3 coyotes (*Canis latrans*), and 3 black bears (*Ursus americanus*) (figure 6). Since the choices of criteria and parameters have not been selected to specifically identify these species, none of these individuals were classified with the MOBIA.

Table 3. Classification results for each flight line using the MOBIA with the visible and thermal infrared imagery.

Species	Flight-Line n°	Detected[1]	Real[2]	Detectable[3]	Present[4]
Bison	2	4	4	4	4
	3	4	4	4	4
	4	0	0	0	0
Fallow deer	2	3	2	2	2
	3	0	0	2	2
	4	3	3	4	4
Wolves	2	4	3	3	3
	3	4	3	4	4
	4	3	2	2	2
Elks	2	3	3	3	3
	3	3	3	3	3
	4	0	0	0	0

[1] Detected: Number of objects or groups of pixels in the "species" class obtained following the classification
[2] Real: Number of individuals correctly classified among those detected in (1)
[3] Detectable: Total number of individuals that can be detected in the flight line excluding those that were hidden by the canopy or other visual obstructions
[4] Present: Total number of deer present

5. DISCUSSION

5.1 Image acquisition and preprocessing

Several factors during the flight campaign affected the quality of the acquired images and their preprocessing. An average wind speed of 19 km/hr, parallel to flight lines, caused yaw, pitch, and roll movements as well as irregular speed of the UAV. These flight conditions require more work from stabilization mechanisms, which increase the energy consumption. Thus, a decrease of the UAV endurance was observed.

This flight instability due to wind conditions led to an image forward overlap between 5% and 38% (figure 7) instead of a theoretical overlap of 57%. This lower performance reduced the ability of image processing procedures to perform an effective image registration. For better results, it is recommended according to Aber et al. (2010) to have a minimum forward overlap of 60% and 70% when wind factors are considered.

Finally, these roll, pitch, and yaw effects also had a direct impact on image quality by deflecting sensors from nadir. In this study, yaw effects were prevailing (figure 7). Several methods can correct these complex distortions such as parametric georeferencing using GPS/INS data, geometric correction with ground control point, image stitching, etc. However, most of these methods were unsuccessful or unavailable in this study. The use of a reference mosaic was the only functional option to correct the imagery in this project.

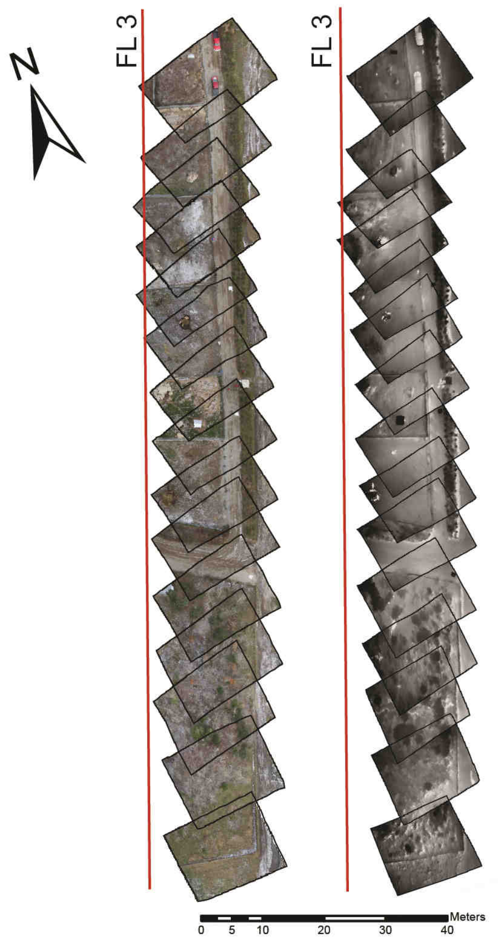

Figure 7. Georeferenced images from flight line n°3 (FL 3). Left: visible imagery. Right: thermal infrared imagery.

5.2 Species analysis

The MOBIA on visible and thermal infrared imagery was effective for detecting and counting different large mammal species. However, fallow deer and wolves were more difficult to identify than bison and elks. A minimum of four classification criteria using visible characteristics were necessary to identify bison and elks whereas it took 2 and 3 criteria using the visible as well as 6 and 4 additional criteria based on the thermal infrared to identify fallow deer and wolves respectively.

Three factors could explain these results:
(1) Fallow deer and wolves have cryptic fur allowing them to better conceal themselves in their environment than bison and elks. Therefore, they have a higher probability of being confused with the elements of the environment. In this study, deer and wolves were confused in the visible and thermal infrared spectra with rocks. This observation is also supported by Garner et al. (1995), Franke et al. (2012), and Chrétien et al. (2015) who observed that thermal emission of rocks and some parts of the forest floor can be similar to wildlife during clear days.

(2) The body size of animals can also influence their detection rate. Large species are more likely to be detected in comparison with small ones (Caughley, 1974). For example, deer and wolves have an average total length of 1.30–1.75 m and 1.27–1.64 m respectively, compared to 2.20–2.50 m and 2.10–3.90 m for elks and bison (Nowak, 1999; Feldhamer et al., 2003). Thus, deer and wolves being smaller, they can be harder to detect. No studies have explored the size limits for detecting wildlife. However, Chrétien et al. (2015) showed that spatial resolution of imagery has an impact on the detection rate of white-tailed deer using the MOBIA. This approach was more efficient at very high spatial resolution (i.e., 0.8 cm) compared to coarser resolutions. Therefore, considering that the choice of an optimal spatial resolution is related to the body size of animals (Woodcock and Strahler, 1987), it can be hypothesized that the spatial resolution used in this study was suboptimal for the body sizes of fallow deer and wolves.

(3) The detection rate for a species varies depending on the composition of the environment. Wildlife visibility decreases with the increase of vegetation density due to the visual obstruction between individuals and the observer. This could lead to an underestimation of the population size (LeResche and Rausch, 1974; Caughley et al., 1976; Samuel et al., 1987; Bayliss and Yeomans, 1989). In this study, a larger canopy was present in the fallow deer and wolves enclosures compared to bison and elk enclosures. This could explain the lower detection rate obtained for fallow deer and wolves. Some authors (Bayliss and Yeomans, 1989; Franke al., 2012) suggest to define for each species a detection rate for each habitat and to apply a correction factor accordingly. Furthermore, the use of dens by wolves is another element that could affect detection rates of this species; although this situation did not occurred in this study. This underlines the importance of taking into account the ecology of each species before performing a multispecies survey.

These three factors represent research avenues to explore to better understand and control elements that influence the detection rate of each species.

5.3 Multispecies analysis with the MOBIA

The MOBIA seems appropriate for multispecies detection of large wildlife. This approach has not only demonstrated its ability to detect multiple species, but also its adaptability to specifically target species of interest for the wildlife manager and to ignore those that are not targeted. Each detected species has its own set of classification thresholds.

The MOBIA approach is more efficient than pixel-based ones to detect wildlife (Chrétien et al., 2015). The cognitive approach used by the MOBIA is based on physical and contextual characteristics of the species (e.g., hue/fur color, thermal contrast with its environment). Thus, an object (or group of pixels) is more informative than a pixel alone because it does not only provide the spectral information, but also the geometric and contextual informations.

Furthermore, unlike pixel-based approaches, the number of individuals present in an image has little or no effect on the MOBIA accuracy due to its sequential approach. It allows for example to indicate the absence of individuals whereas pixel-based approaches usually require training sites (i.e., requiring the presence of individuals) to initiate or finalize the classification process.

Although the MOBIA gave promising results in this project, it would be interesting to test the generalization potential of this approach in a variety of environments and weather conditions. Additionally, this approach should be tested to detect taxonomically related species or morphologically similar species (e.g., white-tailed deer and red deer (*Cervus elaphus*)).

5.4 Advantages and limitations of image acquisition by UAVs

UAVs represent a new accessible option to detect and count wildlife. Low altitude operations with manned aircrafts are relatively risky since they leave a small margin of error to the pilot. For wildlife biologists, manned aircraft crashes are the primary cause of work-related death (Wiegman and Taneja, 2003; Jones IV et al., 2006). UAVs can be a safe alternative for the acquisition of census data.

UAVs equipped with autopilots also have the ability to follow flight lines more precisely than manned aircraft (Hodgson et al., 2010) allowing more accurate sampling patterns with straight and parallel flight lines. Separating flight lines by a precise distance between them can avoid double counting of individuals who move between each pass of the aircraft.

Moreover, UAVs have a relatively low noise impact on wildlife (Jones IV et al. 2006, Chabot 2009). It reduces wildlife stress and prevents random behaviors (e.g., escape behaviour) which can cause blurry image acquisitions or errors in animal counting (Bartmann et al., 1986; Wiggers and Beckerman, 1993; Frid, 2003).

The time and costs required to operate UAVs (e.g., material, flight authorization and data acquisition, transportation, flight site preparation, etc.) and to process data can be relatively high. The use of UAVs in remote sensing also requires highly trained personnel to perform UAV operations and image processing. However, this multispecies approach has the potential to standardize and automate the detection and count which will reduce costs in the medium term. Moreover, a rapid technological progress in the fields of UAVs and image processing was observed in the past few years. An increased accessibility of this technology in the future can reasonably be predicted.

The use of UAVs in wildlife studies is facing several limitations. UAVs cannot cover large areas compared to manned aircrafts used for traditional censuses. Three factors are responsible for these limitations: (1) Endurance and flight speed of these devices is limited and can only cover small areas. (2) Canadian regulation restricts flights to visual range. Operating UAVs out of visual range requires sense and avoid technology as well as real time communication with ground control station which is not adapted yet for civil UAVs (Gupta et al., 2013). (3) Data storage space onboard the UAV limits flights to relatively short distances. Advances in the field of onboard data processing and computer vision are expected to reduce these limitations in the short term. This limited coverage area remains very useful to census wildlife by targeting specific areas critical to the ecology of some species (e.g., calving grounds, wintering areas) or to simultaneously census species that coexist spatially (e.g., birds).

As shown in this project, UAVs have some flight restrictions that impact the quality of the acquired data. Improving sensor parameterization is critical to increase the quality of images as well as the use of 3-axis gyro-stabilized gimbals (Aber et al., 2010; Anderson and Gaston, 2013). This system is a rotating support which compensates for angular motions (i.e., roll, pitch, yaw) caused by the movement of the aircraft to maintain a stable angle at nadir (Jones, 2000). This equipment can reduce the effects of deformation and vibration on the images to perform more effective imagery selection and preprocessing.

6. CONCLUSIONS AND FUTURE WORK

The multicriteria object-based image analysis using very high spatial resolution visible and thermal infrared images acquired by a UAV is an efficient approach to detecting several species simultaneously. This method also demonstrated its potential to perform the census of a single targeted species using its own specific threshold values. However, more research is needed to improve the detection rate of each species. For example, the use of multiple spectral band combinations needs to be explored. These results open the way for the development of a reproducible and adaptable approach to other species.

This project validates the potential of UAVs to acquire high quality imagery allowing the extraction of census data. However, the current Canadian regulation and the technology limit the coverage of study areas. Applications related to UAV-based imagery will be closely related to UAV regulation and technology developments in the future.

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