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Utilizing Remote Sensing and Geospatial Techniques to Determine Detection Probabilities of Large Mammals

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UTILIZING REMOTE SENSING AND GEOSPATIAL TECHNIQUES TO

DETERMINE DETECTION PROBABILITIES OF LARGE MAMMALS

by

Patricia A. Terletzky-Gese

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

of

DOCTOR OF PHILOSOPHY

in

Wildland Resources

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UTAH STATE UNIVERSITY
Logan, Utah

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ABSTRACT

Utilizing Remote Sensing and Geospatial Techniques to Determine Detection

Probabilities of Large Mammals

by

Patricia A. Terletzky-Gese, Doctor of Philosophy

Utah State University, 2013

Major Professor: R. Douglas Ramsey
Department: Wildland Resources

Whether a species is rare and requires protection or is overabundant and needs control, an accurate estimate of population size is essential for the development of conservation plans and management goals. Wildlife censuses in remote locations or over extensive areas are logistically difficult, frequently biased, and time consuming. My dissertation examined various techniques to determine the probability of detecting animals using remotely sensed imagery.

We investigated four procedures that integrated unsupervised classification, texture characteristics, spectral enhancements, and image differencing to identify and count animals in remotely sensed imagery. The semi-automated processes had relatively high errors of over-counting (i.e., greater than 60%) in contrast to low (i.e. less than 19%) under-counting errors. The single-day image differencing had over-counting errors of 53% while the manual interpretation had over-counting errors of 19%.

The probability of detection indicates the ability of a process or analyst to detect animals in an image or during an aerial wildlife survey and can adjust total counts to estimate the size of a population. The probabilities of detecting an animal in remotely sensed imagery with semi-automated techniques, single-day image differencing, or manual interpretation were high (e.g. $\geq 80\%$). Single-day image differencing resulted in the highest probability of detection suggesting this method could provide a new technique for managers to estimate animal populations, especially in open, grassland habitats. Remotely sensed imagery can be successfully used to identify and count animals in isolated or remote areas and improve management decisions.

Sightability models, used to estimate population abundances, are derived from count data and the probability of detecting an animal during a census. Global positioning systems (GPS) radio-collared bison in the Henry Mountains of south-central Utah provided a unique opportunity to examine remotely sensed physiographic and survey characteristics for known occurrences of double-counted and missed animals. Bison status (detected, missed, or double-counted) was determined by intersecting helicopter survey paths with bison travel paths during annual helicopter surveys. The probability of detecting GPS-collared bison during the survey ranged from 91% in 2011 to 88% in 2012.

(179 pages)

PUBLIC ABSTRACT

Utilizing Remote Sensing and Geospatial Techniques to Determine Detection

Probabilities of Large Mammals

Whether a species is rare and requires protection or is overabundant and needs control, an accurate estimate of population size is essential for the development of conservation plans and management goals. Wildlife science has traditionally relied on human observers in airplanes, helicopter, or ground vehicles to count the number of individuals seen during wildlife surveys. However, these traditional surveys of wildlife require significant resources, are difficult to conduct quickly and safely over remote and/or extensive locations, are disruptive to the studied species, and are prone to significant error due to unobserved or missed animals and multiple counts of single animals. One method to correct an observed count of animals is to physically "mark" a certain number of animals prior to an aerial or ground survey of wildlife and record the number of marked animals visually observed during the survey. The proportion of marked animals observed relative to the known number of marked animals in a survey area is the probability of detection, which is then applied to the count of animals from a survey to provide a corrected population size.

My dissertation examined various techniques to improve the probability of detecting animals in remotely sensed aerial imagery. Counting animals in remotely sensed imagery, such as in photographs obtained from an airplane or images from satellites, are advantageous as the images can be acquired for large areas quickly and can

reveal spectral information not readily visible by humans (i.e., near infrared and thermal information). In addition, techniques employing computer evaluation have the potential to reduce analysis time, and increase accuracy and precision when estimating animal population sizes.

Patricia Terletzky-Gese

ACKNOWLEDGMENTS

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CHAPTER 1

INTRODUCTION

The enumeration of wildlife populations has developed from the simple counting of individuals in a given area (Leopold *et al.*, 1947) to the development of models estimating bias (Caughley, 1974), to complex, statistically based estimators and their associated correction factors (Miller *et al.*, 2011; Rivest *et al.*, 1998; Thompson and Seber, 1994; White and Lublow, 2002). Conventional methods to estimate wildlife population abundances include counting marked or unmarked individuals via ground or aerial surveys. Although aerial transects can cover large areas in a relatively short time (Freddy *et al.*, 2004; Potvin *et al.*, 2004), the validity of population abundance estimates derived from aerial transect counts is questionable (Eberhardt, 1978). Problems associated with aerial and ground surveys have been well-documented (Brockett, 2002; Caughley, 1974; Jackmann, 2002; Samuel *et al.*, 1987; Steinhorst and Samuel, 1989; White *et al*., 1989; Willaims *et al.*, 2002) and can be broadly classified into environmental, biological, and survey biases (Hosack *et al.*, 2012; Ransom, 2012; Steinhorst and Samuel, 1989). Environmental biases are uncontrollable factors such as weather or topography of the survey area. Biological biases are (Gasaway *et al.*, 1985; Jackmann, 2002) due to characteristics of the species surveyed such as habitat preference and whether the species is solitary or in groups. Survey biases are influenced by observer experience, aircraft type, and speed, altitude of the aircraft, and survey design (Caughley, 1974; Ransom, 2012). In addition to the three types of biases reported with ground and aerial wildlife surveys, there are misclassification errors (i.e., incorrect species identification) and missed individuals or groups (i.e., individuals present in the study area

but not detected) or double-counted (i.e., individuals present in the study area and counted twice, Hosack *et al.*, 2012). Methodological techniques that attempt to address missed animals include using two independent observers (Duchamp *et al.*, 2006; Potvin *et al.*, 2004; White *et al.*, 1989), distance sampling (Williams *et al.*, 2002), concurrent or nearly concurrent ground and aerial counts (Jackmann, 2002; Samuel *et al.*, 1987), mark-recapture or mark-resight methods (White *et al*., 1982; Williams *et al.*, 2002), and photographic interpretation (Koski *et al*., 2010; Lubow and Ransom, 2009). Statistical techniques that minimize errors in detection generally adjust abundance estimates by accounting for missed individuals or groups (Hosack *et al., 2*012; Walsh *et al.*, 2009; Williams *et al.*, 2002). Sightability models indicate how environmental, survey, and biological variables influence the probability of detecting an animal and can be used to adjust population abundance estimates (Samuel and Pollock, 1981; Steinhorst and Samuel, 1989). An additional concern with aerial surveys is the potential ungulate response to helicopters by flushing or moving away from the survey area (Anderson and Lindzey, 1996; Bernatas and Nelson, 2004; Brockett, 2002) which can increase the potential for in individuals to be missed or double-counted (Bartmann *et al*., 1987; DeYoung, 1985; Eberhardt, 1978). Although many modifications have been made to traditional wildlife ground and aerial surveys techniques (Bartmann *et al.*, 1987; Caughley, 1974; Eberhardt, 1978; Rivest *et al.*, 1998; Thompson and Seber, 1994; White and Lubow, 2002) there continues to be a need to improve the accuracy, precision, and repeatability of methods used to estimate wildlife population abundances.

   Aerial photography provides an alternative for counting animals over extensive

areas or remote areas (e.g., Fretwell *et al.*, 2012) and has been used to estimate bird

colony size (e.g., greater flamingos [*Phoenicopterus roseus*], Descamps *et al.*, 2011;

emperor penguins [*Apenodytes foster*], Fretwell *et al.*, 2012), marine mammals (e.g.,

bowhead whales [*Balaena mysticetus*], Koski *et al.*, 2010) and large ungulates (feral

horse [*Equus caballus*], Lubow and Ransom, 2009). Counting animals in aerial

photography is labor intensive, subjective and can result in inconsistent counts (Bajzak

and Piatt, 1990; Gilmer *et al.*, 1988; Sinclair, 1973). Erwin (1982) found that variation

was high among photo-interpreters and neither experience nor training influenced counts

of canvasback ducks (*Aythya valisineria*). Conversely, Couturier *et al.* (1994) indicated

that two photo-interpreters achieved similar values when counting caribou (*Rangifer

tarandus*). Bajzak and Piatt (1990) developed a computer-based technique to automate

the identification and counting of snow geese (*Chen caerulescens*) in remotely sensed

imagery. The uniformly colored snow geese and simple habitat features facilitated

identification of individual birds. These studies suggest that obtaining accurate counts of

animals from aerial imagery is best applied in areas with little vegetation structure and/or

with larger bodied species that are readily differentiated from their background

(Descamps, 2011). Aerial photography has been commonly used in coastal environments

(Hiby *et al.*, 1988) and for counting birds (Bajzak and Piatt, 1990; Erwin, 1982; Gilmer *et

al.*, 1988; Harris and Lloyd, 1977) but only a few studies have used it to estimate

ungulate populations (Couturier *et al.*, 1994; Lubow and Ransom, 2009; Russell *et al.*,

1994; Sinclair, 1973).

Counting of individual ungulates from remotely sensed imagery has the potential

to reduce survey bias of conventional wildlife censuses while accurate counting, facilitated by automated or semi-automated image analysis, could reduce over- and under-counting errors. In addition, remotely sensed imagery is a permanent record of a surveyed area that can be repeatedly re-examined and allows a diversity of researchers to utilize a wide range of analysis techniques without influencing or modifying the original image. Furthermore, acquiring remotely sensed imagery of survey areas, whether from airplanes or satellites, will likely have fewer negative effects on animals than conventional aerial surveys (Bernatas and Nelson, 2004; DeYoung, 1985).

One of the central assumptions of this project is that in remotely sensed imagery animals can be distinguished from the surrounding features (i.e., background soils or vegetation). Laliberte and Ripple (2003) found that cattle were discernible in 1 m IKONOS satellite imagery but the final count was higher compared to manual photo-interpretation. Homogenous background influenced the identification of deer (*Odocoileus spp.*) in remotely sensed images obtained in winter where deer were discernible from the surrounding snow in the near infrared portion of the electromagnetic spectrum (EM) but not in the visible region (Wyatt *et al*., 1985). There was little distinction between deer and non-snow covered backgrounds (i.e., vegetation and soil) in the thermal region of the EM spectrum (Wyatt *et al.*, 1985). Complex, non-homogenous backgrounds reduced the detection and identification of deer by 50% - 80% with higher detections achieved when near infrared (NIR) spectral information was included in the analysis but varied with the amount of non-photosynthetic material (i.e., desiccated vegetation, Trivedi *et al.* (1982). These studies suggest that detecting wildlife in remotely sensed imagery is best

accomplished with NIR spectral information and when animals are surrounded by homogenous, non-complex habitats.

Although analysts can qualitatively identify animals in remotely sensed imagery, the objective of this research was to develop an automated or semi-automated analysis of remotely sensed imagery for the identification and counting of animals to reduce errors. Examination was limited to grassland systems due to the increased complexity of cover in shrub dominated habitats and forests.

The probability of detecting an animal during ground or aerial surveys can be used to correct count data to obtain a more accurate population abundance estimate for wild animals (White, 2005). Although several methods have been developed that estimate the probability of detection (Williams *et al.*, 2002), most assume a constant probability, which are incorrectly applied for large ungulates in rugged terrain or in habitats that obstruct vision (Fieberg and Giudice, 2008). Incorporating landscape variables and survey parameters into sightability models extends the ability of detection probabilities to correct population abundance estimates. Habitat, group size, and amount of vegetative cover have all been shown to influence sightability (Gasaway *et al.*, 1985; Giudice *et al.*, 2012; Jackmann, 2002; Ransom, 2012; Rice *et al.*, 2009; Samuel *et al.*, 1987; Samuel and Pollock, 1981).

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CHAPTER 2

SPECTRAL CHARACTERISTICS OF DOMESTIC AND WILD MAMMALS

Abstract

Few studies have recorded the spectral signatures of domesticated live animals and in particular few have examined wild species. Using *in situ* radiometry, we acquired visual and near infrared spectral signatures of wild elk (*Cervus elaphus*) and domesticated cattle (*Bos taurus*) and horses (*Equus caballus*). Signatures were significantly different among species across all bands with the exception of cattle and horses in the red band. Further research is needed to determine if the shallower slopes in the red-shift region of the animal signatures would allow for distinction from vegetation using various remote sensors. Application of *in situ* spectral signatures to remotely sensed imagery could provide an efficient method for counting wildlife.

Introduction

The regions of the electromagnetic (EM) spectrum measured by sensors encompass visible wavelengths, long and shortwave infrared wavelengths, and even thermal wavelengths. Remote sensing instruments obtain spectral information at a wide range of spatial scales from kilometers to meters and recently sub-meter (Jensen, 2005). In contrast, hand-held devices such as spectrometers, spectroradiometers, and radiometers measure radiance at spatial scales of centimeters to millimeters and can record a variety of wavelengths from short wave ultraviolet to long wave far-infrared (Clark, 1999). Hand-held devices obtain signatures under controlled conditions that allow for correction

of atmospheric attenuation and sensor anomalies, and can be considered fundamental information for features in remotely sensed imagery (Schill et al., 2009). As spatial resolution of remote sensing instruments increases, application of *in situ* spectral signatures could be applied to remotely sensed imagery for feature identification. Spectrometers and radiometers have been utilized to measure the spectral reflectance of agricultural crop health (Pethybridge et al., 2007), to quantify the amount of nitrates in liquids (Fernández-Ramos et al., 2008), to identify the effect of contaminants and snowflake size in snow reflectance (Singh et al., 2010), and to classify volcanic rock origins (Rukieh et al., 2007). Spectral libraries, consisting of standardized spectral signatures measured from hand-held devices, have successfully been utilized to classify soils, minerals, rocks, man-made materials, and even space bodies (Baldrigde et al., 2009). Uses of spectral libraries include functioning as a standard for comparison with other data sources, identification of spectral outliers, and predicting spectral characteristics of features (Shepherd and Walsh, 2002).

Spectral information on animals has previously focused on the interaction of skin and hair relative to heat conductance and transference (Hutchinson and Brown, 1969; Dawson and Brown, 1970; Gates, 1980; da Silva et al., 2003). Hutchinson and Brown (1969) found cattle with lighter hair had higher reflectance and reduced absorbance, which reduced the heat load. Dawson and Brown (1970) examined two desert kangaroo species (*Megaleia rufa* and *Macropus robustus*) and concluded the lighter colored species exhibited behavioral traits influenced by hair color.

Detection of live animals with hand-held, thermal sensors initially occurred in the late 1960s and early 1970s (Croon et al., 1968; McCullough et al., 1969; Graves et al., 1972; Parker and Driscoll, 1972) and has continued more recently (Burn et al., 2006; Betke et al., 2008; Udevitz et al., 2008). Early studies suggest that although animal detection was possible, detection was not consistent and required very specific conditions (i.e., consistent background conditions). Improved thermal resolution has increased the reliability of detection and identification (Bernatas and Nelson, 2004) and may allow for counting of individuals and the eventual estimation of populations. Investigation of mammalian detection and identification in the visible portion of the spectrum is more limited. Trivedi et al. (1982) determined that far red (0.67 μm) and near infrared (NIR, 0.79–0.98 μm) wavelengths best identified mule deer (*Odocoileus hemionus*) in winter. Errors of commission were highest when the image contained shrubs or dried vegetation and lowest with a consistent background such as snow (Trivedi et al., 1982, 1984). Trivedi et al. (1982) recognized that errors of omission occurred but considered them negligible and did not specifically address them.

Conventional wildlife population estimates using aerial surveys are rife with inconsistencies and errors (Eberhardt, 1978; Bartmann et al., 1987; White et al., 1989; Jackmann, 2002; Freddy et al., 2004). Therefore, there is a need for a systematic, efficient, and accurate method of identifying and counting wildlife for population estimates. Traditionally, remotely sensed imagery was utilized to map static landscape features, but recent applications include wildlife populations surveys (Heide-Jørgensen, 2004). Compared to conventional visual counts of wildlife from aircraft, remotely sensed

imagery as a source of wildlife population estimates provides a permanent record,

allowing for repeated analysis by multiple investigators or application of different

techniques. In addition, there is the potential for classification of large-bodied mammals

in high spatial resolution ($< 1 \times 1$ m) remotely sensed imagery. An initial challenge of an

accurate supervised classification of animals in a remotely sensed image is the

application of basic spectral information of animal species (Lubin et al., 2001; Balridge et

al., 2009; Kokaly et al., 2009). Trivedi et al. (1982) and Wyatt et al. (1985) obtained

spectral signatures for deer species (*Odocoileus spp.*)*,* but no research has recorded

spectral signatures of elk (*Cervus elaphus*), horses (*Equus caballus*), or cattle (*Bos

taurus*). Obtaining basic spectral information on common domestic animals and a wild

ungulate can facilitate understanding of animals in aerial or satellite remotely sensed

imagery.

The objective of this research was to compare visible and near-infrared spectrum

reflectance values of domestic and wild ungulates. Specifically, we examined to what

extent elk, cattle, and domestic horse spectral signatures were unique and distinguishable

among themselves.

Methods

A portable, shortwave, four-band EXOTECH radiometer (blue band: 0.45–0.52

μm; green band: 0.52–0.60 μm; red band: 0.63–0.69 μm; and NIR band: 0.76–0.90 μm)

was used to obtain spectral measurements of cattle, elk, and horses in northern Utah

under generally cloud free skies. Elk and horse readings were acquired at the Hardware

Ranch Wildlife Management Area in late January 2009. The cattle readings were

acquired in a private pasture in Cache Valley in early February 2009. Attribute data included angle of readings (top or side of the animal). The radiometer was fitted with a 1° field-of-view lens and held 50–100 cm over individual animals resulting in a reading of 0.76–3.05 cm^2 area. We converted radiometer voltages to reflectance values (Jackson et al., 1987; Neale and Crowther, 1994; Schill et al., 2009) based on known bidirectional properties collected over a barium sulfate panel reflecting incoming solar radiation (Jackson et al., 1992; Neale et al., 2005). The barium sulfate panel was placed close to the study sites but far enough away so that airborne particles (i.e., dust) generated from the corrals or pasture would not obscure the incoming solar radiation nor settle onto the panel itself. The radiometer, held approximately 0.5 to 1 meter above the panel without shadowing, obtained panel values intermittently throughout the day. Calibration of the radiometer to zero radiance occurred at the beginning and end of each day by covering the radiometer lens to eliminate outside light and represented inherent radiometer noise. Removal of radiometric noise occurred during the voltage to reflectance conversion.

Obtaining an optimal sample required correct animal positioning, adequate access for the radiometer, and a stationary animal. These conditions presented themselves infrequently and were available only for a few seconds. Thus, obtaining samples directly above animals was not always possible and sometimes required a radiometer reading of the animals' side. Due to the quickness with which samples had to be acquired, some samples did not have the angle of acquisition recorded and thus were labeled as unknown. Each session consisted of five radiometer readings with the average of the five readings considered as the sample. Readings of elk took place while adults were in a

squeeze chute and usually stationary (Fig. 2.1). Because elk moved through the chute

rapidly, only one sample occurred for each elk. Samples consisted of only the back or

side of the elk, not the head or white rump. Imaging of cattle (Black Angus and Angus

mix) occurred in an open pasture while they were eating and could move freely about, but

only readings of stationary cattle were included in analysis. For horses (Belgian,

Clydesdale, and Percheron breeds), data acquisition occurred within a corral and only for

stationary horses. Sampling of cattle and horses occurred with replacement, so some

individuals were sampled more than once.

Optimally the instantaneous field of view (IFOV) consisted entirely of the animal

without shadow or neighboring features but unpredicted animal movement sometimes

incorporated unexpected features (i.e., the ground or shadow). To reduce the intrusive

error, as defined by Schill et al., 2009), analysis consisted of signatures within ±2 STD of

the mean for each spectral band. Because samples represented the average of five

readings, we used the standard error to represent the variation across samples (Streiner,

1996). A one-way analysis of variance (ANOVA, Zar, 1996) tested the null hypothesis

that the mean reflectance values for each band were not significantly different among the

three species. The Tukey Honest Significant Differences test (HSD) tested pair-wise

differences. We conducted t-tests to determine if there were significant differences in

mean reflectance values for the angle of acquisition (top vs. side) for all three species.

The t-tests determined if black cattle were significantly different from brown cattle and if

brown horses were significantly different from grey horses. All t-tests assumed unequal

variances and used the Welch-Scatterthwaite equation to determine the degrees of freedom (Zar, 1996).

Results

Analysis consisted of 53 readings: 27 elk, 17 cattle, and 9 horses. Elk had the highest mean reflectance and highest within-species standard error (SE) for all spectral bands, except the blue (Table 2.1). Cattle had the lowest mean reflectance and lowest within-species standard error for all bands (Fig. 2.2 and Table 2.1). Mean reflectance values for horses were intermediate between cattle and elk in all bands, although the values were closer to cattle.

One of the assumptions of an ANOVA is that the data are normally distributed and that variances are homoscedastic among the independent variables. Although the spectral values were normally distributed, they exhibited heteroscedasticty, so prior to conducting the ANOVA, we log-transformed the blue, green, and NIR spectral values. The red spectral values required a square root transformation to reduce heteroscedasticty without reducing normality. ANOVAs conducted on transformed data indicated there were significant differences between elk and cattle in all four bands (Table 2.2). Elk and horses were significantly different in the visible bands (blue, green, and red) at the 0.05 significance level and in the NIR band at the 0.07 level of significance. The transformed reflectance values were significantly different between cattle and horses in the blue, green, and NIR band but not the red band (Table 2.2).

The general spectral pattern of the signatures exhibited a decrease in reflectance values from blue to the green, an increase from the green to the red, with a steeper

increase from the red to the NIR (Fig. 2.2). Although spectral values of all three

ungulates increased in the "red shift" region (change from the red band to the NIR band),

similar to that of vegetation, there was a distinct difference in pattern among vegetation

and the three ungulates in the shorter wavelengths. Spectral values for vegetation

increased from the blue to green bands, while elk values increased and cattle and horses

exhibited little change (Fig. 2.3). In addition, the slope of vegetation in the red shift

region is generally steeper than that of the three animal species measured.

There was no significant difference in the angle of acquisition (side or top) on

mean reflectance values in any bands measured ($p > 0.05$) for elk or cow (Fig. 2.3). We

did not examine statistical differences in angle of acquisition for horses due to low

sample size.

We examined reflectance values relative to coloration for cattle and horses but not

on elk, because their coloration is similar among individuals. There was no significant

difference ($p > 0.05$) in the mean reflectance values of brown and black cattle in the blue

and green bands. Brown cattle exhibited significantly ($p < 0.001$) higher reflectance

values in the red and NIR bands than black cattle (Fig. 2.4). The lack of significant

differences in the mean reflectance values between brown and grey horses in all four

bands is likely due to high variation with low sample size (Fig. 2.4).

Discussion

Accurate identification of landscape features in remotely sensed imagery requires

unique and discernible spectral signatures. *In situ* measurements result in basic spectral

information that if applied to remotely sensed imagery has the potential to increase the

accuracy and precision of feature identification. We examined spectral signatures for three ungulate species: domestic cattle, elk, and domestic horses. Our data suggested that cattle, elk, and horses spectral signatures are uniquely identifiable in the visible and NIR regions of the electromagnetic spectrum when collected with hand-held radiometers. While their signature patterns are similar, the spectral values are significantly different. Hair structure, type, and pigmentation determine the coloration of a species, which in turn influences the spectral reflectance and absorption for that species. Most terrestrial mammals have two hair types: guard hairs and underfur. Guard hairs are typically longer, thicker, and have a complex physical structure. Underfur is short, fine, and dense, with a simple physical structure and little variability in coloration (Adorjan and Kolenosky, 1969; Moen and Severinghaus, 1984). Underfur provides insulation and is more prevalent during colder months (Toweill and Thomas, 2002) while guard hairs provide species-specific coloration and are present throughout the year. Elk shed their winter coats in the spring and their summer coats in late summer to early fall, so the spectral reflectance of elk included both guard hair and underfur. Elk underfur is wavy, wooly, and lighter in color than guard hairs, whereas cattle underfur is long, straight, and similar to guard hair (Moen and Serveringhaus, 1984). The winter coat of horses is simply thicker and longer than their summer coat. Elk have three distinct regions of banding on individual body hair, while the rump and neck hair lack banding. Cattle and horses can vary from having banded hair to non-banded hair. The presence of the light-colored underfur in elk and an overall light tan color resulted in higher reflectance values. The higher variation in the elk reflectance values is due to the greater complexity of the elk pelage rather than variation

in coat coloration alone. The lower variation in reflectance values for cattle and horses is likely due to sampling with replacement, resulting in individuals being represented by multiple samples. The darker pelage of cattle (predominately black to brown) and horses (predominately brown) resulted in greater absorption and lower reflectance values for all spectral bands examined, although de Silva et al. (2003) found brown- and black-colored cattle skin had similar reflectance values in the visible wavelengths. The darker colors also contributed to the relatively small change in reflectance from the blue to green region for cattle.

Because vegetation surrounds both domestic and wild ungulates, spectrally distinguishing vegetation from animals is paramount for accurate identification. While the overall spectral pattern of the animals studied is in opposition to that of vegetation (Fig. 2.3), the variance about those patterns precludes easy distinction with vegetation. Past research indicates that animal hide is discernible from vegetation in the 0.6 to 0.7 μm region of the electromagnetic spectrum (Wyatt et al., 1985; Bortolot and Prater, 2009) and that wild deer were most discernible with a consistent layer of snow and no shrubs present (Trivedi et al., 1982). The lower slopes of the ungulate spectral patterns in the red shift region, relative to vegetation, may aid in distinguishing cattle, elk, and horses in remotely sensed imagery.

The spectral differences among cattle, elk, and horses create the possibility of discerning these species in high-spatial-resolution aerial or satellite remotely sensed imagery. Standardized signatures could aid in the segmentation of an image by removing

pixels or features that lie outside the range of the animals' spectral signature. Enhancement of pixels lying within the signature would facilitate feature classification.

While continued recording of the spectral signatures of domestic and wild species is needed, future research should focus on the application of standardized cattle, elk, and horse signatures to segment an image and identify these species in aerial or satellite imagery. Applying *in situ* spectral signatures to aerial or satellite imagery to identify and count animals across large areas has the potential to initiate surveys in areas that have previously been too extensive to sample with conventional survey techniques. Vast areas of interest, such as the Great Basin Desert of the western United States or the Mongolian Steppe, cannot reasonably be surveyed from the ground or air for endemic populations of wild ungulates. Attempting to survey such large areas would require many days during which animals would continuously move and potentially be counted multiple times or even missed being counted completely. Yet there is a need to survey these areas for contentious species such as the wild horse (*Equus ferus*) or critically endangered species such as the Mongolian Antelope (*Saiga tatarica*; IUCN, 2011). Using remotely sensed imagery, a large area could be completely imaged in a relatively short amount of time, thus avoiding drastic animal movements and increasing counting precision. Identification of domestic and wild species with standardized signatures creates an additional wildlife survey technique not currently possible.

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Table 2.1. Mean ± Standard Error (SE) of Untransformed Spectral Reflectance Measures of Four Radiometer Bands for Cattle, Elk, and Horses

Species	Blue	Green	Red	NIR
Cattle	0.029 ± 0.003	0.017 ± 0.002	0.036 ± 0.006	0.080 ± 0.016
Elk	0.152 ± 0.017	0.126 ± 0.014	0.285 ± 0.030	0.376 ± 0.380
Horses	0.076 ± 0.027	0.036 ± 0.008	0.090 ± 0.011	0.181 ± 0.021

Table 2.2. Results of Four, One-Way ANOVA and Tukey Honest Significant Differencing (Tukey HSD) Tests for Transformed Spectral Reflectance Differences among Cattle, Elk, and Horses

				Tukey HSD		
Band	df	F value	p value	Elk-cattle	Elk-horses	Cattle-horse
Blue	2,50	31.07	< 0.001	< 0.001	0.001	0.016
Green	2,50	47.22	< 0.001	< 0.001	< 0.001	0.034
Red	2,50	33.05	< 0.001	< 0.001	< 0.001	0.102
NIR	2,50	26.54	< 0.001	< 0.001	0.072	0.004

Fig. 2.1. Radiometric readings of elk in a squeeze chute, northern Utah.
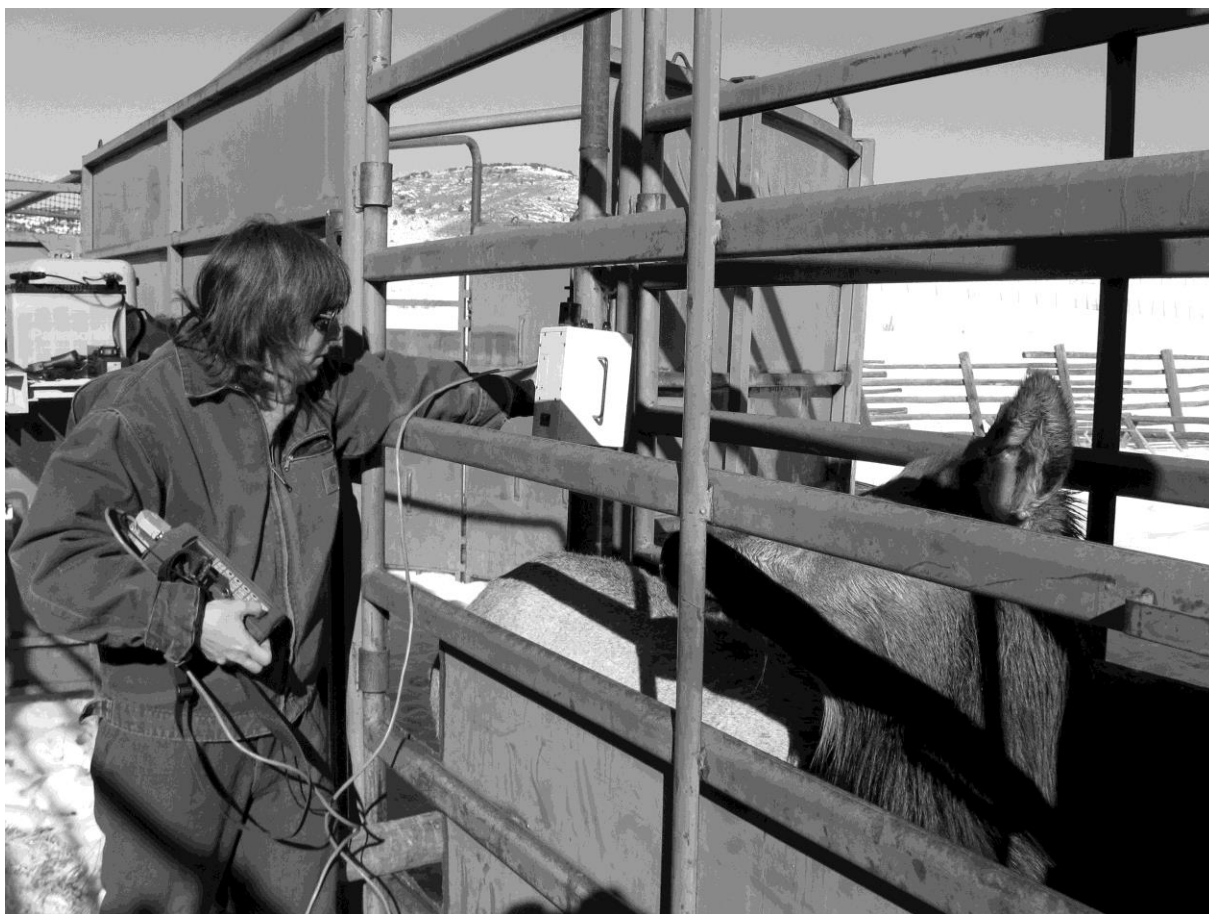
Fig. 2.2. Blue, green, red, and NIR untransformed spectral reflectance 95% confidence intervals (± 2 STD) for cattle (A), elk (B), and horses (C).
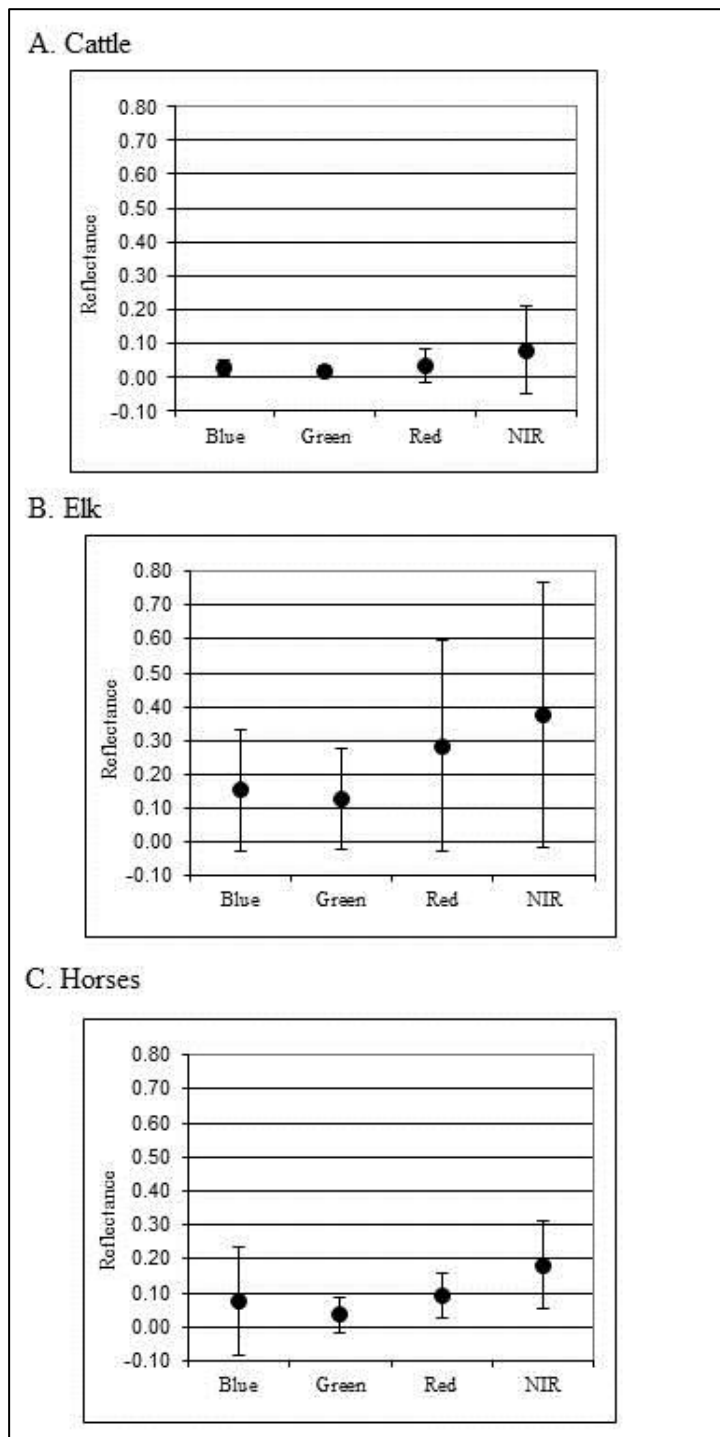
Fig. 2.3. Untransformed spectral reflectance graphs of cattle (A), elk (B), and horses (C) relative to angle of acquisition. Typical vegetation spectral signature (D) printed for signature comparison (from Jensen 2005). Samples of individuals without angle of acquisition were not included; *t*-tests indicated no significant differences among any
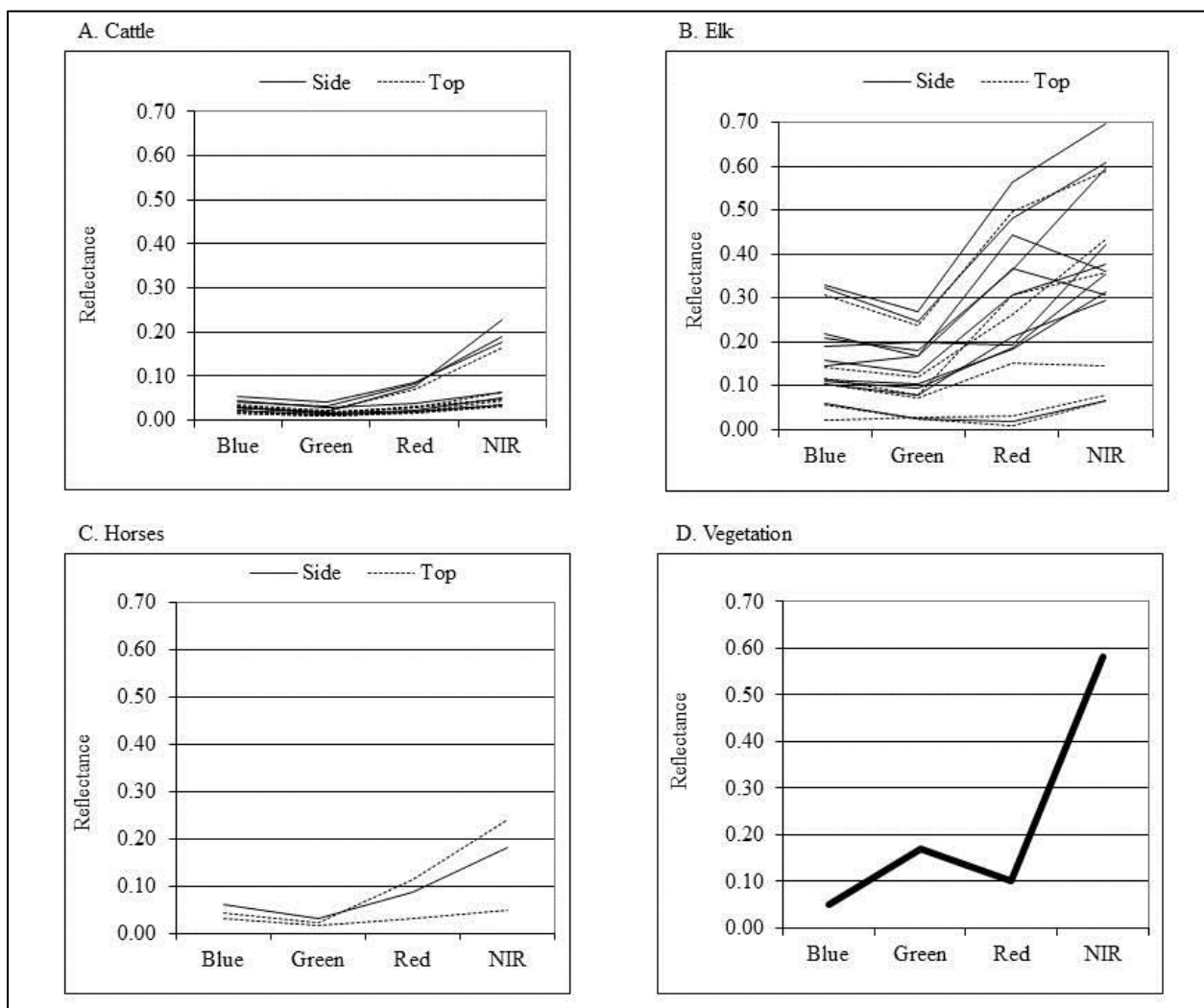
species relative to angle of acquisition.

Fig. 2.4. Coloration effects on spectral signatures of (A) cattle and (B) horses. Samples of individuals without color recorded were not included; * denotes $p \leq 0.001$.
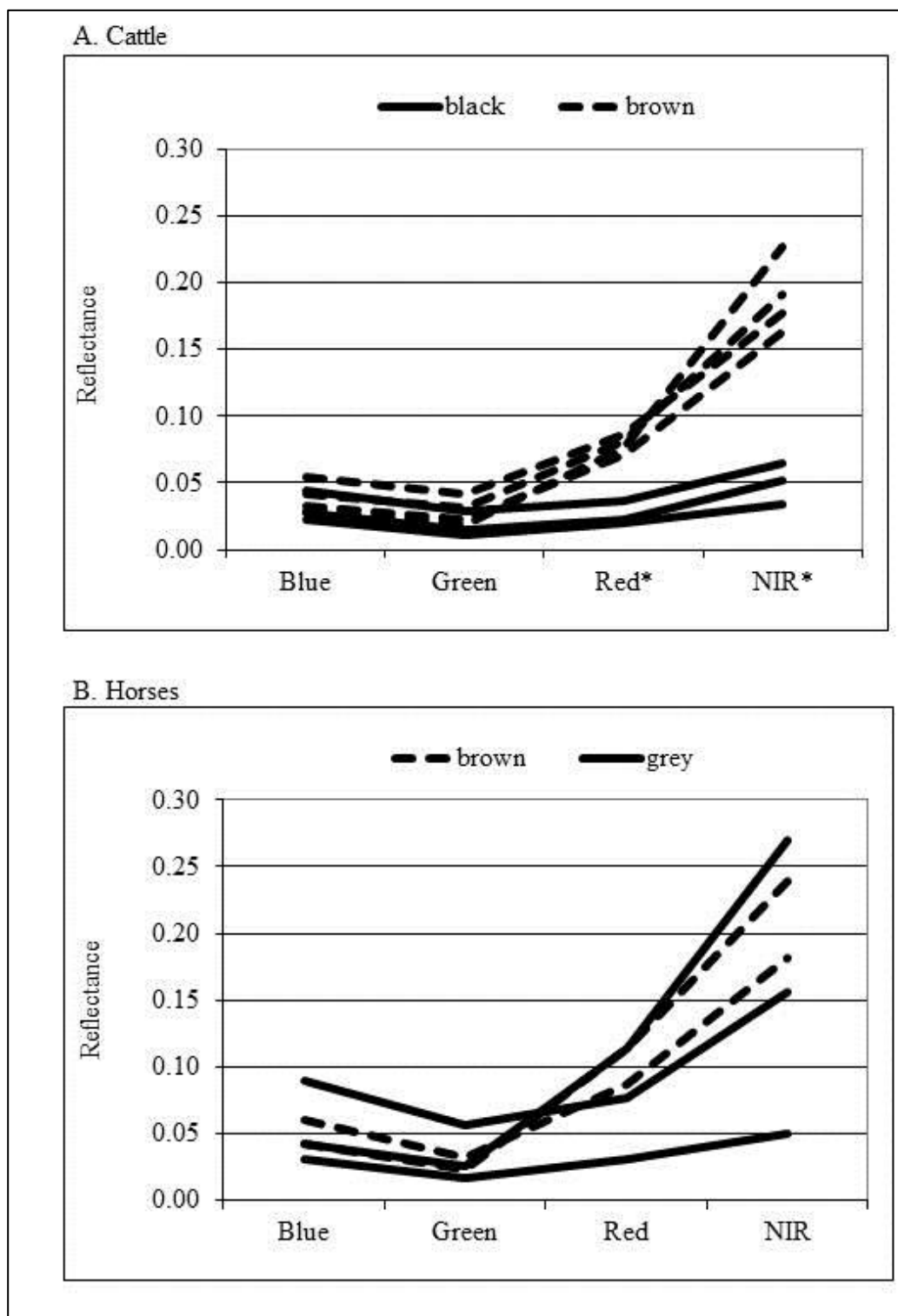
CHAPTER 3

COMPARISON OF TECHNIQUES TO IDENTIFY AND COUNT INDIVIDUAL ANIMALS IN REMOTELY SENSED IMAGERY

Abstract

There is a need to improve the accuracy and precision of survey methods for censusing wildlife species. We compared the relative accuracy of manual photo interpretation, an unsupervised classification, and multi-image, multi-step technique to enumerate animals in remotely sensed imagery. Using images of pastures containing a known number of cattle, we compared the performance of the three techniques based on the probability of correctly detecting animals, the probability of under-counting animals (false positives), and the probability of over-counting animals (false negatives). Manual photo-interpretation was the most accurate and had the highest probability of detecting an animal if it was present and the lowest probability of under- or over-counting animals. An unsupervised, ISODATA classification with subtraction of a background image had the second highest probability of detecting an animal. The third technique integrated multiple images, such as texture and spectral reflectance, with multiple procedures, such as subtraction and principal components analysis, to isolate animal features in aerial imagery and had the lowest probability of detecting an animal. The 2 semi-automated techniques had high probabilities of over-counting animals but low probabilities of under-counting animals.

Introduction

Monitoring and detecting changes or trends in population abundances requires accurate enumeration of animals and is essential for managing wildlife species and evaluating of conservation goals (Garton *et al.*, 2005; Gregory *et al.*, 2004; McComb *et al.*, 2010; Williams *et al.*, 2002). Current methods used to obtain counts of animals include aerial or ground surveys and manual photographic interpretation (Silvy, 2012). Regardless of the type of survey conducted, counts in remote, hard to access, locations or over extensive areas are logistically difficult to obtain, time consuming, and frequently biased (Bartmann *et al*., 1987; Brockett, 2002; Caughley, 1974; Jackman, 2002; Storm *et al.*, 2011; White *et al.*, 1989; Williams *et al.*, 2002). Given the biases inherent to aerial and ground surveys and photographic interpretation, a method to identify and enumerate animals that is economical, repeatable, and accurate would provide wildlife managers another tool for estimating population abundances of wildlife species.

Counts of animals from remotely sensed imagery or aerial photographs have been used to estimate population abundances of a diverse array of wildlife species, from birds (Erwin, 1982; Fretwell *et al.*, 2012; Gilmer *et al.*, 1988; Harris and Lloyd, 1977) to terrestrial species (Lubow and Ransom, 2009; Russell *et al.*, 1994) to oceanic mammals (Hiby *et al*., 1988; Koski *et al*., 2010). Unfortunately, manual counts from aerial photographs are labor intensive, subject to human interpretation and error, and can result in inconsistent counts (Bajzak and Piatt, 1990; Erwin, 1982; Frederick *et al.*, 2003; Gilmer *et al*., 1988; Sinclair, 1973). For example, Erwin (1982) found manual counting of canvasbacks ducks (*Aythya valisineria*) in aerial photographs had high variation

among interpreters and neither experience or the amount of training influenced counts.

Conversely, Couturier *et al*. (1994) reported two independent interpreters achieved

similar results when counting caribou (*Rangifer tarandus*) from aerial photography.

Although these studies found conflicting results, other researchers have found that lower

errors are correlated to areas with little vegetation structure and/or with large bodied

species (Trivedi *et al.* 1982; Wyatt *et al*., 1985). As with conventional wildlife aerial

surveys (Jackman, 2002; Potvin *et al.*, 2004), detection using aerial photographs requires

high contrast between animals and their background (Descamps, 2011; Laliberte and

Ripple, 2003; Storm *et al.*, 2011). For example, Bajzak and Piatt (1990) found the

uniformly white-colored bodies of snow geese (*Chen caerulescens*) facilitated separation

of the birds from their background. Similarly, Fretwell *et al.* (2012) used an iterative

process in which an analyst subjectively determined if features in satellite imagery were

guano-stained snow or Emperor penguin (*Aptenodytes fosteri*) colonies based on

differences in texture and color.

Other applications of remotely sensed imagery for wildlife studies have focused

on identification of individual animals rather than groups of animals or colonies of birds

(Descamps *et al*., 2011; Fretwell *et al.*, 2012). For example, Laliberte and Ripple (2003)

used 1 m, pan-sharpened, multi-spectral IKONOS satellite imagery to identify domestic

cattle in Oregon but found they overestimated the final count. As with aerial photography

and conventional wildlife surveys, the importance of the homogeneity of the background

that surround an animal was a factor in the detection of deer (*Odocoileus* spp.) in

northern Utah during winter (Wyatt *et al*., 1985). Deer were discernible from snow in the

near-infrared (NIR, 0.7 to 1.4μm and 1.5 to 4.0μm) region of the electro-magnetic (EM)

spectrum but not in the visible region due to confusion with vegetation and soil. There

was little ability to differentiate between deer and their background (vegetation and soil)

using the thermal portion (3.0 to 5.0 μm and 7.5 to 10μm) of the EM spectrum (Wyatt *et

al*., 1985). Trivedi *et al.* (1982) found that complex, non-heterogeneous background and

increased cover of dry bushy vegetation reduced the probability of detecting deer.

As the amount of available satellite and aerial imagery increases, there is a

concomitant need for automated or semi-automated image analysis to reduce analysis

time, allow non-photogrammetric specialists to interact with imagery, facilitate faster

searches, and identify quantitative information not readily recognizable with human

interpretation (Aitkenhead and Aalders, 2011; Baraldi and Boschetti, 2012; Walter and

Luo, 2011). An objective of this research was the development of an automated or semi-

automated technique to identify and count animals in remotely sensed aerial imagery. We

developed a proof of concept using aerial imagery of fenced pastures containing known

numbers of animals (i.e., domestic cattle [*Bos Taurus*] and horses [*Equus caballus*]). We

examined one technique that relied solely on human interpretation (i.e., manual photo-

interpretation) and two techniques that had minimal input from analysts (i.e., an

ISODATA classification (Jensen, 2005) with subtraction of a background image and a

multiple image, multiple step technique). We compared the performance of each

technique based on the probability of correctly detecting animals, the probability of

under-counting animals (false negative), and the probability of over-counting animals

(false positive). A correction factor integrating all detection probabilities adjusted the

final count estimate for each image. The study was limited to grassland ecosystems due to the reduced complexity of cover as compared to dense, tall shrublands, and forests.

Study Areas

We acquired aerial imagery across portions of Cache County (i.e., Cache Valley) and a portion of Box Elder County in northern Utah. Cache Valley (CV) is a north-south trending valley surrounded by the Wellsville Mountains to the west and the Bear River Mountain Range to the east. Cache Valley has an average annual precipitation of 45 cm (Moller and Gillies, 2008) with an elevation of 1,355 m (U.S. Geological Survey, 1981) in the center of the valley. Sites in CV were located in the valley bottomlands dominated by grasslands. Brigham City (BC) is located in Box Elder County and sits on the western base of the north-trending Wellsville Mountains. The average precipitation of the BC sites was 47 cm (Moller and Gillies, 2008) with an elevation of 1,289 m (U.S. Geological Survey, 1981). BC study sites were dominated by sparse grasslands.

Aerial Imagery

On October 31, 2006, under mostly clear skies, we collected aerial imagery between 10:44 AM and 3:07 PM with three Kodak Megaplus 4.2i digital cameras (Kodak Company, Rochester, New York, New York) each recording a specific spectral region: green (0.54 – 0.56 μm), red (0.66 – 0.68 μm), and near-infrared (0.7 – 0.9 μm) with an approximate spatial resolution of 25 cm (Cai and Neale, 1999). An Exotech four-band radiometer included with the cameras allowed for the conversion of digital numbers to reflectance values (Neale and Crowther, 1994). We acquired two images for

each pasture, with at least 48 minutes between acquisitions of the first image (A) and the

second image (B). Rectification of images to the Universal Transverse Mercator System

(UTM), NAD83 datum occurred in ERDAS Imagine 9.1.0. (Leika Geosystems,

Heerburg, Canton St. Gallen, Switzerland). Image acquisition likely did not affect

animal movements since the aircraft flew at an average elevation of 549 m above ground

level (Bernatas and Nelson, 2004; DeYoung, 1985).

Animal Ground Counts

Rather than compare one estimate to another estimate, we compared the number

of animals identified by each technique to the known number of animals in each pasture.

Ground enumeration of cattle and horses occurred concurrently with image acquisition.

We determined the final count of the known number of animals per pasture from visual

ground counts, available landowner counts, and a qualitative assessment of animal

movement in the imagery (Figure 3.1). Pastures containing ≥ 50 animals were difficult to

enumerate on the ground and resulted in unreliable counts, thus those pastures were not

included in the analysis. Although no probability of detection was determined for the

ground counts, by limiting analysis to those pastures with ≤ 50 animals, the detection

probability was likely high but still less than 100%. We considered pastures independent

samples since they were geographically separated across the study sites.

Accuracy Measures

The output from the manual photo-interpretation was an image containing circles

around suspected animals (Figure 3.1). The two semi-automated techniques generated

individual polygons. We were able to evaluate when circled features (or polygons) were properly identified by comparing against known animal locations. We classified polygons (or circles in the photo-interpretation) into three categories: "mapped polygons" consisted of all polygons generated in a particular technique, "correctly mapped" polygons were those generated using one of the three techniques that accurately depicted animals, and "incorrectly mapped" polygons were those polygons that were not associated with an animal. We assumed that features that moved location from one image to another image were animals and thus were able to determine a specific location for each animal. Because we knew specific locations of animals in each pasture, we were able to identify when an animal was not linked with a polygon (missed). Any animal not associated with a polygon was considered a "missed animal".

The probability of detection (PD) is a proportion of correctly identified animals relative to a known number of animals (Williams *et al*., 2002). In this paper, the PD calculation was defined as the number of correctly mapped polygons (or a circle in the photo-interpretation) divided by the number of known animals in the pasture. The probability of under-counting animals (P_{under}) indicated the proportion of animals known to be in a pasture but not associated with a polygon (or a circle in the photo-interpretation) identified and was calculated as the number of missed animals divided by the number of known animals in the pasture. The probability of over-counting (P_{over}) was calculated by dividing the number of polygons (or circles in the photo-interpretation) not associated with an animal by the number of mapped polygons (or circles in the photo-interpretation) in the pasture. We incorporated the three error estimates into a single

correction factor (CF) that we multiplied by the number of mapped polygons to generate

a population abundance estimate for each pasture. Abundance estimates, adjusted for

false positives (over-counting animals) and false negatives (missed animals), have greater

validity and are more robust than unadjusted estimates. The CF was calculated as (PD +

P_{under} - P_{over}) / PD.

Methods

Manual Image Interpretation

We evaluated the ability of lay-people (L), remote sensing analysts (R), and

wildlife biologists (W) to count animals in aerial photographs of fenced pastures

containing cattle. Each group was composed of five people, five lay people, five remote

sensing analysts, and five wildlife biologists from the Utah Division of Wildlife

Resources. None of the individuals in the L group had any experience in remote sensing

analysis or participated in wildlife surveys, none of the individuals in the R group

participated in wildlife surveys, but some of the individuals in the W group had limited

remote sensing experience (i.e., had previously examined remotely sensed imagery). All

participants examined the same seven images (i.e., fenced pastures). The number of

animals in each pasture ranged from five to 32. The photos of each pasture were

presented to the photo-interpreters in natural color on a single standard 8.5 x 11-inch

piece of paper. There was unlimited time for evaluation and individuals circled each

feature interpreted as an animal (Figure 3.1). Although participants received pastures in

the same order, the evaluation sequence was at the individual's discretion. Due to the data

being highly skewed across the three groups, (Figure 3.2) the use of an ANOVA (Zar, 1996) was inappropriate. Log, squared, and square root transformations did not normalize these distributions. Additionally, a generalized linear model fit with a binomial distribution was not suitable since PD, P_{under}, and P_{over} were probabilities. Theefore, we used a Kruskal-Wallis test (Zar, 1996) to determine if there were significant differences in the probability of detection, the probability of under-counting, and the probability of over-counting animals. All statistical tests were conducted in the R statistical software (R Core Development Team, 2012).

Semi-Automated, `Unsupervised Classification: ISODATA with image subtraction

We used a semi-automated, multi-step technique to identify animals in remotely sensed imagery (Figure 3.3) that included ISODATA segmentation and the generation of a background image. Unsupervised classification, commonly used to segment and classify remotely sensed imagery, has the ability to identify unique features on the landscape and separates spectral information into distinct statistical clusters so that pixels with similar spectral characteristics are assigned to the same cluster (Jensen, 2005). One advantage of unsupervised classification is that it requires little analyst input beyond determination of the number of output clusters. The iterative self-organizing data analysis technique (ISODATA; ERDAS, 2003; Jensen, 2005) places a pixel into the cluster with the closest Euclidean spectral distance. ISODATA is iterative in that after the initial pixel assignment, cluster means are recalculated and used as the cluster centroid for the subsequent iterations. The process, therefore, attempts to optimize cluster distribution within the multi-dimensional feature space of the image. At each iteration, pixel-to-

cluster assignments are re-assessed and if appropriate, pixels are placed into a different

cluster. Analyst input determines the number of iterations to run and a convergence

threshold, which specifies the percentage of pixels that remain assigned to a specific

cluster between iterations. Once the ISODATA segmentation is complete, the analyst

determines the class assignment for each cluster, for example, vegetation classes such as

grassland, forest, or urban. The ISODATA segmentation generated 20 clusters from each

3-band image that were then converted into polygons, with each polygon assigned the

mean spectral value of the pixels that it encompassed. We determined that clusters with

the three lowest spectral values represented potential animal polygons (PAPs) and

focused our subsequent analysis on these polygons. We intersected the PAPs with the

associated 3-band image to extract the original spectral response for each polygon to

maintain as much spectral information as possible through the image differencing process

(Figure 3.4).

Image differencing is a change detection technique in which an image collected at

time *X* is subtracted from a second, geographically identical image, collected at time *Y*. In

a differenced image, pixels with small spectral values represent areas that have changed

little, while pixels with large spectral differences represent areas of change (Jensen,

2005). Generally, image differencing has been used to identify land-cover changes

between images acquired on two different dates (Key *et al.*, 2001; Lu *et al.*, 2003; Lu *et

al.*, 2005). Rather than the subtraction of temporally different images, we tested the

feasibility of subtracting a simulated background image from an image containing

animals to highlight differences between animal features and their surrounding

background. As temporal image differencing detects changes over time, changes between

a background image without animal features and an image of the same area with animal

features should, in theory, isolate animal features.

Since the ISODATA segmentation alone generated many false positives (i.e.,

over-counted animal features, Figure 3.4), we needed to further isolate animal features

from the surrounding background. Based on a heuristic evaluation, we determined that

low spectral values consistently represented animals. To generate a background image,

we removed pixels with low spectral values (i.e., animal clusters) using a two-step

process (Figure 3.3B). First, we applied a 7 x 7 maximum convolution kernel to the

original image, which generated an image consisting of pixels with the highest spectral

values in the kernel. Next, we applied a 9 x 9 low-pass filter to the maximum kernel

image, which reduced spatial variation sufficiently to produce a smoothed background

image (Figure 3.5). We then intersected the PAPs with the simulated background to

generate pixel groupings that contained only background spectral values. We subtracted

the PAP pixel groupings generated in the ISODATA step from the background pixel

groups. Based on image differencing theory, pixels in the subtracted image with higher

difference values should represent animal polygons (i.e., animal spectral values

subtracted from the background spectral values) and lower difference values should

represent non-animal features (i.e., background spectral values subtracted from

background spectral values, Figure 3.6).

To further isolate animal features, a 20-class ISODATA segmentation was

conducted on the differenced pixel groups. As with the previous 20-class ISODATA

segmentation process, we heuristically identified pixels with the three lowest spectral

values as representing animals (Figure 3.7). We eliminated pixel clusters with spectral

values greater than the third lowest value and converted the remaining clusters to

polygons. We heuristically identified spatial thresholds which described known animal

shapes from the training images and removed polygons that were too large or too small to

be animals.

Multi-image, multi-step (MIMS) Technique

We examined a multi-image, multi-step (MIMS) technique to isolate animals in

remotely sensed imagery (Figure 3.8) with eight training images containing 143 animals

and seven test images containing 158 animals. The training images were chosen so the

number of animals in the training images was approximately the same as in the testing

images. The MIMS technique generated three output images from each original 3-band

pasture image: a texture image, the first principal component image, and a background

image (see ISODATA methods above).

Texture represents spatial change in spectral values within a specified

neighborhood and therefore characterizes spatial patterns across an image (Jensen, 2005).

Since texture quantifies variation within a neighborhood, we theorized that a

neighborhood, which encompassed both an animal and its surrounding background,

would exhibit greater variance (texture) than a neighborhood composed entirely of

animal or background pixels. The size of a single bull can range from 1.6 to 2.2 m^2 while

the size of a single cow can range from 1.4 to 1.5 m^2 (B. Bowman, personal

communication); thus, an area of 1.5 m^2 would encompass a small bull or a large cow. To

generate a texture image, we used a neighborhood of 7 x 7 pixels (3.1 m^2) that would

theoretically encompass two animals standing next to each other. A mean Euclidean

distance texture function representing the mean spectral difference between the central

pixel and all other pixels in the neighborhood was used (ERDAS, 2003). Neighborhoods

with little spectral change resulted in low texture values while neighborhoods with many

changes had higher texture values. The texture images represented animals as "doughnut"

features due to a higher spectral variance at the edge of an animal compared to a lower

spectral variance within an animal (Figure 3.9A). A 7 x 7 median kernel filled in the

"doughnuts" without substantially affecting the outer edge (Figure 3.9B). We

heuristically determined maximum texture threshold values for animal features at 50% of

the texture image maximum (Figure 3.8A). To reduce heuristic determination of

thresholding values and thus reduce potential for automation, we defined the minimum

texture thresholding value based on the Rosin corner threshold technique (Figure 3.10;

Rosin, 2001). We removed non-animal pixels that were above the maximum texture

threshold and below the minimum texture threshold and converted pixel clusters into

polygons (Figure 3.11).

Principal components analysis (PCA) is commonly used with remotely sensed

imagery to reduce dimensionality by combining redundant information in highly

correlated bands (Chavez and Kwarteng, 1989; Jensen, 2005). The output of a PCA is an

image, which is composed of the same number of layers as the input image (3 bands in

this case), in which the first layer contains the highest amount of correlated information

between the spectral bands. The second PCA layer contains the second highest amount of

correlated information and so on (Jensen, 2005). We conducted a PCA on each 3-band

training image and used the first principal component for subsequent analysis because it

contained the highest amount of spectral variation (81% vs. 17% and 2%, 1st, 2nd, and 3rd

components, respectfully). We subtracted the background image derived from our

ISODATA methods (above) from the first principal component (Figure 3.8B) and applied

the Rosin corner thresholding method (Rosin, 2001) to eliminate non-animal features

(Figure 3.12). The resulting image was converted to polygon format to match the texture

image. We spatially intersected the texture derived polygons (Figure 3.11) with polygons

derived from the PCA-background subtraction technique (Figure 3.12) and considered

the spatial locations where both polygons intersected as an animal. The final step

eliminated polygons based on thresholding values for area, perimeter-area ratio (PA), and

compactness ratio (CR). We examined the PA to assess the circularity of a feature

relative to a perfect circle. The CR also assesses the circularity of a feature but without

influence of feature size, unlike PA. We heuristically determined thresholds of shape

characteristics that encompassed animal features from the training imagers. Individual

shape characteristics alone were unable to successfully threshold animal features so we

used a combination of all three characteristics to eliminate non-animal polygons (Figure

3.8C). The final output resulted in polygons classified as animal features (Figure 3.13).

The coefficient of variation (CV) is a measure of variation that is normalized with

respect to the mean of a data set (Zar, 1996) and is an appropriate statistic to compare the

amount of variation from one technique to another especially when there is a wide range

in the mean values examined. The CV for the probability of detection for the

ISDODATA technique is 12%, 30% for the manual photo-interpretation, and 52% for the

MIMS technique indicating that the ISODATA has the lowest variance relative to the

mean, followed by manual photo-interpretation, and the MIMS had the highest variance.

An analysis of variance (ANOVA, Zarr, 1996) determined if there were significant

differences among the three techniques examined (i.e. manual interpretation, ISODATA

unsupervised classification with image subtraction, and the multi-image, multi-step

process).

Results

Manual Image Interpretation

There were no significant differences ($p \geq 0.20$) among individuals within the L,

W, or R groups for PD, P_{under}, or P_{over}, so we collapsed individuals within each group and

examined differences among the groups. There were no significant differences among the

three groups for PD, P_{under}, and P_{over} ($p \geq 0.10$, Figure 3.14). Collapsing across groups, the

overall mean PD was 83% ($\pm$ 1%, Standard error), the mean P_{under} was 19% ($\pm$ 1%), the

mean P_{over} was 8% ($\pm$ 3%), and the mean CF was 1.26 ($\pm$ 0.07, Table 3.1).

Unsupervised Classification: ISODATA with image subtraction

The mean PD for the seven pastures examined was 82% ($\pm$ 10%, SD) and ranged

from 55% to 100%. There was a general trend for the number of animals not mapped

(i.e., missed) to increase as the number of known animals in the pasture increased. The

mean P_{under} for the seven pastures was 18% ($\pm$ 18%) and ranged from 0% to 45%. The

mean P_{over} for the seven images was 69% ($\pm$ 27%) and ranged from 28% to 98%. As with

the PD, there was a general trend for the CF to increase as the number of known animals in a pasture increased. The mean CF for the seven images was 0.40 (± 0.37) and ranged from 0.04 to 0.91. The ISODATA unsupervised classification with a background subtraction successfully identified animals but greatly over-estimated animal numbers. While there appeared to be a positive relationship between increasing number of known animals in a pasture with increasing number of animals missed and increasing CF's, there was no significant relationship ($p > 0.05$) between the actual number of animals in each pasture and any image feature characteristic (i.e., total number of polygons in an image, PD, P_{under}, P_{over}, or CF).

MIMS Technique

Similar to the ISODATA-background subtraction technique, there was a general trend for the number of missed animals to increase as the number of known animals in a pasture increased. The mean PD across the testing pastures was 50% (± 26%) and ranged from 0% to 74%. The mean P_{under} for the testing pastures was 50% (± 26%) and ranged from 26% to 100%. The mean P_{over} was 72% (± 26%) and ranged from 23% to 100%. The mean CF was 0.54 (± 32) and ranged from 0.24 to 1.09 (Table 3.3).

Discussion

Manual interpreters were better able to discriminate between animal and non-animal features and identified fewer over-counting errors (i.e., false positives) than either the ISODATA or the MIMS techniques (Table 3.4). Most individuals had a CF of 1.00 for at least a single image indicating no correction was needed to the count.

Distinguishing between animal and non-animal features was likely due to the ability of interpreters to integrate qualitative information (Russ, 1999) on spectral and shape. Human vision evaluates features in a qualitative and comparative manner and integrates multiple dimensions of information to discern features (Baraldi and Boschetti, 2012; Russ, 1999). The objective of this research was to use existing image processing techniques to develop an automated or semi-automated approach that emulated human interpretation of imagery. The multi-step techniques incorporated into both the ISODATA and MIMS procedures attempted to isolate and refine new information at each step. For example, the texture image generated in the MIMS technique was an attempt to isolate and categorize the differences within a neighborhood similar to how human vision might qualify spectral differences in an area of interest. The fact that the MIMS had the lowest PD coupled with the highest P_{under} and P_{over} suggests that increased complexity does not equate to increased accuracy nor does it represent how humans evaluate imagery.

The PD is generally calculated as the ratio of the number of marked animals observed during a wildlife survey to the known number of marked animals on the survey area. The PD serves as a correction and is applied to the total count of animals observed to estimate population abundance for the surveyed area. Reported values of PD for conventional ground and aerial surveys range from 52% in caribou (*Rangifer* spp., Rivest *et al*., 1998), 34 – 82% for mule deer (*Odocoileus hemionus*, Freddy *et al*., 2004), and 53 -71% for feral ungulate species (Bayliss and Yeomans, 1989). The mean PD of 50% for the MIMS procedure is within reported levels of the PD for wildlife surveys but indicates

that the technique would detect only 50% of the animals present in an image. The mean

PD of the manual interpretation and the ISODATA procedures, 81% and 80%,

respectively, are above reported levels for ground and aerial surveys. The higher PD

variability of the manual interpretation compared to the semi-automated, ISODATA

technique (Table 3.4) is similar to reported photo-interpretation values (Erwin, 1982;

Frederick *et al.*, 2003) and supports the contention that manual counts are inconsistent

and thus estimates derived from them should consider those inconsistencies.

The MIMS technique identified too few polygons as animals in pastures 29B,

21A, and 3B, which resulted in a low PD. The MIMS technique generated multiple

polygons, some of which were correctly associated with animal features but at later steps,

these polygons were erroneously eliminated. The MIMS removed polygons at three steps:

1) via the Rosin corner thresholding method on spectral values, 2) due to thresholding of

the texture image, and 3) due to thresholding of shape and size characteristics. Incorrect

removal of polygons at each stage was not consistent across all pastures. The Rosin

thresholding method incorrectly removed polygons that represented animals in pasture

29B but not in other pastures. Incorrect removal of polygons that represented animals in

pastures 21A and 3B occurred because they were outside the shape thresholding values.

Incorrect polygon removal of polygons representing animal features occurred in pasture

3B because some animal features (i.e., polygons) included shadow pixels, which

increased the area of the polygon beyond the size threshold.

Consideration of the PD alone indicated the population abundance estimates

derived from the manual interpretation and ISODATA techniques would identify animals

if they were present in an image, with the ISODATA technique being more consistent. Because we have a known number of animals, we can calculate additional measures of error with the over-counted, under-counted, and missed animals. The high P_{over} for the ISODATA and MIMS techniques indicate the population size estimates would be overestimated with semi-automated techniques but less so with the manual photo-interpretation. Thus, the ISODATA technique will identify 80% of the animals in remotely sensed imagery, but it will overestimate the population size due to consistent over-counting. Population estimates, left unadjusted for over and under-counting errors could have serious management implications. Over estimates of population size could lead to a larger than appropriate harvest quota which could result in a population decline. Conversely, under estimating the size of a population could lead to inappropriate management objectives and result in a larger population size than desired. Regardless of biases in counting, incorrect population abundance estimates could lead to improper management of a population. If biases or errors are known and quantified, they can be incorporated into population abundances and result in potentially more precise and accurate estimates, which in turn can better inform management decisions.

There are several advantages to automated or semi-automated techniques to analyze aerial imagery with the objective of identifying individual animals. One of the principal benefits of automation is non-subjective analysis of imagery which has the potential to increase repeatability and consistency within techniques and across analysts. A second benefit, previously unavailable in wildlife surveys, is the permanent, unchanging record of animal locations for an instant in time i.e. 'a survey', thus allowing

for repeated assessments using the same or different techniques. Remotely sensed imagery can be assessed by different personnel to determine the validity of a technique without degradation to the image regardless of the number of times it is analyzed. Although aerial and ground transects can be repeated they cannot be replicated. Additionally, acquisition of remote sensing imagery has the potential to reduce or even eliminate negative responses of animals to low flying aircraft during wildlife surveys (DeYoung, 1985; Anderson and Lindzey, 1996; Brockett, 2002; Bernatas and Nelson, 2004). Aerial wildlife surveys frequently require multiple days to complete thus allowing animals to move throughout the study area and increase the probability of double-counting or missing individuals. It is possible to completely cover large areas, such as the Mongolian steppe or Utah's west desert, with one acquisition of remotely sensed imagery in a shorter time than an aerial survey. Aerial wildlife surveys across large study areas are prohibitively expensive due to aircraft cost and personnel time so remotely sensed imagery could provide population abundance estimates for previously inaccessible areas.

Although automated or semi-automated image segmentation and classification is desirable, it may come at the expense of severe bias (Baraldi and Boschetti, 2012) or may require various amounts of human input and guidance (Evans *et al*., 2012; Skelsey *et al*., 2004). To facilitate automation or semi-automation, we based each technique on image characteristics, such as the mean and variance of spectral reflectance values for each band, rather than animal feature characteristics. One drawback of the semi-automated ISODATA and MIMS techniques is the assumption that animal features are represented by pixels with low spectral values, thus similar features were always present that were

identified as animals. An additional disadvantage of the techniques we examined is that they are limited to grasslands or low-density shrublands that facilitate the visibility of animals. Tall shrubs and trees would obstruct the view of animals that are under the canopy.

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Table 3.1. The mean and standard deviation (STD) of the probability of detection (PD), the probability of under-counting animals (P_{under}), the probability of over-counting (P_{over}), and the correction factor (CF) resulting from a manual count of animals in remotely sensed imagery by three groups of people: laymen, remote sensing analysts, and wildlife biologists. The across group mean and standard error (SE) are presented to evaluate the variance across groups.

Group	PD[1]	P_{under}[2]	P_{over}[3]	CF[4]
Laymen	0.80 ± 0.24	0.20 ± 0.24	0.13 ± 0.24	1.14 ± 0.29
Remote Sensing Analysts	0.83 ± 0.24	0.17 ± 0.24	0.04 ± 0.08	1.25 ± 0.55
Wildlife Biologists	0.81 ± 0.23	0.19 ± 0.23	0.07 ± 0.12	1.40 ± 1.00
Mean ($\pm$ SE)	0.81 ± 0.01	0.19 ± 0.01	0.08 ± 0.03	1.26 ± 0.07

[1.] (Correctly mapped polygons / Known number of animals in pasture)
[2.] (Missed Animals / Known number of animals in pasture)
[3.] (Incorrectly mapped polygons/ Number of mapped polygons)
[4.] $(PD + P_{under} - P_{over}) / PD$

Table 3.2. The probability of detection (PD), the probability of under-counting animals

(P_{under}), the probability of over-counting (P_{over}), and the correction factor (CF) for the

population abundance estimate resulting from an ISODATA unsupervised classification

and subtraction technique.

Pasture	Known number animals in pasture	Mapped polygons	Correctly mapped polygons	Missed animals	Incorrectly mapped polygons	PD[1]	P_{under}[2]	P_{over}[3]	CF[4]
22B	5	125	3	2	122	0.60	0.40	0.98	0.04
22A	3	63	3	0	60	1.00	0.00	0.95	0.05
21B	13	98	12	1	86	0.92	0.08	0.88	0.13
29A	29	117	28	1	89	0.97	0.03	0.76	0.25
32A	38	62	32	6	30	0.84	0.16	0.48	0.61
15B	37	46	33	4	13	0.89	0.11	0.28	0.80
4A	20	22	11	9	11	0.55	0.45	0.50	0.91
Mean	21	76	17	3	59	0.82	0.18	0.69	0.40
STD	14	38	13	3	43	0.10	0.18	0.27	0.37

[1.] (Correctly mapped polygons / Known number of animals in pasture)

[2.] (Missed Animals / Known number of animals in pasture)

[3.] (Incorrectly mapped polygons/ Number of mapped polygons)

[4.] ($PD + P_{under} - P_{over}$) / PD

Table 3.3. The probability of detection (PD), the probability of under-counting animals (P_{under}), the probability of over-counting (P_{over}), and the correction factor (CF) for the population abundance estimate resulting from a multi-image, multi-step (MIMS) technique to identify and count animals in remotely sensed imagery across seven test pastures in north central Utah.

Pasture	Known number of animals in pasture	Mapped polygons	Correctly mapped polygons	Polygons representing 2 animals	Missed animals	Incorrectly mapped polygons	PD[1]	P_{under}[2]	P_{over}[3]	CF[4]
28B	15	62	10	0	5	52	0.67	0.33	0.84	0.24
29B	29	96	12	0	17	84	0.41	0.59	0.88	0.30
32B	38	89	27	1	10	62	0.74	0.26	0.70	0.41
21A	13	28	5	0	8	23	0.38	0.62	0.82	0.46
4A	20	25	11	1	8	14	0.60	0.40	0.56	0.73
15A	38	35	27	0	11	8	0.71	0.29	0.23	1.09
3B	5	10	0	0	5	10	0.00	1.00	1.00	-
Mean	23	49	13	0	6	36	0.50	0.50	0.72	0.54
STD	13	33	10	0	4	30	0.26	0.26	0.26	0.32

[1.] (Correctly mapped polygons / Known number of animals in pasture)
[2.] (Missed Animals / Known number of animals in pasture)
[3.] (Incorrectly mapped polygons/ Number of mapped polygons)
[4.] $(PD + P_{under} - P_{over}) / PD$

Table 3.4. The mean and standard deviation of the probability of detection (PD), the probability of under-counting animals (P_{under}), the probability of over-counting (P_{over}), and the correction factor (CF) for the count estimate of three techniques to identify animals in remotely sensed aerial imagery.

Group	PD[1]	P_{under}[2]	P_{over}[3]	CF[4]
Manual Interpretation	0.81 ± 0.24	0.19 ± 0.24	0.08 ± 0.16	1.26 ± 0.68
ISODATA	0.82 ± 0.10	0.18 ± 0.18	0.69 ± 0.27	0.40 ± 0.37
Multi-image, multi-step	0.50 ± 0.26	0.50 ± 0.26	0.72 ± 0.26	0.54 ± 0.32

[1.] (Correctly mapped polygons / Known number of animals in pasture)
[2.] (Missed Animals / Known number of animals in pasture)
[3.] (Incorrectly mapped polygons/ Number of mapped polygons)
[4.] $(PD + P_{under} - P_{over}) / PD$

Figure 3.1. Images of the first (A) and second (B) acquisitions of pasture 15 indicating animal movement. Circles in B represent how a photo-interpreter would indicate which features were animals.
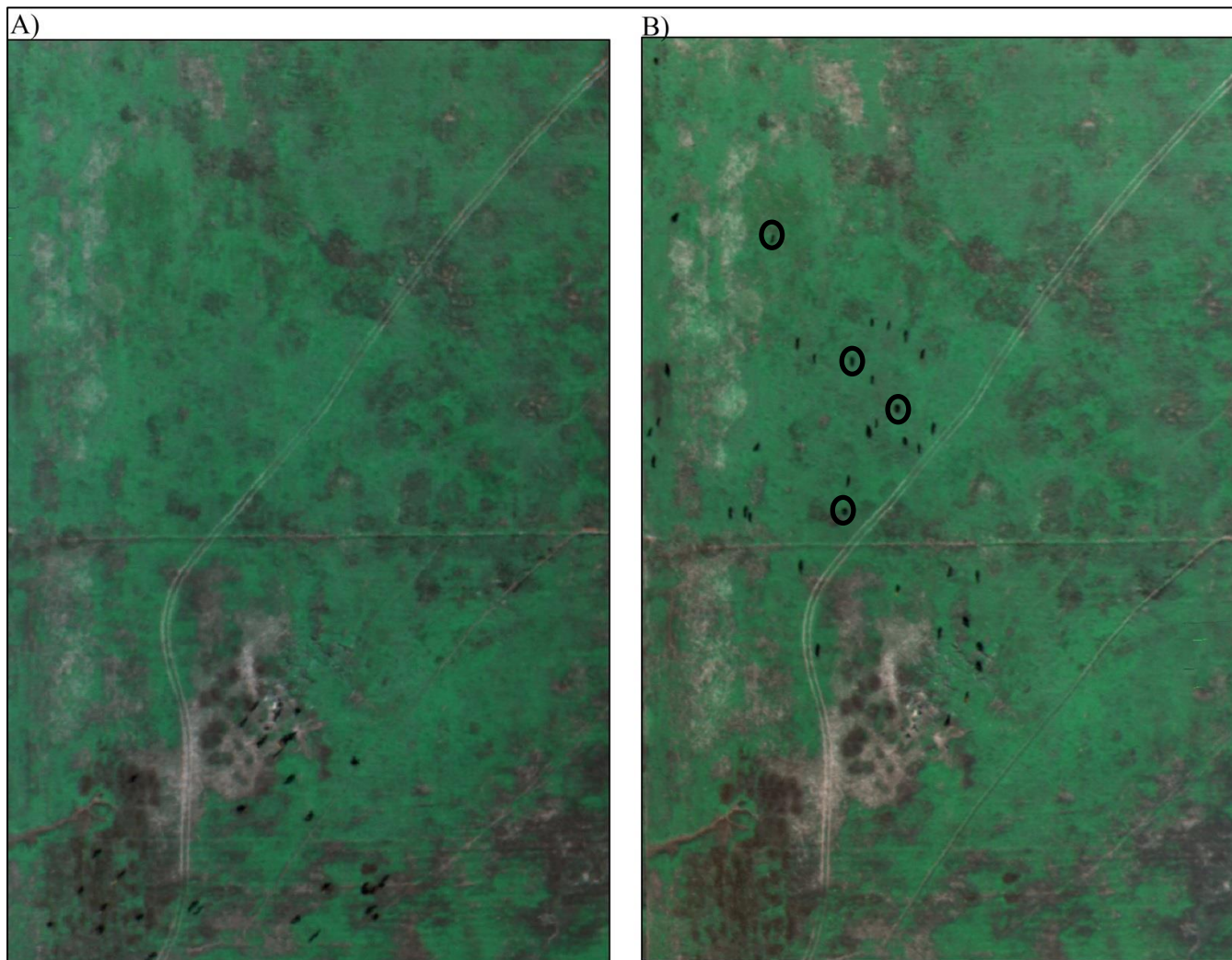
Figure 3.2. Distributions of A) probability of detection, B) probability of under-counting, C) probability of over-counting, and D) a correction factor from the manual identification of domestic animals in seven fenced pastures by 5 laymen, 5 wildlife biologist, and 5 remote sensing analysts.
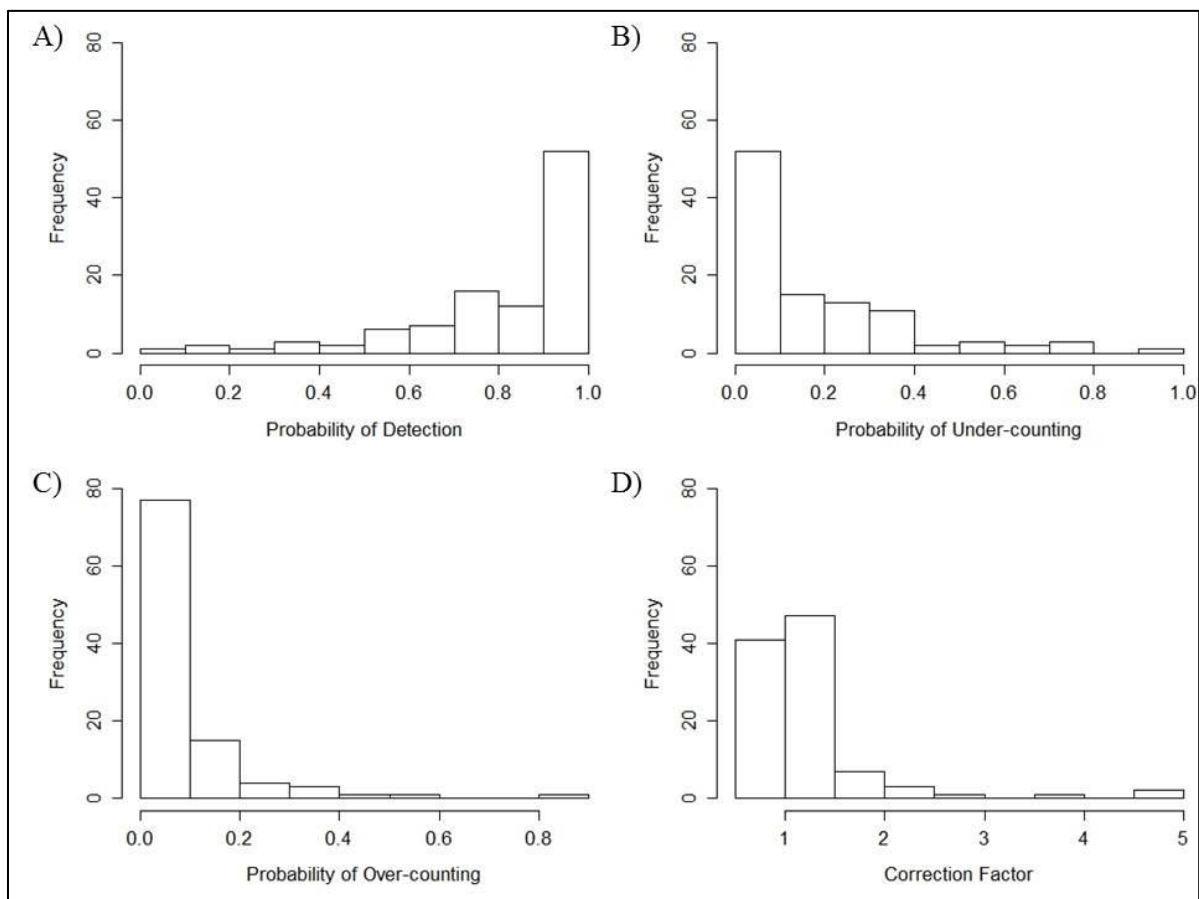
Figure 3.3. Outline of the steps taken in an ISODATA and background subtraction technique to identify animals in aerial imagery. A) outlines generation of potential animal polygons (PAPs) from an unsupervised ISODATA process, B) outlines the background image generation , and C) outlines the subtraction of the ISODATA segmented image from the background image.

A) **ISODATA unsupervised classification on original image**

Pasture image containing animals

↓

20 cluster image

↓

Polygons of the 3 lowest clusters (PAPs)

↓

Subset (PAPs) with original pasture image spectral information

B) **Smoothed background image**

Pasture image containing animals

↓

Generation of background image with a 7x7 maximum kernel, followed by a 9x9 low pass filter

↓

Subset background image with PAPs

C)

Subtract background PAPs from ISODATA PAPs

↓

ISODATA classification on differenced PAPs

↓

Polygons of the 4 lowest clusters

↓

Polygons eliminated based on size

Figure 3.4. Generation of potential animal polygons (PAPs) containing spectral values from the original image. A) is the original 3-band imagery, B) shows the PAPs after removal of all polygons except those with the three lowest spectral vlaues, and C) indicates the PAPs after subsetting with the original 3-band imagery.
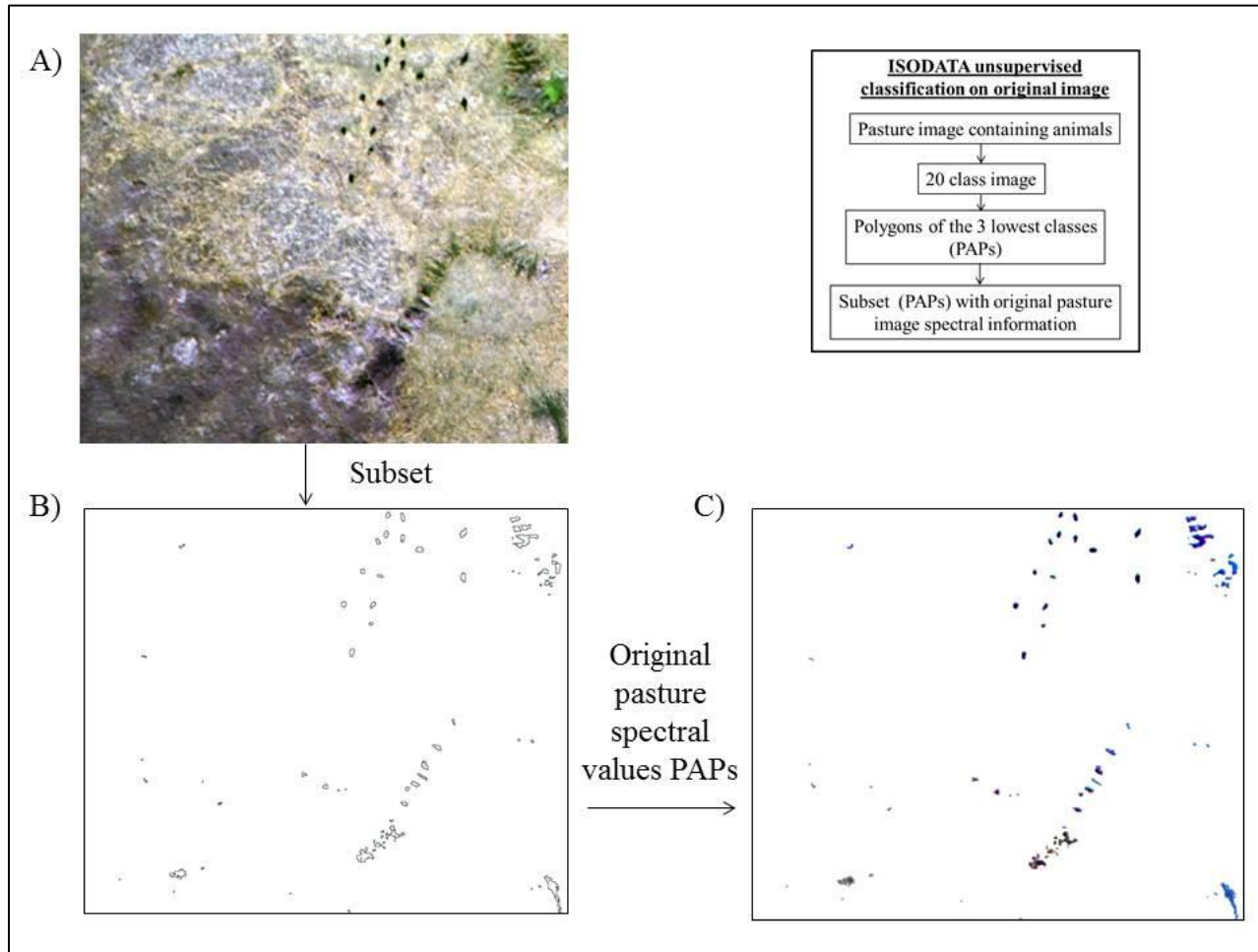
Figure 3.5. Generation of potential animal polygons (PAPs) containing spectral values from the smoothed background image.

A) is the resulting background image, B) are the PAPs and C) is the intersection of PAPs containing background spectral
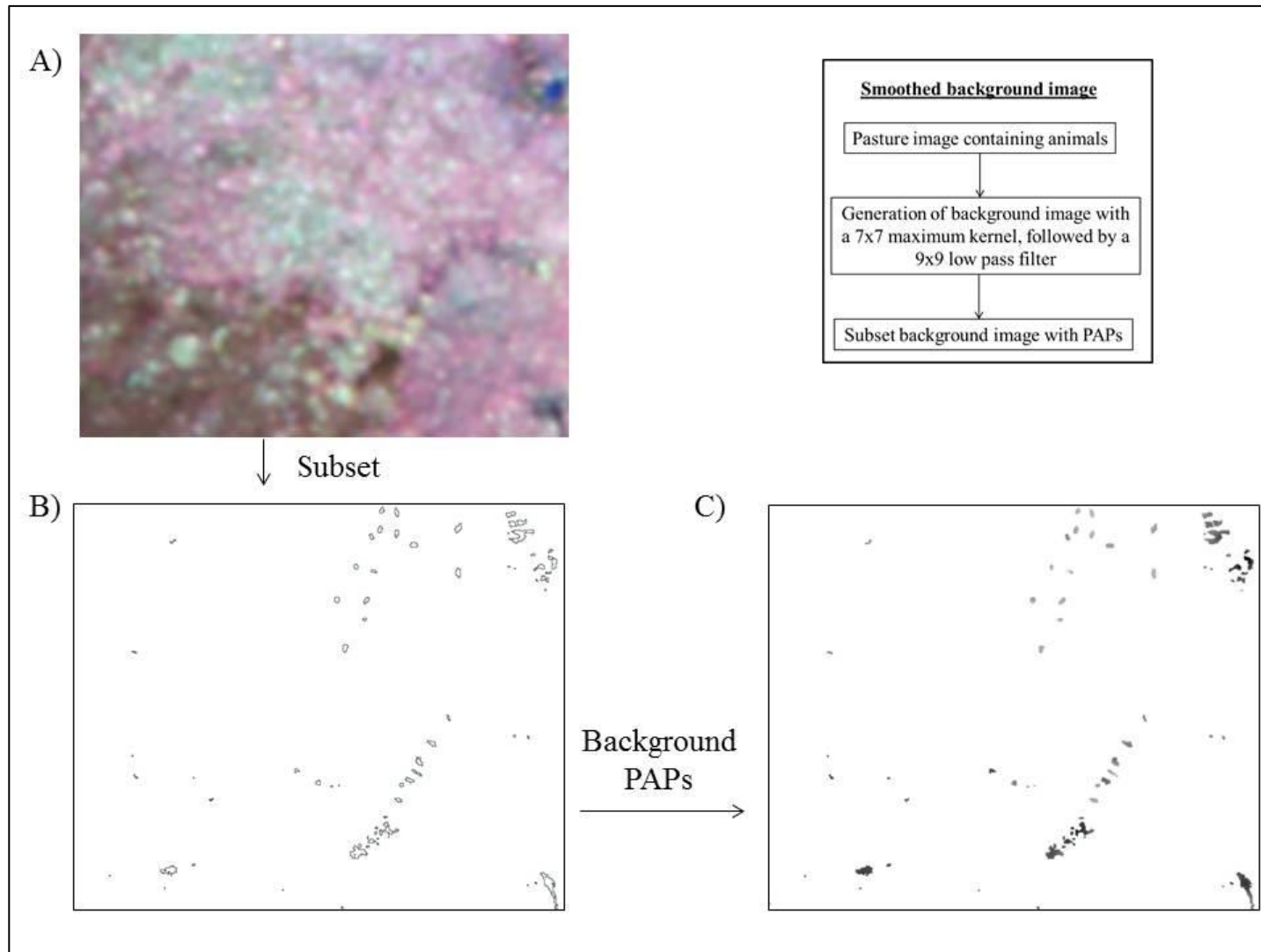
values.

Figure 3.6. Generation of potential animal polygons (PAPs) with original spectral values subtracted from background spectral values. A) PAPs with 3-band spectral values, B) PAPs containing background spectral values, and C) PAPs with subtracted spectral values. Differences should be larger for pixels with animals compared to pixels of background.
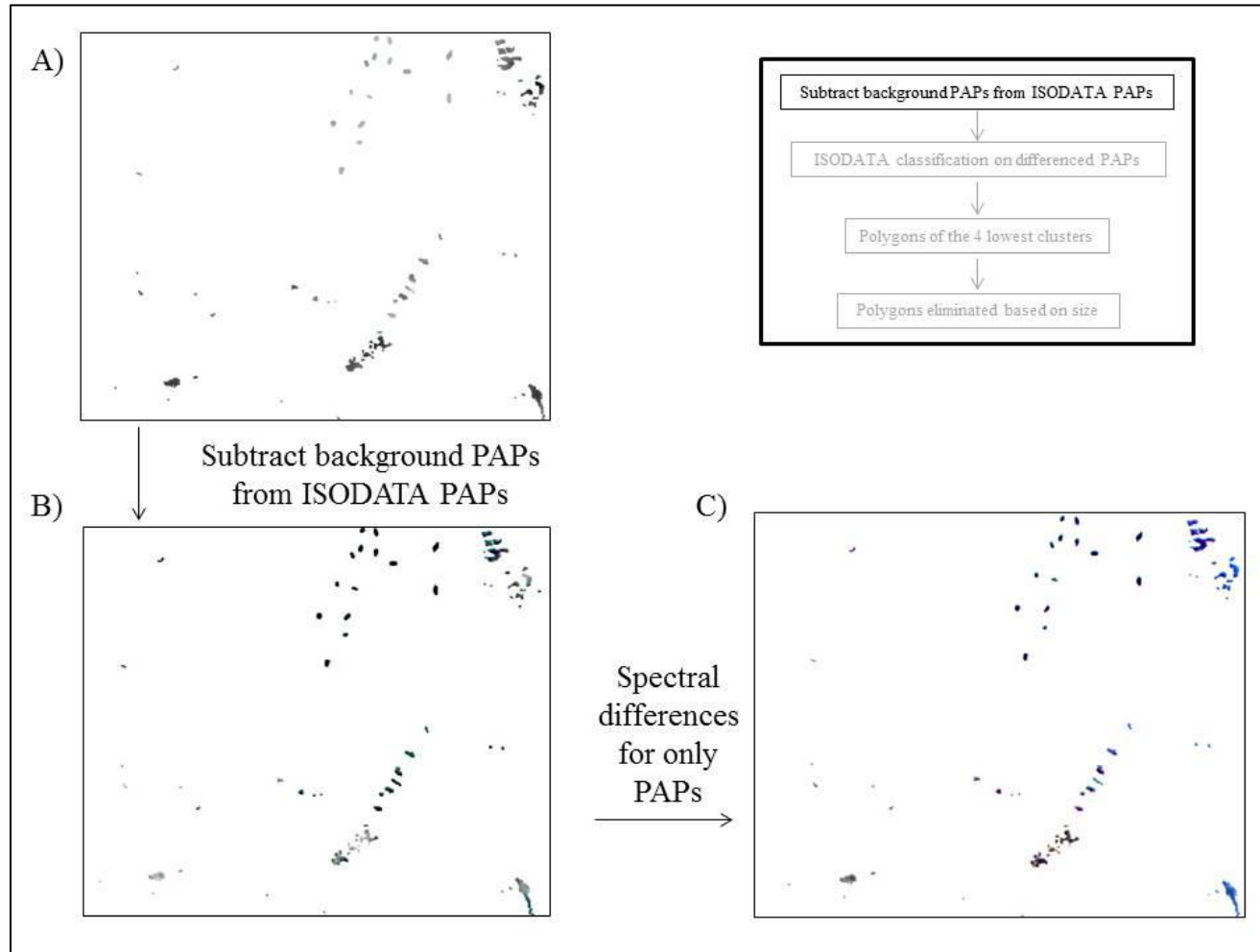
Figure 3.7. Final steps in identifying animals by eliminating polygons based on size and polygon value. A) PAPs of all sizes and B) final sized PAPs.
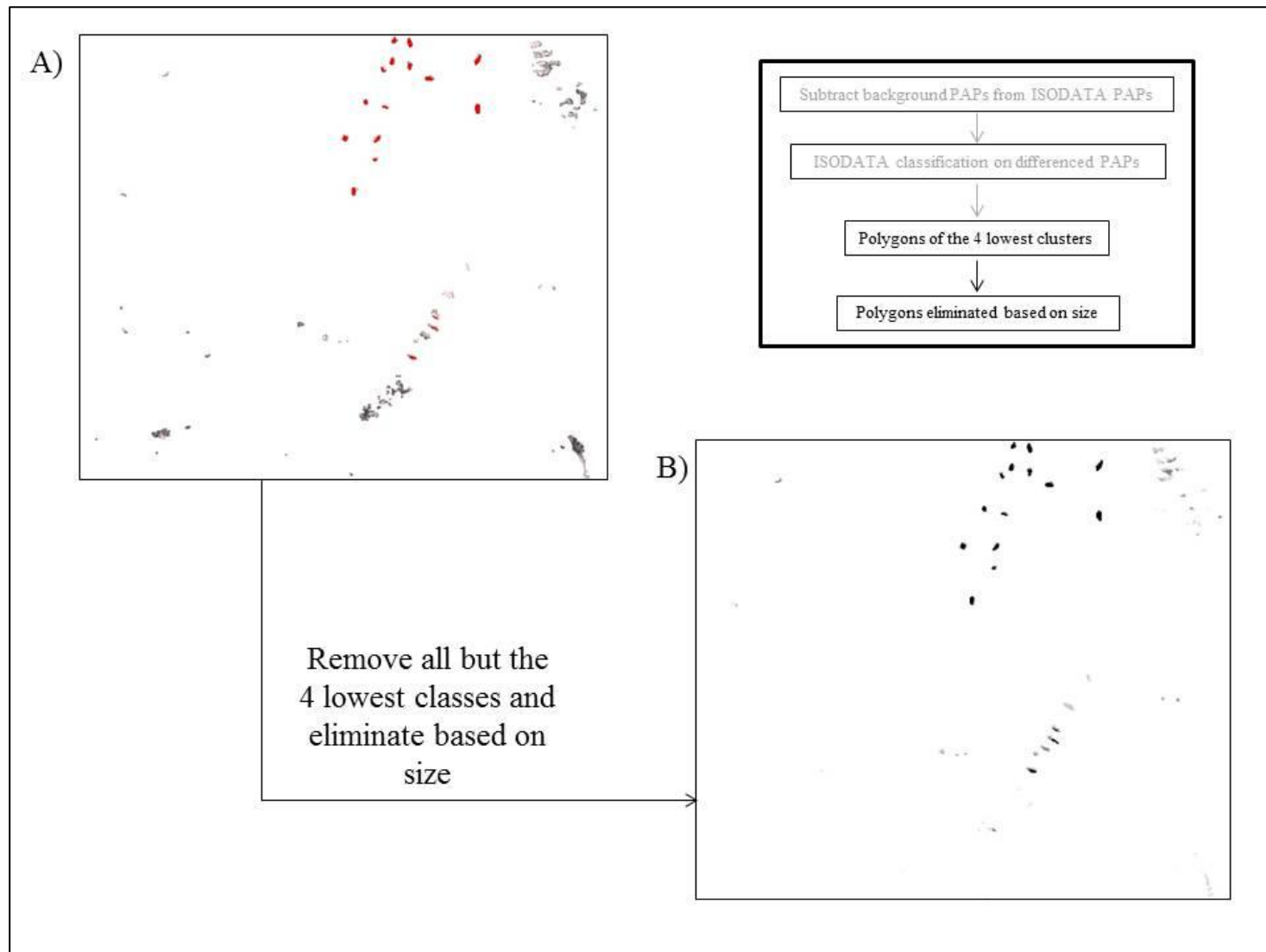
Figure 3.8. Outline of the steps taken in a multi-image, multi-step technique to identify animals in aerial imagery. A) outlines generation of a texture image, B) outlines the principal components analysis (PCA) and background subtraction and C) outlines the subtraction of the texture and PCA images.
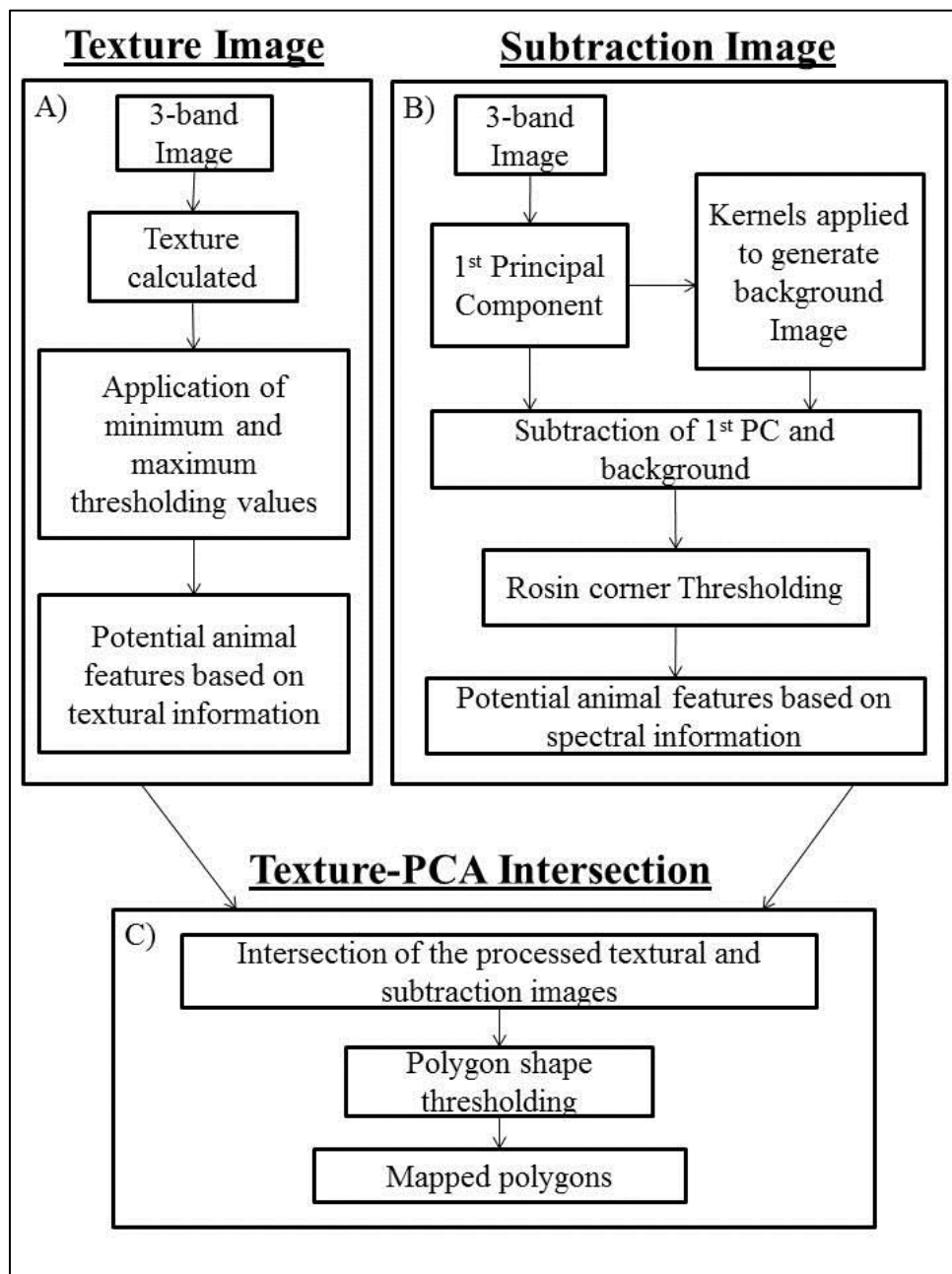
Figure 3.9. Images displaying A) a 1st order Euclidean texture analysis displaying animal "doughnuts" and B) the "filling in" of the doughnuts after application of a median kernel.
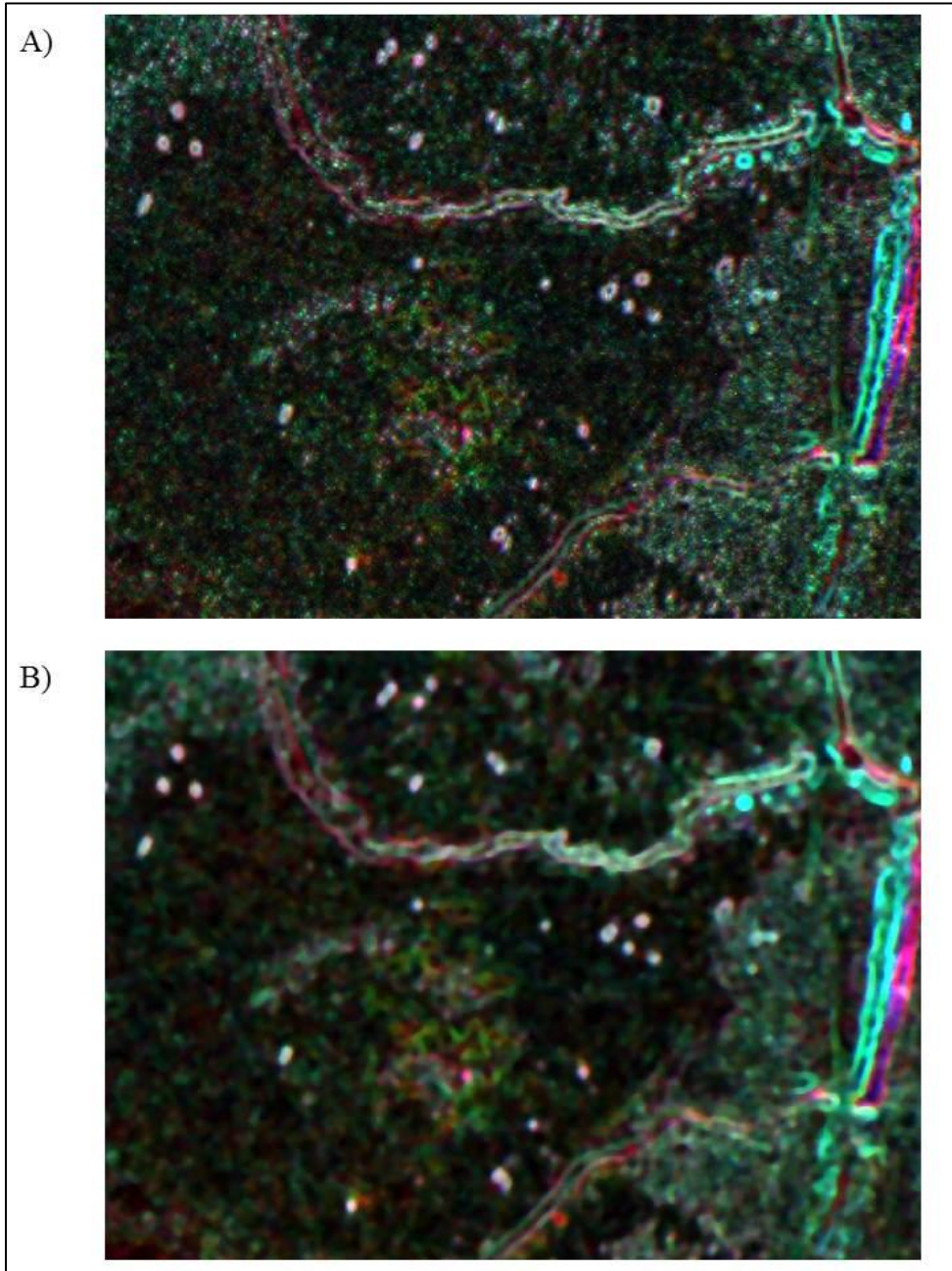
Figure 3.10. Graphical depiction of the Rosin corner method of determining a thresholding value for a histogram of texture values from an image containing animals. The peak of the histogram is the starting point of a straight line that ends at the first instance of an X-axis value of zero. The dashed line perpendicular to the straight line with the longest distance to the histogram curve is the threshold value.
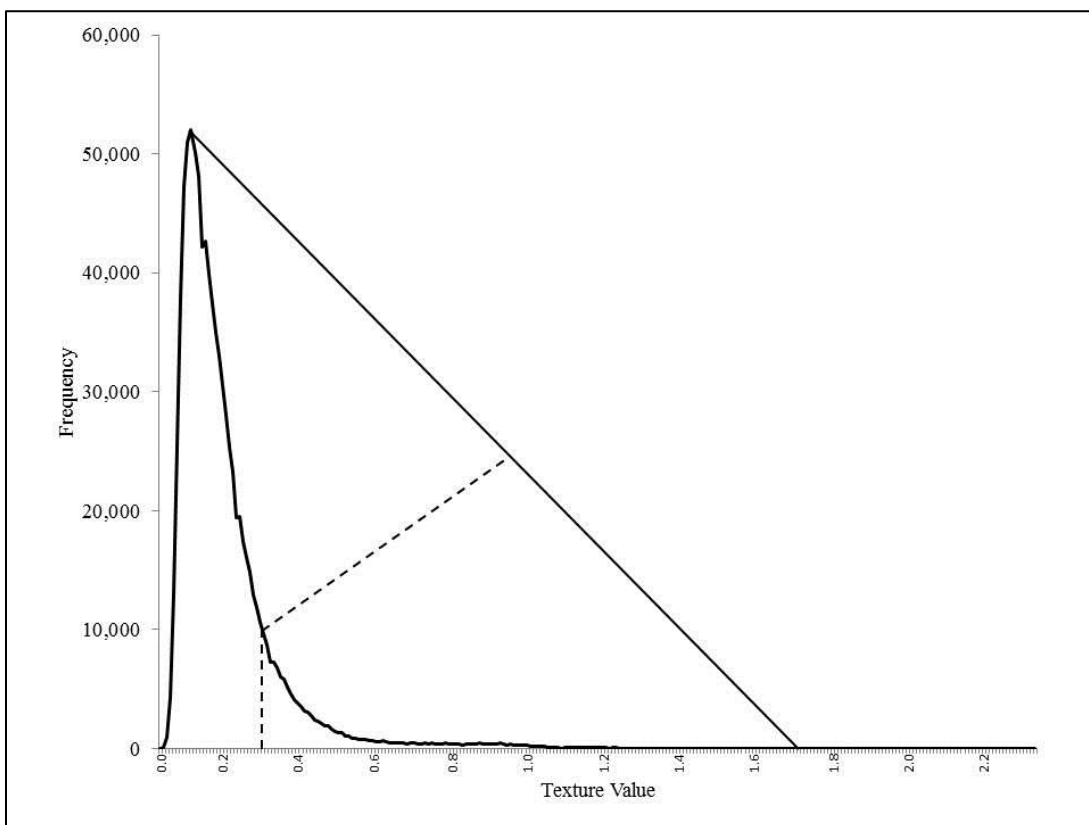
Figure 3.11. Texture image after removal of pixels less than a minimum threshold and greater than a maximum threshold.

Figure 3.12. Image resulting from the subtraction of the first principal component and a simulated background image, followed by the Rosin corner thresholding method.

Figure 3.13. Output of the multi-image, multi-step (MIMS) technique. Circled polygons
are correctly mapped animal features.
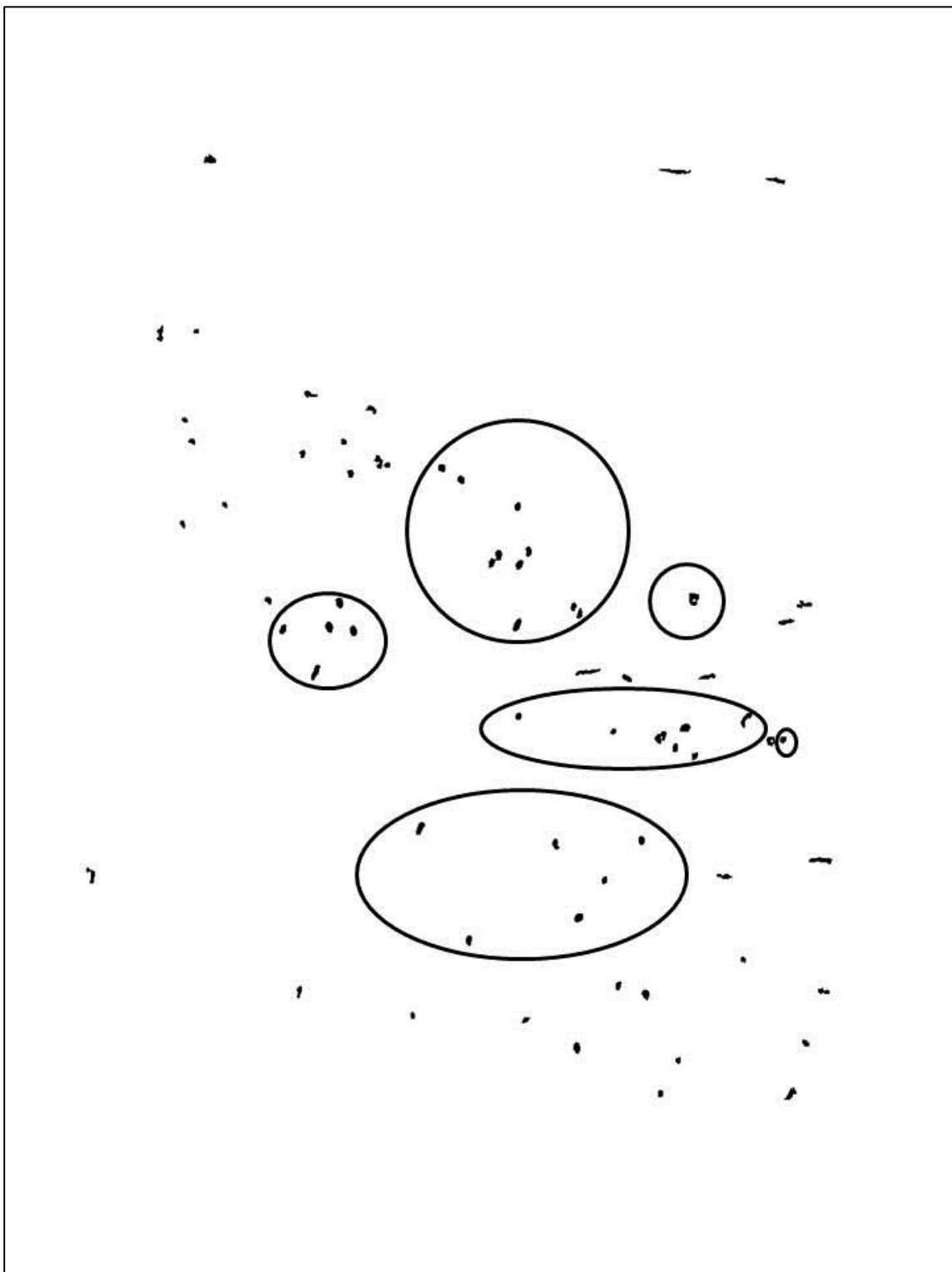
Figure 3.14. Graphs indicating no significant difference (p ≥ 0.05) among laymen (L), remote sensing analysts (R), and wildlife biologists (W) for the A) probability of detecting an animal, B) probability of under-counting animals, C) probability of over-counting animals, and D) correction factor in aerial imagery of fenced pastures containing animals.
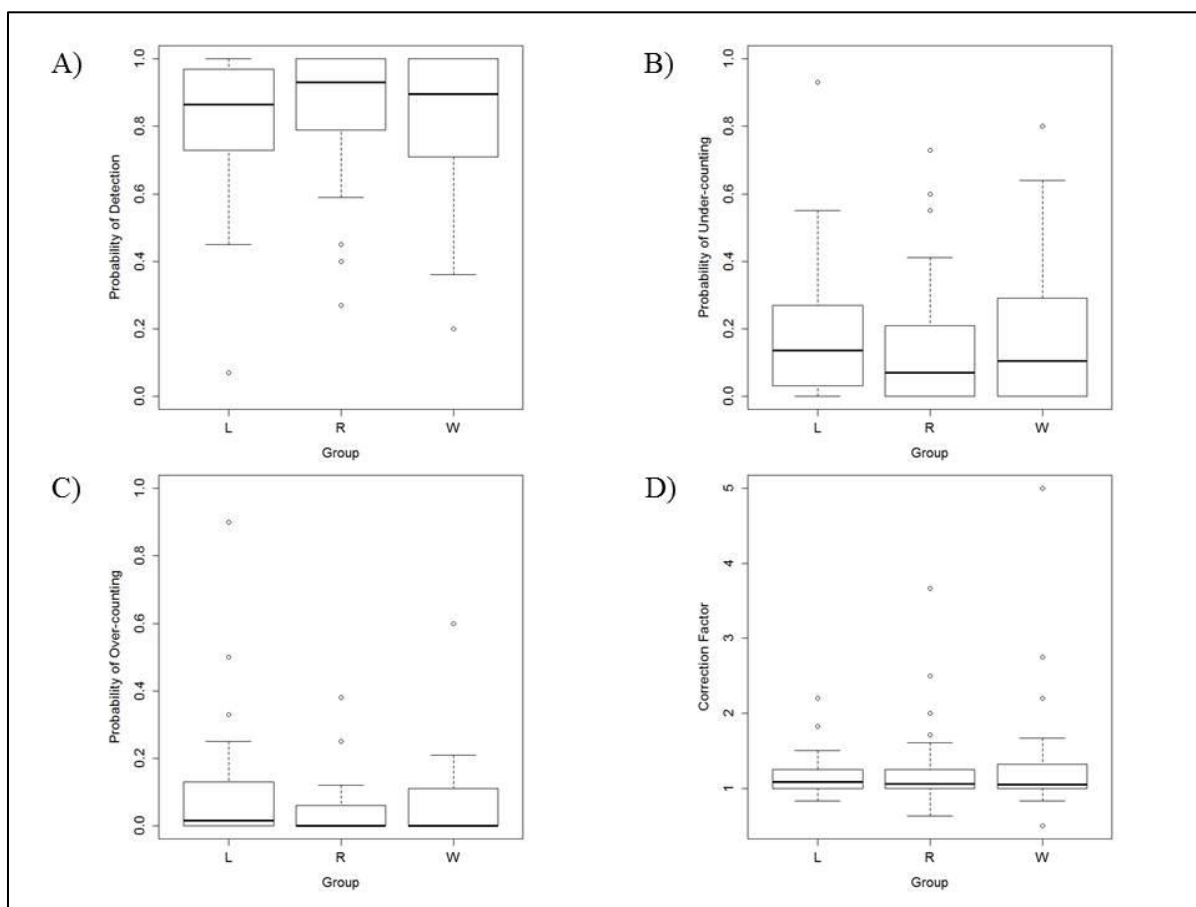
CHAPTER 4

SINGLE DAY IMAGE DIFFERENCING TO ESTIMATE ANIMAL COUNTS

Abstract

We assessed the ability to detect large ungulates by differencing two aerial images acquired on the same day at different times. Although the ultimate application of this technique is to estimate wildlife population sizes, we examined domestic cattle (*Bos taurus*) and horses (*Equus caballus*) as a proof of concept since they were confined to fenced areas and their numbers could be readily counted from the ground. The probability of detecting an animal with image differencing (82%) was higher than those reported from conventional aerial and ground surveys of wildlife species. The average per pasture probability of detecting animals in aerial imagery was 82%, the probability of under-counting animals was 18%, while the average per pasture probability of over-counting was 53%. Image differencing identified many false positives (i.e., features that were not animals) likely due to misalignments during image registration and possible grouping behavior of animals. The high detection probability suggests single day image differencing could provide a new technique to identifying, counting, and estimating the population abundances of wildlife species, especially in isolated or difficult to access areas. To our knowledge, this is the first attempt to use standard change detection techniques to identify and enumerate large ungulates.

Introduction

Although counts of wildlife individuals obtained from surveys are commonly

used by state and federal wildlife agencies to estimate wildlife population abundances,

these methods are often fraught with inaccuracies and have wide margins of error

(Freddy *et al*., 2004). Not only are the survey methods themselves questioned

(Eberhardt, 1978) but the resulting population abundance estimates, if not corrected for

known errors, may have significant over-counting (Bartmann *et al*., 1987; White *et al*.,

1989) or undercounting biases (Jackmann, 2002; Williams *et al*., 2002). In Pilanesberg

National Park, South Africa, Brockett (2002) noted that black rhinoceros (*Diceros*

bicornis) counts from helicopters resulted in abundance estimates being overestimated by

approximately 5% to 15% for 2 of the 19 years surveyed while the remaining years

resulted in underestimates of approximately 5% to 60%. Given the uncertainty associated

with conventional wildlife surveys, measures of bias and errors frequently accompany

population abundance estimates. The probability of detection (PD) is the proportion of

marked or known animals counted relative to the known number of marked animals in a

survey area. The PD is used to adjust the observed count to obtain a more accurate

estimate of population size of a specific species in a specific area (Thompson *et al*., 1998;

Williams *et al*., 2002). Given the inconsistent results of conventional wildlife surveys, a

method that is economically feasible, more accurate and consistent, as well as repeatable

would result in population abundance estimates with greater credibility.

Remotely sensed aerial photographs have been used to count and estimate

population abundances of a diverse array of wildlife species, from birds (Erwin, 1982;

Fretwell *et al*., 2012; Gilmer *et al*., 1988; Harris and Lloyd, 1977) to terrestrial species

(Russell *et al*., 1994) to oceanic mammals (Hiby *et al*., 1988). Unfortunately, manual

counts from aerial photographs are labor intensive, subject to human interpretation and

error, and can result in inconsistent counts (Bajzak and Piatt, 1990; Frederick *et al*., 2003;

Gilmer *et al*., 1988; Sinclair, 1973). Erwin (1982) found manual counting of

canvasbacks ducks (*Aythya valisineria*) in aerial photographs had high variation among

surveyors and neither experience or the amount of training influenced counts.

Conversely, Couturier *et al*. (1994) reported two independent surveyors achieved similar

results when counting caribou (*Rangifer tarandus*) from aerial photography, suggesting

lower errors may be correlated to areas with little vegetation structure and/or with large

bodied species. To facilitate greater precision and accuracy in counts from aerial

photographs, Bajzak and Piatt (1990) developed an automated, computer based system to

classify image pixels into either snow geese (*Chen caerulescens*) or non-snow geese

(i.e., background). The uniform white color of the snow geese facilitated separation of the

birds from their background. Fretwell *et al*. (2012) used a supervised classification

technique to segment satellite imagery into emperor penguin (*Aptenodytes fosteri*)

colonies, snow cover, guano patches, and shadows. They used an iterative process where

an analyst determined which areas were penguin colonies and which were guano stained

snow. These studies suggest that bird species, and possibly other wildlife, can be counted

in colonies or large groups when they are easily differentiated from the surrounding

background.

   The importance of background homogeneity was also influential in the detection

of an ungulate (Wyatt *et al*., 1984) in which complex, non-homogenous backgrounds reduced detection and identification of deer (*Odocoileus* spp.). Deer were discernible from snow in the near infrared (NIR, 0.7 to 1.4 μm; 1.5 to 4.0 μm) portion of the electromagnetic spectrum (EM) but not in the visible portion due to confusion with vegetation and soil. In addition, there was little distinction between deer and vegetation or soil in the thermal region of the EM spectrum (3.0 to 5.0 and 7.5 to 10 μm, Wyatt *et al*., 1985). Trivedi *et al*. (1982) found deer had a detection of 50% - 80% with a combination of red (0.6 to 0.7 μm) and NIR bands ratios, although accuracy was affected by the amount of dried brush in the background.

Temporal change detection from remotely sensed imagery has been regularly used to quantify changes of landscapes including land cover and habitat types, forests species composition, monitoring landscape health (i.e., flooding, landslides, drought), and mapping urban growth (Lu *et al*., 2003; Lu *et al*., 2005). The temporal scales used to detect change has ranged from seasonal to decadal (Agarwal *et al*., 2002; Easson *et al*., 2010; Laube *et al*., 2005; Martínez and Gilabert, 2009) and frequently focused on the detection or differentiation of change versus no-change. More complex change detection methods quantify the magnitude, direction, and/or rate of change and require advanced techniques such as calculating spectral band ratios, image differencing, or principal component analysis and image construction (Coppin *et al*., 2004; Lu *et al*., 2005). Regardless of the object of interest, change detection with remotely sensed imagery requires precise spatial registration, and correction/normalization of atmospheric interference (Lu *et al*., 2003).

We assessed the potential of differencing two high-resolution, aerial images collected within a single day to detect animals and potentially determine a correction factor for population abundance estimates derived from remotely sensed aerial imagery. We compared our population abundance estimate to a known number of animals (domesticated cattle (*Bos taurus*) and horses *(Equus caballus)*. Fenced pastures provided a convenient test case where the number of animals in a pasture did not change over the course of image acquisition, animals did not move outside an identifiable boundary (the fenced pasture), definitive numbers of individuals in a pasture could be determined from ground counts or verbal confirmation obtained from ranchers, and multiple pastures were available across the study area.

Data and Methods

Study areas

On October 31, 2006, we acquired aerial imagery under mostly clear skies across portions of Cache Valley (CV) and a portion of Box Elder County west of Brigham City (BC) in northern Utah. Cache Valley is a north-south trending valley with an average annual precipitation of 45 cm (Moller and Gillies, 2008) and an elevation of 1,355 m (U.S. Geological Survey, 1981) at the center of the valley. CV sites were located in the valley bottomlands dominated by a mixture of dense and sparse grasslands. Brigham City (BC) is located in the Basin and Range physiographic province and sits on the western base of the north-trending Wellsville Mountains. The average precipitation of the BC

sites was 47 cm (Moller and Gillies, 2008) with an elevation of 1,289 m (U. S Geological Survey, 1981). BC study sites were dominated by sparse grasslands.

Animal ground counts

Rather than compare one estimate to another estimate, we were able to compare the number of animals identified by image differencing to the known number of animals in each pasture. Ground enumeration of domestic cattle and horses occurred concurrently with image acquisition. When possible, we contacted landowners to corroborate the ground count of animals. We determined the final count of the known number of animals per pasture from visual ground counts, available landowner counts, and a qualitative assessment of animal movement in the imagery. Pastures containing ≥ 50 animals were difficult to enumerate and resulted in unreliable counts, thus those pastures were not included in the analysis. Although no PD was determined for the ground counts, by limiting analysis to those pastures with ≤ 50 animals, the PD was likely high. We considered pastures independent samples since they were geographically separated across the study sites.

Aerial Imagery

Aerial imagery was collected between 10:44 AM and 3:07 PM using an airborne remote sensing system consisting of three Kodak Megaplus 4.2i digital cameras, each recording a specific spectral region: green (0.54 – 0.56 μm), red (0.66 – 0.68 μm), and near-infrared (0.7 – 0.9 μm) with an approximate spatial resolution of 25 cm (Cai and Neale, 1999). Each pasture was imaged twice, with at least 48 minutes between the first

image (T1) and the second image (T2). Image acquisition likely did not affect animal movements since the aircraft flew at an average elevation of 549 m above ground level (Bernatas and Nelson, 2004; DeYoung, 1985).

Image Analysis

An Exotech four-band radiometer nested with the camera system allowed for the conversion of digital numbers to reflectance values for each image (Neale and Crowther, 1994). Rectification of images to the Universal Transverse Mercator System (UTM), NAD83 datum occurred in ERDAS Imagine 9.1.0. We used a feature based registration process to register the T1 image to the T2 image for each pasture by linking features common to both images. A second-order polynomial transformation and nearest neighbor re-sampling method was used to achieve a maximum root mean square error (RMSE) ≤ 1 (Jensen, 2005). No active farm equipment was present in any of the pastures during image acquisition thus animals were the only features that moved between image acquisitions.

A common use of principal component analysis (PCA) is the reduction of dimensionality for multi- and hyper-spectral imagery by combining redundant information in highly correlated bands (Chavez and Kwarteng, 1989; Jensen, 2005). The output of a PCA is an image, which is composed of the same number of layers as the input image (3 bands in this case), in which the first layer contains the highest amount of correlated information between the spectral bands. The second PCA layer contains the second highest amount of correlated information and so on (Jensen, 2005). We conducted a PCA on each image to reduce the 3-band image to a single component (1st component)

containing the majority of the variance across all three bands. A differenced image was obtained by subtracting the first principal component of the T1 image from the T2 image (Figure 4.1). To reduce differences in edge effects, we clipped the differenced images to the minimum extent of T1 and T2. The analyst heuristically determined, from the differenced image, the maximum and minimum thresholding values that best described animal features and reduced over-counting (false positives) and under-counting (false negatives) errors. Polygons exceeding a heuristically determined area size (> 10 m^2) or too small (< 0.99 m^2) to be animals were removed with the resulting polygons considered potential animals.

Distinguishing animal features in remotely sensed imagery is best accomplished when homogenous, non-complex backgrounds (i.e. the neighboring vegetation; Trivedi et al., 1982; Wyatt et al., 1985) surround animals. For each pasture, we calculated the normalized difference vegetation index (NDVI) to quantify plant productivity and biomass (Jensen, 2005) and to assess the similarity of vegetation across pastures. We conducted linear regressions (Zar, 1996) between NDVI and the four error measurements in R (R Core Development Team, 2012) to determine if pasture productivity influenced error rates.

Accuracy Assessment

The output of the differencing technique generated individual polygons that represented animal features. We identified when a polygon was properly placed by comparing polygon locations with known animal locations. We classified polygons into three categories: "mapped polygons" consisted of all polygons generated in a particular

technique, "correctly mapped" polygons were those generated using one of the three techniques that accurately depicted animals, and "incorrectly mapped" polygons were those polygons that were not associated with an animal. In addition, because we had two images and could isolate moved features, we were able to identify specific locations of animals in each pasture. Knowing the specific location of each animal in both images, we were able to identify when an animal was not linked with a polygon (missed). Any animal not associated with a polygon was considered a "missed animal".

The probability of detection (PD) was calculated as the number of correctly mapped polygons divided by number of known animals in the pasture. The probability of under-counting (P_{under}) indicated missed animals, and was calculated as the number of missed animals divided by the number of known animals in the pasture. The probability of over-counting (P_{over}) indicated incorrectly mapped polygons and was calculated by dividing the number of incorrectly polygons by the number of mapped polygons in the pasture. We incorporated the three error estimates into a single correction factor (CF) that we multiplied by the number of mapped polygons to generate a population abundance estimate for each pasture. Abundance estimates, adjusted for over-counting animals (false positives) and missed animals (false negatives), have greater validity and are more robust than unadjusted estimates. The CF was calculated as $(PD + P_{under} - P_{over}) / PD$.

Results

The number of known animals present in the eight pastures ranged from three to 38 individuals and the number of mapped polygons ranged from 10 to 136 (Table 4.1). The differencing process resulted in few polygons representing multiple individuals

(adjacent animals). One pasture had a single polygon representing two animals, one pasture had two polygons representing two individuals, and one pasture had three polygons representing two individuals (Table 4.1). We found no significant relationship ($p > 0.50$) between any of our error measurements and NDVI, suggesting that plant productivity did not influence separation between animals and their surrounding background.

The mean PD across the eight pastures was 82% ($\pm$ 17 (STD), Table 4.1). The mean P_{under} was 18% ($\pm$ 17%) and ranged from 0% to 50%. The PD and P_{under} are in direct opposition of each other due to the equation to calculate them, thus as PD increases, P_{under} decreases (Table 4.1). The mean P_{over} was 53% ($\pm$ 36%) and ranged from 0% to 95%. The mean CF was 0.64 ($\pm$ 0.51) and ranged from 0.05 to 1.29. The relationship between CF and known number of animals was significantly linear ($p = 0.02$, $R^2 = 0.62$) with higher number of known animals associated with higher CFs (Table 4.1). Although low CF values were associated with fewer known animals in a pasture, low sample size prevented application of a specific CF for pastures with low animal densities, another CF for pastures with intermediate animal densities, and a third CF for pastures with high animal densities.

To determine if the correction factor would allow us to effectively estimate population, we averaged the CFs of four randomly selected pastures and applied that mean to the remaining four pastures to assess the validity of our population abundance estimates (Table 4.2). Examining the difference between known numbers of animals in the pastures to the adjusted population abundance estimate indicates that image

differencing will in general overestimate the population size when there are fewer animals present and underestimate the population when there are more animals present.

Discussion

The PD is an important adjustment variable for population abundance estimates obtained from ground or aerial wildlife surveys. Reported values of PD for conventional wildlife surveys range from 62% in bats (Order *Chiroptera*, Duchamp *et al*., 2006), 52% in caribou (*Rangifer* spp., Rivest *et al*., 1998), 53 -71% for feral ungulate species (Bayliss and Yeomans, 1989), and 34 – 82% for mule deer (*Odocoileus hemionus*) depending on group size and habitat type (Freddy *et al*., 2004). Reported detection probabilities of bison (*Bison bison bison*) are higher (> 92%) than other wildlife species regardless of habitat or season (Wolfe and Kimball, 1989; Hess, 2002). Our mean PD of 82% is above reported levels for wildlife surveys and suggests single day image differencing could provide an alternative method for estimation of ungulate population abundances. Population estimates, left unadjusted for over and under-counting errors could have serious management implications. Over estimates of population size could lead to a larger than appropriate harvest quota which could result in a population decline. Conversely, under estimating the size of a population could lead to inappropriate management objectives and result in a larger population size than desired. Regardless of biases in counting, incorrect population abundance estimates could lead to improper management of a population. If biases or errors are known and quantified, they can be incorporated into population abundances and result in potentially more precise and accurate estimates, which in turn can better inform management decisions.

The increase in the CF as the known number of animals in a pasture increased is likely due to the removal of large ($> 10 \text{ m}^2$) polygons that could represent multiple animals. Cattle and horses are herding species that frequently stand next to each other and individuals that were in close proximity during image acquisition could be represented as a single large polygon. Animals in pastures with more individuals (29 and 38) were more likely to be grouped together resulting in polygons that represented more than one animal. Pastures with fewer animals were less likely to be in groups and had no polygons that represented multiple animals (Table 4.1). Pasture 29 had 29 known animals present but the 22 correctly mapped animals were relatively isolated individuals (Figure 4.2), while two of the missed individuals were represented by large polygons that were removed due to size. Thus, when animals were in groups, image differencing tended to remove clustered animals resulting in an underestimate the number of individuals in an image.

Thresholding is an exploratory process that frequently requires human interpretation (Coudray *et al*., 2010; Medina-Carnicer *et al*., 2010; Rosin and Hervás, 2005; Russ, 1999). A limitation of heuristic thresholding is the dependency on a human analyst, which is subjective, cannot be replicated, and is often inconsistent. Bajzak and Piatt (1990) recognized the need for automation to count "large aggregations of birds" and developed a technique to enumerate bird clusters in remotely sensed imagery. We attempted to identify automatic thresholding criteria to automate animal identification in remotely sensed imagery but without success (see Chapter 2). Automation of this type is notoriously difficult and inconsistent (Endsley, 1996; Skelsey *et al*., 2004; Walter and

Luo, 2011). We believe, given the current capabilities for automation, human

determination of thresholds for defining animals provides the most appropriate method

available.

Image registration is the process of spatially transforming one or more images to

accurately overlay each other with the result that identical features in registered images

should have the same geographic coordinates (Jensen, 2005). Image differencing for

change detection requires precise and accurate registration between images to avoid false

detections of change (Coppin *et al.*, 2004; Jensen, 2005). Although the root mean square

error (RMSE) for all image registrations was ≤ 1, small misalignments occurred because

linking features were irregular or non-distinct. Another source of error can be attributed

to the non-linear spatial nature of imagery collected through a camera lens at lower

elevations (barrel distortion). While non-linear errors were accounted for using lens

models, residual non-linear errors could still exist. Stow *et al.* (2002) indicated that image

registration with fine scale imagery is notoriously difficult with small mis-registration

errors resulting in large local variation. We calculated the coordinate difference for five

features in each pasture between the T1 and T2 images to assess mis-registration. Total

mis-registration error was calculated by summing the errors in the X and Y direction.

Mis-registration errors occurred in six of the eight pastures examined with errors of more

than two meters in two pastures, and three pastures with errors greater than one meter but

less than two meters (Table 4.3). The mean total mis-registration error of 1.31 m could

effectively encompass the width of a small adult cow (B. Bowmen, personnel

communication), thus a RMSE ≤ 1 is not sufficient for aerial imagery to prevent

misalignments from being interpreted as animals and added to the high over-counting (P_{over}) error.

Because animal movement was the basic premise behind the ability to detect animals in the differenced images, the time interval between image acquisitions was important. Since we had specific locations of each individual, we were able to identify individuals that did not move between the acquisition of T1 and T2. Pasture 32 had the lowest time difference (48 minutes) between image acquisitions and had the second highest P_{under} indicating the reduced time interval between the T1 and T2 images was not sufficient to allow for significant movement of individuals. The time interval between acquisitions should therefore be long enough to ensure animal movement. Images collected on successive days should be acquired as close to the same time of day and if possible when the sun is directly over-head to reduce shadow effects (Jensen, 2005). The number of days separating T1 and T2 image acquisitions should not be more than a week to avoid changes in sun angle. Additionally, 1-2 days, with 7 days maximum, separating image acquisitions should ensure both spatial and temporal population closure so that differences in the number of animals are minimal and only due to births and deaths and not movement of individuals into (i.e. immigration) or out of (i.e. emigration) the population (Williams *et al*., 2002). Additions of newborn animals to the population should be minimal for most species except in spring. Unless imagery acquisition occurs during hunting season or during a catastrophic die-off, deaths should be minimal between 1-2 days.

Although image differencing will detect 82% of the animals present in an image, certain precautions should be addressed prior to applying this technique for estimating animal population sizes. First, although P_{under} was relatively low, P_{over} was high and resulted in an over estimate of the animal population for all pastures. This was similar to counts in remotely sensed imagery for Canada geese, snow geese, and caribou (Laliberte and Ripple, 2003) that were over-estimated due to inclusion of erroneously classified background areas. Second, identification of spectral thresholds that represent animals is a heuristic process that relies on human interpretation and thus may not be without bias. Third, image differencing requires precise image registration to avoid spurious areas of change that can result in large numbers of incorrectly mapped polygons. Fourth, enough time must pass for animal movement to occur between image acquisitions. Fifth, the non-animal portions of the image (i.e., the background) should be as homogenous as possible to enhance differentiation between animals and their background.

The advantages of airborne or satellite imagery to count animals include reduced survey time, a permanent record of the survey, and potentially less expensive than conventional wildlife surveys. Conventional aerial wildlife surveys frequently require multiple days to complete thus allowing animals to move throughout the study area and increase the probability of double-counting or missing individuals. Acquisition of remotely sensed imagery is readily obtained over isolated or difficult to reach areas whereas conventional aerial surveys require complex advanced planning (i.e. multiple people conducting surveys over multiple days). In large, remote areas, such as the Mongolian steppe and some parts of the South African continent, aerial transects are

often not feasible due to limited access to airplanes or the high cost of airplane rental or purchase (Rabe *et al.*, 2002). Because of this isolation, surveys are not conducted or are less rigorously conducted which could lead to flawed management decisions. While it would require a significant number of days to acquire remotely sensed imagery of large areas, such as the Mongolian steppe or the western desert of Utah, conventional wildlife aerial surveys are prohibitively expensive due to aircraft cost and personnel time. The reduction in time required to acquire remotely sensed imagery of a large study area could facilitate counting of animals in areas previously too large or too isolated to survey. Additionally, acquisition of remote sensing imagery has the potential to reduce or even eliminate negative responses of animal to low flying aircraft during aerial wildlife surveys (DeYoung, 1985; Anderson and Lindzey, 1996; Brockett, 2002; Bernatas and Nelson, 2004). Automated image analysis has an additional advantage of reduced subjectivity within a technique and across analysts. The permanent, unchanging record of animal locations for an instant in time i.e. 'a survey', allows for repeated assessments using the same or different techniques. Remotely sensed imagery can be assessed by different personnel to measure the validity of a technique without degradation to the image regardless of the number of times it is analyzed. Although aerial and ground transects can be repeated animals are not in the same locations from one survey to the next, thus a specific survey cannot be replicated whereas data contained within remotely sensed imagery can.

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Table 4.1. The probability of detection (PD), the probability of under-counting (P_{under}), the probability of over-counting (P_{over}), and the correction factor (CF) for the population abundance estimates resulting from a differencing process between two images acquired on a single day.

Pasture	Known number of animals in pasture	Mapped polygons	Correctly mapped polygons	Polygons representing 2 animals	Missed animals	Incorrectly mapped polygons	PD[1]	P_{under}[2]	P_{over}[3]	CF[4]
4	18	15	9	0	9	6	0.50	0.50	0.40	1.20
32	38	26	22	3	13	4	0.66	0.34	0.15	1.29
27	4	10	3	0	1	7	0.75	0.25	0.70	0.40
29	29	33	22	1	6	11	0.79	0.21	0.33	0.84
21	13	71	12	0	1	59	0.92	0.08	0.83	0.18
28	15	136	14	0	1	122	0.93	0.07	0.90	0.11
15	38	35	35	2	1	0	0.97	0.03	0.00	1.03
22	3	59	3	0	0	56	1.00	0.00	0.95	0.05
Sum	158	385	120	6	32	265	-	-	-	-
Mean	20	48	15	1	4	33	0.82	0.18	0.53	0.64
STD	14	41	11	1	5	43	0.17	0.17	0.36	0.51

[1.] (Correctly mapped polygons a / Known number of animals in pasture)

[2.] (Missed Animals / Known number of animals in pasture)

[3.] (Incorrectly mapped polygons/ Number of mapped polygons)

[4.] $(PD + P_{under} - P_{over}) / PD$

Table 4.2. Application of the mean correction factor (CF, 0.64) from four randomly selected pastures to determine the adjusted animal population abundance estimates for four pastures in north central Utah.

Pasture	Known number of animals in pasture	Mapped polygons	Adjusted population abundance	Difference between known and adjusted abundances
29	29	33	21	-8
4	18	15	10	-8
21	13	71	45	32
22	3	59	38	35

Table 4.3. Mean mis-registration errors (STD, standard deviation and SE, standard error) across 5 points from registering image T1 to T2 in the X and Y directions for eight pastures. Errors are mean differences of five samples, measured as distance, of five locations. Total error is the sum of the X and Y errors.

Pasture	Mean X	STD X	Mean Y	STD Y	Total
4	0.00	0.12	0.00	0.69	0.00
21	0.00	0.00	0.00	0.00	0.00
28	0.14	0.15	0.82	0.06	0.95
15	0.29	1.41	0.74	1.91	1.03
27	0.27	0.14	0.97	0.82	1.23
29	0.70	0.40	0.63	0.33	1.33
22	0.60	0.74	1.90	4.67	2.50
32	1.01	0.21	2.38	0.61	3.39
Mean	0.37		0.93		1.31
SE	0.13		0.30		0.41

Figure 4.1. Section of pasture 29 depicting 22 known animals. Figure A is the 1st principal component of the first image acquired (T1), figure B is the 1st principal component of the second image acquired (T2), and figure C is the differenced image resulting from subtracting T1 from T2.
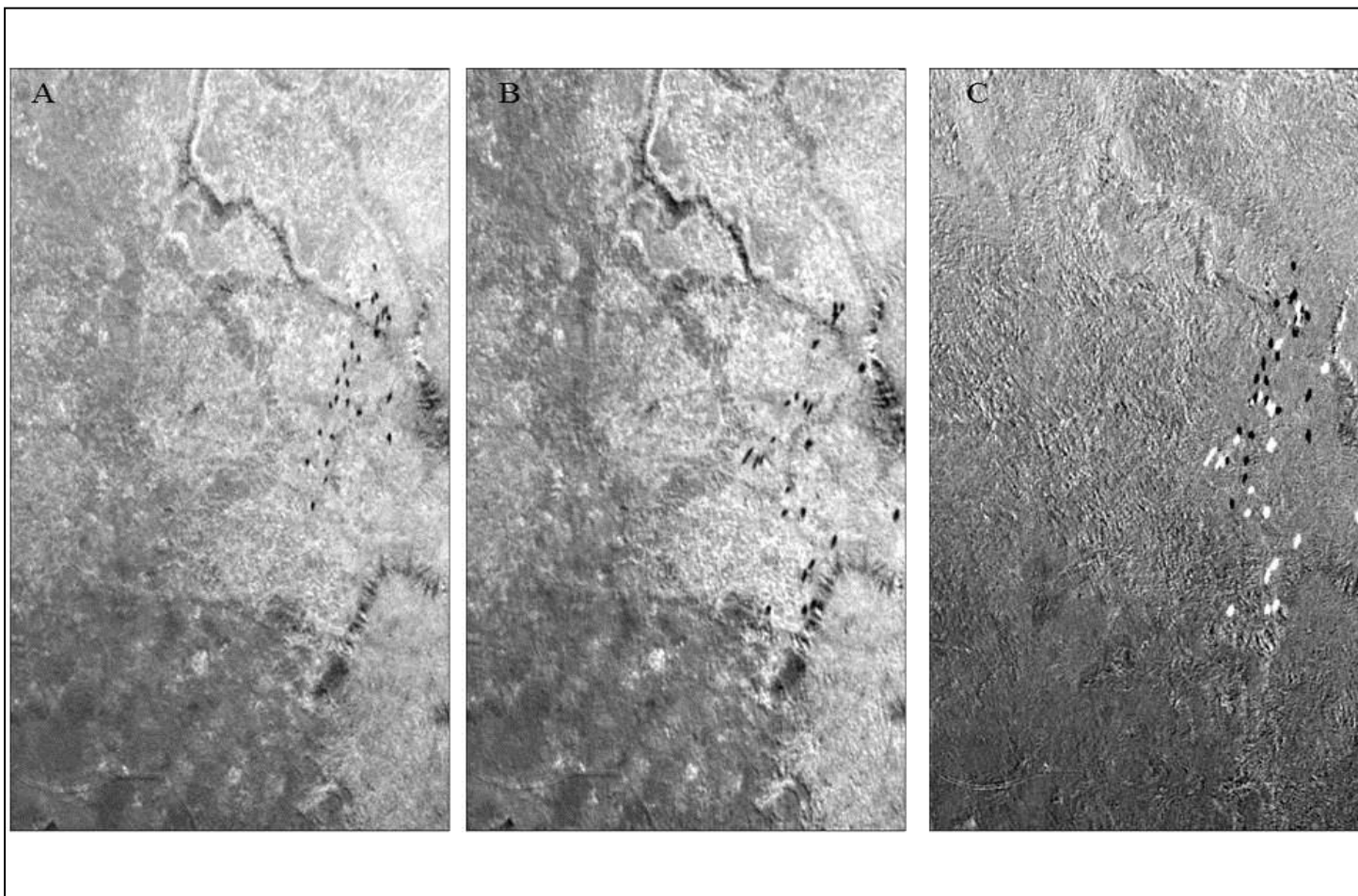
Figure 4.2. Thirty-three mapped polygons resulting from an image differencing process for pasture 29. Twenty-two grey outlined polygons indicate correctly mapped animals, the 11 solid black polygons indicate polygons incorrectly mapped as animals, and the six black triangles indicate animals not associated with a polygon i.e., missed animals.

CHAPTER 5

BISON SIGHTABILITY IN THE SATELLITE AGE

Abstract

The probability of detection is essential for accurately estimating animal population abundance. With the advent of programmable GPS radio-collars, biologists have access to data at resolutions previously unavailable, allowing for the identification of double-counted and missed animals during aerial surveys. We equipped 44 bison (*Bison bison bison*) with GPS-collars and documented the spatial and temporal relationship between bison travel paths and annual helicopter survey paths. Using GPS-collar locations, we examined aerial survey results at multiple resolutions and determined the probabilities of detection (i.e., sightability) for bison in south-central Utah. Four data resolutions separated double-counts and missed animals based on temporal and spatial designations. The coarsest resolution (Level 1) did not identify double-counted or missed bison and represented the "crudest" detection probability, similar to conventional aerial surveys. Sightability models were developed for Levels 2 - 4 with physiographic variables (aspect, majority habitat type, surface roughness) and survey variables (distance between the helicopter and a group, movement at initial detection, habitat visibility, and group size). The surface roughness index and distance between the helicopter and a group significantly affected sightability ($P \leq 0.10$) at most levels of data resolution. Horvitz-Thompson population abundance estimates for each data resolution were higher when double-counts were included than when double-counts were not included. Incorporating

known double-counted and missed bison into aerial survey counts will result in a more accurate population abundance estimate.

Ground and aerial surveys are common methods used to estimate population abundance and density of free-ranging animals (Silvy 2012). Raw counts without a correction factor often yield biased population abundance estimates due to imperfect detection caused by animal movements or clustering, visual obstructions (e.g., dense habitat), or observer error (Caughley 1974, Eberhardt 1978, Samuel et al. 1987, White et al. 1989, Jackmann 2002). Variation in the raw counts can thus be incorrectly interpreted as variation in population size. Estimating the probability of detecting an individual animal (or group of animals) can be used to correct count data and attain more robust estimates of population abundance (White 2005). A number of methods have been developed to estimate the probability of detection, such as the double-observer method (White et al. 1989, Potvin et al. 2004, Duchamp et al. 2006), concurrent or nearly concurrent ground and aerial counts (Samuel et al. 1987, Jackmann 2002), photographic interpretation (Koski et al. 2011, Lubow and Ransom 2009), distance sampling (Buckland et al. 1993), and capture-mark-recapture (White et al. 1982). However, these methods either suffer from the assumption of a constant probability of detection, or are difficult to implement for large ungulates in rugged terrain and dense habitats that obscure visibility (Fieberg and Giudice 2008). In such cases, sightability models are often used to estimate how detection probabilities change with variable landscape attributes, animal behavior, and survey parameters (Samuel and Pollock 1981, Steinhorst and Samuel 1989).

Habitat type, group size, and the amount of vegetative cover have all been shown to influence detection of ungulates and have been included in sightability models (Gasaway et al. 1985, Samuel et al. 1987, Rice et al. 2009, Giudice et al. 2012, Ransom 2012). In addition to environmental and survey covariates, spatially explicit variables such as physiographic characteristics in the vicinity of animal locations (e.g., aspect, elevation, slope) could affect sightability. These variables have rarely been considered, possibly due to the coarse-scale information that is obtained when using high frequency (VHF) collars to determine the probability of detection for a species during a survey.

The current generation of global positioning system (GPS) radio-collars for wildlife can be reprogrammed after deployment to modify the frequency and timing at which locations are acquired. Thus, location acquisition rates can be adapted to take advantage of unforeseen management or research opportunities. A post-deployment increase in acquisition rates for specific times of the year, such as during annual surveys, can provide nearly continuous information on animal movements and locations. Hence, locations of GPS-collared individuals can be assessed almost instantaneously relative to a (helicopter) survey path. The nearly continuous locations can inform biologists which GPS-collared individuals are within a surveyed area, and if they were successfully detected or missed by survey observers. In addition, monitoring fine-scale movements of GPS-collared animals allows for greater insight into double- or multi-counts on a per individual basis, and the physiographic, behavioral, and survey variables influencing probability of detection during a survey.

Our primary objective was to estimate sightability of GPS-collared bison (*Bison bison bison*) during annual helicopter surveys flown by the Utah Division of Wildlife Resources (UDWR) in south-central Utah. We did not attempt to evaluate or improve the existing survey design. Rather, we used the GPS-collared bison and remotely sensed imagery to develop a spatially-explicit sightability model for UDWR's existing survey design. Combining landscape features and known locations of GPS-collared bison during surveys will allow managers to evaluate the sightability on an individual (or group) basis and calculate a more robust estimate of population abundance for guiding harvest and translocation management decisions.

Study Area

The study area included the Henry Mountains and surrounding rangelands in Wayne and Garfield counties, in south-central Utah. The study area was extremely rugged with elevations ranging from 1,127 m at the lower benches and desert areas to 3,512 m at Mount Ellen (U.S. Geological Survey 1981). The low elevation desert areas were a combination of high, steep-walled mesas interspersed with semi-arid, sagebrush steppe habitats. The upper elevations and mountainous areas were characterized by deep, V-shaped valleys with alpine patches on the ridges (Nelson 1965). Average annual precipitation changed dramatically between the lower elevation slopes and desert areas (15 cm) and the upper elevation, forested slopes (50 cm; Van Vuren and Bray 1986). Precipitation was highly variable over time and influenced reproductive success of the bison (Koons et al. 2012). Vegetation changed with elevation, such that lower elevations and desert areas were dominated by saltbush (*Atriplex* spp.), greasewood (*Sarcobatus*

spp.), sagebrush (*Artemisia* spp.), and grasses (*Aristida* spp., B*outeloua* spp.). The highest elevations were dominated by spruce (*Picea* spp.), Douglas fir (*Pseudotsuga menziesii*), oak (*Quercus gambelii*), and small patches of aspen (*Populous tremuloides*). Intermediate elevations were a mixture of shrublands and pinyon pine (*Pinus edulis*) - juniper (*Juniperus* spp.) woodlands; Van Vuren and Bray 1986).

Methods

We captured 59 bison using a net-gun fired from a helicopter (Barrett et al. 1982) between January 30 and February 3, 2011. We equipped 44 bison with 2 collars: a radio-collar furnished with GPS unit (Lotek Wireless, Ontario, Canada) and a VHF radio-collar (Telonics, Mesa, Arizona, USA, and Advanced Telemetry Solutions, Isanti, Minnesota, USA) with white belting. An additional 15 bison were fit with a single black-colored VHF radio-collar (for the purposes of monitoring survival). Between January 2012 and January 2013, we captured and attached a VHF collar on 27 bison and replaced 35 non-functioning GPS collars with functioning GPS collars (i.e., recaptures). Capture and handling protocols were in compliance with the UDWR (permit 6BAND8393) and the Utah State University - Institutional Animal Care and Use Committee (IACUC #1452). The GPS collars obtained locations every 4 hours, except during helicopter surveys when locations were obtained every 2 minutes. Location data was uploaded via satellite and we received emails containing bison locations approximately every 3 days. The VHF collars were equipped with a mortality sensor and had a life expectancy of $\geq$5 years while the GPS collars had a life expectancy of 3 years.

Helicopter Surveys.—The UDWR counted bison across the study area in August 2011 and 2012 using a Eurocopter A Star 350 B2 ECUREIIL (Grand Prairie, Texas, USA) helicopter. The helicopter and observation crew consisted of the same individuals for all years with the exception of a new pilot in 2012. For all surveys, the primary observer sat next to the pilot with the secondary observer in the back seat, behind the primary observer. A dedicated recorder, in the middle back seat, logged all observations while a third observer sat behind the pilot. Both the primary and secondary observers had over 5 years of wildlife survey experience. None of the observers knew the locations of GPS-collared bison prior to conducting the survey. Rugged topography prevented adherence to strict transect lines so flight paths were dictated by and followed the terrain. The primary observer determined the flight path direction and extent of the survey area for all years. We divided the study area into 4 "strata" (Fig. 5.1) outlined by common flight paths across all years and based on physiographic regions such as drainages and ridge tops. Strata were flown in a different order each year. Surveys took no more than two consecutive days and occurred on rain-free days with moderate to low cloud cover.

We recorded helicopter flight paths with a GPS unit collecting locations every 2-3 seconds. At first detection of an individual or a group of bison, the primary observer estimated the distance between the helicopter and the initial sighting of the group or individual to the nearest 0.40 km (0.25 mile). The helicopter then flew towards the group or individual and circled until the observers had determined group size, number of adults and calves, and counted the number of GPS-collared bison. Upon completion of group enumeration, the helicopter then returned to the original flight path.

In addition to recording the distance between the helicopter and individual or group of bison, the primary observer classified vegetation density at the initial detection point into 3 visibility classes: low visibility (dense tree cover), moderate visibility (a mixture of trees, shrubs, and grasses), and high visibility (open grasslands and low-density shrub-lands). The primary observer also indicated whether the individual or group was moving at the time of initial detection.

Physiographic and Habitat Variables.—Post survey, we determined physiographic variables (aspect, elevation, majority habitat type, slope, surface roughness index) in a 300-m radius (282, 618-m^2 area) around all bison locations. We derived the aspect, elevation, and slope from a 10-m resolution National Elevation Dataset (NED; Gesch et al. 2007) of the study area. We converted aspect into a categorical variable representing the four cardinal and four inter-cardinal directions (8 directions). A surface roughness index (hereafter termed roughness index) represented topographical extremes measured within a 10×10-m neighborhood (Russ 1999). A single roughness value for each neighborhood represented the mean elevation difference between the center pixel and all other pixels in the neighborhood. We normalized the surface roughness values so the minimum was zero and the maximum was 100 to allow for comparison across the study site.

We also classified seven habitats from a 1-m resolution, 4-band (blue, green, red, and near infrared) National Agricultural Imagery Program (NAIP) aerial image of the study area. The classes consisted of alpine (ALP), desert/grassland/barren (DGB), low-density juniper (LDJ), moderate-density juniper (MDJ), shrubland (SHB), and high-

density pinyon-juniper woodlands (WDLD), and unknown (UNK). We calculated the

normalized difference vegetation index (NDVI; Jensen 2005), a measure of the amount of

healthy vegetation biomass, from the NAIP imagery to separate DGB habitat from SHB,

and LDJ from SHB. We separated MDJ from dense WDLD with a supervised

classification (Jensen 2005) of the NAIP imagery. Elevation separated ALP from DGB,

with ALP habitats limited to higher elevations than DGB and above the WDLD habitat.

Based on field-accessed locations, the overall accuracy for the habitat classification was

52% indicating that over half of the reference points were correctly classified. The overall

accuracy does not indicate errors of omission or commission and thus does not

completely represent the ability of a classification scheme to identify specific classes.

The KHAT statistic is a measure of the agreement between a classification scheme and

the associated reference data that ranges from -1 to 1 with 1 representing perfect

agreement (Congalton and Green 2009). The KHAT for our classification scheme was

0.39, suggesting fair agreement (Landis and Koch 1977) between the mapped classes and

ground reference data. The habitat with the highest percent cover in a 300-m radius circle

around each GPS-radio collared bison location was the WDLD habitat class which had a

19% omission error and only a 4% commission error (Table 5.1). Bison were also

frequently located in the MDJ habitat, which had a 75% omission error and a 65%

commission error.

     Bison Observation Status.—Temporal and spatial overlap between a travel path of

a GPS-collared bison and the helicopter flight path were used to determine which bison

were successfully detected (bison present in the survey area and detected), which were

duplicate counts (bison present in the survey area and detected more than once), and which were missed (bison present in the survey area but not detected). We considered a bison successfully detected if the following three criteria were met: 1) GPS locations were within the distance and direction noted in the survey when a group was first detected, 2) a GPS location was temporally and spatially congruent with the helicopter flight path, and 3) white-colored collars (2011) or double-collared bison (2012) were observed in the target group (Fig. 5.2). A more direct determination of individually-based detection was not possible because alpha-numeric markings on the white-colored collars were not uniquely identifiable from the air, nor could they be read from video taken during the surveys. We received locations from the GPS collars with an associated time stamp 3-5 days post survey. We connected bison locations in ArcGIS 10 (ESRI, Redlands, California, USA) to form a bison travel path during survey days.

For each missed GPS-collared bison (Fig. 5.3), we determined distance to the helicopter flight path, group size, whether the bison was moving or not, and visibility class post survey. We used ArcMap 10 (ESRI, Redlands, CA) to obtain distances and visualize intersections of the helicopter flight path and the bison travel path. We calculated distance between the helicopter and the missed GPS-collared bison by assuming a 90˚ angle between the missed bison and the helicopter flight path (Fig. 5.3). Based on a regression with high explanatory strength ($R^2 = 0.70$, $P < 0.05$) between group size and the number of GPS-collared bison in observed groups and habitat density (i.e. visibility class) of observed groups, we used the regression parameters to interpolate an associated group size for each missed bison based on their known covariate values (Fig.

5.4). We considered a missed bison as 'moving' if the distance traveled in two minutes was more than 200 m. We determined the visibility class (low, moderate, or high) for each missed bison from visual inspection of NAIP imagery relative to that of observed bison.

Analysis Levels.—Sightability is usually based on the comparison of two survey methods: a fixed-wing flight that determines the presence of each collared animal in a survey strata using VHF radio-telemetry, followed by a 'blind' helicopter survey crew that attempts to visually observe radio-collared individuals and count all individuals (Unsworth et al. 1990, Giudice et al. 2012, Ransom 2012). The resulting data indicate the number of detected and missed animals but determination of multiple counts of the same animal is more problematic with VHF collars. Numerous flights are required to enhance the sample size of detected and missed animals, which increases the total cost and can cause potential problems with lack of independence among surveys. Additionally, increased flights can negatively affect animal behavior and result in potentially biased behavior towards airplanes or helicopters during each successive survey (Anderson and Lindzey 1996, Brockett 2002, Bernatas and Nelson 2004).

The GPS-collar data allowed us to alleviate many of these problems, and examine four levels of data resolution to estimate sightability. The lowest resolution (Level 1) represented the manner in which conventional wildlife surveys would record animal detections. That is, Level 1 data resolution represented the number of white-collared bison detected throughout the surveyed area relative to the number of white-collared bison present in the study area in 2011. In 2012, 18 of the bison outfitted with white VHF

collars had either lost their white belting, or the status of the white belting was unknown. The primary observer felt that double-collared bison (all GPS-collared animals had a VHF collar) could be effectively identified from the helicopter (W. Paskett, UDWR, personal communication). Thus, for 2012, Level 1 data represented the number of double-collared bison observed during the entire survey relative to the number of double-collared bison present in the study area.

Collar failure and premature drop-off occurred throughout the study such that in 2011 and 2012, 13 and 10 collars, respectively, were not transmitting locations. Levels 2, 3, and 4 data resolution included only bison with functioning GPS-collars at the time of the survey. Level 2 data resolution was temporally restricted such that each functioning GPS-collared bison was assigned a single observation status across the entirety of each annual survey. Thus, double-counts could not be ascertained at this level or at the Level 1 resolution. However, at the Level 2 resolution, 'missed animals' were defined as those bison present in the study area (a geographically closed system) but never observed during an annual survey. For Level 2 and Level 3 data resolutions, detection superseded a miss, so if a bison was both detected and missed in the respective survey area for a given resolution, the bison was recorded as detected. Level 3 data resolution was spatially restricted and consisted of stratum-specific observations. Consistent with most other sightability studies (Steinhorst and Samuel 1989, Jenkins et al. 2012), we recorded a single observation for each GPS-collared bison counted per stratum as it was flown. Thus, at the Level 3 data resolution a bison could be classified as detected, missed, or double-counted across strata but not within a stratum. The Level 4 resolution of data,

which was not spatially or temporally limited, allowed for multiple observations within and across strata. The observations were temporally and spatially separated enough to be considered unique sampling observations. For example, bison 30401 was missed in 2011 at 8:05 am but detected later in the same stratum at 1:14 pm (Figs. 5.2 and 5.3). Thus, at the Level 3 data resolution 30401 was recorded as detected but not missed. At the Level 4 data resolution, spatial and behavioral data for bison 30401 was recorded at both its 8:05 am miss and its 1:14 pm detection. Level 3 and Level 4 data resolutions provide greater sample size of double-counted and missed bison for the development of sightability models (described below). The Level 4 resolution is akin to the multiple flights that are often flown in VHF-based sightability studies, in that animals can contribute multiple observations to the dataset, but without the repetitive flights that can affect animal behavior.

Sightability Models.—We used generalized linear models (GLM) with a binomial distribution and logit link function to examine the influence of bison behavior, physiographic variables, and survey parameters on the probability of successfully detecting marked bison (i.e., 'sightability'). For each level of data resolution that included GPS-based locations (i.e., Levels 2, 3, and 4), we developed GLMs that examined univariate and additive effects of aspect, roughness index, and majority habitat type on the probability of detection. Separately, we developed GLMs for each data resolution (i.e., Level 2, 3, and 4) to examine the univariate and interactive effects of distance between the helicopter and a group, group size, movement at initial detection, and visibility class on the probability of detection. We excluded slope and elevation because

the roughness index incorporated these variables and was positively correlated with them

($\rho > 0.25$, $P < 0.05$). In addition, other multicolinear variables were not allowed to enter

the same statistical model as additive effects.

We ranked all GLMs and the null model within each category of the predictor

variables (physiographic and survey) using the Bayesian Information Criteria (BIC,

Schwarz 1978). We then created a set of GLMs with combinations of predictor variables

that were significant ($P \leq 0.10$) and supported by BIC in the physiographic and survey

tiers of model comparison, and again used BIC to compare models. The sightability

models took the form: $y = \dfrac{\exp(\mu)}{(1 + \exp(\mu))}$ where y is a binary response variable of detected

($y = 1$) or missed ($y = 0$) and u is the logit of the best-fit sightability model with

covariates.

We investigated mixed models with either a random group effect or a random

'individual nested within group' effect to account for lack of independence among

marked bison that were within the same group (Bolker et al. 2008). However, these

models did not converge, perhaps due to small sample size. As the study progresses, we

will further investigate mixed models to address any lack of independence among bison

within a group.

Horvitz-Thompson Estimator.—The Horvitz-Thompson (HT) abundance

estimator (Steinhorst and Samuel 1989, Williams et al. 2002) utilizes individually-based

detection probabilities from a sightability model to adjust raw survey counts in the form

of: $\hat{N} = \sum\limits_{i=1}^{c} \dfrac{1}{p_i}$ where i pertains to each counted individual up to the total number

counted *C*, and *p* is the estimated probability of detection for each individual based on the selected sightability model and the attributes of the animal's location relative to those included in the selected model (i.e. it's covariate values). To increase the accuracy and precision of population abundance estimates, we estimated sightability models based on multiple covariates (see above) rather than assuming a constant detection probability across the survey (Steinhorst and Samuel 1989). We applied a HT estimator to our top-ranked sightability models and generated unbiased 95% confidence intervals using 1,000 boot-strapped abundance estimates (Efron and Tibshirani 1993, Heide-Jørgensen et al. 1993, Jackson et al. 2006). At data resolution Levels 2, 3, and 4, we calculated the HT abundance estimates with and without known double-counted individuals in the total *C*.

Results

Observers detected 11 groups and counted 372 bison (303 adults, 69 calves) in 2011 and 12 groups and 505 bison (439 adults, 66 calves) in 2012. At the Level 4 data resolution, there were 3 GPS-collared bison that were double-counted in both 2011 and 2012. In 2011, the double-counted bison were in a single group of 23 individuals. In 2012, two groups were double-counted, one consisting of a GPS-collared bison in a group of 5 individuals and the other group consisting of two GPS-collared bison in a group of 21 individuals. The mean group size across both years was 38 (± 35, standard deviation, SD). Observed group sizes were similar in both years with a range of 1 to 108 bison in 2011 and 5 to 103 bison in 2012.

The mean distance between the helicopter and each initial sighting of each group was almost three times higher in 2012 than in 2011. To determine the area surveyed on

each flight path for each year, we selected the mean or the median distance to a group based on the smallest value and buffered the flight line accordingly. Across both years, observers detected 11 groups in the high visibility class (grasslands and low-density shrublands), 9 in the moderate visibility class, and 3 in the low visibility classes (dense juniper woodlands). Of the 23 groups detected across both years, 20 groups were moving when first sighted and 3 groups were not moving. Most bison groups were located in strata A and B (Fig. 5.1).

Regardless of data resolution, observers consistently detected groups further away from the helicopter and in larger mean group sizes than missed groups. No missed groups were considered moving at data resolution Levels 2 and 3 but a single missed group was considered as moving at data resolution Level 4. Detected groups were located in all three visibility classes, while we determined post survey that missed groups were either in low (dense tree cover) or moderate (mixed juniper shrublands) visibility classes but never in the high visibility class. Although locations from GPS-collared bison were on eastern, southeastern, southern, southwestern, and western aspects, most missed groups were on southwestern and western aspects while detected bison groups were primarily on southwestern aspects. Missed groups were located in areas with higher roughness indices than detected groups. Regardless of data resolution, most missed groups consisted of one or two GPS-collared bison except in 2011 a group of 9 GPS-collared bison were missed at the Level 4 data resolution.

Sightability Models. —At all data resolutions 2 - 4, the top-ranked physiographic sightability models based on individual GPS-collared bison consisted of a single variable,

the roughness index. The top-ranked survey model for Level 2 was a univariate model consisting of group size, while the top-ranked survey model for Level 3 included distance between the helicopter and a group, and group size. The variables included in the top-ranked survey model for Level 4 included an interaction between distance between the helicopter and a group, and movement (Table 5.2). No top-ranked models included majority habitat classified from the NAIP imagery.

When considering combinations of physiographic and survey variables, we found that the roughness index significantly affected sightability. At the Level 2 and 4 data resolutions, roughness index reduced sightability (Table 5.2; $\beta_{Roughness\ Index\ L2\ =}$ -10.75, 95% CI: -20.28 to -1.23, $P = 0.03$; $\beta_{Roughness\ Index\ L4=}$ -40.59, 95% CI: -68.85 to -12.32, $P = 0.005$). Distance to a group significantly influenced sightability only at the Level 3 data resolution (Table 5.2; $\beta_{Distance\ =}$ 0.01, 95% CI: 0.00 to 0.02, $P = 0.01$). Group size was included in the top-ranked combined models for resolution Level 3 but it was not significant (Table 5.2; $\beta_{Group\ Size\ L3\ =}$ 0.16, 95% CI: -0.50 to -0.18, $P = 0.35$). Although the top ranked model for Level 3 data resolution was an additive model of distance to a group, plus group size, neither the distance to a group or group size variables were significant (Appendix A). As such, the next ranked univariate model of distance to a group was considered the most supported combined model based on the principle of statistical plurality (Scheiner 2004).

The top-ranked sightability models based on 'bison group observations' with at least one functioning GPS-collared bison in them were generally less complex and included fewer covariates (Table 5.3) than sightability models based on individuals as the

sampling unit (Table 5.2). At all data resolution levels, the top-ranked physiographic

models consisted of a single variable, the roughness index or the null model. The top-

ranked survey model for Level 2 consisted of the null model and for Level 3 consisted of

a single variable, distance between the helicopter and a group (Table 5.3). The top-ranked

survey model for Level 4 data resolution was a multivariate model consisting of distance

between the helicopter and a group, plus movement of the group at the initial sighting.

The null model was the top-ranked combined model for the Level 2 data

resolution. Distance between the helicopter and a group was a significant variable in the

combined models for data resolution Levels 3 and 4 with longer distances between the

helicopter and a group being correlated with higher sightability ($\beta_{Distance\ L3}$ = 0.01, 95%

CI: 0.00 to 0.03, P = 0.06; $\beta_{Distance\ L4}$ = 0.02, 95% CI: 0.00 to 0.04, P = 0.09). As we found

with the individually-based sightability models, none of the group-based sightability

models included majority habitat as a significant variable. The top-ranked model at Level

4 data resolution was an additive model of distance to a group plus movement (Appendix

B).

Abundance Estimates. — At the Level 1 data resolution, the probability of

detecting a GPS-collared bison was 91% in 2011 and 88% in 2012. The corresponding

estimated population size was 410 (± 79) bison in 2011 and 571 (± 124) bison in 2012

(Table 5.4). The abundance estimates derived from the sightability models and the

Horvitz-Thompson estimator for data resolutions 2 – 4 varied by 18 bison when double-

counts were included and 39 bison when double-counts were not included in 2011 (Table

5.4). We found similar variation in the estimates in 2012 with a difference of 15 bison

among Levels 2 – 4 data resolutions when double-counts where included, and a difference of 33 bison without double-counts included.

Discussion

One of the objectives for this research was to determine the probability of detection for the current UDWR bison survey in the Henry Mountains and develop an approach for attaining more accurate estimates of population abundance while providing statistical measures of uncertainty. With only 2 years of data, we feel that our results are preliminary but they suggest that the current UDWR survey technique for the Henry Mountain herd has a high probability of detection with few missed bison.

Aerial sightability surveys of ungulates are targeted at addressing imperfect detection but few have formally identified double-counted marked individuals. While conducting bison composition counts, Wolfe and Kimball (1989) noted when potential double-counts occurred but never indicated if that information was integrated into their detection probability. Van Vuren and Bray (1986) required 4-6 days to completely census the Henry Mountain bison herd because they would end a count and initiate a new one if they suspected duplicate counts of individuals had occurred. Double counts of elk were removed from the survey count in Montana when multiple ground surveyors detected the same group (Unsworth et al. 1990). Although the assumption is that double-counting individuals occurs infrequently (Walsh et al. 2011), even small numbers of duplicate counts could greatly influence a population density estimate (Steinhorst and Samuel 1989, Unsworth et al. 1990, McClintock et al. 2010). Levels 2 – 4 data resolutions allowed us to examine the influence of small differences in double-counted

and missed bison on population abundance estimates. As additional data is recorded on double-counted individuals, we will be able to explicitly incorporate the double-counting error process into abundance estimation models, and like sightability, model the error in relation to temporal and spatial covariates such as the time between double-counts and the distance between double-counted animals.

The mean probability of detection ($90 \pm 2\%$) for the Level 1 data resolution across both years of the study was comparable to detection probabilities of other ungulates in open habitats (86% for bighorn sheep [*Ovis canadensis*)] Brodie et al. 1995; 83% for deer [*Odocoileus* spp.] Habib et al. 2012), and identical to the probability previously assumed by UDWR (90%). Reported detection probabilities of bison are high regardless of habitat or season. Individual bison in Yellowstone National Park (YNP) had a 92% detection probability in winter and a 97% detection probability in summer (Hess 2002). The probability of detecting bison using aerial surveys of the Antelope Island arid grasslands (Great Salt Lake, Utah) was also high (94%, Wolf and Kimball 1989).

Group size has been shown to influence sightability in other species (Samuel et al. 1987, Unsworth et al. 1990, Jenkins 2012, Ransom 2012), and Hess (2002) found that bison in large groups (≥ 27) had higher detection probabilities (100%) than solitary bison (89%). However, we did not find a statistically significant relationship between group size and sightability during our two-year study. Bison generally congregate in herds but it is not uncommon to observe small groups or even solitary individuals. Our mean observed group size (38 ± 35) was less than reported for bison in meadow areas (46 ± 36, SD; (Fortin et al. 2009), but the range of group sizes we observed (1 to 108) was similar

to that reported in central Canada (3 to 150, Fortin et al. 2009). If most of the bison are grouped into a few large herds, errors of over-estimation due to large group size could increase bias in population abundance estimates (Walsh et al. 2009). Conversely, small groups have reduced detection probabilities (Rice et al. 2009, Ransom 2012), which can result in a higher proportion of small groups missed and increase errors in abundance estimates if not accounted for (Hess 2002). Over the 2 years of study, we observed seven groups greater than the mean group size and seven groups composed of less than 10 individuals, suggesting the bison in the Henry Mountains congregate equally in large and small groups that may have balanced out any influence of group size on sightability. Alternatively, we simply lack the statistical power to detect an existing relationship between group size and sightability although the estimated relationships were, as expected, positive.

While the visibility class was not a statistically significant covariate in the models, in both survey years the missed groups were determined to be in dense juniper woodlands (low visibility) and shrublands (moderate visibility). The combination of small group size in moderate to dense vegetation cover may have decreased sightability, thereby causing bison to be missed even when they were closer to the helicopter. The interaction between small group size (solitary individuals) and dense cover was demonstrated in moose (*Alces alces*) in Minnesota where detection probabilities were lower than other ungulates (0.48 ± 0.08, SD, range 0.37 to 0.56; Guidice et al. 2012). As additional data is recorded on groups in the low visibility class, we will be able to

evaluate if the interaction of group size and the amount of vegetation influences sightability and thus population abundance estimates.

According to distance sampling theory, detection should decrease as distance between observers and groups increases (Buckland et al. 1993). In some aerial surveys, however, increased distances also allows more time for observers to detect animals in the field of view which can increase detection probabilities (Williams et al. 2002). In our study, missed individuals and groups were, on average, closer to the helicopter than observed groups and sightiability increased with distance. We believe that our measure of distance between the helicopter and a group might be effectively integrating information about 'group size' and 'habitat visibility' in a single parameter. Large groups in open habitats (i.e. grasslands and shrublands) were first detected at longer distances than small groups in closed habitats (i.e. dense woodlands). With addition surveys and larger sample sizes we expect to separate the effects of distance and visibility on sightability and further investigate issues of multicolinearity among distance from the helicopter to a bison group, group size, roughness index, or visibility class.

In addition, most missed groups of bison were small (≤ 10) and were in areas with high roughness indices. Terrain characteristics influenced predicted detection probabilities such that GPS-collared bison in areas with high roughness indices (i.e., steep or variable slopes) had detection probabilities between 30-70% while in areas with few topographical differences (i.e., open grassland or the tops of mesas) detection probabilities were generally 100%. Terrain characteristics similarly influenced bighorn sheep detection probabilities which were reduced on steep slopes and talus areas (65%

probability of detection) compared to flat areas (86%, Brodie et al. 1995). Additionally, rock outcrops, which would be represented by high roughness indices in our study, could directly restrict observer's view of bison during surveys. Our roughness index could be loosely compared to the "terrain obstruction" variable that reduced sightability of mountain goats (*Oreamnos americanus;* Rice et al. 2009) in Washington. Distinguishing animals from their background is essential to detecting animals during aerial surveys (Trivedi et al. 1982, Hess 2002, Laliberte and Ripple 2003) but bison on steep slopes were not as distinct from their background as on flat surfaces, thus reducing the detection probability in areas with high roughness indices.

The Horvitz-Thompson population abundance estimates derived from individual- and group-based sightability models were consistently higher for data resolutions 3-4 when double-counted bison were considered than when double-counted animals were removed from the survey count *C* (Table 5.4). Although the numbers of double-counted animals in a survey may be small relative to the number of counted individuals, incorporating the information will be essential for obtaining more precise abundance estimates. Additional surveys with potentially more locations in low visibility classes and rugged terrain could result in more precise and accurate sightability estimates, which would reduce the high variability in population abundance estimates derived from the current sightability models based on different resolutions of the data.

Management Implications

Programmable GPS collars can potentially increase the accuracy and precision of population abundance estimates by incorporating knowledge of the proportion of double-

counted and missed animals across heterogeneous landscapes and individual behavior characteristics during aerial surveys. The locations from GPS-collared animals can be evaluated to reveal subtle differences, such as considering double-counts across an entire survey or within strata, in successfully determining the number of detected, double-counted, and missed animals. Modeling these subtleties can then assist in determining the sightability for each observation type and predict which locations across the landscape, in conjunction with group size or distance to a group, may have higher probabilities for double-counted and missed animals of the target species. Although we did not incorporate observer covariates (e.g., years of surveyor experience, etc.), in 2012 the primary observer suspected two groups of bison to be double-counted, but no groups were suspected of being double-counted in 2011. By integrating qualitative information on group detections from the observer, as well as spatial and temporal information between each group, abundance estimators could incorporate both sightability and double-counting processes; thereby increasing the accuracy and precision of population abundance estimates. Additional surveys are needed to increase confidence in the proportion of missed and double-counted bison and thus generate a more robust population abundance estimate for bison in the Henry Mountains of south-central Utah in order to guide harvest and translocation management.

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Table 5.1. Habitat classification scheme error matrix for the Henry Mountains study area derived from the National Agricultural Imagery Program (NAIP) imagery.

Habitat	User's Accuracy and Commission error (%)	Producer's Accuracy and Omission error (%)
Alpine	100, 0	40, 60
Desert/grassland/barren	4, 59	77, 23
Low density juniper	22, 78	17, 83
Moderate density juniper	35, 65	25, 75
Shrubland	30, 70	34, 66
Woodlands	96, 4	81, 19

Table 5.2. The top ranking generalized linear models (GLMs) for sightability with a

ΔBIC ≤ 2 for individual GPS-collared bison in the Henry Mountains as a function of a)

physiographic variables (aspect, majority habitat, and roughness index), b) survey

variables (distance between helicopter and a group (Distance), group size, movement at

initial sighting (Y or N), and visibility class), and c) combined models for three levels of

data resolution.

Resolution	Model Type	Model	K	ΔBIC
Level 2	Physiographic	Roughness Index	2	0.0
	Survey	Group Size	2	0.0
	Combined	Roughness Index	2	0.0
Level 3	Physiographic	Roughness Index	2	0.0
	Survey	Distance + Group Size	3	0.0
		Distance	2	0.2
		Distance + Visibility Class	3	1.8
	Combined	Distance + Group Size	3	0.0
		Distance	2	0.2
		Distance + Roughness Index	3	0.8
Level 4	Physiographic	Roughness Index	2	0.0
	Survey	Distance + Movement	3	0.0
	Combined	Distance * Roughness Index	4	0.0
		Distance + Roughness Index	3	0.8
		Distance + Movement	3	1.6

Table 5.3. The top ranking generalized linear models (GLMs) for sightability with a ΔBIC of ≤ 2 for groups of bison in the Henry Mountains as the sample unit (i.e., the groups containing 1 or more individuals with a functioning GPS collar). Sightability was modeled as a function of a) physiographic variables (aspect, majority habitat, and roughness index), b) survey variables (distance between a helicopter and a group (Distance), group size, movement at initial sighting (Y or N), and visibility class), and c) combinations of physiographic and survey variables for three levels of data resolution.

Resolution	Model Type	Model	K	ΔBIC
Level 2	Physiographic	Null	1	0.0
		Roughness Index	2	0.7
	Survey	Null	1	0.0
		Group Size	2	1.5
	Combined	Null	1	0.0
		Roughness Index	2	0.7
		Group Size	2	1.5
Level 3	Physiographic	Null	1	0.0
		Roughness Index	2	0.5
	Survey	Distance	2	0.0
	Combined	Distance	2	0.0
Level 4	Physiographic	Roughness Index	2	0.0
		Null	1	0.4
	Survey	Movement + Distance	3	0.0
	Combined	Movement + Distance	3	0.0
		Movement + Distance + Roughness Index	4	0.4

Table 5.4. Horvitz-Thompson (HT) population abundance estimates of bison based on individual sightability models in the Henry Mountains for four levels of data resolution (see Table 5.3) in 2011 and 2012 with double-counts considered and without double-counts considered (lower and upper 95% confidence limits provided). Level 1 estimates in 2011 are based on the number of white-belted collars counted relative to the number of white-belted collared bison in the study area and in 2012 are based on the number of double-collared bison counted relative to the number of double-collared bison in the study area, not on a sightability model as for Levels 2-4.

Year	Bison survey count	Data Resolution	HT density estimate with double-counts included	HT density estimate without double-counts included
2011	372	Level 1	410 (371, 449)	385 (348, 422)
		Level 2	377 (371, 378)	373 (371, 379)
		Level 3	395 (392, 400)	391 (392, 400)
		Level 4	381 (380, 387)	352 (351, 352)
2012	505	Level 1	571 (509, 633)	548 (488, 607)
		Level 2	530 (514, 553)	529 (515, 553)
		Level 3	515 (511, 520)	512 (510, 521)
		Level 4	526 (519, 532)	496 (492, 505)

Figure 5.1. The Henry Mountain helicopter survey strata designations for 2011 and 2012. The square in the center of the image represents the helicopter landing zone and refueling area.
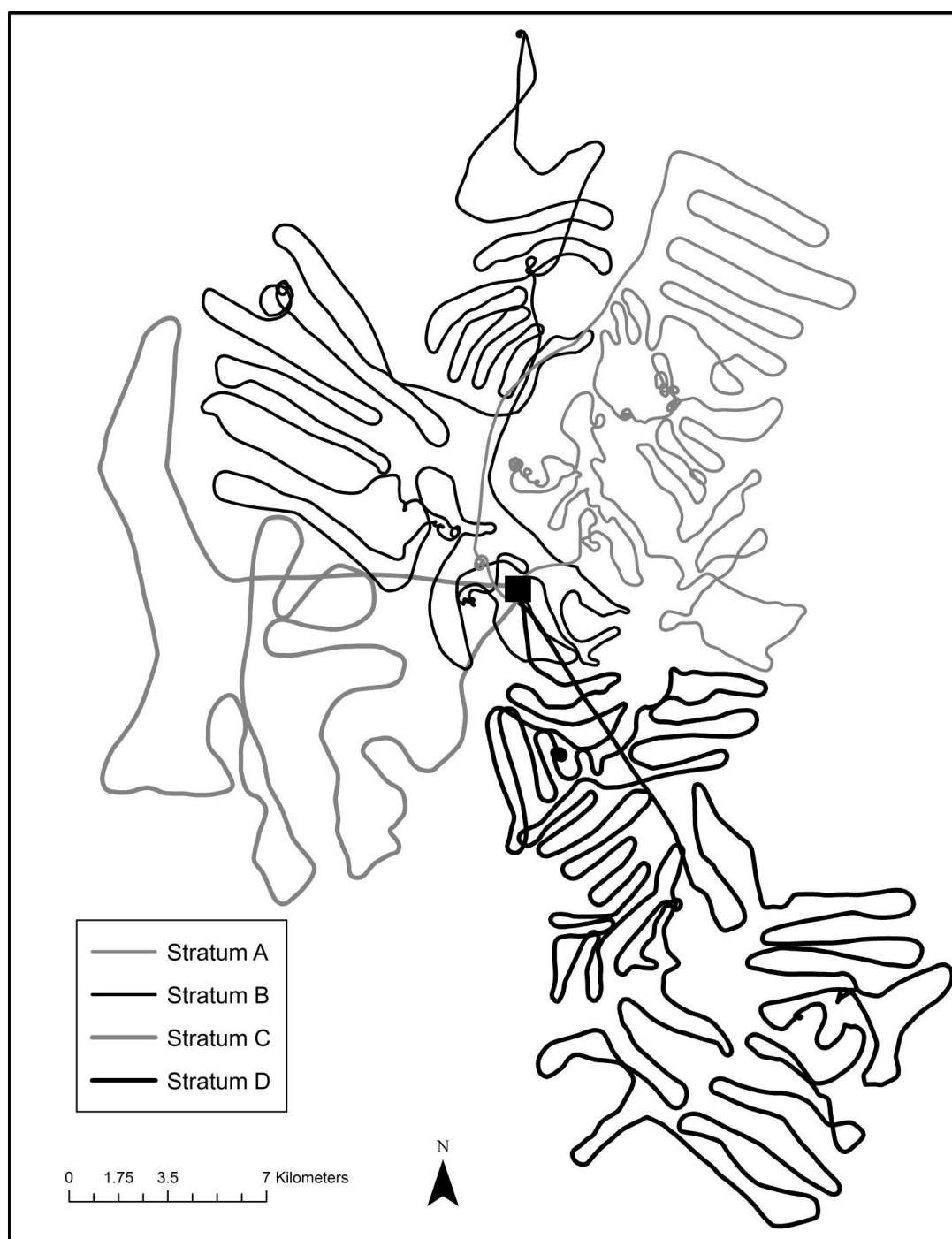
Figure 5.2. Temporal and spatial intersection of a helicopter flight path (solid line) with bison 30401 travel path (stippled line). The circular path of the helicopter indicates the observation crew was counting bison at this location.
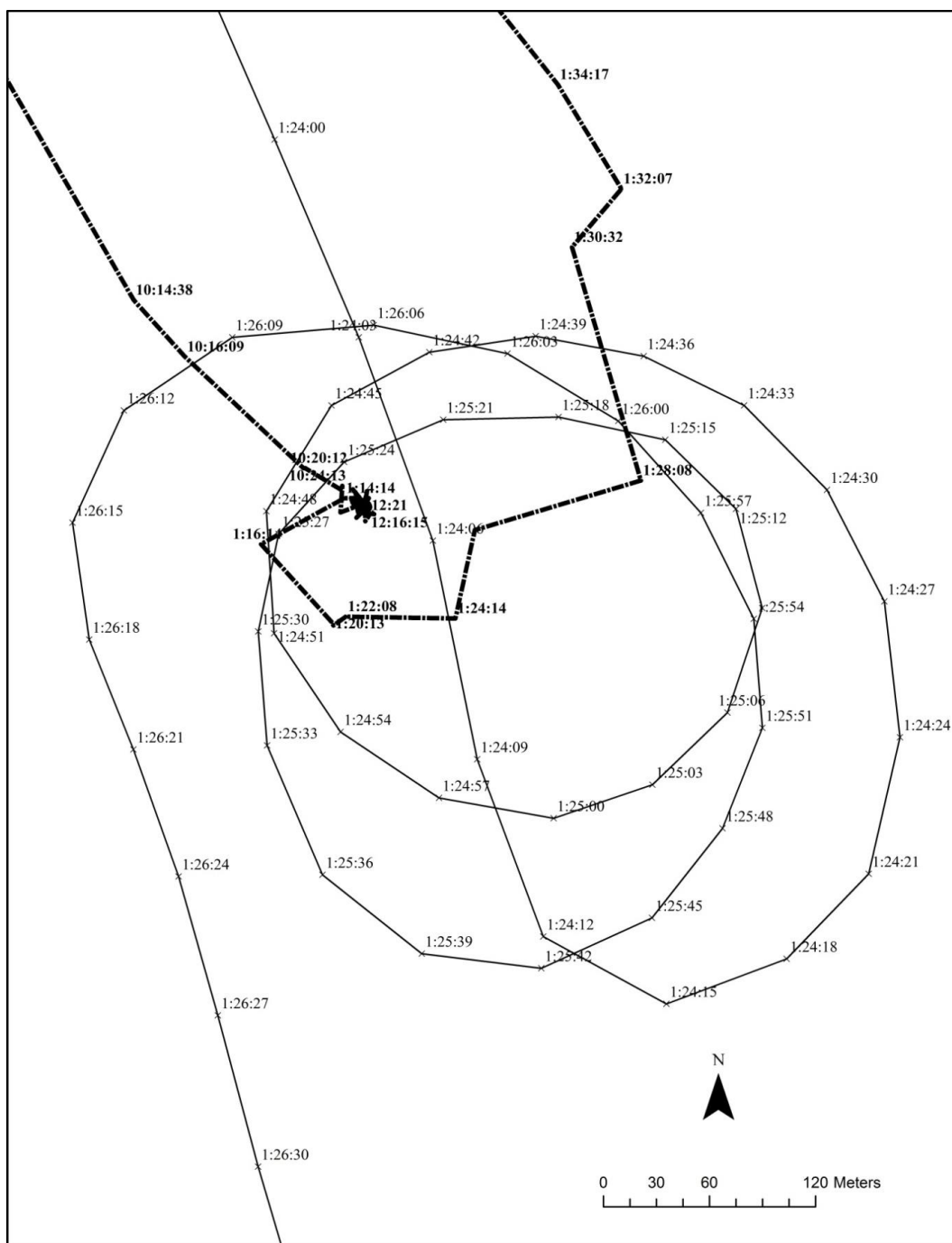
Figure 5.3. Temporal and spatial intersection of bison 30401 travel path (heavy stippled line) and a helicopter flight path (solid line) indicating a miss (non-detection) at 8:05. The light stippled line measured the distance between the interpolated bison location at 8:05 and the helicopter flight line at a 90˚ angle.
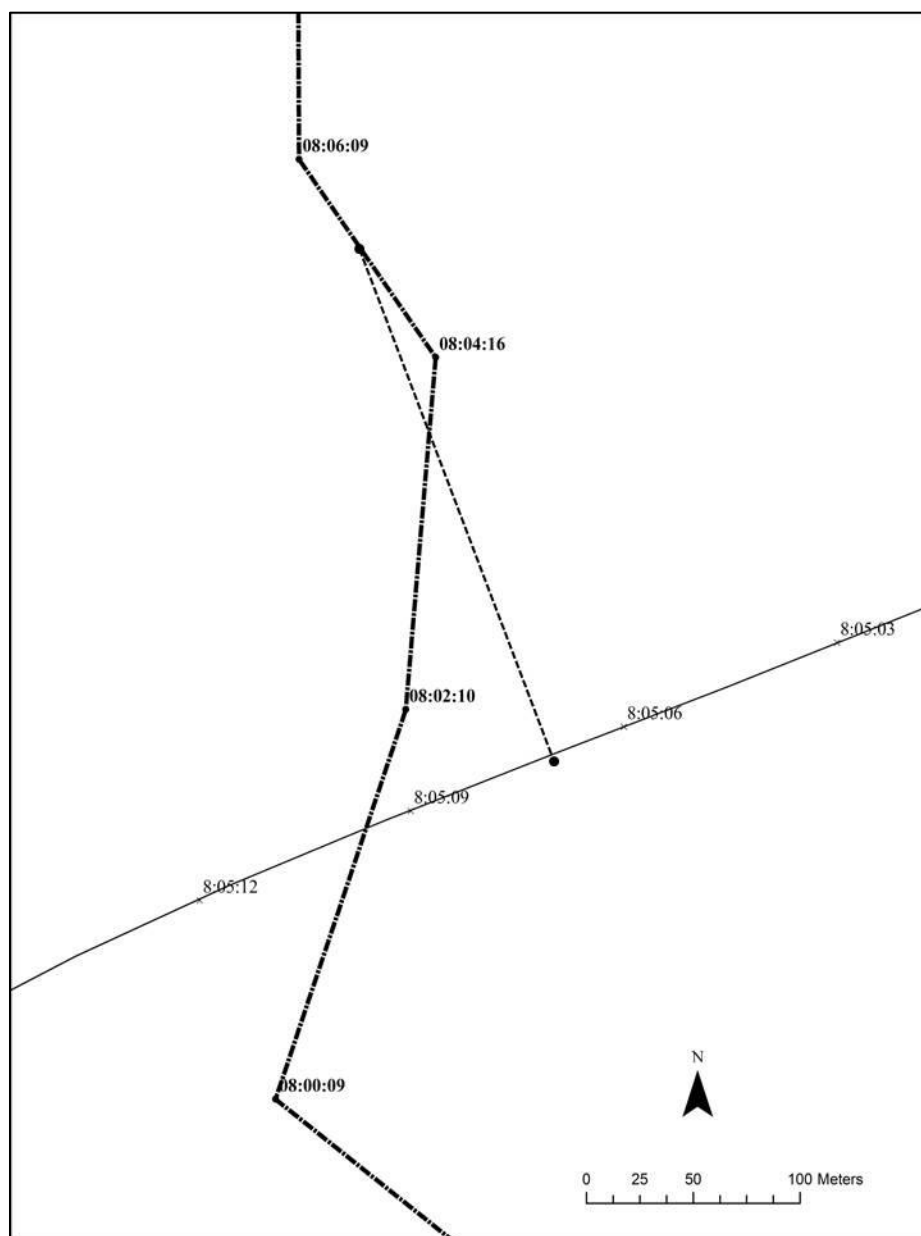
Figure 5.4. Linear regression ($R^2 = 0.70$, $P < 0.05$) of group size against number of observed GPS collared bison with consideration of visibility class of the utilized habitat (low visibility: dense tree cover; moderate visibility: a mixture of trees, shrubs, and grasses; and high visibility: open grasslands and low-density shrub-lands).
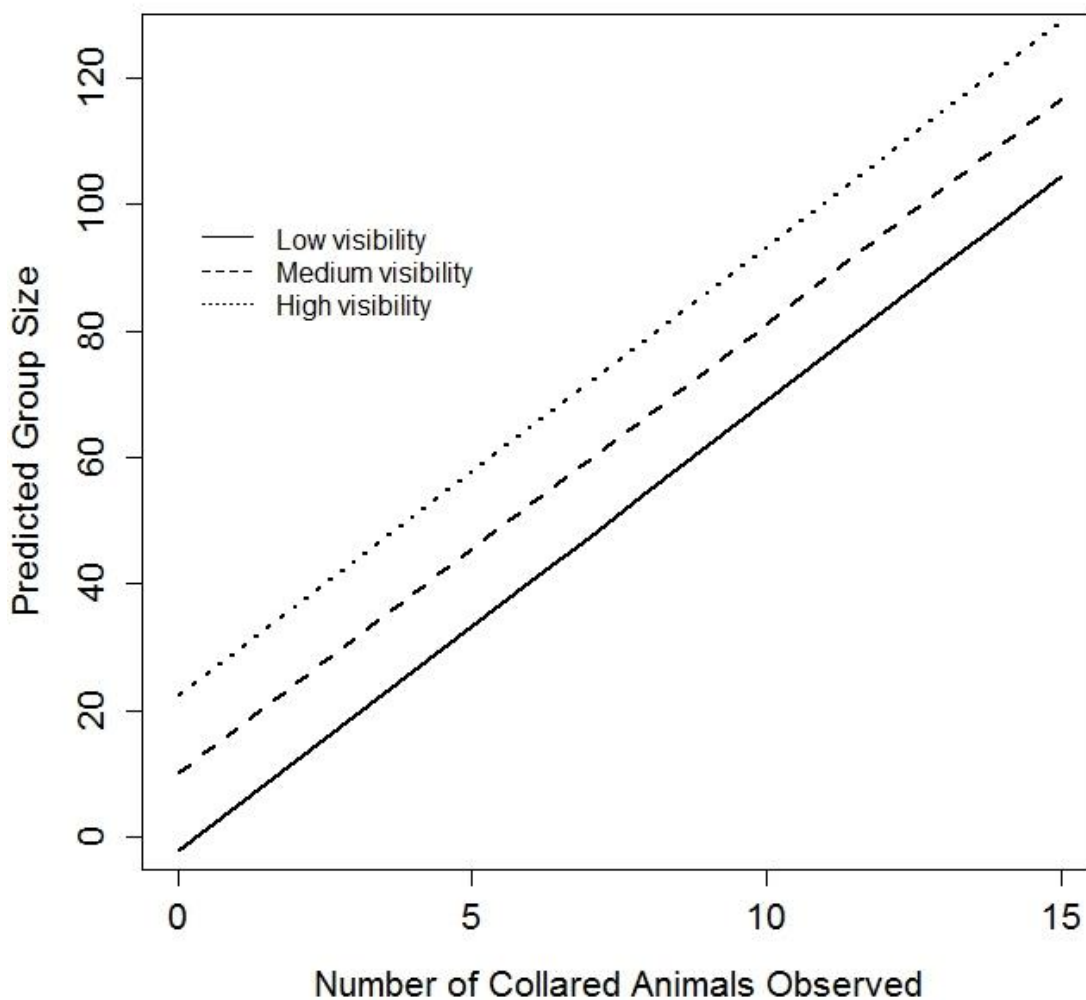
Appendix A. Statistics for generalized linear models (GLMs) for sightability with a ΔBIC ≤ 2 for individual GPS-collared bison in the Henry Mountains as a function of a) physiographic variables (aspect, majority habitat, and roughness index), b) survey variables (distance between helicopter and a group (Distance), group size, movement at initial sighting (Y or N), and visibility class), and c) combined models for three levels of data resolution.

| Resolution	Model Type	Model	ΔBIC	K	Intercept	SE	P	Variable	Beta	SE	P
Level 2	Physiographic	Roughness Index	0.0	2	6.26	2.09	0.00	Roughness Index	-10.75	4.86	0.03
	Survey	Group Size	0.0	2	0.14	1.09	0.90	Group Size	0.07	0.04	0.06
	Combined	Roughness Index	0.0	2	6.26	2.09	0.00	Roughness Index	-10.75	4.86	0.03
Level 3	Physiographic	Roughness Index	0.0	2	5.28	1.46	0.00	Roughness Index	-9.56	3.68	0.01
	Survey	Distance + Group Size	0.0	3	-6.98	6.06	0.25	Distance	0.02	0.01	0.16
								Group Size	0.16	0.17	0.35
		Distance	0.2	2	-2.80	1.62	0.08	Distance	0.01	0.01	0.01
		Distance + Visibility Class	1.8	3	-5.34	2.70	0.05	Distance	0.02	0.01	0.02
								Visibility Class	2.32	1.58	0.14
	Combined	Distance + Group Size	0.0	3	-6.98	6.06	0.25	Distance	0.02	0.01	0.16
								Group Size	0.16	0.17	0.35
		Distance	0.2	2	-2.80	1.62	0.08	Distance	0.01	0.01	0.01
		Distance + Roughness Index	0.8	3	-0.16	2.23	0.94	Distance	0.01	0.01	0.02
								Roughness Index	-8.09	4.62	0.08
Level 4	Physiographic	Roughness Index	0.0	2	6.56	1.75	0.00	Roughness Index	-14.82	4.11	0.00
	Survey	Distance + Movement	0.0	3	-11.79	3.70	0.00	Distance	0.03	0.01	0.00
								Movement	4.90	2.12	0.02
	Combined	Distance * Roughness Index	0.0	4	7.07	2.52	0.01	Distance	0.00	0.00	0.16
								Roughness Index	-40.59	14.42	0.00
								Distance * Roughness Index	0.08	0.03	0.01
		Distance + Roughness Index	0.8	3	-0.89	2.25	0.69	Distance	0.02	0.01	0.00
								Roughness Index	-12.53	4.96	0.01
		Distance + Movement	1.6	3	-11.79	3.70	0.00	Distance	0.03	0.01	0.00
								Movement	4.90	2.12	0.02

Appendix B. Statistics for generalized linear models (GLMs) for sightability with a ΔBIC ≤ 2 for groups containing at least one GPS-collared bison in the Henry Mountains as a function of a) physiographic variables (aspect, majority habitat, and roughness index), b) survey variables (distance between helicopter and a group (Distance), group size, movement at initial sighting (Y or N), and visibility class), and c) combined models for three levels of data resolution.

Resolution	Model Type	Model	ΔBIC	K	Intercept	SE	*P*	Variable	Beta	SE	*P*
Level 2	Physiographic	Null	0.0	1	2.08	0.75	0.01				
		Roughness Index	0.7	2	4.37	2.24	0.05	Roughness Index	-6.60	5.05	0.19
	Survey	Null	0.0	1	2.08	0.75	0.01				
		Group Size	1.5	2	0.98	1.13	0.39	Group Size	0.03	0.04	0.35
	Combined	Null	0.0	1	2.08	0.75	0.01				
		Roughness Index	0.7	2	4.37	2.24	0.05	Roughness Index	-6.60	5.05	0.19
		Group Size	1.5	2	0.98	1.13	0.39	Group Size	0.03	0.04	0.35
Level 3	Physiographic	Null	0.0	1	1.50	0.55	0.01				
		Roughness Index	0.5	2	3.28	1.49	0.03	Roughness Index	-5.49	3.73	0.14
	Survey	Distance	0.0	2	-3.79	2.60	0.15	Distance	0.01	0.01	0.06
	Combined	Distance	0.0	2	-3.79	2.60	0.15	Distance	0.01	0.01	0.06
Level 4	Physiographic	Roughness Index	0.0	2	3.45	1.53	0.02	Roughness Index	-6.26	3.76	0.10
		Null	0.4	1	1.34	0.50	0.01				
	Survey	Movement + Distance	0.0	3	-7.87	4.52	0.08	Movement	3.75	1.96	0.06
								Distance	0.02	0.01	0.09
	Combined	Movement +Distance	0.0	3	-7.87	4.52	0.08	Movement	3.75	1.96	0.06
								Distance	0.02	0.01	0.09
		Movement + Distance +Roughness Index	0.4	4	-16.10	19.31	0.40	Distance	0.06	0.08	0.41
								Movement	9.84	11.40	0.39
								Roughness Index	-26.70	34.58	0.44

CHAPTER 6

SUMMARY

This dissertation examined multiple methods of processing pixel based, remotely sensed imagery to identify and count large mammals and determine the corresponding probability of detection. Chapters 2-4 evaluated methodological techniques to automate the identification and enumeration of animals in remotely sensed imagery. The fifth chapter examined the probability of detecting bison in the Henry Mountains of south-central Utah while considering known occurrences of double-counted and missed animals.

Chapter 2 determined that there were empirical differences in spectral values between cattle (Bos Taurus), elk (*Cervus elephus*), and horses (*Equus caballus*). Although signature patterns from in-situ spectral measurement were similar, cattle, elk, and horses are uniquely identifiable in the visible and NIR regions of the electromagnetic spectrum. An important issue in discerning animals in remotely sensed imagery is distinguishing between the spectral signatures of animals and that of the surrounding vegetation. The spectral patterns of cattle, elk, and horses can be separated from vegetation most effectively in the "red shift" region of the electromagnetic spectrum that is used specifically for estimating vegetation biomass (Mutanga and Skidmore, 2007). Reflectance values of animals in the three spectral bands we studied showed that animals are generally much darker (lower reflectance values) than the surrounding environment. This distinct reflectance allowed us to separate individual animals from the surrounding environment with the exception of other features with similar spectral responses.

Therefore, errors of omission tended to be low (few animals missed), but errors of

commission (classifying a feature as animals when it was not) were very large.

Chapter 3 explored multiple techniques to identify animals in remotely sensed

imagery. Manual counting of animals in aerial photographs has been commonly used as a

wildlife census technique (Erwin, 1982; Fretwell *et al.*, 2012; Gilmer *et al.*, 1988; Harris

and Lloyd, 1977; Hiby *et al.*, 1988; Koski *et al.*, 2010; Lubow and Ransom, 2009;

Russell *et al.*, 1994). We tested this technique utilizing three categories of photo-

interpreters. There were few errors of under-counting (not counting animals when they

were known to be present) or over-counting (features incorrectly identified as animals)

and all three groups of interpreters were able to discriminate between non-animal and

animal features. Manual interpreters were able to integrate qualitative information

derived from spectral and shape characteristics in a comparative process to distinguish

non-animal from animal features (Baraldi and Boschetti, 2012; Russ, 1999). In an attempt

to emulate the human ability to integrate multiple dimensions of contextual information,

we explored techniques that integrated spatial and spectral information to isolate animal

features in remotely sensed imagery.

Employing conventional remote sensing techniques, an unsupervised ISODATA

classified image (Jensen, 2005) subtracted from a simulated background image was used

to highlight differences in areas containing animals compared to differences in areas

without animals. Although the mean probability of detection was high (82% ± SD, 10%)

the probability of under-counting animals was relatively low (18% ± 18%) and the

probability of over-counting was high (69% ± 27%). If animals were present in an image,

the ISODATA classification image, subtracted from a background image, correctly identified the animals but greatly over-estimated numbers.

Additional information was needed to reduce over-counting errors while maintaining low under-counting errors. A multi-dimensional technique attempted to reduce over-counting errors by integrating texture images, principal components analysis, heuristic thresholding, and image subtraction. The first principal component provided the highest amount of spectral information (i.e., the most variation) and was the basis for a multi-image, multi-step (MIMS) technique. Contrary to the ISODATA–background image subtraction technique, the MIMS errors of under-counting were high (50% ± 26%) but like the ISODATA technique, errors of over-counting also were high (72% ± 26%).

Chapter 4 employed same-day image differencing to identify animals in remotely sensed imagery. This technique assumed that images collected a few hours apart would capture animal movement which could be used to separate animals from their non-moving background through image differencing. This technique resulted in an 82% probability of detecting an animal. As with the ISODATA and background image subtraction technique, under-counting errors were low (18%) and over-counting errors were moderate (53%). Although thresholding the differenced image eliminated some non-animal features, over-counting animals was a result of slight misregistration errors. Image differencing at high spatial resolution requires precise image registration with minimal misalignments that were interpreted as animal features.

Although image differencing can be used as a new method to estimate population abundances of wildlife species, certain precautions should be addressed prior to applying

this technique for estimating animal population sizes. First, the method over-estimated

population sizes. Second, heuristically identifying spectral thresholds may not be without

bias. Third, image differencing requires precise image registration to avoid spurious areas

of change that can result in large numbers of incorrectly mapped polygons. Fourth,

enough time must pass for animal movement to occur between image acquisitions. Fifth,

the non-animal portions of the image (i.e., the background) should be as homogenous as

possible to enhance differentiation between animals and their background.

The advantages of airborne or satellite imagery to count animals include reduced

survey time, a permanent record of the survey, and potentially less expensive than

conventional wildlife surveys. Conventional aerial wildlife surveys frequently require

multiple days to complete thus allowing animals to move throughout the study area and

increase the probability of double-counting or missing individuals. While it would require

a significant number of days to acquire remotely sensed imagery of large areas, such as

the Mongolian steppe or the western desert of Utah, conventional wildlife aerial surveys

are prohibitively expensive due to aircraft cost and personnel time. The reduction in time

required to acquire remotely sensed imagery of a large study area could facilitate

counting of animals in areas previously too large or too isolated to survey. Automated

image analysis has an additional advantage of reduced subjectivity within a technique and

across analysts. The permanent, unchanging record of animal locations for an instant in

time i.e. 'a survey', allows for repeated assessments using the same or different

techniques. Although automated analysis techniques are desirable and feasible in some

instances (Davies *et al.*, 2010), it may come at the expense of accuracy (Baraldi and

Boschetti, 2012) or may require various amounts of human input and guidance (Evans *et al.*, 2012; Skelsey *et al*., 2004).

Semi-automated counts of wildlife and the subsequent estimates of population size using remotely sensed imagery could revolutionize how ungulate counts are conducted and be a beneficial tool in management decisions. This method not only has the potential to improve accuracy and precision of counts and thus estimates of population size, it could aid in tracking grazing patterns of wild and domestic animals across large natural systems.

Chapter 5 extended the analysis of remotely sensed imagery to wildlife enumeration and examined the probability of detection for GPS-collared bison with sightability models that included variables derived from remotely sensed imagery. The Utah Division of Wildlife Resources conducts annual bison surveys to estimate bison abundance in the Henry Mountains of south-central Utah. Incorporating physiographic features such as surface roughness into sightability models has the potential to improve detection probabilities of animals and thus generate more robust population abundance estimates. Variables that were examined included group size, vegetation cover and type, and terrain characteristics (Giudice *et al.*, 2012; Ransom, 2012; Rice *et al*., 2009; Samuel and Pollock, 1981; Samuel *et al*., 1987). Group size and visibility were assessed during the annual survey while vegetation type was determined from a supervised classification of remotely sensed imagery and terrain characteristics derived from a digital elevation model. Although counts of missed animals are possible to detect (Duchamp *et al.*, 2006; Jackmann, 2002; Potvin *et al.*, 2004; Samuel *et al.*, 1987; White *et al.*, 1989), very little

information is available on double-counting animals during wildlife censuses. Detected, missed, and double-counted bison were identified by intersecting helicopter paths with GPS-collared bison travel paths during the surveys. This is the first instance of incorporating confirmed double-counted and missed bison errors into the probability of detection and subsequent sightability models. The 90% average probability of detecting GPS-collared bison between 2011 and 2012 was comparable to other reported detection probabilities of bison (Wolfe and Kimball, 1989; Hess, 2002). When double-counted and missed bison were included, the probability of detection ranged from 88% to 109% depending on how the double–counted and missed bison were tallied. Sightability models that best fit the data included two survey variables (group size and distance between the helicopter and a detected bison group) and one physiographic variable (roughness). Sightability decreased for bison in smaller groups, in dense vegetative cover, and in areas with high topographical variability (i.e., a high roughness index). Missed groups were closer to the helicopter, in smaller groups and with low to moderately visibility, and in areas with a higher roughness index than detected groups.

As additional data is acquired from future surveys, sightability models will be developed specifically for double-counted bison that incorporate current physiographic and survey variables in addition to temporal and spatial covariates such as time and distance between the first and second counts.

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APPENDICES

Appendices

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VITA

Pat Terletzky

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EDUCATION

- **Ph.D Candidate**, Utah State University, Wildland Resources and Ecology Center, "Utilizing remote sensing and geospatial techniques to determine detection probabilities of large mammals", 2006 – Present
- **Master of Science**, University of Texas – San Antonio, Biology Department, s: "Hillside cedar glades and microglades of the southern Edwards Plateau of central Texas", 1993 – 1995
- **Bachelor of Science**, University of Wisconsin, Wildlife Ecology, 1985 – 1989
- **Undeclared**, University of Michigan – Dearborn, 1984 – 1985

GIS/REMOTE SENSING/DATABASE SKILLS

- **Proficient** with: ArcGIS, Erdas Imagine, Microsoft Office
- **Experienced** with: R, Fragstats, QGIS, Visual Basic
- **Managed and maintained** a large spatially explicit database of over 43 GPS collared bison locations

FIELD SKILLS

- **Determined herd composition** of the Henry Mountain bison herd in south-central Utah, 2012 – 2013
- **Highly experienced with radio-telemetry** on bighorn sheep, bison, coyotes, pronghorn antelope, seabirds, and white tail deer, 1986 – 2013
- **Conducted avian surveys** in the desert of western Utah, 1996 – 1997
- **Highly experienced with behavioral** observations of bighorn sheep, coyotes, and pronghorn antelope, 1986 – 1990
- **Conducted vegetation studies** in the Texas Hill Country, Texas and Yellowstone National Park, Wyoming, 1992 – 1993

- **Recorded nesting success** of sea birds in Maryland, 1987
- **Captured, trapped, handled, and processed** coyote adults and pups in south-eastern Colorado and Yellowstone National Park, Wyoming, 1986, 1992

GIS TRAINING

- Object Oriented **Image Classification**, 2012
- Introduction to **R** programming, 2011
- Customizing **ArcIMS** with HTML/Java Script, 2004
- Learning **ArcIMS,** 2004
- Maintaining **SDSFIE** Data Using ArcGIS, 2003
- **Avenue programming** – ArcView 3.x, 1997-2002
- Introductory and Intermediate **Visual Basic** 6 Programming, 2001
- Introduction to Programming **ArcObjects** with VBA, 2001

PROFESSIONAL EXPERIENCE

- Utah National Guard **GIS Manager**. Implemented new GIS directives, 2003 – 2007
- **GIS Research Technician** III (USGS/Utah Cooperative Fish and Wildlife Research Unit), Wrote programs for Forest Inventory Analysis Programs, 2002 – 2003
- **GIS Research Technician** (RS/GIS Labs, Utah State University), Wrote GIS analysis programs for Utah National Guard, 1997 – 2002

PUBLICATIONS

- Guttery, M. R., D. K. Dahlgren, T. A. Messmer, J. W. Connelly, K. P. Reese, **P. A. Terletzky**, and D. N. Koons. PLoS ONE (accepted). Effects of landscape-scale environmental variation on greater sage-grouse chick survival.
- **Terletzky, P**., R. D. Ramsey, and C. M. U. Neale. 2012. Spectral Characteristics of Domestic and Wild Mammals. GIScience. 49(4):597-608.
- D. N. Koons, P**. Terletzky**, P. B. Alder, M. L. Wolfe, D. Ranglack, F. P. Howe, K. Hersey, W. Paskett, and J. T. DuToit. 2012. Climate and density-dependent drivers of recruitment in plains bison. Journal of Mammalogy. 93(2):475-481.
- Young, J. K., W. F. Andelt, **P. A. Terletzky**, and J. A. Shivik. 2006. A comparison of coyote ecology after 25 years: 1978 versus 2003. Canadian Journal of Zoology 84(4):573-582.
- **Terletzky, P.;** Frescino, T.S. 2004. Integrating spatial components into FIA models of forest resources: some technical features. In: McRoberts, R.E.; *et al.,* eds. Proceedings, 4th annual forest inventory analysis symposium; 2002 November 19–21; New Orleans, LA. Gen. Tech. Rep. NC-252. St. Paul, MN: U.S. Department of Agriculture, Forest Service, North Central Research Station.

- **Terletzky, P. A**. and O. W. VanAuken. 1996. Comparison of cedar glades and associated woodlands of the southern Edwards Plateau. Texas Journal of Science 48 (1):55-67.

PRESENTATIONS

- **Terletzky, P**. and R. D. Ramsey. 2012. Spectral Characteristics of Domestic and Wild Mammals. American Society for Photogrammetry and Remote Sensing annual meeting, March 2012, Sacramento.
- Koons, D.N., **P. Terletzky**, P.B. Adler, M.L. Wolfe, D. Ranglack, F.P. Howe, K. Hersey, W. Paskett, J.T. du Toit. 2012. Climate and density-dependent drivers of reproductive success in plains bison. Utah Chapter, The Wildlife Society annual meeting.
- **Terletzky, P**. and D. Koons. 2012. Henry Mountain Bison Sightability. A poster presentation at the Annual Cooperative Research Unit Coordinating Meeting, Logan, Utah.
- **Terletzky, P.,** R. D. Ramsey, and D. Koons. 2011. Assessment of a new survey technique for bison in grassland habitats. Poster presentation at the American Bison Society Meeting, Tulsa, Oklahoma.
- **Terletzky, P.** and R. D. Ramsey. 2008. Using temporal differences to detect livestock in aerial imagery. 12th Biennial USDA Forest Service Remote Sensing Applications Conference, Salt Lake City, Utah.
- **Terletzky, P**. and E. Gese. 2009. Estimating coyote numbers across Wyoming, USA. Poster presentation at the 11th International Mammalogical Conference, Mendoza, Argentina.
- **Terletzky, P**., A. S. Chavez, and E. M. Gese. 2005. Simulation of wolf movements in an agriculture-wildland interface in northwestern Minnesota. Poster presentation at the 9th International Mammalogical Conference, Sapporo, Japan.
- Shultz, L. M., R. D. Ramsey, and **P. Terletzky**. 2004. Determining patterns of biodiversity from the Atlas of Vascular Plants of Utah. Botany Conference, Snowbird, Utah.
- **Terletzky, P.** and T.Frescino. 2002. Integrating Spatial Components into FIA models of Forest Resources: Some Technical Features. Forest and Inventory and Analysis Conference, New Orleans.
- Shultz, L., R.D. Ramsey, and **P. Terletzky**. 2000. Using an atlas of vascular plants to determine patterns of biodiversity in Utah. Poster presentation at the Ecological Society of America meetings 2000, in Snowbird Utah.

- Patraw, K., P**. Terletzky**, and D. Ramsey. 1998. Using ArcVeiw 3.0, the Spatial Analyst Extension, and Avenue to conduct a kriging process on ecological data. 1998 ESRI International User Conference, San Diego.
- Patraw, K., **P. Terletzky**, T. VanNiel, A. Falconer, and J. Crane. 1998. Environmental Spatial Analysis and Statistics Package Programmed in Avenue. 1998 ESRI International User Conference, San Diego.
- **Terletzky, P**. 1995. Cedar glades in the southern part of the Edwards Plateau of Texas. American Botanical Meetings, Seattle.
- **Terletzky, P**. 1995. Microglades of the southern part of the Edwards Plateau. Eighth Annual Meeting of the Texas Academy of Sciences, Waco, Texas.

PRESENTATIONS CONTINUED

- **Terletzky, P**. 1994. Comparison of cedar glades and associated woodlands in the southern Edwards Plateau of Texas. Seventh Meeting of the Texas Academy of Sciences, Houston, Texas.

SCHOLARSHIPS AND GRANTS

- Improved monitoring for management of the Henry Mountains Bison herd. D. N. Koons, F. P. Howe, P. Terletzky and J. du Toit, **$330,286**, Utah Department of Wildlife Resources, USFWS, and BLM, 2011 – 2014
- Research Support Award, **$4,000,** Ecology Center, Utah State University, 2008
- Graduate Student Competitive Research Support Grants, **$24,400**, Intermountain Region Digital Image Archive Center, 2007
- Research Support Award, **$3,000**, Ecology Center, Utah State University, 2007
- Stipend Award, **$6,500**, Ecology Center, Utah State University, 2007
- Travel grants to attend conference: College of Natural Resources, Ecology Center, Graduate Student Senate, Wildland Department, **$1,600**, 2012
- Travel grants to attend conference: Wildland Department; College of Natural Resources, Graduate Student Senate, **$1,000**, 2009

TEACHING EXPERIENCE

- Teaching Assistant for Wildland Ecosystems (WILD 3800), Utah State University, 2012
- Geographic Information Analysis (AWER 3700). Utah State University, Logan, Utah, 2005
- Introductory ArcGIS (co-taught). Utah State University, Logan, Utah, 2004

- Authorized ESRI ArcView Spatial Analyst Instructor, 2002-2003
- Programming Basics with Visual Basic as an example. Southwestern ESRI Users Conference. Moab Utah, 2000
- Database Management. National Guard Bureau Five Day Instructor Course. Draper, Utah, 1999
- GIS for BLM Managers. Logan, Utah, 1999
- Advanced ArcView. National Guard Bureau Five Day Course. Logan, Utah, 1998
- Teaching Assistant for General Ecology, University of Texas – San Antonio, 1993 – 1995
- Taught environmental education to elementary and high school students and adults at The Wolf Ridge residential nature center in Minnesota, 1989 – 1990

PROFESSIONAL AFFILIATIONS

- Member of American Society for Photogrammetry and Remote Sensing, 2008 – Present

COMMUNITY SERVICE

- Board member of local domestic violence shelter, CAPSA, 2004 – Present
- CAPSA liaison to local non-profit thrift store, Somebody's Attic, 2008 – 2013
- Board President of CAPSA, 2007 – 2008
- Board chair of modern dance company, Valley Dance Ensemble, 2003 – 2005