2015-03-01

Rangeland Monitoring Using Remote Sensing: An Assessment of Vegetation Cover Comparing Field-Based Sampling and Image Analysis Techniques

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Rangeland Monitoring Using Remote Sensing: An Assessment of Vegetation Cover

Comparing Field-Based Sampling and Image Analysis Techniques

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A thesis submitted to the faculty of
Brigham Young University
in partial fulfillment of the requirements for the degree of

Master of Science

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March 2015

ABSTRACT

Rangeland Monitoring Using Remote Sensing: An Assessment of Vegetation Cover Comparing Field-Based Sampling and Image Analysis Techniques

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Rangeland monitoring is used by land managers for assessing multiple-use management practices on western rangelands. Managers benefit from improved monitoring methods that provide rapid, accurate, cost-effective, and robust measures of rangeland health and ecological trend. In this study, we used a supervised classification image analysis approach to estimate plant cover and bare ground by functional group that can be used to monitor and assess rangeland structure. High-resolution color infrared imagery taken of 40 research plots was acquired with a UltraCam X (UCX) digital camera during summer 2011. Ground estimates of cover were simultaneously collected by the Utah Division of Wildlife Resources' Range Trend Project field crew within these same areas. Image analysis was conducted using supervised classification to determine percent cover from Red, Green, Blue and infrared images. Classification accuracy and mean difference between cover estimates from remote sensed imagery and those obtained from the ground were compared using an accuracy assessment with Kappa statistic and a t-test analysis, respectively. Percent cover estimates from remote sensing ranged from underestimating the surface class (rock, pavement, and bare ground) by 27% to overestimating shrubs by less than 1% when compared to field-based measurements. Overall accuracy of the supervised classification was 91% with a kappa statistic of 0.88. The highest accuracy was observed when classifying surface values (bare ground, rock) which had a user's and producer's accuracy of 92% and 93%, respectively. Although surface cover varied significantly from field-based estimates, plant cover varied only slightly, giving managers an option to assess plant cover effectively and efficiently on greater temporal and spatial extents.

Keywords: aerial imagery, cover, rangeland, rangeland monitoring, remote sensing, supervised classification, Utah Division of Wildlife Resources

ACKNOWLEDGEMENTS

I would like to express my deepest gratitude for all those who helped me in completing my project and thesis. I am very grateful to Dr. Steven Petersen for his never ending words of encouragement and patience in seeing that I make it through to the end. I am grateful for his time, feedback, and guidance while leading me down this path we call a “Master’s degree.” I am grateful to the Utah Division of Wildlife Resources for funding and field support given for this project. I am especially thankful to Jason Vernon, Danny Summers, Kevin Gunnell, and Jason Cox for providing data and technical assistance which helped me finish this project. I would like to thank Dr. Bruce Roundy and Dr. Ryan Jensen for being on my committee and for the input, feedback, and ideas that were given. Most important, I want to express by deepest love, gratitude and appreciation for my wife Christa, my kids Evelyn and Norah, my cousin Jesse and my parents James and Vicki in pushing me to finish what I’ve started. Truly without the help of my family (those mentioned and unmentioned) I would not have been able to complete such a great task.

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INTRODUCTION

Rangeland monitoring is employed by rangeland managers to quantify, evaluate, and monitor semi-arid plant communities throughout the West, particularly where multiple-use land management practices require adaptive management strategies. By definition, rangeland monitoring is the gathering of basic ecological information that describes rangeland attributes using systematic and repeatable methods (Schalau, 2010). An understanding of rangeland attributes can be used to better understand range condition or the current state of rangeland health and trend (Holechek et al., 2004). Information derived from rangeland monitoring can be used to track the progress of range improvement projects, to determine the efficacy of particular management practices, and to assess seed germination and establishment that leads to greater forage production and higher plant biodiversity (Godinez-Alvarez et al., 2009; NRC, 2000). Rangeland trend and monitoring can be used to characterize ecological succession, in particular states and transitions within a state-and-transition conceptual framework, identify potential impacts from invasive species, assess potential impacts from fire and changes in fire regimes, and characterize ecological resilience following disturbance (Miller and Tausch, 2001, Stringham et al. 2003; Herrick et al., 2002).

Of the vegetation attributes measured using rangeland monitoring practices, the most meaningful, adequate, and economically efficient are percent canopy (ground) cover and percent bare ground (Booth and Tueller, 2003; Booth et al., 2008). The primary reason that cover plays such an important role in rangeland monitoring are that these attributes have a direct relationship to plant community resilience, soil stability, and soil conservation (NRC, 1994; Society for Range Management, Task Group on Unity in Concepts and Terminology, 1995). Fox et al. (1997) showed that raindrop impact on bare ground can dislodge soil particles which can transform the soil surface and reduce infiltration. Briske et al. (2008) suggested that intact plant communities with cover of desired species increases ecological resilience and resistance to natural and human-related disturbance. Therefore, ground cover by vegetation and litter, and its inverse of bare ground become important attributes in assessing hydrologic function and need for soil conservation practices, and is a good indicator of dominance and relative resource use in a community (Pierson et al. 2002).

In the state of Utah, the Division of Wildlife Resources' (UDWR) Big Game Range Trend Study Program was established during the early 1980s to monitor, evaluate, and report range trend at key areas throughout the state. The UDWR selects these sites primarily based on areas of critical winter (and in some cases spring and or summer) range for deer (*Odocoileus hemionus*) and elk (*Cervus canadensis*) (Gunnell et al., 2011). These data are intended to provide biologists, land managers, and private landowners with data describing significant changes in plant community composition, for assessing project success and vegetation response to range treatments, and for monitoring ecological succession following treatment (Gunnell et al., 2011). Each year UDWR field crews collect range inventory data in one of five regions to determine range condition and trend for those sites. Using this approach, each site is scheduled to be monitored every five years. Intervals greater than this can result in gaps, which make the data unreliable for assessing change or response to treatment (Holechek et al., 2004). Because the UDWR has an archive of each site dating back to the beginning of the project, these data can be used to compare range conditions every five years for identifying current condition and trend (i.e. upward, downward, stable; Gunnell et al., 2011). These data can then be used to assist wildlife biologists and land managers in habitat improvement planning, and reviewing BLM and USFS allotment management plans. These data are also used as one of several sources of information for revising deer and elk herd management plans, and used in addressing local resource management problems (Gunnell et al., 2011).

Some of the indicators used by the UDWR to aid in determining trend include cover, density, frequency, species composition, and utilization. Of these, cover is one of the key indicators of rangeland health because it can provide additional information pertaining to ecological processes, and as a management indicator for monitoring erosion, wildlife habitat, and forage availability (Booth et al., 2005; Petersen and Stringham, 2008a; Krebs 1998). Though cover is a key indicator used in trend programs, one of the weaknesses in estimating cover is the few advances in ground sampling methods (Booth et al., 2006). This can be a problem because traditional methods are costly in time and resources which can lead to fewer data and less accurate estimates. Cover can be assessed using a wide variety of methods, making it difficult to standardize these methods for comparison across space and time (Godinez-Alvarez et al., 2009). This often leads to alterations or changes in methods for monitoring programs over time. The efficiency of the cover method chosen is crucial due to the large spatial and temporal scales involved in rangeland monitoring. Specifically, more accurate and precise methods are complex in nature and require significant time and funding commitments (Laliberte et al., 2010). Therefore cover methods utilized are those in which a certain level of accuracy and precision (repeatability) can be achieved at a certain cost (Godinez-Alvarez et al., 2009). Because of these limitations, managers need new methods that are rapid, accurate, cost-effective, and robust for monitoring range health and trend (Petersen and Stringham, 2008a; Moffet, 2009; Afinowicz et al., 2005).

Remote sensing can offer a rapid method for effectively and efficiently detecting vegetation cover with an acceptable level of error (Booth and Cox, 2008; Hunt et al. 2003; Booth et al., 2005). There is evidence that remote sensing may prove superior to conventional ground measurement methods for several reasons: (1) it facilitates extensive data collection by reducing the labor requirement for monitoring, (2) it reduces human bias by limiting the influence of human judgment, (3) it is more precise, and (4) it provides a permanent record of information that can be retained for future scrutiny (Booth et al., 2005).

The objective of this study is to test the effectiveness of remote sensing as a surrogate for field-based sampling techniques for detecting cover based on plant community functional groups (i.e. trees, shrubs, herbaceous cover, bare ground), and to compare these with field-based measurements collected by the Utah DWR RTP. Additionally, this research provides an evaluation of remote sensing as a simple and practical approach that can be used by agencies with minimal training and expertise in GIS and remote sensing.

METHODS

Study Site Description

Each year UDWR field crews survey approximately 100 key sites within one of Utah's five regions (Figure 1). Range inventory data are collected to determine range condition and trend, in particular following treatments (i.e. chaining, fire, disking, herbicide application). Sample sites were chosen using 2011 Utah Division of Wildlife Resources Range Trend Project (RTP) and Watershed Restoration Initiative (WRI) monitoring sites. Range trend sites for 2011 are within the Northern Region of Utah as defined by the UDWR RTP. Since range trend sites are selected using statewide vegetation type data, we used this same classification for site selection. When examining the vegetation layer (or data), we decided that only three vegetation types (Wyoming big sagebrush [*Artemisia tridentata* var. *wyomingensis*], mountain big sagebrush [*Artemisia tridentata* var. *vaseyana*], and mountain brush [a mixture of mountain shrub species]) would represent a land cover type that would be adequately replicated to meet statistical rigor (power). WRI sites are areas that have received pinyon and juniper reduction treatments. WRI sites sampled in 2011 by the UDWR WRI crew are dispersed throughout southern and central Utah. Due to higher costs associated with longer flight times in regards to image acquisition, WRI points that were not within a reasonable proximity of other sites were not included in study site selection. Of the 15 remaining WRI sites, 10 were randomly selected. 71 sites (RT and WRI) were imported into ArcGIS to randomly select 40 sites (Figure 1).

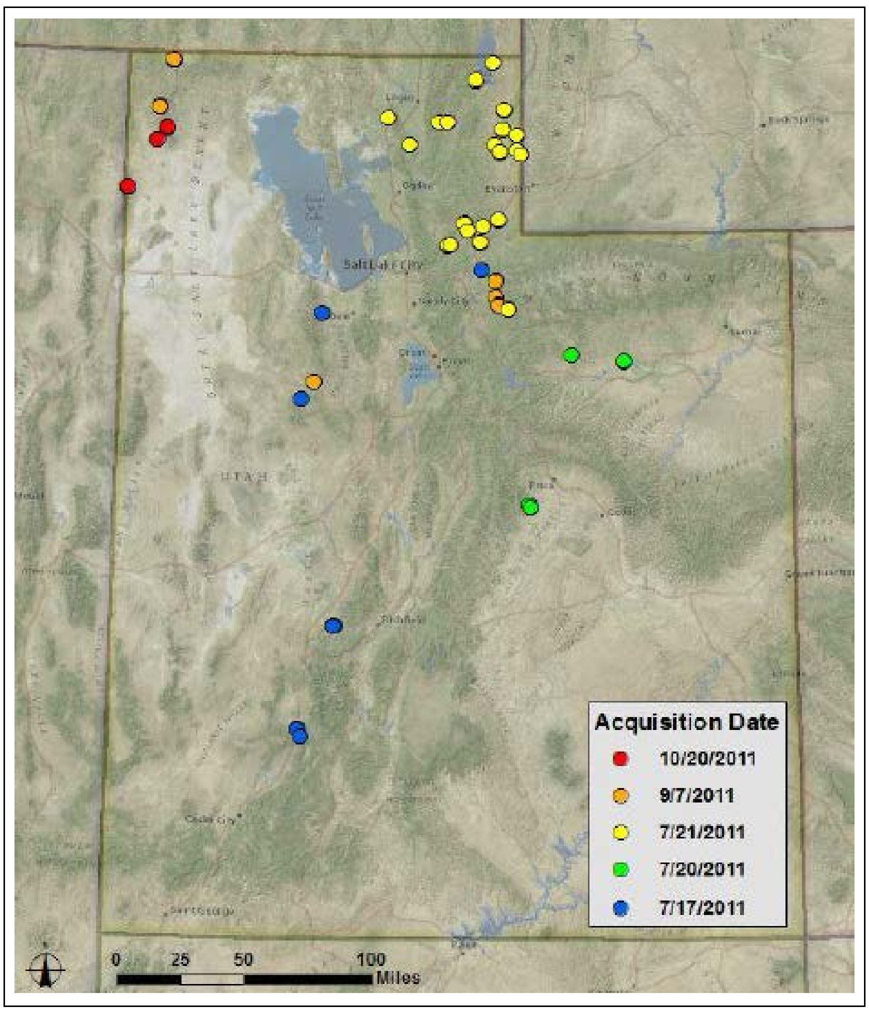

Figure 1. Hill-shaded map of the State of Utah indicating the 40 random sites where both field information and remotely-sensed data were collected.

Ground Measurements

Ground measurement data were collected by the UDWR Range Trend crews for each site using the Range Trend protocol (Gunnell et al., 2011). Each key area is typically defined with five 30.48 m sections (a total of a 152.4 m baseline). Within each 30.48 m section a random distance mark (i.e. 17 m) was chosen and another 30.48 m belt was laid perpendicular to the baseline at that point. The 30.48 m perpendicular line was centered at 15.24 m, with 15.24 m on each side of the baseline (Gunnell et al., 2011; Figure 2). Percent cover data were collected along each transect using a modified Daubenmire frame ocular estimate (used to measure herbaceous vegetation and surface cover), and the line intercept method (used in measuring tree and shrub cover). Using the Daubenmire ocular estimate for herbaceous and surface estimates, ¼ m^2 quadrats were centered every 1.5 m along the same side of the belt, starting at the 1.5 m mark for a total of 20 quadrats per transect (Gunnell et al., 2011). Cover for each species or cover variable was estimated in each quadrat using 7 cover classes: 1) .01-1%, 2) 1.1-5%, 3) 5.1-25%, 4) 25.1-50%, 5) 50.1-75%, 6) 75.1-95%, and 7) 95.1-100%. Average cover was calculated for each transect. The average of the five belts provided an average percent cover value attributed to each site.

The line intercept method used in estimating tree and shrub cover was adopted from a U.S. Bureau of Land Management sampling protocol, which measures the intersect distance along each belt to produce a total cover value, sampled at the species level. This total is divided by the total length of the belt to provide percent canopy cover (Gunnell et al., 2011). The traditional method utilized by the UDWR measures cover by species along multiple canopy layers. While this information can be useful for assessing plant community structure, it provides a challenge when it is used as a comparison to remote sensing data which measures the top canopy layer only. The UDWR also initiated a modified line intercept protocol (BYU line intercept protocol), which would be used to measure all potential cover classes (tree, shrub, herbaceous, surface). This was done in an attempt to make it possible to compare potential differences between field-based and image analysis methods being used. The UDWR Range Trend dropped the new BYU line intercept protocol after performing measurements on approximately half of the sites, due to increased length of time required to complete the protocol. This had no effect on UDWR RTP cover values, but limited the study only in being able to direct comparisons in distinguishing where possible differences between field-based and remote sensed methods occurred.

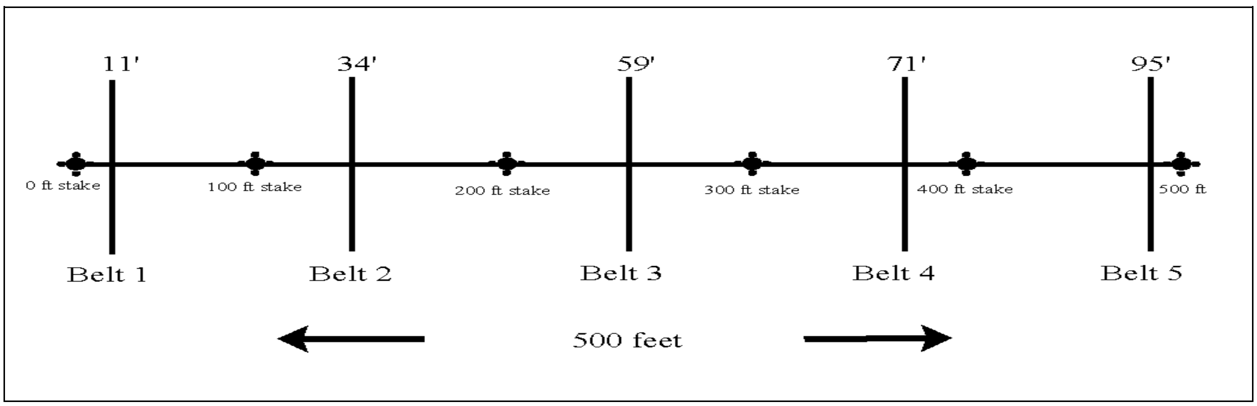

Figure 2. Diagram of 500' baseline set up with one transect in each of the 100' stretches.

Since multiple layer sampling was used in the collection of ground-based cover values, it became theoretically possible to produce cover estimates equal to or greater than 100%. To account for this, percent cover estimates made by field crews using the BYU line intercept protocol was compared to the original protocol (quadrats for herbaceous and surface estimates, and line intercept for tree and shrub) using a paired t-test (significance level of $p< 0.05$), employed to determine if the methods were different from each other. Sites used in this test did not match exactly with those analyzed later in the results section, but all sites were within the 40 original sites of this study. The t-test showed that among all functional groups (except for surface), that the two field-based methods did not differ from each other in percent cover estimates (Tree $p=0.36$, Shrub $p=0.38$, Herbaceous $p=0.33$, Surface $p<0.001$, $N=16$). It was decided that although there was a difference in methods with the surface class, it was not necessary to normalize or transform the UDWR estimates, since the difference lied in sampling method for that class. Therefore UDWR Range Trend estimates were used as reported from their normal protocol.

Image Acquisition

Four-band red, green, blue, and near infrared images were contracted and flown by Aero-Graphics Inc., Salt Lake City, Utah, in July, September and October of 2011 (Figure 1). The camera used throughout this study was an UltraCam X (UCX) digital camera (Vexcel Imaging GmbH, Graz, Austria), carried on-board a Piper PA-46 Malibu at a maximum cruise speed of 213 knots. Imagery was acquired at an average altitude of 833.6 m above ground level (AGL), and 110 individual images collected over 40 flightlines at a 0.06 m Ground Surface Distance (GSD). The images were radiometrically corrected and balanced. The UCX is equipped with precision GPS/IMU which was used in geometrically correcting images within ±1.5 m accuracy of true horizontal position. The UCX was also equipped with Forward Motion Compensation and was mounted in a GSM-3000 gyro-stabilized mount that works with the Intertial Measurement Units (IMU) to automatically correct up to 5° roll, 8.4° pitch, and 6.2° yaw prior to each exposure being fired. Continuously Operating Reference Stations (CORS) base stations were used to ensure that the image data maintained their true geographic integrity, and SmartBase solutions were used to differentially correct the aircraft's trajectory data. Imagery was projected in UTM Zone 12 and used NAVD88 as the vertical datum and NAD83 as the horizontal datum. Due to an unforeseen circumstance the contractor's server crashed prior to relaying all of the imagery and four images were never recovered, bringing our total sitecount down to 36.

Image Classification and Processing

The objective of image classification was to place each pixel into a discrete vegetation cover class (Clark et al., 2001). Two methods of image classification are supervised and unsupervised classification, both commonly used in vegetation cover classifications (Petersen et al., 2005; Clark et al., 2001). Using ENVI image classification GIS software, an unsupervised classification was performed on a subsample of the sites, but was found to not represent classes as well and was less efficient than a supervised classification. For this reason unsupervised classification was left out as an analysis technique in this study.

For the supervised classifications, pixels are manually identified and placed in categories, known as training sites. A maximum likelihood algorithm is run on each image that compares the training site pixels to each individual pixel in the image and then assigns each pixel to a cover class that it most closely identifies with. After visually inspecting images and through iterations of supervised classifications, cover classes were developed (Table 1). Using a specific number of training sites was not feasible for this study especially with the tree classification since in certain sites there was only one tree in the study area. The "polygon" method, in which a polygon is drawn around the area representing a certain class, was utilized in defining training sites (Petersen et al. 2005). In this manner, training sites included as much variation as could occur within each feature class. Instead of the number of training sites, a minimum of ~250 pixels were used (unless a particular cover class was in low abundance, in which number of pixels would be as much as possible without total census of that cover class) over all training sites for that class.

The total number of pixels per training class ranged between 30-1,000 pixels per cover class. A combination of photos taken from the field by UDWR range trend crew, true color aerial images, a tasseled cap transformation, and a Normalized Difference Vegetation Index (NDVI; a measure of greenness in plants) image were used in creating training sites (Figure 3). Training sites were then used to run the classification, and classified images were inspected visually for accuracy before proceeding (Figure 4). If classifications were incorrect (by visual assessment) failing to represent what was in the image, additional training sites for a particular class would be added until the image appeared accurate to the user's eye

Table 1. Cover Classes and Descriptions Used in Study.

Cover Class	Description
Tree	Tree cover included primarily juniper (*Juniperus osteosperma* and *Juniperus occidentalis*) and pinyon (*Pinus edulis*) and on one site maple (*Acer grandidentatum*) was present.
Shrub	Dominant shrub cover primarily included sagebrush and dead shrubs. On some sites there were other dominant shrubs such as snowberry (*Symphoricorpos occidentalis*), serviceberry (*Amelanchier alnifolia*), and antelope bitterbrush (*Purshia tridentate*). Rabbitbrush species (*Chrysothamnus*) was identifiable on some sites when large enough and was included in the shrub cover class. When rabbitbrush was too small to identify with confidence, it and other small shrubs unidentifiable by remote sensing were lumped in with the herbaceous class.
Herbaceous	The herbaceous cover class encompasses perennial grasses, annual grasses, forbs, small shrubs, and litter. This class is broad due to the inability to distinguish between the different types within the class.
Surface	Surface cover primarily included rock, pavement, and bare ground.

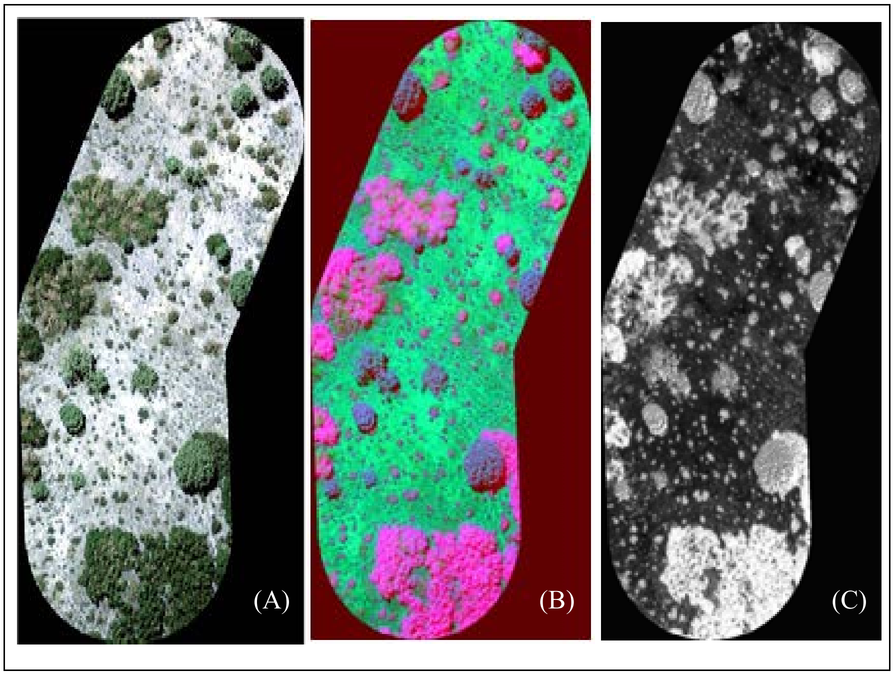

Figure 3. True color image of Crandall Canyon (A), Tasseled cap transformation (B), NDVI transformation (C).

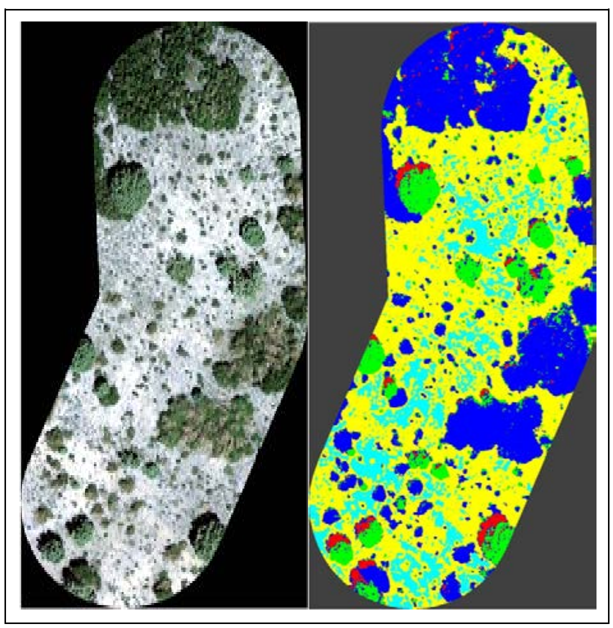

Figure 4. True Color image of Crandall canyon side by side with resulting Supervised Classification image. Cover classes are as follows: Trees (Green), Shrub (Blue), Herbaceous (Yellow), Surface (Cyan), and Shadow (Red).

A low pass filter which utilizes a spatial filter that blocks high-frequency radiation, resulting in a smoother image (7x7 window) was applied to the images twice in post processing for a subset of images prior to classification to reduce the salt and pepper effect and increase accuracy (Figure 5). Salt and pepper effect is a phenomenon in which misclassified pixels occur within a specific feature class due to variances in brightness values associated with edge or shadows (i.e. a shrub pixel showing up in the middle of a tree). The same subset of images was classified with and without the low pass filter and an accuracy assessment was performed to determine if post processing would improve classification accuracy for this analysis. Results of testing the subset found that the image processing without the filter had a 9% higher overall accuracy and a 13% higher kappa statistic. For this reason the original unfiltered images were used and minimization of the salt and pepper effect occurred during the classification process.

During the classification process, we noted several images that were excessively distorted or blurred during the acquisition phase, or had significant shadow that reduced image quality and classification reliability and resulted in incorrect image classification. Subsequently, these images were considered unsuitable for accurately assessing feature cover classes, and were removed from the analysis. This reduced the initial total of 36 images received to 26 that were able to be classified. During classification we found that in all remaining WRI sites we were not able to distinguish between trees and shrubs with any level of confidence, and lumped these into a browse category. Since we could not distinguish between trees and shrubs in all WRI images, we were not able to sufficiently analyze the data by functional groups. Therefore WRI sites were discarded bringing the total number of sites being analyzed statistically to 18 sites.

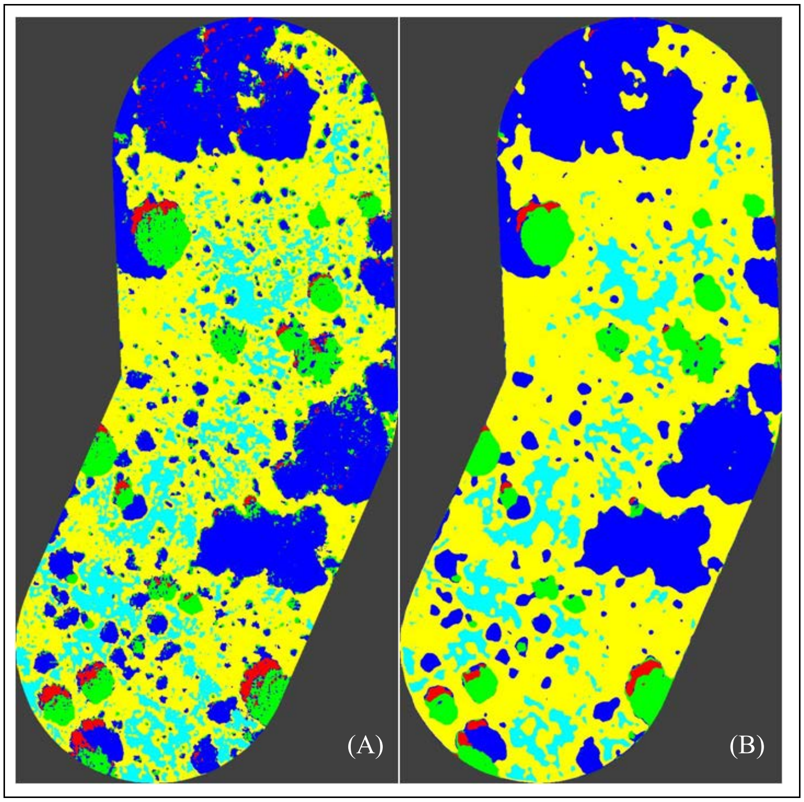

Figure 5. Aero-Graphics classified image (A), Classified image using a low pass 7x7 filter twice prior to classification (B).

Accuracy Assessment and Statistical Analysis

The accuracy in detecting canopy cover was assessed using ERDAS Imagine® software (Intergraph Corp., Madison, Alabama). Each cover class was assigned ≥35 random points using a stratified random approach (Congalton, 2001). This was repeated on all 18 sites analyzed for this study (N = 3,297 points, Table 3). Rather than validating points in the field, we used image interpretation with the belief that 0.06 m pixel size was sufficient to distinguish between the cover classes that were specified for this study (Hulet, 2013). A confusion matrix was produced summarizing all tabular output data from ERDAS rendering a table showing how assessment points were classified, producers and user's accuracy, overall accuracy, an overall kappa statistic, and conditional kappa statistics for each cover class (Jensen, 2005).

We used program R to analyze differences between mean tree, shrub, herbaceous and surface cover from remotely sensed images and ground based samples. To test for significance, we conducted a paired t-test for each cover class, setting a significance level at $p < 0.05$.

RESULTS

There was no statistical difference between remotely-sensed and field-sampled estimates for tree, shrub, and herbaceous cover (Table 2). Remotely-sensed cover data underestimated tree cover by an average of 0.26%, overestimated shrub cover by an average of 0.41%, and underestimated herbaceous cover by an average of 5.61%. The relatively low mean difference values represented in Table 2 support the data and decision to use the UDWR original protocol when comparing mean differences as it was believed that there was no difference in methods.

The surface cover class was shown to be significantly different with a $P < 0.001$, and was underestimated by remote sensing by an average of 26.9% (Figure 6). These differences are likely due to the difference in methods where UDWR RTP protocol is to measure bare ground even when covered by a shrub or tree, as well as the potential for overestimation on field-based data using an ocular estimate.

Statistical tests of the classified images show the agreement between ground reference data and remotely-sensed estimates to be “almost perfect” according to Landis and Koch (1977) measure of agreement, where overall accuracy across all sites was 91%, with an overall Kappa statistic of 0.88 (Table 3). Interestingly, the results from the Conditional Kappa statistics (for each category) were opposite those from the paired t-test; in that the highest level of agreement was among the surface class and lowest among tree cover although all classes were shown to be in agreement according to the Conditional Kappa (measurements of agreement, producers and users accuracy are comparing classified images to reference images). We found that each cover class was most often misrepresented by pixels near the edge of the class either in the above and/or below strata (i.e. shrub cover was most often misrepresented to be either tree or herbaceous cover). This can be attributed to less dense foliage and more or less light reflectance near the edge of a particular class (Hulet, 2013).

Table 2. Comparison of Mean Percent Cover Estimates between Remotely-Sensed and Field-Based Data Using a Paired T-Test (N=18 sites)

Cover Class	p-value	Mean Difference (% Cover)	95% CI (% Cover)
Tree	0.6517	0.26	-0.94 – 1.46
Shrub	0.8004	-0.41	-3.75 – 2.93
Herbaceous	0.2576	5.61	-4.49 – 15.71
Surface	5.80E-08	26.86	20.65 - 33.07

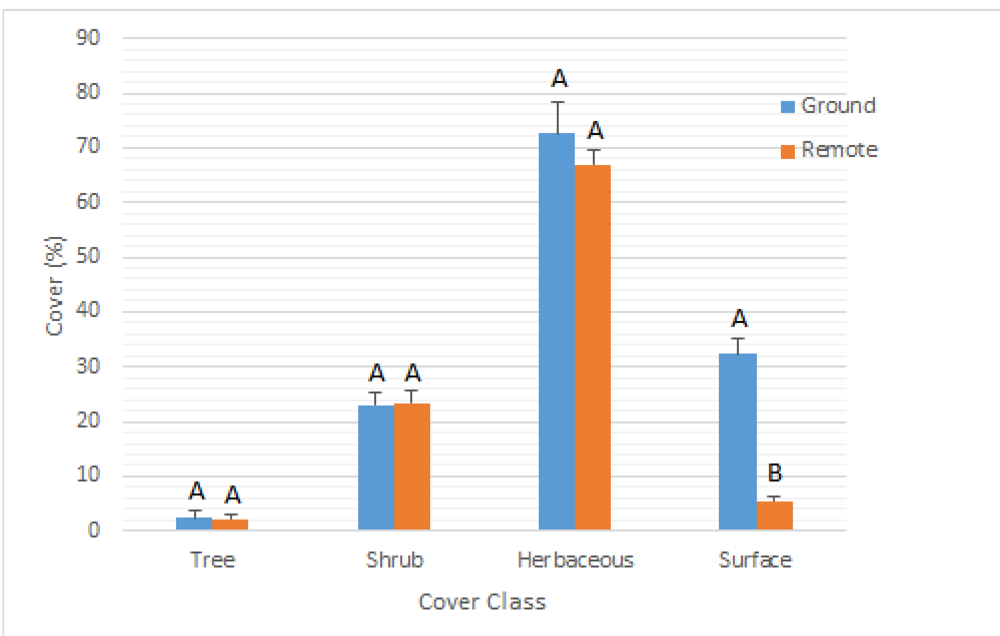

Figure 6. Comparison between ground based measurements and remotely sensed estimates of mean percent cover. Standard error bars shown with letters showing significant difference where α = 0.05.

Table 3. Confusion Matrix Showing Classification Accuracy across all Sites.

Cover Class	Tree	Shrub	Herbaceous	Surface
Tree	<u>302</u>	47	17	1
Shrub	20	<u>817</u>	51	2
Herbaceous	1	47	<u>1196</u>	47
Surface	0	0	57	<u>692</u>
Producer's Accuracy	93%	90%	91%	93%
User's Accuracy	82%	92%	93%	92%
Conditional K_{hat}	0.8	0.89	0.88	0.9
Overall Accuracy = 91% K_{hat} = 0.88 N = 3,297				

K_{hat} = Coefficient of Agreement (Kappa Statistic); N = number of points evaluated.
Underlined values indicate correct number of points classified within a cover class.

DISCUSSION

Vegetation monitoring is necessary for accurately assessing plant community structure, rangeland productivity and health, and plant community succession (Havstad and Herrick, 2003; Herrick, 2000). Both field-based measurements and remotely-sensed information provides insight into these important functions and have proven to be effective methods in gathering data used to assess these different ecosystem processes (Booth et al., 2006; Godinez-Alvarez et al. 2009).

High resolution remote sensing provides an effective tool for quantifying surface features that predict and assess primary ecological processes. In this study, high resolution RGB images provided cover estimates that did not differ ($p<0.05$) from field-based estimates, with a 91% overall accuracy when classifying total plant cover. Remote sensing can be effectively used to classify vegetation using spectral classification techniques. Booth et al. (2003) among others (Bennett et al., 2000; Louhaichi and Johnson, 2001) found that image analysis cover estimates were not significantly different from field-based measurements and could be done in a fraction of the time. Booth et al. (2008) found that although ground measurements are sometimes considered to be more accurate, the overall accuracy of an assessment can be called into question when there are constraints such as time and seasonal demands, cost, and sample size. The ability to capture images and analyze them at a later date, which is typical of remote sensing, can address these concerns (Booth et al., 2008). Fewer time constraints combined with greater spatial and temporal extent would allow land managers that use remote sensing to make more effective and efficient plans at the landscape level.

An advantage of using remote sensing for collecting vegetation measurements is that images can 1) provide a census of total plant cover by life form, 2) characterize vegetation arrangement, 3) identify vegetation and soil patchiness, and 4) quantify the juxtaposition of different surface feature classes. This knowledge could allow managers to assess potential risks of soil erosion, and employ management methods in areas of highest risk. According to Petersen and Stringham (2008b), the arrangement of vegetation and surface properties (litter, bare ground) had a significant effect on infiltration rates within a juniper encroached sagebrush system. Additionally, they used these remotely-sensed data to assess risk of impact due to lower plant cover and higher exposure of bare ground to raindrop impact and surface runoff.

Our results indicate that very high resolution imagery (0.06 m) can be effectively used to estimate cover by functional groups using spectral reflectance patterns discriminated by a supervised classification. Hulet et al. (2013) similarly found that remote sensing was effective in detecting vegetation cover in similar vegetation communities but could not reliably estimate bare ground. For this study we chose the finest resolution available as the most fitting comparison for ground sampling measurements. Other studies have been successful in utilizing coarser resolution imagery in determining trends that cover greater spatial extents (i.e. riparian ecology, juniper encroachment, and change in tree cover: Petersen et al., 2005; Madsen et al., 2010; Sankey and Germino, 2008; Platt and Schoennaggel, 2009). Further studies are needed to describe the minimum pixel size necessary for distinguishing functional groups, such as shrub and herbaceous cover, with an acceptable level of error.

In this study, image analysis was not capable of distinguishing perennial grasses from annual grasses. Perennial tall grasses are known to be a key component in resisting cheatgrass invasion in a sagebrush system (Roundy et al., 2014). This is a drawback of remote sensing since it would not allow managers to detect if a site had effectively resisted cheatgrass invasion following land treatments. In this study imagery was contracted to be flown in the first part of July to separate annual vegetation from perennial grasses spectrally, since it had been suggested that during this time plants would be most phenologically different from each other. However due to a wet year in 2011, and image acquisition being spread out through the summer, this difference was not detectable within a single photograph. One way in which perennial and annual herbaceous cover could be distinguished would be accomplished by taking photos at two different times of the season (one picture taken when cheatgrass is greened up and one taken when perennials would be green and annuals are decadent).

Managers can use remote sensing as a means of detecting vegetation response in shrub cover following mechanical treatment in conifer-encroached shrublands where differences in remote sensing and field-based methods are less than 1%. Miller et al. (2014) showed that mechanical treatments in conifer encroached systems increased by an average of 2% in 3 years versus fire which only increased from 0.5% in sagebrush to 1.7% in other shrub species. For a trend program such as UDWR which revisits a site every 5 years this should be sufficient in detecting shrub cover in mechanically treated sites. Perhaps in 5 or 10 years remote sensing could be used to detect changes in shrub cover with confidence in areas where fire has occurred.

The lack of difference observed between remote-sensed imagery and field-based samples in vegetation cover is likely associated with the method used for assessing cover in the field. However there was a significant difference in field and remote sensed data when comparing the surface class estimates. This is likely because surface class was estimated in the field using ocular sampling techniques, which could have potential human bias. More importantly, the field-based methods used in this research measured cover beneath the top-most canopy layer, which can and in this study likely overestimated cover. This does not mean that bare ground cannot be classified correctly using remote sensing, as it is the class in which users and producer’s accuracy was highest with 92% and 93% respectively. Booth et al. (2008) showed that bare ground was a more consistent indicator in ground and air measurement comparisons then even vegetation cover, indicating that there is a difference in the methods used in this study.

Further evidence of this is seen in the comparison between ground sampling protocols. The BYU line intercept method and the UDWR RTP protocol utilizing ocular estimates with a modified Daubenmire approach resulted in a significant difference ($p<0.001$) in bare ground cover estimates, where the line intercept method underestimated bare ground by an average of 28% in comparison to the UDWR RTP protocol. Remote sensed data underestimated cover by 27% which means that the line intercept method and remote sensing data measured on average only 1% different from each other. Further investigation is required to determine where the differences lie and how methods need to be adapted to account for those differences.

If differences in methods are due to multiple layer measuring in the UDWR protocol, then remote sensing can be used to effectively measure bare ground as a single layer (what a raindrop would hit first). Surface sealing, a phenomenon in which raindrop impact breaks up soil particles that become free-moving or airborne, eventually fill cracks and macro-pores that can result in decreased infiltration rates (Fox et al., 1997). The ability to detect bare ground and its inverse of ground cover is important in rangeland monitoring, as detected by Petersen and Stringham (2008b) who showed that presence of litter, shrubs, and herbaceous cover lead to higher infiltration rates. This would allow managers to make predictions regarding hydrologic processes and to establish methods that improve management decisions accordingly. Other sources of error associated with remotely sensed imagery may include 1) the time of day when images were taken that result in distortion or confusion related to shadow, 2) potential errors in the georectification process, 3) similarities in reflectance patterns between different feature classes, and 4) pixel blending where two features occur within the same area as one pixel in the image (Booth and Tueller, 2003).

Although this study supports previous studies that indicate remote sensing as an effective tool for detecting cover, other factors were also informative and provided additional insight into selecting remote sensing as a monitoring method. First, field techniques can provide information which is not acquired remotely. Distinguishing between different species using remote sensing imagery can be difficult. For example, field-based sampling can detect differences in different small structure shrubs and forbs and between annual and perennial grasses. One limitation with remote sensing is that surface classes may be more difficult to distinguish with a decrease in image resolution. Also, extraneous circumstances can arise between image acquisition and analysis that are difficult to predict or control such as failed computer systems and servers, ensuring that images are collected within the optimal time window, and that unfavorable weather patterns are minimized. These factors all influenced our ability to acquire and process imagery in this study, resulting in a loss of information from more than half of the sites originally identified. If rapid image processing time could be ensured, and precise flight times recorded, images could be resampled if found to be insufficient.

Despite these limitations, this study found that remote sensing can be used as an effective surrogate for field-based sampling techniques for estimating cover based on functional groups. The techniques used in this study play to the strength of agencies by relying on the expertise of the user to distinguish between functional groups, and require little additional training, making remote sensing a suitable alternative to the ground sampling methods currently used by agencies.

CONCLUSION

Rangeland monitoring is important in assessing plant community structure and soil erosion potential. Eighteen sites were evaluated across Northern Utah to determine if remote sensing can effectively detect plant community structure and total surface cover. This study showed that remote sensing effectively detects plant cover across the image, separated into meaningful life forms (herbaceous cover, shrubs and trees). Although bare ground can be detected by high resolution remote sensed data, this study did find a significant difference in UDWR field-based estimates from remotely sensed estimates. This is likely due to the method used by the UDWR to assess bare ground.

MANAGEMENT IMPLICATIONS

By utilizing remotely sensed imagery, managers now have the option to sample cover more rapidly on a landscape scale without the high expenditure of resources required by field-based sampling methods. Cover measurements can now be measured in remote locations where the use of a field crew may not be feasible. Remote sensing provides a quick and efficient way to detect plant cover by functional groups with increased precision. Remote sensing can be used by managers to make hydrologic inference, detect vegetation response to treatments, and assist in monitoring of invasive species (Petersen and Stringham, 2008b; Miller et al., 2014; Roundy et al., 2014, Madsen et al., 2010). In agreement with other studies, these results demonstrate that remote sensing facilitates extensive data collection by reducing labor requirements and human bias and by providing a record that can be scrutinized at later points in time. (Booth et al., 2005; Petersen et al., 2005; Hunt et al., 2003).

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