2012-03-07

An Object-Based Image Analysis of Treated and Untreated Pinyon and Juniper Woodlands Across the Great Basin

April Hulet
Brigham Young University - Provo

An Object-Based Image Analysis of Treated and Untreated

Pinyon and Juniper Woodlands Across the Great Basin

April Hulet

A dissertation submitted to the faculty of
Brigham Young University
In partial fulfillment of the requirements for the degree of

Doctor of Philosophy

Bruce A. Roundy, Chair
Steven L. Petersen
Ryan R. Jensen
Randy T. Larsen
Stephen C. Bunting

Department of Plant and Wildlife Sciences

Brigham Young University

April 2012

ABSTRACT

An Object-Based Image Analysis of Treated and Untreated
Pinyon and Juniper Woodlands Across the Great Basin

April Hulet
Department of Plant and Wildlife Sciences
Doctor of Philosophy

Land managers need to rapidly assess vegetation composition and bare ground to effectively evaluate, manage, and restore shrub steppe communities that have been encroached by pinyon and juniper (P-J) trees. A major part of this process is assessing where to apply mechanical and prescribed fire treatments to reduce fuel loads and maintain or restore sagebrush steppe rangelands. Geospatial technologies, particularly remote sensing, offers an efficient option to assess rangelands across multiple spatial scales while reducing the need for ground-based sampling measurements.

High-spatial resolution color-infrared imagery (0.06-m pixels) was acquired for sagebrush steppe communities invaded by P-J trees at five sites in Oregon, California, Nevada, and Utah with a Vexcel Ultra CamX digital camera in June/July 2009. In addition to untreated P-J woodlands, imagery was acquired over P-J woodlands where fuels were reduced by either prescribed fire, tree cutting, or mastication treatments. Ground measurements were simultaneously collected at each site in 2009 on 0.1-hectare subplots as part of the Sagebrush Steppe Treatment Evaluation Project (SageSTEP). We used Trimble eCognition Developer to 1) develop efficient methods to estimate land cover classes found in P-J woodlands; 2) determine the relationship between ground measurements and object-based image analysis (OBIA) land cover measurements for the following classes: trees (live, burned, cut, and masticated), shrubs, perennial herbaceous vegetation, litter (including annual species), and bare ground; and 3) evaluate eCognition rule-sets (models) across four spatial scales (subplot, site, region, and network) using untreated P-J woodland imagery.

At the site scale, the overall accuracy of our thematic maps for untreated P-J woodlands was 84% with a kappa statistic of 0.80. For treatments, the overall accuracy and kappa statistic for prescribed fire was 85% and 0.81; cut and fell 82% and 0.77, and mastication 84% and 0.80, respectively, each indicating strong agreement between OBIA classification and ground measured data. Differences between mean cover estimates using OBIA and ground-measurements were not consistently higher or lower for any land cover class and when evaluated for individual sites, were within 5% of each other; all regional and network OBIA mean cover estimates were within 10% of the ground measurements. The trade-off for decreased precision over a larger area (region and network scale) may be useful to prioritize fuel-management strategies but will unlikely capture subtle shifts in understory plant communities that site and subplot spatial scales often capture. Although cover assessments from OBIA differed somewhat from ground measurements, they were accurate enough for many landscape-assessment applications such as evaluating treatment success and assessing the spatial distribution of fuels following fuel-reduction treatments on a site scale.

Keywords: eCognition Developer, mastication, object-based image analysis, pinyon-juniper woodlands, prescribed fire, remote sensing, SageSTEP, spatial scales, tree cutting

ACKNOWLEDGEMENTS

I would like to thank my major professor Dr. Bruce A. Roundy for the opportunity to pursue my Doctoral degree and increase my understanding of wildlands across the Great Basin. I am truly indebted and thankful for his guidance, support, and encouragement throughout my time at Brigham Young University. I would also like to thank Dr. Steven L. Petersen, Dr. Stephen C. Bunting, Dr. Ryan R. Jensen, and Dr. Randy T. Larsen for their direction and continual support throughout my academic career. This dissertation would not have been possible without their valuable insights and optimistic attitudes.

I would like to thank the SageSTEP research team, particularly James McIver and the sagebrush woodland principle investigators Richard Miller, Robin Tausch, and Jeanne Chambers, as well as the woodland site managers for their substantial field support and advice. Additionally, I would like to thank the numerous research technicians and my fellow graduate students for their willingness to collect data and share ideas. I am grateful to have had the opportunity to collaborate with them.

And finally, I would like to express my gratitude for my family. Their encouragement and love has proven invaluable. I truly appreciate the sacrifices they have made for me as I have pursued this degree!

Table of Contents

Chapter 1: Assessing the Relationship between Ground Measurements and Object-Based Image Analysis of Land Cover Classes in Pinyon and Juniper Woodlands

April Hulet[a*], Bruce A. Roundy[a], Steven L. Petersen[a], Ryan R. Jensen[b] and Stephen C. Bunting[c]

[a]Department of Plant and Wildlife Sciences, 275 WIDB, Brigham Young University, Provo, UT 84602 USA; april.hulet@gmail.com, bruce_roundy@byu.edu, steven_petersen@byu.edu

[b]Department of Geography, 920 SWKT, Brigham Young University, Provo, UT 84602 USA; rjensen@byu.edu

[c]Department of Rangeland Ecology and Management, PO Box 441135, University of Idaho, Moscow, ID 83844-1135 USA; sbunting@uidaho.edu

*Correspondence to: april.hulet@gmail.com, 435.590.1192

Manuscript prepared for submission to *Remote Sensing of Environment*

Abstract

Land managers need to rapidly assess vegetation composition and bare ground to effectively evaluate, manage, and restore shrub steppe communities that have been encroached by pinyon (*Pinus*) and juniper (*Juniperus*) trees. Remote sensing offers an efficient option to assess rangelands while reducing ground sampling measurements. High-spatial resolution color-infrared imagery (0.06-m pixels) was acquired for sagebrush steppe communities invaded by pinyon-juniper trees at five sites in Oregon, California, Nevada, and Utah with a Vexcel UltraCam X digital camera in June/July 2009. Ground cover measurements were also collected in 2009 on 30x33 m subplots as part of the Sagebrush Steppe Treatment Evaluation network. To georeference ground subplots onto the aerial imagery, global positioning system (GPS) points were collected at the center and northwest corner of each ground subplot; subplots were then extracted for image processing and analysis. We used Trimble eCognition Developer 8 to 1) develop an efficient method to estimate land cover classes found in pinyon-juniper woodlands, and 2) to determine the relationship between ground measurements and object-based image analysis (OBIA) land cover measurements for the following classes: live trees, shrubs, perennial herbaceous vegetation, litter (including annual species), and bare ground. OBIA classification means ranged from underestimating litter by 3% to overestimating live trees by 1% when compared to ground-based measurements. Overall accuracy for our thematic maps was 84% with a kappa statistic of 0.80, indicating strong agreement between OBIA classification and ground measured data. Correlations between OBIA and ground measurements were relatively high for live trees (r =0.94), bare ground (r =0.90), shrubs (r =0.88), and perennial herbaceous vegetation (r=0.79). Although cover assessments varied slightly between OBIA and ground-based measurements, they represent an accurate landscape-level assessment for applications used by land managers.

Keywords

eCognition, remote sensing, pinyon-juniper woodlands, SageSTEP, object-based image analysis.

1. Introduction

Landscape management agencies inventory and monitor rangelands across broad and heterogeneous landscapes. Many of these lands in the western United States are converting from sagebrush steppe communities into pinyon (*Pinus)* and juniper (*Juniperus)* (P-J) woodlands as trees invade and infill (Miller et al., 2000; Miller & Tausch, 2001; Romme et al., 2009; Tausch, 1981). Increased tree dominance typically results in the loss of understory plant community structure and composition and an associated decline in ecological function across these heterogeneous landscapes (Miller et al., 2000). On sites with high soil erosion potential, loss of understory cover can result in accelerated soil erosion rates, greater runoff, and increased soil hydrophobicity (Madsen et al., 2011; Petersen & Stringham, 2008; Pierson et al., 2010; Roundy & Vernon, 1999). An increase in tree canopy cover and biomass associated with lengthened fire return intervals within these communities can also increase the potential for intensive crown fires (Miller & Tausch, 2001).

Accurate assessment of understory and overstory cover within expansion woodlands is needed to properly time fuel reduction treatments to restore ecological function and resilience (Miller et al., 2005; Tausch et al., 2009). Remote sensing can offer an efficient alternative to assess these rangelands with reduced monitoring costs (Booth et al., 2008; Booth & Tueller, 2003; Hunt et al., 2003; Tueller, 1989), and more complete and representative measurements across a landscape than from ground-based measurements alone (Booth et al., 2005; Tueller, 1996). Object-based image analysis (OBIA) techniques that group similar, neighboring pixels into distinct image objects within designated parameters (Burnett & Blaschke, 2003; Ryherd & Woodcock, 1996), have shown success in describing landscape patches evaluated with high-resolution imagery (Karl & Maurer, 2010; Laliberte et al., 2004; Laliberte et al., 2010; Yu et al., 2006). However, remotely-sensed image research for shrub steppe communities encroached with P-J woodlands is limited (Davies et al., 2010; Madsen et al., 2011; Sankey & Glenn, 2011; Weisberg et al., 2007; Yang et al., 2012).

Our objective is to test the accuracy of OBIA cover measurements from high-spatial resolution imagery (0.06-m pixels) relative to ground-based measurements within P-J expansion woodlands. We propose that cover estimates from high-resolution remotely sensed imagery and Trimble eCognition Developer image analysis is sufficiently similar to ground measurements for accurately assessing P-J woodland cover.

2. Methods

2.1. Study Area

Our study includes five pinyon and/or juniper woodlands located in 4 western US states (Oregon, California, Nevada, and Utah) that are associated with the Joint Fire Sciences Sagebrush Steppe Treatment Evaluation Project (SageSTEP; Fig. 1). The five sites are referred to as Blue Mountain (BM), Devine Ridge (DR), Marking Corral (MC), Stansbury (ST), and Onaqui (ON). Site characteristics have been described by McIver et al*.* (2010). We selected sites that represented all phases of woodland encroachment (Miller et al., 2005) and exhibited a substantial understory shrub component. These sites provided us with a wide range of semi-arid woodland types with the following most common vegetation: western juniper (*Juniperus occidentalis*; BM, DR); Utah juniper (*Juniperus osteosperma*; MC, ON, ST); singleleaf pinyon (*Pinus monophylla*; MC); mountain big sagebrush (*Artemisia tridentata* ssp. *vaseyana*; BM, DR, ST); Wyoming big sagebrush (*Artemisia tridentata* ssp. *wyomingensis*; MC, ON); Idaho fescue (*Festuca idahoensis*; BM, DR); bluebunch wheatgrass (*Pseudoroegneria spicata*; BM, MC, ON, ST); and

Indian ricegrass (*Achnatherum hymenoides*; MC, ON). Cheatgrass (*Bromus tectorum)* is present on all sites with a wide range of density and cover values.

2.2. Ground Measurements

Ground data was collected by the SageSTEP team during the summer of 2009 on 80, 0.1-ha subplots (30 x33 m) found within larger study plots (5-20 hectares). Cover measurements were collected within subplots using the line-point intercept method (Canfield 1941) on five, 30-m transects placed systematically across the subplot (McIver et al 2010). First contact intercept data (top vegetation canopy or ground surface) was collected every 0.5 -m totaling 60 points per transect or 300 points per subplot. This same area represents the aerial view captured in each remotely-sensed image. Measurements used in the data analysis from the line-point intercept method included shrubs, forbs, grasses, litter, standing and down woody debris, and ground surfaces (mineral soil, rock, lichen or moss) cover estimates. Tree cover used in the data analysis was measured using the crown-diameter method (Mueller-Dombois and Ellenberg 1974).

2.3. Acquisition of Imagery

Color-infrared (red, green, blue, and infrared) imagery was acquired for all sites in late June to early July 2009 with a Vexcel UltraCam X digital camera (Vexcel Imaging GmbH, Graz, Austria) on board a turbocharged Cessna 206 aircraft. The camera was equipped with forward motion compensation, airborne GPS capabilities and an ApplAnix inertial measurement unit (IMU). Imagery was processed to meet or exceed national map accuracy standards using software created by the Vexcel/Microsoft digital imaging partnership by Aero-graphics, Inc., Salt Lake City, Utah. Imagery collection time was based on phenological vegetation characteristics found within the Great Basin; in late June/early July, perennial grasses typically approach maximum yearly growth and annual grasses have begun to senesce, ideally providing spectral differences between perennial and annual plants in the aerial imagery.

2.4. Subplot Extraction

Global positioning system (GPS) points were collected using a GPSmap® 60CS unit in the center and northwest corner of each of the 80, 0.1-ha subplots, to georeference subplots on collected imagery. Although the true image location may have some inaccuracies due to GPS readings, subplot shifts were estimated to be within 1-2 m of the field-based subplots. Individual subplots were then extracted from landscape scenes so that measurements would be made on the same experimental unit for both OBIA and ground-measured cover classes.

2.5. Image Processing (eCognition)

For our object-based image analysis we used eCognition Developer 8.64 (Trimble Germany GmbH, Munich, Germany) (Fig. 2). eCognition allows the user to create rule sets or process trees to classify image objects into meaningful land cover classes by outputting hundreds of features (spectral, spatial, textural, and contextual information) that describe image objects created during the segmentation process (Benz et al., 2004; Frohn & Chaudhary, 2008; Laliberte et al., 2007). Process trees were developed from an initial subset of the total subplots (training subplots; 12% of the total number of subplots) to determine object features and thresholds that would identify land cover classes. Thresholds associated with object features were adjusted to optimize the remotely-sensed cover estimates with the ground reference cover data within an acceptable measure of error of ± 5%, depending on land cover class. Training subplots were selected that captured the greatest amount (or degree) of variation between land cover classes found within the site. Once the process tree was developed from the training subplots, the designated features and thresholds were applied to the secondary subset of subplots (validation subplots; 88% of the total number of subplots) for data analysis.

Using the training subplots, multiple classification trials were performed to extract cover data. We found that our data extracted from the relatively high-spatial resolution imagery was obscured by extraneous information (Karl & Maurer 2010). Therefore, our process trees were developed for each research site by initially reducing the complexity of the data by using both a convolution and median filter on the original RGB bands. For the convolution filter, we used the Gauss Blur formula to remove noise and detail from the imagery (Trimble, 2011). The median filter used an algorithm that replaced the pixel value with the median value of neighboring pixels which typically preserves more image detail than a mean filter (Trimble, 2011).

Once our imagery was filtered, we used a multiresolution segmentation algorithm embedded in the eCognition Developer software to create our objects using the convolution filtered data. The multiresolution segmentation algorithm has been successfully applied in numerous studies (Frohn & Chaudhary, 2008; Karl, 2010; Karl & Maurer, 2010; Ko et al., 2009; Laliberte et al., 2007a & b; Laliberte & Rango, 2009; Lucas et al., 2007; Tian & Chen, 2007) and is a bottom-up segmentation algorithm based on a pairwise region merging technique; it minimizes the average heterogeneity and maximizes object homogeneity (Trimble, 2011) essentially capturing patterns of interest. Through the visual assessment of the segmentation results and several iterative classification trials, scale, shape and compactness parameters were determined that best represented land cover classes (Table 1) of interest for this particular study. Following the multiresolution segmentation, a spectral difference segmentation algorithm was applied that merged neighboring image objects according to their mean image layer intensity values (Trimble, 2011), visually refining our objects into more representative land cover classes.

Following segmentation, classification of the homogeneous objects were explored using training samples for each land cover class. One of the strengths of eCognition is that process trees have a hierarchical approach (Lucas et al., 2007), which essentially removes objects that have been classified from further analysis of unclassified objects. Utilizing this hierarchical approach, multiple classification features and thresholds were investigated to determine which represented ground reference data most accurately, which had the highest overall classification accuracy of the thematic map produced, and what hierarchical order of land cover classes should generally be classified for each specific site. Often, multiple combinations of features were used to classify land cover classes. Spectral information included: mean layer intensity values for RGB bands (mean value, brightness and maximum difference), pixel based values within image objects (band ratios), normalized difference vegetation index (Rouse et al., 1973), soil adjusted vegetation index (Huete, 1998), and Hue, Saturation, Intensity (HSI) transformations (including HSI transformation using median filtered RGB bands). Contextual information or class-related features consisted of relative borders (neighboring objects) that were most often used to expand land cover classes to adjacent unclassified objects. Area (number of pixels within object) of classified objects was the only spatial feature utilized in this study. No textural information was used for the classification due to our segmentation size restrictions. Cover was measured from imagery by calculating total area of land cover class divided by total area of subplot.

2.6. Statistical Analysis

To determine whether the mean value responses were different between the remotely-sensed data and ground-reference data, we used a paired t-test for each land cover class. Results from the paired t-test were evaluated for significance using the Bonferroni correction ($p < 0.05/5$). Statistical assumptions for normality and variance were assessed. Mean difference values for each land cover class by site were compared using one-way ANOVA and the Tukey-Kramer honestly significant difference multiple comparison method with a significance level of $p < 0.05$. Ground measurements, which are considered to be correct, were always subtracted from estimates derived from OBIA, to determine if OBIA consistently overestimated or underestimated the land cover class of interest. To assess the relationship between ground-reference data and OBIA data, a simple linear regression model was used. These regression models only apply within the context of the data set from which they are derived.

2.7. Accuracy Assessments

Accuracy assessments were conducted on classified thematic maps for each site to determine the statistical reliability of classified data using ERDAS Imagine 11.0 software (ERDAS Inc., Atlanta, GA). For each cover type, we used a stratified random approach to generate ≥35 points per cover class (Congalton, 2001) for the 5-6 cover classes found at each of the five sites. This was repeated for 3 subplots per site totaling 15 subplots evaluated (N = 4,228 points; Table 4). An error matrix was then populated by summing the totals from all sites, followed by the calculation of producer's accuracy (omission error), user's accuracy (commission error), overall accuracy, conditional K_{hat} coefficient of agreement, and K_{hat} coefficient of agreement (Jensen, 2005).

3. Results and Discussion

Live trees, shrubs, and perennial herbaceous vegetation measurements did not differ between OBIA and ground-measurement methods across all sites (Table 2). When individual sites were analyzed, there was a significant difference for live tree measurements at the Stansbury site ($p = 0.0013$), where OBIA overestimated cover by 3% when compared to the ground measurements (Table 3). Live tree ground measurements were collected for all trees rooted within the subplot. With our OBIA technique, it was difficult to distinguish what was rooted within or outside the subplots and may have contributed to differences between methods.

Differences in shrub cover estimates between the two methods did not differ among sites (Table 3). However, trees were most often misclassified as shrubs (Table 4), especially on western juniper sites (BM and DR). Tausch et al., (unpublished data) found that when Utah juniper and western juniper trees average the same height, Utah juniper trees average up to three times the foliage biomass of western juniper trees. Consequently, Utah juniper image objects were more compact with minimal variations in spectral reflectance values. Western juniper image objects were less compact and often exhibit numerous spectral reflectance values that were very similar to other vegetation types, particularly antelope bitterbrush in our imagery.

Litter and bare ground cover differed significantly (litter $p = 0.0006$; bare ground $p = 0.0095$) between the OBIA and ground-measurement methods across all sites (Table 2). OBIA estimates for both land cover classes were on average 2-3% less than ground measurements. When individual sites were analyzed, Devine Ridge was the only site where OBIA estimates were 2.3% more than the ground measured bare ground cover (Table 3). The bare ground land cover class was composed of >90% mineral soil at all sites except for Devine Ridge, where mineral soil comprised 70% with rock (>5 mm) comprising 24% (Table 1). The soil adjusted vegetation index was used to classify bare ground cover and may have a substantial spectral difference for rocks versus the mineral soil at this site for our collected imagery.

Cover estimates from OBIA and ground measurements were highly correlated across all sites for live trees (r = 0.95), bare ground (r = 0.90), shrubs (r = 0.88), and perennial herbaceous vegetation (r = 0.80)

(Fig. 3). Litter cover correlation between OBIA and ground measurements were low compared to other cover classes (r = 0.53). OBIA litter cover estimates were on average 3% lower than ground measurements which is likely due to shadows found within the imagery from overstory vegetation.

Across all sites and land cover classes overall accuracy was 84%, with a kappa statistic of 0.80 (Table 4) indicating a strong agreement between the OBIA classification and the reference data (Landis & Koch, 1977). Live trees had the highest conditional K_{hat} coefficient of agreement (0.92) which is expected since trees are the largest vegetation type with little interference from understory vegetation. Interestingly, there is a dissimilarity between the producer's (82%) and user's (94%) accuracies for live trees that suggests omission errors (how well a live tree can be classified) were higher than commission errors (probability that a sample classified on the image actually represents a live tree) (Congalton, 2001). These differences are also reflected in the minimum and maximum difference between the OBIA and ground measurements for live trees (-10.6 – 14.7% cover; Table 4), that may average out across a landscape but, may be substantially different on a subplot scale. Although filters were used to reduce heterogeneity found within objects, the combination of less tree foliage around the perimeter of the canopy and increased light reflecting off the soil through foliage, increased our inaccuracies for correctly classifying tree canopy edges.

The use of high-resolution imagery across multiple sites within the Great Basin allowed us to evaluate differences in classification accuracy between tree species (Table 5). At the Marking Corral site, we were able to differentiate between Utah junipers and singleleaf pinyon trees that were dispersed throughout the subplots using a hue transformation parameter on our median filtered RGB bands. Although species were combined for mean comparison, results from the accuracy assessment of these tree species have a conditional K_{hat} coefficient of agreement of 0.88 for Utah juniper and 0.85 for singleleaf pinyon.

Differentiating shrubs into species was feasible with our high-resolution imagery when species ground cover was more than 5% of the total ground cover. BM, DR, and ST had both sagebrush species and antelope bitterbrush dispersed throughout the subplots. At these sites, sagebrush species averaged 48% and antelope bitterbrush averaged 38% of the total shrub composition. Sagebrush had similar producer's and user's accuracy; however, antelope bitterbrush accuracies were dissimilar suggesting that antelope bitterbrush is misclassified more than sagebrush (Table 5). Among all of our sites, Stansbury had the lowest accuracy for separating shrubs into species. This was likely due to an overlap in shrub species growth patterns among sagebrush and bitterbrush. Using eCognition techniques to merge and combine adjacent objects with one another, it is likely that interspersed vegetation was classified as the more dominate species for one particular area.

Other life forms (grasses and forbs) were not distinguished by species and, as reported by Laliberte et al. (2010), forbs could not be distinguished from grasses. Therefore these life forms were combined to compose one perennial herbaceous vegetation cover class. Targeted phenological timing of imagery collection allowed us to distinguish annual from perennial life forms rather well. However, we were not able to distinguish litter from annual species (Table 1), particularly cheatgrass. This is likely due to the size of cheatgrass patches and the pixel resolution of our imagery. Jensen (2005) suggests a heuristic rule of thumb that in order to detect a feature, the nominal spatial resolution of the sensor system should be less than one-half the size of the feature measured in its smallest dimension. Cheatgrass typically composed less than 10% of the total litter composition (Table 1) and was often dispersed throughout the subplots as individual shoots instead of larger bunches.

4. Conclusions

Our results indicate that object-based image analysis can produce accurate estimates for designated land cover classes. The averaged means from the OBIA cover analysis across the landscape is within 3% of the ground measured cover. Although the classification may have limitations (i.e. quantifying litter cover for individual subplots), when averaged across the landscape it is sufficiently accurate in quantifying land cover classes to be of major use in land management.

The lower correlation values for land cover classes with a high kappa statistic may be attributed to several discrepancies between OBIA and ground quantifications. Use of two GPS points to extract subplots from imagery may result in subplot shifts that result in dissimilar subplot comparisons between image and ground measurements. Estimates of litter and smaller vegetation cover classes could especially be sensitive to subplot-shift differences. Also, line-intercept measurements on the ground may not adequately represent the entire subplot (Davies et al., 2010) whereas, with the aerial imagery every object is assigned to a class. In addition, in the image analysis, perennial herbaceous vegetation, litter, and bare ground can be obscured by shadows from larger woodland species such as sagebrush and juniper trees. Shadows within vegetation canopies (i.e. juniper trees) can be calculated correctly through merging or combining neighboring classified objects. Perennial herbaceous vegetation, litter, and bare ground land cover classes however, found within a shadow were often misclassified or classified into a separate shadow category. Shadows ranged from 2-6% cover of the total subplot imagery for our study which likely contributed to the overall underestimation of these land cover classes when compared to our ground measurements.

Although species level classification varies in accuracy, remote sensing can aid land managers in prioritizing preventative management practices (Bestelmeyer, 2006) instead of focusing on restoration efforts. Remote sensing provides an opportunity for more timely measurements than ground-based measurements. This may allow detection of areas experiencing small shifts in land cover, such as increases in patches of weed dominance. Management actions such as site-specific weed control could be implemented before catastrophic shifts occur (Hunt, et al., 2004; Shaw, 2005; Thorp & Tian, 2004). As another example, repeated aerial photography could be used to assess bare ground patch size and connectivity and signal when to implement vegetation treatments to prevent rilling and the crossing of an erosion threshold (Booth & Tueller, 2003; Davenport et al., 1998; Pyke et al., 2002).

Our data suggest that remote sensing of land cover classes such as live trees, shrubs, and bare ground could reduce field data collection for monitoring and assessments, therefore enabling monitoring on a much larger extent than is currently practiced. By utilizing aerial imagery and object-based image analysis techniques, land managers can move in the direction of "addressing the inadequacies of conventional rangeland monitoring" (Booth et al., 2008). The methods used in this study show that aerial imagery does have the potential to complement and even replace some ground measurements for evaluating rangeland health and determining when to implement vegetation treatments on a landscape scale.

Acknowledgments

Financial support for this study was provided by the Joint Fire Sciences Sagebrush Steppe Treatment Evaluation Project, the Bureau of Land Management, Brigham Young University, and the University of Idaho. We thank the SageSTEP research team, particularly James McIver and the sagebrush-woodland principle investigators Richard Miller, Robin Tausch and Jeanne Chambers, as well as the woodland site managers, Jaime Ratchford, Neil Frakes, Travis Miller and Brad Jessop for substantial field support and advice.

References

Benz, U. C., Hofmann, P., Willhauck, G., Lingenfelder, I., & Heynen, M. (2004). Multi-resoltuion, object-oriented fuzzy analysis of remote sensing data for GIS-ready information. *ISPRS Journal of Photogrammetry & Remote Sensing*, *58,* 239-258.

Bestelmeyer, B. T. (2006). Threshold concepts and their use in rangeland management and restoration: the good, the bad, and the insidious. *Restoration Ecology, 14,* 325-329.

Booth, D. T., Cox, S. E., Meikle, T., & Zuuring, H. R. (2008). Ground-cover measurements: Assessing correlation among aerial and ground-based methods. *Environmental Management, 42*, 1091-1100.

Booth, D. T., Cox, S. E., Fifield, C., Phillips, M., & Williamson, N. (2005). Image analysis compared with other methods for measuring ground cover. *Arid Land Research & Management, 19*, 91-100.

Booth, D. T., & Tueller, P. T. (2003). Rangeland monitoring using remote sensing. *Arid Land Research and Management, 17,* 455-467.

Burnett, C., & Blaschke, T. (2003). A multi-scale segmentation/object relationship modeling methodology for landscape analysis. *Ecological Modelling*, *168,* 233-249.

Canfield, R. (1941). Application of line interception in sampling range vegetation. *Journal of Forestry*, *39,* 388-394.

Congalton, R. G. (2001). Accuracy assessment and validation of remotely sensed and other spatial information. *International Journal of Wildland Fire, 10,* 321-328.

Davenport, D. W., Breshears, D. D., Wilcox, B. P., & Allen, C. D. (1998). Viewpoint: Sustainability of piñon-juniper ecosystems—a unifying perspective of soil erosion thresholds. *Journal of Range Management, 51,* 231-240.

Davies, K. W., Petersen, S. L., Johnson, D. D., Davis, D. B., Madsen, M. D., Zvirzdin, D. L., & Bates, J. D. (2010). Estimating juniper cover from national agriculture imagery program (NAIP) imagery and evaluating the relationship between potential cover and environmental variables. *Rangeland Ecology & Management, 63,* 630-637.

Frohn, R. C. & Chaudhary, N. (2008). Multi-scale image segmentation and object-oriented processing for land cover classification. *GIScience & Remote Sensing, 45,* 377-391.

Huete, A. R. (1988). A soil-adjusted vegetation index (SAVI). *Remote Sensing of Environment, 25,* 295-309.

Hunt, E. R., Jr., McMurtrey, J. E., III, Parker Williams, A. E., & Corp, L. A. (2004). Spectral characteristics of leafy spurge (*Euphorbia esula*) leaves and flower bracts. *Weed Science, 52,* 492-497.

Hunt, E. R., Jr., Everitt, J. H., Ritchle, J. C., Moran, M. S., Booth, D. T., Anderson, G. L., Clark, P. E., & Seyfried, M. S. (2003). Applications and research using remote sensing for rangeland management. *Photogrammetric Engineering & Remote Sensing, 69,* 675-693.

Jensen, J. R. (2005). *Introductory digital image processing: a remote sensing perspective.* (3rd ed.). Prentice Hall, New Jersey, p 526.

Karl, J. W., & Maurer, B. A. (2010). Multivariate correlations between imagery and field measurements across scales: comparing pixel aggregation and image segmentation. *Landscape Ecology, 25,* 591-605.

Karl, J. W. (2010). Spatial Predictions of cover attributes of rangeland ecosystems using regression kriging and remote sensing. *Rangeland Ecology& Management, 63,* 335-349.

Ko, D., Bristow, N., Greenwood, D., & Weisberg, P. (2009). Canopy cover estimation in semiarid woodlands: comparison of field-based and remote sensing methods. *Forest Science, 55,* 132-141.

Laliberte, A. S., Rango, A., Havstad, K. M., Paris, J. F., Beck, R. F., McNeely, R., & Gonzalez, A. L. (2004). Object-based image analysis for mapping shrub encroachment from 1937-2003 in southern New Mexico. *Remote Sensing of Environment, 93,* 198-210.

Laliberte, A. S., Herrick, J. E., Rango, A., & Winters, C. (2010). Acquisition, orthorectification, and object-based classification of unmanned aerial vehicle (UAV) imagery for rangeland monitoring. *Photogrammetric Engineering & Remote Sensing, 76,* 661-672.

Laliberte, A. S., Fredrickson, E. L., & Rango. A. (2007a). Combining decision trees with hierarchical object-oriented image analysis for mapping arid rangelands. *Photogrammetric Engineering & Remote Sensing, 73,* 197-207.

Laliberte, A. S., Rango, A., Herrick, J. E., Fredrickson, E. L., & Burkett, L. (2007b). An object-based image analysis approach for determining fractional cover of senescent and green vegetation with digital plot photography. *Journal of Arid Environments, 69,* 1-14.

Laliberte, A. S. & Rango, A. (2009). Texture and scale in object-based analysis of subdecimeter resolution unmanned aerial vehicle (UAV) imagery. *IEEE Transactions on Geosciences & Remote Sensing, 47*, 761-770.

Landis, J., & Koch, G. (1977). The measurement of observer agreement for categorical data. *Biometrics, 33,* 159-174.

Lucas, R., Rowlands, A., Brown, A., Keyworth, S., & Bunting, P. (2007). Rule-based classification of multi-temporal satellite imagery for habitat and agricultural land cover mapping. *ISPRS Journal of Photogrammetry & Remote Sensing*, *62*, 165-185.

Madsen, M. D., Zvirzdin, D. L., Petersen, S. L., Hopkins, B. G., Roundy, B. A., & Chandler, D. G. (2011). Soil water repellency within a burned piñon-juniper woodlands: spatial distribution, severity, and ecohydrologic implications. *Soil Science Society of America Journal, 75,* 1543-1553.

McIver, J. D., Brunson, M., Bunting, S. C., et al. (2010). The Sagebrush Steppe Treatment Evaluation Project (SageSTEP): a test of state-and-transition theory. Gen. Tech. Rep. RMRS-GTR-237. Fort Collins, CO: U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station. 16 p.

Miller, R. F., Bates, J. D., Svejcar, T. J., Pierson, F. B., & Eddleman, L. E. (2005). Biology, ecology and management of Western juniper. Oregon State University, Agricultural Experiment Station Technical Bulletin 152.

Miller, R. F., Svejcar, T. J., & Rose, J. A. (2000). Impacts of western juniper on plant community composition and structure. *Journal of Range Management, 53,* 574-585.

Miller, R. F., & Tausch, R. J. (2001). The role of fire in pinyon and juniper woodlands: a descriptive analysis. Pages 15-30 *in* K.E.M. Galley and T. P. Wilson (eds). Proceedings of the Invasive Species Workshop: the Role of fire in the control and spread of invasive species. Fire conference 2000: the First National Congress on Fire Ecology, Prevention, and Management. Miscellaneous Publication No 11, Tall Timbers Research Station, Tallahassee, FL.

Mueller-Dombois D., & Ellenberg, H. (1974). *Aims and Methods of Vegetation Ecology*. John Wiley and Sons, New York.

Petersen, S. L., & Stringham, T. K. (2008). Infiltration, runoff, and sediment yield in response to western juniper encroachment in southeast Oregon. *Rangeland Ecology & Management, 61,* 74-81.

Pierson, F. B., Williams, C. J., Kormos, P. R., Hardegree, S. P., Clark, P. E., & Rau, B. M. (2010). Hydrologic vulnerability of sagebrush steppe following pinyon and juniper encroachment. *Rangeland Ecology & Management, 63*, 614-629.

Pyke, D. A., Herrick, J. E., Shaver, P., & Pellant, M. (2002). Rangeland health attributes and indicators for qualitative assessment. *Journal of Range Management, 55,* 584-597.

Romme, W. H., Allen, C. D., Bailey, J. D., Baker, W. L., Bestelmeyer, B. T., Brown, P. M., Eisenhart, K. S., Floyd, M. L., Huffman, D. W., Jacobs, B. F., Miller, R. F., Muldavin, E. H., Swetnam, T. W., Tausch, R. J., & Weisberg, P. J. (2009). Historical and modern disturbance regimes, stand structures, and landscape dynamics in piñon-juniper vegetation of the western United States. *Rangeland Ecology & Management, 62,* 208-222.

Roundy, B. A., & Vernon, J. L. (1999). Watershed values and conditions associated with pinyon-juniper communities. Pages 172-187. In Proceedings: Ecology and management of pinyon-juniper communities in the Interior West. Monsen, S. B. and R. Stevens, compilers. USDA Forest Service Rocky Mountain Research Station, RMRS-P-9, Ogden, Utah.

Rouse, J. W., Haas, R. H., Schell, J. A., & Deering, D. W. (1973). Monitoring vegetation systems in the Great plains with ERTS, Third ERTS Symposium, NASA SP-351 I, 309-317.

Ryherd, S., & Woodcock, C. (1996). Combining spectral and textural data in the segmentation of remotely sensed images. *Photogrammetric Engineering & Remote Sensing, 62,* 181-194.

Sankey, T., & Glenn, N. (2011). Landsat-5 TM and lidar fusion for sub-pixel juniper tree cover estimates in a western rangeland. *Photogrammetric Engineering & Remote Sensing, 77,* 1241-1248.

Shaw, D. R. (2005). Remote sensing and site-specific weed management. *Frontiers in Ecology & the Environment, 3,*526-532.

Thorp, K. R., & Tian, L. F. (2004). A review of remote sensing of weeds in agriculture. *Precision Agriculture, 5,* 477-508.

Tausch, R. J., Frakes, N. O., Miller, R. F., & Roundy, B. Unpublished data. Geographic variation in crown structure and foliage biomass of woodland tress across the Great Basin. USDA Forest Service Rocky Mountain Research Station All Scientist Meeting, March 24, 2010, Fort Collins, Colorado.

Tausch, R. J., West, N. E., & Nabi, A. A. (1981). Tree age and dominance patterns in Great basin pinyon-juniper woodlands. *Journal of Range Management, 34,* 259-264.

Tausch, R. J., Miller, R. F., Roundy, B. A., & Chambers, J. C. (2009). Piñon and juniper field guide: Asking the right questions to select appropriate management actions: U. S. Geological Survey Circular 1335, 96 p.

Tian, J., & Chen, D. –M. (2007). Optimization in multi-scale segmentation of high-resolution satellite images for artificial feature recognition. *International Journal of Remote Sensing, 28,* 4625-4644.

Trimble. (2011). eCognition *Developer 8.64.1 reference book*, version 8.64.1, Trimble Germany GmbH, Műnchen, Germany.

Tueller, P. T. (1996). Near-earth monitoring of range condition and trend. *Geocarto International, 11,* 53-62.

Tueller, P. T. (1989). Remote sensing technology for rangeland management applications. *Journal of Range Management, 42,* 442-453.

Weisberg, P. J., Lingua, E., & Pillai, R. B. (2007). Spatial patterns of pinyon-juniper woodland expansion in Central Nevada. *Rangeland Ecology & Management, 60,* 115-124.

Yang, J., Weisberg, P. J., & Bristow, N. A. (2012) Landsat remote sensing approaches for monitoring long-term cover dynamics in semi-arid woodlands: comparison of vegetation indices and spectral mixture analysis. *Remote Sensing of Environment, 119,* 62-71.

Yu, Q., Gong, P., Clinton, N., Biging, G., Kelly, M., & Schirokauer, D. (2006). Object-based detailed vegetation classification with airborne high spatial resolution remote sensing imagery. *Photogrammetric Engineering & Remote Sensing, 72,* 799-811.

Tables

Table 1. Land cover class descriptions that were used in the study.

Land cover class	Description
Live Trees*	Live tree cover includes Utah juniper (*ON, ST,* and *MC*), western juniper (*BM* and *DR*), and singleleaf pinyon (*MC*).
Shrubs*	Dominant shrub cover includes sagebrush (*all sites*), antelope bitterbrush (*BM, DR,* and *ST*), and dead shrubs. Yellow rabbitbrush (*Chrysothamnus viscidiflorus*) and other small non-dominant shrubs could not confidently be distinguished from bunchgrasses and forbs so were included as part of the perennial herbaceous cover class.
Perennial Herbaceous Vegetation (Per Herb)	Native perennial herbaceous vegetation cover includes the following dominant species: Idaho fescue (*BM* and *DR*), Sandberg bluegrass (*all sites*), bluebunch wheatgrass (*MC, ON,* and *ST*), Thurber's needlegrass (*DR* and *MC*), and needle and thread grass (*MC*).
Litter	Litter cover consists of non-living plant or animal material that rests on top of the soil surface including detached woody material. Also includes annual species, particularly cheatgrass which typically comprises <10% of the total litter composition with the exception of Stansbury, where cheatgrass comprises approximately 20% of the litter cover class.
Bare Ground	Bare ground cover is primarily composed of mineral soil (>90 %) and rock with <3% lichen or moss. Devine Ridge is the only exception where bare ground is comprised of 70% mineral soil and 24% rock.

* indicates species classifications

Site codes: Blue Mountain (*BM*), Devine Ridge (*DR*), Marking Corral (*MC*), Onaqui (*ON*), Stansbury (*ST*).

Table 2. Comparison of land cover classes mean percent cover estimates from object-based image analysis and ground-measured data using a paired t-test (N = 71 subplots).

Land cover class	*p*-value	Mean Difference (% Cover)	95% CI (% Cover)
Live Trees	0.0628	1.09	-0.06-2.23
Shrubs	0.7083	0.20	-0.85-1.24
Per Herb	0.1706	0.78	-1.90-0.34
Litter	0.0006*	-2.87	-4.46--1.28
Bare Ground	0.0095*	-2.06	-3.61--0.52

Per Herb = Perennial herbaceous vegetation
CI = Confidence interval
* indicates significant differences between image analysis and ground sampling mean values using the Bonferroni correction ($p < 0.01$).

Table 3. (A) Summary statistics for land cover classes by site for object-based image analysis (OBIA) and ground-measurement sampling (Gnd) methods. (B) Comparison statistics between site average cover mean differences. Differences are calculated by subtracting Gnd cover means from OBIA cover means.

	(A)					(B)				
Cover Type	Site[t]	Method	Mean (% Cover)	SE	Range (% Cover)	Site[t]	Average Mean Difference (% Cover)	SE	Mean Difference Range (% Cover)	N
Live Trees	BM	OBIA	28.33	2.66	10.8-46.2	BM	1.51^{a}	1.36	-10.6-14.7	12
		Gnd	26.83	2.59	17.0-42.3	DR	1.44^{a}	1.26	-8.4-9.3	14
	DR	OBIA	25.19	3.1	8.0-47.6	MC	-1.9^{a}	1.36	-7.8-7.7	12
		Gnd	23.75	3.6	1.7-46.3	ON	0.78^{a}	1.11	-7.0-4.9	18
	MC	OBIA	34.5	5.42	8.6-64.8	ST	3.17^{a}	1.22	-2.8-8.8	15
		Gnd	36.39	6.16	7.6-72.6					
	ON	OBIA	15.84	1.75	4.4-28.9					
		Gnd	15.06	1.8	3.2-30.8					
	ST*	OBIA	28.03	3.48	8.4-50.7					
		Gnd	24.87	3.58	8.2-50.0					
Shrubs	BM	OBIA	13.8	1.14	8.1-19.7	BM	3.59^{a}	1.21	-7.5-8.6	12
		Gnd	10.22	1.63	2.3-21.6	DR	-0.73^{ab}	1.12	-5.9-4.6	14
	DR	OBIA	7.86	1.68	1.6-25.2	MC	0.24^{ab}	1.21	-4.2-5.7	12
		Gnd	8.59	1.42	2.0-22.7	ON	0.13^{ab}	0.99	-6.3-9.4	18
	MC	OBIA	6.74	1.55	1.2-19.5	ST	-1.61^{b}	1.08	-8.7-4.1	15
		Gnd	6.5	1.33	0.0-14.4					
	ON	OBIA	10.47	1.65	0.7-22.7					
		Gnd	10.34	1.08	1.3-18.3					
	ST	OBIA	19.55	3.46	0.8-37.7					
		Gnd	21.16	3.3	3.3-41.9					
Perennial Herbaceous Vegetation	BM	OBIA	15.18	1.93	7.8-28.8	BM	-1.59^{a}	1.35	-8.4-9.4	12
		Gnd	16.8	1.05	12.0-24.2	DR	-0.74^{a}	1.25	-8.8-3.8	14
	DR	OBIA	10.84	1.84	2.2-27.7	MC	1.32^{a}	1.35	-6.4-7.7	12
		Gnd	11.58	1.74	1.9-26.5	ON	-2.29^{a}	1.11	-10.5-4.8	18
	MC	OBIA	10.85	2.04	4.5-23.8	ST	-0.02^{a}	1.21	-9.3-8.9	15
		Gnd	9.53	1.69	2.0-21.7					
	ON	OBIA	11.39	1.11	3.6-19.4					
		Gnd	13.68	1.77	4.8-27.0					
	ST	OBIA	20.96	1.29	13.1-31.5					
		Gnd	20.97	2.10	7.7-30.5					
Litter	BM	OBIA	13.24	0.68	10.2-17.7	BM	-3.21^{a}	1.86	-20.1-5.4	12
		Gnd	16.46	1.73	9.6-32.6	DR	-2.66^{a}	1.72	-11.4-6.0	14
	DR	OBIA	16.44	2.16	7.4-30.6	MC	-4.59^{a}	1.86	-14.6-7.3	12
		Gnd	19.1	2.07	4.5-33.3	ON	0.39^{a}	1.52	-11.5-9.6	18
	MC	OBIA	8.24	1.27	2.1-16.2	ST	-4.29^{a}	1.66	-11.7-6.0	15
		Gnd	14.13	3.42	0.0-30.0					
	ON	OBIA	18.36	0.63	14.2-22.6					
		Gnd	17.98	1.45	7.3-33.4					
	ST*	OBIA	13.59	1.11	4.5-20.1					
		Gnd	17.88	0.8	10.3-23.0					
Bare Ground	BM	OBIA	18.87	2.08	9.2-31.6	BM	-1.06^{ab}	1.75	-7.2-5.9	12
		Gnd	19.93	1.18	12.3-25.7	DR	2.25^{a}	1.62	-6.4-14.0	14

DR	OBIA	30.29	3.61	10.6-53.4	MC	-2.65^{ab}	1.75	-11.0-3.3	12
	Gnd	28.04	3.39	10.7-56.0	ON	-6.02^{b}	1.43	-14.5-10.4	18
MC	OBIA	36.24	3.05	16.1-50.4	ST	-1.67^{ab}	1.56	-12.5-8.8	15
	Gnd	38.89	3.43	16.7-55.0					
ON*	OBIA	40.2	1.81	28.3-54.4					
	Gnd	46.22	2.21	29.0-62.3					
ST	OBIA	15.01	2.07	4.1-30.5					
	Gnd	16.69	2.30	6.7-31.0					

SE = standard error; N = subplots sampled

[t] Blue Mountain (BM), Devine Ridge (DR), Marking Corral (MC), Onaqui (ON), Stansbury (ST).

Average mean differences with different letters within land cover class are significantly different ($p < 0.05$) using Tukey-Kramer honestly significant difference multiple comparison procedure.

* Indicates a significant difference (Bonferroni correction $p < 0.01$) between the two methods for that site using the paired t-test.

Table 4. Contingency table comparing classification accuracy for land cover classes across all sites.

Land cover classes	Live Trees	Shrubs	Per Herb	Litter	Bare Ground
Live Trees	**744**	14	13	16	6
Shrubs	81	**830**	54	37	24
Per Herb	38	26	**561**	40	18
Litter	35	24	62	**803**	70
Bare Ground	7	13	43	54	**615**
Producer's accuracy	82%	92%	77%	85%	84%
User's accuracy	94%	81%	82%	81%	84%
Conditional K_{hat}	0.92	0.76	0.78	0.75	0.81
Overall accuracy = 84%	K_{hat} = 0.80	N = 4,228			

Per Herb = Perennial herbaceous vegetation
K_{hat} = Coefficient of Agreement (Kappa statistic); N = number of points evaluated
Bold values indicate correct number of points classified within a land cover class.

Table 5. Species specific producer's and user's accuracy and conditional K_{hat} coefficient of agreement.

Land Cover Class	Producer's accuracy	User's accuracy	Conditional K_{hat}
Utah Juniper	83%	90%	0.88
Western Juniper	79%	97%	0.96
Singleleaf Pinyon	83%	88%	0.85
Sagebrush ssp.	79%	82%	0.79
Antelope Bitterbrush	96%	75%	0.72

Figures

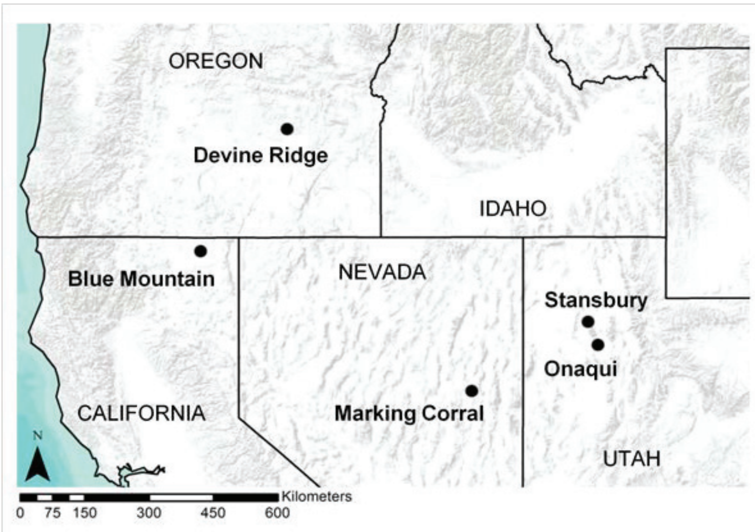

Fig. 1. Study site locations (circles) across the Great Basin overlaid on imagery obtained from ArcGIS online basemap gallery.

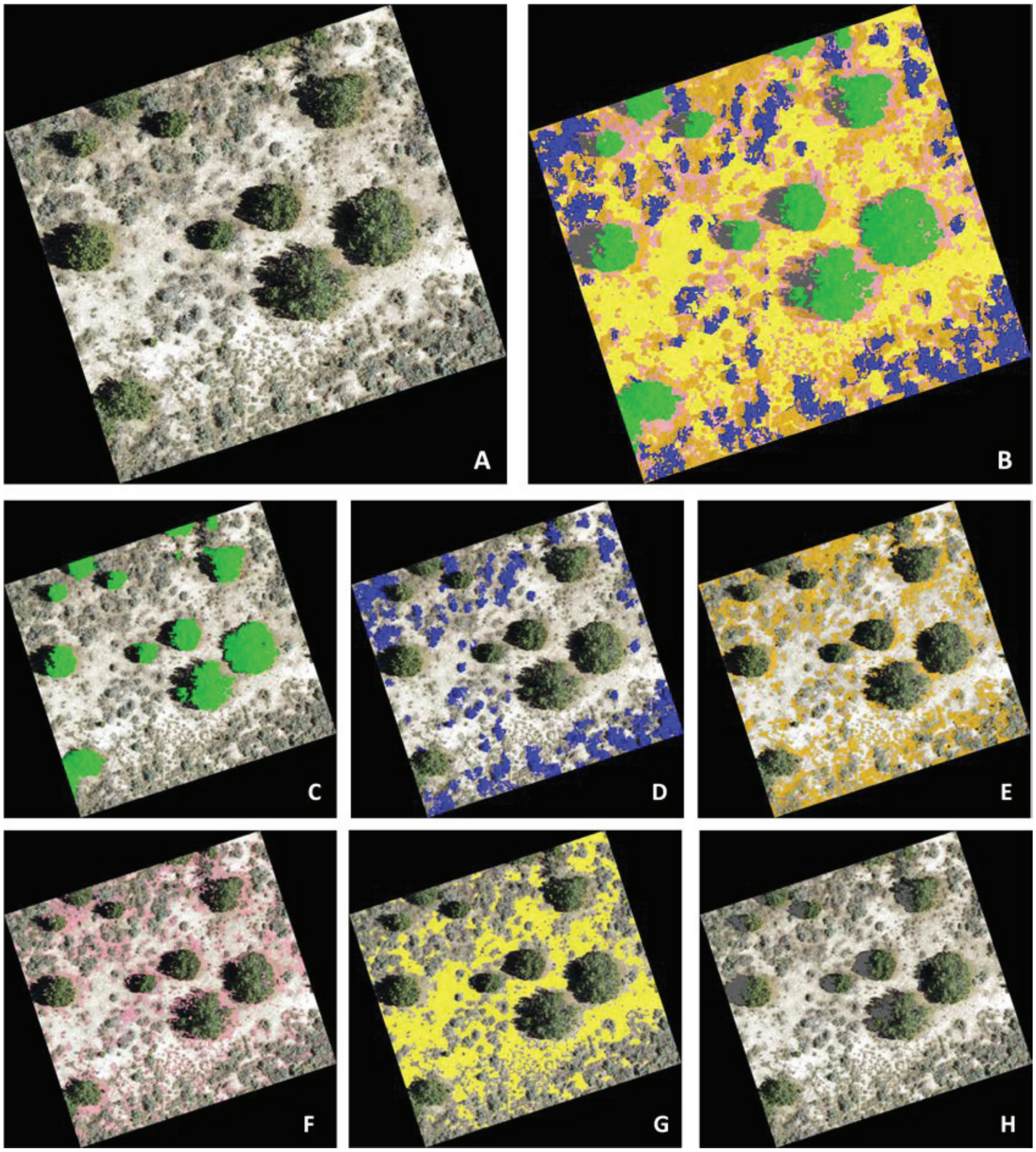

Fig. 2. Example of a juniper subplot RGB image at the onaqui Utah site (A), and the classification results using object-based image analysis (B). Individual land cover classification colors are shown that represent live trees (C; green), shrubs (D, blue), perennial herbaceous vegetation (E, orange), litter (F, pink), bare ground (G, yellow), and shadows (H, gray).

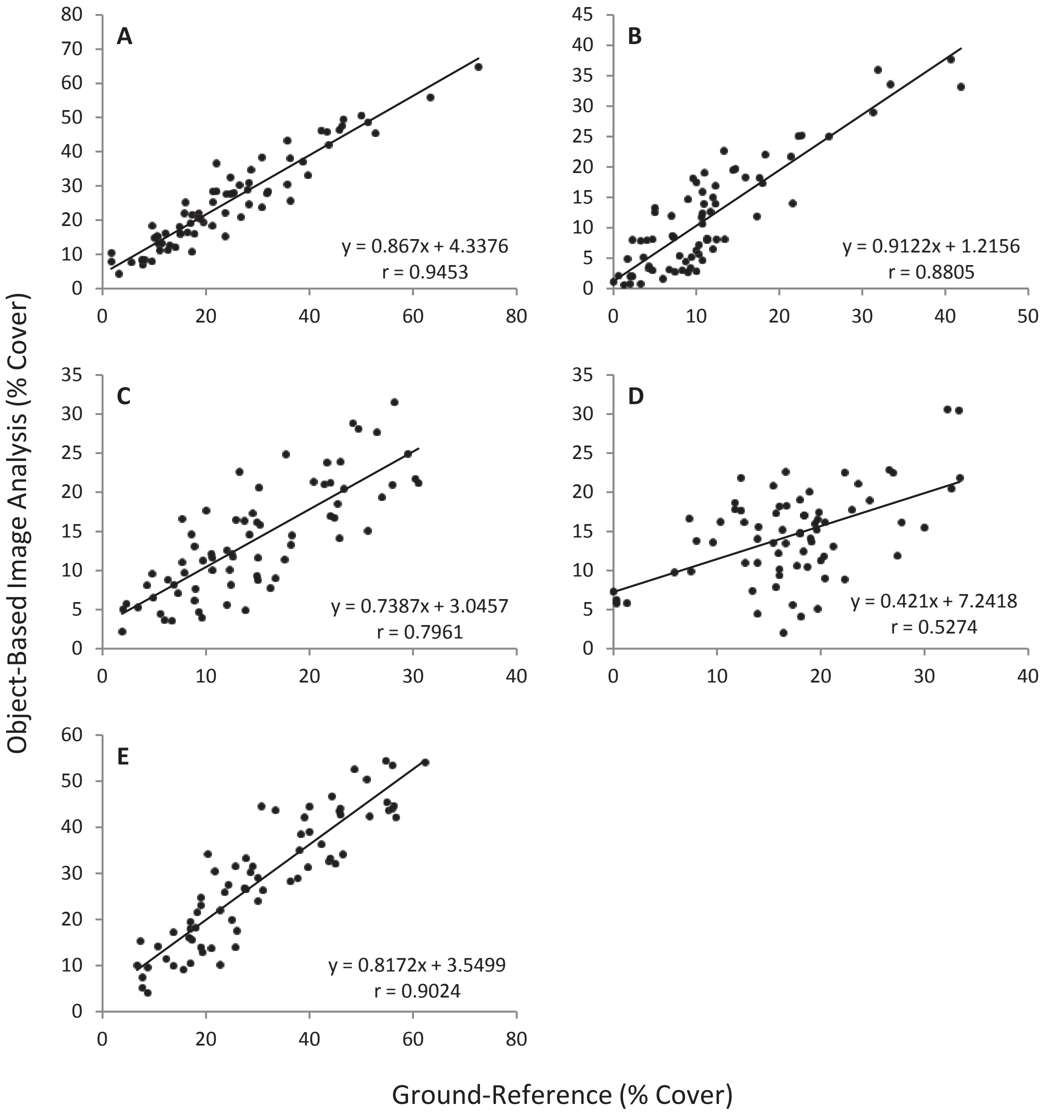

Fig. 3. Regressions of percent cover estimates from an object-based image analysis (y-axis) on ground-reference cover (x-axis) using subplots for all study sites for (A) live trees, (B) shrubs, (C) perennial herbaceous vegetation, (D) litter, and (E) bare ground.

Chapter 2: An Object-Based Image Analysis of Pinyon and Juniper Woodlands Treated to Reduce Fuels

April Hulet[a*], Bruce A. Roundy[a], Steven L. Petersen[a], Ryan R. Jensen[b] and Stephen C. Bunting[c]

[a]Department of Plant and Wildlife Sciences, 275 WIDB, Brigham Young University, Provo, UT 84602 USA; april.hulet@gmail.com, bruce_roundy@byu.edu, steven_petersen@byu.edu

[b]Department of Geography, 920 SWKT, Brigham Young University, Provo, UT 84602 USA; rjensen@byu.edu

[c]Department of Rangeland Ecology and Management, PO Box 441135, University of Idaho, Moscow, ID 83844-1135 USA; sbunting@uidaho.edu

*Correspondence to: april.hulet@gmail.com, 435.590.1192

Manuscript prepared for submission to *Remote Sensing of Environment*

Abstract

Mechanical and prescribed fire treatments are commonly used to reduce fuel loads and maintain or restore sagebrush steppe rangelands across the Great Basin where pinyon (*Pinus*) and juniper (*Juniperus*) trees are encroaching and infilling. Geospatial technologies, particularly remote sensing, could potentially be used to: 1) evaluate the longevity of these treatments, 2) prioritize maintenance for treatments, 3) increase land managers understanding of the spatial distribution and cover of fuels following treatment, and 4) provide valuable data for planning and designing future fuel-reduction treatments. High-spatial resolution color-infrared imagery (0.06-m pixels) was acquired for pinyon and juniper woodlands plots where fuels were reduced by either prescribed fire, tree cutting, or mastication at five sites in Oregon, California, Nevada, and Utah. Imagery was taken with a Vexcel UltraCam X digital camera in June/July 2009. Within each treatment plot, subplots (30x33 m) were measured on the ground in 2009 using the line-point intercept method as part of the Sagebrush Steppe Treatment Evaluation Project. Trimble eCognition Developer 8 was used to classify land cover class (live, burned, cut, and masticated trees, shrubs, perennial herbaceous vegetation, litter, and bare ground) using object-based image analysis (OBIA) techniques. Results from the OBIA and ground measurements were then evaluated to determine the relationship between the two methods. Differences between mean cover estimates using OBIA and ground-measurements were not consistently higher or lower for any land cover classes and when evaluated for individual sites, were within ± 5% of each other. Correlations of cover between the two methods were high ($r = 0.77$—0.96) for most land cover classes. Correlations were lower for cover of masticated debris ($r = 0.73$), and shrub cover in the prescribed burn treatment ($r = 0.55$). The overall accuracy and the kappa statistic for classified thematic maps for each treatment were: prescribed burn 85% and 0.81; cut and fell 82% and 0.77, and mastication 84% and 0.80. Although cover assessments from OBIA differed somewhat from ground measurements, they are

sufficiently accurate to evaluate treatment success and assess the spatial distribution of fuel following fuel-reduction treatments.

Keywords

eCognition, object-based image analysis, prescribed burn, tree cutting, mastication, pinyon-juniper woodlands, SageSTEP

1. Introduction

Risks and uncertainties associated with the management of shrub steppe communities, particularly those where pinyon (*Pinus*) and juniper (*Juniperus*) trees (PJ) are invading and infilling (Romme et al., 2009), are complex and vary across time and space. Geospatial technologies, such as remote sensing are a logical approach for acquiring appropriate information to design and plan adaptive management practices over large areas in short time periods (Booth & Tueller, 2003; Boyd & Svejcar, 2009), and on specific sites where management treatments will achieve long-term objectives (Weisberg et al., 2007). High-resolution imagery from remote sensing can be used to rapidly evaluate cover variables of PJ woodland communities prior to implementing fuel reduction treatments (Hulet et al., *in review*). However, limited research has been conducted to evaluate the potential use of these technologies to assess cover after fuel reduction treatments.

Fuel reduction treatments, such as prescribed burns, chainsaw cutting , mastication, or a combination of treatments are commonly used across the Great Basin in PJ woodlands to decrease woody fuels and to maintain or restore sagebrush ecosystems (Bates, et al., 2000; Bates & Svejcar, 2009; McIver et al., 2010; Miller et al., 2005; Tausch et al., 2009). These treatments are designed to remove trees and promote understory growth, but may be limited in their effects if trees are incompletely burned, cut, masticated or re-establish from seeds (Archer & Stokes, 2000; Bates et al., 2005; Chambers et al., 1999; Tausch & Tueller, 1977). Remote sensing offers an option to evaluate the longevity of fuel-reduction treatments on a large scale and to prioritize maintenance treatments on residual or reestablishing trees to sustain more balanced and functional landscapes.

Fuel reduction treatments also vary in immediate effectiveness. Reduction of woody fuels by prescribed fire is highly dependent on the heterogeneity of the landscape and weather conditions during implementation (Fernandes & Botelho, 2003). Mechanical treatments such as cut and drop are effective in removing tree canopy fuels but increase surface fuels (Schwilk et al., 2009). By altering fuel structure and patterns through various treatments, wildland fire behavior is modified (Agee & Skinner 2005; Cram et al., 2006; Fernandes & Botelho 2003; Finney 2007). Although remote sensing has limitations in describing biomass, size, and bulk density of fuels (Arroyo et al., 2008; Keane et al., 2001), its use to accurately classify fuel cover could complement field-based measurements for evaluating fire hazard and risk.

This study was conducted to assess the relationship between object-based image analysis and field-measured land cover classes found in PJ woodlands after implementation of fuel-reduction treatments (prescribed fire, cut and fell, and mastication). We propose that OBIA cover estimates from high-resolution imagery will be sufficiently similar to ground measurements to accurately assess the spatial distribution and cover of vegetation, bare ground, litter, and down woody debris resulting from the prescribed burn and mechanical treatments.

2. Methods

2.1. Study Area

We conducted our study on five pinyon/juniper woodlands treated to reduce fuels as part of the Joint Fire Sciences Sagebrush Steppe Treatment Evaluation Project (SageSTEP). Sites include Blue Mountain (41°49'N 120° 53'W), Devine Ridge (43°42'N 118°57'W), Marking Corral (39°28'N 115° 07'W), Onaqui (40°13'N 112°28'W) and Stansbury (40°34'N 112°39'W). Site area ranged from 5-20 hectares. Detailed descriptions of each plot are described by McIver et al. (2010). Fuel reduction treatments included prescribed fire and mechanical cut and fell at all sites, with an additional mastication treatment on the

Utah sites. Treatments were implemented at the Marking Corral and Onaqui sites in summer and fall 2006. Blue Mountain, Devine Ridge, and Stansbury were treated fall 2007. Prescribed burn treatments generally resulted in a patchy burn across the treatment plots. Follow-up ignition was used to ensure that >70% of the area of individual subplots was burned. The cut treatment consisted of cutting all trees > 0.5 m in height and dropping them perpendicular to the slope where possible. The mastication treatment consisted of shredding all trees in place with a rotating drum armed with carbide teeth. Further treatments details are given by McIver et al. (2010).

2.2. Ground Measurements

Ground data was collected during summer 2009 on 86 prescribed burn, 82 mechanical cut and fell, and 31 masticated 0.1-ha subplots (30x33 m). Cover measurements were collected within subplots using the line-point intercept method (Canfield 1941) on five, 30-m transects placed systematically across the subplot (McIver et al 2010). First contact intercept data (top vegetation canopy or ground surface) was collected every 0.5-m totaling 60 points per transect or 300 points per subplot, which represents the aerial view captured in the imagery. Cover data used in the analysis from the line-point intercept method included live trees, burned trees, cut trees, masticated debris, shrubs, forbs, grasses, litter, standing and down woody debris, and ground surfaces (mineral soil, rock, lichen or moss).

2.3. Acquisition of Imagery

Color-infrared (red, green, blue, and infrared) imagery was acquired for all treatment plots in late June to early July 2009 with a Vexcel UltraCam X digital camera (Vexcel Imaging GmbH, Graz, Austria) on board a turbocharged Cessna 206 aircraft. Imagery was processed to meet or exceed national map accuracy standards using software created by the Vexcel/Microsoft digital imaging partnership by Aero-graphics, Inc., Salt Lake City, Utah. Timing of imagery was selected to capture phenological differences between perennial and annual vegetation. Ground-measured subplots were extracted from the landscape imagery for each treatment using subplot extraction techniques described in Hulet et al. (*in review*).

2.4. Image Processing

We used eCognition Developer 8.64 (Trimble Germany GmbH, Munich, Germany) for our object-based image analysis. We developed rule-sets for each treatment using an initial subset of the total subplots (training subplots). Training subplots were selected to capture the variation in cover found across treatment plots within each site; training subplots consisted of 10% of the total number of subplots for the prescribed burn plots, 18% for the mechanical cut and fell, and 19% for the mastication plots. The number of training subplots varied among treatments due to variations found within individual sites and size of treatment plots.

We used the multiresolution segmentation algorithm described by Hulet et al. (*in review*) for our object-based image analysis. Through several iterative classification trials, scale, shape, and compactness parameters were determined that best represented land cover classes (Table 1) for each treatment. Because there is no single parameter that is appropriate for classifying all features simultaneously (Frohn & Chaudhary, 2008), we took the approach of using a smaller scale parameter to segment our objects that could then be merged into neighboring classified objects. We found that with this technique, we could better optimize the segmentation of our land cover classes that are highly dependent on atmospheric conditions when imagery was acquired (Jensen, 2005). We could also account for small spaces between plant canopies that may have been incorporated into surrounding objects if larger scale parameters had been used. The designated features and thresholds developed using the training subplots were then tested on the remaining subplots for each treatment (validation subplots).

2.5. Statistical Analysis

We used a paired t-test to determine whether the mean value responses were different between OBIA and ground-measured data for each treatment plot and land cover class. Additional paired t-tests were used to determine whether the mean value responses for individual sites were different between OBIA and ground-measurements for each land cover class. All paired t-tests were evaluated for significance differences using the Bonferroni correction ($p < 0.05/5$). Statistical assumptions for normality and variance were assessed. Mean difference values for each land cover class by site and treatment were compared using one-way ANOVA and the Tukey-Kramer honestly significant difference multiple comparison method with a significance level of $p < 0.05$. To determine if OBIA consistently overestimated or underestimated land cover classes, ground measurements (considered to be correct) were always subtracted from OBIA data. A simple linear regression model was used to assess the relationship between ground-measured data and OBIA data. These regression models only apply within the context of the data set from which they are derived.

2.6. Accuracy Assessments

Accuracy assessments were conducted on classified thematic maps for each treatment to determine the statistical reliability of classified data using ERDAS Imagine 11.0 software (ERDAS Inc., Atlanta, GA). For each cover type, we used a stratified random approach to generate ≥35 points per cover class (Congalton, 2001) for the 5-6 cover classes found in each of the treatment plots. This was repeated for three subplots per site per treatment totaling 36 subplots evaluated (prescribed burn = 15 subplots;

mechanical cut and fell = 15 subplots; mastication = 6 subplots; Table 6). An error matrix was then populated by summing the totals from all treatments, followed by the calculation of producer's accuracy (omission error), user's accuracy (commission error), overall accuracy, conditional K_{hat} coefficient of agreement, and K_{hat} coefficient of agreement (Jensen, 2005).

3. Results and Discussion

3.1. Prescribed fire

Land cover classes found within the prescribed fire treatments (Fig. 1 A & B) did not differ significantly between the OBIA and ground-measurement methods (Table 2A). However, when individual sites were analyzed, live trees land cover classes did differ between the two methods (Table 3). OBIA estimates were on average 4% more than ground measurements for live tree cover of western juniper (*Juniperus occidentalis*) plots, and on average 1% less than ground measurement for live tree cover of Utah juniper (*Juniperus osteosperma*) plots. Live trees were most often misclassified as perennial herbaceous vegetation (Table 6) with most misclassified objects located around the perimeter of tree canopies. Tree canopy edges are difficult to correctly classify due to reduced foliage and increased reflectance of light off understory vegetation or bare ground through the canopy edge (Hulet et al., *in review*).

Burned tree land cover classes varied across sites depending on the intensity of the prescribed burn. For subplots with higher intensity burns (higher severity), more tree biomass was consumed leaving less material to be classified. In areas with a less intense fire, where needles and branches were not completely consumed, objects had more prominent spectral differences from other land cover classes and could be more easily classified. Few shrubs survived the prescribed fire treatment (15 total subplots); where shrubs survived, OBIA cover estimates were within ± 5% of the ground-measured estimate (Table 3).

Prescribed fire generally consumes above-ground plant canopies and allows aerial photography to capture perennial herbaceous vegetation recovery, annual vegetation invasion, and bare ground connectivity. Cover estimates from OBIA and ground measurements were highly correlated (perennial herbaceous vegetation r = 0.90; litter r = 0.92; and bare ground r = 0.91; Fig. 2). OBIA cover estimates for these classes were within ±5 % of ground measurements (Table 3). Conditional K_{hat} values for these classes was lower than tree and shrub (Table 6) however, they still indicate a strong agreement between the OBIA classification and ground-reference data. For both perennial herbaceous vegetation and litter land cover classes, user's accuracy was slightly higher than producer's accuracy resulting in those land cover classes being underestimated across the subplot.

3.2. Mechanical cut and fell

Within the mechanical cut and fell treatment (Fig. 1 C & D), cover of cut trees and litter differed significantly between OBIA and ground-measured methods (Table 2B). Compared to ground measurements, cut tree land cover classes were typically underestimated by OBIA (2%) whereas litter was overestimated by OBIA (3%). As with the prescribed burn plots, differences occasionally occurred between the two estimation methods within and among sites for certain land cover classes (Table 4). At Devine Ridge, OBIA estimates of cut tree cover were on average 5.7% less than ground cover measurements. With the exception of Stansbury, OBIA estimates of cut tree cover were generally lower then ground measurements (Table 4). To reduce the heterogeneity found within objects, we used the median filtered RGB imagery and a hue transformation parameter for the classification. This minimized object variation within the cut tree canopy but also compromised other land cover classes (i.e. litter) found within the canopy of the cut tree as reflected in the error matrix (Table 6B). Although the conditional K_{hat} coefficient of agreement is 0.89 for cover of cut trees, the producer's and user's error are dissimilar suggesting that errors of omission were higher than commission error resulting in the underestimation of cut trees proportionally to the remaining land cover classes.

OBIA litter cover estimates were significantly different from ground-measurements at Blue Mountain, Marking Corral, and Onaqui (Table 4). At all sites, OBIA litter cover estimate were approximately 3% greater than ground measurements which is likely due to the filtering techniques mentioned above. Spectrally, needles retained on cut tree branches were very similar to litter. In addition to spectral parameters, multiple textural parameters were explored to better classify or distinguish the two land cover classes from one another. We found that our multiresolution segmentation parameters were too fine to capture any textural differences between the two classes. However, it may be possible to mask out cut trees and improve the classification of litter cover by utilizing eCognition's ability to perform multiple segmentation processes on a single image (Laliberte, et al. 2007a).

The best correlation between image and ground cover values for mechanical cut and fell treatments was for cover of bare ground (r = 0.96) while perennial herbaceous vegetation had the lowest correlation (r = 0.84) (Fig. 3). The overall accuracy for the mechanical cut and fell treatment was 82% with a kappa statistic of 0.77 (Table 6B). With the exception of cut tree cover, our OBIA cover estimates are within reasonable error for many land management decisions (average mean difference range <±10% of ground measured cover).

3.3. Mastication

Cover did not differ between OBIA and ground-measurement methods across the masticated subplots (Table 2C; Fig. 1 E & F). Although there was no significant difference between measurement methods, correlation of cover estimates for masticated debris was lower than the other land cover classes (r = 0.73, Fig. 5). The lower correlation for this variable may have resulted from capturing images 2-3 years post treatment. Although masticated debris was still present on treatment plots, debris was scattered away from the initial pile, presumably due to wind and precipitation. As masticated debris was dispersed throughout the plots, ground-measurement methods could still account for individual debris material. However, our pixel resolution was inadequate to capture individual pieces of smaller clumps of masticated debris which were most often misclassified as bare ground (Table 6C).

Cover values for land cover classes were only significantly different between methods at the Onaqui site where OBIA shrub cover was 2% lower than ground measured shrub cover (Table 5). The averaged mean difference across all land cover classes in the masticated treatment plots between the two methods were ±3% (Table 5). For the mastication treatment plots, the overall accuracy was 84% with a kappa statistic of 0.80 (Table 6C). Perennial herbaceous vegetation was most often misclassified according to our error matrix, however there was still a strong correlation between the two measurement methods (r = 0.89; Fig. 4). Additionally, correlations between the two methods for cover of shrubs, litter, and bare ground were relative high (Fig. 4) providing evidence that these methods could be used to assess treatment plots across a landscape.

4. Conclusions

This study demonstrates that high-resolution imagery and object-based image analysis techniques that estimate cover described by Hulet et al. (*in review*), have the potential to assess the spatial distribution and cover of vegetation, bare ground, litter and down woody debris resulting from treatments. Differences between mean estimates using OBIA and ground-measurements were not consistently higher or lower for any of our land cover classes (Table 2) and when evaluated for individual sites, are within ± 5% of each other.

Although OBIA cover estimates were strongly correlated with ground measurements, they were least similar for the mechanical cut and fell treatment and more similar for the prescribed burn and mastication treatments. Aerial photography is limited to the horizontal land cover class distribution that omits important understory characteristics and height estimates that play a critical role in fire behavior (Arroyo et al., 2008) and in determining ecological resiliency. For example, our imagery and techniques do not account for understory vegetation cover of shrubs, perennial grasses, and invasive grasses found under cut trees that likely influences ecological processes and function. As needles fall off of cut trees over subsequent years, there may be more potential for remotely-sensing these land cover classes. Prescribed fire and mastication remove overstory vegetation (i.e. juniper trees) allowing for the detection of smaller shifts within a plant community and bare ground that would impact treatment maintenance as well as rangeland conditions (Pyke et al., 2002).

Remote sensing does have limitations, however, correctly classifying land cover classes is a step to better modeling and understanding fire behavior (Andrews, et al., 2008; Finney, 2004; Scott & Burgan, 2005), planning future fuel-reduction treatments (Ager et al., 2010; Finney, 2001), making strategic decisions about fire suppression (Rollins, et al., 2004), quickly gauging the success of treatments, and prioritizing maintenance treatments. Future research should explore how cover estimates from OBIA of fuels can be integrated with field sampled physical characteristics such as loading, size, and bulk density for PJ woodlands to quantify fuel loads following treatments. Both an accurate knowledge of the spatial distribution and quantity of fuel loads is critical when analyzing, modeling, and predicting fire behavior (Andrews et al., 2008; Arroyo et al., 2008; Finney, 1999; Hall & Burke, 2006). Additionally, further research should be conducted that links ground measurements and OBIA measurements across multiple spatial scales (Herrick et al., 2006; Laliberte et al., 2007b) and remote sensing platforms (Gibbes et al., 2010) that could potentially provide land managers with a rapid assessment of rangeland conditions and trends.

Acknowledgments

Financial support for this study was provided by the Joint Fire Sciences Sagebrush Steppe Treatment Evaluation Project, the Bureau of Land Management, Brigham Young University, and the University of Idaho. We thank the SageSTEP research team, particularly James McIver and the sagebrush-woodland principle investigators Richard Miller, Robin Tausch and Jeanne Chambers, as well as the woodland site managers, Jaime Ratchford, Neil Frakes, Travis Miller and Brad Jessop for substantial field support and advice.

References

Agee, J .K. & Skinner, C. N. (2005). Basic principles of forest fuel reduction treatments. *Forest Ecology and Management, 211,* 83-96.

Ager, A. A., Vaillant, N. M., & Finney, M. A. (2010). A comparison of landscape fuel treatment strategies to mitigate wildland fire risk in the urban interface and preserve old forest structure. *Forest Ecology and Management, 259,* 1556-1570.

Andrews, P. L., Bevins, C. D., & Seli, R. C. (2008). BehavePlus fire modeling system, version 4.0: User's guide. General Technical Report RMRS-GTR-106WWW. Ogden, UT; Department of Agriculture, Forest Service. Rocky Mountain Research Station.

Archer, S. & Stokes, C. (2000). Stress, disturbance and change in rangeland ecosystems. In O. Arnalds & S. Archer (Eds.), *Rangeland desertification*, (pp. 17-38). Netherlands: Kluwer Academic Publishers.

Arroyo, L .A., Pascual, C., & Manzanera J. A. (2008). Fire models and methods to map fuel types: the role of remote sensing. *Forest Ecology and Management, 256,* 1239-1252.

Bates, J. D., Miller, R. F., & Svejcar, T. J. (2000). Understory dynamics in cut and uncut western juniper woodlands. *Journal of Range Management, 53,* 119-126.

Bates, J. D., Miller, R. G., & Svejcar, T. J. (2005). Long-term successional trends following western juniper cutting. *Rangeland Ecology and Management, 58,* 533-541.

Bates, J. D., & Svejcar, T. J. (2009). Herbaceous succession after burning of cut western juniper trees. *Western North American Naturalist, 69,* 9-25.

Booth, D. T., & P. T. Tueller. (2003). Rangeland monitoring using remote sensing. *Arid Land Research and Management, 17,* 455-467.

Boyd, C. S., & T. J. Svejcar. (2009). Managing complex problems in rangeland ecosystems. *Rangeland Ecology and Management, 62,* 491-499.

Canfield, R. (1941). Application of line interception in sampling range vegetation. *Journal of Forestry*, *39,* 388-394.

Chambers, J. C., Vander Wall, S. B., & Schupp, E. W. (1999). Seed dispersal and seedling establishment of pinyon and juniper species within the pinyon-juniper woodland. Pages 29-34. In S. B. Monson, R. Stevens, R. J. Tausch, R. Miller, and S. Goodrich. Proceedings: Ecology and Management of Pinyon-Juniper Communities within the Interior West. USDA Forest Service, Rocky Mountain Research Station, General Technical Report, RMRS-P-9.

Congalton, R. G. (2001). Accuracy assessment and validation of remotely sensed and other spatial information. *International Journal of Wildland Fire, 10,* 321-328.

Cram, D. S., Baker, T. T., & Boren, J. C. (2006). Wildland fire effects in silviculturally treated vs. untreated stands of New Mexico and Arizona. Research Paper RMRS-RP-55. Fort Collins, CO: U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station. 28 p.

Fernandes, P. M., & Botelho, H. S. (2003). A review of prescribed burning effectiveness in fire hazard reduction. *International Journal of Wildland Fire, 12,* 117-128.

Finney, M A. (2007). A computational method for optimizing fuel treatment locations. *International Journal of Wildland Fire, 16,* 702-711.

Finney, M .A. (2004). FARSITE: Fire area simulator—model development and evaluation. Res. Pap. RMRS-RP-4, Ogden, UT: U. S. Department of Agriculture, Forest Service, Rocky Mountain Research Station. 47 p.

Finney, M .A. (2001). Design of regular landscape fuel treatment patterns for modifying fire growth and behavior. *Forest Science, 47,* 219-228.

Finney, M. A. (1999). FARSITE—a program for fire growth simulation. Fire management notes. 59:13.

Frohn, R. C. & Chaudhary, N. (2008). Multi-scale image segmentation and object-oriented processing for land cover classification. *GIScience and Remote Sensing, 45,* 377-391.

Gibbes, C., Adhikari, S., Rostant, L., Southworth, J., & Qiu, Y. (2010). Application of object based classification and high resolution satellite imagery for savanna ecosystem analysis. *Remote Sensing, 2,* 2748-2775.

Hall, S. A., & Burke, I. C. (2006). Considerations for characterizing fuels as inputs for fire behavior models. *Forest Ecology and Management, 227,* 102-114.

Herrick, J. E., Bestelmeyer, B. T., Archer, S., Tugel, A. J., Brown, J. R. (2006). An integrated framework for science-based arid land management. *Journal of Arid Environments, 65,* 319-335.

Hulet, A., Roundy, B. A., Petersen, S. L., Jensen, R. R., and Bunting, S. C. (*in review*) An approach to assess the relationship between ground measurements and object-based image analysis of land cover classes found in pinyon and juniper woodlands. *Remote Sensing of Environment*

Jensen, J. R. (2005). *Introductory digital image processing: a remote sensing perspective.* (3rd ed.). Prentice Hall, New Jersey, p 175.

Keane, R. E., Burgan, R., Van Wagtendonk, J. (2001). Mapping wildland fuels for fire management across multiple scales: Integrating remote sensing, GIS, and biophysical modeling. *International Journal of Wildland Fire, 10,* 301-319.

Laliberte, A. S., Fredrickson, E. L., & Rango, A. (2007a). Combing decision trees with hierarchical object-oriented image analysis for mapping arid rangelands. *Photogrammetric Engineering* & Remote Sensing, 73, 197-207.

Laliberte, A. S., Rango, A., Herrick, J. E., Fredrickson, E. L., & Burkett, L. (2007b). An object-based image analysis approach for determining fractional cover of senescent and green vegetation with digital plot photography. *Journal of Arid Environments, 69,* 1-14.

Miller, R. F., Bates, J. D., Svejcar, T. J., Pierson, F. B., & Eddleman, L. E. (2005). Biology, ecology, and management of western juniper. Oregon State University, Agricultural Experiment Station Technical Bulletin 152.

McIver, J. D., Brunson, M., Bunting, S. C., et al. (2010). The Sagebrush Steppe Treatment Evaluation Project (SageSTEP): a test of state-and-transition theory. Gen. Tech. Rep. RMRS-GTR-237. Fort Collins, CO: U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station. 16 p.

Pyke, D. A., Herrick, J. E., Shaver, P., & Pellant, M. (2002). Rangeland health attributes and indicators for qualitative assessment. *Journal of Range Management, 55,* 584-597.

Rollins, M .G., Keane, R. E., & Parsons, R. A. (2004). Mapping fuels and fire regimes using remote sensing, ecosystem simulation, and gradient modeling. *Ecological Applications, 14,* 75-95.

Romme, W. H., Allen, C. D., Bailey, J. D., Baker, W. L., Bestelmeyer, B. T., Brown, P. M., Eisenhart, K. S., Floyd, M. L., Huffman, D. W., Jacobs, B. F., Miller, R. F., Muldavin, E. H., Swetnam, T. W., Tausch, R. J., & Weisberg, P. J. (2009). Historical and modern disturbance regimes, stand structures, and landscape dynamics in piñon-juniper vegetation of the western United States. *Rangeland Ecology and Management, 62,* 208-222.

Schwilk, D. W., Keeley, J. E., Knapp, E. E., McIver, J., Bailey, J. D., Fettig, C. J., Fiedler, C. E., Harrod, R. J., Moghaddas, J. J., Outcalt, K. W., Skinner, C. N., Stephens, S. L., Waldrop, T. A., Yaussy, D. A., & Youngblood, A. (2009). The national fire and fire surrogate study: effects of fuel reduction methods on forest vegetation structure and fuels. *Ecological Applications, 19,* 285-304.

Scott, J. H., & Burgan, R. E. (2005). Standard fire behavior fuel models: a comprehensive set for use with Rothernel's surface fire spread model. Gen. Tech. Rep. RMRS-GTR-153. Fort Collins, CO: U. S. Department of Agriculture, Forest Service, Rocky Mountain Research Station. 72 p.

Tausch, R. J., & Tueller, P. T. (1977). Plant succession following chaining of pinyon-juniper woodlands in eastern Nevada. *Journal of Range Management, 30,* 44-49.

Tausch, R. J., Miller, R. F., Roundy, B. A., & Chambers, J. C. (2009). Piñon and juniper field guide: Asking the right questions to select appropriate management actions: U. S. Geological Survey Circular 1335, 96 p.

Weisberg, P. J., Lingua, E., & Pillai, R. B. (2001). Spatial patterns of pinyon-juniper woodland expansion in Central Nevada. *Rangeland Ecology and Management, 60,* 115-124.

Tables

Table 1. Land cover class descriptions that were used in the study.

Land cover class	Description
Live Trees	Live tree cover found on prescribed burn subplots.
Burned Trees	Burned tree cover found on prescribed burn subplots, includes burned needles retained on tree branches.
Cut Trees	Cut tree cover found on the mechanical cut and fell treatment subplots, includes needles retained on tree branches.
Masticated Debris	Masticated debris cover found in masticated (Bullhog®) subplots for Utah sites only (*ON* and *ST)*. Masticated debris includes pieces of wood or bark on the ground that are obvious results of the treatment.
Shrubs	Dominant shrub cover includes sagebrush (*all sites*), antelope bitterbrush (*BM, DR,* and *ST*), and dead shrubs. Yellow rabbitbrush (*Chrysothamnus viscidiflorus*) and other small non-dominant shrubs could not confidently be distinguished from bunchgrasses and forbs so were included as part of the perennial herbaceous cover class.
Perennial Herbaceous (Per Herb)	Native perennial herbaceous vegetation cover includes the following dominant species: Idaho fescue (*BM* and *DR),* Sandburg's bluegrass *(all sites*), bluebunch wheatgrass (*MC, ON,* and *ST)*, Thurber's needlegrass (*DR* and *MC)*, and needle and thread grass (*MC*).
Litter	Litter cover consists of non-living plant or animal material that rests on top of the soil surface including detached woody material. Also includes annual species, particular cheatgrass which typically comprises <10% of the total litter composition with the exception of Stansbury where cheatgrass comprises > 20% of the litter cover class.
Bare Ground	Bare ground cover is primarily composed of mineral soil (>90 %) and rock with <3% lichen or moss.

Site codes: Blue Mountain (*BM*), Devine Ridge (*DR*), Marking Corral (*MC*), Onaqui (*ON*), Stansbury (*ST*).

Table 2. Comparison of land cover class mean percent cover estimates from object-based image analysis (OBIA) and ground-measured data using a paired t-test for (A) prescribed burn, (B) cut and fell, and (C) mastication fuel-reduction treatments. Live trees, burned trees, cut trees and masticated debris are results of specific treatments. Differences were calculated by subtracting ground measurements from OBIA data.

	(A)			**(B)**			**(C)**		
Land cover class	*p*-value	Mean Difference (% cover)	95% CI (% cover)	*p*-value	Mean Difference (% cover)	95% CI (% cover)	*p*-value	Mean Difference (% cover)	95% CI (% cover)
Live Trees	0.9773	-0.02	-1.02-0.99	-	-	-	-	-	-
Burned Trees	0.8062	-0.12	-1.10-0.86	-	-	-	-	-	-
Cut Trees	-	-	-	0.0006*	-2.00	-3.11--0.90	-	-	-
Masticated Debris	-	-	-	-	-	-	0.4568	-0.59	-2.23-1.03
Shrubs	0.5255	-0.34	-2.39-1.28	0.1453	0.78	-0.28-1.84	0.5751	-0.35	-1.61-0.92
Per Herb	0.7826	-0.17	-1.38-1.04	0.8538	0.11	-1.03-1.24	0.0580	1.80	-0.07-3.65
Litter	0.1698	1.17	-0.51-2.85	< 0.0001*	3.00	1.95-4.05	0.1727	1.24	-0.58-3.06
Bare Ground	0.2918	-0.77	-2.25-0.68	0.3804	-0.46	-1.52-0.59	0.3844	0.96	-1.28-3.19

Per Herb = Perennial herbaceous vegetation; CI = Confidence interval

* indicates significant differences (Bonferroni correction $p < 0.01$) between OBIA and ground measured mean values.

Table 3. (A) Summary statistics for land cover classes in prescribed burn treatment subplots by site for object-based image analysis (OBIA) and ground-measured sampling (Gnd) methods. (B) Comparison statistics between site average mean differences for each land cover class. Differences were calculated by subtracting ground measurements from OBIA data.

	(A)					(B)				
Land Cover Class	Site[t]	Method	Mean (% Cover)	SE	Range (% Cover)	Site[t]	Average Mean Difference (% Cover)	SE	Average Mean Difference Range (% Cover)	N
Live Trees	BM	OBIA	10.70	2.57	7.5-16.0	BM	3.81[a]	0.98	1.8-7.0	3
		Gnd	7.13	0.98	5.7-9.0	DR	4.11[a]	0.85	3.1-5.8	4
	DR*	OBIA	5.53	0.76	4.0-7.5	MC	-1.02[b]	0.42	-4.1-3.6	16
		Gnd	1.43	0.38	0.3-2.0	ON	-1.95[b]	0.76	-4.5--1.0	5
	MC	OBIA	2.02	0.65	0.0-7.6	ST	-0.77[b]	0.98	-1.7--0.3	3
		Gnd	3.04	0.56	0.3-7.7					
	ON	OBIA	0.65	0.40	0.0-1.8					
		Gnd	2.60	0.99	1.0-6.3					
	ST	OBIA	0.00	0.00	0.0-0.0					
		Gnd	0.77	0.47	0.3-1.7					
Burned Trees	BM	OBIA	7.64	4.89	1.1-18..2	BM	-2.88[b]	1.13	-19.2-5.4	13
		Gnd	10.52	9.44	0.3-31.3	DR	-0.98[ab]	1.13	-5.7-3.8	13
	DR	OBIA	6.30	5.79	0.9-17.1	MC	1.94[a]	0.87	-4.5-8.1	22
		Gnd	7.28	5.41	0.3-19.3	ON	-0.48[ab]	0.99	-6.7-5.6	17
	MC	OBIA	4.86	2.67	0.5-9.7	ST	0.54[ab]	1.18	-3.5-8.9	12
		Gnd	2.93	1.95	0.3-8.0					
	ON	OBIA	12.11	5.94	3.1-21.3					
		Gnd	12.59	5.30	3.9-22.8					
	ST	OBIA	4.76	6.34	0.2-22.8					
		Gnd	4.23	6.34	0.0-23.0					
Shrubs	BM	OBIA	5.04	0.89	3.0-7.7	BM	-1.62[a]	1.23	-2.7--0.3	5
		Gnd	6.67	1.00	4.9-10.4	DR	1.86[a]	1.13	-3.4-4.9	6
	DR	OBIA	4.13	0.96	0.8-6.9	MC	-2.85[a]	1.38	-5.2-0.7	4
		Gnd	2.27	0.72	0.0-5.3					
	MC	OBIA	7.40	1.43	4.5-10.1					
		Gnd	10.25	1.30	7.7-13.7					
Perennial Herbaceous Vegetation	BM	OBIA	33.02	3.70	10.2-60.7	BM	-2.78[a]	1.45	-10.5-3.2	13
		Gnd	35.80	4.24	8.6-52.0	DR	2.01[a]	1.45	-8.3-12.4	13
	DR	OBIA	18.48	2.47	5.7-33.1	MC	0.27[a]	1.11	-9.4-9.5	22
		Gnd	16.47	2.40	3.9-31.9	ON	0.61[a]	1.27	-8.1-9.0	17
	MC	OBIA	25.10	1.75	9.5-41.4	ST	-1.60[a]	1.51	-9.0-7.9	12
		Gnd	24.83	1.43	10.9-35.9					
	ON	OBIA	20.22	1.73	11.5-35.5					
		Gnd	19.62	1.10	12.2-30.3					
	ST	OBIA	20.90	5.49	2.9-50.5					
		Gnd	22.50	4.78	1.4-48.3					
Litter	BM	OBIA	31.38	1.82	14.8-40.6	BM	2.93[a]	2.01	-12.4-10.7	13
		Gnd	28.45	2.40	14.6-43.7	DR	2.85[a]	2.01	-14.4-16.6	13
	DR	OBIA	40.52	2.92	23.6-57.9	MC	2.02[a]	1.55	-14.2-18.7	22
		Gnd	37.67	2.33	21.6-53.0	ON	-2.86[a]	1.76	-13.9-11.4	17
	MC	OBIA	20.89	1.46	6.4-34.8	ST	1.57[a]	2.09	-7.5-9.9	12
		Gnd	18.86	1.37	5.0-34.0					
	ON	OBIA	40.82	2.15	21.4-53.7					
		Gnd	43.68	1.66	34.9-56.3					
	ST	OBIA	67.14	5.58	35.2-88.9					

		Gnd	65.57	6.03	25.3-92.4					
Bare Ground	BM	OBIA	21.21	2.68	11.1-42.7	BM	2.36[a]	1.74	-9.4-14.0	13
		Gnd	18.85	2.24	5.0-31.3	DR	-4.39[a]	1.74	-16.0-2.4	13
	DR	OBIA	29.57	3.23	9.0-54.9	MC	-1.39[a]	1.34	-12.7-10.8	22
		Gnd	33.95	2.44	22.0-53.0	ON	-0.77[a]	1.52	-15.8-14.6	17
	MC	OBIA	45.71	2.02	28.0-64.1	ST	0.82[a]	1.81	-2.5-7.0	12
		Gnd	47.10	1.59	35.7-65.0					
	ON	OBIA	25.65	1.64	13.7-36.6					
		Gnd	26.42	1.52	10.7-36.3					
	ST	OBIA	8.16	0.86	4.5-13.9					
		Gnd	7.34	0.92	2.0-13.0					

SE = standard error; N = subplots sampled

[t] Blue Mountain (BM), Devine Ridge (DR), Marking Corral (MC), Onaqui (ON), Stansbury (ST).

Average mean differences with different letters within land cover class are significantly different ($p < 0.05$) from other sites in that land cover class using Tukey-Kramer honestly significant difference multiple comparison procedure.

* Indicates a significant difference (Bonferroni correction $p < 0.01$) between the two methods for that site using the paired t-test.

Table 4. (A) Summary statistics for land cover classes in cut and fell treatment subplots by site for object-based image analysis (OBIA) and ground-measured sampling (Gnd) methods. (B) Comparison statistics between site average mean differences for each land cover class. Differences were calculated by subtracting ground measurements from OBIA data.

	(A)					(B)				
Land Cover Class	Site[t]	Method	Mean (% Cover)	SE	Range (% Cover)	Site[t]	Average Mean Difference (% Cover)	SE	Average Mean Difference Range (% Cover)	N
Cut Trees	BM	OBIA	26.69	3.38	9.6-52.7	BM	-1.75[ab]	1.11	-7.2-6.5	14
		Gnd	28.44	2.76	12.3-48.9	DR	-5.79[b]	1.25	-12.2-1.2	11
	DR*	OBIA	18.39	2.44	6.8-34.5	MC	-0.21[a]	1.04	-5.3-5.8	16
		Gnd	24.17	3.03	5.6-46.3	ON	-3.16[ab]	1.11	-10.6-2.3	14
	MC	OBIA	13.17	1.50	2.7-23.3	ST	0.12[a]	1.20	-6.5-6.4	12
		Gnd	13.38	1.56	0.6-23.3					
	ON	OBIA	12.11	1.46	4.1-22.0					
		Gnd	15.27	1.56	3.6-25.4					
	ST	OBIA	28.46	2.33	18.8-43.1					
		Gnd	28.34	1.45	21.9-36.7					
Shrubs	BM	OBIA	17.03	2.50	5.9-34.7	BM	-0.25[a]	1.13	-8.4-6.3	14
		Gnd	17.29	2.40	3.3-30.3	DR	2.34[a]	1.28	-5.7-12.9	11
	DR	OBIA	13.59	2.49	0.9-25.6	MC	-0.90[a]	1.06	-6.3-3.0	16
		Gnd	11.25	2.59	0.0-23.4	ON	2.40[a]	1.13	-7.5-9.5	14
	MC	OBIA	15.26	1.93	1.6-30.1	ST	0.91[a]	1.23	-5.1-6.0	12
		Gnd	16.16	1.64	3.0-28.0					
	ON	OBIA	11.64	2.18	1.4-26.9					
		Gnd	9.24	2.55	1.0-28.3					
	ST	OBIA	8.91	1.64	1.9-17.8					
		Gnd	8.01	1.26	2.0-15.7					
Perennial Herbaceous Vegetation	BM	OBIA	21.32	2.11	10.6-33.4	BM	0.29[a]	1.22	-4.9-8.2	14
		Gnd	21.03	1.72	11.3-31.7	DR	-0.90[a]	1.37	-9.5-8.2	11
	DR	OBIA	18.37	2.02	8.2-32.3	MC	2.47[a]	1.14	-4.9-8.6	16
		Gnd	19.27	2.12	10.7-33.1	ON	-1.21[a]	1.22	-8.2-7.0	14
	MC	OBIA	22.30	0.92	16.5-30.2	ST	-0.81[a]	1.31	-9.1-6.5	12
		Gnd	19.84	1.45	7.9-29.3					
	ON	OBIA	24.70	1.83	11.6-34.5					
		Gnd	25.91	1.55	14.3-34.6					
	ST	OBIA	32.71	2.47	19.7-47.2					
		Gnd	33.52	2.37	21.6-46.2					
Litter	BM*	OBIA	20.26	1.48	12.0-29.9	BM	3.65[a]	1.17	-2.0-9.9	14
		Gnd	16.61	1.24	10.7-28.6	DR	1.72[a]	1.32	-6.6-8.6	11
	DR	OBIA	23.73	1.90	10.7-32.9	MC	3.00[a]	1.10	-1.2-7.6	16
		Gnd	22.01	1.74	11.9-31.4	ON	3.33[a]	1.17	-3.2-9.0	14
	MC*	OBIA	7.09	1.97	0.7-14.1	ST	3.05[a]	1.27	-7.0-9.7	12
		Gnd	4.09	0.82	0.7-15.1					
	ON*	OBIA	23.22	1.09	16.1-30.1					
		Gnd	19.89	1.27	11.6-30.7					
	ST	OBIA	27.20	1.20	17.1-33.2					
		Gnd	24.16	1.76	16.0-34.4					
Bare Ground	BM	OBIA	14.56	1.52	4.3-23.5	BM	0.51[a]	1.17	-7.3-9.5	14
		Gnd	14.05	0.98	6.3-19.7	DR	0.11[a]	1.32	-7.7-6.7	11
	DR	OBIA	14.96	1.65	5.4-24.2	MC	-1.74[a]	1.09	-7.7-4.0	16
		Gnd	14.86	1.50	3.4-21.3	ON	-0.09[a]	1.17	-6.8-8.9	14
	MC	OBIA	41.80	1.46	28.7-50.7	ST	-0.87[a]	1.26	-8.2-1.8	12
		Gnd	43.54	1.16	33.7-49.0					

ON	OBIA	29.07	2.41	11.3-39.4
	Gnd	29.16	2.07	12.3-40.0
ST	OBIA	4.43	0.48	1.9-6.7
	Gnd	5.30	0.93	1.3-13.6

SE = standard error; N = subplots sampled

[t] Blue Mountain (BM), Devine Ridge (DR), Marking Corral (MC), Onaqui (ON), Stansbury (ST).

Average mean differences with different letters within land cover class are significantly different ($p < 0.05$) between sites in that land cover class using Tukey-Kramer honestly significant difference multiple comparison procedure.

* Indicates a significant difference (Bonferroni correction $p < 0.01$) between the two methods for that site using the paired t-test.

Table 5. (A) Summary statistics for land cover classes in masticated treatment subplots by site for object-based image analysis (OBIA) and ground-measured sampling (Gnd) methods. (B) Comparison statistics between site average mean differences for each land cover class. Differences were calculated by subtracting ground measurements from OBIA data.

	(A)					(B)				
Land Cover Class	Site[t]	Method	Mean (% Cover)	SE	Range (% Cover)	Site[t]	Average Mean Difference (% Cover)	SE	Average Mean Difference Range (% Cover)	N
Masticated Debris	ON	OBIA	14.00	1.36	9.1-22.7	ON	0.21[a]	1.21	-5.9-7.3	13
		Gnd	13.79	1.66	5.7-27.7	ST	-1.47[a]	0.99	-6.8-4.8	12
	ST	OBIA	9.10	1.15	3.4-15.8					
		Gnd	10.57	1.43	3.3-21.3					
Shrubs	ON*	OBIA	4.21	0.64	0.6-9.5	ON	-1.85[a]	0.51	-4.8-1.1	13
		Gnd	6.05	0.96	0.3-12.9	ST	1.28[a]	0.97	-4.1-7.2	12
	ST	OBIA	9.72	2.10	0.5-22.7					
		Gnd	8.44	2.04	1.7-21.3					
Perennial Herbaceous Vegetation	ON	OBIA	24.19	1.80	15.8-39.3	ON	2.30[a]	1.20	-3.9-9.9	13
		Gnd	26.49	1.87	11.9-40.2	ST	1.24[a]	1.37	-2.7-11.9	12
	ST	OBIA	38.51	2.16	26.9-51.1					
		Gnd	39.75	1.99	28.0-51.9					
Litter	ON	OBIA	21.41	1.68	14.3-38.2	ON	0.86[a]	1.57	-8.6-12.1	13
		Gnd	20.55	1.76	12.4-35.2	ST	1.65[a]	0.77	-2.4-6.0	12
	ST	OBIA	37.13	2.85	22.9-56.2					
		Gnd	35.48	2.27	25.3-52.3					
Bare Ground	ON	OBIA	36.25	1.75	26.3-45.5	ON	1.24[a]	1.47	-9.4-12.1	13
		Gnd	35.01	1.74	25.0-44.7	ST	0.65[a]	1.68	-8.5-12.3	12
	ST	OBIA	7.44	1.17	3.4-16.6					
		Gnd	6.78	0.93	2.0-12.7					

SE = standard error; N = subplots sampled

[t] Blue Mountain (BM), Devine Ridge (DR), Marking Corral (MC), Onaqui (ON), Stansbury (ST).

Average mean differences with different letters within land cover class are significantly different ($p < 0.05$) from other sites within that land cover class using Tukey-Kramer honestly significant difference multiple comparison procedure.

* Indicates a significant difference (Bonferroni correction $p < 0.01$) between the two methods for that site using the paired t-test.

Table 6. Error matrix comparing classification accuracy for land cover class across all sites for prescribed burn (A), cut and fell (B), and mastication (C) treatments.

(A) **Prescribed burn**	Live Trees	Burned Trees	Shrubs	Per Herb	Litter	Bare Ground
Live Trees	**185**	2	6	4	3	1
Burned Trees	2	**536**		12	28	20
Shrubs		2	**103**	13	3	1
Per Herb	8	15		**590**	49	9
Litter	3	17	5	65	**597**	42
Bare Ground	2	26	1	29	91	**520**
Producer's accuracy	93%	90%	90%	83%	77%	88%
User's accuracy	92%	90%	84%	88%	82%	78%
Conditional K_{hat}	0.91	0.87	0.84	0.76	0.72	0.84
Overall accuracy = 85%	K_{hat} = 0.81	N = 2,990				

(B) **Cut and fell**	Cut Trees	Shrubs	Per Herb	Litter	Bare Ground
Cut Trees	**586**	4	13	16	25
Shrubs	25	**893**	55	34	9
Per Herb	47	27	**527**	42	17
Litter	62	8	64	**483**	35
Bare Ground	59	14	42	74	**498**
Producer's accuracy	75%	94%	75%	74%	85%
User's accuracy	91%	88%	80%	74%	73%
Conditional K_{hat}	0.89	0.84	0.75	0.68	0.67
Overall accuracy = 82% K_{hat} = 0.77	N = 3,659				

(C) **Mastication** (*Utah only*)	Masticated Debris	Shrubs	Per Herb	Litter	Bare Ground
Masticated Debris	**218**	1	14	9	6
Shrubs	7	**211**	13	7	6
Per Herb	7	4	**253**	14	6
Litter	8		31	**219**	18
Bare Ground	11	3	18	26	**210**
Producer's accuracy	87%	96%	77%	80%	85%
User's accuracy	88%	87%	89%	79%	78%
Conditional K_{hat}	0.85	0.84	0.85	0.74	0.73
Overall accuracy = 84% K_{hat} = 0.80	N = 1,320				

Per Herb = Perennial herbaceous vegetation

K_{hat} = Coefficient of Agreement (Kappa statistic); N = number of point evaluated

Bold values indicate correct number of points classified within a land cover class by fuel reduction treatment.

Figures

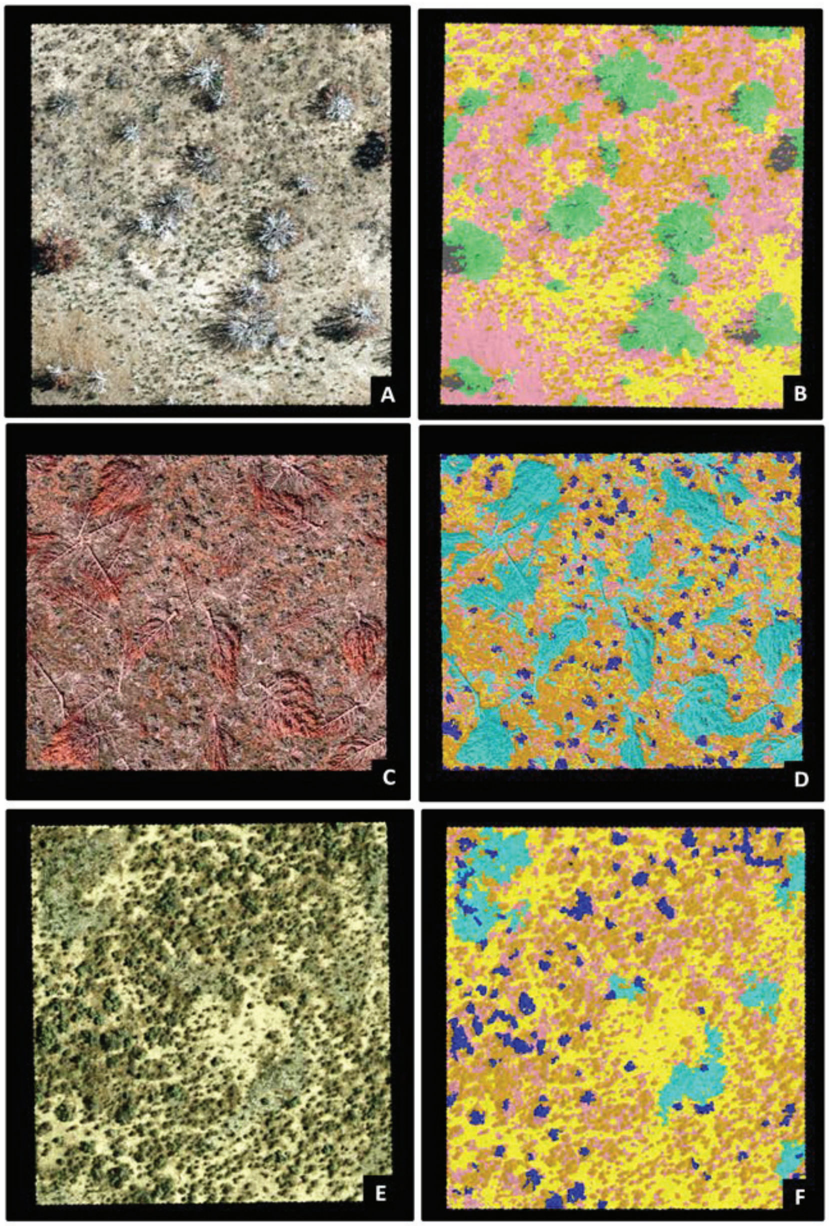

Fig. 1. Example of juniper subplot RGB imagery and classification results using object-based image analysis for a prescribed burn at Stansbury (A, B), cut and drop at Blue Mountain (C, D), and mastication at Onaqui (E, F). Individual land cover classification colors represent burned trees (B, green), cut and felled trees (D, aqua), masticated debris (F, aqua), shrubs (blue), perennial herbaceous vegetation (orange), litter (pink), bare ground (yellow), and shadows (gray).

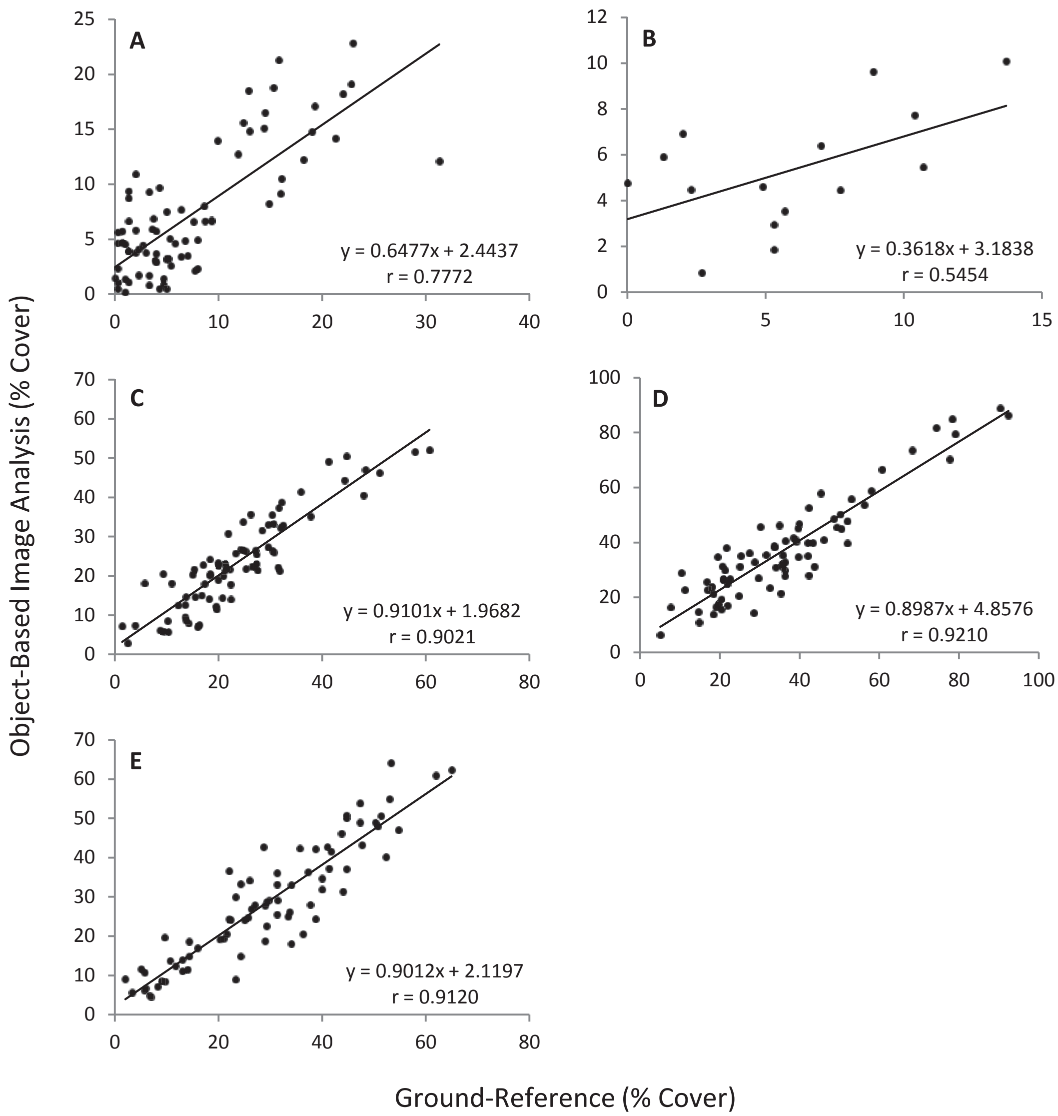

Fig. 2. Regressions of percent cover estimates from an object-based image analysis (y-axis) on ground-reference cover (x-axis) using subplots for all prescribed burn treatment plots across all study sites. Cover classes include (A) burned trees, (B) shrubs, (C) perennial herbaceous vegetation, (D) litter, and (E) bare ground.

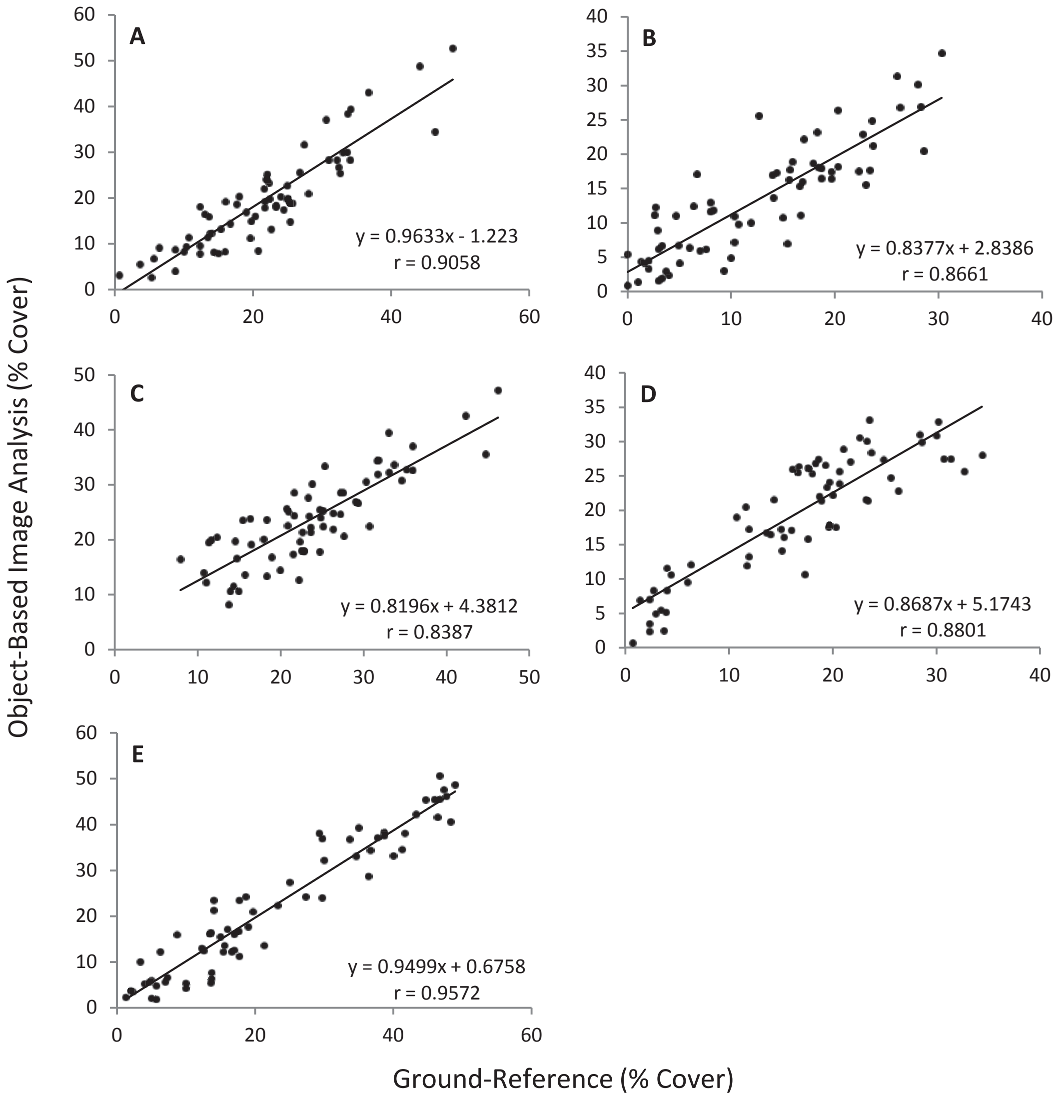

Fig. 3. Regressions of percent cover estimates from an object-based image analysis (y-axis) on ground-reference cover (x-axis) using subplots for cut and fell treatment plots across all study sites. Cover classes include (A) cut trees, (B) shrubs, (C) perennial herbaceous vegetation, (D) litter, and (E) bare ground.

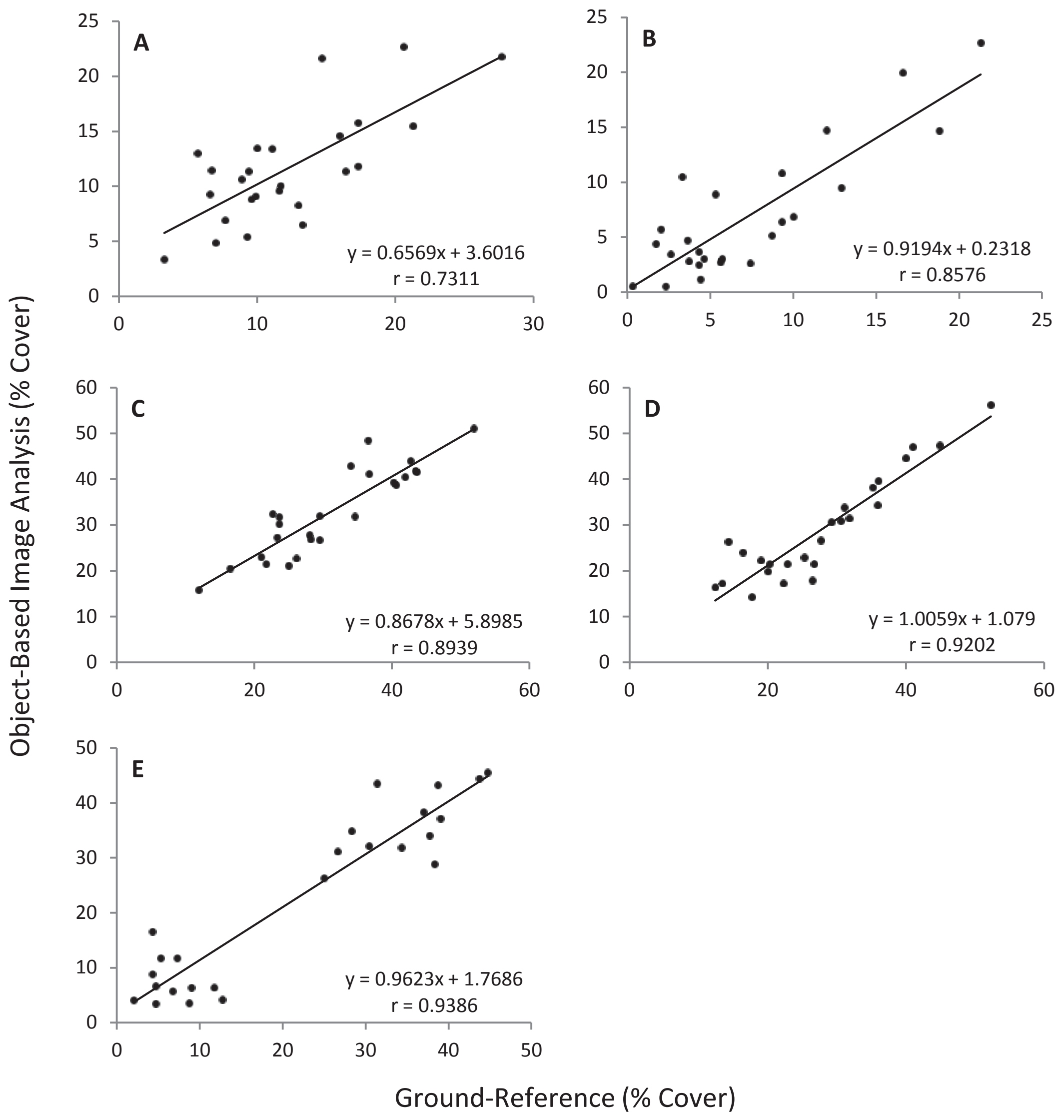

Fig. 4. Regressions of percent cover estimates from an object-based image analysis (y-axis) on ground-reference cover (x-axis) using subplots for masticated treatment plots across all Utah study sites. Cover classes include (A) masticated debris, (B) shrubs, (C) perennial herbaceous vegetation, (D) litter, and (E) bare ground.

Chapter 3: Cover Estimations using Object-Based Image Analysis Techniques across Multiple Scales in Pinyon and Juniper Woodlands

April Hulet[1], Bruce A. Roundy[2], Steven L. Petersen[3], Ryan R. Jensen[4] and Stephen C. Bunting[5]

Authors are [1]Graduate Student, [2]Professor, [3]Assistant Professor, Plant and Wildlife Sciences Department, Brigham Young University, Provo, UT 84602 USA; [4]Associate Professor, Geography Department, Brigham Young University, Provo, UT 84602 USA; and [5]Professor, Department of Rangeland Ecology and Management, University of Idaho, Moscow, ID 83844-1135 USA.

Research was funded in part by the Joint Fire Sciences Sagebrush Steppe Treatment Evaluation Project, the Bureau of Land Management, and Brigham Young University.

Correspondence: April Hulet, Email: april.hulet@gmail.com

Manuscript prepared for submission to *Rangeland Ecology and Management*

ABSTRACT

Numerous studies have been conducted that evaluate the utility of remote sensing for monitoring and assessing vegetation and ground cover to support land management decisions and complement ground-measurements. However, few land cover comparisons have been made using high-resolution imagery and object-based image analysis (OBIA) to evaluate rule-sets across multiple spatial scales. In this study, we investigate the accuracy of OBIA rule-sets (models) developed using eCognition Developer that estimate cover measurements from high-spatial resolution imagery (0.06-m pixel), relative to ground based measurements on *Pinus* L. (pinyon) and *Juniperus* L. (juniper) woodlands. Rule-sets evaluated include four spatial scales: 1) individual 30 X 33-m subplots, 2) individual sites (5-20 hectares), 3) regions (western juniper vs. Utah juniper), and 4) P-J woodlands across the Great Basin. Color-infrared imagery was acquired over five sites in Oregon, California, Nevada, and Utah with a Vexcel UltraCamX digital camera in June/July 2009 as part of the Sagebrush Steppe Treatment Evaluation Project (SageSTEP). Ground cover measurements were also collected at study sites in 2009 on 80, 0.1-hectare subplots. Correlations between OBIA and ground measurements were relatively high for individual subplots and site spatial scales (ranging from r = 0.52 to r = 0.98). Correlations for regional and network spatial scales were lower (ranging from r = 0.24 to r = 0.63) which was expected due to reflectance differences within the imagery as well as vegetation differences found at each site. All site and subplot OBIA average cover estimates were within 5% of the ground measurements, and all region and network OBIA average cover estimates were within 10%. The trade-off for decreased precision over a larger area (region and network scale) may be useful to prioritize fuel-management strategies but will unlikely capture subtle shifts in understory plant communities that site and subplot spatial scales often capture.

Keywords:

eCognition Developer, Object-Based Image Analysis, Pinyon and Juniper Woodlands, SageSTEP, Scale

INTRODUCTION

Monitoring to assess vegetation and ground cover to detect shifts in plant community diversity, structure, and function is the basis for planning local and regional vegetation management actions. In order to effectively and efficiently monitor and assess ecosystems, one must first identify which vegetation characteristics and attributes should be measured to meet management objectives (Pellant et al. 2005); and secondly, address what data collection methods will be economically feasible, as well as accurate and precise enough to meet management objectives (Coulloudon et al. 1999; MacKinnon et al. 2011).

Remote-sensing technologies and platforms are continually being developed and evaluated to improve our ability to monitor, inventory, and assess large and diverse landscapes (Booth and Tueller 2003; Hunt et al. 2003; Toevs et al. 2011), and to reduce or complement costly field data (Laliberte et al. 2007a; Booth et al. 2008). These studies are utilizing multiple remote sensing platforms such as satellite imagery (Ramsey et al. 2004; Bradley and Mustard 2005; Laliberte et al. 2007b; Bradley and Fleishman 2008; Karl and Maurer 2010), high-spatial resolution imagery (Petersen and Stringham 2008; Greenwood and Weisberg 2009; Madsen et al. 2011; Hulet et al. *in review* b), and very large scale aerial imagery (Booth and Cox 2008; Laliberte and Rango 2009; Moffet 2009) across the Intermountain West. Ultimately, remote sensing should be assessed for its ability to provide land managers with tools and information at multiple spatial scales to select and timely implement management actions that benefit system resilience or restoration.

Because management decisions are often made at both local and regional scales, remote sensing research is needed to evaluate the selection of the appropriate scale which often depends on the objective of the investigations (Turner et al. 2001; Karl and Maurer 2010). Processes and parameters important at one scale may not be as important or predictive at another scale (Turner 1989), and often the complexity of a particular ecological system depends on the objective of the investigation (Wu 1999). This research focuses on classifying *Juniperus* L. (juniper) and *Pinus* L. (pinyon) (P-J) woodlands across multiple spatial scales using object-based image analysis (OBIA) techniques to describe five land cover classes (live trees, shrubs, perennial herbaceous cover, litter, and bare ground). As P-J woodlands expand and infill into shrub-steppe communities, understory plant species decrease (Miller et al. 2008), bare soil increases and becomes more interconnected (Pierson et al. 2010), and fire return intervals increase resulting in more stand-replacement fires (Miller and Tausch 2001). By evaluating multiple spatial scales, land managers can better prioritize fuel-management strategies and restoration efforts to reduce catastrophic wildfire events and maintain desirable understory plant communities.

Our primary objective is to test the accuracy of OBIA rule-sets (models) developed using eCognition Developer 8 (Trimble Germany GmbH, Munich, Germany) that estimate cover measurements from high-spatial resolution imagery (0.06-m pixel), relative to ground based measurements on P-J expansion woodlands. Rule-sets evaluated include four spatial scales: 1) individual 30 X 33-m subplots, 2) individual sites (5-20 hectares), 3) regions (western juniper vs. Utah juniper), and 4) P-J woodlands across the Great Basin. We propose that cover estimates from high-spatial resolution imagery will fall within an acceptable error rate when compared to ground measurements using rule-sets that were developed for subplot and individual site scales. For regional and Great Basin rule-sets, we expect that cover estimates from high-spatial resolution imagery will be less accurate than ground measurements for all land cover classes, but that estimates will be sufficiently accurate to support the management of sagebrush steppe ecosystems. In order to further improve the application of remote-sensing technology, our secondary objective is to identify classification feature outputs from eCognition Developer that can be used to distinguish land cover classes found in P-J woodlands across the Great Basin at the four spatial scales discussed above.

METHODS

Study Locations

This study was conducted on five pinyon and/or juniper woodlands which are part of the Joint Fire Sciences Sagebrush Steppe Treatment Evaluation Project (SageSTEP). Sites span the Great Basin and are found in Oregon (Devine Ridge), California (Blue Mountain), Nevada (Marking Corral), and Utah (Stansbury and Onaqui). These sites provide a wide range of semi-arid sagebrush steppe communities that have been invaded by *Juniperus occidentals* Hook. (western juniper), *Juniperus osteosperma* (Torr.) Little (Utah juniper), and *Pinus monophylla* Torr. & Frém. (singleaf pinyon). Specific site characteristics have been described by McIver et al. (2010).

Ground Measurements

Ground data was collected by the SageSTEP team during the summer of 2009 on 80, 0.1-ha subplots (30 by 33 m). Cover measurements were collected within each subplot using the line-point intercept method (Canfield 1941) on five, 30-m transects that were placed systematically across the subplot (McIver et al. 2010). First contact intercept data (top vegetation canopy or ground surface) was collected every 0.5-m totaling 300 points per subplot (5 transects X 60 points per transect) which represents the aerial view captured in the imagery. Measurements from the line-point intercept method used in the data analysis included cover of shrubs, forbs, grasses, litter, standing and down woody debris, and ground surface (mineral soil, rock, lichen or moss) cover estimates. Tree cover used in the data analysis was measured using the crown-diameter method (Mueller-Dombois and Ellenberg 1974).

Land Cover Classes

Cover classes used in this study consist of live trees, shrubs, perennial herbaceous vegetation, litter, and bare ground. Cover classes are described below with associated sites (Devine Ridge, DR; Blue Mountain, BM; Marking Corral, MC; Stansbury, ST; Onaqui, ON) in parenthesis; if no sites are associated with the cover class it is found at all sites evaluated. Live tree cover includes Utah juniper (ON, ST, MC), western juniper (BM, DR), and singleleaf pinyon (MC). Dominant shrub cover includes *Artemisia tridentata* Nutt. ssp. *wyomingensis* Beetle & Young (Wyoming big sagebrush; ON, MC), *Artemisia tridentata* Nutt. ssp. *vaseyana* (Rydb.) Beetle (mountain big sagebrush; BM, DR, MC), and *Purshia tridentata* (Pursh) DC. (antelope bitterbrush; BM, DR, ST). *Chrysothamnus viscidiflorus* (Hook.) Nutt. (yellow rabbitbrush) and other small non-dominant shrubs could not confidently be distinguished from bunchgrasses and forbs in the aerial imagery so were included as part of the perennial herbaceous cover class. The perennial herbaceous vegetation cover also included the following dominant species: *Festuca idahoensis* Elmer (Idaho fescue; BM and DR), *Poa secunda* J. Presl (Sandberg bluegrass), *Pseudoroegneria spicata* (Pursh) Á. Löve (bluebunch wheatgrass; MC, ON, and ST), *Achnatherum thurberianum* (Piper) Barkworth (Thurber's needlegrass; DR and MC), and *Hesperostipa comata* (Trin. & Rupr.) Barkworth (needle and thread grass; MC). Litter cover consists of non-living plant or animal material that rests on top of the soil surface including detached woody material. Litter also includes annual species, particularly *Bromus tectorum* L. (cheatgrass) which typically comprised <10% of the total litter composition with the exception of Stansbury, where cheatgrass comprised approximately 20% of the total litter cover class. Bare ground cover is primarily composed of mineral soil and rock (>90%), with <3% lichen or moss.

Imagery Acquisition

Color-infrared (red, green, blue, and infrared) imagery was acquired for all sites in late June to early July 2009 with a Vexcel UltraCamX digital camera (Vexcel Imaging GmbH, Graz, Austria) on board a turbocharged Cessna 206 aircraft. Imagery was processed to meet or exceed national map accuracy standards using software created by the Vexcel/Microsoft digital imaging partnership by Aero-graphics, Inc., Salt Lake City, Utah.

Subplot Extraction

Ground subplots were georeferenced on imagery using global positioning system (GPS) points collected with a GPSmap® 60CS unit in the center and at a designated corner of each of the 80, 0.1-ha subplots. Individual subplots were then drawn using ArcMap 10.0 (ESRI®AcrMap™ 1999-2010) and extracted from the landscape scene imagery so that measurements would be made on the same experimental unit for both OBIA and ground measured cover classes. GPS accuracy allowed us to define remotely-sensed subplots to within 1-2 m of field subplots.

Image Processing

eCognition Developer 8 was used for our object-based image analysis (OBIA). Rule sets, which are a sequence of processes that are executed in a defined order (Trimble 2011), were developed at four spatial scales: 1) individual 30x33 m subplots, 2) individual sites (Devine Ridge, Blue Mountain, Marking Corral, Stansbury, and Onaqui), 3) regions (western juniper vs. Utah juniper), and 4) all sites evaluated in this study across the SageSTEP network (which will be referred to as network from here on out). Within rule sets, imagery was filtered to remove extraneous noise and detail, segmented to create meaningful objects of land cover classes, and classified using features and thresholds using techniques described by

Hulet et al. (*in review* a) (Table 1; Fig. 1). By using rule sets, the user is able to examine what cover classes are least distinguishable from others and refine specific thresholds to better capture the variation of that class for a particular image or group of imagery.

Experimental Design

Site scale

Rule-sets for each site were first developed using an initial subset of the total subplots (training subplots, 3 subplots per site) to determine features (spectral, spatial, textural, and contextual information) and thresholds that would correctly classify image objects created in the segmentation process. Training subplots were selected that captured the largest range in plant community composition and bare ground cover, and were spatial distributed across the study area. Thresholds associated with specific features and land cover classes were adjusted to optimize our OBIA cover estimates with the ground-measured cover data within an acceptable error of ±5%, depending on land cover class. Once a rule-set was developed for the training subplots, it was applied to a secondary subset of the subplots or validation subplots. Validation subplot cover extractions were then used for the data analysis.

Subplot scale

For individual 30x33 m subplots, rule-sets that were developed for the individual sites were used. Thresholds associated with features in these rule-sets were adjusted or refined for each subplot, essentially creating 65 rule-sets with a range of thresholds used to estimate cover.

Regional and Network scale

Rule-sets on the regional and network scale were also based on site rule-sets. Specific features used in site rule-sets for each cover class were first summed (e.g. if NDVI was used in 40 of the 65 rule-sets to classify live trees, it received a score of 40). Features that were used most often (had the highest score) were selected for each land cover class. Those features selected were then evaluated using the training subplots to determine which one(s) would most accurately estimate the specified land cover class for both the region and network scale. Thresholds associated with the features were adjusted to optimize our OBIA cover estimates with the ground measured cover data. Because both our regional and network rule-sets needed to account for more variation found within the imagery due to atmospheric conditions and timing of imagery acquisition, and vegetation differences across all sites, we increased our acceptable error rate to ±10% depending on land cover class for the regional and network spatial scales evaluated. Once our training subplot rule-set was developed for each spatial scale, it was applied to the secondary subset of the subplots (validation subplots, 65 subplots for each model) for the data analysis.

Statistical Analysis

To determine whether the mean value responses were different between the OBIA data and ground-measured data, we used a paired t-test for each land cover class by spatial scale. Results from the paired t-tests were evaluated for significance using the Bonferroni correction ($p < 0.05/5$). Statistical assumptions for normality and variance were assessed. Mean difference values for each land cover class by spatial scale were compared using one-way ANOVA and the Tukey-Kramer honestly significant difference multiple comparison method with a significance level of $p < 0.05$. Ground measurements were always subtracted from estimates derived from OBIA, to determine if OBIA consistently overestimated or underestimated the land cover class of interest. A simple linear regression model was used to assess the relationship between ground-measurement data and OBIA data for each land cover class by spatial scale. These regression models only apply within the context of the data set from which they are derived.

RESULTS

Live tree canopy cover measurements for site and subplot scales did not differ between the OBIA and ground-measurement methods however, for both network and regional scales, OBIA rule-sets were significantly less than ground measurements of live tree cover (Table1). When running the network rule-set for individual sites, OBIA estimates for tree cover were significantly ($p < 0.05$) less than ground measurements on an average of 10.5% at Devine Ridge, Marking Corral, and Stansbury. With the regional rule-set, OBIA estimates were significantly ($p <0.05$) less than ground measurements for tree cover on average by 10% at Marking Corral and Stansbury.

Shrub canopy cover measurements did not differ between the OBIA and ground-measurement methods for the network, region, and site rule-sets (Table 1). However, when individual sites were analyzed using the site rule-set, sites where antelope bitterbrush was present (Blue Mountain, Devine Ridge, and Marking Corral) did differ significantly between the OBIA and ground-measurement methods but were not consistently more or less than ground measured shrub cover estimates. At the Blue Mountain site, OBIA shrub cover estimates were 5% higher than ground measurements. At Devine Ridge and Stansbury, OBIA shrub cover estimates were lower than ground measurements by approximately 3%. Shrub canopy cover measurements also differed significantly between the OBIA and ground-measurements methods for the subplot rule-set. OBIA shrub cover was on average 1.3% less than ground measurements however, the average mean difference range for the subplot rule-set was smaller than the other rule-sets but skewed towards underestimating shrub cover when compared to ground measurement which likely contributed to the significant difference (Table 1).

Although no significant differences were found between the OBIA and ground-measurement methods for perennial herbaceous vegetation at any of the spatial scales evaluated (Table 1), interesting trends were observed. OBIA estimates from the network rule-set for western juniper sites (Blue Mountain and Devine Ridge) on average were 10% greater than the ground estimates for perennial herbaceous vegetation. For Utah juniper sites (Marking Corral, Stansbury, and Onaqui), OBIA estimates were less than the ground estimates on average for the perennial herbaceous vegetation by 4% when using the network rule-set.

Litter cover estimates were significantly different between OBIA and ground-measurement methods at all spatial scales. When comparing regional differences, western juniper sites were not significantly different between the two methods however, OBIA litter cover estimates on Utah juniper sites were on average 9% less than ground measured litter cover. Bare ground estimates were not significantly different between OBIA and ground-measurements methods using the network, region, and site rule-set (Table1). However, at the Stansbury site OBIA estimates were significantly less than ground measurements for bare ground for our network (14% less) and regional (11% less) rule set. Bare ground OBIA cover was consistently less than ground measurements at all sites by an average of 2% for the site and subplot rule sets with the exception of Devine Ridge, where bare ground OBIA cover was 1.3% higher than the ground measurements. When running the region and network rule set, bare ground OBIA cover was consistently more than the ground measurements by an average of 5.5% with the exception of Blue Mountain, where OBIA bare ground estimates were less than ground measurements by an average of 5.6%.

Cover estimates from OBIA and ground measurements were highly correlated for land cover classes (excluding litter) using the subplot rule sets ($r = 0.94$ to 0.98) and only slightly lower for the site rule-sets ($r = 0.78$ to 0.95). Litter correlations were lower for all spatial scale rule-sets ($r = 0.24$ to 0.74) which is likely an artifact of our hierarchical classification techniques for litter. Because coarser rule-sets (region and network) account for more subplot variation over larger spatial scales, lower correlation values were expected (Fig. 2).

DISCUSSION

Karau and Keane (2007) suggest that when determining the optimal landscape extent (or spatial scale), the grain should be small enough to detect subtle changes resulting from management actions, but large enough to reflect the characteristic variability of important ecological processes such as fire, succession, and the biophysical environment in the appropriate spatial context. Our research suggests that high-spatial resolution imagery and object-based image analysis techniques can capture most variations across the multiple spatial scales evaluated for our designated land cover classes. When analyzing region and network scales, the trade-off for decreased precision of our land cover classes may be useful to prioritize fuel-management strategies but will unlikely capture subtle shifts in understory plant communities that may be detected at the subplot or site scale.

For live trees, perennial herbaceous vegetation, and bare ground, OBIA cover estimates continually improved as spatial scale decreased. Average mean differences were only significantly different between spatial scales for live trees where both network and region rule-sets underestimated tree cover. This underestimation is likely due to shadows. Shadows influence most remote sensing classification processes and although shadow effects can be minimized by collecting imagery close to solar noon or even creating high dynamic range nadir images (Cox and Booth 2009), shadow inaccuracies often occur. On a site level, we could adjust for specific shadows using expert knowledge of tree canopies however, when total shadow cover ranges from <1% to 15.5% of the total subplot cover, it is difficult to merge and grow known tree objects (Hulet et al. *in review* a) consistently across all sites for both the region and network rule-sets.

Our underestimation of litter at all scales may be an artifact of the hierarchical design we used to classify litter. Because we typically classified the more distinguishable land cover classes first (e.g., trees, bare ground, and shrubs), unclassified objects were often classified as litter without establishing features specific for litter cover. When analyzed by site, Stansbury's OBIA litter cover was consistently underestimated while bare ground cover was consistently overestimated when compared to ground measurements. One probable cause for this is the patchy nature of cheatgrass cover. Although cheatgrass was present at all sites, it comprised approximately 20% of the litter land cover class at Stansbury and <5% at all other sites. Because it was a small component specific to Stansbury, regional and network rule-sets did not likely account for this anomaly and cheatgrass was often misclassified as bare ground.

Atmospheric properties typically play the largest role in feature class selection and are often the most difficult to control. Although our high-spatial resolution imagery was collected within one week, spectral reflectance values for specific land cover classes (i.e. live trees) had wide ranges of values. Thresholds must be adjusted to compensate for these differences. Many of the classes were difficult to distinguish with spectral features alone; by incorporating other features such as neighbor relationships (relative border), we could accurately grow and merge segmented objects to better define our desired land cover classes. Texture was not included in this analysis due to our segmentation parameter selection (Fig. 1). Although we explored multiple texture features in combination with segmentation parameters, we found that neighbor relations were most effective in capturing the variation of the land cover classes found in P-J woodlands. With smaller objects, we essentially increased our edge effect reducing texture analysis possibilities (Laliberte and Rango 2009). As shown in figure 1, we consistently classified more spectrally-distinguishable land cover classes first. However, we do not necessarily recommend adhering to any specific order of classification. Hierarchical, self-organization criteria were useful when describing our land cover classes and when possible, should be consistent if extending across multiple spatial scales.

Results are specific for our high spatial-resolution imagery and should not automatically be extended to other P-J woodlands. Further research should include testing the repeatability of our rule-set across multiple spatial resolution and extents. Additionally, further research will relate classified images and patterns extracted through OBIA techniques to ecological functions and processes.

MANAGEMENT IMPLICATIONS

Our intent was to test the accuracy between object-based image analysis cover and ground-measured cover estimates from high-spatial resolution imagery across multiple spatial scales. Our results suggest that site and subplot scales most accurately account for specific site anomalies however, network and regional rule-sets were within 10% of the ground data for all land cover classes. Although land management objectives will ultimately drive the selection of the spatial extent, we recommend using site specific rule sets for high-spatial resolution imagery when possible. Site specific rule sets can better account for variations found in vegetation and ground cover while reducing shadow effects. Also, because imagery is often collected at different temporal scales, it is difficult to account for atmospheric variations found within the imagery when classifying a broad range of site which will ultimately require more time to select features and threshold for the classification. And finally, site specific rule sets sufficiently represent most management needs at an operational level. As shown in Hulet et al. (*in review* a&b), site specific rule-sets developed for high-spatial resolution imagery can be used to monitor and evaluate rangeland health, determine when to implement vegetation treatments, and assess the spatial distribution of fuels following fuel-reduction treatments. Regional and network scales may aid in prioritizing areas that have a higher risk for catastrophic wildfires events or increased soil erosion potential however, subtle shifts in understory vegetation including weed invasions, may be missed.

This study shows the utility of high-spatial resolution imagery and object-based image analysis techniques for monitoring and assessing vegetation and ground cover. Rule sets developed on ground-measured subplots (30x33 m) were compared over larger extents using a secondary subset of ground-measured subplots. In combination with imagery acquisition, land managers could systematically place ground-measured subplots across an area of interest that would capture the variation found on that specific site. Then, use those subplots to develop rule sets that could be applied across the site to support land management decisions and complement ground-measurements on a landscape level.

Acknowledgements

Financial support for this study was provided by the Joint Fire Sciences Sagebrush Steppe Treatment Evaluation Project, the Bureau of Land Management, Brigham Young University, and the University of

Idaho. We thank the SageSTEP research team, particularly James McIver and the sagebrush-woodland principle investigators Richard Miller, Robin Tausch and Jeanne Chambers, as well as the woodland site managers, Jaime Ratchford, Neil Frakes, Travis Miller and Brad Jessop for substantial field support and advice.

LITERATURE CITED

Booth, D. T., and P. T. Tueller. 2003. Rangeland monitoring using remote sensing. *Arid Land Research & Management* 17:455-467.

Booth, D. T., and S. E. Cox. 2008. Image-based monitoring to measure ecological change in rangeland. *Frontiers in Ecology & the Environment* 6:185-190.

Booth, D. T., S. E. Cox, T. Meikle, and H. R. Zuuring. 2008. Ground-cover measurements: assessing correlation among aerial and ground-based methods. *Environmental Management* 42:1091-1100.

Bradley, B. A., and J. F. Mustard. 2005. Identifying land cover variability distinct from land cover change: Cheatgrass in the Great Basin. *Remote Sensing of Environment* 94:204-213.

Bradley, B. A., and E. Fleishman. 2008. Relationships between expanding pinyon-juniper cover and topography in the central Great Basin, Nevada. *Journal of Biogeography* 35:951-964.

Canfield, R. (1941). Application of line interception in sampling range vegetation. *Journal of Forestry*, *39,* 388-394.

Coulloudon, B., K. Eshelman, J. Gianola, N. Habich, L. Hughes, C. Johnson, M. Pellant, P. Podborny, A. Rasmussen, B. Robles, P. Shaver, J. Spehar, and J. Willoughby. 1999. Sampling vegetation attributes, interagency technical reference. Denver, CO, USA: US Department of the Interior, Bureau of Land Management, National Science and Technology Center, Tech Ref 1734-4. 61 p.

Cox, S. E., and D. T. Booth. 2009. Shadow attenuation with high dynamic range images. *Environmental Monitoring & Assessment* 158:231-241.

Greenwood, D. L. and P. J. Weisberg. 2009. GIS-Based modeling of pinyon-juniper woodland structure in the Great Basin. *Forest Science* 55:1-12.

Hulet, A., B. A. Roundy, S. L. Petersen, R. R. Jensen, and S. C. Bunting. *In review* a. Assessing the relationship between ground measurements and object-based image analysis of land cover classes in pinyon and juniper woodlands.

Hulet, A., B. A. Roundy, S. L. Petersen, S. C. Bunting, R. R. Jensen, and R. T. Larsen. *In review* b. An object-based image analysis of pinyon and juniper woodlands treated to reduce fuels.

Hunt, E. R., Jr., J. H. Everitt, J. C. Ritchie, M. S. Moran, D. T. Booth, G. L. Anderson, P. E. Clark, and M. S. Seyfried. 2003. Applications and research using remote sensing for rangeland management. *Photogrammetric Engineering & Remote Sensing* 69:675-693.

Karau, E. C., and R. E. Keane. 2007. Determine landscape extent for succession and disturbance simulation modeling. *Landscape Ecology* 22:993-1006.

Karl, J. W., and B. A. Maurer. 2010. Multivariate correlations between imagery and field measurements across scales: comparing pixel aggregation and image segmentation. *Landscape Ecology* 25: 591-605.

Laliberte, A. S., A. Rango, J. E. Herrick, E. L. Fredrickson, and L. Burkett. 2007a. An object-based image analysis approach for determining fractional cover of senescent and green vegetation with digital plot photography. *Journal of Arid Environments* 69:1-14.

Laliberte, A. S., E. L. Fredrickson, and A. Rango. 2007b. Combining decision trees with hierarchical object-oriented image analysis for mapping arid rangelands. *Photogrammetric Engineering & Remote Sensing* 73:197-207.

Laliberte, A. S., and A. Rango. 2009. Texture and scale in object-based analysis of subdecimeter resolution unmanned aerial vehicle (UAV) imagery. *IEEE Transactions on Geosciences & Remote Sensing* 47: 761-770.

MacKinnon, W. C., J. W. Karl, G. R. Toevs, J. J. Taylor, M. Karl, C. S. Spurrier, and J. E. Herrick. 2011. BLM core terrestrial indicators and methods. Denver, CO, USA: US Department of the Interior, Bureau of Land Management, National Operations Center. Tech Note 440. 13 p.

Madsen, M .D., D. L. Zvirzdin, B. D. Davis, S. L. Petersen, and B. A. Roundy. Feature extraction techniques for measuring piñon and juniper tree cover and density, and comparison with field-based management surveys. *Environmental Management* 47:766-776.

McIver, J. D., Brunson, M., Bunting, S. C., et al. 2010. The Sagebrush Steppe Treatment Evaluation Project (SageSTEP): a test of state-and-transition theory. Fort Collins, CO, USA: US Department of Agriculture, Forest Service, RMRS-GTR-237. 16 p.

Miller, R. F., and R. J. Tausch. 2001. The role of fire in pinyon and juniper woodlands: a descriptive analysis. *In:* K. E. M. Galley and T. P. Wilson, editors. Proceedings of the invasive species workshop: the role of fire in the control and spread of invasive species. Tall Timbers Research Miscellaneous Publication 11. p. 15-30.

Miller, R. F., R. J. Tausch, E. D. McArthur, D. D. Johnson, and S. C. Sanderson. 2008. Age structure and expansion of piñon-juniper woodlands: a regional perspective in the Intermountain West. Fort Collins, CO, USA: US Department of Agriculture, Forest Service, RMRS-RP-69. 15 p.

Moffet, C. A. 2009. Agreement between measurements of shrub cover using ground-based methods and very large scale aerial imagery. *Rangeland Ecology & Management* 62:268-277.

Mueller-Dombois D., and H. Ellenberg. 1974. *Aims and methods of vegetation ecology*. John Wiley and Sons, New York.

Pellant, M., P. Shaver, D. A. Pyke, and J. E. Herrick. 2005. Interpreting indicators of rangeland health (Version 4). Denver CO, USA: US Department of the Interior, Bureau of Land Management, National Science and Technology Center. Tech Ref 1734-6. 122 p.

Petersen, S. L., and T. K. Stringham. 2008. Development of GIS-based models to predict plant community structure in relation to western juniper establishment. *Forest Ecology & Management* 256:981-989.

Pierson, F. B., C. J. Williams, P. R. Kormos, S. P. Hardegree, P. E. Clark, and B. M. Rau. 2010. Hydrologic vulnerability of sagebrush steppe following pinyon and juniper encroachment. *Rangeland Ecology & Management* 63:614-629

Ramsey, R. D., D. Wright, C. McGinty. 2004. Evaluating the use of Landsat 30 m enhanced thematic mapper to monitor vegetation cover in shrub-steppe environments. *Geocarto International* 19:39-47.

Toevs, G. R., J. W. Karl, J. J. Taylor, G. S. Spurrier, M. Karl, M. R. Bobo, and J. E. Herrick. 2011. Consistent indicators and methods and a scalable sample design to meet assessment, inventory, and monitoring information needs across scales. *Rangelands* 33: 14-20.

Trimble. 2011. eCognition Developer 8.64.1 reference book, version 8.64.1, Trimble Germany GmbH, Műnchen, Germany.

Turner, M. G. 1989. Landscape ecology: the effect of pattern on process. *Annual Review of Ecology & Systematics* 20:171-197.

Turner, M .G., R. H. Gardner, and R. V. O'Neill. 2001. Landscape Ecology in theory and practice pattern and process. New York, NY, USA: Springer-Verlag New York, Inc.

Wu, J. 1999. Hierarchy and scaling: extrapolating information along a scaling ladder. *Canadian Journal of Remote Sensing* 25:367-380.

Tables

Table 1. Description of filters, segmentations, and features used to classify land cover classes in this study. Further detail and formulas for calculating filters and features can be found in Trimble's eCognition Developer reference book (Trimble 2011).

	Description
Image Filters	
Median Filter	Replaces the pixel value with the median value of neighboring pixels.
Convolution Filter - Gauss Blur	Gaussian smoothing filter (Guass Blur) uses a kernel, which is a square matrix of a value that is applied to the image pixels. Each pixel value is replaced by the average of the square area of the matrix centered on the pixel.
Segmentations	
Multiresolution Segmentation *(Convolution filtered R, G, B bands)*	Applies an optimization procedure which locally minimizes the average heterogeneity of image objects for a given resolution.
Spectral Difference Segmentation	Merges neighboring objects according to their mean layer intensity value.
Features	
Spectral	
Mean Brightness	Sum of mean values of RGB for an image object divided by 3.
Mean *(B & NIR bands)*	Layer mean value calculated from the values of all pixels forming an image object.
Band Ratio *(G bands)*	Layer mean value of an image object divided by the sum of all layer mean values.
NDVI	Normalized difference vegetation index = (NIR - R)/(NIR + R)
SAVI	Soil-adjusted vegetation index = ((NIR - R)/(NIR + R + L)) * (1 + L); L = 0.5
HSI transformation: Hue *(median filtered R, G, B bands)*	Hue (color) transformation equations are based upon the maximum (greatest) RGB value and the minimum (smallest) RGB values.
Spatial	
Area	Number of pixels forming an image object.
Contextual	
Relative border	Describes the ratio of the shared border length of an image object (with a neighboring image object assigned to a defined class) to the total border length.

R = Red, G = Green, B = Blue, NIR = Near Infrared, HSI = Hue, Saturation, Intensity

Table 2. (A) Summary statistics for land cover classes by spatial scale for object-based image analysis (OBIA) and ground-measured (Gnd) sampling methods (N = 65). (B) Comparison statistics of land cover classes mean percent cover estimates from OBIA and Gnd data using a paired t-test. (C) Comparison statistics between spatial scale average mean differences by land cover class. Differences were calculated by subtracting ground measurements from OBIA data.

	(A)					(B)			(C)			
Land Cover Class	Method	Spatial Scale	Mean (% Cover)	SE	Range (% Cover)	Spatial Scale	*p*-value	95% CI (% Cover)	Spatial Scale	Average Mean Difference (% Cover)	SE	Average Mean Difference Range (% Cover)
Live Trees	Gnd	-	25.64	1.88	1.7-72.6							
	OBIA	Network	19.83	1.57	4.5-54.0	Network	0.0003*	-8.85--2.77	Network	-5.81[b]	1.18	-40-17.3
		Region	21.33	1.57	4.5-56.0	Region	0.0062*	-7.34--1.26	Region	-4.30[b]	1.18	-38.5-23.0
		Site	25.98	1.57	4.4-61.2	Site	0.2039	-0.43-1.97	Site	0.77[a]	1.18	-18.5-14.7
		Subplot	25.76	1.57	3.3-64.8	Subplot	0.8328	-1.05-1.30	Subplot	0.12[a]	1.18	-10.8-14.7
Shrubs	Gnd	-	11.59	1.06	0.0-41.9							
	OBIA	Network	12.61	0.97	2.5-30.5	Network	0.2930	-0.90-2.94	Network	1.02[a]	0.77	-14.8-22.0
		Region	11.64	0.97	2.4-31.2	Region	0.9586	-1.77-1.86	Region	0.05[a]	0.77	-13.6-20.9
		Site	11.41	0.97	0.8-37.7	Site	0.8827	-1.04-1.20	Site	0.08[a]	0.77	-12.2-11.5
		Subplot	10.27	0.97	0.0-41.6	Subplot	0.0008*	-2.06--0.57	Subplot	-1.32[a]	0.77	-11.0-3.8
Perennial Herbaceous Vegetation	Gnd	-	14.05	0.90	1.9-30.5							
	OBIA	Network	15.71	1.17	0.7-57.0	Network	0.2520	-1.21-4.54	Network	1.67[a]	0.91	-20.2-32.6
		Region	15.06	1.17	1.2-38.9	Region	0.2683	-0.80-2.84	Region	1.02[a]	0.91	-19.5-19.1
		Site	13.59	1.17	2.2-31.5	Site	0.4389	-1.64-0.72	Site	-0.46[a]	0.91	-10.5-9.4
		Subplot	14.09	1.17	0.4-30.7	Subplot	0.8723	-0.45-0.53	Subplot	0.04[a]	0.91	-5.8-6.5
Litter	Gnd	-	19.12	0.97	0.0-38.6							
	OBIA	Network	11.66	0.90	2.1-23.0	Network	<0.0001*	-9.50--5.43	Network	-7.46[a]	0.03	-30.1-6.9
		Region	13.76	0.90	1.9-43.9	Region	0.0003*	-8.14--2.58	Region	-5.36[a]	0.03	-26.5-25.2
		Site	14.27	0.90	2.1-30.6	Site	<0.0001*	-6.64--3.07	Site	-4.85[a]	0.03	-26.1-9.4
		Subplot	13.84	0.90	0.0-30.5	Subplot	<0.0001*	-6.54--4.03	Subplot	-5.28[a]	0.03	-21.7-6.6
Bare Ground	Gnd	-	30.20	1.83	6.7-62.3							
	OBIA	Network	34.11	1.92	3.8-64.7	Network	0.0504	-0.01-7.84	Network	3.91[a]	1.46	-47.9-37.2
		Region	32.73	1.92	3.8-63.5	Region	0.1900	-1.29-6.35	Region	2.53[a]	1.46	-47.9-37.1
		Site	28.88	1.92	2.8-53.4	Site	0.0946	-2.86-0.23	Site	-1.31[a]	1.46	-21.0-14.0
		Subplot	29.17	1.92	5.8-55.8	Subplot	0.0068*	-1.77--0.30	Subplot	-1.03[a]	1.46	-14.5-3.5

SE = standard error; CI = confidence interval

* indicates significant differences using the Bonferroni correction ($p < 0.01$) between image analysis and ground measurement mean values using the paired t-test.

Average mean differences with different letters within land cover class are significantly different ($p < 0.05$) from other spatial scale rule-sets using Tukey-Kramer honestly significant difference multiple comparison procedure.

Figures

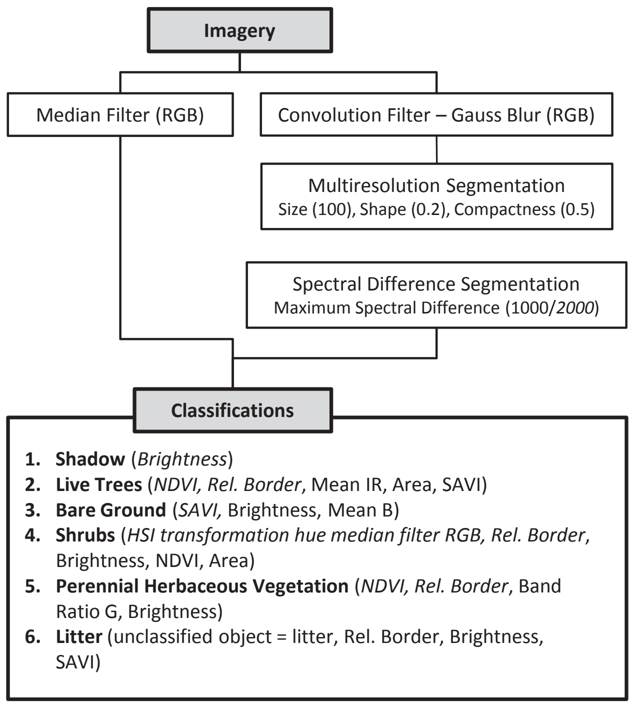

Figure 1. Hierarchical classification process using eCognition Developer. Bold print represents land cover classes listed in the order classified. Notes in parentheses indicate feature(s) and band(s) used to classify land cover classes for individual subplot and site rule-sets. Italicized features were used to classify land cover classes for the region and network models. RGB = Red, Green, and Blue bands; NDVI = Normalized Difference Vegetation Index; Rel. border = Relative border; IR = Infrared band; SAVI = Soil-Adjusted Vegetation Index, HSI = Hue, Saturation, and Intensity transformation.

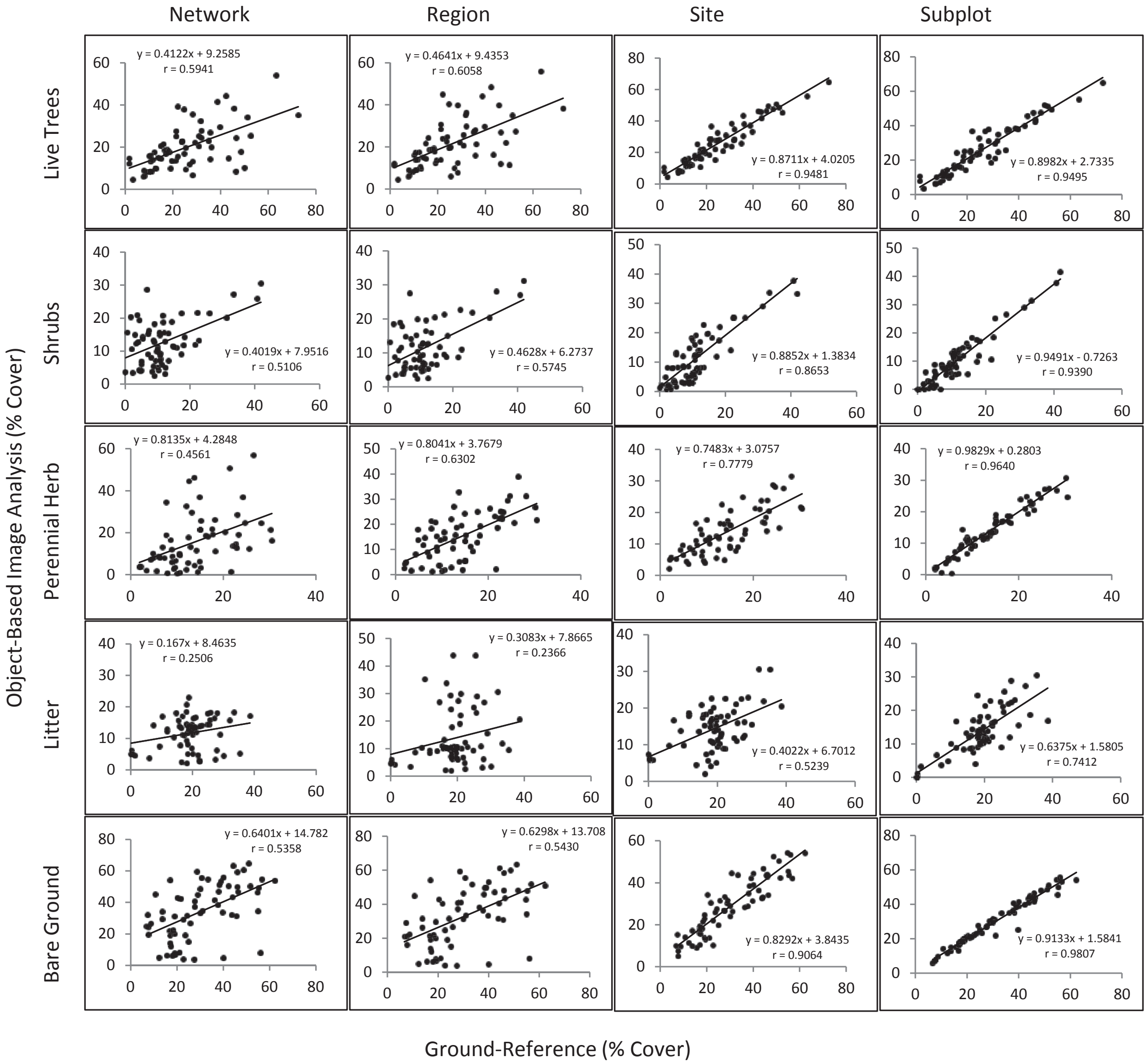

Figure 2. Regressions of percent cover estimates from an object-based image analysis (y-axis) on ground-measurements (x-axis) using subplots across all study sites (N = 65). Each row represents a land cover class (live trees, shrubs, perennial herb = perennial herbaceous vegetation, litter, and bare ground). Columns represent each spatial scale rule-set (network, region, site, and subplot) used to evaluate land cover classifications.