Interpretation of high-resolution imagery for detecting vegetation cover composition change after fuels reduction treatments in woodlands☆

Jason W. Karl [a,*], Jeffrey K. Gillan [a], Nichole N. Barger [b], Jeffrey E. Herrick [a], Michael C. Duniway [c]

[a] United States Department of Agriculture – Agricultural Research Service (USDA-ARS), Jornada Experimental Range, P.O. Box 30003, MSC 3JER, New Mexico State University, Las Cruces, NM 88003-8003, USA
[b] University of Colorado at Boulder, Department of Ecology and Evolutionary Biology, CB 334 Ramaley N285, Boulder, CO 80309, USA
[c] U.S. Geological Survey, Southwest Biological Science Center, 2290 SW Resource Blvd., Moab, UT 84532, USA

ARTICLE INFO

ABSTRACT

The use of very high resolution (VHR; ground sampling distances < ~5 cm) aerial imagery to estimate site vegetation cover and to detect changes from management has been well documented. However, as the purpose of monitoring is to document change over time, the ability to detect changes from imagery at the same or better level of accuracy and precision as those measured in situ must be assessed for image-based techniques to become reliable tools for ecosystem monitoring. Our objective with this study was to quantify the relationship between field-measured and image-interpreted changes in vegetation and ground cover measured one year apart in a Piñon and Juniper (P–J) woodland in southern Utah, USA. The study area was subject to a variety of fuel removal treatments between 2009 and 2010. We measured changes in plant community composition and ground cover along transects in a control area and three different treatments prior to and following P–J removal. We compared these measurements to vegetation composition and change based on photo-interpretation of ~4 cm ground sampling distance imagery along similar transects. Estimates of cover were similar between field-based and image-interpreted methods in 2009 and 2010 for woody vegetation, no vegetation, herbaceous vegetation, and litter (including woody litter). Image-interpretation slightly overestimated cover for woody vegetation and no-vegetation classes (average difference between methods of 1.34% and 5.85%) and tended to underestimate cover for herbaceous vegetation and litter (average difference of −5.18% and 0.27%), but the differences were significant only for litter cover in 2009. Level of agreement between the field-measurements and image-interpretation was good for woody vegetation and no-vegetation classes (r between 0.47 and 0.89), but generally poorer for herbaceous vegetation and litter (r between 0.18 and 0.81) likely due to differences in image quality by year and the difficulty in discriminating fine vegetation and litter in imagery. Our results show that image interpretation to detect vegetation changes has utility for monitoring fuels reduction treatments in terms of woody vegetation and no-vegetation classes. The benefits of this technique are that it provides objective and repeatable measurements of site conditions that could be implemented relatively inexpensively and easily without the need for highly specialized software or technical expertise. Perhaps the biggest limitations of image interpretation to monitoring fuels treatments are challenges in estimating litter and herbaceous vegetation cover and the sensitivity of herbaceous cover estimates to image quality and shadowing.

Published by Elsevier Ltd.

1. Introduction

Ground cover and plant composition are important ecological indicators used to assess soil and site stability, hydrologic function and biological integrity in rangelands and woodlands (Pyke et al., 2002; Booth and Tueller, 2003). Thus collecting quantitative monitoring data on these indicators is important to assess trends of the

biophysical components of an ecosystem to support land-use management and policy decisions at multiple scales (National Research Council, 1994).

Remote-sensing approaches have been proposed to monitor vegetation cover and composition in rangelands because ground-based sampling is often not economical due to logistical (e.g., inaccessibility) and budget (e.g., cost of field visits) constraints (Booth and Tueller, 2003; Hunt et al., 2003; Washington-Allen et al., 2006). Estimating ground cover from aerial or satellite imagery can, under the right conditions, have advantages including increased speed, flexibility, repeatability, and convenience in the time and place to make measurements (Booth and Tueller, 2003).

Remote-sensing approaches to monitoring include area-wide predictions of cover and composition (Dymond et al., 1992; Marsett et al., 2006; Homer et al., 2012) and deriving estimates for selected sample locations and extrapolating those estimates to a larger area (Hengl et al., 2004; Karl, 2010). Additionally, cover can be estimated from imagery via classification techniques (e.g., Shupe and Marsh, 2004; Bork and Su, 2007; Navulur, 2007), biophysical models (e.g., Running et al., 2004; Schott, 2007), and image interpretation (e.g., Booth et al., 2005a; Booth and Cox, 2008; Duniway et al., 2011; Karl et al., 2012a).

Vegetation cover across landscapes has been estimated with moderate-resolution image products (e.g., Qi et al., 2002; Scanlon et al., 2002; Ramsey et al., 2004; Xiao and Moody, 2005). However, very high-resolution (VHR) imagery (i.e., less than 5 cm ground-sample distance [GSD]) is often necessary to estimate vegetation cover and composition from imagery at site scales because of the importance of distinguishing plant species (or life forms), dead plant material (i.e., litter), and bare ground (Booth and Cox, 2008) and the potential for resolving individual plants, rocks, and other soil surface components such as biologic and physical crusts.

Vegetation cover and composition in rangelands has been successfully estimated from VHR imagery using both automated image classification techniques (Fensham and Fairfax, 2003a; Laliberte et al., 2006, 2010; Luscier et al., 2006) and manual image interpretation (Booth and Tueller, 2003; Seefeldt and Booth, 2006; Moffet, 2009). Duniway et al. (2011) and Knapp et al. (1990) showed that image interpretation to measure rangeland ground cover and community composition was repeatable among independent observers. Karl et al. (2012b) used interpretation of VHR imagery to classify vegetated and non-vegetated areas and calculate vegetation canopy gaps consistent with field measurements.

Several studies have examined the ability to detect changes in rangelands from VHR imagery due to management. Booth and Cox (2008) used detected livestock stocking rate differences in short-grass prairie using 1 mm GSD imagery. In a separate study, Booth and Cox (2009) used VHR imagery ranging from 1 mm to 20 mm GSD to assess oil and gas pipeline reclamation in Wyoming. Both of these studies, however, compared different areas within the same image acquisition campaign (i.e., the same time period). Few studies correlating image-interpretation to field-based estimates have looked at detecting changes in rangelands over multiple dates of imagery.

As the purpose of monitoring is to assess change over time, the ability to accurately detect changes from imagery commensurate with changes measured in situ must be assessed. Two studies typify approaches to detecting change with VHR imagery using automated classification techniques. Zerger et al. (2012) looked at a 6-month time series of images taken every 90 minutes from a nadir-pointing ground camera (1 m² field of view [FOV], 0.55 mm GSD) and estimated ground cover (classified into live vegetation, attached litter, detached litter, and bare ground). They saw high temporal agreement between image and field measurements for live vegetation and bare ground classes, but found poor agreement for litter classes that were difficult to discriminate in the imagery.

Bennett et al. (2000) also evaluated a time series of very-high resolution ground images (1 m² FOV, 2 mm GSD) to assess changes in total vegetation cover in seven images over a two-year span. They were able to detect ground cover changes from classified images consistently over time and among treatments using field measures of biomass. Both of these studies used ground-based cameras with small FOV and GSD. Thus there is need to examine the concordance of field- and image-measured vegetation change at landscape scales using aerial imagery.

Since the early 2000s extensive fuel reduction treatments have been implemented across hundreds of thousands of hectares of Piñon and Juniper (P–J) woodlands and rangelands with encroaching P–J. The goal of the national fuels program is to reduce the risk of wildland fire while restoring forests and rangeland ecosystems to a more historical structure, function, and diversity (http://nationalatlas.gov/mld/firplnp.html). Funding for monitoring the effects of fuels reduction treatments, however, is limited. Following this, there is a clear need to develop treatment-monitoring approaches that: are economically feasible within limited fuels budgets, require limited expertise, and may be implemented by staff with limited training in high resolution imagery analysis. Our objective was to assess agreement between field-measured and image-interpreted changes in vegetation and ground cover taken one year apart in a P–J ecological site in southern Utah, USA that was subject to an extensive fuel (woody vegetation) removal treatment.

2. Materials and methods

2.1. Study area

This study was conducted within the Colorado Plateau region of southeastern Utah on Shay Mesa (37.9858°N, 109.5575°W), on an Upland Shallow Loam P–J ecological site (Site ID: R035XY315UT, U.S.D.A. Soil Conservation Service, 1991), approximately 31 ha in size (Fig. 1). At an elevation of 2237 m, Shay Mesa is located approximately 45 km northeast of Monticello, UT, USA. The mean annual precipitation is 317 mm and follows a bimodal distribution with monsoonal rains in the summer and snow in the winter. The mean annual maximum and minimum temperatures are 18.2 °C and 3.0 °C, respectively (http://www.prism.oregonstate.edu, Accessed 22 March, 2013).

Shay Mesa was chained to remove trees and shrubs and seeded in 1959 but has since undergone rapid recolonization by two needle piñon (*Pinus edulis* Engelm.) and Utah juniper (*Juniperus osteosperma* (Torr.) Little), which were the primary overstory species. Other common native plants found within the study site included mountain big sagebrush (*Artemisia tridentata* Nutt. ssp. *vaseyana* (Rydb.) Beetle), broom snakeweed (*Gutierrezia sarothrae* (Pursh) Britton & Rusby), Indian ricegrass (*Achnatherum hymenoides* (Roem. & Schult.) Barkworth), and blue grama (*Bouteloua gracilis* (Willd. ex Kunth) Lag. ex Griffiths).

2.2. Vegetation treatments

In the summer of 2009, a fuel reduction vegetation treatment was conducted to reduce risk of catastrophic wildfire and restore the historic vegetation structure and diversity. Three methods were used to determine which best promoted native understory species growth while preventing exotic grass establishment and minimizing soil erosion: mechanical P–J mastication (M), lopping of P–J with the slash collected in piles then burned (P), and lopping of P–J with the slash scattered and followed by a broadcast burn (B). An additional area was left untreated to serve as a control site (C) (Fig. 1).
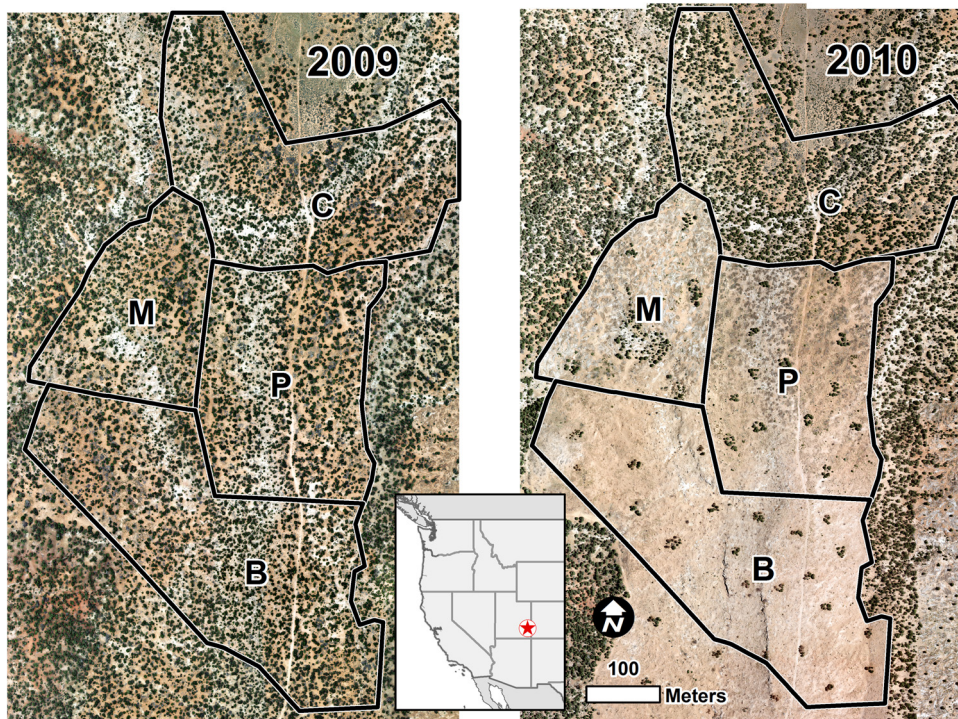
Fig. 1. Location of the Shay Mesa study area in southern Utah, USA showing the treatment configuration and aerial views of the study area before (2009) and after (2010) treatment. Letters correspond to treatments where M: mechanical P–J mastication, P: lopping of Pinon-Juniper with the slash collected in piles then burned, B: lopping of P–J with the slash scattered and followed by a broadcast burn, and C: untreated control site.

2.3. Field measurements

Prior to vegetation treatments, ten 35-m transects were randomly established within each of the eight plots on slopes of 8% or less and on the Bond-Rizno fine sandy loam soil map unit (U.S.D.A. Soil Conservation Service, 1991). Each transect line ran approximately parallel to the contour of the slope. Beginning and end locations of the transects were permanently marked with PVC stakes and recorded with a handheld GPS with an estimated precision of 3 m.

Along each transect, vegetation composition was measured using the line-point intercept method (Herrick et al., 2009) before treatment (May to June, 2009) and again one year following treatment (May to June 2010). A 1 mm pin was dropped at every 0.5-m point along the transect line from a height of ∼1 m (70 points per transect). At each point, all species intercepting the pin were recorded, as well as tree and shrub canopies that were directly above the dropped pin. Each species was recorded only once per pin-drop. Litter and soil surface were also recorded at each pin drop following Herrick et al. (2009). For this image interpretation study, only the first species intercepted (i.e., the "top hit") or litter or soil surface if no species were encountered was used in the analysis.

Several factors influence the ability to identify plant species reliably in VHR images including timing of image acquisition relative to plant phenology (Lass and Callihan, 1997), distinctiveness of color (i.e., spectral signature) and shape of plant species (Foran and Cellier, 1980), and variability among image interpreters (Foran and Cellier, 1980; Booth et al., 2005b). For these reasons, and because rangeland management (see Pellant et al., 2005) and assessment of wildfire fuels (see Sandberg et al., 2001) often focus on plant functional groups, we aggregated the species-level data to general and fine cover types for this study (Table 1). These data were used for the estimation of vegetation and ground cover at the transect and landscape scale (i.e., all transects in a treatment).

2.4. Image acquisition

Aerial imagery was acquired in June 2009 and June 2010 from a fixed wing aircraft to coincide temporally with the field vegetation measurements. The images were taken using an UltraCamX digital frame camera (Vexcel Imaging; Graz, Austria) at an average flying height of 480 m above ground level (AGL), yielding a GSD of ∼4 cm. The images included four color bands (blue, green, red, near-infrared) and were recorded at 16-bit depth. A total of 40 raw images were acquired for each year with 60% forward overlap and 30% sidelap to photogrammetrically create orthophotos covering the entire study area (Fig. 2). All image acquisition, georeferencing, and orthorectification was completed by Aerographics, Inc. (Salt Lake City, UT).

2.5. Image interpretation of cover composition

Using ArcGIS 9.3 (ESRI, Redlands, CA), we digitized virtual transects on the orthophotos as straight lines between the recorded transect beginning and end locations. Image interpretation was performed in ArcGIS using the Image-Interpreter Tool (IIT; Schrader

Table 1
Image-interpreter classification types.

General cover types	Fine cover types
No-vegetation	Lichen/crust/moss
	Rock
	Exposed mineral soil (i.e., bare ground)
Herbaceous	Grass
Litter	Forb
	Litter
	Woody litter
Woody	Shrub
	Succulent (i.e., cactus)
	Tree
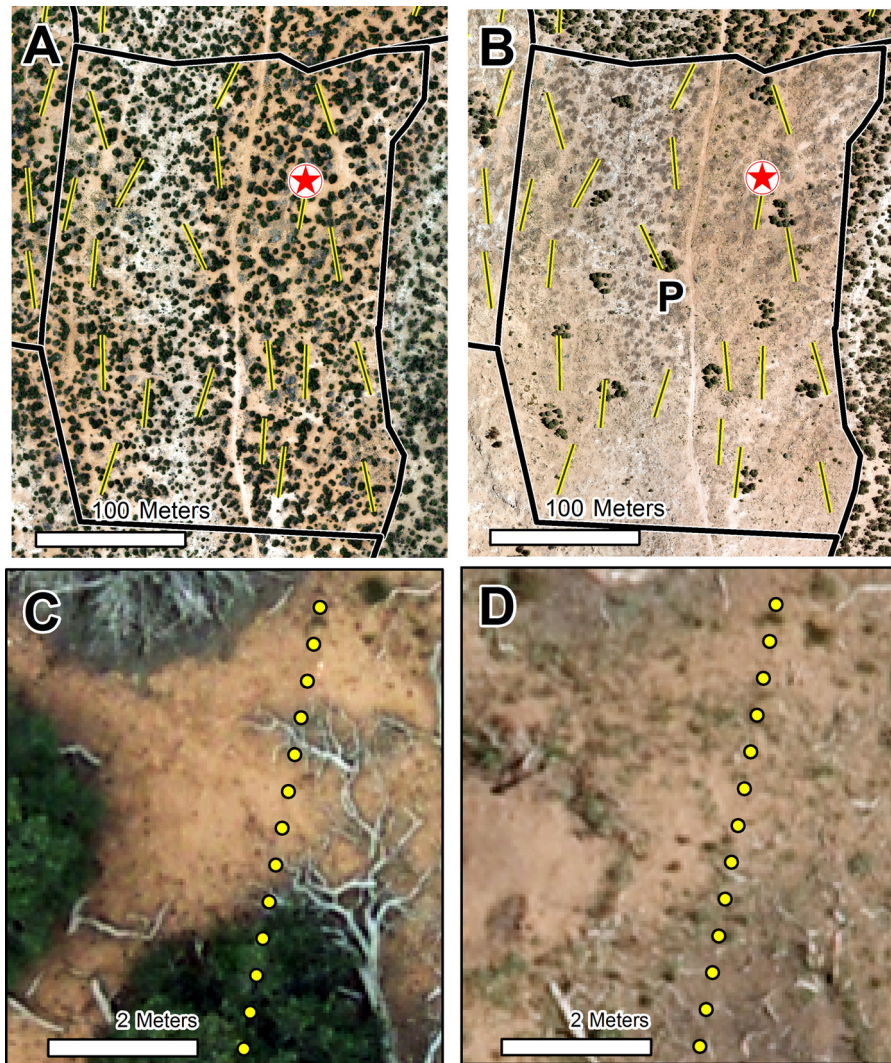
Fig. 2. Example of locations of field and image interpretation transects for the Pinon-Juniper lop and pile burn treatment (P, see text for description of treatments) for (A) 2009 and (B) 2010. Image interpretation occurred at points along virtual transects at a scale of 1:40, using the same transect and point locations for (C) 2009 and (D) 2010.

and Duniway, 2011) at points spaced every 0.5 m along each virtual transect (Fig. 2) to mirror the field collection techniques as closely as possible. At each point the interpreter identified the cover type occurring at that location according to the cover classes in Table 1. At the conclusion of each transect, the IIT calculated the proportion of the points in each cover type as estimates of percent cover.

Due to imprecision in GPS locations and challenges in laying out transect tapes between permanent stakes in sites with tall vegetation, we considered the virtual transects to be only in approximately the same locations as the field transects (Fig. 2). Because indicator estimates for each transect were intended to represent an area around the transect, the slight differences in transect locations should not have a significant effect on the results.

Interpretation was performed at a fixed scale (1:40) and the user could toggle between true-color (red, green, blue) and false-color composite (near-infrared, red, green) image displays to aid in interpretation (Fig. 2). Because Duniway et al. (2011) found generally low between-observer variability and little bias between observers, we conducted image interpretation with a single interpreter who followed the training protocol of Duniway et al. (2011). The observer trained in recognizing objects and plant species in the aerial imagery by reviewing ground and aerial photos of the study area, working from identification keys that described properties

of different cover types (e.g., color, texture, pattern). The interpreter was asked to identify each point along the digital transects as belonging to one of 10 fine cover classes. However, because of difficulties in discriminating between some of these classes in imagery in other areas, particularly between grasses and forbs or between exposed mineral soil, soil crusts and rock (Duniway et al., 2011), the fine classes were aggregated into four general cover classes for this study (Table 1). We further evaluated the ability to discriminate between herbaceous vegetation and litter from the imagery of the study area in both years.

2.6. Cover composition change detection analysis

We assessed agreement between field-based and image-interpreted estimates of cover types using a limits-of-agreement analysis and an analysis of variance (ANOVA) with random effects. Assessments were conducted for cover estimates from each year separately and for the difference between the two years. Transects were considered the sample unit within the 4 treatments ($n = 20$ per treatment).

Because the field and image-based methods provide estimates of the same properties (i.e., cover), high correlation between the two measures is expected even if there is systematic bias between

the methods (Bland and Altman, 2003). The limits of agreement (LOA) technique (Bland and Altman, 1986, 2003) was developed as a metric of the average bias and precision of the two methods relative to each other when the true values for a parameter are unknown. The LOA estimates the mean difference, $\bar{d}$, between the two methods (i.e., bias) and the standard deviation of the differences, s_d. If the differences are normally distributed, then 95% of the differences will be $LOA_{95} = \bar{d} \pm 1.96 s_d$. The smaller $\bar{d}$ and LOA_{95} are, the better the agreement between the two methods.

We calculated $\bar{d}$ and LOA_{95} between the field and image-based cover estimates. We tested whether $\bar{d}$ followed a normal distribution using the Wilk-Shapiro test (Royston, 1982). Differences between the two methods for each sample plot were plotted against the average plot value from the two methods (see Bland and Altman, 1999). We also calculated linear correlation between the field and image-based cover estimates by treatment.

To test whether the ability to estimate cover change from imagery varied by treatment, we conducted one-way mixed-effects ANOVAs on the difference between the field and image-based cover estimates. Treatment was considered a fixed effect, and transect a random effect. Separate ANOVAs were performed for 2009, 2010, and the change between years. Significant ANOVA results at the $\alpha = 0.05$ level, indicating differences in the ability to estimate cover by treatment, were followed-up with two-way comparisons (using Tukey's HSD test to control for Type I error rate with multiple comparisons) to determine which treatments were different.

The analyses described above assess the correspondence between field and image-based estimates of cover at the scale of a transect. To evaluate the ability of image-based methods to monitor vegetation change at larger scales – treatments in this case – we averaged the transect-level estimates by treatment for each year and the difference between the two years. We then tested for significant differences between the cover estimates at the treatment level using t-tests.

3. Results

Estimates of cover by indicator were similar between field-based and image-interpreted methods in 2009 and 2010 (Fig. 3). The only significant difference ($\alpha = 0.05$) observed was litter cover being underestimated by the image-interpretation method in 2009.

At the transect level, agreement between field-based and image-interpreted estimates of cover varied by indicator and year (Table 2, Fig. 4). However, average LOA was not statistically different than zero for any indicator ($\alpha = 0.05$), and limits of agreement plots did not show any evidence of trend in agreement with indicator value.
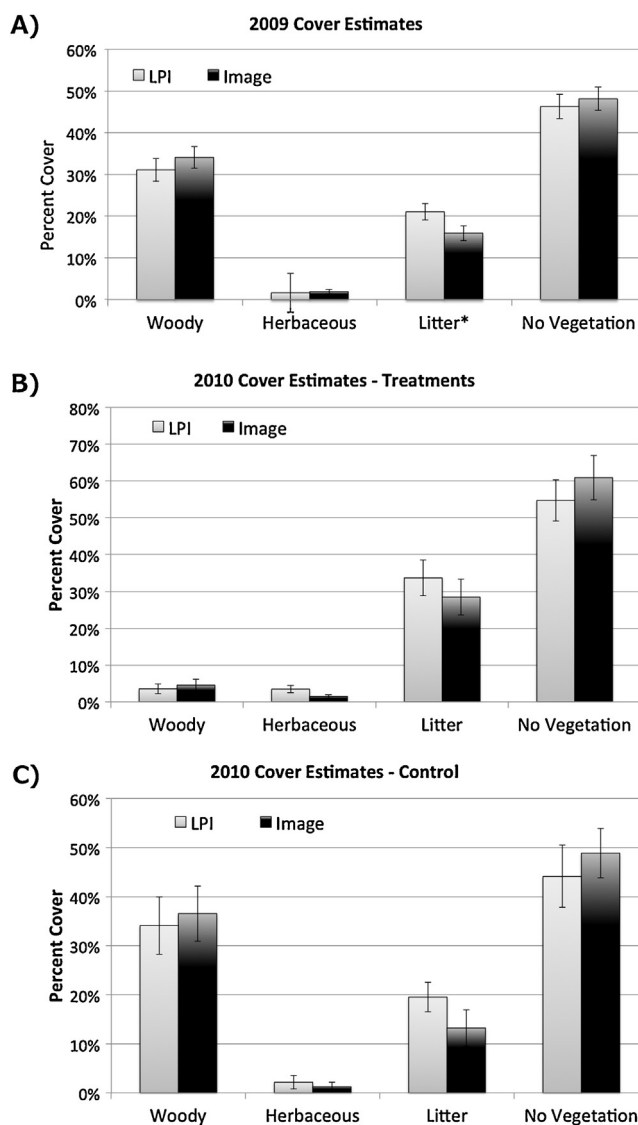
Fig. 3. Estimates of cover by cover type and method for 2009 (treatments and control combined), 2010 (treatments combined), and 2010 control plots. Error bars represent 95% confidence intervals. Herbaceous/litter includes woody litter, including significant amounts of large (>10 cm) pieces of wood in some treatments. Asterisk indicates differences that are statistically significant ($\alpha = 0.05$).

Table 2

Agreement between estimates of cover indicators from line-point intercept (LPI) measured in the field and interpretation of high-resolution aerial imagery for two years and the estimated change between those years. Average difference between methods is positive if image-based indicator estimates tend to be higher than LPI-based estimates.

Year	Indicator	Limits of agreement				Correlation
		Average difference between methods	Std. error	Lower 95% CI	Upper 95% CI	Pearson's r
2009	Woody	3.06%	1.38%	−20.86%	26.97%	0.47
	Herbaceous	0.27%	0.25%	−3.99%	4.53%	0.58
	Litter	−5.13%	1.16%	−25.23%	14.97%	0.24
	No vegetation	1.81%	1.44%	−23.17%	26.79%	0.51
2010	Woody	1.34%	0.81%	−12.73%	15.40%	0.89
	Herbaceous	−2.00%	0.51%	−10.77%	6.77%	0.18
	Litter	−5.18%	1.50%	−31.07%	20.71%	0.81
	No vegetation	5.85%	1.66%	−22.82%	34.52%	0.76
Change	Woody	−1.72%	1.23%	−23.02%	19.57%	0.76
	Herbaceous	−2.27%	0.60%	−12.59%	8.05%	−0.05
	Litter	−0.05%	1.67%	−28.96%	28.86%	0.75
	No vegetation	4.04%	1.66%	−24.67%	32.76%	0.77
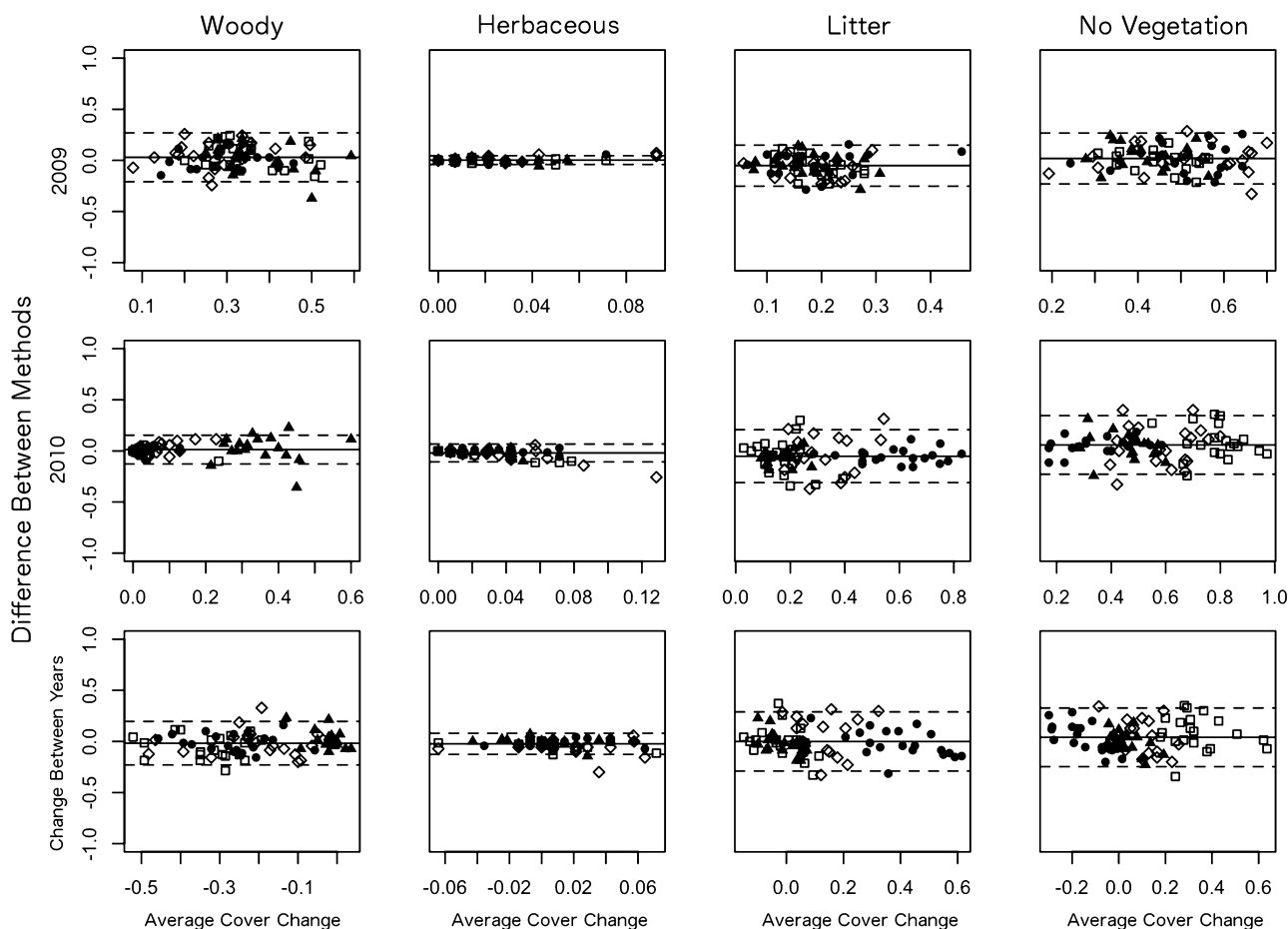
Fig. 4. Limits of agreement (LOA) plots for correspondence between field and image-estimates of cover by the four general land cover categories: woody vegetation, herbaceous vegetation, litter, and no-vegetation. Average cover change (*x*-axis) is the average value between the two methods. Symbols are for control (C, black triangles); mechanical mastication (M, black circles); lop, pile and burn (P, gray diamonds), and lop, scatter and broadcast burn (B, gray squares).

Average LOA for the difference between years indicated no bias between methods. LOA_{95} for the differenced indicators was slightly higher than for 2010.

For woody vegetation and no-vegetation, average LOA and LOA_{95} for 2009 was considerably higher than for 2010 (Table 2, Fig. 4). This result also manifested as low Pearson correlations between methods in 2009 for both indicators. For these two indicators, agreement between methods was higher 2010, with good agreement (i.e., low LOA_{95}) and strong correlation between methods for all indicators.

The average LOA and LOA_{95} for herbaceous vegetation in 2009 were small (0.27% and ±4.51%, respectively), yielding a good Pearson correlation ($\rho = 0.58$). However, in 2010, agreement between the two methods for herbaceous vegetation was poor with an average LOA of −2.00%, LOA_{95} of ±8.77% and Pearson correlation of ($\rho = 0.18$). Agreement of litter cover in both years showed the opposite pattern with good agreement in 2009 ($LOA_{95} = \pm 20.1\%$ and $\rho = 0.24$) and poorer agreement in 2010 ($LOA_{95} = \pm 25.9\%$ and $\rho = 0.81$).

No difference in agreement between methods by treatment (i.e., treatment effect) was observed for the woody cover, litter cover, or no-vegetation indicators in either 2009, 2010, or the difference between years (Table 3). However, for the herbaceous cover indicator, we found a significant treatment effect ($p \leq 0.05$) in 2010 and in the difference between years and a marginally-significant treatment effect ($0.1 < p < 0.05$) in 2009. Pairwise comparisons revealed this was due to a difference in agreement between the pile-and-burn (P) treatment and the other treatments and control.

At the treatment level, we found a high level of agreement between the field-based and image-interpreted when looking at estimates of change (i.e., difference between years) in all four indicators (Fig. 5). In all treatments, and for all indicators, the only significant difference between the field-based and image-interpreted estimates was for herbaceous cover in the pile-and-burn (P) treatment.

4. Discussion

Our results suggest that image interpretation to detect vegetation changes has utility for monitoring fuels reduction treatments through quantifying reduction in woody vegetation cover. However, difficulties in estimating litter and herbaceous vegetation cover may limit the utility of image interpretation to monitor

Table 3
Analysis of variance results for tests of differences in field and image-interpretation estimates of cover by treatment for 2009, 2010, and the change between years. Values reported are *p*-values for *F* test of treatment effect for the difference between the field (LPI) and image-interpreted estimates of cover. *p*-Values <0.05 indicate that the agreement between field and image-interpreted estimates of cover varied by treatment.

Year	Cover indicator			
	Woody	Herbaceous	Litter	No vegetation
2009	0.5629	0.0519	0.6672	0.8120
2010	0.4753	0.0289	0.9407	0.8666
Change	0.2011	0.0042	0.5580	0.4445
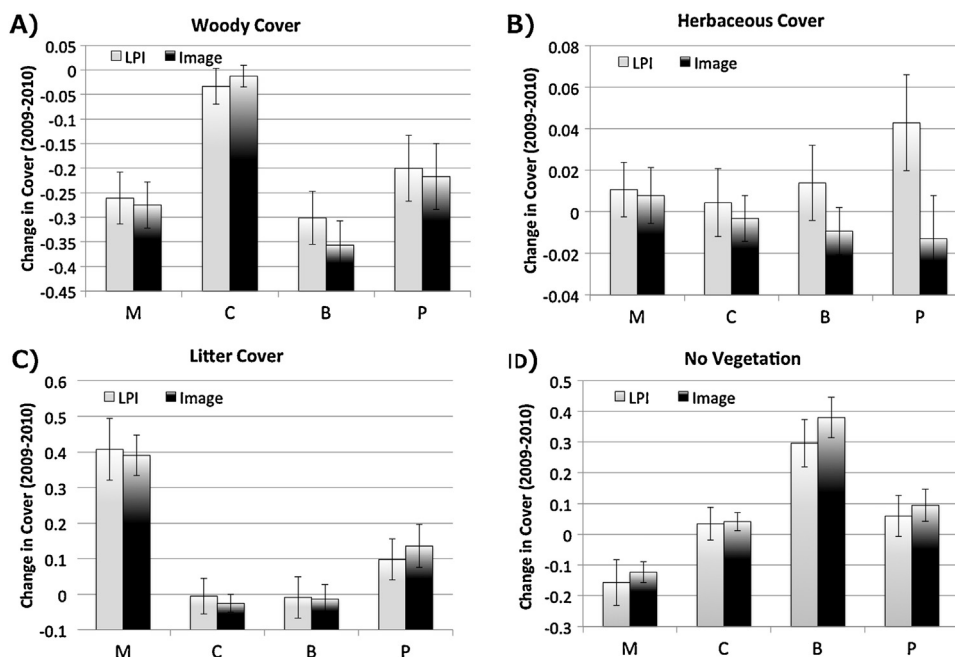
Fig. 5. Agreement between image interpretation and line-point intercept by treatment for (A) woody vegetation cover, (B) herbaceous vegetation, (C) litter cover, and (D) no vegetation (including exposed mineral soil, soil crusts and rock). Treatments are mechanical Pinon-Juniper (P–J) mastication (M), lopping of P–J with the slash collected in piles then burned (P), and lopping of P–J with the slash scattered and followed by a broadcast burn (B), and a control area (C). Error bars are 95% confidence intervals around treatment mean. A significant difference between the methods was found only for herbaceous cover in the lopping and pile-burn treatment (*t*-test: $\alpha = 0.05$).

responses of other vegetation classes following fuels-reduction treatments. We found good correspondence between image-interpreted and field-based estimates of woody vegetation cover change for the study area, and our results for single-year indicator estimates were in line with other VHR image-interpretation studies conducted in rangelands (Knapp et al., 1990; Fensham and Fairfax, 2003b; Booth et al., 2006b; Seefeldt and Booth, 2006; Booth and Cox, 2008; Duniway et al., 2011).

Discrepancies between field- and image-based indicator estimates at the transect level may have come from several sources. First, there is an inherent scale mismatch between the LPI field method, which measures vegetation intercepts of a ~1-mm-diameter point and the interpretation of images with a pixel resolution of ~4 cm. Studies have shown that accuracy of vegetation cover estimates from image-interpretation can improve as image resolution increases (Fensham and Fairfax, 2003a; Booth and Cox, 2009), especially for coarsely-defined cover types like those used here. Second, field transects and image-interpretation transects were only approximately coincident in space, and this could result in slight differences in portions of the site that were sampled. Third, we implemented a streamlined version of the image-interpretation protocol described by Duniway et al. (2011), employing only one observer and using a limited amount of training and calibration plot data. While this reduced the implementation time of the image interpretation, we did not have the ability to test for observer bias prior to conducting the image interpretation.

Several factors could present challenges in using this approach to monitor fuels treatments. First, the ability of image-interpretation to accurately estimate cover may be variable in different systems (Fensham and Fairfax, 2003b) or over time. The poor agreement between field-measured and image-based indicators in 2009 compared to 2010 was unexpected. Our results suggested that the poor agreement was due to misclassifications between the herbaceous/litter and no vegetation classes (Fig. 3). The significant underestimation of herbaceous/litter class in the control area in 2010 corroborates this. Difficulty in discriminating senescent herbaceous vegetation and litter from soil surfaces has been documented (Duniway et al., 2011; Karl et al., 2012b; Zerger et al., 2012). The treatment areas in 2010 were floristically much simpler than in 2009 with much of the vegetation and litter cover removed. This may have contributed to the improved agreement in 2010.

Second, image interpretation may be more reliable for some indicators than for others, and vegetation composition may influence image interpretation results (see Foran and Cellier, 1980). Similar to other studies (e.g., Tueller et al., 1988; Knapp et al., 1990; Fensham and Fairfax, 2003b), we found trees and large woody shrubs were typically easy to recognize in our imagery, and as a result the estimates of woody cover between the two methods were usually close. Discrimination of herbaceous litter from senescent vegetation (especially with annuals that lack distinctive shape) can be difficult owing to their similar spectral signatures (Tueller et al., 1988). Additionally, we found it difficult to discriminate herbaceous litter from the light-colored soils in the study area. This contributed to our underestimation of herbaceous cover and overestimation of non-vegetated area with image interpretation. Our study was fairly simple in terms of vegetation composition and structure, and this fact likely contributed to the image interpretation being successful (Foran and Cellier, 1980; Fensham and Fairfax, 2003a). Systems with more vegetation and litter cover or greater structural diversity may be more challenging to interpret via imagery (Fensham and Fairfax, 2003a; Duniway et al., 2011). Tree and shrub cover are important indicators for assessing and monitoring fuel loads (Stephens et al., 2009) and can be reliably estimated via interpretation of VHR imagery. However, in rangelands, cover of herbaceous vegetation and litter, especially in systems dominated by invasive annual grasses, are also important in assessing wildfire risk (Pellant, 1990). For this reason, more research is needed into techniques and image properties (e.g., scale, spectral bands, timing relative to plant phenology) to improve estimates of herbaceous vegetation and litter from VHR imagery.

Third, differences in site conditions (e.g., illumination, shadows, soil moisture) at the time of image acquisition may affect image interpretation (Fensham and Fairfax, 2003a). Image acquisitions for

this study took place on the same day in 2009 and 2010, ensuring consistent sun illumination angle. Image acquisition was intended to take place when the sun was at its zenith, but image acquisition in 2010 occurred earlier in the morning causing shadows that made it difficult to interpret regions northwest of trees and shrubs. In 2009, the sky was overcast with high clouds creating diffuse illumination that minimized shadows. In 2010, the sky was clear, and the direct sunlight accentuated shadowing. In addition to shadowing, the overall color of the soil surface and vegetation was slightly different between years, but this difference was not quantified. These factors may have contributed to misclassifications between soil surfaces and herbaceous cover and litter between years. Controlling imagery specifications is a challenging aspect of any image acquisition. However, human observers performing image interpretation are capable of accounting for differences in image characteristics and quality that would challenge traditional image classification and change detection techniques (Fensham and Fairfax, 2003a; Booth et al., 2006a). Still, our results highlight the need to ensure that image and ground properties are as close as possible among acquisitions.

5. Conclusion

Our results show that image interpretation to detect vegetation changes has utility for monitoring fuels reduction treatments as long as certain limitations of the technique are acknowledged. The benefits of this technique are that it provides objective and repeatable measurements of site conditions that could be implemented relatively inexpensively and easily without the need for highly specialized software or technical expertise (Booth and Cox, 2008). Image-based techniques also present the opportunity to reanalyze the imagery in the future for different objectives. Perhaps the biggest limitations of image interpretation to monitoring fuels treatments in rangelands are the difficulty in challenges in estimating litter and herbaceous vegetation cover and the sensitivity of herbaceous cover estimates to image quality and shadowing. Fuels treatments like mastication produce a lot of litter, and the inability to separate litter from herbaceous vegetation could impair monitoring of plant community response to treatments.

This study examined the utility of image interpretation to detect changes in vegetation cover over time as a result of management activities. Further research needs to be conducted to determine when and where image interpretation could be useful as a rangeland monitoring tool. Specifically, techniques for better discriminating litter from herbaceous vegetation need to be developed. Also, the influence of annual variation in precipitation on image interpretation results should be explored, and the value of image interpretation for monitoring systems where changes are not as dramatic as in our study area should be evaluated. Finally, comparison studies of image interpretation to automated image classification should be conducted in a variety of rangeland systems to assess the accuracy and efficiency of each approach.

Acknowledgements

Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.ecolind.2014.05.017. These data include Google maps of the most important areas described in this article.

References

Bennett, L.T., Judd, T.S., Adams, M.A., 2000. Close-range vertical photography for measuring cover changes in perennial grasslands. J. Range Manage., 634–641.

Bland, J.M., Altman, D.G., 1999. Measuring agreement in method comparison studies. Stat. Methods Med. Res. 8, 135–160.

Bland, J.M., Altman, D.G., 2003. Applying the right statistics: analyses of measurement studies. Ultrasound Obst. Gynecol. 22, 85–93.

Bland, M.J., Altman, D., 1986. Statistical methods for assessing agreement between two methods of clinical measurement. Lancet 327, 307–310.

Booth, D.T., Cox, S.E., 2009. Dual-camera, high-resolution aerial assessment of pipeline revegetation. Environ. Monit. Assess. 158, 23–33.

Booth, T.D., Cox, S.E., 2008. Image-based monitoring to measure ecological change in rangeland. Front. Ecol. Environ. 6, 185–190.

Booth, T.D., Cox, S.E., Berryman, R.D., 2006a. Point sampling digital imagery with "Samplepoint". Environ. Monit. Assess. 123, 97–108.

Booth, T.D., Cox, S.E., Fifield, C., Phillips, M., Williamson, N., 2005a. Image analysis compared with other methods for measuring ground cover. Arid Land Res. Manage. 19, 91–100.

Booth, T.D., Cox, S.E., Johnson, D.E., 2005b. Detection-threshold calibration and other factors influencing digital measurements of ground cover. Rangeland Ecol. Manage. 58, 598–604.

Booth, T.D., Cox, S.E., Meikle, T.W., Fitzgerald, C., 2006b. The accuracy of ground-cover measurements. Rangeland Ecol. Manage. 59, 179–188.

Booth, T.D., Tueller, P.T., 2003. Rangeland monitoring using remote sensing. Arid Land Res. Manage. 17, 455–467.

Bork, E.W., Su, J.G., 2007. Integrating LIDAR data and multispectral imagery for enhanced classification of rangeland vegetation: a meta analysis. Remote Sensing Environ. 111, 11–24.

Duniway, M.C., Karl, J.W., Schrader, S., Baquera, N., Herrick, J.E., 2011. Rangeland and pasture monitoring: an approach to interpretation of high-resolution imagery focused on observer calibration for repeatability. Environ. Monit. Assess. 184 (6), 3789–3804.

Dymond, J.R., Stephens, P.R., Newsome, P.F., Wilde, R.H., 1992. Percentage vegetation cover of a degrading rangeland from SPOT. Int. J. Remote Sensing 13, 1999–2007.

Fensham, R.J., Fairfax, R.J., 2003a. Aerial photography for assessing vegetation change: a review of applications and the relevance of findings for Australian vegetation history. Aust. J. Bot. 50, 415–429.

Fensham, R.J., Fairfax, R.J., 2003b. Assessing woody vegetation cover change in north-west Australian savanna using aerial photography. Int. J. Wildland Fire 12, 359.

Foran, B.D., Cellier, K.M., 1980. An evaluation of large scale aerial photography for assessing range condition in central Australia. Aust. Rangeland J. 2, 189–200.

Hengl, T., Heuvelink, G.B.M., Stein, A., 2004. A generic framework for spatial prediction of soil variables based on regression-kriging. Geoderma 120, 75–93.

Herrick, J.E., Van Zee, J.W., Havstad, K.M., Burkett, L.M., Whitford, W.G., 2009. Monitoring Manual for Grassland, Shrubland, and Savanna Ecosystems. USDA-ARS Jornada Experimental Range, Las Cruces, New Mexico.

Homer, C.G., Aldridge, C.L., Meyer, D.K., Schell, S.J., 2012. Multi-scale remote sensing sagebrush characterization with regression trees over Wyoming, USA: laying a foundation for monitoring. Int. J. Appl. Earth Observation Geoinformation 14, 233–244.

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

Karl, J.W., 2010. Spatial predictions of cover attributes of rangeland ecosystems using regression kriging and remote sensing. Rangeland Ecol. Manage. 63, 335–349.

Karl, J.W., Duniway, M.C., Nusser, S.M., Opsomer, J.D., Unnasch, R.S., 2012a. Using very-large scale aerial (VLSA) imagery for rangeland monitoring and assessment: some statistical considerations. Rangeland Ecol. Manage. 65, 330–339.

Karl, J.W., Duniway, M.C., Schrader, T.S., 2012b. A technique for estimating rangeland canopy-gap size distributions from very-high-resolution digital imagery. Rangeland Ecol. Manage. 65, 196–207.

Knapp, P.A., Warren, P.L., Hutchinson, C.F., 1990. The use of large-scale aerial photography to inventory and monitor arid rangeland vegetation. J. Environ. Manage. 31, 29–38.

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 Eng. Remote Sensing 76, 661–672.

Laliberte, A.S., Rango, A., Fredrickson, E.L., 2006. Separating green and senescent vegetation in very high resolution photography using an intensity-hue-saturation transformation and object based classification. In: Proceedings of the American Society for Photogrammetry and Remote Sensing Annual Conference, May 1–5, 2006, Reno, Nevada.

Lass, L.W., Callihan, R.H., 1997. Effects of phenological stage on detectability of yellow hawkweed (hieracium pratense) and oxeye daisy (chrysanthemum

leucanthemum) with remote multispectral digital imagery. Weed Technol. 11, 248–256.

Luscier, J.D., Thompson, W.L., Wilson, J.M., Gorham, B.E., Dragut, L.D., 2006. Using digital photographs and object-based image analysis to estimate percent ground cover in vegetation plots. Front. Ecol. Environ. 4, 408–413.

Marsett, R.C., Qi, J., Heilman, P., Beidenbender, S.H., Watson, M.C., Amer, S., Weltz, M., Goodrich, D., Marsett, R., 2006. Remote sensing for grassland management in the arid southwest. Rangeland Ecol. Manage. 59, 530–540.

Moffet, C.A., 2009. Agreement between measurements of shrub cover using ground-based methods and very large scale aerial imagery. Rangeland Ecol. Manage. 62, 268–277.

National Research Council, 1994. Rangeland Health: New Methods to Classify, Inventory, and Monitor Rangelands. National Academy Press, Washington, DC.

Navulur, K., 2007. Multi-spectral Image Analysis Using the Object-oriented Paradigm. CRC Press, Taylor and Francis Group, LLC, Boca Raton, FL.

Pellant, M., 1990. The Cheatgrass-Wildfire Cycle – Are There Any Solutions? Pages 11–18. General Technical Report. USDA Forest Service Intermountain Research Station, Ogden, UT.

Pellant, M., Shaver, P., Pyke, D.A., Herrick, J.E., 2005. Interpreting Indicators of Rangeland Health, Version 4. BLM/WO/ST-00/001+1734/REV05. U.S. Department of the Interior, Bureau of Land Management, National Science and Technology Center, Denver, CO.

Pyke, D.A., Herrick, J.E., Shaver, P., Pellant, M., 2002. Rangeland health attributes and indicators for qualitative assessment. J. Range Manage. 55, 584–597.

Qi, J., Marsett, R., Heilman, P., Biedenbender, S., Moran, M.S., Goodrich, D., 2002. Ranges improves satellite-based information and land cover assessments in southwest United States. EOS, Trans. Am. Geophys. Union 83, 601, 605–606.

Ramsey, R.D., Wright, D.L., McGinty, C., 2004. Evaluating the use of landsat 30m enhanced thematic mapper to monitor vegetation cover in shrub-steppe environments. Geocarto Int. 19, 39–47.

Royston, J.P., 1982. An extension of Shapiro and Wilk's W test for normality to large samples. Appl. Statistics 31, 115–124.

Running, S.W., Nemani, R.R., Heinsch, F.A., Zhao, M., Reeves, M.C., Hashimoto, H., 2004. A continuous satellite-derived measure of global terrestrial primary production. BioScience 54, 547–560.

Sandberg, D.V., Ottmar, R.D., Cushon, G.H., 2001. Characterizing fuels in the 21st century. Int. J. Wildland Fire 10, 381–387.

Scanlon, T.M., Albertson, J.D., Caylor, K.K., Williams, C.A., 2002. Determining land surface fractional cover from NDVI and rainfall time series for a savanna ecosystem. Remote Sensing Environ. 82, 376–388.

Schott, J.R., 2007. Remote Sensing: The Image Chain Approach, second edition. Oxford University Press, Inc., New York.

Schrader, T.S., Duniway, M.C., 2011. Image interpreter tool: an ArcGIS tool for estimating vegetation cover from high-resolution imagery. Rangelands 33, 35–40.

Seefeldt, S.S., Booth, T.D., 2006. Measuring plant cover in sagebrush steppe rangelands: a comparison of methods. Environ. Manage. 37, 703–711.

Shupe, S.M., Marsh, S.E., 2004. Cover- and density based vegetation classification of the Sonoran Desert using landsat TM and ERS-1 SAR imagery. Remote Sensing Environ. 131.

Stephens, S.L., Moghaddas, J.J., Edminster, C., Fiedler, C.E., Haase, S., Harrington, M., Keeley, J.E., Knapp, E.E., McIver, J.D., Metlen, K., Skinner, C.N., Youngblood, A., 2009. Fire treatment effects on vegetation structure, fuels, and potential fire severity in western U.S. forests. Ecol. Appl. 19, 305–320.

Tueller, P.T., Lent, P.C., Stager, R.D., Jacobsen, E.A., Platou, K.A., 1988. Rangeland vegetation changes measured from helicopter-borne 35-mm aerial photography. Photogrammetric Eng. Remote Sensing 54, 609–614.

U.S.D.A. Soil Conservation Service, 1991. Soil survey of Canyonlands Area, Utah, parts of Grand and San Juan Counties. Page 293. Washington, DC.

Washington-Allen, R.A., West, N.E., Ramsey, R.D., Efroymson, R.A., 2006. A protocol for retrospective remote sensing-based ecological monitoring of rangelands. Rangeland Ecol. Manage. 59, 19–29.

Xiao, J., Moody, A., 2005. A comparison of methods for estimating fractional green vegetation cover within a desert-to-upland transition zone in central New Mexico, USA. Remote Sensing Environ. 98, 237–250.

Zerger, A., Gobbett, D., Crossman, C., Valencia, P., Wark, T., Davies, M., Handcock, R.N., Stol, J., 2012. Temporal monitoring of groundcover change using digital cameras. Int. J. Appl. Earth Observation Geoinformation 19, 266–275.