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Cover Estimations Using Object-Based Image Analysis Rule Sets Developed Across Multiple Scales in Pinyon-Juniper Woodlands

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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 comparisons have been made that evaluate the utility of object-based image analysis (OBIA) to accurately classify a landscape where rule sets (models) have been developed at various scales. In this study, OBIA rule sets used to estimate land cover from high–spatial resolution imagery (0.06-m pixel) on *Pinus* L. (pinyon) and *Juniperus* L. (juniper) woodlands were developed using eCognition Developer at four scales with varying grains—1) individual plot, 2) individual sites, 3) regions (western juniper vs. Utah juniper sites), and 4) pinyon-juniper woodland network (all plots)—that were within the same study extent. Color-infrared imagery was acquired over five sites in Oregon, California, Nevada, and Utah with a Vexcel UltraCamX digital camera in June 2009. Ground cover measurements were also collected at study sites in 2009 on 80 0.1-ha plots. Correlations between OBIA and ground measurements were relatively high for individual plot and site rule sets (ranging from $r=0.52$ to $r=0.98$). Correlations for regional and network rule sets were lower (ranging from $r=0.24$ to $r=0.63$), which was expected due to radiance differences between the images as well as vegetation differences found at each site. All site and plot OBIA average cover percentage estimates for live trees, shrubs, perennial herbaceous vegetation, litter, and bare ground were within 5% of the ground measurements, and all region and network OBIA average cover percentage estimates were within 10%. The trade-off for decreased accuracy over a larger area (region and network rule sets) may be useful to prioritize management strategies but will unlikely capture subtle shifts in understory plant communities that site and plot rule sets often capture.

Key Words: eCognition Developer, high–spatial resolution imagery, object-based image analysis, rule sets, SageSTEP

INTRODUCTION

Monitoring and assessing 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). Second, data collection methods must be determined that are 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. 2007b; Booth et al. 2008). Research studies have utilized multiple remote-sensing spatial scales and platforms such as satellite imagery (Ramsey et al. 2004; Bradley and Mustard 2005; Laliberte et al. 2007a; 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. 2014), and very large scale aerial imagery (Booth and Cox 2008; Laliberte and Rango 2009; Moffet 2009) across the Intermountain West. However, few studies have evaluated how the specificity of object-based image analysis (OBIA) rule sets affect the accuracy of remotely sensed cover estimates compared to ground-measured cover estimates of designated land cover classes.

OBIA methods differ from traditional pixel-based classification methods (e.g., supervised classification) in that OBIA techniques group similar, neighboring pixels into distinct image objects within designated parameters (Riggan and Weih 2009; Burnett and Blaschke 2013). Rule sets, which are a sequence of processes that are executed in a defined order (Trimble 2011), include segmentation parameters that create meaningful objects and features and thresholds that are used to classify objects according to designated land cover classes. Rule sets allow the user to examine what cover classes are least distinguishable from others and to refine specific thresholds to better capture the variation of that class for a particular image or group of imagery.

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Table 1. Land cover class descriptions with associated sites.[1]

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 Wyoming big sagebrush (*Artemisia tridentata* Nutt. ssp. *wyomingensis* Beetle & Young; ON and MC), mountain big sagebrush (*Artemisia tridentata* Nutt. ssp. *vaseyana*; BM, DR, and MC), antelope bitterbrush (*Purshia tridentata* [Pursh] DC.; BM, DR, and ST), and dead shrubs. Yellow rabbitbrush (*Chrysothamnus viscidiflorus* [Hook.] Nutt.) and other small nondominant shrubs could not confidently be distinguished from bunchgrasses and forbs and thus 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 (*Festuca idahoensis* Elmer; BM and DR), Sandberg bluegrass (*Poa secunda* J. Presl; all sites), bluebunch wheatgrass (*Pseudoroegneria spicata* [Pursh] Á. Löve; MC, ON, and ST), Thurber's needlegrass (*Achnatherum thurberianum* [Piper] Barkworth; DR and MC), and needle and thread grass (*Herperostipa comata* [Trin. & Rupr.] Barkworth; MC).
Litter	Litter cover consists of nonliving plant or animal material that rests on top of the soil surface, including detached woody material. Due to the size of cheatgrass (*Bromus tectorum* L.) patches and the pixel resolution of the imagery, we were not able to distinguish litter from annual species. Cheatgrass typically makes up less than 10% of the total litter composition with the exception of Stansbury, where cheatgrass makes up approximately 20% of the total litter cover class.
Bare ground	Bare ground cover is composed primarily of mineral soil (> 90 %) and rock with less than 3% lichen or moss.

[1]BM indicates Blue Mountain; DR, Devine Ridge; MC, Marking Corral; ST, Stansbury; and ON, Onaqui.

Because management decisions involve ecological considerations that vary from local to regional scales, further research is needed to evaluate the selection of the appropriate size of an area that can be accurately classified using a particular OBIA rule set or model. This research focuses on classifying *Juniperus* L. (juniper) and *Pinus* L. (pinyon) (P-J) woodlands across multiple scales using OBIA techniques to describe five land cover classes (Table 1). P-J woodlands are particularly of interest due to their expansion and infilling into shrub–steppe communities. As P-J woodlands expand, 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).

Our primary objective was to test how the specificity of OBIA rule sets affected remotely sensed cover measurements from high–spatial resolution imagery (0.06-m pixel), relative to ground-based measurements on P-J expansion woodlands. Rule sets were developed at four scales with varying grains: 1) individual 0.1-ha plots nested within individual sites (65 rule sets evaluated); 2) individual plots grouped by site (five rule sets evaluated); 3) plots grouped by region, or western juniper (*Juniperus occidentalis* Hook.) sites vs. Utah juniper (*Juniperus osteosperma* [Torr.] Little) sites (two rule sets evaluated); or 4) all P-J woodlands plots that span across the Great Basin (one rule set evaluated). We hypothesized that cover percentage estimates from high–spatial resolution imagery would fall within an acceptable error rate ($\pm 5\%$) when compared to ground measurements, which were considered to be correct, using rule sets that were developed for individual plots and plots grouped by site. For rule sets developed from plots grouped by region and network (all plots), we expected that cover percentage estimates from high–spatial resolution imagery would be sufficiently accurate (within $\pm 10\%$ of ground cover measurements) to support the management of sagebrush–steppe ecosystems. In order to further improve the application of remote-sensing technology, our secondary objective was to identify diagnostic features (e.g., mean brightness) of land cover types that could be used to classify P-J woodlands across the Great Basin.

METHODS

Study Locations

This study was conducted on five pinyon and/or juniper woodlands that were part of the Joint Fire Sciences Sagebrush Steppe Treatment Evaluation Project (SageSTEP). Sites span the Great Basin and were found in Oregon (Devine Ridge: lat 43°71′38″N, long –118°96′01″E), California (Blue Mountain: lat 41°′92″N, long –120°89′55″E), Nevada (Marking Corral: lat 39°39′44″N, long –115°15′75″E), and Utah (Stansbury: lat 40°58′17″N, long –112°66′16″E; Onaqui: lat 40°21′31″N, long –112°47′27″E). These sites provided a wide range of semiarid sagebrush–steppe communities that varied in elevation, soil type, and climate and have been invaded by *Juniperus occidentals* Hook. (western juniper), *Juniperus osteosperma* (Torr.) Little (Utah juniper), and/or *Pinus monophylla* Torr. & Frém. (singeleaf pinyon). Specific site characteristics have been described by McIver et al. (2010). Dominant vegetation types associated with land cover classes used in this study are described in Table 1.

Ground Measurements

Ground data were collected by SageSTEP field crews during the summer of 2009 on 0.1-ha plots (30 $\times$33 m). Plot locations within site were randomly assigned across all phases of woodland encroachment (Miller et al. 2005). Total plots per site included 15 from each of Stansbury, Marking Corral, and Blue Mountain; 18 from Onaqui; and 17 from Devine Ridge for a total of 80 plots. Cover percentage measurements were collected within each plot using the line-point intercept method on five 30-m transects systematically placed across the plot. First-contact intercept data (top vegetation canopy or ground surface) was collected every 0.5 m, totaling 300 points per plot (five transects with 60 points per transect), representing the aerial view captured in the imagery. Estimates 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. Percent tree cover used in the data analysis was measured using the crown-diameter method (Mueller-Dombois and Ellenberg 1974).

Imagery Acquisition

Four-band red, green, blue, and near-infrared (0.7–1.0 μm) imagery was acquired at Blue Mountain, Devine Ridge, and Marking Corral on 18 June 2009 and at Onaqui and Stansbury on 19 June 2009 by Aero-graphics, Inc. (Salt Lake City, UT). Imagery was collected with a Vexcel UltraCamX digital camera (Vexcel Imaging GmbH, Graz, Austria) on board a turbocharged Cessna 206 aircraft at an approximate photo scale of 1:5 556 (0.06-m pixel size). The aircraft was flown between 2 100 and 2 800 m above ground level, depending on individual site conditions, at an approximate speed of 180 $km \cdot h^{-1}$. The camera was equipped with forward-motion compensation, airborne global positioning system (GPS) capabilities, and an Applanix inertial measurement unit (IMU). To support the airborne GPS data, the flight crew utilized US Continuously Operating Reference Station/International Global Navigation Satellite System Service stations or dedicated GPS base station at regional airports within the project area. Ground control points were used to post process the airborne GPS/IMU data to yield air point coordinates for each exposure accurate to within ± 0.06 m. Analytical digital aerotriangulation was used to extend full control for each stereomodel and to tie ground control points and airborne GPS/IMU air point data. Digital images were orthorectified using specialized software created by the Vexcel/Microsoft digital imaging partnership by Aero-graphics, Inc.

Plot Extraction

Ground plots were georeferenced on imagery using GPS points collected with a WAAS-enabled Garmin GPSmap 60CS unit (Olathe, KS) in the center and at a designated corner of each of the 80 plots. On the ground, plots were positioned so that the 33-m baseline was at the bottom of the slope parallel to the contour of the landscape. To minimize true image location inaccuracies, we utilized the two WAAS-enabled GPS points, protocols for positioning each plot on the landscape as explained above, and two photographs collected on the baseline of each plot. Individual plots from the landscape scene were visually shifted until the estimated inaccuracies were within 1–2 m of the ground plots. Individual plots from the imagery were then extracted so that measurements would be made on the same experimental unit for both OBIA and ground-measured cover classes using ArcMap 10.0 (ESRIArc-Map 1999–2010).

Image Processing

The software eCognition Developer 8 (Trimble Germany GmbH, Munich, Germany) was used for our OBIA. Rule sets were developed at four spatial scales with varying grains: 1) individual 0.1-ha plots, 2) individual sites (Devine Ridge, ~15 ha; Blue Mountain, ~15 ha; Marking Corral, ~16 ha; Stansbury, ~5 ha; and Onaqui, ~20 ha), 3) regions (i.e., Devine Ridge and Blue Mountain make up the western juniper region and Marking Corral, Stansbury, and Onaqui make up the Utah juniper region), and 4) all sites evaluated in this study across the SageSTEP network (henceforth be referred to as "network").

Rule sets were developed using an initial subset of the total plots (three training plots per site for a total of 15 plots) to determine features (spectral, spatial, textural, and contextual information) and thresholds (e.g., reflectance values associated with the brightness feature) that would correctly classify image objects created in the segmentation process (Hulet et al. 2013; Table 2; Fig. 1). Prior to segmentation, imagery was filtered to remove noise and detail (extraneous information irrelevant to the OBIA due to the scale of our land cover classes vs. the pixel resolution). The segmentation process consisted of a multi-resolution segmentation algorithm followed by a spectral difference segmentation algorithm that created meaningful image objects from pixels based on relative homogeneity criteria (Trimble 2011; Table 2; Fig. 1). Plots that captured the largest range in plant community composition and bare ground cover and that were distributed across the study site were selected as training plots. Rule set thresholds associated with specific features and land cover classes were manually adjusted through several iterative classification trials to optimize our OBIA cover estimates with the ground-measured cover data. Once a rule set was developed from the training plots, it was applied to a second subset of the plots (validation plots). Cover estimates generated from validation plots were calculated by totaling the area of each land cover class and dividing it by the total area of the plot. Remotely sensed cover estimates were then compared to ground-measured cover estimates for the data analysis.

Study Design

Site and Plot Rule Sets. Site-specific rule sets were developed first using the image processing steps described above. Thresholds were adjusted to optimize OBIA cover estimates with ground-measured cover data within an acceptable error of ± 5% for each land cover class by site. For individual 0.1-ha plots, rule sets that were originally developed for each of the individual sites were used. Thresholds associated with features in the individual site rule sets were adjusted or refined for each validation plot, essentially creating 65 rule sets with a range of thresholds used to estimate cover percentage.

Regional and Network Rule Sets. Rule sets on the regional (western juniper vs. Utah juniper sites) and network (all sites) scales were also based on site-specific rule sets. Specific features used in site rule sets for each cover class were first summed (e.g., if the 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 (i.e., had the highest score) were selected for each land cover class. The selected features were then evaluated using the training plots to determine which one(s) would most accurately estimate the specified land cover class for both the

Table 2. Description of filters, segmentations, and features used to classify land cover classes in this study. Image layer or band(s) used in specific processes are italicized. Further detail and formulas for calculating filters and features can be found in Trimble's eCognition Developer reference book (Trimble 2011).[1]

	Description
Image filters	
Median filter	Replaces the pixel value with the median value of neighboring pixels.
Convolution filter	Gaussian smoothing filter (Gaussian 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 a center-weighted average of the square areas of the matrix centered on the pixel.
Segmentations	
Multiresolution segmentation (convolution filtered RGB bands)	Applies an optimization procedure that 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 and 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 $= [(\mathrm{NIR} - \mathrm{R})/(\mathrm{NIR} + \mathrm{R} + \mathrm{L})] \cdot (1 + \mathrm{L})$; $\mathrm{L} = 0.5$.
HSI transformation: hue (median filtered RGB bands)	Hue (color) transformation equations are based on 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.

[1]R indicates red; G, green; B, blue; NIR, near infrared; and HSI, hue, saturation, and intensity.

region and the network rule set. Thresholds associated with the features were adjusted to optimize our OBIA cover estimates with the ground-measured cover data. Because both our regional and our network rule sets needed to account for more variation found within the imagery due to atmospheric conditions, timing of imagery acquisition, and vegetation differences across all sites, we increased our acceptable error rate to ± 10% for each land cover class. Once our training plot rule set was developed for each scale, it was applied to a second subset of the plots (65 validation plots) for 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 rule set scale. Results from the paired *t* tests were evaluated for significance using the Bonferroni correction ($P < 0.05/5$). Statistical assumptions for normality and homogeneity of variance were assessed. Ground measurements were always subtracted from estimates derived from OBIA to determine if OBIA consistently overestimated or underestimated the land cover class of interest. Mean difference values for each land cover class by rule set scale were compared using 1-way ANOVA and the Tukey–Kramer honestly significant difference multiple comparison method with a significance level of $P < 0.05$. The correlation coefficient (r) was used to assess the relationship between ground-measured data and OBIA data for each land cover class by rule set scale. It should be noted that for each of the rule set scales evaluated, the same ground-measured data were used in the comparisons; therefore, the difference lies in the OBIA cover estimates extracted from the various rule sets.

RESULTS

Live Trees

Live tree canopy cover percentage measurements for site and individual plot rule sets did not differ between the OBIA and ground measurement methods; however, for both network and regional rule sets, OBIA estimates were significantly less ($P < 0.05$) than ground measurements of live tree cover (Table 3). When running the network rule set for individual sites, OBIA estimates for tree cover were significantly less than ground measurements by an average of 10.5% at Devine Ridge, Marking Corral, and Stansbury. With the regional rule set, OBIA estimates were significantly less than ground measurements for tree cover on average by 10% at Marking Corral and Stansbury.

Shrubs

Shrub canopy cover percentage measurements did not differ between the OBIA and ground measurement methods for the

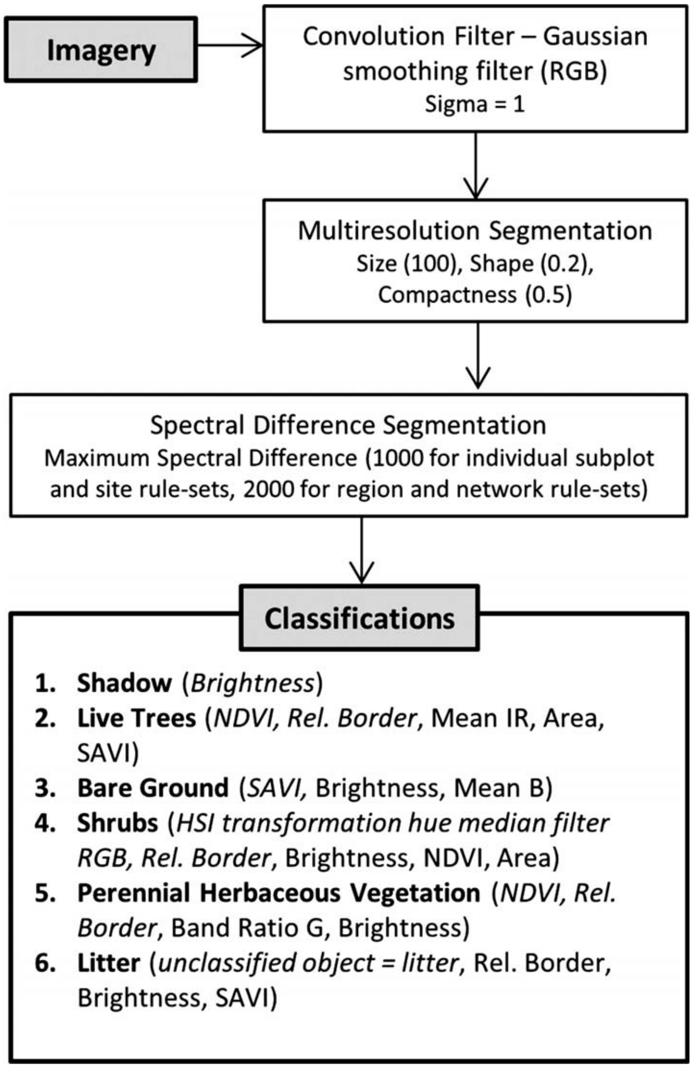

Figure 1. Hierarchical classification process using eCognition Developer for all plots. Bold print represents land cover classes listed in the order classified. Notes in parentheses indicate feature(s) and band(s) used to classify land cover classes. Italicized features were used to classify land cover classes for all rule sets (individual plot, site, region, and network); standard text features were used to classify land cover classes for individual plot and site rule sets only. RGB indicates red, green, and blue bands; NDVI, Normalized Difference Vegetation Index; Rel. border, relative border; IR, infrared band; SAVI, Soil-Adjusted Vegetation Index; and HSI, hue, saturation, and intensity transformation.

network, region, and site rule sets (Table 3). However, at sites where antelope bitterbrush was present (Blue Mountain, Devine Ridge, and Marking Corral), significant differences between the OBIA and ground measurement methods were observed ($P < 0.05$). Using site rule sets, Blue Mountain 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%. Differences between OBIA shrub and ground-measured cover were significant ($P < 0.05$) for the individual plot rule set and were on average 1.3% less than ground measurements. However, the average mean difference range for the individual plot rule set was smaller than the other rule sets but skewed toward underestimating shrub cover when compared to ground measurement, and this likely contributed to the significant difference (Table 3).

Perennial Herbaceous Vegetation

Although no significant differences were found between the OBIA and ground measurement methods for perennial herbaceous vegetation at any of the rule set scales evaluated (Table 3), 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 4% less than the ground estimates on average for the perennial herbaceous vegetation when using the network rule set.

Litter and Bare Ground

Litter cover percentage estimates were significantly different between OBIA and ground measurement methods for all rule set 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 (Table 3). 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 plot 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 estimates of percent cover were 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%.

Correlation Coefficients

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

DISCUSSION

Karau and Keane (2007) suggested that when determining the optimal landscape scale, the grain should be small enough to detect subtle changes resulting from management actions but large enough to reflect the characteristic variability of

Table 3. (A) Summary statistics for land cover classes by rule set scale for object-based image analysis (OBIA) and ground-measured (Gnd) sampling methods ($N=65$). P value derived using comparison statistics of land cover class mean percent cover estimates from OBIA and Gnd data using a paired t test. (B) Comparison statistics between spatial scale average mean differences by land cover class. Differences were calculated by subtracting ground measurements from OBIA data.[1]

	(A)						(B)			
Land cover class	Method	Rule set scale	Mean (% cover)	SE	Range (% cover)	P value	Rule set 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	0.0003*	Network	−5.81 b	1.18	−40–17.3
		Region	21.33	1.57	4.5–56.0	0.0062*	Region	−4.30 b	1.18	−38.5–23.0
		Site	25.98	1.57	4.4–61.2	0.2039	Site	0.77 a	1.18	−18.5–14.7
		Plot	25.76	1.57	3.3–64.8	0.8328	Plot	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	0.2930	Network	1.02 a	0.77	−14.8–22.0
		Region	11.64	0.97	2.4–31.2	0.9586	Region	0.05 a	0.77	−13.6–20.9
		Site	11.41	0.97	0.8–37.7	0.8827	Site	0.08 a	0.77	−12.2–11.5
		Plot	10.27	0.97	0.0–41.6	0.0008*	Plot	−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	0.2520	Network	1.67 a	0.91	−20.2–32.6
		Region	15.06	1.17	1.2–38.9	0.2683	Region	1.02 a	0.91	−19.5–19.1
		Site	13.59	1.17	2.2–31.5	0.4389	Site	−0.46 a	0.91	−10.5–9.4
		Plot	14.09	1.17	0.4–30.7	0.8723	Plot	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	< 0.0001*	Network	−7.46 a	0.03	−30.1–6.9
		Region	13.76	0.90	1.9–43.9	0.0003*	Region	−5.36 a	0.03	−26.5–25.2
		Site	14.27	0.90	2.1–30.6	< 0.0001*	Site	−4.85 a	0.03	−26.1–9.4
		Plot	13.84	0.90	0.0–30.5	< 0.0001*	Plot	−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	0.0504	Network	3.91 a	1.46	−47.9–37.2
		Region	32.73	1.92	3.8–63.5	0.1900	Region	2.53 a	1.46	−47.9–37.1
		Site	28.88	1.92	2.8–53.4	0.0946	Site	−1.31 a	1.46	−21.0–14.0
		Plot	29.17	1.92	5.8–55.8	0.0068*	Plot	−1.03 a	1.46	−14.5–3.5

[1]SE indicates standard error; CI, confidence interval; and *, 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 rule set scales using the Tukey–Kramer honestly significant difference multiple comparison procedure.

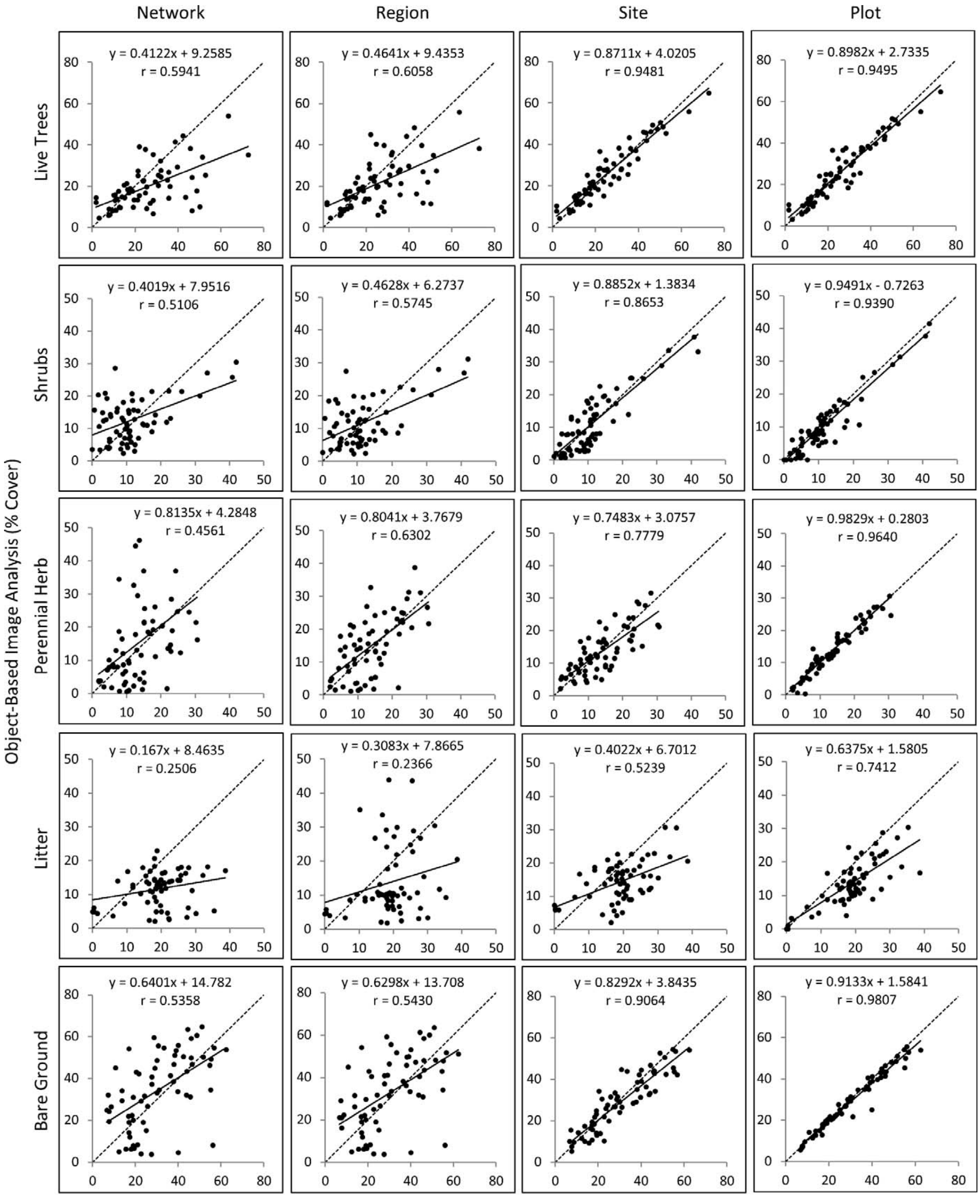

Figure 2. Regressions of percent cover estimates from object-based image analysis (y-axis) on ground measurements (x-axis) using plots across all study sites ($N=65$). Each row represents a land cover class (live trees, shrubs, perennial herb=perennial herbaceous vegetation, litter, and bare ground). Columns represent each rule set scale (network, region, site, and individual plot) used to evaluate land cover classifications. A 1:1 dashed line is shown to aid comparison.

important ecological processes, such as fire, succession, and the biophysical environment. The complexity of a particular ecological system (e.g., number of components and interaction among components) often will depend on the scale of the analysis (Turner 1989; Wu 1999), which in turn will influence the selection of the rule set scale. Our research suggests that high–spatial resolution imagery and OBIA rule sets can capture most variations for our designated land cover classes; however, trade-offs regarding the specificity of rule sets are likely. For example, the trade-off for decreased accuracy of our land cover classes over larger areas (region and network rule sets) may be useful to prioritize fuel management strategies in P-J woodlands but will unlikely capture subtle shifts in understory plant communities that may be detected using individual plot or site rule sets. On the other hand, the trade-off for increased accuracy using individual plot rule sets is that it is likely not a practical scale for most management practices and requires the greatest amount of time to adjust thresholds for each individual plot.

For live trees, perennial herbaceous vegetation, and bare ground, OBIA cover percentage estimates continually improved as the grain used to create rule sets decreased. For live trees, average mean differences between OBIA and ground measurements were observed for both network and region rule sets. Live tree cover was underestimated for these rule sets, 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 plot cover, it was difficult to combine (merge and grow) tree objects (Hulet et al. 2013) consistently across all sites for both the region and the network rule sets.

The distinction of litter from other land cover classes is not always possible due to similar colors, textures, and shapes between image objects (Duniway et al. 2012). Our underestimation of litter for all rule sets may be an artifact of the hierarchical design we used to classify litter (Fig. 1). Because we typically classified the more distinguishable land cover classes first (i.e., trees, bare ground, and shrubs), unclassified objects were often classified litter without establishing features specific for litter cover. When analyzed by site, Stansbury's OBIA litter cover percentage was consistently underestimated, while bare ground cover percentage 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 made up approximately 20% of the litter land cover class at Stansbury and $< 10\%$ at all other sites. Because it was a small component specific to Stansbury, regional and network rule sets did not 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 2 d, spectral radiance values for specific land cover classes (i.e., live trees) had wide ranges of spectral values. Thresholds associated with object features must be adjusted to compensate for these differences, thus explaining one potential factor influencing our results from rule sets applied over various spatial scales. In addition to spectral features, other features, such as relative border (spatial feature) and the associated thresholds, were also adjusted to accurately classify land cover types. For example, western juniper canopies were less compact than Utah juniper canopies, requiring different thresholds to grow and merge segmented objects. Variations in plant structure and composition will also likely contribute to the overall accuracy of the rule set. Site and individual plot rule sets had thresholds that were refined for smaller areas, increasing the accuracy of the OBIA when compared to ground measurements. Region and network rule sets had thresholds that were more general to capture more of the variation over larger areas, decreasing the accuracy somewhat when compared to ground measurements.

Multiple texture features were explored but were not included in this analysis due to our segmentation parameter selection (Fig. 1). With smaller objects, we essentially increased the homogeneity of each object and 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 for all rule sets. Hierarchical, self-organization criteria were useful when describing our land cover classes, especially when extending rule sets to larger areas.

Results are specific for our high–spatial resolution imagery and should not automatically be extended to other P-J woodlands. One of the limitations of OBIA is that it is highly dependent on the user and will likely vary even among experienced analysts; however, the trends found in this study concerning the utility of rule sets at multiple scales will likely be consistent. Further research should include testing the repeatability of features used to describe P-J woodland cover classes across multiple spatial resolutions and extents. Additionally, further research should relate classified images and patterns extracted through OBIA techniques to ecological functions and processes.

MANAGEMENT IMPLICATIONS

Our intent was to test how the specificity of OBIA rule sets affected the accuracy between object-based image analysis cover and ground-measured cover percentage estimates from high–spatial resolution imagery. Our results suggest that rule sets created for site and individual plot scales most accurately account for specific site anomalies; however, network and regional rule sets average cover percent estimates were within 10% of the ground data for all land cover classes. Although land management objectives will ultimately drive the selection of the spatial scale and extent, we recommend using site-specific rule sets for high–spatial resolution imagery when possible. Site-specific rule sets can better account for variation 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 sites. Rule sets defined at regional and network scales may aid in prioritizing P-J woodlands that have a higher risk for catastrophic wildfire events due to the accumulation and continuity of fuels or increased soil erosion potential; however, subtle shifts in understory vegetation, including weed invasions, may be missed.

Furthermore, 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 plots (0.1 ha) were compared over larger scales using a secondary subset of ground-measured plots. In combination with imagery acquisition, land managers could systematically place ground-measured plots across an area of interest that would capture the variation found on that specific site and then use those plots to develop rule sets that could be applied across the site to support land management decisions and complement ground measurements at the landscape level.

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