2015-06-01

Estimating Pinyon and Juniper Cover Across Utah Using NAIP Imagery

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

Master of Science

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June 2015

ABSTRACT

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Expansion of *Pinus L.* (pinyon) and *Juniperus L.* (juniper) (P-J) trees into sagebrush (*Artemisia* L.) steppe communities can lead to negative effects on hydrology, loss of wildlife habitat, and a decrease in desirable understory vegetation. Tree reduction treatments are often implemented to mitigate these negative effects. In order to prioritize and effectively plan these treatments, rapid, accurate, and inexpensive methods are needed to estimate tree canopy cover at the landscape scale. We used object based image analysis (OBIA) software (Feature Analyst™ for ArcMap 10.1®, ENVI Feature Extraction®, and Trimble eCognition Developer 8.2®) to extract tree canopy cover using NAIP (National Agricultural Imagery Program) imagery. We then compared our extractions with ground measured tree canopy cover (crown diameter and line point) on 309 subplots across 44 sites in Utah. Extraction methods did not consistently over- or under-estimate ground measured P-J canopy cover except where tree cover was > 45%. Estimates of tree canopy cover using OBIA techniques were strongly correlated with estimates using the crown diameter method ($r = 0.93$ for ENVI, 0.91 for Feature Analyst, and 0.92 for eCognition). Tree cover estimates using OBIA techniques had lower correlations with tree cover measurements using the line-point method ($r = 0.85$ for ENVI, 0.83 for Feature Analyst, and 0.83 for eCognition). Results from this study suggest that OBIA techniques may be used to extract P-J tree canopy cover accurately and inexpensively. All software packages accurately evaluated accurately extracted P-J canopy cover from NAIP imagery when imagery was not blurred and when P-J cover was not mixed with *Amelanchier alnifolia* (Utah serviceberry) and *Quercus gambelii* (Gambel's oak), which are shrubs with similar spectral values as P-J.

Keywords: Object-based image analysis, canopy cover, National Agriculture Imagery Program, eCognition, Feature Analyst, ENVI Feature Extraction.

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Introduction

Pinus L. (pinyon) and *Juniperus* L. (juniper) (P-J) expansion has become a serious problem for rangeland habitat management in the western United States over the last century (Miller and Tausch 2001; Miller et al. 2005). As these woodlands expand and infill in shrub-steppe ecosystems, herbaceous understory decreases and soil erosion increases (Miller et al. 2000; Bates et al. 2005; Pierson et al. 2010; Roundy et al. 2014). A reduction in shrub-steppe ecosystems poses a problem for sagebrush (*Artemisia* L.) obligate species, as well as numerous other wildlife species supported by sagebrush (Knick et al. 2014). Increased fuel loads can also lead to catastrophic wildfires and subsequent weed dominance (Gruell 1999; Miller et al. 2013; Young et al. 2014, 2015). One way land managers mitigate these negative effects is to apply fuel reduction treatments. Remote sensing techniques, as opposed to ground measurements (which can be time consuming and labor intensive) may aid land managers in planning and prioritizing fuel reduction treatments by providing a way to rapidly assess tree canopy cover across a landscape.

Measuring tree canopy cover on the ground can be time consuming and labor intensive. One alternative to ground measurements is the use of remote sensing technologies, particularly object-based image analysis (OBIA) and per-pixel image analysis techniques. For this study, we chose to focus on OBIA techniques as opposed to per pixel image analysis due to the numerous studies (included below) that were similar to ours that utilized OBIA. For example, Weisberg et al. (2007) used aerial panchromatic photos to quantify P-J expansion from 1966-1995. Hulet et al. (2013a, 2013b, 2014a) utilized high-resolution imagery and OBIA to evaluate pre- and post-fuel reduction treatments in P-J woodlands. Hulet et al. (2014b) utilized OBIA to assess fuel loads by extracting tree canopy cover from NAIP imagery and relating it to ground-measurement aboveground biomass estimates. In another study, Madsen et al. 2011 used Feature Analyst to estimate P-J canopy cover from NAIP imagery. Image-based analysis may also be useful in assessing pretreatment tree cover from aerial imagery in post-hoc studies of tree removal effects (Bybee 2013).

There are multiple OBIA software packages that have been used in the past to classify and extract tree canopy cover as described above. However, studies that compare cover estimates using different image analysis programs to ground measurements are limited (Booth et al. 2005; Ko et al. 2009). For this study, three potentially useful OBIA software packages (ENVI Feature Extraction 4.5® (Exelis Visual Information Solutions, Boulder, Colorado), Feature Analyst™ (Visual Learning System's Inc 2002) for ArcMAP 10.1® and Trimble eCognition Developer 8.2® (Trimble Germany GmbH, Munich, Germany)) were selected to evaluate their ability to extract P-J canopy cover from NAIP imagery. These programs were selected because of their availability to universities and researchers alike, and because they have been used in other studies that utilized OBIA techniques to estimate vegetation cover (Laliberte et al. 2007a, 2007b, 2009, Weisberg et al. 2007; Ko et al. 2009; Davies et al. 2010; Madsen et al. 2011; Hulet et al. 2013a, 2013b, 2014).

Each program uses an OBIA approach to segment pixels within an image into homogenous objects that can then be classified into different land cover categories. ENVI Feature Extraction allows the user to extract information about each object from imagery based on spatial, spectral, and textural characteristics. The user selects objects that represent the desired landscape feature to be classified and then the software uses a nearest neighbor algorithm to classify each image (Visual Information Solutions, 2008). Feature Analyst utilizes similar extraction techniques as ENVI Feature Extraction but instead of selecting image objects, the user digitizes around landscape features that represent the desired classification categories (Blundell et al. 2008). eCognition allows the user to develop a list of rules (i.e., rule-set) that first segments the imagery into objects, and then classifies the objects of interest based on spatial, spectral, and texture characteristics (Trimble 2011).

Although these software packages have many similarities (i.e., classification based on multiple spatial and spectral parameters), they also have substantial differences in affordability and ease of use. Hence, our objective was to evaluate which OBIA software package (ENVI Feature Extraction, Feature Analyst, and eCognition) best extracts P-J canopy cover when compared to two ground P-J canopy cover measurements (line-point intercept and crown diameter). For the OBIA we used National Agricultural Imagery Program (NAIP) data because of its extensive coverage, and free availability to land managers. Because of the variable amounts of P-J woodland canopy cover found across a landscape, we also compared how well the different OBIA techniques extracted P-J canopy cover when broken into categories based on total tree canopy cover (category 1 or low tree canopy cover <15%; category 2 or intermediate tree canopy cover 15-45%; and category 3 or high tree canopy cover >45%).

Methods

Study Sites

Study sites are located within the state of Utah in the Great Basin and Colorado Plateau physiographic provinces on lands managed by either the Bureau of Land Management (BLM) or US Forest Service (USFS) (Figure 1). Within our 44 study sites (plots) we randomly selected 3 to 9 potential subplots (0.1-ha) for sampling that represented a range of tree canopy cover categories: low (<15%), intermediate (15-45%), and high (>45%). Not all study sites had all tree canopy cover categories, so the number of subplots ranged from a minimum of three (1 tree cover category x 3 subplots = 3) to 9 (3 tree cover categories x 3 subplots= 9). The only exception to this sampling scheme was for three sites originally treated and measured in a previous study known as SageSTEP (McIver et al. 2010). On those sites, 61 subplots were measured across the range of tree canopy cover categories.

Ground Measurements

We used the line-point intercept and crown diameter methods to measure tree cover as described by McIver et al. (2013) and Miller et al. (2014) on each 0.1-ha subplot. The line-point intercept method was used to measure cover on five, 30-m transects per subplot. Pin flags were dropped every 0.5-m (60 points x 5 transects= 300 points in each subplot); at each point P-J canopy hits were recorded. To calculate cover for a subplot, P-J hits were summed and divided by 300.

The crown diameter method was used to measure every tree > 0.5-m in height that was rooted within the established subplot. The longest canopy diameter (or maximum foliage spread: *Dia1*) and the measurement perpendicular to the longest diameter (*Dia2*) were measured and used to calculate the crown area (*A*) for each tree using the following equation:

$$A = \pi/4\ (Dia1 * Dia2)$$

Percent tree canopy cover for each subplot was calculated by dividing the total tree canopy cover for a subplot by the total area of the subplot.

Imagery Acquisition

Digital ortho quarter quad tiles (DOQQs) of the study sites were acquired from the National Agricultural Imagery Program (US Department of Agriculture 2008). All images were collected in 2006 with the exception of the South Creek site, which was collected in 2009. All DOQQs have 1-m spatial resolution. The spectral resolution bands used in our analysis were red, green, and blue for all sites. The 4-7 year difference between ground-measurements and imagery acquisition is presumed to be minimal for tree canopy cover. Of the 44 study sites, NAIP imagery at 4 sites was too blurred to perform the classification. Additionally, 2 sites had shrubs (*Amelanchier alnifolia* (Utah serviceberry) and *Quercus gambelii* (Gambel's oak) that had similar spectral characteristics as P-J canopies on NAIP imagery. Hence, our study sites were reduced to 38.

Image Processing

Prior to extracting P-J canopy cover, UTM coordinates that were collected for each established 0.1-ha subplot were projected onto NAIP imagery to identify where ground-measurements occurred in ArcMap®. UTM coordinates were collected in the middle and bottom left corner (downslope of the middle point) in the field using a Delorme PN-60 global positioning system (GPS) unit with accuracy to within 3 m (http://shop.delorme.com, accessed 5 June 2015). The 2 points collected for each subplot were used to reference the individual subplots locations on the DOQQs so measurements would be made on the same experimental unit for both OBIA and ground-measured tree canopy cover.

Through trial and error, we found better agreements between cover estimates when we reduced the variation (i.e., amount of P-J canopy cover) across the site by clipping DOQQs to smaller areas (Figure 2). Smaller sized imagery also led to faster processing times when classifying tree cover for all three OBIA software packages. Once the plots were clipped into smaller, workable areas from the DOQQs, we used eCognition, ENVI Feature Extraction, and Feature Analyst independently to estimate P-J cover. For each OBIA we distinguished two classes: 1) a "tree" class, consisting of pinyon and juniper trees, and 2) an "other" class which primarily included all other vegetation types, bare ground, and shadows. These methods are further described below in the corresponding section for each software package.

eCognition

The eCognition Developer software package (Trimble Germany GmbH, Munich, Germany) utilizes OBIA techniques that allow the user to develop rule-sets to classify objects of interest. We used a multiresolution segmentation algorithm (Baatz and Schäpe 2000) and spectral difference algorithm to create image objects with a median scale of 3 m^2. The spectral difference algorithm reduces the complexity of the image objects by merging them according to their mean image layer intensity values (Trimble 2011). After the segmentation was completed, we combined brightness values (spectral parameter) and relative border (a contextual feature which the user can use to enlarge or reduce objects based on neighboring image objects; Trimble 2011) to classify P-J canopy cover.

Because of eCognition's ability to easily refine parameters within a rule-set, we used training subplots (approximately 12 % of the total sampled subplots) to create a rule-set to extract P-J canopy cover, and validation subplots (approximately 88% of the total sample subplots) to test the accuracy of the rule-set. For each clipped DOQQ, a training subplot that best represented the variation (i.e., had similar vegetation and bare ground cover and brightness values) of the clip was used to define thresholds for each parameter used to extract P-J canopy cover within the rule-set. Thresholds were refined for each parameter until the extracted P-J canopy cover and ground measurements (crow diameter method) were ±1%.

Once thresholds for each parameter were developed using the training subplot(s), the rule-set was applied to the clipped, smaller DOQQ. Validation subplots found within the classified DOQQs were then clipped in ArcMap. Tree canopy cover was calculated for each subplot in ArcMAP 10.1 by extracting the area of each polygon that represented the “tree” class, and then dividing the “tree” class area by the total area of the subplot. Only validation subplots were used for the statistical analysis. Training and validation subplots were an unnecessary step with ENVI Feature Extraction and Feature Analyst as they did not use rule-sets, therefore we only used them with eCognition.

Feature Analyst and ENVI Feature Extraction

Feature Analyst (Visual Learning System’s Inc 2002) for ArcMAP® 10.1 and ENVI Feature Extraction (ENVI Zoom 4.5, Exelis Visual Information Solutions, Boulder, Colorado) have similar processing methods and both use an object-based image analysis approach to segment an image into homogenous objects. For each clipped DOQQ, Feature Analyst classified “tree” or “other” classes using 100 image objects that represented the two classes (50 each) that were digitized or defined by the user. For ENVI Feature Extraction, objects were automatically created using spectral characteristics. The user then defined these objects as either “tree” or “other”. The selected image objects (ENVI Feature Extraction) and digitized objects (Feature Analyst) captured the variation found within the imagery for these two categories. For example, within the “other” category, shadows, bare ground, and vegetation other than P-J trees were selected. Following the digitization of classes, Feature Analyst then uses an automated feature extraction (AFE) model which takes into account the shape, size, color, texture, and pattern of the image objects (Blundell et al. 2008) to classify the imagery. Likewise, ENVI Feature Extraction takes into account spectral values (shape, size, color, texture, and pattern) of each defined object and utilizes the Nearest Neighbor algorithm (computes the Euclidean distance from each segment in the segmentation image to every object that we defined; Visual Information Solutions 2008) to classify the image. Following classification, we digitized

(Feature Analyst) or selected (Feature Extraction) 10 examples of errors (or misclassified objects) and re-ran the classification in order to refine the P-J tree canopy cover classification. This correction process was cycled through 5 times – until 100 objects had been digitized/selected for each category. Once the smaller, clipped DOQQ had been classified, we clipped the subplots from the DOQQ using ArcMap so all measurements (OBIA and ground) would be made on the same experiment unit. We then extracted the area of each polygon that represented the "tree" class with a subplot, and divided that area by the total area of the subplot.

Accuracy Assessment

We used Erdas Imagine 11.0 (Erdas Inc., Atlanta, GA) to run an accuracy assessment on each clipped DOQQ, which tested our tree cover classification's reliability for each OBIA technique. We randomly selected sixty points per clip (30 points were assigned to the "tree" class and 30 points for "other"). Using the unclassified NAIP imagery and expert knowledge we then decided if each point was correctly classified or not. The total points for each class were then summed, and an error matrix was produced which includes a measurement of overall accuracy of the classified images, a kappa statistic (indicating percentage-wise the reliability of the classification in comparison to a randomly assigned cover type for each pixel), producer's (omission) and user's (commission) errors (Congalton 2001).

Statistical Analysis

To assess the relationship between ground measured tree canopy cover and OBIA canopy cover estimates, we used a Pearson Correlation. Additionally, a partial correlation by tree canopy cover category was also used to evaluate the relationship between the methods.

To determine whether tree canopy cover estimates were different between OBIA methods and ground measurements by tree canopy cover, we used a one-way ANOVA. Mean differences for each tree cover category were compared using the Tukey-Kramer HSD ($p > 0.05$). Since actual tree canopy cover is unknown, the statistical analysis in this study should be used conservatively.

Results

When evaluating the relationship between OBIA methods and ground measurements, we had strong correlations (Figure 3). Our best correlation was between tree cover estimates using Feature Analyst and those using the crown diameter method (r = 0.93), however, estimates from both eCognition and Feature Extraction were also strongly correlated (r = 0.92 and r = 0.91 respectively) with crown diameter estimates. Our best correlation between line point cover and image analysis estimates was with ENVI Feature Extraction (r = 0.85). Cover estimates from line point measurements and from eCognition and Feature Analyst were also strongly correlated (r=0.83 for both). Since tree canopy cover varies greatly across a landscape, we also evaluated the relationship between each method by tree canopy cover category.

Average estimated tree canopy cover for tree category 1 was 10.45%, 9.61%, 10.07%, 10.02%, and 10.88% for crown diameter, line point, Feature Extraction, eCognition, and Feature Analyst, respectively (Figure 4). Correlation coefficients (r) between OBIA methods and line point cover estimates were 0.51, 0.57, and 0.63 for Feature Analyst, eCognition, and ENVI Feature Extraction respectively; the correlation between line point and crown diameter was 0.70 (Table 1). The correlation coefficients between cover estimates from OBIA and crown diameter were 0.57, 0.57, and 0.69 for Feature Analyst, eCognition, and ENVI Feature Extraction respectively. Cover estimates between ENVI Feature Extraction and Feature Analyst, eCognition and ENVI Feature extraction, and Feature Analyst and eCognition had correlation coefficients of 0.81, 0.84, and 0.86, respectively (Table 1).

Average estimated tree canopy cover for category 2 was 29.29%, 25.50%, 29.64%, 28.43%, and 29.36% for crown diameter, line point, Feature Extraction, eCognition, and Feature Analyst respectively (Figure 4). Correlation coefficients (r) between OBIA methods and line point were 0.62, 0.64, and 0.68 for Feature Analyst, eCognition, and ENVI Feature Extraction respectively; the relationship between line point and crown diameter was 0.78 (Table 2). The correlation coefficients between OBIA and crown diameter were 0.83, 0.78, and 0.80 for Feature Analyst, eCognition, and ENVI Feature Extraction respectively. ENVI Feature Extraction and Feature Analyst, eCognition and ENVI Feature extraction, and Feature Analyst and eCognition had correlation coefficients of 0.80, 0.83, and 0.89 respectively (Table 2).

Average estimated tree canopy cover for tree category 3 was 48.38%, 40.92%, 49.90%, 49.99%, and 50.40% for crown diameter, line point, Feature Extraction, eCognition, and Feature Analyst respectively (Figure 4). Correlation coefficients (r) between OBIA methods and line point were 0.32, 0.35, and 0.44 for Feature Analyst, eCognition, and ENVI Feature Extraction respectively; the relationship between line point and crown diameter was 0.60 (Table 3). The correlation coefficients between OBIA methods and crown diameter were 0.79, 0.77, and 0.73 for Feature Analyst, eCognition, and ENVI Feature Extraction, respectively. ENVI Feature Extraction and Feature Analyst, eCognition and ENVI Feature extraction, and Feature Analyst and eCognition had correlation coefficients of 0.78, 0.76, and 0.88 respectively (Table 3).

Across all sites, the overall accuracy for our OBIA classified imagery was 94%, 92%, and 91% for ENVI Feature Extraction, Feature Analyst, and eCognition, respectively (Table 4). The average kappa statistics were 0.88 for ENVI Feature extraction, 0.84 for Feature Analyst, and 0.83 for eCognition 0.83 (Table 4). These kappa statistics indicate a strong agreement between OBIA classification and ground reference data (Landis and Koch 1977). The most common misclassified objects were shadows and patches of darker green shrubs such as *Purshia tridentata* (antelope bitterbrush) and *Cercocarpus ledifolius* Nutt (curl-leaf mountain mahogany).

There was no significant difference in tree cover estimated by our OBIA classification methods using NAIP imagery and the crown diameter ground measurement for each tree cover category (Figure 4). The Tukey-Kramer HSD did show a significant difference between OBIA and line point cover estimates with line point's cover estimates consistently lower than each of the other methods.

Discussion

Using OBIA methods and NAIP imagery is a viable method for estimating pinyon and juniper cover across Utah. This is most evidenced by the comparisons of each OBIA method and the crown diameter method for detecting tree canopy cover. There was a difference between OBIA method tree cover and line point. This is what we would expect since each OBIA method attempts to classify all trees on a subplot and line point only measures trees along portions of the subplot and then extrapolates. OBIA methods varied in comparison to our ground reference measurements from subplot to subplot (shown by our regressions) but averaged out when all subplots were combined (as shown by our ANOVAs), indicating that our extractions were accurate on a landscape level. Variation from subplot to subplot could be due to imagery limitations (i.e. shadows that appear to be trees, and blurry imagery). It could also be due to the 3-m accuracy of the GPS units we used to mark subplot locations. GPS points being off by up to 3 m is enough to affect estimations on a subplot level but not when evaluated across a landscape. Likewise, when measuring in the field, we measured each tree in its entirety, whereas with NAIP imagery, tree canopies often blended together when overlapping which may have lead to the variation on some subplots, thus, we feel that the variation from subplot to subplot is acceptable.

ENVI Feature Extraction and Feature Analyst were easy to learn and use and less expensive than eCognition, however, once a rule-set was created in eCognition it was possible to classify tree cover in each clip in as little as 20 minutes. One advantage to using eCognition is the user's ability to create one rule-set and then apply it to multiple sites with similar spectral, spatial, and contextual properties producing similar results. In contrast, ENVI and Feature Analyst require the user to train the program on an image-by-image basis. No one OBIA program was more accurate at classifying P-J canopy cover than another.

Management Implications

Data derived from OBIA techniques and coupled with geospatial data layers (Johnson and Miller 2006; Weisberg et al. 2007; Davies et al. 2010) provides managers with tools that aid in planning and prioritizing management practices such as fuel-reduction treatments including the feasibility of management activities (Mirik and Ansley 2012), fire behavior analysis and fire suppression strategies (Arroyo et al. 2008), and habitat management at broad spatial scales. Because NAIP imagery is regularly collected and affordable, baseline measurements of P-J woodland canopy cover can be evaluated and temporal changes monitored through various disturbances and climate regimes.

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Tables and Figures

Table 1: Parameter estimates of the simple linear regression model of all possible combinations of the canopy cover estimation for tree cover category 1 (<15%).

Tree Category 1

Dependent Variable	Predictor Variable	Intercept (SE)	Slope (SE)	r
ENVI	Line Point	4.11 (0.94)	0.62 (0.08)	0.631
ENVI	Crown Diameter	1.22 (0.99)	0.85 (0.08)	0.693
ENVI	eCognition	2.22 (0.59)	0.78 (0.05)	0.840
ENVI	Feature Analyst	2.61 (0.63)	0.70 (0.05)	0.806
Feature Analyst	Line Point	5.08 (1.23)	0.60 (0.11)	0.512
Feature Analyst	Crown Diameter	2.24 (1.30)	0.80 (0.12)	0.570
Feature Analyst	eCognition	1.41 (0.65)	0.91 (0.06)	0.860
eCognition	Line Point	3.71 (1.18)	0.66 (0.11)	0.582
eCognition	Crown Diameter	1.98 (1.29)	0.78 (0.12)	0.574
Line Point	Crown Diameter	0.30 (1.19)	0.89 (.10)	0.700

Table 2: Parameter estimates of the simple linear regression model of all possible combinations of the canopy cover estimation for tree cover category 2 (15-45%).

Tree Category 2

Dependent Variable	Predictor Variable	Intercept (SE)	Slope (SE)	r
ENVI	Line Point	11.40 (1.82)	0.72 (0.06)	0.678
ENVI	Crown Diameter	5.59 (1.51)	0.82 (0.05)	0.798
ENVI	eCognition	4.31 (1.52)	0.89 (0.05)	0.828
ENVI	Feature Analyst	5.35 (1.54)	0.83 (0.05)	0.795
Feature Analyst	Line Point	13.44 (1.84)	0.64 (0.06)	0.624
Feature Analyst	Crown Diameter	5.5 (1.37)	0.81 (0.04)	0.825
Feature Analyst	eCognition	3.49 (1.19)	0.90 (0.04)	0.887
eCognition	Line Point	12.23 (1.88)	0.64 (0.07)	0.640
eCognition	Crown Diameter	6.30 (1.56)	0.75 (0.05)	0.784
Line Point	Crown Diameter	5.12 (1.49)	0.70 (0.05)	0.775

Table 3: Parameter estimates of the simple linear regression model of all possible combinations of the canopy cover estimation for tree cover category 3 (>45%).

Tree Category 3

Dependent Variable	Predictor Variable	Intercept (SE)	Slope (SE)	r
ENVI	Line Point	27.57 (7.04)	0.55 (0.16)	0.436
ENVI	Crown Diameter	12.25 (5.36)	0.79 (0.11)	0.728
ENVI	eCognition	14.15 (4.92)	0.72 (0.09)	0.758
ENVI	Feature Analyst	4.04 (5.48)	0.92 (0.11)	0.781
Feature Analyst	Line Point	36.30 (6.27)	0.34 (0.15)	0.316
Feature Analyst	Crown Diameter	15.10 (4.00)	0.73 (0.08)	0.794
Feature Analyst	eCognition	14.28 (3.03)	0.72 (0.06)	0.883
eCognition	Line Point	31.40 (8.14)	0.45 (0.19)	0.346
eCognition	Crown Diameter	8.02 (5.62)	0.87 (0.11)	0.765
Line Point	Crown Diameter	16.15 (4.34)	0.51 (0.09)	0.600

Table 4: Error matrix comparing object-based image analysis classification accuracies of cover classes (tree and other) for (A) eCognition, (B) Feature Analyst, and (C) ENVI Feature Extraction.

(A) eCognition				
Classified Data	Tree	Other	Row Totals	User's Accuracy
Tree	**1223**	29	1252	98%
Other	217	**1411**	1628	87%
Column Total	1440	1440	2880	
Producer's Accuracy	85%	98%		
Overall Accuracy: 91%	Kappa Statistic: 0.83		N=2880	
(B) Feature Analyst				
Classified Data	Tree	Other	Row Totals	User's Accuracy
Tree	**1247**	35	1282	97%
Other	193	**1405**	1598	88%
Column Total	1440	1440	2880	
Producer's Accuracy	87%	98%		
Overall Accuracy: 92%	Kappa Statistic: 0.84		N=2880	
(B) ENVI Feature Extraction				
Classified Data	Tree	Other	Row Totals	User's Accuracy
Tree	**1299**	39	1338	97%
Other	141	**1401**	1542	91%
Column Total	1440	1440	2880	
Producer's Accuracy	90%	97%		
Overall Accuracy: 94%	Kappa Statistic: 0.88		N=2880	

N = number of points evaluated.

Bold values indicate correct number of points classified within the cover class

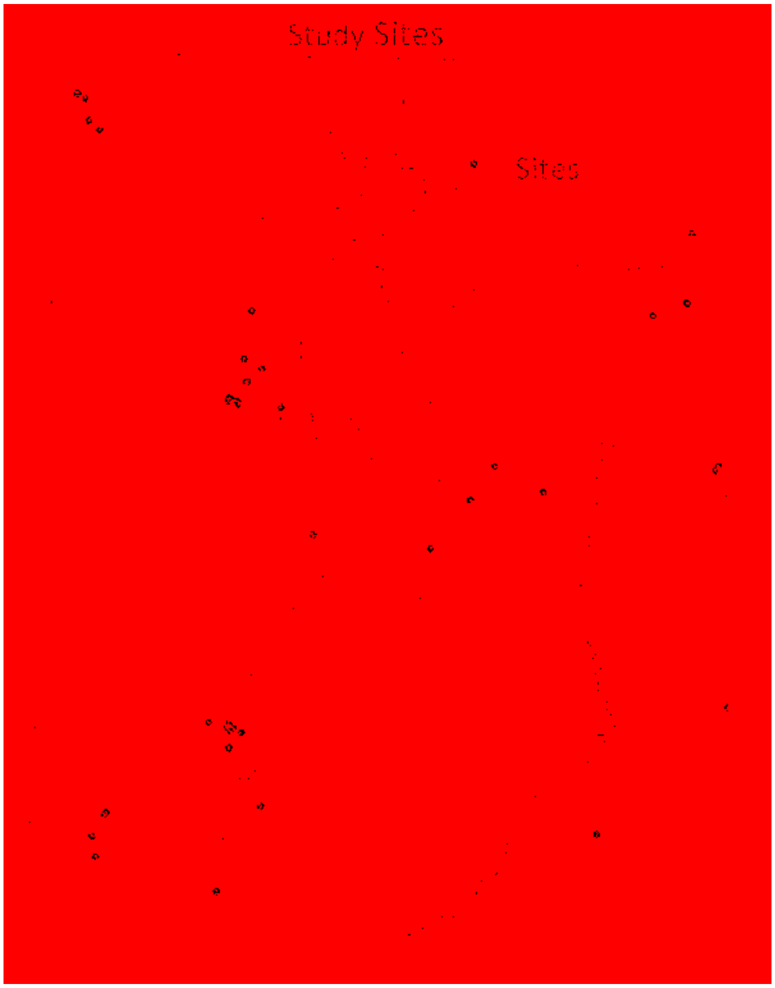

Figure 1**.** Map of study sites across Utah.

Figure 2. Example of NAIP imagery from one research site that was clipped into two smaller images (area within red boxes) based on P-J canopy cover prior to classification.

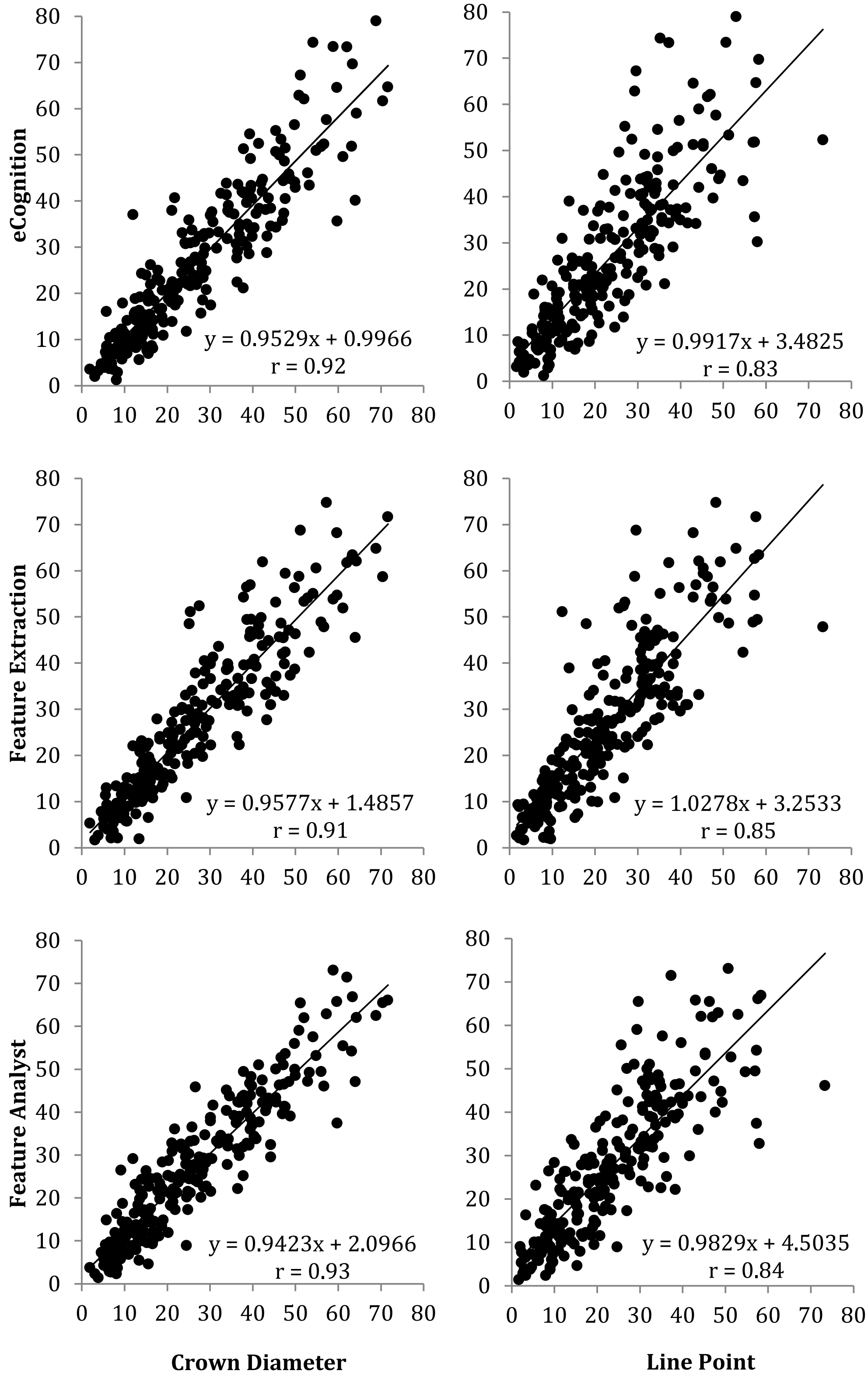

Figure 3. Pearson correlation of tree canopy cover (%) between OBIA methods (eCognition, Feature Extraction, and Feature Analyst) and ground measurements (Crown Diameter and Line Point).

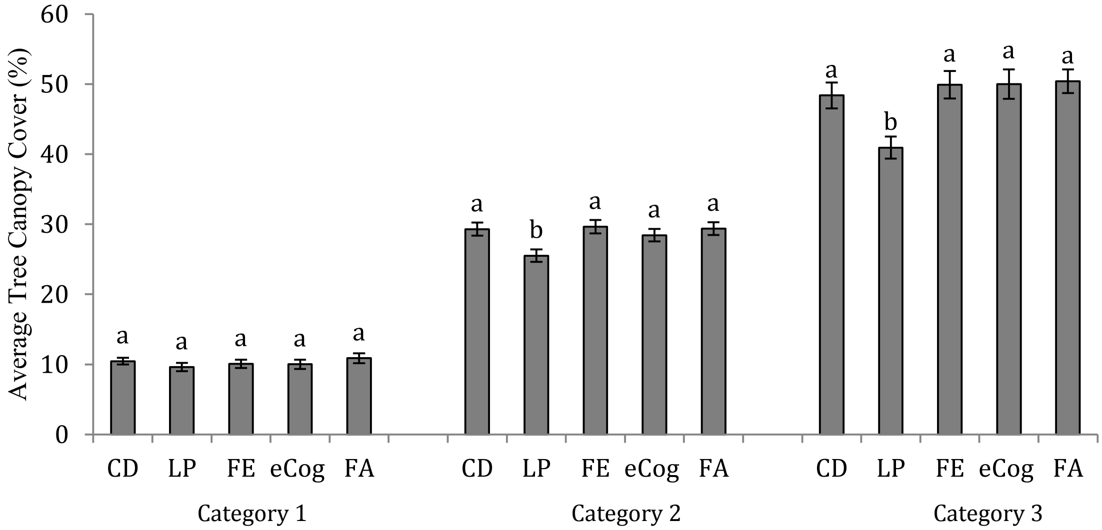

Figure 4. Comparison between methods to estimate P-J canopy cover by category. Methods include: CD = crown diameter, LP = line point, FE = ENVI Feature Extraction, eCog = eCognition, and FA= Feature Analyst. Category 1, 2, and 3 refer to P-J canopy cover that is <15%, 15-45%, and >45%, respectively. Letters that differ within category are significantly different from one another according to Tukey-Kramer HSD ($p > 0.05$). Small vertical bars are ± 1 standard error.