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Feature Extraction Techniques for Measuring Piñon and Juniper Tree Cover and Density, and Comparison with Field-Based Management Surveys

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Abstract Western North America is experiencing a dramatic expansion of piñon (*Pinus* spp.) and juniper (*Juniperus* spp.) (P-J) trees into shrub-steppe communities. Feature extracted data acquired from remotely sensed imagery can help managers rapidly and accurately assess this land cover change in order to manage rangeland ecosystems at a landscape-scale. The objectives of this study were to: (1) develop an effective and efficient method for accurately quantifying P-J tree canopy cover and density directly from high resolution photographs and (2) compare feature-extracted data to typical in-situ datasets used by land managers. Tree cover was extracted from aerial-photography using Feature Analyst®. Tree density was calculated as the sum of the total number of individual polygons (trees) within the tree cover output file after isolation using a negative buffer post-processing technique. Feature-extracted data were compared to ground reference measurements from Utah's Division of Wildlife Resources Range Trend Project (DWR-RTP). We found that the proposed feature-extraction techniques used for measuring cover and density were highly correlated to ground reference and DWR-RTP datasets. Feature-extracted measurements of cover generally showed a near 1:1 relationship to these data, while tree density was underestimated; however, after calibration for juvenile trees, a near 1:1 relationship was realized. Feature-extraction techniques used in this study provide an efficient method for assessing important rangeland indicators, including: density, cover, and extent of P-J tree encroachment. Correlations found between field and feature-extracted data provide evidence to support extrapolation between the two approaches when assessing woodland encroachment.

Keywords Aerial photography · Geographic information systems (GIS) · Remote sensing · Woodland encroachment · Rangeland monitoring

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Introduction

Since European settlement, the western United States has seen a dramatic expansion of piñon (*Pinus* spp.) and juniper (*Juniperus* spp.) (P-J) woodlands (Tausch and others 1981; Miller and Wigand 1994; Miller and Rose 1995; Romme and others 2009). Expansion of these woodlands can have several important ecological and socioeconomic consequences by influencing soil resources, water and nutrient cycles, plant community structure and composition, forage quality and quantity, fire regimes, wildlife habitat, and biodiversity (Miller and Tausch 2001; Miller and others 2008; Petersen and Stringham 2008). While degradation is site-dependent (Miller and Tausch 2001), P-J canopy cover and density can be important indicators of the degree that encroachment is controlling physical and biological processes (Miller and others 2008). Consequently, land managers are actively involved in monitoring these parameters to develop appropriate management plans.

In Utah, the Division of Wildlife Resources Range Trend Project (DWR-RTP) has collected rangeland trend data across the state since 1983 (Summers and others 2006). The DWR-RTP uses the line-intercept and point-quarter methods to measure tree cover and density respectively (Summers and others 2006). However, due to the heterogeneity of rangeland systems, it is difficult to extrapolate these data beyond the area where the measurements were made. Rangelands are also generally extensive and difficult to access. Consequently, monitoring such large areas through field methods alone is often economically infeasible (Hunt and others 2003).

With the recent availability of remote sensors and platforms that can measure canopy reflectance at resolutions finer than individual trees, tree canopy cover can be effectively characterized over large landscapes (Hunt and others 2003). Feature-extraction (FE) techniques for classifying tree cover using high resolution panchromatic and multispectral data have been proposed by several authors (i.e., Hunt and others 2003; Afinowicz and others 2005; Petersen and others 2005; Weisberg and others 2007). These methods use software that can incorporate spatial, textural, and spectral information from remotely sensed imagery to segment tree cover from the surrounding landscape. However, few studies have quantified the level of correlation between field-based measurements and FE data (Anderson and Cobb 2004; Everitt and others 2001). While accuracy assessments verify the reliability of FE data, this approach does not quantify how these values relate to measurements derived from typical field-based techniques.

Research is needed to explore more accurate and efficient ways to assess P-J woodland encroachment. Measurements of cover have received a significant amount of attention (i.e., Weisberg and others 2007), but remote sensing methods for measuring density need refinement. The primary objectives of this study were to: (1) develop an efficient method for accurately quantifying P-J tree canopy cover and density directly from high resolution aerial photographs, and (2) compare FE data to typical in-situ datasets used by land managers in assessing rangeland conditions. Results of this study will have important applications in monitoring P-J woodland encroachment, fuel loads, biomass energy potential, and rangeland health.

Materials and Methods

Study Site

Statewide in-situ data collected by the DWR-RTP was selected for comparison with FE data because of its large spatial distribution of study sites, reliability, and repeated use in land management policy and decision making (Summers and others 2006). At the time of the study, the DWR-RTP was monitoring 287 sites that contained P-J vegetation. In Utah, P-J woodlands consist predominantly of Utah juniper (*Juniperus osteosperma* (Torr.) Little), occurring either alone or together with singleleaf piñon (*Pinus monophylla* Torr. and Frém.) or two needle piñon (*Pinus edulis* Engelm). The most dominant understory shrub across most sites is big sagebrush (*Artemisia tridentata* Nutt.). Dominant grass species also vary across the region, with cool season bunchgrasses common in the northwest and warm season sod grasses in the southeast (West 1989).

For comparison of FE data with DWR-RTP methods, 35 DWR-RTP monitoring sites were selected based on piñon or juniper presence, absence of tree control treatments, imagery availability, and timing of field measurements (with locations chosen that had been sampled by the DWR-RTP between 2004-2008 (Fig. 1). Cover and density were measured at each site by the DWR-RTP along five 30.5 m belt transects centered perpendicular to a 152.4 m baseline transect at 3.4, 40.8, 78.9, 113.1, and 150.9 m (Summers

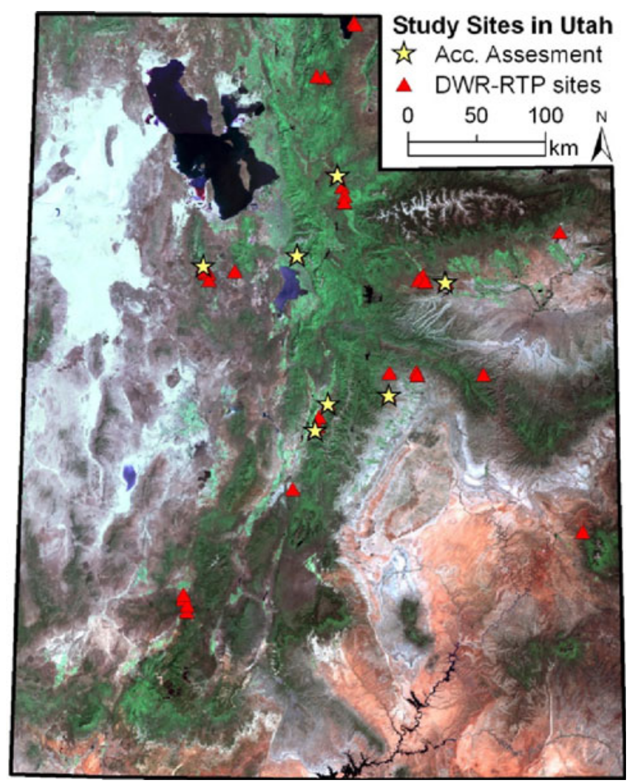


Fig. 1 Landsat TM imagery of the state of Utah, overlaid by Utah Division of Wildlife Resources Range Trend Project (DWR-RTP) locations analyzed through feature extraction techniques, and those DWR-RTP sites for which ground reference measurements were also performed for in-situ accuracy assessments. Imagery obtained from Intermountain Region Digital Image Archive Center, Utah State University

and others 2006) (Fig. 2a). Canopy cover was measured along the 30.5 m belt transects with the line-intercept method (Canfield 1941). Tree density was determined using the point-quarter method (Cottam and Curtis 1956). Individual trees were additionally classified by height as follows: C1, < 30 cm; C2, 30-122 cm; C3, 122-244 cm; C4, 244-366 cm; and C5, > 366 cm.

Image Processing

A flow diagram of the FE process to derive tree cover and density is shown in Fig. 3. Feature-extraction was performed on 25 cm High Resolution Orthophotography (HRO), color (RGB) aerial-photographs obtained from the Utah Automated Geographic Reference Center (AGRC), projected in Universal Transverse Mercator (UTM) coordinates, Zone 12 NAD83 datum (AGRC 2008). Photographs were taken in the fall (October-November) of 2006. Imagery obtained during this period was particularly valuable for this study because the evergreen P-J vegetation was easily differentiated from seasonally-dormant vegetation.

At each DWR-RTP study site, tree cover and density were remotely measured within a 75.0 m buffer area surrounding the DWR-RTP 152.4 m baseline transect. Comparisons between the measurements were performed within the area directly measured by the DWR-RTP, which was estimated to be a 15.3 m buffer area surrounding the DWR-RTP baseline transect, with 15.3 m being the distance belt transects were extended from the baseline transect. Feature-extraction was performed on a larger area than was used by the DWR-RTP to demonstrate the ability of the FE methods to delineate vegetation data over large land areas.

Feature Extraction (Cover)

Tree cover of P-J vegetation was extracted from the imagery using the Feature Analyst software extension (Visual Learning System's Inc. 2002) for ArcGIS® 9.3 (Fig. 2a). Training for the Feature Analyst classifier was performed by providing input in the form of digitized polygons that were representative of P-J tree cover, or non-P-J features (e.g., bare ground, non-P-J vegetation, etc.). Training sets for these two classes were then combined into one multi-class input layer, and the software then extracted features representing input data using several custom feature extraction options, which were a part of the Feature Analyst "Set Up Learning" dialog box. We experimented with several of the extraction options associated with the learner. Based on best visual assessment for this type of imagery, we concluded that a pre-defined foveal pattern of nine cells was the most accurate search pattern for P-J canopy extraction. Images were modeled by digitizing a minimum of 10 P-J trees (training sets) per site. An

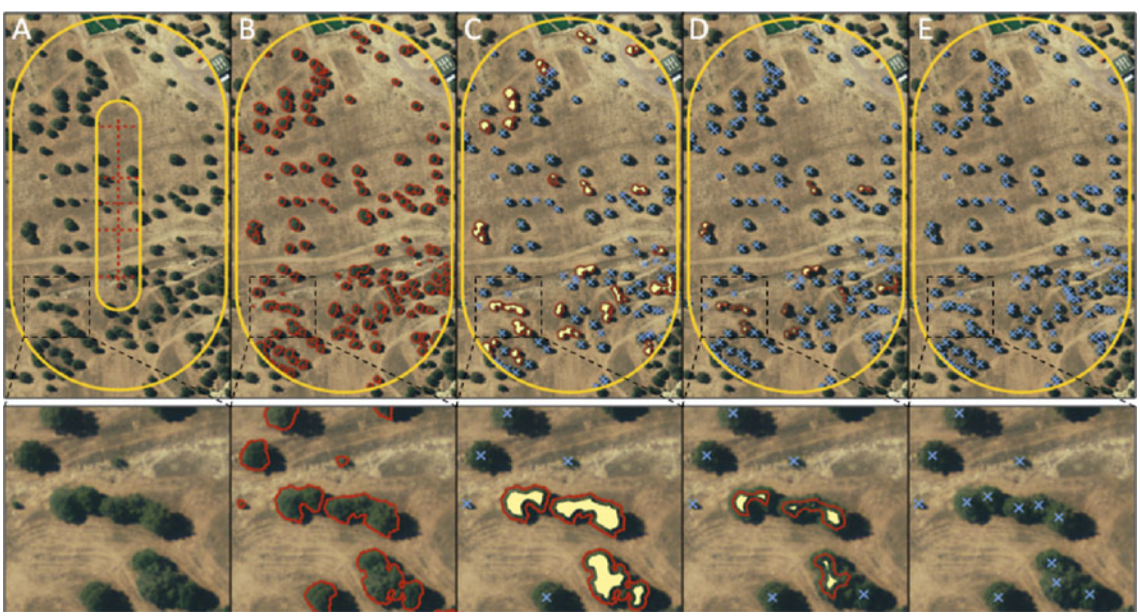
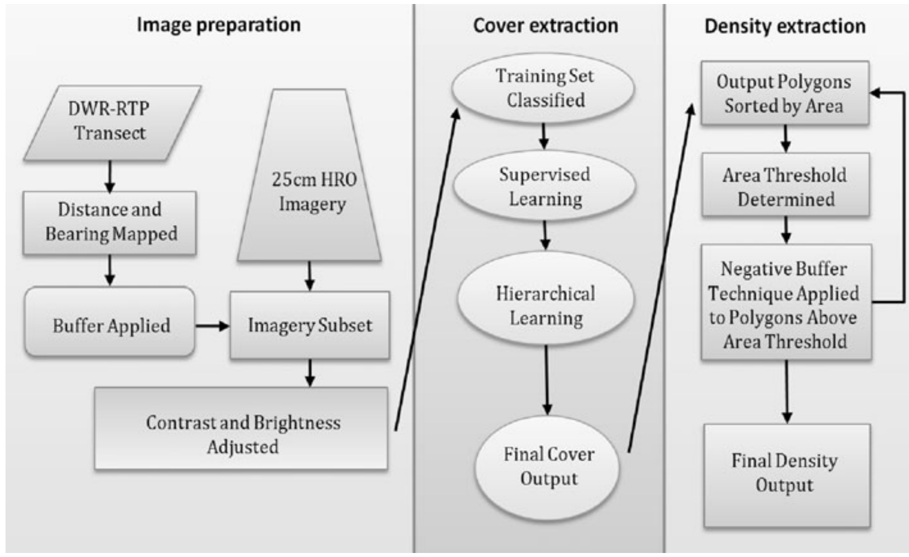


Fig. 2 **a** Utah Division of Wildlife Resources Range Trend Project (UDWR RTP) 121.9 m baseline transect and associated 30.5 m transects displayed as dashed red lines; 15.3 m and 75 m plot buffers shown in gold. **b** Final feature extraction results of tree cover shown in red. **c** Feature extracted polygons representing individual trees were converted to points, shown as blue X's; polygons representing multiple individuals had a negative buffer technique applied, results shown in light yellow. **d** Results from the negative buffer technique were then sorted by area and smaller polygons representing individuals were converted to points (blue X's); larger polygons (outlined in red) had a second negative buffer applied (light yellow). **e** Final density extraction results from polygons representing individual trees which were then converted to points (blue X's)

Fig. 3 Flow diagram of the feature extraction process to derive tree cover and density



additional set of 10 or more training sets were provided if images contained vegetation types with brightness values similar to P-J vegetation. Following the initial extraction we used various hierarchical learning tools (i.e. removing clutter, adding missed features) to modify the output file until the feature class was a visually accurate representation of tree canopy cover. Cover was calculated by dividing the classified tree canopy area by the total land area within the plot.

Feature Extraction (Density)

Within all DWR-RTP sites, there were locations where the canopy of individual trees either overlapped or appeared to be overlapping other trees' canopies. Consequently, single polygons often represented more than one tree, preventing us from directly extracting density (Fig. 2c). To resolve this problem, we initially applied a negative buffer technique to each output file that separated polygons representing multiple trees into subsets representing individual trees. Unfortunately, this method also eliminated low-area polygons representing smaller trees. To circumvent this: (1) polygons were ranked by area and two categories were created, one with low-area polygons representing single trees and the other with high-area polygons representing multiple trees, and (2) a negative buffer was applied to the high-area polygons, separating them into smaller polygons representing individual trees. The dividing point between the two categories was determined by visually selecting polygons in ascending order, based on area, until polygons representing more than one tree began to be selected. Different sizes of negative buffers were applied to each cover output file until an optimal buffer distance was identified that most accurately separated polygons, such that individual trees were represented (Fig. 2c). Following the application of the negative buffer, if individual polygons still represented more than one tree these steps were repeated. Density was then calculated as the total number of polygons within the plot.

Accuracy Assessment

Several approaches were used to assess the accuracy of the DWR-RTP and FE data. The first approach assessed the on-screen accuracy of the produced thematic cover maps through random point generation (RPG), to determine if additional post-processing was required. Classified images that had an overall accuracy of less than 90% received additional training in the Feature Analyst classifier, until 90% or greater accuracy was achieved. On-screen accuracy assessment of cover was performed for each site using ERDAS Imagine 9.1 (ERDAS Inc., Atlanta, GA). For each class (P-J canopy or non-P-J features), 35 random points were generated, with sample size calculated directly from a binomial distribution, with a 95% confidence level and acceptable error of 10% (Jensen 2005). This approach produced a total of 70 validation points per site and 2,450 points in the study (35 points per class × two classes × 35 sites = 2,450 points). Assessment of on-screen accuracy for tree density was performed by comparing the total number of trees visually detected to the number identified through FE.

In-situ accuracy assessments of tree cover measured by the DWR-RTP and FE techniques were conducted on seven randomly selected DWR-RTP sites within a 110 mile radius of Provo, Utah (Fig. 1). Two separate in-situ approaches were used for evaluating cover. The first approach assessed FE techniques through RPG. In this approach, 35 random points per class were downloaded onto a handheld Trimble GeoXH global positioning system

(GPS) receiver (Trimble, Sunnyvale, CA) and validated for accuracy in the field. This approach produced a total of 70 validation points per site and 490 points for the study (35 points per class × 2 classes × 7 sites = 490 points).

While the standard accuracy assessment methods performed above in conjunction with ERDAS Imagine evaluated the accuracy of the produced thematic map in distinguishing trees from other features, its relationship to actual tree cover and density is indirectly assumed. Therefore, ground reference (GR) measurements were also performed for comparison with FE and DWR-RTP measurements. GR estimates of canopy cover were obtained by measuring the total area of all tree canopies within the plot using the crown-diameter method (Mueller-Dombois and Ellenberg 1974). Tree density was obtained by counting each tree within the plot. To better understand the sources of error associated with FE techniques in this study, a GPS point was taken for each tree in the plot, its position relative to other trees was noted, and its height was recorded. In the laboratory, GPS points that correlated with a tree on the produced thematic tree density map were marked as extracted. Trees not extracted were grouped into one of four categories based on the possible reasons for the lack of extraction, including: (1) trees that were underneath larger trees, (2) trees that formed conglomerates with other trees, (3) trees in close proximity to other trees (i.e. trees that appeared to be touching as a result of shadow or pixel blending), and (4) trees below the extraction limit (i.e., trees below a specific size).

Statistical Analysis

Error matrix tables showing classification accuracy, species-level producers and user accuracy, and kappa statistic were generated from the on-screen and in-situ classification of the random points generated in ERDAS Imagine (Congalton 1991). Comparisons of tree cover and density values were made between GR, FE, and DWR-RTP data collected from the seven DWR-RTP sites used to assess accuracy. Comparisons of tree cover and density were made between FE and DWR-RTP data for all plots in the study. Tree density comparisons were also made between calibrated FE data and DWR-RTP data. Two different approaches were tested for calibrating FE density. The first approach calibrated FE density by adding the average number of unextracted trees to the original FE density at each of the seven sites, according to equation 1:

$$\text{FE (calibrated density)} = \frac{\text{FE}}{1 - d/100} \qquad (1)$$

where d is equal to the percent of the GR trees not detected by FE techniques. The second approach calibrated FE density using the trend-line developed between GR and FE density, according to equation 2:

$$\text{FE(calibrated density)} = (\alpha * \text{FE}) + \beta \qquad (2)$$

where α is equal to the slope and β is the y-intercept.

Statistical analysis to compare between the measurement methods was performed using Sigma Stat 3.1 (Systat Software, Inc. Richmond, CA). For all comparisons, a significance level of $P < 0.05$ was used. Datasets were found to be normally distributed by the Kolmogorov–Smirnov test. Comparisons were made using linear regression and summary statistics (mean, standard error, range, and relative percent difference). Differences between mean values were determined through a paired t-test, while differences between mean relative percent difference values were assessed through a two-sample t-test. Relative percent difference was calculated according to equation 3:

$$\text{Relative percent difference} = \frac{|x_2 - x_2|}{(x_2 + x_2)/2} \times 100 \qquad (3)$$

where the absolute difference of two measurement approaches (x_1 and x_2) is divided by their mean, and multiplied by 100. The smaller the relative percent difference, the more accurate the method is assumed to be when compared to GR data. When making comparisons between the DWR-RTP and FE data, the smaller the relative percent difference, the higher the correlation between the two methods.

Logistic regression was used to determine (with a 95% probability) the minimum size a tree needs to be in order to be extracted (detected) from an aerial photograph (Hosmer and Lemeshow 1989). In performing the analysis, we used trees that were identified in the field using a GPS receiver (as explained above), but excluded those trees that were not discernable as a single tree, such as trees underneath larger trees, in conglomeration with other trees, or proximal to other trees. Probability of extraction was determined according to equation 4:

$$\text{Probability of extraction} = \ln\left(\frac{p_z}{1 - p_z}\right) = \beta_1 + \beta_2 * x \qquad (4)$$

where P_z is the probability of extraction, given x which equals either canopy width, canopy area or canopy height; $\ln(P_z$ / $(1\text{-}P_z)$ represents the log odds ratio linearized through the logit transformation; β_1 and β_2 are probability variables derived from logistic regression analysis.

As land management field-based surveys often correlate tree height with various ecological parameters, such as tree age, fuel loads and woodland encroachment phase (e.g., Miller and others 1981; Dixon 2003; Summers and others 2006), we determined the correlation between canopy width, area and tree height, to correlate FE data with field-based surveys that record only height.

Results

Random Point Generation Accuracy Assessment

Tree cover measurements generated through FE methods were found to be highly accurate, as verified with both on-screen and in-situ RPG accuracy assessments. On-screen and in-situ RPG assessments had overall accuracies of 95.1% and 93.1%, and Kappa statistics of 0.90 and 0.86 respectively (Table 1). User and producer accuracy were similar, indicating an equal number of omission and commission errors (Table 1).

Table 1 Error matrix showing number of sample points stratified between feature-extracted tree and non-tree locations, and the classification accuracy and Kappa statistic, tested on-screen and in-situ

Classified data	Tree	Non-tree	Total	User's accuracy
On-screen				
Tree	1295	70	1365	95%
Non-tree	63	1302	1365	95%
Total	1358	1372		
Producer's accuracy	95%	95%		
Overall accuracy		95%		
Kappa statistic		0.90		
In-situ				
Tree	194	16	210	92%
Non-tree	13	197	210	94%
Total	207	213		
Producer's accuracy	94%	92%		
Overall accuracy		93%		
Kappa statistic		0.86		

Ground Reference Accuracy Assessment of Tree Cover

Summary statistics were similar between the measurement approaches, with mean cover values of 15.0 ± 3.4%, 14.1 ± 3.3%, and 12.8 ± 2.2% for GR, FE, and DWR-RTP respectively. Average percent difference between GR and FE cover was 11.0 ± 3.4%, the average percent difference between DWR-RTP and GR cover was statistically higher at 29.9 ± 6.3% ($P = 0.021$) (Table 2). A high correlation was found between GR and FE cover ($r = 0.99$, $P < 0.001$), with a near 1:1 relationship ($\alpha = 1.01$), and y-intercept near zero ($\beta = 0.768$) (Fig. 4). Tree cover measured by the DWR-RTP was not as strongly correlated to GR data ($r = 0.75$, $P = 0.053$); the y-intercept was near zero, but the slope of the regression line was greater than one, indicating an underestimation of tree cover on sites with higher cover values ($\alpha = 1.15$, $\beta = 0.29$). Correlation between GR and DWR-RTP was weak, in part by one site, which was an outlier with a value beyond the 95% confidence interval. Further examination of the outlier site showed that the randomly-placed line transects missed the majority of the trees in the plot, which were found in patches (Fig. 4). After excluding this site, a significant correlation was found ($r = 0.87$, $P = 0.025$), with the trend line close to the 1:1 line ($\alpha = 0.98$, $\beta = 0.48$). Feature extracted data were less affected by this patchiness. Even after the removal of the outlier point, the percent difference between GR vs. DWR-RTP remained statistically higher than GR vs. FE ($P = 0.048$), with percent differences of 24.6 ± 4.1% and 12.3 ± 3.7% respectively (compare with Table 2).

Table 2 Summary statistics and the percent difference between: ground reference (GR), feature extracted (FE), and Division of Wildlife Resources Range Trend Project (DWR-RTP) measurements approaches for plots selected for accuracy assessment

Accuracy assessment									
Summary statistics					Relative percent difference				
Method	N	Mean	SE	Range	Comparison	N	Mean	SE	Range
Cover		%			Cover		%		
GR	7	15.0 ^{a}	3.4	6.5–28.8	GR vs. FE	7	11.0^{a}	3.4	0.3–26.3
FE	7	14.1^{a}	3.3	5.0–27.9	GR vs. DWR-RTP	7	29.9^{b}	6.3	13.6–61.3
DWR-RTP	7	12.8 ^{a}	2.2	4.5–19.1	FE vs. DWR-RTP	7	27.1^{a,b}	7.5	6.0–58.4
Density		trees ha^{-1}			Density		%		
GR	7	214.8^{a}	42.5	28.3–339.0	GR vs. FE	7	38.1^{a}	6.9	10.5–64.7
FE	7	137.0^{b}	23.5	25.5–220.0	GR vs. DWR-RTP	7	24.6^{a}	10.0	3.4–73.0
DWR-RTP	7	203.2^{a}	44.4	61.0–360.7	FE vs. DWR-RTP	7	45.0^{a}	8.6	18.3–81.9

N plots sampled, *SE* standard error

Means without a common letter differ at $P < 0.05$

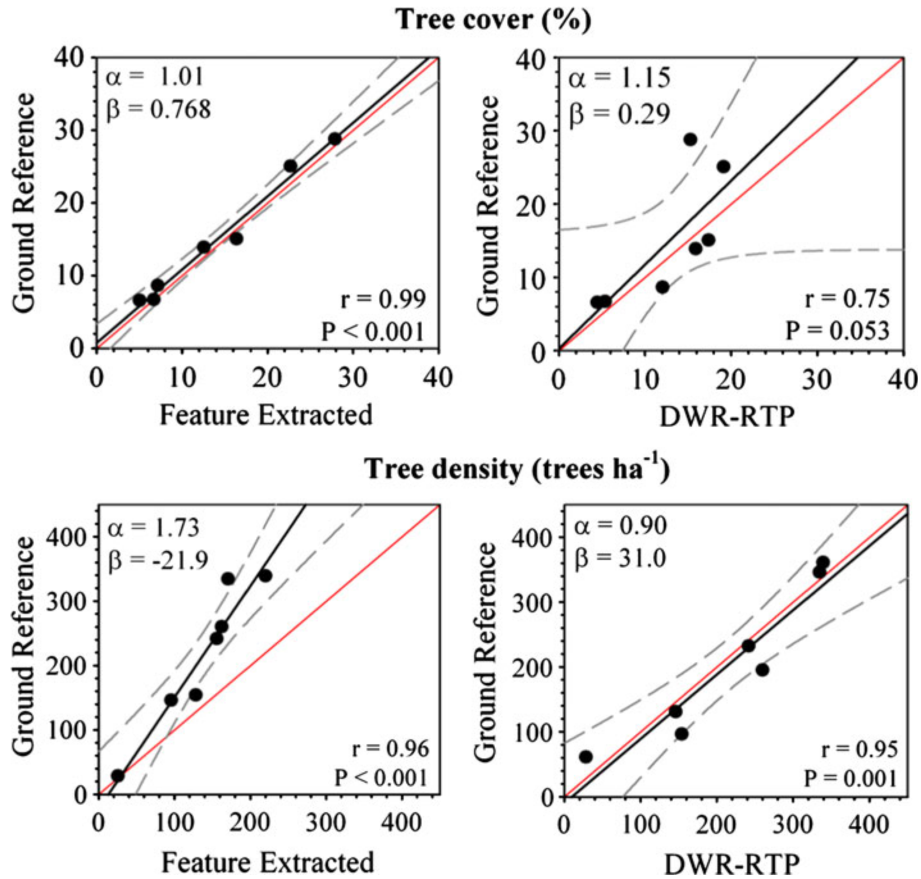


Fig. 4 Linear regression analysis for tree canopy cover and density accuracy assessment results; comparing ground reference, Utah Division of Wildlife Resources Range Trend (DWR-RTP), and feature extracted data. Correlation line and confidence intervals at 95% is show in relationship to the data. A 1:1 line is draw in red for reference of a perfect correlation (i.e. y = x). Correlation coefficient, *r*, and *P* value are shown, with $P < 0.05$ indicating a significant relationship

Ground Reference Accuracy Assessment of Tree Density

There was a strong correlation between GR and FE density ($r = 0.96$, $P < 0.001$) (Fig. 4). With the exception of one site, FE methods consistently underestimated tree density ($\alpha = 1.73$, $\beta =$ -21.9). Tree density measured by the DWR-RTP through the point-quarter method was also highly correlated to GR data ($r = 0.95$, $P = 0.001$), with a near 1:1 relationship between the measurements ($\alpha = 0.90$, $\beta = 31.0$).

Mean GR density was 214.8 trees ha^{-1}, while FE density was statistically lower with 137.0 trees ha^{-1}. DWR-RTP density was similar to GR density with 203.2 trees ha^{-1}. Analysis of the percent difference between GR vs. FE and GR vs. DWR-RTP showed no significant differences between the two comparisons ($P = 0.287$). The mean percent differences for GR vs. FE, GR vs. DWR-RTP, and FE vs. DWR-RTP were 38.1 ± 6.9%, 24.6 ± 10.0%, and 45.0 ± 8.6%, respectively.

Source of Error Analysis

The majority of the trees not extracted for both cover and density were below the minimum extraction limit size (Table 3). These trees had no significant influence on overall cover, comprising only 1.0% of the total GR tree cover. Analysis of density showed 38.7% of the GR trees remained undetected, with 23.8% below the extraction limit, 9.1% underneath larger trees, 4.5% in close proximity, and 1.3% in conglomerate with other trees.

Canopy area and tree width were the strongest predictor variables of tree extraction ($P < 0.001$ for both variables), as illustrated by the quick transition from almost no trees being detected to 95% or more of the trees detected (Fig. 5). The 95% probability of extraction for canopy area and average tree width are 2.0 m^2 and 1.4 m respectively. With respect to canopy area, based on the 25 cm resolution imagery used in this study, trees would need to encompass 32 pixels or more to be consistently extracted from the imagery. Tree height was also a significant predictive

Table 3 Tree cover and density data not extracted from 7 DWR-RTP sites, through feature extraction techniques, as compared to ground reference

Types of trees not extracted from imagery	Cover		Density	
	Area (m^2)	Percent of total	Count	Percent of total
Underneath larger trees	N/A	0.0	62	9.1
Conglomerate with larger trees	N/A	0.0	9	1.3
Proximity to larger trees	N/A	0.0	31	4.5
Below detection limit	47.13	1.0	163	23.8
Total	47.13	1.0	265	38.7

Total tree cover measured by ground reference techniques was found to be 4,617.3 m^2; total number of trees counted equaled 684

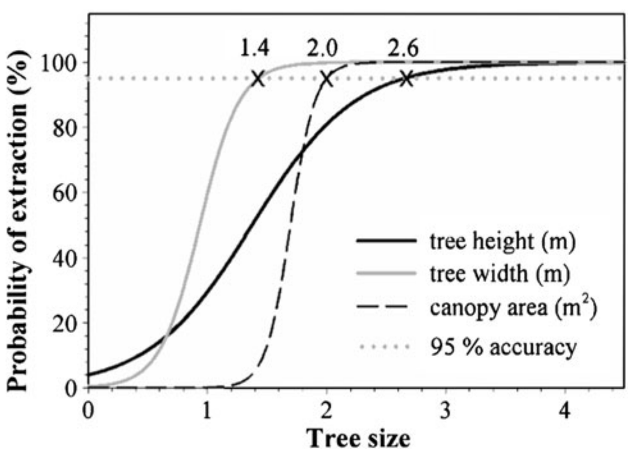


Fig. 5 Logistic regression models predicting the probability of tree extraction based on tree height, mean canopy width, or canopy area. Extraction limit at 95% accuracy is shown by a dashed horizontal line

variable for tree extraction ($P < 0.001$). The 95% probability of extraction for tree height was 2.6 m (Fig. 5). The utility of tree height as a predictive variable is due to the strong correlation between canopy area and tree height (Fig. 6).

Comparison of Feature Extracted and DWR-RTP Data (Global Dataset)

There was a strong correlation between FE and DWR-RTP cover for all sites ($r = 0.96, P < 0.001, \alpha = 0.92, \beta = 1.14$) (Fig. 7). FE and DWR-RTP cover were similar (Table 4). Average FE and DWR-RTP cover was estimated to be 14.3 ± 2.1% and 14.1 ± 2.2% respectively. Average percent difference between the two data sets was 44.3 ± 8.9%.

Tree density derived from the FE and DWR-RTP methods was significantly correlated ($r = 0.83$, $P < 0.001$), with the majority of FE data points underestimating tree density ($\alpha = 1.6$, $\beta = 21.5$) (Fig. 7). Calibration of FE data with Eq. 1 produced a similar correlation ($r = 0.83$, $P < 0.001$), with a near 1:1 relationship ($\alpha = 0.96$, $\beta = 31.5$) (Table 4). Calibration of FE with Eq. 2 produced the same correlation ($r = 0.83$, $P < 0.001$), and a similar near 1:1 relationship ($\alpha = 0.90$, $\beta = 41.3$).

On average, FE techniques significantly underestimated tree density as compared to DWR-RTP methods ($P = 0.013$), averaging 149.3 ± 18.6 and 254.9 ± 34.9 trees ha^{-1}, respectively (Table 4). Calibration of FE data with Eq. 1 and Eq. 2 increased the average density to 243.5 ± 30.3 and 236.4 ± 32.8 trees ha^{-1} respectively, which were similar to DWR-RTP measurements ($P = 0.807$ and 0.698 respectively). The average relative percent difference between FE and DWR-RTP density was 53.9 ± 7.6% (Table 4). While not significant, calibration of FE data with Eq. 1 and Eq. 2 decreased the relative percent difference to 44.8 ± 8.4% and 40.6 ± 5.9%, respectively ($P = 0.174$ and 0.427).

Discussion

Tree Cover

We found that P-J canopy cover can be distinguished from various other attributes such as bare ground, shrubs, grass, herbaceous vegetation, and shadow (Table 1). These results are consistent with similar studies that use FE software to determine woody vegetation coverage from aerial photography (i.e., Anderson and Cobb 2004; Afinowicz and others 2005; Petersen and others 2005; Weisberg and others 2007; Smith and others 2008).

Our method for extracting P-J tree density from produced thematic cover maps, using a negative buffer post-processing technique, is unique to this study. Our approach is highly correlated to GR data, but consistently underestimates tree density. The highest source of error involved trees below the extraction limit (Table 3). In this study, tree area was the best predictor of tree extraction; the minimum tree area required for consistent tree extraction (95% probability) was 2.0 m^2 (Fig. 5). Regression analysis from the data collected in this study (Fig. 6) would predict trees of this area to be 2.1 m tall.

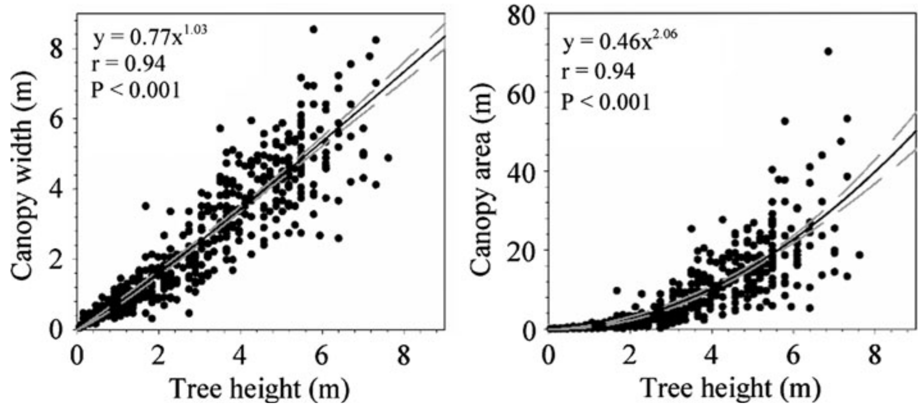


Fig. 6 Scatter plot for tree height and mean canopy width estimated from 684 trees sampled within 7 DWR-RTP sites. The data was best-fit by a power regression line. This line and confidence intervals at 95% are show in relationship to the data. Correlation coefficient, *r*, and *P* value is shown, with $P < 0.05$ indicating a significant relationship

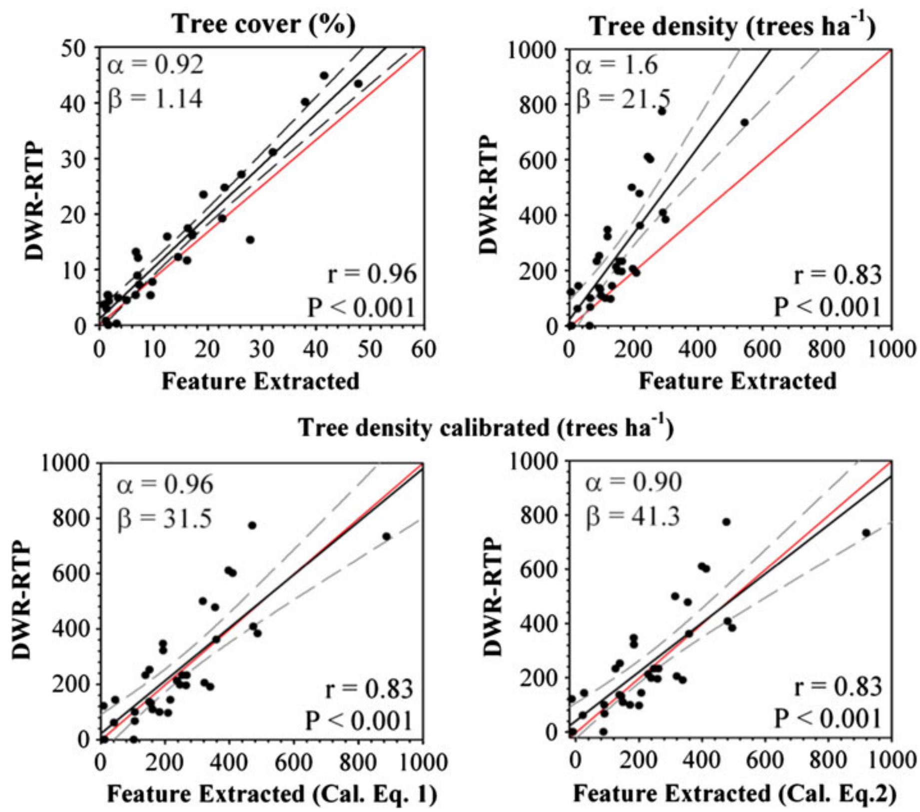


Fig. 7 Linear regression analysis for tree canopy cover and density global data sets; comparing Utah Division of Wildlife Resources Range Trend (DWR-RTP), and feature extracted data. Density correlation is also shown between DWR-RTP and feature extracted data calibrated by increasing each measurement point according to Eq. 1, and Eq. 2. Correlation line and confidence intervals at 95% is show in relationship to the data. A 1:1 line is draw in red for reference of a perfect correlation (i.e. $y = x$). Correlation coefficient, *r*, and *P* value is shown, with $P < 0.05$ indicating a significant relationship

The remaining sources of error include trees proximal to other trees, trees forming conglomerates, and trees underneath larger trees. The nature of the latter two precludes extraction, regardless of the imagery resolution. We estimate that increasing resolution to 0.035 m would allow accurate estimation of all trees except seedlings (defined by the DWR-RTP as trees below 0.03 m) and those forming conglomerates or underneath larger trees. Rationale for this resolution is based on the assumption that the image resolution required to extract a 0.03 m tall tree would be equal to the area of this tree (0.0385 m^2, based on the tree height-canopy area correlation developed previously) divided by the minimum number of pixels required to realize a 95% probability of extraction (as shown above we calculated for this study the minimum number of pixels for a 95% probability of extraction to be equal to 32 pixels). Therefore, 0.0385 m^2 tree area/ 32 pixels = 0.001203 m^2 pixels, which will have a pixel length on each side of $\sqrt{0.001203\ m^2} = 0.035$ m. However, it is important to acknowledge that several factors can influence the quality of the aerial photography and subsequent tree sizes detected. Motion blur, tree shadow, color aberrations, atmospheric variability, georectification, as well as methods and instrumentation used in acquiring the images can all influence image quality (Booth and Cox 2006; Booth and others 2008; Moffet 2009).

Table 4 Summary statistics and the percent difference between: ground reference (GR), feature extracted (FE), and Division of Wildlife Resources Range Trend Project (DWR-RTP) measurements approaches for all plots tested (global data set)

Global data set									
Summary statistics					Relative percent difference				
Method	*N*	Mean	SE	Range	Comparison	*N*	Mean	SE	Range
Cover		%			Cover		%		
FE	32	14.3 [a]	2.1	0.9–47.8	FE vs DWR-RTP	31	44.3	8.9	1.7–197.6
DWR-RTP	32	14.1 [a]	2.2	0.01–44.8					
Density		trees ha^{-1}			Density		%		
FE	34	149.3[a]	18.6	5.6–544.1	FE vs DWR-RTP	31	53.9[a]	7.6	2.5–182.4
FE (cal. Eq. 1)	34	243.5[b]	30.3	9.0–887.6	FE (cal. Eq. 1) vs DWR-RTP	31	44.8[a]	8.4	0.6–245.0
FE (cal. Eq. 2)	35	236.4[b]	32.8	−12.3 to 919.4	FE (cal. Eq. 2) vs DWR-RTP	31	40.6[a]	5.9	0.5–172.0
DWR-RTP	34	254.9[b]	34.9	0.0–773.4					

N plots sampled, *SE* standard error

Means without a common letter differ at $P < 0.05$

Our use of FE techniques in this study produced a more accurate measure of tree cover than the DWR-RTP techniques. However, this was a small dataset (7 sites); and results were significantly influenced by one outlier that contributed to the poor correlation found between the DWR-RTP and GR data (Fig. 4). The fact that FE cover data were strongly correlated with GR and to DWR-RTP global cover data (Fig. 7) would imply the DWR-RTP has similar accuracy to FE. Furthermore, the high correlation between FE and the DWR-RTP global cover datasets shows that the two approaches could be used interchangeably when making management decisions based on cover.

Tree Density

Based off of field observations, we believe that measurements of tree density by the DWR-RTP are more accurate than FE techniques because the DWR-RTP methods are more apt at detecting juvenile trees (Fig. 4). To overcome this limitation, we propose that Eq. 1 or Eq. 2 can be used to calibrate measurements for those trees smaller than FE limit. Because estimates derived from Eq. 1 have shown the highest correlation to the DWR-RTP data, with a near 1:1 relationship, we suggest the use of Eq. 1 in calibrating FE density data.

Where density calibration is required, our results indicate that FE measurements could be used by land management personnel to accurately determine tree density at larger scales. Where empirical calibrations are not possible or desirable, density data obtained through the proposed technique may still have application for land managers, depending on how the data are used. In general, DWR-RTP study sites used in this analysis represented phase I and II woodlands, with several of the sites experiencing a high degree of P-J stand infilling and tree encroachment (Summers and others 2006). We speculate empirical calibration of density data will be less important for phase III P-J woodlands where mature trees are the dominant component.

Conclusions and Management Implications

Feature-extraction techniques used in this study provide an efficient procedure for assessing tree cover, density, and extent of P-J tree encroachment. We conclude that FE techniques provide a useful measure of tree canopy cover and were comparable to GR and DWR-RTP data obtained through the crown diameter and line intercept methods, respectively. Tree density estimated through FE techniques was highly correlated to GR data and DWR-RTP point-quarter measurements. However, FE methods have the potential to underestimate tree density, primarily due to their inability to detect trees that are below the extraction threshold. We speculate that increased image resolution could significantly increase the accuracy of our newly-developed FE density technique. From these results we postulate that an ideal resolution for tree density extraction would be around 0.0347 m if the extraction of all but seedlings and unextractable trees is desired. Future work should be conducted at different resolutions to help land managers and research personnel understand the appropriate resolutions needed to accomplish specific objectives.

Correlations found between field plot data and remotely sensed imagery provides evidence to support extrapolation of cover data between the two approaches when assessing rangeland status. Because of the high accuracy of the DWR-RTP methods, these range trend plots throughout the state could be used to calibrate FE density data. Such approaches are desirable because the number of undetectable trees may vary by site, and while increased resolution could improve accuracy of extracting tree density through FE techniques, it is important to note that a small percentage of trees growing in a conglomerate with other trees or growing underneath larger trees may never be detected regardless of resolution. Coupling field-based measurements with FE techniques magnifies the utility of both measurement types, allowing for monitoring to take place at the landscape rather than the plot level.

Time and resources required for measuring rangeland conditions is an important advantage of this and other FE techniques, providing land managers with the ability to monitor woodland change over large land areas. Feature-extraction techniques proposed in this study could be used for a host of monitoring applications, such as woodland encroachment of all but immature trees, fuel loads, timber value, wildlife habitat, and grazing suitability.

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