Landsat-5 TM and Lidar Fusion for Sub-pixel Juniper Tree Cover Estimates in a Western Rangeland

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Abstract
Pinyon-juniper woodlands comprise the third most common land-cover type in the United States and have been documented to have drastically increased both in density and extent in recent decades. We explored Landsat-5 TM and Light Detection and Ranging (lidar) data, individually and fused together, for estimating sub-pixel juniper cover. Linear spectral unmixing (LSU), Constrained Energy Minimization (CEM), and Mixture Tuned Matched Filtering (MTMF) techniques were compared along with spectral-lidar fusion approaches. None of the Landsat-5 TM-derived estimates were significantly correlated with field-measured juniper cover (n = 100), while lidar-derived estimates were strongly correlated (R^2 = 0.74, p-value <0.001). Fusion of these estimates produced superior results to both classifications individually (R^2 = 0.86, p-value <0.001). The MTMF technique performed best, while a multiple regression-based fusion was the best approach to combining the two data sources. Future studies can use the best sub-pixel classification and fusion approach to quantify changes in associated ecosystem properties such as carbon.

Introduction
Pinyon-juniper woodlands comprise the third most common land-cover type in the United States (Huang et al., 2009). Both the tree density and the geographic extent of pinyon-juniper woodlands are documented to have increased by an order of magnitude since the mid-Nineteenth Century throughout the Great Basin, US (Romme et al., 2009). Reported increases in areal extent have ranged between 30 to 625 percent (Romme et al. 2009), while encroachment rates have varied between 0.4 to 4.5 percent per year (Sankey and Germino 2008). Intensive land treatments, including prescribed burning and cutting, are now regularly performed to reduce tree cover where the encroachment is perceived to decrease understorey vegetation, increase soil erosion, and deteriorate wildlife habitat for species such as sage-grouse. Most evidence for pinyon-juniper woodland changes is provided by field-based dendrochronological and demographic studies or historical aerial photograph comparisons, which often provide detailed and accurate records of tree stand history and development, but generally cover relatively small spatial extent (Romme et al., 2009). Efficient remote sensing methods to accurately map pinyon-juniper distribution and estimate woodland cover changes over large areas are needed to guide regional policy and identify priority areas for intensive management. In particular, robust methods to estimate sub-pixel tree percent cover are necessary to assess recent decadal-scale changes in pinyon-juniper woodlands due to: (a) the relatively sparse tree distribution in these vast woodlands, (b) the slow growth rates of trees, and (c) recent temporal coverage and moderate resolution of most satellite data.

Satellite image-based approaches have not been commonly used to monitor pinyon-juniper woodland cover changes. Previous Landsat-5 TM-based studies demonstrated binary classifications of juniper presence and absence (Sankey and Germino, 2008; Sankey et al., 2010). Traditional thematic classification approaches, however, do not provide the details and resolution necessary to detect subtle changes in these woodlands, while high-resolution satellite imagery do not cover the required temporal extent. Only Landsat-type satellite data used with sub-pixel tree cover estimates can allow remote sensing-based monitoring across the vast woodland areas. Once determined, the best approach for sub-pixel tree cover estimates would also enable quantitative estimates of the associated changes in ecosystem properties such as carbon, nitrogen, and water fluxes (e.g., Asner et al., 2003; Huang et al., 2009; Huang et al., 2010). Quantitative estimates of such effects have been limited, although woody vegetation encroachment is thought to have important implications for global and regional carbon dioxide uptake and nitrogen oxide emissions. In this study, we explore: (a) Landsat-5 TM imagery, (b) airborne lidar data, and (c) Landsat-5 TM and lidar fusion for estimating sub-pixel tree cover. We compare: (a) linear spectral unmixing, (b) Mixture Tuned Matched Filtering, and (c) Constrained Energy Minimization to determine the best spectral unmixing technique for sub-pixel juniper tree cover estimates. Our objective was to determine the most appropriate image source, fusion approach, and spectral unmixing technique for estimating sub-pixel tree cover in a semi-arid rangeland environment of southwestern Idaho.

Lidar data, which have been most commonly used in forestry applications, are now increasingly used for vegetation classification of semi-arid rangelands (Weltz et al., 1994; Ritchie et al., 1995; Rango et al., 2000; Streutker and Glenn, 2006; Mundt et al., 2006; Bork and Su, 2007; Riano et al., 2007; Su and Bork, 2007). Lidar applications, however, have not been explored in woodland encroachment studies. Lidar data are potentially well suited to distinguish
sparsely-distributed individual trees from lower-statured background vegetation of shrubs and herbaceous species. Previous lidar fusion with spectral data has incorporated lidar data with hyperspectral (Andersen et al., 2008), multispectral (Lee and Shan, 2003; Wulder et al., 2009), and multi-angle spectral data (Kimes et al., 2006) as well as synthetic aperture radar data (Hyde et al., 2006 and 2007). In particular, lidar data has been fused to improve accuracies of tree canopy metrics with Landsat ETM+, Ikonos, and QuickBird imagery using regression and kriging models (Hudak et al., 2002; Donoghue and Watt, 2006; Mutlu et al., 2008). Some lidar fusion studies report that lidar data alone accurately estimates tree crown metrics and the fusion with spectral data results in marginal or no improvements in accuracies (Hyde et al., 2006; Erdody and Moskal, 2010). The utility of lidar fusion in improving sub-pixel estimates of a target cover type has not been widely tested, especially in rangeland ecosystems. Lidar fusion has greater potential to improve classification accuracies in rangeland environments, because rangeland vegetation can be spectrally indeterminate (Okin et al., 2001) and the structural derivatives from lidar data can provide a unique opportunity to separate varying vegetation functional groups.

Pixels in Landsat-5 TM imagery cover 900 m² (30 m × 30 m) in size and thus often include a mixture of vegetation cover types. This is particularly evident in woodlands and juniper-encroached rangelands where juniper trees are dispersed amongst herbaceous and sagebrush cover types. Linear spectral unmixing (LSU) analysis produces a mixture, which represents a linear combination of the endmembers or cover types, weighted by the areal coverage of each endmember in a pixel (Rencz, 1999). Compared to these models, the Mixture Tuned Matched Filtering (MTMF) is thought to be better suited for mixed pixels with cover types having similar spectral signatures, because the MTMF suppresses background noise and provides a measure of false positives (Boardman, 1998) that are inherent in remote sensing of semiarid vegetation (e.g., Okin et al., 2001). The MTMF also allows less than 100 percent abundance of the training spectrum (e.g., use of mean spectra) (Glenn et al., 2005), in comparison to LSU which assumes pure training endmembers of 100 percent abundance. Similar to the unconstrained linear spectral unmixing, the matched filter of the MTMF is an unconstrained spectral mixture analysis technique. Both the LSU and MTMF techniques produce negative target cover estimates as well as estimates greater than 100 percent, which are difficult to correlate to 0 to 100 percent cover range observed in ground-truth data. Similar to the matched filtering of the MTMF, the Constrained Energy Minimization (CEM) suppresses the unknown spectral background while highlighting the known target signature. The CEM is a linear operator which minimizes the total energy in the image while the target signature is constrained (Harsanyi, 1993). CEM and MTMF are useful when not all spectral endmembers are known.

Methods

Study Site Description

The data presented here were collected at the Reynolds Creek Experimental Watershed (RCEW), which is administered by the United States Department of Agriculture &hyphen; Agricultural Research Service. The RCEW was established in 1960 as one of several experimental watersheds for hydrologic and natural resources research (Slaughter et al., 2001). The watershed is 238 km² in extent and ranges in elevation from 1000 m to 2000 m. Corresponding annual precipitation ranges from 230 mm/year at the lower elevations to >1100 mm/year at the higher elevations. Soils are derived from granitic and volcanic rocks as well as lakebed sediments. Plant communities at lower elevations are typical of the Great Basin Desert and dominated by mixed sagebrush ( Artemisia spp.) and herbaceous species. At higher elevations, mountain big sagebrush ( Artemisia tridentata vaseyana), aspen ( Populus tremuloides), and Douglas-fir ( Pseudotsuga menziesii) are common. Detailed information on watershed geography, vegetation, soils, hydrology, and weather can be obtained from previously published references (Hanson, 2001; Hanson et al., 2001; Pierson et al., 2001; Seyfried et al., 2001,a,b,c, and d). Within the RCEW, this study focused on three areas of historic western juniper ( Juniperus occidentalis) distribution (Plate 1) which is documented to be increasing in extent and density (Sankey et al., 2010).

Landsat-5 TM image Analysis

A multi-temporal composite of summer- and fall-season Landsat-5 Thematic Mapper (TM) satellite images (30 m × 30 m pixels) was used. The Landsat-5 TM multi-temporal composite consisted of two images (Path 42 and Row 30) acquired on 09 July 2008 and 29 October 2008. First, both images were: (a) corrected for atmospheric effects using the FLAASH module (Atmospheric model: sub-arctic summer; No aerosol and water retrieval; Aerosol model: rural; Water column multiplier: 1; Initial visibility: 40 km) in ENVI software (ENVI, Version 4.5, ITT Industries Inc., 2008, Boulder, Colorado), (b) projected in UTM Zone 11N, NAD 1983 projection and datum, (c) georectified and co-registered (all root mean square errors <7 m), and (d) subset to the study areas. Spectra from corresponding stable targets (e.g., roads, bare ground) in both images were compared and found to be similar and thus, image normalization was not deemed necessary. Then, the summer image bands 2 (0.52 to 0.60 μm), 3 (0.63 to 0.69 μm), 4 (0.76 to 0.90 μm), and 5 (1.55 to 1.75 μm) were spectrally subset and stacked with the fall image bands 2, 3, and 4 to generate the multi-temporal composite. This combination of bands and dates was used to separate evergreen junipers from the background sagebrush-herbaceous vegetation mix by taking advantage of the spectral reflectance changes due to the senescent herbaceous vegetation and lower greenness of the shrubs in the fall compared to the summer. Furthermore, the multi-temporal stacking increased the number of relevant bands available for the spectral unmixing (see Singh and Glenn, 2009). The multi-temporal composite image was then classified using constrained (sum of 1) and unconstrained linear spectral unmixing (LSU), Mixture Tuned Matched Filtering (MTMF), and Constrained Energy Minimization (CEM) techniques in ENVI software to estimate sub-pixel juniper percent cover. The LSU requires an input of all cover types as training endmembers. A field-mapped pixel of maximum juniper canopy cover of ~95 percent (juniper foliage, woody stems, and shade combined) along with pure pixels of rangeland vegetation (sagebrush and herbaceous species combined) and bare ground were used as training endmembers. Previous studies documented that a user-guided endmember pixel with high percentage target cover performed better than extreme or variant n-dimensional visualizer (ND-V) endmember pixels and the mean of all ND-V endmember pixels (Mitchell and Glenn, 2009). The MTMF and CEM both produce a raster band that estimates the target cover abundance within each pixel. The MTMF technique produces two raster bands: (a) matched filtering scores that estimates target cover abundance, and (b) infeasibility values which represent the likelihood of false positives in the matched filtering scores. In the first band, a matched filtering (MF) score near 0 indicates background signal or noise, while a score of 1 corresponds to 100 percent abundance of the target spectrum within a pixel. In the second
band, high infeasibility scores indicate greater likelihood that pixels are false positives.

Lidar Data Analysis

The lidar data were acquired in November 2007 through Watershed Sciences, Inc. using a Leica ALS50 Phase II laser mounted on a Cessna Caravan 208B fixed wing aircraft flying at a 900 m height and 105 knot speed with 50 percent flightline overlap. The study sites spanned across 15 post-processed lidar data tiles, which included a total of 38 original flightlines. The Leica ALS50 Phase II is a discrete return system that measures up to four laser returns per pulse. The lidar point cloud data had a maximum of four returns and mean point density of 5.6 points/m². The mean horizontal relative and absolute accuracies were 32 cm and 33 cm, respectively, as reported by the vendor. The vertical accuracy was approximately 10 cm. Each point had the following attribute information: scan angle, return number, intensity, X, Y, and Z. Using the methods and associated publically available lidar processing tools described in Streutker and Glenn (2006) (http://bcal.geology.isu.edu/envitools.shtml), the point cloud data were subset to the three study areas, height-filtered to separate ground returns and vegetation returns, and converted into a raster format (30 m × 30 m pixels) to generate three raster bands: maximum vegetation height, mean vegetation height, and vegetation roughness, which is the standard deviation of vegetation heights within each pixel. In addition, a separate raster band was created using the height-filtered lidar point data to generate a maximum vegetation height map in 3 m raster cell size. A binary maximum vegetation height map was then produced from this raster image using a 3 m height threshold. All pixels having maximum vegetation height of >3 m were classified as juniper presence, while all other pixels were classified as juniper absence. This height threshold was chosen based on the following: (a) field-based and lidar-derived big sagebrush and bitterbrush heights at the RCEW ranged up to 3 m (Sankey et al., 2010), and (b) the lidar-derived tree heights at the RCEW were significantly correlated with field-measured tree heights (Sankey et al., 2010; \( R^2 = 0.80 \) and p-value <0.0001). The 3 m-resolution binary height map was used in ArcMap® 9.3 software to classify juniper percent cover within 30 m × 30 m cells. A grid of 30 m × 30 m...
cells of each study area was overlaid on the 3 m resolution binary height map and the number and percent of the 3 m pixels classified as having juniper presence within each 30 m × 30 m cell was calculated to estimate juniper percent cover. The 3 m raster cell size was selected as the most appropriate for juniper sizes in the study area after examining several different pixel sizes. The 3 m cell size was also most appropriate to scale up to 30 m cell sizes, since 100 of these cells fit into one 30 m cell thereby automatically converting the juniper presence counts into a percent estimate. The result was a lidar-derived sub-pixel juniper cover estimate in each 30 m cell.

**Landsat-5 TM and Lidar Fusion**

Two different fusion approaches were explored. First, the three rasterized lidar bands of maximum vegetation height, mean vegetation height, and vegetation roughness were stacked with the Landsat-5 TM multi-temporal composite image bands to generate a fusion of Landsat-5 TM and lidar bands (hereafter referred to as “TM-lidar band fusion”). The TM-lidar band fusion resulted in ten bands (seven TM bands and three lidar bands). The TM-lidar band fusion image was then classified using the constrained and unconstrained LSU, MTMF, and CEM techniques. Second, a regression-based fusion approach was explored by combining the sub-pixel juniper cover estimates resulting from the TM-lidar band fusion with the lidar-derived juniper cover estimates in a multiple regression. The multiple regression only used the MTMF estimates of sub-pixel juniper cover, since the MTMF classification performed best of all the spectral unmixing techniques.

**Field Methods**

Field work was completed during the months of July and August 2009 to estimate juniper percent cover. Prior to field work, a total of 100 random points were generated within the three study areas using Hawth’s tools in Esri ArcMap® 9.3 software (Esri, Inc., 1999-2006). A 30 m × 30 m (Landsat-5 TM) pixel at each of these random points was selected and the coordinates of the four corners of each pixel determined from the imagery. We established field plots by navigating with a Trimble GeoXT GPS receiver (sub-meter post-processing horizontal accuracy) to the four corners of the corresponding 30 m × 30 m area on the ground (Plate 1). Within each 30 m × 30 m field plot, every juniper stem was mapped, measured for height, and classified as either mature tree (>8 cm in diameter at 30 cm height) or seedling (<3 cm in diameter at 30 cm height). Canopy width of all individual juniper stems was measured. Total juniper canopy percent cover in each plot was then estimated by adding canopy area measurements of all trees in the plot (Miller and Rose, 1999) and then subtracting overlapping canopy areas. Overlapping canopy areas were estimated using the canopy width measurements as a buffer around each tree point location and calculating the areas with overlapping buffers in ArcMap® 9.3 software.

**Statistical Analysis**

Regression analyses were used to correlate the image-derived and field-measured juniper cover estimates (SPSS 14.0 for Windows, 2005). The LSU, CEM, and lidar-derived estimates of juniper cover were assessed using simple linear regression models. The MTMF estimates of sub-pixel juniper cover in both the Landsat-5 TM image and TM-lidar band fusion were assessed using multiple regression models, where the matched filtering scores, infeasibility values, and their interaction term were the predictor variables and the field-measured juniper cover was the response variable. A separate multiple regression model was constructed to combine the TM-lidar band fusion MTMF estimates with the lidar-derived estimates of juniper cover. In this model, the MTMF matched filtering scores, infeasibility values, and their interaction term and the lidar-derived juniper cover estimates were the predictor variables, while the field-measured juniper cover was the response variable.

To further evaluate the agreement between field-measured and model-predicted juniper cover, mean squared deviation (MSD) between the two measurements was examined. The MSD is an important statistic that can be used to compare predicted and measured values. It can be divided into three components: Standard Bias (SB), Non-Unity Slope (NU), and Lack of Correlation (LC) using the following Equations 1 through 4 (Gauch et al., 2003):

\[
MSD = \sum \frac{(\text{measured} - \text{predicted})^2}{N} \tag{1}
\]

\[
SB\% = \frac{(\mu(\text{measured}) - \mu(\text{predicted}))^2}{MSD} \tag{2}
\]

\[
NU\% = \frac{(1 - b^2) \sum (n(\text{predicted}) - \mu(\text{predicted}))^2}{N} \tag{3}
\]

\[
LC\% = \frac{(1 - r^2) \sum (n(\text{measured}) - \mu(\text{measured}))^2}{N} \tag{4}
\]

where \(n\) refers to the sample size of either measured or predicted values, \(\mu\) is the mean of either measured or predicted values, \(b\) is the slope of the regression line through the plot of predicted values as a function of measured values, \(N\) is the number of pairs of measured and predicted values, and \(r^2\) is the square of the correlation. SB quantifies the proportion of the MSD related to the deviance of the regression fit from a 1:1 relationship (Sankey et al., 2008) and SB > 0 if the intercept \(a \neq 0\) (Gauch et al., 2003). NU quantifies the proportion of the MSD related to the deviance of the regression fit from a 1:1 relationship in the slope of the regression line (Sankey et al., 2008) and NU > 0 if slope \(b \neq 1\). LC quantifies the proportion of the MSD related to the scatter of the points around the regression line (Sankey et al., 2008).

**Results**

A total of 745 juniper stems were mapped in the 100 plots. Of these, 59 percent were mature and >3 m in height, while 41 percent were seedlings with <3 m height. Mean mature tree height was 4.6 m, while mean seedling height was 1.5 m. Mean juniper stem density was 92 stems/ha. Mean juniper canopy cover was 7.3 percent at the 30 m × 30 m plot scale.

The constrained and unconstrained LSU estimates of sub-pixel juniper cover in the Landsat-5 TM image alone were the same and not significantly correlated with the field-measured juniper cover (\(R^2 = 0.003\) and \(p\)-value = 0.571 for both models). The MTMF infeasibility values in the Landsat-5 TM image were significantly correlated with field-measured juniper cover (\(R^2 = 0.09, p\)-value = 0.004), but the matched filtering scores were not significantly correlated (\(p\)-value = 0.533). The CEM estimates of sub-pixel juniper cover in the Landsat-5 TM image were also not significantly correlated with the field-measured juniper cover (\(R^2 = 0.004, p\)-value = 0.550).

The lidar-derived juniper cover estimates were significantly correlated with the field-measured juniper cover (\(R^2 = 0.74, p\)-value <0.001) (Figure 1). The TM-lidar band fusion estimates of sub-pixel juniper cover using constrained and unconstrained LSU were similar and both significantly correlated with field-measured juniper cover (both \(R^2 = 0.27; p\)-values <0.001). The CEM estimates of sub-pixel juniper cover in the TM-lidar band fusion were also significantly
correlated with the field-measured juniper cover ($R^2 = 0.21$, $p$-value $< 0.001$). The MTMF infeasibility values, matched filtering scores, and their interaction term in the TM-lidar band fusion were all significant predictors ($p$-values of $< 0.001$, 0.016, and $< 0.001$, respectively) leading to $R^2$ of 0.42. Finally, when the lidar-derived juniper cover estimates were combined with the TM-lidar band fusion estimates using the MTMF classification, the $R^2$ increased to 0.80 (Figure 2) and all predictor variables (MTMF infeasibility values, matched filtering scores, and their interaction term, and lidar-derived estimates) were significant ($p$-values $< 0.05$). Further analysis of the regression fit in relation to a 1:1 line and MSD components produced SB of 0 percent for all models. The NU was 20 percent, 19 percent, and 17 percent for TM-lidar band fusion, lidar-derived estimates, and the regression-based fusion, respectively, while LC was 80 percent, 99 percent, and 95 percent, respectively (Figures 1 and 2).

**Discussion**

**Comparison of Image Sources**

Sub-pixel juniper cover was estimated using three different image sources: (a) multi-temporal Landsat-5 TM composite image, (b) lidar data, and (c) Landsat-5 TM-lidar fusion. The Landsat-5 TM-derived estimates of sub-pixel juniper cover did not perform well. Indeed, none of the Landsat-5 TM spectral unmixing results was significantly correlated with the field-measured juniper cover. This might be due to the sparse distribution, low density, and canopy cover of juniper trees. The mean juniper percent cover within pixels was 7.3 percent at our study areas and a Landsat-5 TM-based estimate of such low target cover within pixels does not appear feasible. However, a previous MTMF-based binary classification of juniper presence/absence had better success (Sankey et al., 2010) and Landsat-5 TM-based estimate of tree cover in the current study appeared more successful in pixels of high juniper density. This might indicate that Landsat-5 TM-derived sub-pixel tree cover estimate might be feasible at sites with greater tree cover, which are more characteristic of the widely distributed pinyon-juniper woodlands than ours and might warrant further investigation. The only Landsat-5 TM-derived variable in this study that was significantly correlated with the field-measured juniper cover was the MTMF infeasibility values. The correlation might have been significant due to the high infeasibility values that are directly related to true negatives. The infeasibility values, however, only explained 9 percent of the variability in the field-measured juniper cover and indicated the likelihood of false positives in the matched filtering scores rather than providing an estimate of juniper cover in each pixel. Given the statistically insignificant matched filtering scores, the infeasibility values provide limited utility in estimating sub-pixel juniper cover.

The lidar-derived sub-pixel juniper cover was significantly correlated with the field-measured juniper cover. The lidar-derived estimates also explained much of the variability in the field-measured juniper cover ($R^2$ of 0.74), although the lidar data was rasterized and then scaled to 30 m × 30 m pixels. Rasterizing and then scaling the lidar point cloud data to such a pixel size would be expected to lose much of the three-dimensional high-resolution information on individual tree canopy characteristics. At the scales of a field plot and a 30 m × 30 m pixel, however, the percent cover estimates performed well overall. The only areas where the lidar-derived estimates did not perform well were the pixels with juvenile junipers even at high density and canopy cover. This is due to the 3 m height threshold, which was set to exclude the large presence of tall shrubs at our study sites. The 3 m height threshold has also been commonly used in juniper demographic studies to separate mature trees from juvenile juniper stems, which are largely <45 years old (Blackburn and Tueller, 1970; Tausch et al., 1981; Johnson and Miller, 2006; Miller et al., 2000). The juvenile junipers <3 m tall at our study sites were estimated to be on average 30 years old (Sankey et al., 2010) and comprise an important priority for juniper management. Future studies at sites without tall shrubs could use a lower height threshold to accurately estimate cover of small junipers or use a lidar-based shape model for separating shrub from juvenile juniper trees.

When the Landsat-5 TM image and all lidar bands were combined in a multiple regression, the fusion produced better estimates of sub-pixel juniper cover than either of the image sources alone. This is similar to the findings of previous rangeland applications of lidar data fusion with spectral data (Mundt et al., 2006; Bork and Su, 2007). The increased predictive accuracy is largely due to the
complimentary characteristics of the two distinct data types. Sparsely-distributed mature juniper trees at low canopy percent cover were represented in the lidar bands due to their heights and, therefore, better classified in the fusion. Meanwhile, juniper seedlings at high density, which were not classified in the lidar-derived classification due to their low stature, were likely represented in the Landsat-5 TM bands. Fused together, the Landsat-5 TM and lidar data better represented both juvenile and mature juniper trees than either of the imagery alone. However, the improvement in juniper cover estimates using the fusion was a marginal 6 percent increase over the lidar data alone. This is consistent with the results of other lidar fusion studies on tree canopy metrics. Erdody and Moskal (2010) reported only 2 to 5 percent improvements when lidar predictions of tree canopy fuel and canopy bulk density were fused with color near-infrared imagery predictions. Hyde et al. (2006) also reported limited improvements of 0 to 5 percent by fusing lidar predictions of tree biomass with INSAR, QuickBird, and Landsat ETM+ data.

Taken together, these results suggest that the ultimate goal of future studies need to be carefully considered before extensively investing into lidar fusion with spectral data. While no significance testing was performed in this study, our objective is to present the utility of each data source in estimating sub-pixel tree cover. We recommend lidar fusion with Landsat-5 TM data for sub-pixel target cover estimates, if the goal is the most accurate target cover prediction possible. However, lidar data alone would suffice, if the goal is to estimate target cover in a simple, efficient manner. In such instances, the limitations introduced by potential vegetation height thresholds such as the one used in this study should be recognized. For example, land managers are particularly interested in detecting juvenile junipers during the early stages of juniper encroachment into rangelands, because juniper encroachment effects of decreased understory vegetation and increased soil erosion are more easily controlled at this stage.

Comparison of Fusion Approaches
The multi-temporal Landsat-5 TM composite image and the lidar data were fused using two different approaches. First, the multi-temporal Landsat-5 TM image bands were stacked with the rasterized lidar bands. This was a simple and straightforward approach. The resulting TM-lidar band fusion produced sub-pixel juniper cover estimates which were all significantly correlated with the field measurements, regardless of the spectral unmixing technique used. The band fusion resulted in substantial improvements over the Landsat-5 TM data, especially considering the poor performance of all the spectral unmixing techniques used with Landsat-5 TM data alone. This might be due to the increased number of relevant bands from the two different types of data, which might indicate that all of the four spectral unmixing techniques used in this study benefit from increased number of bands well above the statistically important number of bands (the required number of bands for spectral unmixing equals \( n - 1 \) endmembers). If the signal to noise ratio (SNR) of the Landsat-5 TM data were improved, for example to 500:1, such as with the Landsat Data Continuity Mission’s Operational Land Imager (OLI) (Irons and Dwyer, 2010), the spectral unmixing analysis might be improved. The TM-lidar band fusion, however, produced poorer results compared to lidar-derived estimates alone. We conclude that Landsat-5 TM and lidar data fusion using simple band stacking is not an effective approach, even though the resulting band combination performs better than Landsat-5 TM data alone. The band stacking approach is also somewhat cumbersome due to image co-registration issues. The results of such a fusion approach are likely to be impacted by pixel misregistration of the images from different platforms, despite thorough efforts to minimize such effects.

Second, a regression-based approach was used to combine the TM-lidar band fusion MTMF outputs with the lidar-derived juniper cover estimates. It was simple to implement and produced better results than the TM-lidar band fusion approach. Indeed, the regression-based fusion provided the most accurate estimates of juniper cover compared to all other estimates. This supports the conclusions of a previous juniper study at the RCEW which focused on juniper presence and absence classification using Landsat-5 TM and lidar fusion (Sankey et al., 2010). When the agreement between the regression-predicted and observed juniper cover estimates were further examined, the regression-based fusion produced smaller MSD, compared to the TM-lidar band fusion approach. While the standard bias was similar between the two fusion approaches, the regression-based fusion also produced a smaller non-unity slope indicating a lesser proportion of the error introduced by the regression slope than in the TM-lidar band fusion approach. We recommend multiple regression-based approaches to fusing lidar data with spectral imagery for future sub-pixel classification studies. The observed superior performance of the regression-based fusion in this study might have been due to the combination of post-classification, sub-pixel estimates rather than the original image bands as in the TM-lidar band fusion approach. When we stacked the lidar-derived sub-pixel juniper cover estimates with all the original bands in the TM-lidar band fusion and then performed MTMF classification for comparison purposes, the resulting coefficient of determination was much lower (\( R^2 \) of 0.36 compared to 0.80 in the regression-based fusion approach). Our results support the recommendations of previous studies that integrated post-classification lidar derivatives with spectral image-based classifications (Mundt et al., 2006; Erdody and Moskal, 2010).

Comparison of Spectral Unmixing Techniques
Three different spectral unmixing techniques were explored: (a) linear spectral unmixing (LSU), (b) Mixture Tuned Matched Filtering (MTMF), and (c) Constrained Energy Minimization (CEM). Among them, CEM performed worst, likely due to the low percent cover of the juniper (mean 7.3 percent cover). When used with the Landsat-5 TM data alone, this technique produced sub-pixel estimates which were not significantly correlated with the field measurements. It produced better results with the TM-lidar band fusion, but the regression coefficient of determination was a low 0.21. The linear spectral unmixing technique produced similarly poor results regardless of whether or not a sum-to-one constraint was enforced. The LSU resulted in no significant correlation and a low regression coefficient of determination of 0.27, when used with Landsat-5 TM data and the TM-lidar band fusion, respectively. These results are contrary to conclusions by other linear spectral unmixing studies that used Landsat imagery to estimate tree fractions within pixels (Chen et al., 2004; Small and Lu, 2006).

The MTMF technique performed best among the three techniques compared. Its estimates of sub-pixel juniper cover had the strongest correlation with the field measurements. This technique, however, provides the least user-friendly approach among the three techniques. The MTMF technique produces two separate bands, which ultimately are combined to leverage their predictive capabilities for target cover mapping. There is, however, no automated approach to combining the two bands. A user-defined approach is required to produce a final map of the target
cover type (Mitchell and Glenn, 2009a and 2009b; Sankey, 2009). Furthermore, the two bands are cumbersome to use even in a regression-based approach. For example, the Landsat-5 TM matched filtering scores in this study resulted in no statistically significant correlation with the field measurements, while the infeasibility values did. If the regression model was to be further fine-tuned, the statistically insignificant band would have to be excluded from the model. In such cases, both bands resulting from MTMF cannot be effectively leveraged.

Conclusions
This study compared different image sources, fusion approaches, and spectral unmixing techniques for estimating sub-pixel tree cover in a semi-arid rangeland environment. We recommend both lidar and Landsat-5 TM data classified using the MTMF spectral unmixing technique and fused in a regression-based approach. The recommended image source, fusion approach, and spectral unmixing technique can be easily applied to mapping other woody vegetation encroachment, which is currently attracting increasing concerns throughout the western US. Our results also indicated that lidar-derived estimates can be effectively used alone for sub-pixel tree cover classification. However, spectral data are necessary for locating juvenile junipers dispersed among tall shrubs.

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