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Estimates of forest canopy fuel attributes using hyperspectral data

Gensuo J. Jia [a,b,*], Ingrid C. Burke [a], Merrill R. Kaufmann [c], Alexander F.H. Goetz [d], Bruce C. Kindel [d], Yifen Pu [e]

[a] *Department of Forest, Rangeland, and Watershed Stewardship, Colorado State University, Fort Collins, CO 80523, USA*
[b] *RCE-TEA, Institute of Atmospheric Physics, Chinese Academy of Sciences, Beijing 100029, China*
[c] *Rocky Mountain Research Station, USDA Forest Service, Fort Collins, CO 80526, USA*
[d] *Center for the Study of Earth from Space, University of Colorado, Boulder, CO 80309, USA*
[e] *Institute of Atmospheric Physics, Chinese Academy of Sciences, Beijing 100029, China*

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Abstract

Increasingly severe forest fires in the west have triggered a high demand for accurate and timely information on forest fuel attributes. There is great interest in the potential for using recent advances in high spectral resolution remotely sensed imagery to estimate fuel characteristics. We combined field forest inventory and field spectroscopy in the Colorado Front Range with airborne imaging spectrometer measurements of the region to test their capacity to estimate fire related forest attributes including canopy cover, forest type, and burn severity in ponderosa pine (*Pinus ponderosa*) and Douglas-fir (*Pseudotsuga menziesii var. glauca*) dominated forests. Spectral angle mapper and mixture-tuned matched filtering techniques were tested for mapping fuel attributes. Estimates of canopy cover using spectral angle mapper techniques found 61% agreement with observed values, while mixture-tuned matched filtering estimates of forest canopy cover matched 78% with field observations. The distinction of ponderosa pine versus Douglas-fir is crucial for predicting fire spread in the Rocky Mountains; we found that spectral discrimination of these species was also promising, with an accuracy of 53–57%. The average canopy cover of mixed conifer forest in the area is 38.6%, 24.7% contributed by ponderosa pine and 13.9% by Douglas-fir. The values of canopy cover ranged from 53% to 56% in US Forest Service planned fuel treatment areas, among the highest in the region. Recent forest fires have created approximately 684 km^2 of burned area, with very low canopy cover (13–22%).

Keywords: Canopy cover; Fire; Burn severity; AVIRIS; Spectral analysis; Colorado Front Range; *Pinus ponderosa*; *Pseudotsuga menziesii*

1. Introduction

Forest fire is a major ecological disturbance mechanism that modifies forest landscapes (Dwire and Kauffman, 2003) and endangers human life and property (Veblen et al., 2000) in large areas of wildland/urban interface. In the Western US, large-scale forest fires have become increasingly frequent and intense in recent years (Brown et al., 2004). In some areas, crown fires that are beyond the historical range of variability have consumed the entire native seed source and the consequences for vegetation recovery are largely unknown (Kaufmann et al., 2004, Lewis et al., 2005). These fires have significant impacts on growing human populations in the Western US, and particularly the Colorado Front Range, where numerous large fires since 1996 have devastated homes and municipal water supplies (e.g., Graham, 2003). The probability of large fires in the region is high, as seen in the Hayman Fire of 2002 (Graham, 2003), and the risk of these fires to humans is increasing rapidly. Had the Hayman fire occurred 20–30 miles farther north, its footprint would have included 8–10,000 homes and could have cost hundreds of lives. Drought (Fried et al., 2004) and increased human pressure on wilderness (Veblen et al., 2000) have been two major factors that triggered high fire damage in those forest fires. However, dense forest that contains a large amount of fuel as a result of long-term fire suppression (Keeley et al., 1999) is likely a more important and manageable influence.

As a result, the reduction of fuels is becoming a major concern for decision makers, and forest fuel management plans

* Corresponding author. Tel.: +1 970 491 0495; fax: +1 970 491 2339.
E-mail address: jiong@colostate.edu (G.J. Jia).

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have been proposed (Fulé et al., 2004) to reduce forest fire risk in highly susceptible areas (Kaufmann et al., 2004; Lewis et al., 2005). Such plans have increased the need for information about the spatial distribution of forest fuel condition and burned areas in order to identify priority areas for fuel treatment (Ustin et al., 2004). However, ideal levels of information are often difficult to obtain from field reconnaissance, or are at too coarse a resolution to be useful. Thus, high resolution remote sensing technologies are increasingly demanded by forest managers for their fuel treatment planning.

Remote sensing has been used in forest studies to assess canopy properties and to map burn severity (Ustin and Trabucco, 2000) in various forest ecosystems such as boreal forest, alpine coniferous forest, and both tropical forest and woodland. Traditional satellite and airborne remotely sensed imagery has been demonstrated to be useful for the description of spatial patterns of these forest fire attributes (e.g., Mbow et al., 2004; Ustin and Trabucco, 2000). At global and regional scales, fuel/fire studies using remote sensing have been focused on deriving fuel moisture (Martin and Aber, 1997), estimating total biomass/fuel, and fire distribution and frequency (de la Riva et al., 2004) using multispectral satellite data with spatial resolutions ranging from 30 to 8 km (Justice et al., 2002). In recent years, imaging spectroscopy, also known as hyperspectral remote sensing, has emerged and been demonstrated to be useful for spectrally and spatially discriminating these fire-related vegetation attributes at a sub-pixel level (Ustin et al., 2004; Green et al., 1998; Clark et al., 2003); experiments with these techniques have been focused on relating various vegetation indices to forest fuel properties (Treitz and Howarth, 1999), separating photosynthetic and non-photosynthetic materials (Asner et al., 1998), estimating canopy biochemistry (Smith et al., 2003), and detecting stress on tree crowns (Ustin and Trabucco, 2000). The high spectral resolution (224 bands) of the Airborne Visible and Infrared Imaging Spectrometer (AVIRIS) in the 400–2500 nm region allows the development of metrics sensitive to many biophysical properties of canopies. Leaf pigments absorb photons at a variety of visible wavelengths (400–700 nm), whereas water and other plant constituents such as cellulose, lignin, and nitrogen, all of which are influenced by canopy type (including species), density and structure absorb in varying intensity in the short-wave infrared region (900–2500 nm). Many approaches have been devised to assess vegetation fractional cover or species composition using hyperspectral image analysis, though most of them were conducted over sparse vegetation in arid and semiarid regions (Ustin et al., 2004). For example, Asner et al. (1998) examined heterogeneity of savanna canopy structure with imaging spectrometry, and Roberts et al. (2003) compared airborne and spaceborne hyperspectral data in evaluating fuel moisture and biomass, while a wide variety of studies have also attempted to detect plant pigments, photosynthetic materials with spectral analysis (Asner, 1998; Smith et al., 2003).

AVIRIS has been the pioneer for hyperspectral data since the early 1990s. Meanwhile, other hyperspectral sensors such as the compact airborne spectrographic imager (CASI), short wave infrared (SWIR), full spectrum imager (SFSI), and Hyperion have enhanced hyperspectral data availability and widened its applications. CASI and SFSI are airborne hyperspectral sensors that observe visible to near-infrared spectra and short-wave infrared (SWIR) region respectively. Hyperion, onboard NASA's Earth Observing-1 (EO-1) satellite, is the only spaceborne hyperspectral sensor at present, and is serving as a prototype for potential future missions. The Hyperion sensor collects 242 spectral channels ranging from 0.357 to 2.576 μm with a 10-nm bandwidth, which is similar to AVIRIS, at a spatial resolution of 30 m (http://edc.usgs.gov/products/satellite/eo1.html). Hyperion has been tested in various applications as a valuable potential spaceborne replacement for AVIRIS, although in many cases it has relatively lower signal-to-noise ratio and thus far yielded lower accuracy (Roberts et al., 2003; Smith et al., 2003). The spectral analysis techniques for assessing forest fuel attributes tested here, though applied to AVIRIS data, could be applied with Hyperion or later versions of this satellite borne technology.

Across much of the Front Range of the Rocky Mountains, from Montana to New Mexico, one of the key features determining fire behavior is the distribution and dominance of ponderosa pine versus Douglas-fir (Kaufmann et al., 2000). Surface fires, common before the era of fire suppression, kill many seedlings and saplings, and help maintain low tree density. Once fires are able to move into the crown, however, stand-replacement generally occurs unless overstory density is low. While ponderosa pine often matures with few lower branches (''ladder fuels''), Douglas-fir maintains foliage and branches near the ground (low crown base height), generating sufficient ladder fuels to alter fire behavior dramatically. Thus the presence and density of Douglas-fir is useful as a predictor of fire behavior (Scott and Reinhardt, 2001). To date, no remote sensing techniques have been developed to adequately separate conifer species such as ponderosa pine and Douglas-fir at a landscape scale. However, some attempts have been made using sub-meter resolution airphotos and in situ spectra of individual trees (Gong et al., 1997), and more recently, using Light Detection and Ranging (LIDAR) data (Andersen et al., 2005), IKONOS, and Quickbird satellite images (Wang et al., 2004).

Our objectives in this study were: (1) to find the most appropriate hyperspectral image processing techniques for assessing forest attributes relevant to fire risk by comparing spectral analysis techniques and (2) to test the techniques for estimating key forest fire risk attributes, including: (a) total canopy cover, (b) cover by ponderosa pine and Douglas-fir, and (c) burn severity. Forest canopy cover is a key fuel property that indicates tree crown coverage and is correlated with crown fire risk. As described above, discriminating ponderosa pine from Douglas-fir is of critical value to managers. Finally, burn area and severity serve as indicators of past fire events and a major source of forest landscape heterogeneity. They provide useful insight for fuel treatment plans and ecological restoration programs.

2. Site description

We conducted our study in the Pike National Forest in Colorado, USA, located southwest of the Denver metro area (Fig. 1). This region is characterized by a semiarid–semihumid montane climate, with annual precipitation of 545–551 mm and annual mean air temperature of 5.6–8.3 °C (Birkeland et al., 2003). Elevations in the areas vary from 1900 m in the east to 2800 m in the west. Vegetation types of concern in the region include ponderosa pine and Douglas-fir forest, mixed conifer (*Pinus ponderosa*, *Pseudotsuga menziesii*, *Pinus contorta*, *Picea pungens*, *Abies lasiocarpa*, *Populus tremuloides*) forest, and woodland dominated by pinyon pine (*Pinus edulis*) and juniper (*Juniperus scopulorum*), with patches of shrub and grassland. Watersheds within the Pike National Forest serve as major recreational and water supply areas for Denver residents. As an area of wildland/urban interface, the area contains about 4000 households, making wildfire a major threat to human life and property.

The forests in the Pike National Forest have been severely impacted by logging, grazing and fire suppression during the past two centuries (Kaufmann et al., 2001). Historically, they were dominated by fire-resistant ponderosa pine, with lesser amounts of Douglas-fir and other fire-sensitive species that are not as well adapted to surviving fire as are mature ponderosa pine. Current forests are generally younger, far denser, and have many more fire-sensitive trees than historical forests (Kaufmann et al., 2001). Historical fires in the ponderosa pine forests occurred with return intervals of 20–60 years, more frequently at lower elevations and less frequently at higher sites (Kaufmann et al., 2004). During most of the 20th century, there were only a few moderate-sized (<1000 ha) forest fires in the region, and fuels gradually built up, including reforestation of many openings due mainly to the century-long fire suppression policy (Brown et al., 2004). During the last century, several large size and severe fires in this national forest occurred from 1996 to 2002, including the Buffalo Creek fire (1996), the Hi Meadow fire (2000) and the Hayman and Schoonover fires (2002). In June 2002, the Hayman Fire, centered at Cheesman Lake, burned 55,751 ha of natural vegetation, destroyed more than 600 structures and cost nearly 40 million dollars in fire suppression and property damage (Romme et al., 2003a). With a mixed burn severity (Schoennagel et al., 2004) in some areas and crown fire over more than 24,280 ha, the Hayman fire killed most of the aboveground biomass around Cheesman Lake, and left patches of unburned or lightly burned conifer forest in the southeastern portion of the fire area. The fire was severe enough that major erosive events occurred, influencing municipal water supplies (Graham, 2003). With all of the attention focused on this area, the US Forest Service is under particular pressure to develop forest fuel treatment projects to systematically reduce fuel loading using prescribed burning and mechanical thinning.

Our study was designed to provide forest managers with needed information on the condition of fuels for mitigation of wildland fire. In particular, we focused on estimating forest canopy cover, separating ponderosa pine and Douglas-fir, and assessing burn severity of two recent fires, namely the Hayman Fire and Hi Meadow Fire.

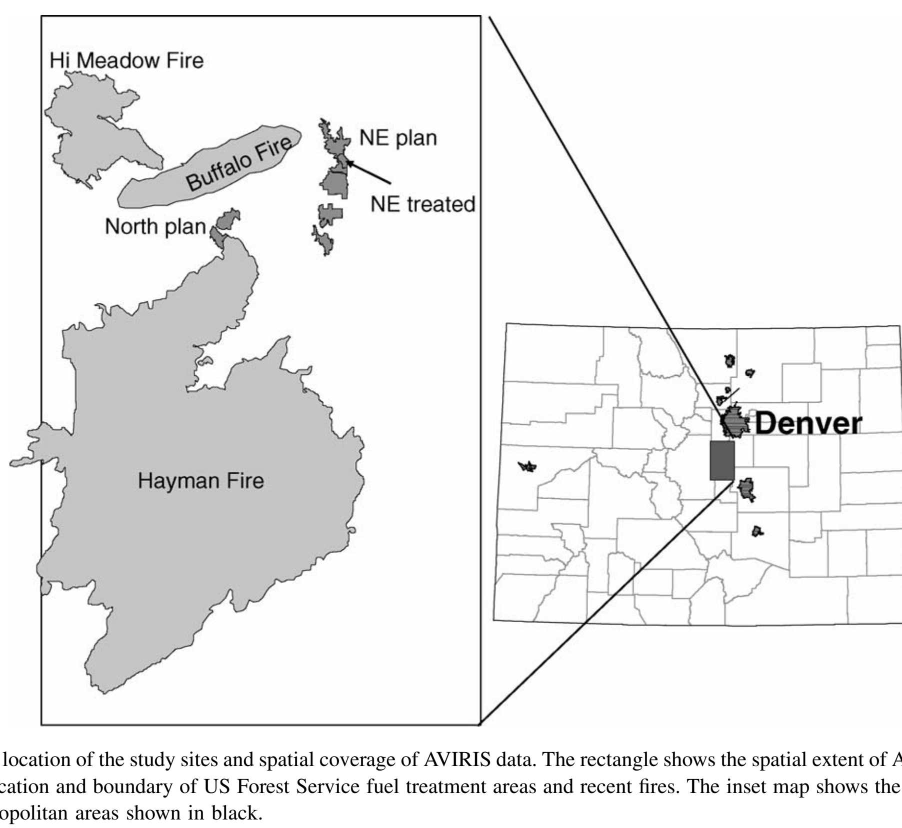

Fig. 1. Index map showing location of the study sites and spatial coverage of AVIRIS data. The rectangle shows the spatial extent of AVIRIS data used in the study; shaded polygons are the location and boundary of US Forest Service fuel treatment areas and recent fires. The inset map shows the study location in the state of Colorado, with major metropolitan areas shown in black.

3. Data and methods

3.1. Field inventory of vegetation/fuel variables

We established 34 100-m forest transects and 128 independent plot-less validation samples randomly selected in the study areas to measure tree species, canopy cover, and burn severity. Both transect starting points and the location of plot-less samples were randomly selected with a geographic information system. We used ENVI (Research System Inc., Boulder, USA) random point module to generate 246 potential sample sites in our study region, then ruled out the points located in non-vegetation areas and in private lands as shown on Landsat images and USFS quadrant maps. In the field, we located and sampled those points that were located within 1.6 km of road and within public lands. Fire events were also considered during sample site selection. The transect data were used to train the classification used in spectral analysis and mapping, while the plot-less sample data were used for field validation of AVIRIS derived maps.

Along each 100-m transect, we randomly selected five points at approximately 20-m intervals, and used modified-Whittaker methods for field sampling (Brown et al., 1982). At each of the points, we laid out a 15-m transect at a randomly selected angle from the original 100-m transect. Along each 15 m sub-transect we measured: (1) species, height, diameter at base height (DBH), crown diameter, and height-to-branch of the four nearest trees in each quadrant at the end of the transect; (2) canopy cover with a hand-held spherical densitometer (Model-A), four readings of canopy cover facing north, east, south, and west (in order to reduce uncertainty during measurement); (3) existence and severity of fire. We measured trees along each transect in two ways: we counted all small trees (less than 3 m tall) within a 3 m radius from the end point of the 15 m transect, and measured four large trees at the beginning point. We used the 15 m transect line to divide the area around the beginning point into four quadrants. We selected the closest tree in each quadrant that was greater than 3 m tall and measured DBH, tree height, height to the first live branch, height of burned parts of the tree and burn severity, bark thickness, and crown width. We also noted the shape, and amount of ladder fuels surrounding the tree. The final step of tree measurements was taking a tree ring sample, which was taken from the largest tree of the dominant species in the area. We used severity classes developed by Omi and Martinson for examining both stand damage and ground char (Table 1). During the transect sampling, we linked a Garmin V GPS unit to a laptop computer with ENVI software to instantly track and mark sample plots and transects on a geo-registered high-resolution QuickBird image (2.8 m pixel size, DigitalGlobe Inc., Longmont, Colorado) and AVIRIS images in term of species composition, canopy cover and burn severity (Fig. 2). Later, we used these GPS waypoints to train classification algorithms based on AVIRIS data.

Plot-less sampling is a vegetation sampling method that does not establish a sample plot and therefore without sample plot boundaries. In this technique, communities are not sampled with delimited plots, but with sampling points, one-dimensional transect lines, or certain distances within the stand (Knapp, 1984). Plot-less methods could be thought of as quadrants shrunk to a line or a point of no dimension. With a sufficient number of points, an exact measurement of percent cover of certain species or functional group is possible (Knapp, 1984). At each plot-less sample site, we randomly laid out two 50-m transects at 90° angles to each other, and at each of the three endpoints we recorded burn severity (if there was a recent fire) and canopy cover with a hand-held spherical densitometer (Model-A), using an approach similar to the one we used with the 100 m transects. At these plot-less sample sites, we also estimated percentage of each tree species and coverage of herbaceous plants, litter, and shrubs.

3.2. Field spectra of tree species and fuel related materials

We collected field reflectance spectra of fuel-related materials at the sample sites. We acquired field reflectance spectra of dominant tree species, char wood, bare soil, and various fuel materials from late September to mid-October with a FieldSpec Pro spectrometer (Analytical Spectral Devices, Boulder, CO) over the 400–2500 nm wavelength region at 1 nm intervals. The measurements were made on cloud-free days between 11:00 and 13:00 to closely match the solar geometry of the field measurements with the AVIRIS overflight. The spectrometer was positioned approximately 1 m from the sample surface at a 0° view zenith angle. With the 18° fore-optics on the spectrometer, the diameter of the field of view at

Table 1
Burn severity classification based on both stand damage and ground char (after Omi and Martinson[*], 2002)

Class	Severity	Stand damage	Ground char
0	Unburned	Tree crown unscorched	No evidence of surface fire
1	Light	Partial scorch on at least one tree, but some unscorched	Some small twigs/leaves remain
2	Moderate	Partial scorch on all tree crowns, but few completely scorched	All twigs, leaves, and standing grasses consumed; mineral soil charred
3	Heavy	Nearly all tree crown completely scorched, but few crowns consumed	Mineral soil altered in color or texture
4	Extreme	Nearly all tree crowns consumed	

[*] Omi, P.N. and Martinson, E.J., 2002. Effect of fuels treatment on wildfire severity. Final Report submitted to the Joint Fire Science Program Governing Board. URL: http://www.warnercnr.colostate.edu/frws/research/westfire/FinalReport.pdf.

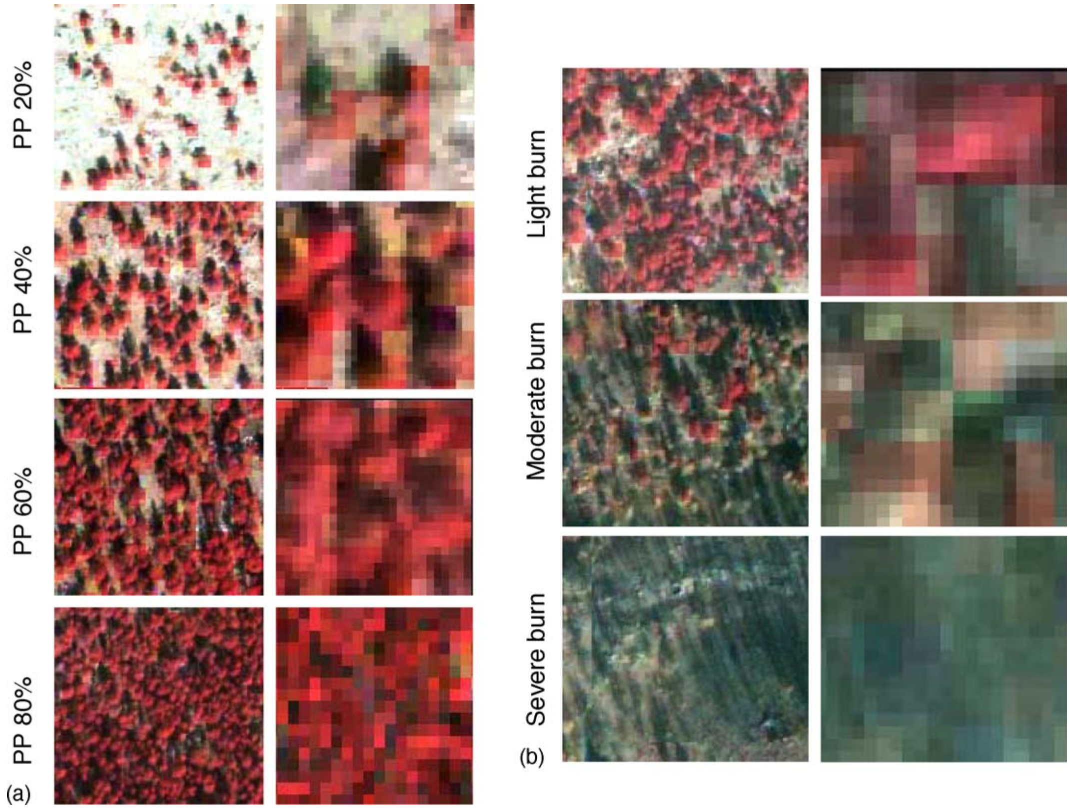

Fig. 2. AVIRIS derived classes of: (a) canopy cover and (b) burn severity as shown on fused 0.7-m QuickBird images over field validation sites. The second column is zoomed in from the center of first column and corresponds to AVIRIS training pixels. Individual live tree crowns (red) and senescent tree crowns (blue–green) are identified with false color composites. Single burned trees (blue–green) are also distinguished on the image. PP: ponderosa pine. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of the article.)

the sample was 28 cm. The sunlight and view angles were chosen to minimize shadowing and to emphasize the fundamental spectral properties of the plant and other materials. We acquired 9–15 spectra of each sample by moving the sensor over the objects to get the average spectra for comparison with the spectra of the AVIRIS pixels. We calibrated the spectrometer prior to measurement of each material using standard protocols (Clark et al., 2003). The spectra collected in the field campaign included live canopy of dominant species of trees, shrubs and herbaceous plants, dead plant materials, charred wood, bare soils and rocks. We averaged together and re-sampled the field reflectance spectra of each endmember (or spectrally pure material) (Adams et al., 1993) to the AVIRIS sampling and bandpass for further processing (Fig. 3).

3.3. AVIRIS data acquisition and processing

High-altitude AVIRIS radiance data (Green et al., 1998) were acquired with an ER-2 plane by NASA's Jet Propulsion Laboratory (JPL) on 15 October, 2002 over the central part of the Pike National Forest. The AVIRIS data for our fuel attributes assessment were acquired through NASA's carbon cycle sciences program upon a data acquisition request. The AVIRIS mission collected data from the wildland/urban interface in the east to the ponderosa pine/Douglas-fir forest in the west, crossing Jefferson County, Park County, and Teller County, Colorado. The flight approximately followed the Front Range from north to south (Fig. 1). The AVIRIS data have approximately 17.5 m spatial resolution, with 224 spectral bands of 10 nm spectral resolution. The swath and length of AVIRIS flight lines are 10.5 and 53 km, respectively in this study. There were patches of snow at high elevation, and the visibility was not limited by clouds or haze.

The AVIRIS data were collected approximately 4 months after the Hayman Fire; this major fire event was one of the dominant features in the images. Due to the frequent recent wildfire in the region, other burned areas and fire-disturbed landscape at different ages were also found across the scenes. During this season, most of the herbaceous species and deciduous trees and shrubs were senescent, making their reflectance spectra maximum contrast with coniferous tree crowns in visible and near infrared wavelengths.

The original JPL AVIRIS datasets were georectified based on aerial photos and USGS 10 m digital elevation model (DEM), and were re-sampled at the same pixel resolution (15 m). The re-sampled AVIRIS datasets were then atmospherically corrected and converted to reflectance using the High-Accuracy ATmospheric Correction for Hyperspectral Data (HATCH) algorithm (Goetz et al., 2003). We merged the five flight lines together to create a mosaic image over our study area.

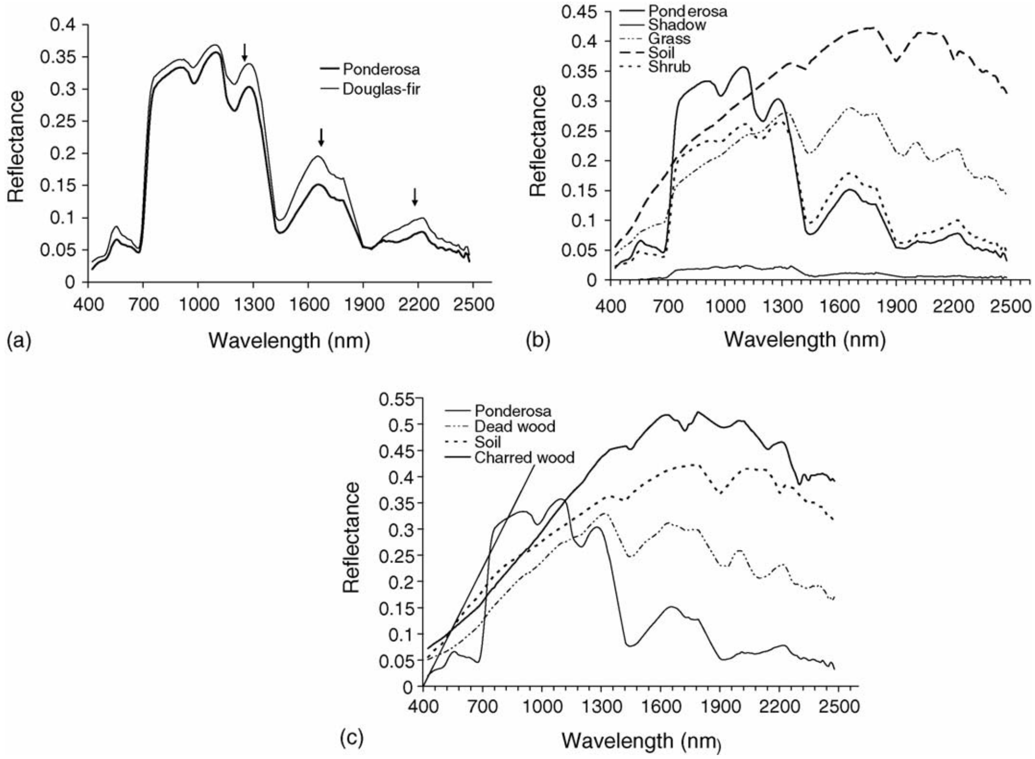

Fig. 3. Spectral reflectance of dominant endmembers and spectral mixtures in the study area: (a) canopies of ponderosa pine and Douglas-fir; (b) common endmembers in a ponderosa pine forest patch showing live tree branch, understory plants, and bare soil; (c) common endmembers in burned forests.

3.4. Spectral analysis and mapping of fuel variables

In most cases, AVIRIS pixels in coniferous forests are a mixture of four ecological entities that we identified as spectral ‘‘endmembers’’ (Adams et al., 1993): live tree crown, understory live plants, dead plant materials (includes litter), and bare soil. In the burned forest, AVIRIS pixels are a mixture of live tree crown, charred tree crown, dead plant materials, and bare soil. Bare soil plays a role as a background spectral signature and often dominates the mixed spectra, while shadow is not as obvious as in conifer pixels. We cannot expect to find pure pixels of conifer crown patches on high-altitude AVIRIS data with 17 m spatial resolution in this region (larger than any single conifer crown, and gaps between crowns). However, the subpixel discrimination capacity of AVIRIS data provides a promising approach for mapping forest type, canopy cover, and burn severity.

We tested the two readily available spectral analysis and mapping techniques, spectral angle mapper (SAM) (RSI, 2004) and mixture-tuned matched filtering (MTMF) (Boardman et al., 1995; RSI, 2004), using the AVIRIS data, with the goal of estimating forest canopy cover, discriminating among the dominant canopy types (Douglas-fir and ponderosa pine), and to assess burn severity, in order to generate the most useful maps for fuel treatment analysis.

We first tested the SAM approach. This is a standard hyperspectral data analysis technique that has been tested for a variety of AVIRIS data (Kruse et al., 1993), and is implemented within the Environment for Visualizing Images (ENVI) software system (RSI, 2004). We used the following steps: (1) a linear transformation (minimum noise fraction, MNF) related to principal components analysis was applied to the original 224 bands to summarize the spectral information in 36 new bands that were orthogonal to one another but maintained 98.8% variability in the dataset, therefore reducing the number of spectral dimensions and any co-linearity in subsequent processing, (2) a pixel purity index (PPI) (RSI, 2004) process was run on the new bands to locate the most extreme (or ‘‘pure’’) pixels that were potentially representative of pure objects such as ponderosa pine tree crown or rock found in image areas. PPI achieved this using convex geometry by determining the edges of the MNF data cloud via multiple rotations of the data: 10,000 rotations were performed here to find the edges. PPI initially screened all the pixels in the image in terms of their relative purity. Based on convex geometry concepts, the PPI method allocated to each pixel in the image a score based on the number of times it was found to occupy a near-vertex position in the repeated projections of the n-dimensional data onto a randomly-oriented vector passing through the mean of a data cloud. The resulting score helped identify image endmembers because those pixels that hold relatively pure spectra will have a high score, (3) the ‘‘pure’’ pixels were used as input to an interactive visualization procedure known as n-dimensional visualization (RSI, 2004) and plotted on original AVIRIS data and GPS/GIS data layers to cross-reference with ground data. Then the resulting clusters of pixels were examined with their key spectral features and compared against field spectral measurements. Through the n-dimension visualization, it became possible to group the pixels in classes based on their clustering in the spectral space. A threshold of 50 pixels or more per group was used to remove dispersed pixels from the selection and to ensure that each cluster of pixels has physical correspondence on the scene, (4) spectral angle mapper classification was performed using the ''pure'' pixels as input classes. This is an automated method for comparing image spectra to reference spectra of input classes. The algorithm determines the similarity between two spectra by calculating the ''spectral angle'' between them, treating the spectra as vectors in a space with dimensionality equal to the number of bands and calculates the angle between them. SAM was run with a maximum angle threshold of 0.10 rad to separate the classes. With this procedure we created maps of nine canopy cover levels in 10% intervals each for ponderosa pine and Douglas-fir dominated forests. Higher canopy cover is characteristic of higher fraction of tree crowns in pixels.

The second spectral analysis technique we tested is the mixture-tuned matched filtering (MTMF). The MTMF is a technique that works by partially unmixing pixel spectra according to user-defined pure spectra. It maximizes the response of a known material (e.g., ponderosa pine canopy) and suppresses the response of the composite unknown background (e.g., shadow, understory vegetation, etc.). Therefore, the technique estimates the abundances of materials at sub-pixel scale within an AVIRIS pixel, and the result is an image showing the abundance (0–100%) of the materials in each pixel and indicating the degree to which the pure material was matched to the pixel spectra and the approximate sub-pixel response of the material (Kruse et al., 1993). With the data products generated from step (3) of the first method as an input layer, we analyzed reference classes of ponderosa pine canopy, Douglas-fir canopy, and charred wood using the MTMF procedure.

We used two approaches to find reference spectra of these conifer species. First, ponderosa pine and Douglas-fir spectra were extracted on AVIRIS images from regions of interest (ROI) corresponding to known pure stands where the transect data indicated these were monospecific patches of either species. Second, the image spectra of those ROIs were extracted and matched with field spectra of the two species. Only matched ROIs were used for further analysis. A series of images was produced for each class where bright pixels indicate high abundance of ponderosa pine or Douglas-fir, and therefore a high MF (matched filtering) score.

We calculated the Pearson correlation coefficient (r^2) to determine the level of agreement between the hyperspectral estimates of total forest canopy cover and field measurements. We also compared AVIRIS estimates of individual tree species cover (ponderosa pine versus Douglas-fir) to measured values. These validation field data came from the non-plot sampling within the image coverage, and the AVIRIS estimates of canopy cover and conifer species were derived from 9-pixel blocks centered at the corresponding field sites.

We spatially summarized the canopy cover over the planned USFS fuel treatment areas and recent fires located within the image and compared canopy cover by species among the areas using ArcGIS spatial analysis module (ESRI, Redland, CA, USA) by overlaying AVIRIS derived maps with the polygons of treatment areas. We also spatially summarized the burn severity in areas of Hayman Fire and Hi Meadow Fire.

4. Results and discussion

4.1. Field and imaging spectroscopy

Theoretically, no pair of materials has the same spectral reflectance in the full range of 400–2500 nm. This is the basis for spectral unmixing techniques (Adams et al., 1993). In field spectra, conifer tree crowns had great contrast with deciduous shrubs (e.g., *Cercocarpus montanus* or mountain mahogany, the most dominant) and grasses (*Bromus tectorum* or cheatgrass), commonly found in canopy gaps (Fig. 3). At wavelengths of 800–850 nm, the peak reflectance of ponderosa pine was 0.35, much higher than mountain mahogany (0.23) and cheatgrass (0.19). High contrast was also located around wavelengths 570 and 1620 nm. The two dominant conifer tree species, ponderosa pine and Douglas-fir have very similar spectral reflectance at a leaf-scale throughout the range. However, with various field spectral samples taken from different locations in the Pike National Forest, we were able to distinguish contrasts of reflectance between the species around three wavelengths, 1240, 1620, and 2200 nm, though the difference was only about 11% on average (Fig. 3a). Visible and near infrared reflectance was lower for ponderosa pine than Douglas-fir. Charred wood is dead woody material; therefore, there was no obvious infrared plateau as found in live plants. In our samples, reflectance of charred wood in infrared bands was about 68% of ponderosa pine. Meanwhile, reflectance of charred wood had a high contrast with standing dead wood and bare soil in the short-wave infrared (SWIR) bands.

Pixels in remotely sensed images are made up of mixed reflectance signals of several pure materials, though strong dominance of one single material is not uncommon (Clark et al., 2003). The dominance of the ponderosa pine signal gradually decreases as canopy becomes more open and the reflectance of understory materials is added into the spectra. In the SAM procedure, this series of pixels was distinguished as a different spectral mixture, whereas in the MTMF procedure this yields a decreasing abundance of the ponderosa pine fraction. Similarly, charred wood is an important part of pixels in burned areas. Forests in different burn severity levels were distinguished with the SAM method as different spectral mixtures with various fractions of charred wood, (e.g., high burn severity is indicated as a spectral mixture with a high fraction of charred wood) but were discriminated by the MTMF method as a different abundance of the charred wood fraction.

As mentioned early, we measured field spectra of tree canopies over the crowns of short trees with a ladder, and harvested tree branches of tall trees and measured them on the ground. Considering the small swath the spectrometer can see, spectra measured with these approaches should be very close to the ones from the top of canopy. However, due to the difference in altitude of sensors and size of measuring units, AVIRIS derived spectra could only match well with field spectra if: (1)

the atmospheric effect of AVIRIS data was corrected using appropriate calibration; (2) an AVIRIS pixel contains a continuous canopy of single species. Here we used the HATCH algorithm to eliminate atmospheric effect and PPI to locate ‘‘pure’’ pixels to match field spectra of referenced species, i.e., ponderosa pine and Douglas-fir in this study. These efforts are critical to make the spectra at different scales more comparable.

4.2. Field validation and comparison between two techniques

To assess the accuracy of AVIRIS derived fraction maps and to evaluate the robustness of SAM/MTMF in the context of conifer forest, field samples were utilized to validate the final results. Despite the growing number of studies on spectral mixture analysis, assessing the accuracy of derived endmember fractions in forest regions through direct quantitative methods is one of the topics that has been remarkably neglected in the present. The difficulty arises from the fact that natural surfaces composed of a single uniform material do not exist in natural forests. This makes it very difficult, if not impossible, to find sufficient ground truth data that can directly be compared against the continuous varying surface of generated endmember fractions over large areas. The alternative solution is to compare the agreement of derived endmember fractions with estimates of fractions derived independently by another method, e.g., field measurements. Here we examined the agreement of AVIRIS derived fuel attributes with estimates from field sampling.

We compared AVIRIS-derived canopy cover, dominant species, and burn severity with the variables measured in the field. The modeled variables from the two spectral analysis techniques were compared against correspondent measured values separately (Fig. 4). Total canopy cover estimated with the SAM technique had an agreement of $r^2 = 0.61$ with measured values, much lower than the results from the MTMF method ($r^2 = 0.78$). It demonstrated that the capacity of sub-pixel unmixing by MTMF is more promising for estimating the abundance of dominant tree canopy than SAM techniques, which has some limitations in discriminating tree canopies from highly heterogeneous background. By examining the grey-scale images derived from AVIRIS and validation plots, we found that areas detected by SAM as dense canopy also have high canopy cover in the MTMF-derived image (Fig. 5), and that both techniques underestimated canopy cover to some extent. However, SAM yielded a greater underestimate at high values (i.e., over 60%) than MTMF. This may have been caused by intrinsic insensitivity of SAM algorithm when handling dense canopy; nevertheless, it indicated that the algorithm is less accurate than MTMF with canopy cover.

The abundance of the two conifer species distinguished with the SAM technique had agreement of $r^2 = 0.57$ with field data, slightly higher than that from the MTMF method ($r^2 = 0.53$, data not shown). In general there was relatively high agreement between observed and predicted canopy cover when the MTMF method was used. The SAM method, however, is more promising for separating the two tree species. Both SAM and MTMF yielded reasonable separation of ponderosa pine and Douglas-fir, with SAM slightly advanced, however, the agreements for species discrimination were not as high as those for canopy cover. The lack of enough sites with large values for these two variables limits the generality of the relationships we found. We suggest that these results indicate evidence of AVIRIS’s capacity to provide estimates of canopy cover and tree species, but additional training for more generalized field spectra for both species, especially spectral measurement over tree crowns, are needed to more accurately separate ponderosa pine from Douglas-fir.

Burn severity derived from the SAM technique had agreement of 87% with measured classes, whereas the value dropped to 64% for MTMF method (Table 2). However, if we exclude the class of ‘‘unburned’’, the agreements for the SAM technique and the MTMF technique were 71% and 55%, respectively.

In general there was relatively high agreement between observed and predicted canopy cover when the MTMF method was used. The SAM method, however, yielded higher agreement for detecting burn severity. Meanwhile, the differences attributed to SAM and MTMF may have been partly caused by endmember selection techniques. PPI selects

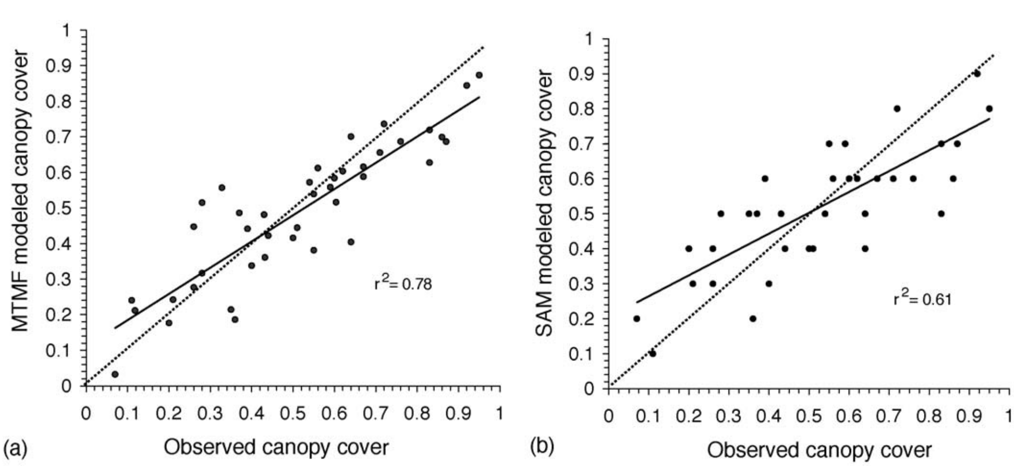

Fig. 4. Comparison of measured and modeled forest canopy cover from test sites. The dotted lines represent the 1:1 lines where observed equal predicted values.

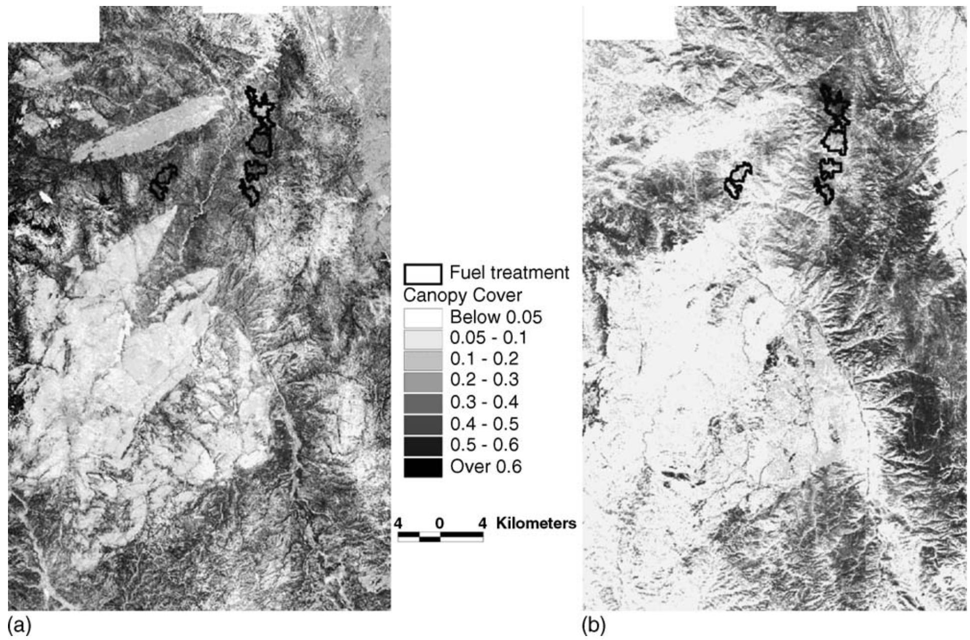

Fig. 5. AVIRIS derived map (grey scale) of: (a) ponderosa pine canopy cover and (b) Douglas-fir canopy cover classes in central Pike National Forest. The map was generated with mixture-tuned matched filtering spectral analysis and classification, and was validated with ground forest inventory. Darker colors represent higher cover values, and values range from 0 to 1. The black polygons represent US Forest Service treatment areas, and perimeters of recent fires are shown in Fig. 1.

the ‘‘most extreme’’ endmembers, while the endmember selection technique used for MTMF would tend to produce more ‘‘representative’’ endmembers. Both field spectra endmember and image spectra endmember have advantages and disadvantages. Field measured spectra tend to ignore the scattering within tree canopies and underestimate the endmember, while image spectra are often mixed with background signatures such as dead branches in tree crowns, and lead to overestimate the endmember. In this case, scattering effects and background spectra are likely the most important sources of error in the SAM and MTMF processes, and not the algorithms themselves.

4.3. Map of fuel attributes and burn severity

We generated a series of maps of canopy cover by dominant tree species from the MTMF spectral analysis procedures (Fig. 5). We then categorized the continuous canopy cover layers into an eight-class forest map based on a US Forest Service forest stand classification system (Kaufmann, Unpublished). The classification separated openings (0–5% canopy cover), scattered woodland (5–10%), woodland (10–30%), and forest (>30%) by dominant species. In these AVIRIS derived fuel attribute maps, 13.2% of the study area had over 60% canopy cover, generally at high risk for crown fire. The average canopy cover over the mixed conifer forest landscape was approximately 38.6%. Of this, ponderosa pine contributed 24.7% and Douglas-fir contributed 13.9%. Canopy cover of both tree species varied substantially across the study region, showing important trends with respect to fire hazard and with respect to fire response. For example, the average canopy cover in the Buffalo Creek fire area was only 13.1% after a 6-year recovery (largely the result of small patches of surviving trees), 40.3% lower than the adjacent unburned Dell Gulch watershed. We were also able to use our maps to assess the appropriateness and effectiveness of fuel treatments planned by the US Forest Service and others in a number of areas, two of which are shown in Fig. 1 (North plan, NE plan). Comparing the two planned areas, the northeast area may merit slightly higher priority (other things being equal), according to our remotely sensed data and analysis (Fig. 6). First, it has a slightly higher total canopy cover and considerably higher Douglas-fir fraction than

Table 2
Confusion matrix for agreement between AVIRIS estimates of burn severity and measured burn severity classes

Severity classes	Low		Moderate		High		Unburned		Total	
	SAM	MTMF	SAM	MTMF	SAM	MTMF	SAM	MTMF	SAM	MTMF
Low	79.7	56.2								
Moderate			73.1	61.7						
High					87.4	83.5				
Unburned							95.7	77.8		
Total									86.8	64.4

Low refers to light, and high refers to heavy and extreme in field burn severity measurements.

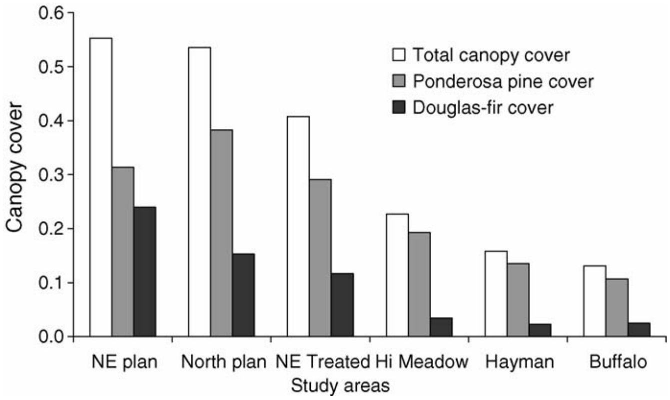

Fig. 6. Distribution of canopy cover of ponderosa pine and Douglas-fir in US Forest Service fuel treatment areas (planned and treated) and recent fires. The *y*-axis represents proportion.

the north area, and therefore is likely to be more vulnerable to wildfire. Second, the northeast area and surrounding landscape has a high Douglas-fir component compared to the north area, which is located between large openings created by Hayman fire and Buffalo Creek fire. Mechanical thinning in the northeast area (NE treated in Figs. 1 and 6) has reduced canopy cover by 25% (mostly small trees). This practice has eliminated some ladder fuels and reduced the chance of crown fire spread.

Four levels of burn severity were distinguished and mapped with the spectral reflectance derived from AVIRIS images. In two recent fires, forests with high, moderate, and low burn severity covered 39.4%, 28.7%, and 20.9% of the landscape, with only 11.2% unburned area (Fig. 7 and Table 3). In the Hi Meadow Fire, a larger percentage (75.9%) burned at moderate and high severity than in the Hayman Fire (60.1%). However, the Hayman fire was much larger and caused more severe effects at a landscape scale (Romme et al., 2003a,b).

Both AVIRIS and burn area emergency rehabilitation (BAER) maps suggest more residual live canopy cover in severely burned areas than is actually present (Table 3). BAER maps are created from satellite imagery immediately after fires. We found in a recent field validation trip that many burned areas have absolutely no surviving overstory in Hayman Fire area even after about 3 years. Therefore, we must take into account that when both the AVIRIS and BAER data were gathered, it

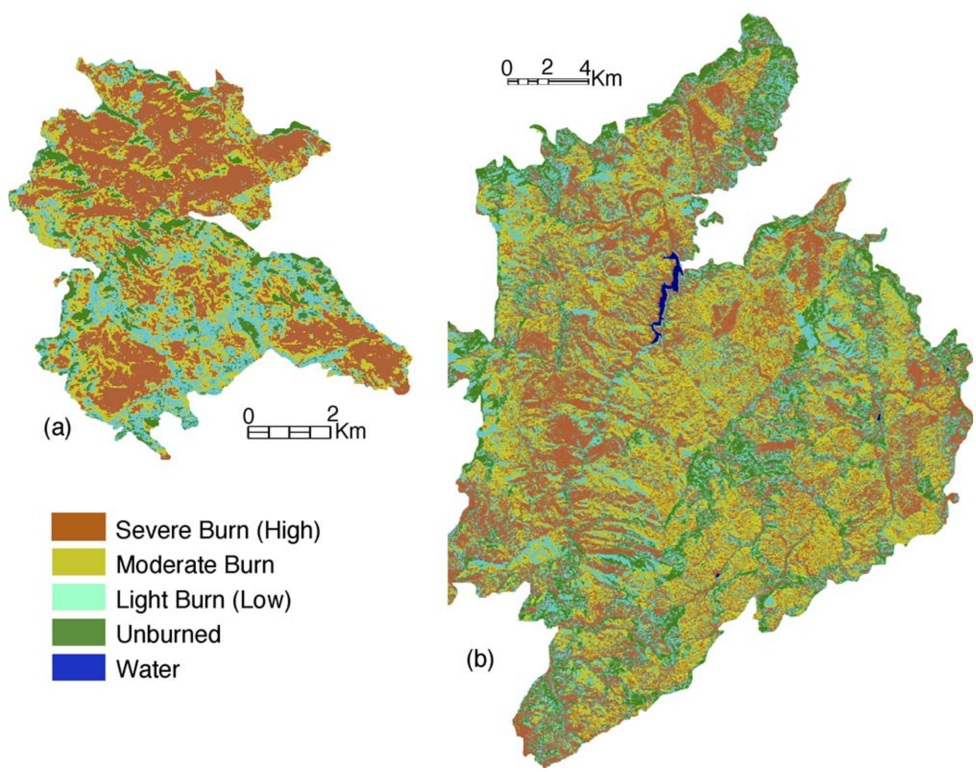

Fig. 7. AVIRIS derived map of burn severity in: (a) 2000 Hi Meadow and (b) 2002 Hayman burn areas. The map was generated with spectral angle mapper classification, and was validated with ground forest inventory.

Table 3
Area in each AVIRIS-derived burn severity class for recent fires in south Platte, and comparison with burn area emergency rehabilitation (BAER) burn severity classes

Fire	Area (km)	AVIRIS burn severity (%)				BAER burn severity (%)			
		Unburned	Low	Moderate	High	Unburned	Low	Moderate	High
Hayman	556.0	12.1	27.8	22.5	37.6	15.5	33.8	15.8	38.9
Hi Meadow	48.2	10.2	13.9	34.8	41.1	2.0	0	53.0	45.0
Summary	604.2	11.2	20.9	28.7	39.4	8.8	16.9	34.4	42.0

was too soon after the fire to be sure trees were alive or dead (and in fact many were dead).

5. Conclusions

This study considered the performance of spectral analysis techniques for estimating fire related forest attributes. We combined forest inventory and field spectroscopy in the Colorado Front Range with airborne imaging spectrometer measurements of the region to estimate canopy cover, tree species fraction, and burn severity in ponderosa pine/Douglas-fir forest. Douglas-fir is much more fire sensitive than ponderosa pine and other conifer species in this type of forest and is also more susceptible to insect herbivores and harmful pathogens that can spread to other trees in the forest (Keane et al., 1990). The rise of Douglas-fir fractional cover due to long-term fire suppression practice increases fire potential and fuel load. Therefore, identifying Douglas-fir and ponderosa pine and estimating their fractional canopy cover are of increasingly importance in fire mitigation in the west.

Our results demonstrated that spectral mixture analysis approaches, such as the ones employed in this study, offer the capacity to assess important fuel attributes including canopy cover, species composition, and burn severity over montane conifer forests. The spectral angle mapper technique performed well in estimates of burn severity, while the mixture-tuned matched filtering method is more promising for estimates of forest canopy cover. Further improvement of the techniques will rely on a field spectra database that considers all possible internal variance of endmembers. The results of spatial analysis based on AVIRIS derived fuel attributes also show that average canopy cover in ponderosa pine dominated forests is lower than in Douglas-fir dominated forests, and that recent wildfires have created approximately 684 km^2 of openings in the region, yet more than 10% of the area within fire perimeters is still covered by continuous dense forests.

Practically, combining these fuel attributes derived from AVIRIS can provide important insights for priority fuel treatment areas. When the maps of these fuel attributes derived from spectral analysis are integrated with fire behavior modeling (Mbow et al., 2004), large-scale fire risk assessment can be improved with respect to detailed fractional fuel structure. The system in which we worked is one of the dominant forest types in the Western US, present from New Mexico to Montana. Further, the techniques tested in the study are highly transferable to other coniferous forests, if localized field spectra and parameters for spectral analysis are properly provided. The limitations of AVIRIS are that it is only available in small areas upon request and that data processing requires special expertise and software. The spectral analysis techniques for assessing forest fuel attributes tested here, though applied to AVIRIS data, could be applied with Hyperion, or future spaceborne hyperspectral instruments.

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