Mapping ground cover using hyperspectral remote sensing after the 2003 Simi and Old wildfires in southern California

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Submission to: a special issue of the Journal of Fire Ecology—from the Association for Fire Ecology Fire Management Congress, November 2006

ABSTRACT

Wildfire effects on the ground surface are indicative of the potential for post-fire watershed erosion response. Areas with remaining organic ground cover will likely experience less erosion than areas of complete ground cover combustion and/or exposed mineral soil. The Simi and Old Fires burned ~67,000 ha in southern California in 2003. Burn severity indices calculated from pre- and post-fire multispectral imagery were differenced (i.e., dNBR) to highlight fire-induced changes in soil and vegetation. Aerial and field hyperspectral data were also collected together with field ground cover measurements soon after the Simi and Old Fires. Spectral endmembers representing charred and uncharred soil and rock, and green, non-photosynthetic, and charred vegetation were used in a constrained linear spectral unmixing process to determine the post-fire fractional ground cover of each surface component. The spectral unmixing results, dNBR, and Relative dNBR (RdNBR) were validated using fractional ground cover estimates from the field to see which product best represented the conditions on the ground. The spectral unmixing results were significantly correlated to all classes of charred and uncharred organics and inorganics, and the dNBR was the best indicator of charred soil and green vegetation. The RdNBR had several significant correlations with the ground data, yet did not consistently correlate well with any specific ground cover types. A map of post-wildfire ground cover and condition, especially soil and remaining vegetative cover, is a good indicator of the fire's effect on the ground surface and the resulting potential for hydrologic response.

Keywords: Hyperspectral; burn severity; remote sensing; southern California wildfires; spectral mixture analysis; dNBR; Relative dNBR

INTRODUCTION

Post-wildfire maps are created from remotely sensed data as soon as the fire is out to capture immediate post-fire conditions of soils and vegetation. These maps are commonly referred to as burn severity maps and are primarily used to assist rapid-response rehabilitation crews assess the immediate and long-term fire effects on vegetation, soil, and related ecological processes (Lentile *et al.*, 2006). Standard burn severity mapping methodologies are based upon the classification of spectral indices (such as the Normalized Burn Ratio, or NBR) calculated from differenced pre- and post-fire multispectral satellite imagery (Key and Benson, 2002; Clark *et al.*, 2003). For these burn severity maps, the landscape is classified into categories of unburned, low, moderate, and high, corresponding to the relative magnitude of change in the post-wildfire appearance of vegetation, litter, and soil (Miller and Yool, 2002; Lentile *et al.*, 2006; Lutes *et al.*, 2006).

Effects of fire on the ground surface with erosion-related implications include an increase in exposed soil and ash and a decrease in protective ground cover such as litter and duff. This post-fire organic ground cover, whether charred or uncharred, can provide protection against soil erosion (Ice *et al.*, 2004; Kokaly *et al.*, 2007). Conversely, areas with exposed mineral soil or ash cover are at an increased risk for erosion by wind and water (DeBano, 2000; Robichaud, 2000; Ravi *et al.*, 2006). Ash cover is indicative of complete organic material combustion. Because water repellent soils may be formed when these organic materials burn on the soil surface, water repellent soils are often found where post-fire ash cover is high (Lewis *et al.*, 2006). Additionally, fire-induced water repellent soil conditions occur when waxy chemicals from plant materials are volatilized during burning coat coarse-textured soil particles at or near the soil surface, which is common in chaparral communities (Barro and Conard, 1991; CDF 2003; Hubbert *et al.*, 2006). Fire can also strengthen and drive a naturally-occurring water repellent soil layer deeper into the soil profile (DeBano, 2000). Fire-induced or enhanced soil water repellency may allow the top 1-5 cm of the soil profile above the water repellent layer to hold water, but once this wettable layer becomes saturated, erosion is likely, particularly on steep slopes with coarse-textured soils coupled with intense rainfall.

The chaparral community is a shrubby, sclerophyllous vegetation type that is common in middle elevations throughout much of California (Barro and Conard, 1991). Common chaparral trees and shrub genera include *Adenostoma, Arctostaphylos, Ceanothus, Cercocarpus, Prunus, Quercus*, and *Rhamnus.* Chaparral vegetation is well adapted to frequent fires that were historically common in the area. Chaparral plant adaptations include rapid post-fire root sprouting, prolific seeding, seed banking, fire-stimulated seed germination, and allelopathy (Hanes, 1977; Keeley, 2006a). Frequent fire results in conversion of shrub-dominated systems to those dominated by a mix of alien annual grasses and forbs from the Mediterranean Basin. Ground cover is relatively sparse when shrubs are dominant, and forb (e.g. *Phacelia, Penstomen, Mimulus* spp.) and grass species are more common in these systems following fire (McAuley, 1996). Following fire the presence of native forbs (e.g., *Phacelia* spp., *Penstomen* spp., *Mimulus* spp.) and grasses (e.g., *Nassella* spp., *Avena* spp., and *Bromus* spp.) tend to be ephemeral (< 2 years), while non-native post-fire invaders (e.g., *Bromus diandrus* (rip-gut brome), *Bromus tectorum* (cheatgrass), *Centaurea solstitialis* (yellow-star thistle), *Erodium* species (filaree), and *Trifolium hirtum* (rose clover) may persist longer (Keeley, 2006b).

Because many chaparral fires occur near homes and other resources in the wildland urban interface in southern California, agencies are often obligated to aggressively pursue fire suppression and rehabilitation activities. Post-fire rehabilitation treatments include seeding, used as a soil stabilization measure, to reduce soil erosion and the threat of debris flow and flooding. Several studies have shown that these measures do not always substantially reduce erosion or flooding (Robichaud *et al.*, 2000; Beyers, 2004), and that native flora may be displaced by non-natives accidentally introduced into seed mixes (Keeley, 2006b). A combination of pre-fire vegetation conditions, soil texture, fire intensity, and post-fire weather events can complicate post-fire mitigation decisions.

One key difference between chaparral and forested ecosystems is the density of pre-fire vegetation. Chaparral systems have more open canopies and tend to have less litter accumulation on the ground than in a typical coniferous forest. This creates a unique situation when classifying the severity of the fire using a differenced index (dNBR) which is dependent on the magnitude of change from pre- to post-fire condition (Miller and Thode, in press). Where vegetation is sparse, the complete removal of vegetation due to fire will be classified as high burn severity, even though the relative change to the pre-fire condition is not as great and the effects on the soil are also likely not as severe. This potentially leads to unnecessary treatment for erosion mitigation based on the perceived burn severity, rather than the physical alteration of the soil. Miller and Thode (in press) have recently proposed a new index, the Relative dNBR or RdNBR which takes into account the relative pre-fire to post-fire change in amount of vegetation across the landscape. They suggest that this relative index may be more appropriate than the dNBR for mapping sparse vegetation or mixed vegetation types.

Higher spatial and spectral resolution airborne hyperspectral data also have the potential to improve upon traditional burn severity maps by providing fine-scale quantitative information about post-fire ground cover and condition (Robichaud *et al.*, in press). Rather than applying a discrete classification to an area, a final product from hyperspectral imagery can provide an estimate of the percent remaining of post-fire charred ground cover and ash for an area (pixel) as small as 4 or 5 meters. This information may be helpful in guiding post-fire assessment to determine locations to apply rehabilitation treatments by better quantifying the effects of the fire on the soil surface.

The reflectance from a specific image pixel is a mixture of the individual reflectance spectra (endmembers) of the mix of surface materials (Adams *et al.*, 1985; Smith *et al.*, 1990; Roberts *et al.*, 1993). Each pixel retains the characteristic features of the individual spectra from each of the component reflective materials. Once endmember spectra are identified, spectral unmixing of individual pixels can estimate the fractional component spectra and, in turn, the physical fractional component of the materials within the pixels (Adams *et al.*, 1985; Roberts *et al.*, 1993; Theseira *et al.*, 2003). Most rural landscape scenes can be mapped as endmember combinations of green vegetation, non-photosynthetic vegetation, soil and rock, and shade (Roberts *et al.*, 1993; Adams *et al.*, 1995; Theseira *et al.*, 2003). More specifically related to fire, hyperspectral imagery has been used to map fractional cover of ash, soil, green and non-photosynthetic vegetation in post-fire scenes (Jia *et al.*, 2006; Kokaly *et al.*, 2007; Robichaud *et al.*, in press). Our objectives were to assess the potential of hyperspectral imagery to provide a better estimate of post-fire soil condition, particularly the amount of high soil burn severity, than had been achieved with traditional multispectral imagery.

METHODS

Study area

The Simi and Old Fires were two of several large wildfires that burned throughout southern California during the fall of 2003 (Figure 1). These fires threatened thousands of homes and impacted air and water quality throughout the region. The Simi Fire began on 25 October 2003 and burned 43,800 ha in Ventura and Los Angeles counties, before being contained on 2 November 2003 (Clark *et al.*, 2003). Driven by strong Santa Ana winds, the fire jumped State Highway 126 and burned around the densely populated towns of Simi Valley, Moorpark and Saticoy, California. The Simi Fire burned in a mix of vegetation types including chaparral (the dominant vegetation type), coastal sage scrub, and annual grasslands and across a diversity of topographic conditions including sandy, rolling hills and very steep, rocky terrain. The underlying bedrock in the area is comprised of sedimentary rock, with overlying sandy loam soils (USDA, 2006). The soils and rock are light colored, and large patches of rocky outcrops are common. Immediately post-fire, a burn severity map for the Simi Fire was created from post-fire airborne multispectral MASTER imagery (masterweb.jpl.nasa.gov) acquired on 1 November 2003 (Clark *et al.*, 2003). The majority of the area within the Simi Fire perimeter was burned at low or moderate severity, and BAER (Burned Area Emergency Response) teams in the field reported that the burn severity map was generally representative of the conditions observed on the ground (CDF, 2003; Clark *et al.*, 2003). However, several watersheds were assessed as having burned at higher severity than indicated on the map and were identified as areas at risk for increased post-fire erosion and debris flow (Cannon *et al.*, 2003; CDF, 2003). The BAER assessment team also noted the presence of white ash in severely burned areas and therefore the potential presence of water repellent soils (CDF, 2003).

The Old Fire began on 28 October 2003 and burned 23,300 ha north of San Bernadino, California. The Old Fire burned in chaparral and interior woodland vegetation, also on rough terrain. The Old Fire burned more in the wildland urban interface than did the Simi Fire, as the area around Lake Arrowhead is densely populated, with homes deep in the wooded areas, which have suffered from a serious mountain pine beetle outbreak. The combined effects of frequent human and natural ignitions, hot dry summers, frequent and extended droughts, the high flammability of chaparral vegetation, and forest trees killed by bark beetles, make these ecosystems extremely susceptible to intense crown fires (Barro and Conard, 1991; Keeley, 2000; Keeley and Fotheringham, 2001). The immediate post-fire burn severity map for the Old Fire was created from post-fire MODIS imagery that was acquired on 5 November 2003 (Clark *et al.*, 2003). These burn severity maps were used in the BAER team's assessment of the potential for increased runoff and erosion and to guide post-fire rehabilitation activities. These maps were also used to guide our field site selection, but were not used in any subsequent analyses.

Field data collection

Post-fire soil and vegetation data were collected in December 2003 at six sites on each fire. These sites were selected using the immediate post-fire burn severity maps as a guide and classified by observation in the field as low, moderate, or high severity if tree/shrub crowns were predominantly green, brown, or black, respectively. On the Simi Fire, two sites we sampled were classified as low burn severity, three as moderate and one as high. On the Old Fire, one site we sampled was classified as low burn severity, three as moderate and two as high. These burn severity classes were only used as a general guide to ensure that the field data covered the full range of burn severity conditions within each fire. More low and moderate burn severity sites were selected at each fire because, as found elsewhere, these sites showed more spatial heterogeneity in fire effects than the high severity sites (Hudak *et al.*, 2004). Each site was centered in a random location 80–140 m from the nearest access road, within a consistent stand and burn severity condition. Each site consisted of nine 9 m x 9 m (figure 2 says 8x8 – need to clarify center to center or edge to edge) plots and each plot was comprised of fifteen 1 m x 1 m subplots, for a total of 135 subplots (Figure 2). Plot centers were geolocated with a Trimble GeoExplorer (trade names are included for the benefit of the reader and do not imply endorsement by the US Department of Agriculture or the University of Idaho) and differentially corrected. Subplot centers were positioned with measurement tape and compass based on systematic distances and bearings from plot center (see detailed description in Hudak *et al.*, 2004 or Hudak *et al.*, this issue).

At the subplot scale, the fractional cover of vegetative cover and percent char of green vegetation, rock, mineral soil, ash, litter (new and old), and any large organic matter (logs, branches or stumps) were ocularly estimated. Minor ground cover fractions were estimated first, and a value of one percent was recorded if there was a trace of the material within the subplot. The more abundant fractional ground cover components (often exposed mineral soil and rock, ash, and litter) were then estimated in 5% increments with the largest cover component estimated last. All cover fractions were required to sum to unity. Exposed mineral soil and rock were considered ground cover for the purpose of accounting for all physical space within a plot. New litter, mostly fallen leaves and needles from scorched shrubs and trees, was estimated separately from the other cover fractions present at the time of the burn, to best capture the ground conditions immediately after the fire. Thus, new litter was not included in the cover fractions that summed to unity. At the center of each site, the depth of new litter (deposited post-fire), old litter, and duff were measured, a convex spherical densiometer was used to measure canopy cover (if any), and a digital photo was taken for reference.

Remotely sensed data collection

Field spectra: Multiple spectra of soil, rock, and green, non-photosynthetic vegetation (NPV), and charred vegetation materials were collected in December 2003 after both the Simi and Old Fires using an ASD (Analytical Spectral Devices, Boulder, Colorado, USA) Pro-FR field spectroradiometer. Spectra were collected with the bare tip foreoptic (FOV 22°) pointed at the target material. The ASD Pro-FR reports reflectance in 2151 channels spaced contiguously at 1 nm intervals over the 350 to 2500-nm wavelength range, spanning nearly the same portion of the electromagnetic (EM) spectrum as the Probe I sensor used for airborne imaging. The field spectrometer was calibrated against a Spectralon (Labsphere, North Sutton, New Hampshire, USA) 100% reflective panel immediately before and at frequent intervals during field spectra collection. Spectralon is a bright calibration target with well-documented reflectance in the 400 to 2500-nm region of the EM spectrum, and is used to convert relative reflectance to absolute reflectance. Representative spectra from the Old Fire are shown in Figure 3.

Airborne hyperspectral: Airborne hyperspectral imagery, which covered the range of burn severities observed and included all field sites, was collected on 4 January 2004. One flight line of data was collected over the Simi Fire (Figure 4) and five flight lines of data were collected over the Old Fire (Figures 5). The Probe I whisk-broom sensor (Earth Search Sciences Inc.(ESSI), Lakeside, Montana, USA) was flown at 2100 m above ground level and data were collected along a track ~28 km long and 2.3 km wide, corresponding to a 512 pixel-wide swath with each pixel 4.2 m by 4.2 m at nadir. Reflected EM energy from the surface was received in 128 contiguous spectral bands that spanned 432 to 2512 nm, with a spectral bandwidth of 11 to 19 nm.

Radiometric pre-processing: The airborne hyperspectral data were converted to reflectance using ACORN (Atmospheric CORrection Now) without any additional artifact suppression (ACORN version 5, Analytical Imaging and Geophysics, 2002). These reflectance data were further refined with a radiative transfer ground-controlled (RTGC) calibration (Clark *et al.*, 2003). This process involved calculating a multiplier from the differences between the mean image-reflectance spectrum over the area where bright target calibration field spectra were collected and the corresponding average field-reflectance spectrum. The multiplier was then applied to the ACORN corrected image-reflectance data (Clark *et al.*, 2003).

Geometric pre-processing: An on-board global positioning system (GPS) and inertial measurement unit (IMU) acquired geolocation data that were matched with the spectral data. The geolocation data, together with a 30-m digital elevation model, were used to generate Input Geometry (IGM) files for georeferencing the imagery. The RTGC reflectance images were georeferenced using these vendor-supplied IGM files. Upon examination, however, these georeferenced images were found to be distorted by up to seven pixels (~30 m). The IGM solution files were unable to rectify even larger, systematic distortions in the underlying imagery delivered by ESSI. Therefore, we rubber sheeted the IGM output images to a 1-m resolution digital orthophoto mosaic produced in ERDAS Imagine (version 8.7), from digital orthophoto quads downloaded from the California Spatial Information Library (http://archive.casil.ucdavis.edu/casil/remote_sensing/doq). Rubber sheeting requires a dense, systematic grid of image tie points, which were obtained using an automated, area-based correlation algorithm coded in Interactive Data Language (IDL) by Kennedy and Cohen (2003). The program allows the user to specify the size and spacing of the image analysis window, define multiple levels of pixel aggregation, and set scale factors to zoom in and more precisely designate tie points. After manually defining a single image tie point in each flight line to provide the program with a starting reference point, the program generated all the rest in a systematic grid across the image. The same parameters were used to produce 810 tie points for the Simi image strip, and between 323 and 647 for the five Old image strips, with the number varying as a function of the length of the flight line. The output ASCII files contain the X and Y coordinates of the tie points from the input and reference images, which can be imported directly into the Imagine georectification utility for rubber sheeting. Each image strip was resampled to a 4 m resolution using cubic convolution resampling. The five rectified images at the Old fire were then mosaicked using nearest neighbor resampling, also in Imagine. Finally, the geolocation accuracy of the rectified Simi fire flight line and Old fire mosaic was verified using approximately a dozen differentially-corrected GPS points collected in the field at the middle of road intersections near our field sites. All of these GPS points were centered where they ought to have been, when displayed over the rectified imagery. We are confident that all of these preprocessing steps produced the fully radiometrically and geometrically rectified hyperspectral imagery desired for this analysis.

Landsat multispectral: Landsat ETM+ data were obtained for the purpose of comparing immediate dNBR and RdNBR index values to the hyperspectral image analysis results. For the Simi Fire, the pre-fire Landsat scene was collected on 12 September 2002 and the post-fire scene was collected on 10 November 2003. For the Old Fire, the pre-fire scene was collected on 7 October 2002 and the post-fire scene was collected on 19 November 2003. The images were provided by the USFS Remote Sensing Applications Center and had been already orthorectified, calibrated, and converted to top-of-atmosphere reflectance.

DATA ANALYSIS

Ground data

The soil and vegetation data were combined into four categories: uncharred organics (e.g., green vegetation and NPV), charred organics (burned shrub stems, grasses, and leaves and needles), uncharred inorganics (rocks and soil), and charred inorganics (rock, soil, and ash) (Table 1). These classes broadly relate to burn severity and erosion potential as post-fire organic ground cover decreases erosion potential by protecting the soil.

Remotely sensed image data

Hyperspectral image analysis: A linear spectral unmixing algorithm was applied to the fully pre-processed hyperspectral data to determine pixel fractions of green vegetation (grveg), charred vegetation (charveg), and uncharred (soil) and charred (charsoil) inorganic ground cover:

$$\rho_{pixel} = \sum\{\rho_e C_e\} + \varepsilon = \{\rho_{grveg} C_{grveg} + \rho_{charveg} C_{charveg} + \rho_{soil} C_{soil} + \rho_{charsoil} C_{charsoil}\} + \varepsilon$$

$$\sum C_e = 1.0 \qquad \text{(Eq. 1 and 2)}$$

where ρ and C are the reflectance and cover fraction of each endmember, respectively, and ε is an error term. The sum of the individual cover fractions sum to unity in Eq. 2. The field spectra used as endmembers are shown in Figure 3. A single image pixel is a mixture of the sum of the individual reflectance spectra (endmembers) of the component reflective surface materials (Adams *et al.*, 1985; Smith *et al.*, 1990; Roberts *et al.*, 1993). Once endmember spectra are identified, spectral unmixing of individual image pixels can estimate the fractional component spectra and, in turn, the physical fractional component of the materials (Adams *et al.*, 1985; Roberts *et al.*, 1993; Theseira *et al.*, 2003). The product of the spectral mixture analysis (SMA) is a fractional cover image for each the input materials, which are scaled from 0 to 1. Zero indicates that none of the target material is present in the pixel, while 1 indicates complete cover. In addition to the fractional cover images, a root mean square error (RMSE) image is also produced. This gives an indication of the degree to which the input endmembers matched the extent of the materials on the ground. The RMSE was 0.04 or less across both fire images, indicating that these endmembers were most likely indicative of the ground cover types in the image.

Landsat data analysis: Landsat data (bands 4 (B4) and 7 (B7)) were used to calculate the Normalized Burn Ratio (NBR) index (Eq. 3), the delta Normalized Burn Ratio (dNBR) (Eq. 4) (Key and Benson 2002) and the Relative dNBR (RdNBR) (Eq. 5) (Miller and Fites 2006). The index values were extracted at the plot locations on both fires and were compared to the ground data.

$$NBR = (B4 - B7)/(B4 + B7) \quad \text{(Eq. 3)}$$

$$dNBR = NBR_{pre} - NBR_{post} \quad \text{(Eq. 4)}$$

$$RdNBR = (NBR_{pre} - NBR_{post}) / \sqrt{(|NBR_{pre}|/1000)} \quad \text{(Eq. 5)}$$

Endmember fractions were extracted from the unmixed hyperspectral and Landsat images at all subplot locations (i.e., 135 per site). These subplot values were aggregated to the plot scale, i.e., 15 subplots to a plot, resulting in 9 plots per site and 54 plots per fire. The spectral fractions and Landsat spectral indices (NBR, dNBR, RdNBR) were compared to the field-measured fractional cover estimates to evaluate how well the image captured the conditions on the ground. Correlations were assessed for each endmember using the Pearson correlation statistic (SAS Institute Inc., 1999) at the subplot (not aggregated) and plot (aggregated) scales.

RESULTS

As burn severity increased, inorganic cover increased and organic cover decreased as expected (Table 1). The sparse vegetation conditions are illustrated by less than 50% organic ground cover on the low burn severity plots after both fires. On the plots burned at high severity, organic ground cover was only ~5%.

Correlations between ground data and remotely sensed data

The spectral fractions from the hyperspectral SMA were significantly correlated to the corresponding ground cover fractions (Table 2). The strongest correlation for both fires was between the green vegetation endmember and the field-measured uncharred organic ground cover (r = 0.67, Simi Fire and r = 0.47, Old Fire). Green vegetation was spectrally distinct in the image and well-matched to the green vegetation field spectrum used as an endmember. On the Simi Fire, charred organics (r = 0.26) and inorganics (r = 0.27) had the lowest correlations between the ground and SMA data. Stronger correlations were found with the Old Fire data, r = 0.38 for the charred organics and r = 0.48 for the charred inorganics. Similar correlations were found for the uncharred inorganics on both fires, r = 0.41 on the Simi Fire and r = 0.37 on the Old Fire.

For comparison, correlations between the ground data and the Landsat-derived dNBR and RdNBR were also calculated (Table 2). As expected, the strongest correlations were found for the satellite imagery with for uncharred organics and charred inorganics because of the greater abundance of these cover types in unburned/low burn severity and high burn severity areas, respectively. Lower overall correlations were found between the other ground cover classes and the dNBR and RdNBR values (Table 2). Charred organics and uncharred inorganics do not singly represent a burn severity class, or a specific degree of change from pre-fire conditions and are found in mixed quantities across the spectrum of burn severity. Therefore, we did not expect that these cover types would be highly correlated with indices that indicate degree of change from pre-fire conditions, such as a burn severity class.

Spectral mixture analysis images

The spectral mixture analysis results for the Simi Fire are shown in Figure 4. In Figure 4a, charred vegetation is shown as red, green vegetation as green, and uncharred soil as blue. This image is a relatively small subset (~15%) of the Simi Fire, however all burn severity conditions are included, as well as some unburned areas at the very north and south ends of the image. Charred vegetation is present across the entire image, much of it mixed with soil, and shows as a purple or magenta color. The only green vegetation in this subset of the fire is in some very discrete areas, mostly in valley bottoms. Large patches of bright blue are rocky outcrops and the darkest areas are topographic shadows. Figure 4b is similar to Figure 4a, however, the red color is charred soil rather than vegetation. This is shown to highlight the similarity of the charred soil and vegetation endmembers in the spectral reflectance plot as well as to show how prevalent soil is across this landscape (red, blue and purple hues all indicate soil cover). Most of the southern half of this image is soil covered (Figure 4b). There are some patches of charred vegetation in the central and northern portion, mixed with charred and uncharred soil.

The Old Fire burned in a mix of vegetation types, some chaparral, but more in interior woodlands. The result was a much greater proportion of burned and unburned vegetation remaining after the fire than on Simi due to the higher proportion of pre-fire vegetation (Figure 5). Again, charred vegetation is shown as red, green vegetation as green, and uncharred soil as blue. The fire perimeter is identifiable on the image where the red color within the burned area turns sharply to a green color outside of the burned area. Roads and the shore of Lake Arrowhead are highly visible within the image (blue).

DISCUSSION

Correlations between ground data and remotely sensed data

Much of the Simi Fire area was characterized by a charred vegetation and soil mix after the fire. These components were difficult to separate both spectrally and in the field. The spectral endmembers were likely a mix of burned shrub stem reflectance and charred soil background reflectance. Charred soil and charred vegetation endmembers were similar (Figure 3), and neither resulted in strong correlations with the ground data at the Simi Fire (Table 2). The strong correlation between uncharred inorganic field component and the SMA results indicates that uncharred soil and rock were easy to identify in the image, and the spectral endmember was a good match for the image data. This is likely due to the high albedo of uncharred rock and soil, the brightest components in the scene.

The sparse vegetation across all burn severity classes on both fires and the mixed vegetation on the Old Fire justified the need to explore alternate methodologies other than dNBR for post-fire mapping. Because there was not much pre-fire vegetation or litter to burn to begin with, dNBR results were likely skewed by the complete absence of vegetation on some sites regardless of the severity of the burn. To fairly assess the RdNBR relative change index, it must be acknowledged that it is not designed to identify specific ground cover types (Miller and Thode, in press). The NBR is derived from a near-infrared band (B4) and a shortwave infrared band (B7) which are highly sensitive to chlorophyll and water content of vegetation—changes in live, green vegetation will therefore have the greatest impact on the index values. The dNBR and RdNBR assign a value to the absolute change (dNBR), or relative change (RdNBR), from a pre-fire to a post-fire condition. Areas with abundant green or non-photosynthetic (non-charred) vegetation after a fire are generally unchanged and classified as low burn severity. Areas that have little or no vegetation remaining and have abundant charred soil and ash have generally undergone a great change and are classified as high burn severity. Therefore, it is reasonable that these cover types had the strongest correlations with the dNBR and RdNBR values (Table 2).

All correlations between the ground and remotely sensed data would likely be improved if the ground data and the hyperspectral image data were collected at the same time. Because of logistical and safety concerns and the presence of smoke, ground data and image data are not easily acquired immediately after a fire, or even at the same time. There was a one-month delay after the ground data were collected before the hyperspectral image was acquired and during this time, the BAER team found that post-fire wind and rain events re-distributed white ash, which is characteristic of severe fire effects (CDF, 2003). Hudak *et al.* (2004) also found weak correlations between similar field and multispectral satellite data across multiple fires that had burned in a variety of forest vegetation types, and speculated that the time between fire and the collection of field data was a factor. Hudak et al. (parallel JFE submission) determined quantitatively that time lags contributed to weaker correlations between image indices and field fire effects across the Simi and Old fires along with four other wildfires in Montana and two in Alaska. The inclusion of a shade component in the spectral unmixing may have improved correlations due to the steep topography in many places on the Simi Fire (Figures 4a, b). It would have been difficult to derive a high-quality shaded soil or vegetation endmember—such an endmember would have had to be an image-derived endmember and we were hesitant to add a mixed image spectrum to the 'pure' field spectra used in the rest of the analysis.

Spectral mixture analysis images

The extent to which the ground surface was burned and the amount of remaining organic ground cover are good indicators of the effects of the fire on the soil surface, or soil burn severity. Figures 4 and 5 are essentially soil burn severity maps, highlighting exposed mineral soil and the charred components in the scene. An assessment of the soil burn severity gives a good indication of the potential for hydrologic response. The steep topography of the area resulted in much of the Simi Fire image being shaded, which is visible in Figures 4a and 4b on the north sides of ridges. The implication of steep terrain coupled with disturbed soils and the lack of vegetative cover was a resulting high-risk for soil erosion. This soil burn severity map, combined with topographic data could be helpful immediately after a fire when BAER teams must determine which areas to treat to mitigate erosion. Currently, hyperspectral data collection, pre-processing, and analysis are in research stages, and are not yet appropriate for rapid, operational post-fire response. Data processing methods are not standardized and given the large sized of these data sets, can be challenging. However, as computer and software technology advances and data are made available more quickly, these methods have promise for improving burn severity mapping, thus improving post-fire assessment.

CONCLUSIONS

The endmembers used in the spectral unmixing process for the Simi and Old Fires were representative of the burned area. There were significant correlations between spectral abundance in the image and fractional cover measured on the ground for each of the endmembers used in the unmixing. The Simi and Old Fires presented unique situations for exploring alternative methods for burn severity mapping. The chaparral vegetation on both fires was sparse pre-and post-fire, and the Old Fire burned in mixed chaparral and woodland vegetation types, creating conditions shown to be incompatible with the relative change indices dNBR and RdNBR. The spectral unmixing results from the hyperspectral imagery were significantly correlated to all classes of charred and uncharred organics and inorganics. The dNBR was the best indicator of charred soil and uncharred vegetation, while RdNBR had several significant correlations with the ground data, yet did not consistently correlate well with any specific ground cover types. Overall, the results of the spectral mixture analysis were slightly better than the dNBR and RdNBR at mapping quantitative ground cover conditions rather than burn severity classes.

While hyperspectral data are currently costly to obtain and time consuming to process, they will be useful burn severity assessments as hyperspectral image acquisition and processing becomes more timely and affordable. The field spectra used as endmembers in the Simi and Old Fire analysis will be useful on future fires in areas with similar vegetation types. The ability to quantify the exposed soil and remaining vegetation provides a better assessment of the fire's effects on the ground surface. In turn, the condition of the soil and the potential for post-fire hydrologic response can be more accurately assessed.

ACKNOWLEDGEMENTS

We would like to thank the US Department of the Interior and Department of Agriculture Forest Service, Joint Fire Science Program (JFSP 03-2-1-02) for funding this project. This research was supported in part by funds provided by the US Department of Agriculture, Forest Service, Rocky Mountain Research Station, to the University of Idaho (03-JV-11222065-279). Troy Hensiek, Jared Yost, Kate Schneider and Carter Stone assisted with field data collection, and Jacob Young and Curtis Kvamme with data entry. We sincerely appreciate the support of local natural resources managers and incident management teams in each location.

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TABLES

Table 1. Mean ground cover characteristics of the field subplots on the Simi and Old Fires by burn severity class—standard error of the mean is in parenthesis. Organic ground cover refers to green and non-photosynthetic vegetation, while inorganic refers to soil, rock and ash.

Ground cover category	Burn severity class		
	Low	Moderate	High
Simi Fire	*n* = 270	*n* = 405	*n* = 135
Organic-uncharred (%)	25 (1.6)	10 (0.8)	2 (0.3)
Organic-charred (%)	15 (1.0)	12 (0.7)	5 (0.6)
Inorganic-uncharred (%)	43 (1.6)	43 (1.4)	53 (2.2)
Inorganic-charred (%)	16 (1.3)	35 (1.4)	40 (2.1)
Old Fire	*n* = 135	*n* = 405	*n* = 270
Organic-uncharred (%)	37 (2.5)	3 (0.2)	0 (0.04)
Organic-charred (%)	14 (1.4)	9 (0.5)	5 (0.3)
Inorganic-uncharred (%)	30 (2.1)	32 (1.4)	18 (1.1)
Inorganic-charred (%)	21 (2.4)	57 (1.4)	77 (1.1)

Table 2. Pearson correlation coefficients (r) comparing measured ground data at the field plots to the hyperspectral spectral mixture analysis (SMA) and the multi-spectral indices dNBR and RdNBR. Bold values are significant at $p < 0.05$. Organic ground cover refers to green and non-photosynthetic vegetation, while inorganic refers to soil, rock and ash.

	Simi Fire			Old Fire		
Ground cover category	SMA	dNBR	RdNBR	SMA	dNBR	RdNBR
Organic-uncharred	**0.67**	**-0.65**	**-0.48**	**0.47**	**-0.79**	**-0.77**
Organic-charred	0.26	-0.27	-0.11	**0.38**	-0.17	-0.27
Inorganic-uncharred	**0.41**	0.13	**0.36**	**0.37**	**-0.48**	-0.23
Inorganic-charred	0.27	**0.47**	0.14	**0.48**	**0.72**	**0.55**

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Figure 1. Map of California showing the locations of the Simi and Old Fires.

Figure 2. Spatial layout of field plots. Need to clarify 8x8 or 9x9 – to center or edge of plots.

Figure 3. Example field spectra of uncharred soil, green vegetation, non-photosynthetic vegetation, charred soil, and charred vegetation field spectra collected from the Old Fire. Water absorption bands in the ranges of 1360-1400 nm and 1800-1980 nm were removed.

Figure 4. a) Image showing charred vegetation (red), green vegetation (green), and uncharred soil (blue) on the Simi Fire, and b) Image showing charred soil (red), green vegetation (green), and uncharred soil (blue) on the Simi Fire. These images are the result of the linear spectral unmixing algorithm that was applied to the hyperspectral data.

Figure 5. Image showing charred vegetation (red), green vegetation (green), and uncharred soil (blue) on the Old Fire. This image is the result of the linear spectral unmixing algorithm that was applied to the hyperspectral data.