Fire and vegetation type effects on soil hydrophobicity and infiltration in the sagebrush-steppe: II. Hyperspectral analysis

C.D. Finley, N.F. Glenn

Abstract

Hyperspectral remote sensing methods were developed to identify and differentiate post-fire characteristics in burned sagebrush-steppe. This shrub-steppe environment is typical of the Intermountain West, where wildfire intervals are frequent. After a 78,000 ha wildfire in 2005 in southern Idaho, soil water repellency and fire severity were evaluated with field and airborne spectroscopy measurements. A hyperspectral analysis correctly identified bare ground, low and high fire severity grass areas and low fire severity shrub areas, with accuracies between 74 and 92%. The differentiation of moderate and high fire severity areas was ambiguous, resulting in accuracies between 39 and 54%. The hyperspectral analysis of soil water repellency resulted in a representative map of its distribution with an accuracy of 65%. The analysis techniques conducted in this project signify spectroscopy to be beneficial for differentiating soil characteristics and fire severity classes in burned shrub-steppe areas, where the mostly bare, spectrally homogenous soils exhibit subtle but significant changes in reflectance. The spatial representation of post-fire soil and vegetation conditions may provide a better understanding of post-fire vegetation and surficial processes (water and wind erosion) in shrub-steppe.

1. Introduction

The occurrence of wildfires in shrub-steppe can severely alter the semiarid environment. Of particular concern to land managers is the acceleration of erosion by wind and/or water and the possibility for subsequent runoff. Significant factors influencing erosion after wildfires are the destruction of biomass and the presence of water repellent soils (Pierson et al., 2008). Past studies have indicated that the formation of fire-induced water repellent soils are a result of several factors; most importantly fire intensity and severity (DeBano, 1981, 2000; DeBano et al., 1998). Fire severity is defined for the current study as the completeness of above-ground vegetation removal due to fire, measured immediately following fire. Measuring post-fire effects across a burned landscape is time intensive and can be spatially incomplete. For example, Woods et al. (2007) found that the patchiness of hydrophobicity may in turn overestimate runoff predictions. In addition, results from Pierson et al. (2001) indicate rapid spatial and temporal changes in post-fire soil and vegetation properties.

Vegetation pattern and biomass significantly affect peak fire temperatures (Gimeno-Garcia et al., 2004), and the formation and distribution of water repellent soil layers. Notably, the vegetative structure of unburned shrub-steppe areas can be evenly dispersed, in areas dominated by perennial grass cover, or can be highly variable within and among mature shrub vegetation.

Soil organic matter often contains aliphatic hydrocarbons that become hydrophobic upon combustion (DeBano et al., 1998). The depth, thickness, and strength of water repellency in these soils depend on the fire intensity and duration (DeBano et al., 1998; DeBano, 2000). Typically fires of higher severity produce a deep water repellent layer, but very hot fires can also volatilize water repellent compounds (DeBano, 2000). In summary, variability in pre-fire vegetation conditions and fire severity can complicate the distribution of hydrophobicity across the landscape.

Remote sensing may provide a synoptic assessment of the heterogeneous distribution of post-fire effects. However, an inherent difficulty in remote sensing of arid regions is the high albedo and spectral similarities found in background soils (Asner and Heidebrecht, 2002; Okin et al., 2001), which are amplified by fire. While conventional multispectral remote sensing platforms have been successfully utilized for assessing post-fire characteristics of forested areas (Cocke et al., 2005; Fraser and Li, 2002; Lentile et al., 2006; van Wagendonk et al., 2004), their application to
semiarid shrub-steppe fire sites have yet to be established. Principal of these limitations is the low level of spectral differentiation in a multispectral image in the visible to shortwave infrared (SWIR) portions of the spectrum, where the bare, burned semiarid soils demonstrate subtle changes in reflectance. Hyperspectral data have the capability of discerning slight spectral variances in the visible to SWIR region of soils and vegetation. These wavelengths hold the most potential for identifying fire-induced chemical changes within the soil and vegetation changes, especially in semiarid environments.

Increasingly, spectroscopy has been utilized to evaluate post-fire effects. Rahman and Gamon (2004) used temporally-spaced hyperspectral data to successfully identify fresh biomass and water content in burned and unburned areas at a grassland-fire site in southern California. Mundt et al. (2006) combined hyperspectral imagery with light detection and ranging (LiDAR) data to map the distribution and structure of sagebrush stands previously affected by fire. Spectroscopy was used at the Hayman, Colorado fire to assess burn severity by adapting the commonly used multispectral normalized burn ratio (NBR) to SWIR hyperspectral bands (Laes et al., 2004). At the same study site, researchers utilized hyperspectral analysis for burn severity (Robichaud et al., 2007) and to identify ash cover corresponding to water repellent soils (Lewis et al., 2008). Kokaly et al. (2007) used hyperspectral analysis for post-fire surface cover. Eva and Lambin (1998) found that SWIR reflectance can decrease when charcoal or soils replace senesced vegetation. The presence of aliphatic hydrocarbons in burned soil can cause significant absorption in the SWIR (Henderson et al., 1992; Hummel et al., 2001).

By analyzing the spectroscopic characteristics of a burned study area in southern Idaho, USA, this study developed and evaluated methods of classifying fire severity and mapping the presence of water repellent soils in sagebrush-steppe. Field-based data and airborne hyperspectral imagery were collected and analyzed in order to identify fire severity classes and the distribution of water repellent soils.

2. Materials and methods

2.1. Study area

The study area for this project was the Clover fire (78,000 ha burned in July 2005) in southern Idaho. The site is approximately 39 km west of Twin Falls, ID, in the Intermountain sagebrush-steppe ecosystem (Fig. 1). The fire boundary extends from Salmon Falls Creek at its eastern boundary (about 8 km west of Castleford, ID) to the Saylor Creek Air Force Range at its western boundary. The elevation of the study area ranges from 750 m in the northern lowlands, to 1355 m at Castleford Butte near the southeast fire boundary. Soils in the area range in texture from loamy sand to clay, lowlands, to 1355 m at Castleford Butte near the southeast fire boundary. The fire boundary extends from Salmon Falls Creek at its eastern boundary (about 8 km west of Castleford, ID) to the Saylor Creek Air Force Range at its western boundary. The fire boundary extends from Salmon Falls Creek at its eastern boundary (about 8 km west of Castleford, ID) to the Saylor Creek Air Force Range at its western boundary. The fire boundary extends from Salmon Falls Creek at its eastern boundary (about 8 km west of Castleford, ID) to the Saylor Creek Air Force Range at its western boundary. The fire boundary extends from Salmon Falls Creek at its eastern boundary (about 8 km west of Castleford, ID) to the Saylor Creek Air Force Range at its western boundary. The fire boundary extends from Salmon Falls Creek at its eastern boundary (about 8 km west of Castleford, ID) to the Saylor Creek Air Force Range at its western boundary. The fire boundary extends from Salmon Falls Creek at its eastern boundary (about 8 km west of Castleford, ID) to the Saylor Creek Air Force Range at its western boundary. The fire boundary extends from Salmon Falls Creek at its eastern boundary (about 8 km west of Castleford, ID) to the Saylor Creek Air Force Range at its western boundary. The fire boundary extends from Salmon Falls Creek at its eastern boundary (about 8 km west of Castleford, ID) to the Saylor Creek Air Force Range at its western boundary.

Prior to data acquisition, three study sections were established based on the variability of fire severity, pre-fire vegetation, and the ecological and geomorphological characteristics of the landscape. This paper focuses on the analysis of flight line image 06 (Fig. 1) which had the highest number of complete field samples and was the least affected by wind erosion that occurred later in the field season.

2.2. Field methods

Field sampling at the study site occurred between August and October 2005. Across the field area, stratified random 9 × 9 m plots were sampled. The sample locations were stratified by fire severity.

The 9 × 9 m plot size was used based on the accuracy and resolution of the hyperspectral imagery. Fire severity assessments were made at the plot scale and categorized into classes of unburned, low, moderate, and high. Plots were further divided by their dominant vegetation group (grass or shrub). Soil water repellency was assessed at three locations within each 9 × 9 m plot using the water drop penetration time (WDPT) test. A WDPT of 30–60 s indicated weak water repellency, 61–180 s indicated moderate water repellency, and 181–360 s indicated strong water repellency. Across the flight line, 29 plots were sampled with a total of 87 points tested with the WDPT. Only WDPT samples collected on the surface were used in the analysis in order to directly correlate with the surface measurements from the hyperspectral data. For more detailed information on field measurements, see Glenn and Finley (in press).

In addition to the fire severity assessment and water repellency tests, a field spectroradiometer [Analytical Spectral Devices (ASD), Boulder, CO] was used to collect radiance data of field materials across the study area. The spectroradiometer acquired information in situ at a range of 0.35–2.50 μm, using a 25° field of view (bare fiber). The targets included bare ground, gravel, basalt rock, unburned grass and shrub, low fire severity grass and shrub, moderate fire severity grass and shrub, high fire severity grass and shrub, and water repellent soils identified by the WDPT.

2.3. Image acquisition

HyMap hyperspectral imagery were acquired by HyVista, Inc. The data were collected on August 26, 2005, between 12:00 noon MST and 12:33 MST. The HyMap imagery consists of 126 bands, with a nearly contiguous spectral range of 0.45–2.50 μm, a pixel resolution of 3 m, and flight lines of 10–15 km long and 1–2 km wide. The HyCorr (Hyperspectral Correction, similar to ATREM, Gao and Goetz, 1990) was used by the vendor to atmospherically correct the imagery.

2.4. Image processing

2.4.1. Image pre-processing

The hyperspectral image processing included a minimum noise fraction (MNF) transform and identification of endmembers (spectrally-pure pixels for targets of interest and used for classification). A classification and accuracy assessment were then performed. The MNF transform consists of linear transformations (spectrally-pure pixels for targets of interest and used for classification). A classification and accuracy assessment were then performed. The MNF transform consists of linear transformations (spectrally-pure pixels for targets of interest and used for classification). A classification and accuracy assessment were then performed. The MNF transform consists of linear transformations (spectrally-pure pixels for targets of interest and used for classification). A classification and accuracy assessment were then performed. The MNF transform consists of linear transformations (spectrally-pure pixels for targets of interest and used for classification). A classification and accuracy assessment were then performed. The MNF transform consists of linear transformations (spectrally-pure pixels for targets of interest and used for classification). A classification and accuracy assessment were then performed. The MNF transform consists of linear transformations (spectrally-pure pixels for targets of interest and used for classification). A classification and accuracy assessment were then performed. The MNF transform consists of linear transformations (spectrally-pure pixels for targets of interest and used for classification). A classification and accuracy assessment were then performed. The MNF transform consists of linear transformations (spectrally-pure pixels for targets of interest and used for classification). A classification and accuracy assessment were then performed. The MNF transform consists of linear transformations (spectrally-pure pixels for targets of interest and used for classification). A classification and accuracy assessment were then performed.
as a mask to separate out the vegetated, unburned areas from the burned areas in the imagery.

### 2.4.2. Endmember identification

Fifty-two potential endmembers were chosen from the MNF-transformed data. Each endmember was visually inspected in projected space alongside the field-collected sample plots and points to verify the field material they constituted. A supervised classification of shrub, grass and bare ground was created from digital multispectral orthophotos acquired the year before the fire, and used for identifying the dominant pre-fire vegetation group within each pixel class. The spectral characteristics of the potential endmembers were also compared to field-collected spectra. Endmember pixels that could not be accurately matched to a field class were discarded from further analysis. In total, 42 endmembers were assigned one of the following categories: low fire severity shrub, moderate fire severity shrub, high fire severity shrub, low fire severity grass, moderate fire severity grass, high fire severity grass, bare ground, and rock.

None of the potential endmembers matched the spectral signature of a water repellent sample plot. Alternatively, a field-collected spectral signature of highly water repellent soil was used as a guide for the identification of those materials in the image (Fig. 2). Next, the average spectral signature of five field-verified water repellent training sites were used for the moderate and high repellency endmembers (Fig. 3).

### 2.4.3. Classifications and accuracy assessment

The fire severity endmembers were used in conjunction with the spectral angle mapper (SAM) algorithm for classifying fire severity. A maximum spectral angle of 1 radian was used for all endmembers along with the MNF-transformed bands. The moderate and strong water repellency endmembers were used with the mixture tuned match filtering (MTMF) classification algorithm for identifying water repellent soil conditions. Because the spectral separation of the presence/absence of water repellency was most prevalent in the SWIR, the imagery was subset to 1.43–2.50 μm for the MTMF analysis. The 61 bands were MNF-transformed, and the unburned region masked out for analysis. The MTMF produced both matched filter (MF) and infeasibility images for both moderate and strong repellency. MF is an orthogonal subspace projection (OSP) operator described by Harsanyi and Chang (1994). An MF score is calculated for each pixel by matching MNF-transformed input data to a spectrally-pure endmember target spectra while suppressing the background. The length of the MF vector equates to target abundance estimations that range from 0 to 100% (Mundt et al., 2007). The mixture tuning component of the MTMF classification is used to reduce the number of false positives by considering noise variance and estimating the probability of MF estimation error in each pixel (Mundt et al., 2007). A correctly classified pixel should have a high MF score and a low infeasibility value. Though the MTMF has been used to estimate abundance at the subpixel level, it does not necessarily reflect true material abundance fractions (Heinz and Chang, 2001; Mitchell and Glenn, 2009). For the purpose of soil water repellency herein, the MTMF classification was used for detection and not quantification of abundance.

Following the classifications, an accuracy assessment was made for each fire severity and water repellency class. The accuracy assessment included a standard error matrix reporting Users, Producer’s and overall accuracies, and Kappa coefficients (Congalton and Green, 1999). The Users and Producer’s accuracies provide a quantitative measure of correctly classified data for each class relative to field data. The Users accuracy provides a map accuracy while the Producer’s accuracy provides a measure of the classification performance. All of the field-collected sample plots...
(29) were used for ground truth for the fire severity classifications. For the water repellency classifications, nine plots with strong WDPT results were available for ground truth verification of the strong repellency classification, and eight plots with moderate WDPT results were available for the moderate repellency classification. No endmember training data were used for the validation.

3. Results

The SAM resulted in a fire severity classification of low, moderate, and high fire severity shrub and low and high fire severity grass areas (Fig. 4). The classification also depicted bare ground and rock (Fig. 4). Moderate fire severity grass areas were not accurately detected, as those areas were spectrally confused with high fire severity grass. Thus this class was removed during further processing. Although the bare ground areas were devoid of vegetation to burn, these areas were affected by the presence of small amounts of litter and ash. The results of the classification indicated that 31% of the image to be moderate severity shrub, 20% high severity shrub, 12% low severity shrub, 10% low severity grass, 7% high severity grass, and 15% was unclassified. Results of the error matrix using the 29 plots across the image demonstrated an overall accuracy of 72% and a Kappa coefficient of 0.65 (Table 1). Producer’s accuracies for bare ground, low severity grass, high severity grass, and low severity shrub ranged between 74 and 92% (Table 1). The high severity and moderate severity shrub classes were confused, as demonstrated by their low Producer’s accuracies of 39 and 54%, respectively. The moderate and high severity shrub classes were combined into one class for a second accuracy assessment, and the overall accuracy increased to 78% (table not shown).

The sample plots of highly water repellent soils exhibited a spectral signature of 10–15% decreased reflectance in the SWIR portion of the spectrum, and moderately water repellent plots displayed a 5–10% decrease, when compared to spectral signatures of plots of non-water repellent soils (Fig. 3). These differences were leveraged in the MTMF classification; however the MTMF did not produce verifiable results for the moderate water repellency class. The 5–10% difference between moderate and non-water repellent soils was likely not large enough to be spectrally distinct in the imagery. Thus, only matched filter and infeasibility images for strong water repellent were analyzed further. After assessing the pixel distribution, an acceptable infeasibility threshold (false positive) of less than or equal to 16, and MF scores (pixel abundance) between 0.5 and 2.0 were used for the presence of strong water repellency. For comparison purposes, the MF score threshold was reduced to 0.3, with infeasibility remaining at 16. A presence/absence error matrix was developed indicating whether pixels in a 9 × 9 m sample plot identified as having water repellent soils are within an area classified as being strongly water repellent, or outside of the classified area (Table 2). Within the threshold ranges of 0.5–2.0 MF score abundance, the Producer’s accuracy of reference positives (strong water repellency present) was 55%, while the accuracy of negative (absence) reference sites was 75%. When the MF threshold was decreased to 0.3, the positive reference accuracies increased to 78%, while the accuracies of negative reference sites decreased to 50%. The decrease in accuracy of the negative reference sites resulted in an over classification of water repellency. However, the increase of the Producer’s accuracy

![Fig. 3. Spectral signatures (from imagery) of non-water repellent, moderately water repellent, and highly water repellent soils within a burned area.](image)

![Fig. 4. SAM burn severity classification.](image)

<table>
<thead>
<tr>
<th>Table 1</th>
<th>Producer’s and Users accuracies for SAM burn severity classification</th>
</tr>
</thead>
<tbody>
<tr>
<td>Class</td>
<td>Producer’s Accuracy</td>
</tr>
<tr>
<td>Bare Ground</td>
<td>74</td>
</tr>
<tr>
<td>Low Severity Grass</td>
<td>76</td>
</tr>
<tr>
<td>High Severity Grass</td>
<td>92</td>
</tr>
<tr>
<td>Low Severity Shrub</td>
<td>81</td>
</tr>
<tr>
<td>Moderate Severity Shrub</td>
<td>54</td>
</tr>
<tr>
<td>High Severity Shrub</td>
<td>39</td>
</tr>
<tr>
<td>Overall Accuracy – 72%</td>
<td></td>
</tr>
<tr>
<td>Kappa Coefficient – 0.65</td>
<td></td>
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</tbody>
</table>

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is a result of an increased identification of strongly water repellent soils. These thresholds were used to plot soil water repellency occurrence as well as likely areas of false positives (Fig. 5).

4. Discussion

The classification of fire severity with the hyperspectral data was confounded by the fact that endmembers were primarily in areas of extremely high and low spectral reflectance. Though the endmember pixels were assigned their respective fire severity based on both their spectral properties and association with the field plots, a certain level of subjectivity was involved. While the assignments were more confident among spectrally unique classes, like low and high severity grass, and low severity shrub, the differentiation of moderate and high severity shrub and moderate severity grass areas was less distinct. Moderate severity grass areas were not detected accurately in the fire severity classification. While not specific to grass communities, recent research has also concluded that remote sensing of moderate fire severity is challenging (e.g. Miller et al., 2009; Murphy et al., 2008). In our study, this challenge was due to the similar spectral characteristics of moderate and low severity grass areas, due to the lack of charring of the soil, the presence of root crowns, and high soil reflectance. Aside from the confusion of moderate and high severity shrub areas, the SAM algorithm was suitable for assessing fire severity because of the high accuracy and detection of continuous zones of fire severity across the landscape as observed in the field. The spatial distribution and connectivity of post-fire soil and vegetation conditions are important for erosion and runoff modeling (see for example, Miller et al., 2003; Moody et al., 2008).

The presence of soil water repellency across the burned area was largely dependent on the amount and type of vegetation burned and soil reflectance characteristics. In locations where dense shrub had been incinerated and the soil was charred, water repellency was often noted. The charred soils exhibited spectral signatures with 10–15% lower reflectance in the SWIR than soils from non-water repellent areas. Although these areas of low reflectance were not the only soils with water repellency, they were the soils that could be spectrally differentiated. We analyzed the spectra of the burned area in search of additional spectral features that may indicate the presence of fire-induced repellency; in particular, the lack of a clay oxide absorption band at 2.3 μm. After heating forest soils to various temperatures, Moody et al. (2005) found that the surface of soils heated to very high temperatures (220–275 °C) exhibited cementation due to the cooking of the clay oxides within the soils. We examined the clay absorption band in spectra from water repellent samples but no quantifiable change was substantiated. In addition, no evidence of clay cementation on the soils (large soil aggregates) was found at the study site. We conclude that the relatively sparse cover and fuel load at the study area did not burn hot enough to induce clay cementation. Thus, detection of water repellent soils with hyperspectral data in this study was reliant on the lower reflectance soils (with charred material). This result is in agreement with the findings of Lewis et al. (2008), where they used the strong correlation between ash and water repellent soils to map water repellency with hyperspectral data. The MTMF output of pixel abundance accurately represented the intermittent nature of soil water repellency across the burned area. Although the MF scores of the MTMF can be related to the subpixel abundance of an endmember, it was unrealistic here because it would not be practical to validate in the field. The image classification of moderate soil water repellency was unreliable because the soils identified in the field as moderately repellent did not exhibit enough reduced reflectance to be grouped separately by the MF scores. The spectroscopic classification depicted high soil water repellency primarily in high fire severity areas. This is likely because the absence of litter and vegetation within high fire severity allows for complete imaging of the soil reflectance, while in moderate fire severity, litter and standing vegetation, though burned, is often present.

In addition, the field classification of fire severity has a degree of subjectivity, and moderate and high severity classes were likely confused in some field areas. Other sources of spectral interference and confusion include shade within the gullies and canyons and the presence of volcanic rocks on the surface. The infeasibility scores of

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Table 2

<table>
<thead>
<tr>
<th>MTMF Class</th>
<th>Reference Positive</th>
<th>Reference Negative</th>
<th>Users Accuracy</th>
<th>Producer's Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>A. MF score threshold – 0.3–2.0</td>
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<td></td>
<td></td>
<td></td>
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<tr>
<td>Classified Positive</td>
<td>45</td>
<td>18</td>
<td>71%</td>
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<tr>
<td>Classified Negative</td>
<td>36</td>
<td>54</td>
<td>60%</td>
<td></td>
</tr>
<tr>
<td>Producer’s Accuracy</td>
<td>55%</td>
<td>75%</td>
<td>65%</td>
<td></td>
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<tr>
<td>B. MF score threshold – 0.3–2.0</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Classified Positive</td>
<td>63</td>
<td>36</td>
<td>64%</td>
<td></td>
</tr>
<tr>
<td>Classified Negative</td>
<td>18</td>
<td>36</td>
<td>67%</td>
<td></td>
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<tr>
<td>Producer’s Accuracy</td>
<td>78%</td>
<td>50%</td>
<td>65%</td>
<td></td>
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</tbody>
</table>

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the MTMF were decisive for differentiating these materials from water repellent soils. An acceptable infeasibility threshold of less than or equal to 16, and MF scores (pixel abundance) between 0.3 and 2.0 were determined for the best detection of the water repellent soils. Determining a lower MF threshold results in an increase in false positives but from a management perspective, it may be better to over predict than under predict soil water repellency. This information would allow land managers to better prioritize for post-fire stabilization and restoration activities.

5. Conclusions

This study presents remote sensing techniques for mapping fire severity and fire-induced soil water repellency in a burned sagebrush-steppe. The lack of spectral separability of soil and vegetation conditions in these areas is magnified by burning. Thus, the use of high spatial and spectral resolution imagery proved valuable. The SAM fire severity classification detected classes of low, moderate and high severity shrub areas, and low and high severity grass areas with an overall accuracy of 72%. In addition to the high accuracy, the classification output classes imitate the nature of fire severity across the rangeland observed in the field. The MTMF algorithm detected water repellent soils in over 30% of the burned portion of the image with an overall accuracy of 65%. The MF and infeasibility results are indicative of the discontinuous, unpredictable character of water repellency across burned rangelands.

The study did not have a replicate design such that one could apply the results to other areas where ground data are not available. However, as a first attempt at predicting soil water repellency in shrub-steppe areas the results are acceptable, and with future research the accuracy and analysis procedures can be refined and improved. Future studies could improve upon our method by increasing the number of soil water repellency samples for validation in both moderate and high fire severity areas. In addition, a library of MF thresholds for vegetation and soil conditions in shrub-steppe needs to be developed in order to integrate hyperspectral data into land management use (e.g., Mitchell and Glenn, 2009).

This project demonstrates the potential for spectroscopy to supplement an analysis of post-fire effects on overstory and soil properties. The image-wide classification of fire severity and water repellent soils is useful for locating areas with potential for runoff and erosion.

The patterns of the spectroscopic classifications of fire severity and soil water repellency indicate that wildfires within rangeland areas are dynamic in nature. It is difficult to represent these patterns with field-based data and thus, remote sensing may provide reliable spatial and temporal input parameters to model runoff and erosion susceptibility following rangeland wildfire.

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