Relative Suitability of Indices Derived from Landsat ETM+ and SPOT 5 for Detecting Fire Severity in Sagebrush Steppe Rangelands

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ABSTRACT
Indices of burn area and fire severity based on remotely sensed data have been developed for forest ecosystems, but not semiarid shrublands in which large wildfires are a common occurrence and a major issue for land management. Our goal was to determine whether available satellite data could be used to remotely sense burn area and fire severity (completeness of vegetation removal) in shrublands. We compared the performance of five remote sensing indices with extensive ground-based cover assessments made before and after the burning of a 3 km^2 area. The different indices were based on either Landsat 7 ETM+ or SPOT 5 data, using either single or multiple dates of imagery. Remote sensing indices delineating burned versus unburned areas had better overall, user, and producer's accuracies than indices delineating levels of fire severity. The Soil Adjusted Vegetation Index (SAVI) calculated from SPOT had the greatest overall accuracy (100%) in delineating burned versus unburned areas. The relative differenced Normalized Burn Ratio (RdNBR) using Landsat provided the highest accuracies (73% overall accuracy) for delineating fire severity. Though SPOT's spatial resolution likely conferred advantages for determining burn boundaries, Landsat's higher spectral resolution (particularly band 7, 2.21 µm) appeared necessary for detecting differences in fire severity.

Keywords: Burn severity, Semi-arid rangelands, Relative differenced Normalized Burn Ratio

INTRODUCTION AND BACKGROUND

Sagebrush steppe communities evolved with regular and extensive wildfires. Fire is a widespread agent of change and has become one of the dominant land management issues today (Arno and Gruell 1983). Remote sensing with satellite imagery offers the ability to evaluate burned areas across multitemporal and multispatial scales, as demonstrated in forest ecosystems (Morgan et al. 2001). Satellite data are useful for examining fire effects because they 1) can be used to qualitatively and quantitatively evaluate vegetation over multi-temporal and -spatial scales, 2) can be relatively low cost, 3) systematically cover large and inaccessible areas (in many instances fires are located in remote areas), and 4) capture data from parts of the electromagnetic spectrum (i.e. infrared) that provide useful information specific to vegetation and soils (Flasse et al. 2004).

Our goal was to determine whether rangeland fire severity could be modeled with remote sensing techniques, using commonly available satellite data and either single date imagery or pre-and post-fire multitemporal differencing incorporated with field data. Definitions of fire severity differ among studies, as does the amount of time elapsed between fires and when severity is assessed (Key and Benson, 2006; Lentile et al. 2006; Miller and Yool, 2002; Roy et al. 2006; and Ryan and Noste, 1983). Fire severity is defined for the current study as the completeness of above-ground vegetation removal due to fire, measured immediately following fire. Thus, remote detection of burns requires sensitivity of imagery and calculations of vegetation change. Fire severity is distinct from burn severity, which incorporates both short- and long-term post-fire effects (Key and Benson, 2006; Lentile et al. 2006). Our study occurred in mountain sagebrush steppe, where wildfires occur frequently from mid-summer through fall. Shrubs and herbs co-dominate foliar cover before fire, while after fires herbs increase in abundance and shrubs are temporarily absent as they reestablish by seed over decades (Harniss and Murray, 1973). Some post-fire green-up by herbs occasionally occurs in the same growth season as the fires.

The objectives of this research were to 1) evaluate the suitability of remote sensing indices for fire severity mapping within a sagebrush steppe rangeland, 2) assess the importance of considering spectral and spatial resolution, and 3) assess the influence of timing of imagery acquisition and seasonality of fire. These objectives are aimed at developing methods for fire severity mapping for land management agencies.

Remote sensing of semiarid vegetation

Several attributes of reflectance to satellite sensors make detecting vegetation change in sparsely vegetated semiarid rangeland ecosystems challenging. These rangeland characteristics contribute to the challenges of remote sensing of vegetation along with: 1) nonlinear mixing due to multiple scattering of light, 2) evolutionary adaptations making desert plants spectrally dissimilar and lacking a strong red edge, 3) spectral variability within the same species due to spatially discontinuous precipitation patterns, 4) open shrub canopies which affect near infrared (NIR) reflectance, 5) low leaf area index, and 6) varying phenological status of plant canopies across space and time (Asner, 2004; Asner and Heidebrecht, 2002; Okin et al. 2001). Because there tends to be an abundance of bare ground in sagebrush steppe rangeland ecosystems and soil reflectance is often brighter than vegetation reflectance, bare ground 'dilutes' the vegetation signature. This is exaggerated in burned ecosystems where soil reflectance is high and little vegetation exists.

Vegetation indices have been developed to detect vegetation and could be used to estimate biomass loss for mapping burn areas and severity (Santos et al. 1999), such as the normalized difference vegetation index (NDVI) (Flasse et al. 2004; Epting and Verbyla, 2005; Roy, 1999; Ruiz-Gallardo et al. 2004; van Wagtendonk et al. 2004; Salvador et al. 2000), soil adjusted vegetation index (SAVI - Huete, 1988; Epting et al. 2005), modified soil adjusted vegetation index (MSAVI - Qi et al. 1994; Epting et al. 2005), atmospherically resistant vegetation index (ARVI) (Kaufman and Tanre, 1992; Santos et al. 1999), and normalized difference shortwave infrared (NDSWIR; Gerard et al. 2003). Alteration of the vegetation:soil

balance is a substantial characteristic of fire; therefore soil adjustments in vegetation indices (e.g. SAVI or MSAVI) are likely to be critical for mapping burn areas and severity. Because SAVI and MSAVI were developed to minimize soil brightness and soil variations using red and near-infrared wavelengths as well as a soil adjustment factor for semiarid vegetation, these indices may be appropriate for rangeland fire applications. NDVI was the primary technique used to detect burn severity until the late 1990s, when Lopez Garcia and Caselles (1991) developed an algorithm later coined as the normalized burn ratio (NBR; equation 1) using Landsat imagery (Key and Benson, 1999b; Key and Benson, 2004a; Key and Benson, 2006; Salvador et al. 2000). Since then, the Landsat-based NBR is the most widely used method on large fires (>200 hectares) for perimeter and burn severity detection (Cocke et al. 2005; Key and Benson, 2006).

$$NBR = \frac{NIR - SWIR_{(2.21\mu m)}}{NIR + SWIR_{(2.21\mu m)}} \qquad (1)$$

The NBR technique uses the near-infrared (Landsat band 4, 0.76 – 0.90μm) and shortwave infrared (Landsat band 7, 2.08 – 2.35μm) because these bands are generally the most sensitive to vegetation change due to fire, which increases the shortwave infrared band and decreases the near infrared band (Lentile et al. 2006).

A differenced NBR (dNBR) is used to offer a quantitative measure of environmental change due to the fire or other temporal difference (Key and Benson, 1999b; Key and Benson, 2004a). The dNBR represents a scaled index of the magnitude of change caused by fire (van Wagtendonk et al. 2004). The dNBR is composed of the post-fire NBR data set subtracted from the pre-fire NBR data set (equation 2).

$$dNBR = NBR_{pre-fire} - NBR_{post-fire} \qquad (2)$$

There are two types of dNBR severity measures, an initial assessment in which post-fire measures occur immediately after fire and are not influenced by biotic recovery, and an extended assessment in which post-fire assessments are made in subsequent growth seasons and thereby reflect recovery. The NBR and dNBR may or may not be applicable in rangeland ecosystems due to vegetation re-growth times with respect to the seasonality of the burn. For instance, it takes longer for forested ecosystems to recover to pre-fire conditions (i.e. having the same reflectance) than rangelands. Likewise, Miller and Thode (2007) found that a Landsat-based relative dNBR (RdNBR, equation 3) performs better than the absolute dNBR at detecting high burn severity areas from moderate burn severity in mixed forest/shrubland study areas.

$$RdNBR = \frac{dNBR}{\sqrt{|NBR_{prefire}|}} \qquad (3)$$

Burn (fire) severity has also been assessed by comparing several single-date and multi-date approaches. For instance, Roy et al. (2006) and Epting et al. (2005) agree that the dNBR may not be the most optimal for estimating fire severity in non-forested areas. Yet Brewer et al. (2005) stated the dNBR has the advantage of using it anywhere in the continental U.S. and pointed out that it (stratified by National Landcover data (NLCD)) does not introduce analyst input error (i.e., human bias). In addition, Gerard et al. (2003) developed an algorithm coined the normalized difference SWIR (NDSWIR, equation 4) to map fire scar burns using SPOT NIR (Band 3, 0.78-0.89μm) and SWIR (Band 4, 1.58-1.75μm).

$$NDSWIR = \frac{NIR - SWIR_{(1.66\mu m)}}{NIR + SWIR_{(1.66\mu m)}} \qquad (4)$$

Many studies have been performed in forested ecosystems to determine burn or fire severity within a burn perimeter (Brewer et al. 2005; Epting and Verbyla, 2005; Epting et al. 2005; Miller and Thode, 2007; Patterson and Yool, 1998; Turner et al. 1994; White et al. 1996; Wimberly and Reilly, 2007). However, few studies have been carried out in areas with reduced vegetation cover (Roy et al. 2006; Smith et al. 2005) or specifically within semiarid sagebrush steppe ecosystems (van Wagtendonk et al. 2004).

MATERIALS AND METHODS

Study area

This study took place within the Hitching Post pasture, a 3.24 km^2 fenced parcel within the U.S. Sheep Experiment Station (USSES) located in Clark County, Idaho, USA, at an elevation of approximately 1800 m (Fig. 1). Average annual precipitation ranges from 250-530 mm with up to seventy percent falling as snow (Seefeldt, 2005). Average annual temperatures are 5-6 °C, with a 70 to 90 day frost-free season. The pasture is a sagebrush steppe ecosystem characterized by extreme seasonal variability and a co-dominance of *Artemisia* with several grass species (West and Young, 2000). The Hitching Post pasture has two primary subspecies of sagebrush (*Artemisia* ssp.): mountain big (*A. tridentata* ssp. *vaseyana*), and threetip (*A. tripartita ssp. tripartita*). Sheep and horses have grazed this pasture for the last decade, but it had not been domestically grazed for 2.5 years prior to the burn. This study area was chosen because it offered an opportunity to take advantage of a prescribed burn, allowing a high degree of control for pre- and post-fire field sampling.
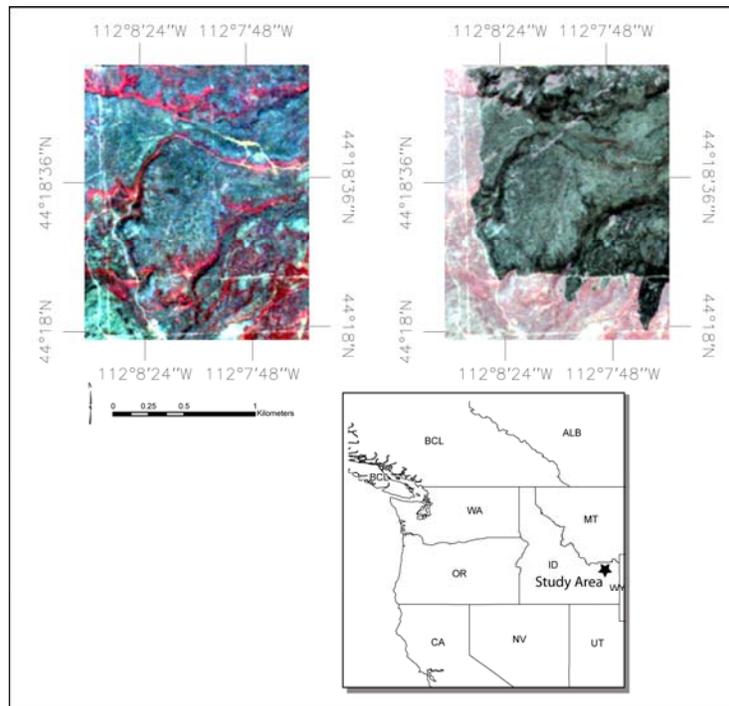

Figure 1. Study area, USDA Sheep Experiment Station, Dubois, Idaho. SPOT 5 images (NIR, red, green) of pre-burn (left) and post-burn (right) of the Hitching Post Pasture.

Fire

The prescribed fire was performed on September 14 and 15, 2005 and consistently burned most of the northern 4/5 of the pasture (approximately 2.82 km^2, Fig. 2) delineated with a bulldozed safety line. Wind direction and speed were monitored throughout the burn every 30 minutes. Using a hand-held anemometer, winds were observed around 20 m/sec in a predominantly northeast direction throughout most of this burn. Flame lengths ranged from approximately 30 cm to 4 m tall as the fire moved from

grass and forbs up to shrubs. Afterward, nine strip burns and spot fires were ignited in the southern portion of the pasture (and burned to the north) (Fig. 2, south of the middle dozerline). The prescribed fire burned approximately 85% of the pasture area including 173 of the sampling sites (described below).
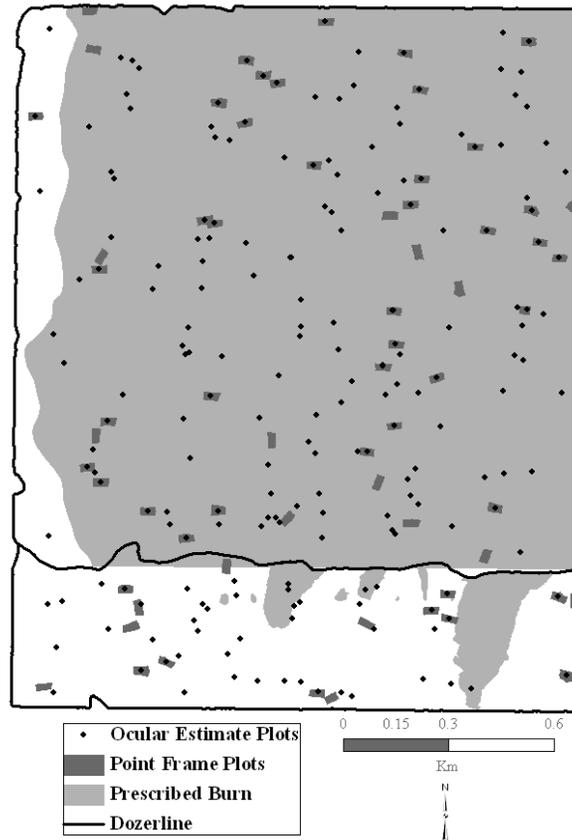
Figure 2. Location of ocular and point frame plots in relation to the fire in the Hitching Post Pasture.

Field methods
This study utilized pre- and post-fire field-based sampling to establish locations of sample sites along with a description of the vegetation, amount of bare ground, and fire severity observed at each site. These data were collected for both training and validation of the remote sensing indices used for the first objective. Two field methods were performed: ocular and point frame. The ocular method was used to quickly estimate percent cover of the upper-most canopy of ground cover across a 60 × 60 m plot with qualitative, coarse resolution. In the ocular method, categorical percent cover (0, 1-5%, 6-15%, 16-25%, 26-35%, 36-50%, 51-75%, >75%) for six categories (shrub, grass, forb, litter, rock, and bare ground) were estimated after thoroughly walking the plot area. Each sample site (n=206) was randomly located within the pasture (Fig. 2; points) to ensure adequate replication across fire severity classes.

The point frame method was also used to provide a relatively more accurate and statistical representation of true ground cover (Floyd and Anderson, 1982; Floyd and Anderson, 1987). The point frame establishes a dot grid overlooking underlying vegetation and bare ground. Observers view vegetation from a near-nadir standing position and record the cover types that are beneath 36 intercepted points (cross-hairs). Plots of 20 × 40 m were sampled with the point frame. The sampling frequency necessary to capture variability was determined using sample effort curves from all cover categories. A maximum of 15 frames of point data were needed within each 20 × 40 m plot to ensure adequate representation of cover in this study area. Point frame data (Fig. 2; rectangles) were collected at 45 of the 206 ocular sample sites

(centered over the sites where ocular estimates were used) as well as 20 additional sample sites (total of 65 point frame samples).

Pre-fire field data collections occurred between mid-June and early August 2005 and included 206 ocular plots and 65 point frame measurements. Post-fire sampling began immediately following the prescribed burn and continued for approximately 1.5 months, prior to any green-up. Post-fire field surveys, intended to provide field validation of fire severity levels, included re-sampling all pre-fire sampling sites. The same field methods as pre-fire sampling (ocular estimates and point frame measurements) were consistently repeated at the same scales and within 3-5 m of the original locations by navigating with a GPS unit. In addition, a fire severity rating (unburned, incompletely burned (moderate), and completely burned (high)) was assigned to each ocular and point frame plot.

We assessed fire severity with a customized ocular method by modifying the field methods of the US Forest Service (Bobbe et al. 2001) and the US Park Service (USDI NPS, 2003), and the composite burn index (CBI) of Key and Benson (1999a; 2004b). Each of these methods incorporates qualitative and quantitative measurements to detect and categorize fire severity; we incorporated and modified the three methods above according to burn conditions in our study area in the context of a semiarid rangeland site. Attributes such as litter condition, shrub condition, surface rock (USDA FS), organic substrate, and vegetation (USDI NPS) were incorporated from the USDA and USDI burn severity. Key and Benson's (1999a) CBI places a ~50% change in the herb/low shrub/tall shrub strata into the moderate burn severity category. The study area predominantly fits into Key and Benson's shrub strata, so we incorporated this ~50% change severity category, referred to herein as 'incompletely burned'. In most plots and pixels, the fire either burned all vegetation (except stumps) or none; there was a very small amount of partly burned vegetation. Therefore, severity at each plot was assessed based on the percent cover of bare ground and rock, and the amount of consumed, above-ground vegetation and litter. Fire severity classes included unburned, incompletely burned (moderate), and completely burned (high).

Remote sensing methods
Image acquisition
Landsat 7 ETM+ and SPOT 5 imagery were chosen for this work due to their reasonable cost, spatial and spectral resolution, and because their data are continuously collected, making them useful and easily available to land/fire managers. In addition to visible and NIR bands, SPOT 5 provides a SWIR band (1.58-1.75µm) with 20m spatial resolution. Pre- and post-fire images were acquired for Landsat (July 4 and October 24, 2005) and SPOT (August 27 and September 28, 2005) (Table 1). All images were chosen as close to the date of the prescribed burn (September 14-15, 2005) as possible with no cloud cover.

Table 1. Dates and location of SPOT and Landsat imagery. The prescribed fire occurred September 14 and 15, 2005.

Imagery	Date	Scene ID/Path Row
SPOT 5 Pre-fire	27-Aug-05	547-260
SPOT 5 Post-fire	28-Sep-05	547-260
Landsat ETM+ Pre-fire	4-Jul-05	39/29
Landsat ETM+ Post-fire	24-Oct-05	39/29

Imagery were processed to at-satellite reflectance using ENVI software (ITT, 2007) to reduce between-scene variability. The SPOT 20 m SWIR band was resampled to 10 m to coregister with the SPOT red and NIR bands of 10 m. Image rectification was performed after remote sensing indices (see below) were calculated in order to reduce error during resampling. The resulting Root Mean Square Error (RMSE) was

less than ½ pixel for both the Landsat (0.2621) and SPOT (0.3489) imagery during the image rectification process. Our study area was not affected by the scan line corrector (SLC) failure in the Landsat images.

Image processing

In order to identify the Landsat and SPOT bands that were most sensitive to changes between the pre- and post-fire images, we investigated 36 field plots in both pre- and post-fire images. These 36 sample sites were chosen for their near homogeneous vegetation cover (type and amount) within each plot pre-fire and similar fire severities within each plot post-fire. Reflectance values for the plots were averaged for each of the pre- and post-fire images and then compared (Figs. 3 and 4).

Based on initial investigations of sensitivity of the SPOT and Landsat data, 5 indices were implemented (Table 2) including single-date and multi-date (pre- and post-burn imagery) manipulation. Indices were applied to determine burned from unburned areas, and then assessed for their ability to differentiate levels of fire severity identified in the field. The multi-date indices include a dNBR (equation 2) and relative dNBR (RdNBR; equation 3) with Landsat imagery. SPOT was not used for the dNBR and RdNBR because of the lack of a SWIR band comparable to Landsat's band 7 (2.21 µm).

Table 2. Remote sensing indices used. Red: Landsat band 3, SPOT band 2; NIR: Landsat band 4, SPOT band 3; SWIR: Landsat band 5 (for NDSWIR), Landsat band 7 (for NBR, dNBR, and RdNBR), SPOT band 4.

Remote Sensing Index	Algorithm	References
SAVI	$\dfrac{(1+L)(NIR-Red)}{NIR+Red+L}$ $(L = 0.5)$	Huete, 1988
MSAVI	$\dfrac{2*(NIR)+1-\sqrt{(2*(NIR)+1)2-8*(NIR-Red)}}{2}$	Qi et al., 1994
NDSWIR	$\dfrac{NIR - SWIR}{NIR + SWIR}$	Gerard et al., 2003
NBR dNBR	$\dfrac{NIR - SWIR}{NIR + SWIR}$ Pre-fire NBR – Post-fire NBR	Lopez Garcia and Caselles, 1991; Key and Benson, 1999b
RdNBR	$\dfrac{dNBR}{\sqrt{|NBR_{prefire}|}}$	Miller and Thode, 2007

The single-date indices, using post-fire imagery only, include the SAVI, MSAVI, and normalized difference shortwave-infrared index (NDSWIR, equation 4). Both Landsat and SPOT imagery were used for all of these indices. As suggested by Huete (1988), we used a soil adjustment factor of 0.5 for the SAVI calculation which can be applied across varying vegetation biomass environments. The MSAVI index calculates a variable soil adjustment factor L (Qi et al. 1994) until soil noise cannot be further removed.

Relating remote sensing indices to field data

Training data were used to relate remote sensing index values to fire severity values. For training purposes, 119 index values from plots (including both ocular and point frame, none of which overlapped) were used. Each field plot was assigned a fire severity rating based on the field methods described above.

Remote sensing index values were acquired at each training site for each index. The fire severity index values were then separated into fire severity classes by first placing all plot values into their respective fire severity classes as determined in the field. The minimum, maximum, and mean index values of each class were determined. The classes were separated by splitting the difference between the maximum of one class with the minimum of the next class. Likewise, if there was a gap between fire severity class data values, then a break was determined by splitting the difference between the maximum of one class with the minimum of the next class. To encompass the variability across the study area, training plots were randomly selected within each burn severity class and the same training plots were used within each burn severity class for each index.

Validation

An accuracy assessment was used to quantitatively determine how well the remotely sensed indices corresponded with the field data. The validation was performed following traditional accuracy assessment techniques (Congalton and Green, 1999). Fifty plots of unburned and 100 plots of burned were used for the unburned versus burned validation. For the fire severity validation, 50 plots for each class (unburned, incompletely burned, completed burned) (n=150) were used for the validation. No training data were used for the validation (Table 3). The remote sensing burn severity values of the validation plots were then compared to the field fire severity classes. Accuracy results were calculated for each index, including a standard error matrix reporting user, producer's, and overall accuracies, kappa statistic, and a Z-test statistic for significance (of a single error matrix) (Congalton and Green, 1999).

Table 3. Number of training and validation plots used to assess remote sensing indices.

Burn Severity Value	# of Training Plots	# of Validation Plots
Unburned	14	50
Moderate	16	50
High	89	50

A pairwise test of significance (equation 5) (Congalton and Green, 1999) was performed for the matrices that had highest accuracies as well as for those that shared similar overall accuracies. This test is a Kappa analysis that determines if two error matrices are significantly different by comparing their KHAT statistics.

$$Z_{pairwise} = \frac{|K_1 - K_2|}{\sqrt{var(K_1) + var(K_2)}} \qquad (5)$$

Where K_1 and K_2 are the Kappa statistics for error matrices 1 and 2 and $var(K_1)$ and $var(K_2)$ are estimates of variance for matrices 1 and 2.

RESULTS

The SPOT and Landsat reflectance values between pre-and post-fire images were different (Figs. 3 and 4). The SPOT green and NIR reflectances had the greatest change, increasing approximately 1.6% and 1.8%, respectively, after the fire. The SPOT red band decreased 0.84% and the SWIR band increased approximately 0.81%. The SPOT pre-fire image was collected in late August, at a time when most herbs/grasses were senesced and soil exposure was high. Alternatively, the Landsat data was acquired at the beginning of July before the onset of seasonal drought and senescence of herbaceous species. In comparing the pre- and post-fire Landsat images, the NIR and SWIR (2.21µm) bands demonstrated the greatest change (Fig. 4). The NIR decreased 3% and the SWIR band increased 5.5% after the fire.
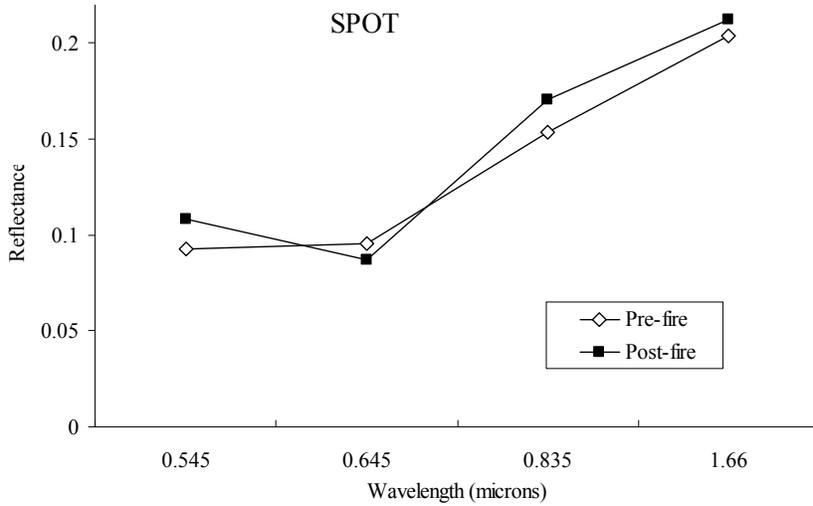
Figure 3. The average value of SPOT 'at satellite' reflectance for 36 plots, pre- and post-fire.
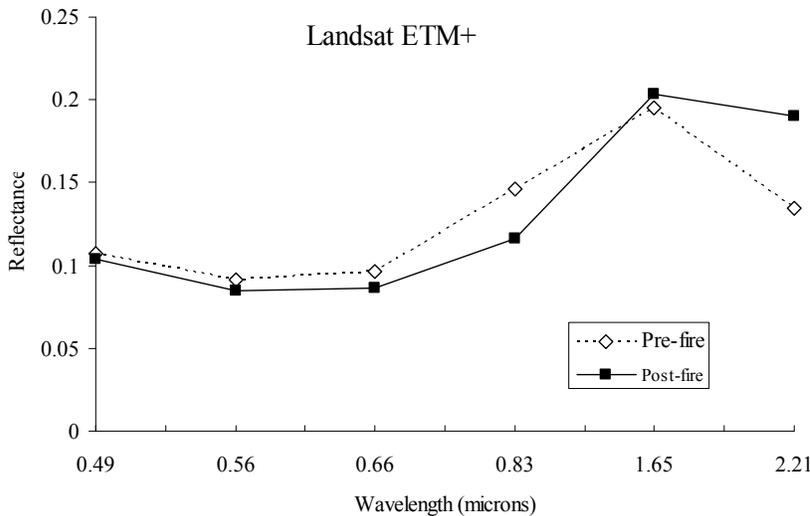

Figure 4. The average value of Landsat 'at satellite' reflectance for 36 plots, pre- and post-fire.

The remote sensing indices assessing burned versus unburned areas had better overall, user, and producer's accuracies (Tables 4 and 5) than those where fire severity was described as unburned, incompletely burned, or completely burned (Tables 6 and 7).

Burned versus unburned
The burned versus unburned indices generated using SPOT imagery (NDSWIR, MSAVI, and SAVI) and the Landsat-derived burned versus unburned indices (dNBR, RdNBR, NDSWIR, MSAVI, and SAVI) had relatively high accuracy (~ 95% overall accuracy). The three burned versus unburned SPOT-derived indices (NDSWIR, MSAVI, and SAVI) had 95% or better overall accuracies (Table 4). SPOT SAVI provided the highest overall, users, and producer's accuracies (100%). Three burned versus unburned Landsat indices (RdNBR, MSAVI, and SAVI) performed nearly equally well at 95% overall accuracy (Table 5). A pairwise test of significance indicated that the SPOT SAVI index was significantly different

than both the SPOT MSAVI and NDSWIR (Table 8). A pairwise test for significance indicates that none of the Landsat-based indices are significantly different. Pairwise tests for significance between the SPOT-based SAVI index and the Landsat-based RdNBR, dNBR, MSAVI, and SAVI indices indicate that the SPOT-based SAVI is significantly better than the Landsat indices (Table 8).

Table 4. 'Burned vs. Unburned' remote sensing index accuracies and kappa statistics using SPOT 5 imagery.

Accuracy Type	NDSWIR	MSAVI	SAVI
Overall Accuracy	96%	95%	100%
Producer's Unburned	96%	98%	100%
Users Unburned	92%	86%	100%
Producer's Burned	96%	93%	100%
Users Burned	98%	99%	100%
KHAT	0.9091	0.8763	1.0000
Z	25.0211	20.6704	*

Table 5. 'Burned vs. Unburned' remote sensing index accuracies and kappa statistics using Landsat ETM+ imagery.

Accuracy Type	dNBR	RdNBR	NDSWIR	MSAVI	SAVI
Overall Accuracy	94%	95%	89%	95%	95%
Producer's Unburned	96%	98%	90%	94%	94%
Users Unburned	86%	86%	74%	90%	90%
Producer's Burned	93%	93%	88%	95%	95%
Users Burned	98%	99%	96%	97%	97%
KHAT	0.862	0.876	0.733	0.879	0.879
Z	19.314	20.670	12.133	21.102	21.102

Fire severity
The best fire severity index differentiating pixels between unburned, incompletely burned, and completely burned was the Landsat RdNBR. This index had a 73% overall accuracy and user accuracies of 56% and 76% for incompletely and completely burned, respectively (Table 6). The producer's accuracy was 61% and 63% for incompletely and completely burned, respectively. The best overall accuracy for the SPOT burn severity indices was the SAVI index at 71% overall accuracy (Table 7). Pairwise tests for significance between matrices indicate that the SPOT fire severity indices were not significantly different from each other; the Landsat fire severity indices were also not significantly different from each other with the exception of the RdNBR and NDSWIR (Table 9). Because the majority of the RdNBR's accuracies (overall, producer's and users) were higher than those of the other Landsat indices, the RdNBR was then compared to the SPOT-based indices. The pairwise test of significance indicated that the RdNBR accuracies were significantly better than the SPOT-based indices (Table 9) for fire severity.

Table 6. Fire Severity (unburned, moderate or incompletely burned, high or completely burned) remote sensing index accuracies using Landsat ETM+ imagery.

Accuracy Type	dNBR	RdNBR	NDSWIR	MSAVI	SAVI
Overall Accuracy	66%	73%	58%	66%	67%
Producer's Unburned	96%	98%	90%	94%	94%
Producer's Moderate	50%	61%	37%	50%	52%
Producer's High	55%	63%	52%	55%	57%
Users Unburned	86%	86%	74%	90%	90%
Users Moderate	38%	56%	34%	42%	44%
Users High	74%	76%	66%	66%	68%
KHAT	0.4900	0.5900	0.37000	0.4900	0.5100
Z	8.4339	10.7668	6.04186	8.4456	8.8829

Table 7. Fire Severity (unburned, moderate or incompletely burned, high or completely burned) remote sensing index accuracies using SPOT 5 imagery.

Accuracy Type	NDSWIR	MSAVI	SAVI
Overall Accuracy	65%	67%	71%
Producer's Unburned	95%	98%	100%
Producer's Moderate	49%	51%	61%
Producer's High	56%	55%	55%
Users Unburned	82%	86%	100%
Users Moderate	40%	38%	38%
User's High	74%	76%	76%
KHAT	0.4800	0.5000	0.5700
Z	8.2319	8.6376	10.391

Table 8. Pairwise test of significance between matrices for burned versus unburned

Pairwise Comparison	$Z_{pairwise}$ (critical value at 95% confidence interval = 1.96)
SPOT SAVI vs. SPOT MSAVI	3.0000
SPOT SAVI vs. SPOT NDSWIR	2.5211
SPOT SAVI vs. Landsat RdNBR	2.7727
SPOT SAVI vs. Landsat dNBR	3.0858
SPOT SAVI vs. Landsat MSAVI	2.7056
SPOT SAVI vs. Landsat SAVI	2.7056

DISCUSSION AND CONCLUSIONS

While studies have been performed in forested ecosystems to reliably detect fire severity, there have not been any established efforts in sagebrush steppe rangelands, an ecosystem type in which fire is common, and is a major factor in management. Fire management would benefit profoundly from research and monitoring of fires, which in turn could be enhanced with efficient remote sensing techniques. As

indicated by the highest overall, user, and producer's accuracies, the best index for determining burned from unburned areas was SPOT SAVI (100% overall accuracy) and the best index for differentiating fire severity within a burn was Landsat RdNBR (73% overall accuracy). Statistical testing indicated that SPOT SAVI was significantly different than other burned versus unburned indices. However, testing of fire severity indices indicate SPOT and Landsat-based indices are significantly different but that when compared within each sensor, the indices are not significantly different. While this conclusion is less compelling to place the Landsat-based RdNBR as the best index, the high users and producer's accuracies in the moderate and high fire severity categories indicate its superiority to other indices.

Table 9. Pairwise test of significance between matrices for fire severity.

Pairwise Comparison	$Z_{pairwise}$ (critical value at 95% confidence interval = 1.96)
Landsat RdNBR vs. Landsat NDSWIR	2.6777
Landsat RdNBR vs. SPOT NDSWIR	6.59
Landsat RdNBR vs. SPOT MSAVI	6.8894
Landsat RdNBR vs. SPOT SAVI	7.9487

Consistent with Sannier (1999), Epting et al. (2005), and Miller and Yool (2002), accuracies were better with fewer severity categories. In all cases, unburned versus burned indices had better results than fire severity indices. We were able to successfully determine if an area was burned or not in rangelands using SPOT-based NDSWIR, MSAVI, and SAVI indices and Landsat-based dNBR, RdNBR, NDSWIR, MSAVI, and SAVI indices.

Our best fire severity index, the Landsat RdNBR, supports Miller and Thode's (2007) results. In a mixed ecosystem study area, they concluded that this index performed better at separating high burn severity from other burn severity classes. Our incompletely and completely burned fire severity users' accuracies (56%, 76%, respectively) and producer's accuracies (61%, 63%, respectively) were higher for RdNBR than all other indices. These results are important to land managers given that high severity areas often require greater rehabilitation efforts.

Timing of imagery acquisition is important in relation to the seasonality of fire and field sampling dates due to phenological vegetation changes. Our fire took place in late summer when vegetation had already senesced. Reflectance (and resultantly, changes in reflectance) values were not as high as if the fire occurred in early to mid-summer (although fire in early to mid-summer is less common than fires in late summer in this ecosystem). Comparing the different indices when the sensors sampled on different days creates the possibility for a confounding factor of change in vegetation over time. Landsat imagery had 112 days between pre-fire and post-fire scenes, whereas SPOT imagery had only 32 days. Furthermore the Landsat pre-fire image was acquired when vegetation was not entirely senesced while the SPOT imagery was collected in late summer when there was a greater degree of senesced herbs in the plant community. Additionally, the Landsat post-fire image was collected 39 days after the fire whereas the SPOT post-fire image was collected 13 days after the fire. As demonstrated in Fig. 4, the longer SWIR band (2.21μm) provided the highest sensitivity (compared to other bands) to the burn. This response is consistent with an increase in soil exposure and a loss of vegetation cover. However, the increase in SPOT's green and NIR reflectances in response to an increase in soil exposure and a decrease in vegetation cover after the fire was not what we expected. Furthermore, the low sensitivity to changes in reflectance (~1%) between pre- and post-fire images in the SPOT imagery was also not expected. The low sensitivity and direction of change in reflectances may be explained by white mineral ash (silica) due to timing of imagery acquisition close after the fire (Smith et al. 2005). Another explanation could be that small changes in SPOT reflectance were within the error bound due to a combined effect of sensor signal to noise ratio and atmospheric path radiance. A previous study indicated a minimum difference in reflectance of 0.1% is needed for accurate retrieval of environmental variables (Brando and Dekker, 2003). While the Brando and Dekker (2003) study focused on retrievals from water bodies, a similar

accuracy may also be needed for fire applications. Changes in SPOT's SWIR band pre- and post-fire was similar to Landsat's band 5; this portion of the electromagnetic spectrum may not have the sensitivity of fire effects for rangelands, regardless of the time span between image acquisitions. SPOT does not have a SWIR band equivalent to Landsat band 7 (2.08-2.35µm), which has demonstrated sensitivities to reduced vegetation cover and increased soil exposure. It is worthwhile to note that the shorter time gap between SPOT images and their acquisition dates (close to field data collection) may explain, in part, why the SPOT NDSWIR accuracy is slightly better than the Landsat NDSWIR (for both burned versus unburned and fire severity), regardless of the sensitivity of this SWIR band. In summary, the multitemporal indices between Landsat and SPOT carry different relationships.

Mapping fire severity patterns at a scale that is coarse enough to capture landscape scales for management, yet fine enough to provide the spectral differentiation between fire severity classes is needed. Though SPOT didn't provide fire severity accuracies as high as Landsat (RdNBR), its spatial resolution may provide other attributes that are useful to land managers, such as burn perimeter. Landsat provides a practical scene size of 170 x 183 km and costs are reasonable if more than one image needs to be purchased. The results of the Landsat RdNBR verify that the Landsat 30 m spatial resolution is high enough to capture spectral variability between fire severity classes in rangelands. However, it is up to the land manager to decide the level of detail needed to determine fire severity and thus the scale of fire recovery efforts.

In this study the majority of the study sites were high fire severity where little vegetation reflectance and high amounts of soil should be detected. SAVI may have performed well in part because the algorithm uses NIR and red bands and not SWIR (1.58-1.75µm), which was less sensitive to the fire. The red band decreased most post-burn as bare ground and ash cover likely increased. However, our results with SAVI are contradictory to those of Epting et al. (2005), whereas their SAVI and MSAVI severity indices performed worse than their indices incorporating mid-infrared bands (2.21 µm). Their study areas were in forested ecosystems with higher standing biomass pre-fire.

Spatial correlation of ground cover and low RMS error (less than ½ a pixel) reduce the likelihood of classification error; however, they do not exclude the possibility of error entirely. Therefore, although error is introduced with multitemporal data sets, these effects likely would not have significantly altered reported accuracies. Georegistration errors between GPS field data and imagery may also have occurred for both single- and multi-date indices.

Hyperspectral imagery should be further explored to detect fire severity in rangelands because it may be more sensitive to fire effects for semiarid vegetation. For instance, AVIRIS channels 60 and 148, as suggested by van Wagtendonk et al. (2004), may discriminate fire effects better than Landsat bands 4 and 7 in rangelands. Improvements to this work may also include using the M-statistic to assess the differences between indices and separability of individual bands. Similar work has been accomplished by Kaufman & Remer (1994), Pereira (1999), and Smith et al (2007). In addition, it may be that rangeland fire severity is best detected with an extended assessment (e.g. burn severity). An extended assessment may delineate areas of high severity better, either where perennial vegetation has not recovered or where introduced annuals have established.

The SAVI and RdNBR indices are reproducible and straightforward. We chose to focus on remote sensing methods that incorporate satellite imagery and fit the needs of land managers (reasonable cost and practical spatial and spectral resolution) and methods that would not require the user to incorporate *large* amounts of field studies. Our findings support the use of the SPOT-SAVI combination for delineating burn versus unburned areas and Landsat RdNBR combination for delineating fire severity. If delineating burn versus unburned is a higher priority than fire severity, only post-fire imagery is necessary. However, if fire severity is needed then both pre-fire and post-fire imagery are required. Though our best results are

with the burned versus unburned algorithms, a 73% overall accuracy for the RdNBR fire severity index encourages future research. Before this index is entirely recommended, however, more studies need to be performed using the RdNBR in rangelands that have heterogeneous fuel loads, and within burns that have variable fire severities.

ACKNOWLEDGEMENTS

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