USE OF MULTIPLE SPECTRAL INDICES TO ESTIMATE BURN SEVERITY IN THE BLACK HILLS OF SOUTH DAKOTA

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ABSTRACT

The Jasper Fire occurred in the Black Hills National Forest, South Dakota, during August and September of 2000. The fire disturbance to ecosystem characteristics was widespread and long-term. The goal of this study is to examine the correlations between spectral indices and field-observed burn severity, and to provide a practical method to estimate burn severity using remote sensing data. We used three Landsat images acquired in June 2000, June 2001, and May 2002. The Normalized Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI), Normalized Burn Ratio (NBR), and Integrated Forest Index (IFI) were calculated from Landsat at-sensor-reflectance data. Differences of these spectral indices in first and second pre/post-burn years were calculated and analyzed with 71 field-based Composite Burn Index (CBI) data collected in May 2002. The results showed that NDVI and EVI differences correlated well with field CBI data in the first post-burn year with R^2 values of 0.69s for all 71 plots and R^2 values of 0.79s for 40 confident forest plots. NBR had good correlations with CBI data in both first and second post-burn years with R^2 values of 0.63 and 0.60 for all plots and R^2 values of 0.76 and 0.74 for confident forest plots. IFI had no correlation with CBI in the first post-burn year and had good correlation with CBI in the second post-burn year with R^2 values of 0.62 for all plots and R^2 values of 0.66 for confident forest plots. To investigate the advantages of spectral indices, multiple variable regressions were performed using two-year pre/post-burn differences of four spectral indices. The correlation of predicted CBI with field CBI is higher than any individual indices. The R^2 values are 0.81 for all CBI plots and 0.87 for confident forests. These results indicated that the spectral indices contained valuable information of fire effects and have the capability to evaluate burn severity in a short period after a fire.

Keywords: burn severity, Normalized Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI), Normalized Burn Ratio (NBR), Integrated Forest Index (IFI), multiple variable regression

INTRODUCTION

The importance of carbon pools and fluxes is receiving increased attention due to the global carbon cycle in affecting global climate. Forests play a major role in the global carbon cycle through photosynthesis, respiration, decomposition, and emissions associated with disturbances such as fire, insects, human activities, and climate anomalies. Because of the recent changing trends in fire frequency, burn severity, and size of wildland fires, detailed fire information is needed that could be used for trend analysis and research of long-term ecological influence by forest fires (Eidenshink et al., 2007).

Due to the high spatial and temporal variation and uncertainty of wildland fires, it is still a challenge to accurately estimate the affected area and the burn severity after a large fire. Remote sensing techniques provide an improved way to detect spatial and temporal variability with lower costs and less time than the traditional field inventory methods. It would be especially useful for fire-influenced ecosystem dynamics research at the regional level if remote sensing data could be used to extrapolate plot-level burn severity inventory information. The objective of this study is to analyze the correlations between remotely sensed spectral indices and field-based burn severity data in a large wildland fire in the Black Hills National Forest of South Dakota. The studied spectral indices include the traditional Normalized Difference Vegetation Index (NDVI) and these relatively new indices: Enhanced Vegetation Index (EVI), Normalized Burn Ratio (NBR), and Integrated Forest Index (IFI).

STUDY AREA AND DATA

The study area was the Jasper Fire area in the Black Hills National Forest in South Dakota (-103.85˚W, 44.82˚N, elevation 1900 m) (Figure 1). Ponderosa pine (*Pinus ponderosa*) was the dominant tree species. Occasional canopy species include paper birch (*Betula papyfira*) and quaking aspen (*Populus tremuloides*). Common understory species at the site include evergreen bearberry (*Arctostaphylos uva-ursi*), choke cherry (*Prunus virginiana*), Oregon grape (*Berberis repens*), Saskatoon serviceberry (*Amelanchier alnifolia*), and snowberry (*Symphoricarpos spp.*) (Uresk and Severson, 1989).

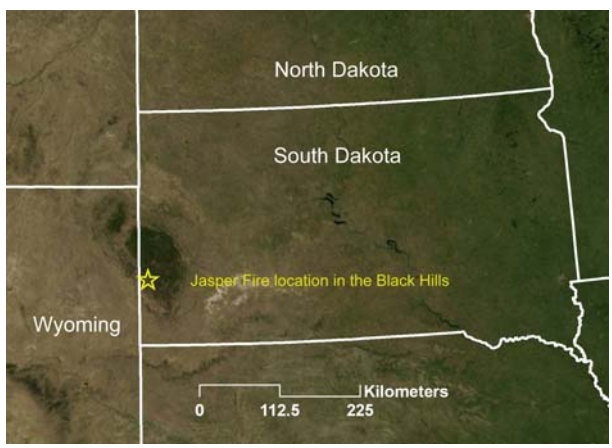

Figure 1. Study area of Jasper Fire in the Black Hills National Forest of South Dakota.

The Jasper Fire was the largest fire that occurred in the Black Hills National Forest in at least a century. The wildfire started on August 24, 2000, and had been controlled by September 25, 2000. The burned area was about 337.9 km^2 (83,508 acres) and the suppression costs were over $8.2 million (USDA, Forest Service, 2003).

Seventy-one plot-based Composite Burn Index (CBI) data were collected 21 months post-burn from May 13 to May 26, 2002, in the Jasper Fire study site (Figure 2). These CBI ground measurements were used to calibrate and validate remote sensing detection on actual fire effects on the ground. The sampling plots are relatively large plots that are compatible with the 30-meter resolution Landsat pixel size. Detailed observable ground information, including organic material consumed, characteristics of residual inorganic carbon and ash, and potential of vegetative mortality and regeneration, were recorded and used for independent burn severity ratings for both individual strata and the

synoptic rating of the whole plot area (Key and Benson, 2006). The CBI value ranges from 0 to 3. The higher CBI value is related to the higher burn severity with fire effects.

The remote sensing data used in this study included Landsat 5 images acquired on June 2, 2000 (pre-burn) and June 5, 2001 (10 months post-burn), and a Landsat 7 image acquired on May 31, 2002 (21 months post-burn).

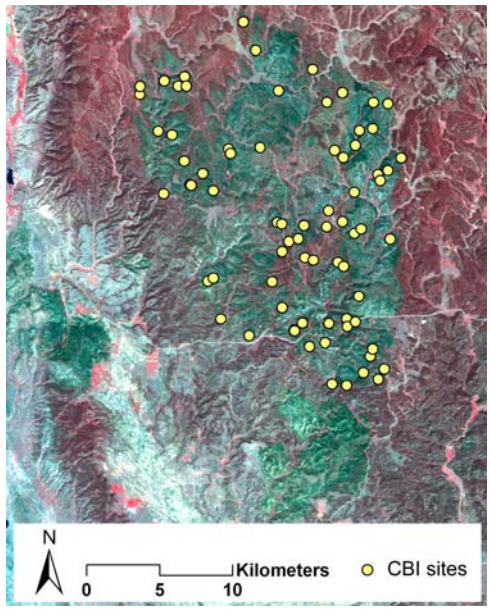

Figure 2. CBI data in the Jasper Fire burned area.
The background is a Landsat 5 image acquired 21 months post-burn on May 31, 2002 (bands 4, 3, and 2).

METHODS

All three Landsat images were converted to at-sensor-reflectance, and four spectral indices were calculated using the following individual equations for each image. The spectral difference data were calculated by subtracting the year-2000 spectral index from the post-burn index.

The NDVI is a traditional vegetation index and is calculated by using the reflectance at red (Landsat band 3) and near-infrared (Landsat band 4) bands (Rouse et al., 1974; equation 1).

$$NDVI = \frac{Band4 - Band3}{Band4 + Band3} \qquad (1)$$

The EVI is calculated by using the reflectance of blue (Landsat band 1), red (Landsat band 3), and near-infrared (Landsat band 4) (Huete et al., 1997; equation 2). Recent research showed that this index could minimize the canopy background influence and reduce atmospheric variation (Miura et al., 2001).

$$EVI = 2.5 \times \frac{Band4 - Band3}{Band4 + 6 \times Band3 - 7.5 \times Band1 + 1} \qquad (2)$$

The NBR is a spectral index frequently used to identify the fire burn area and burn severity. It is calculated by using the reflectance of near-infrared (Landsat band 4) and mid-infrared (Landsat band 7) (Key and Benson, 1999; equation 3).

$$NBR = \frac{Band4 - Band7}{Band4 + Band7} \quad (3)$$

The IFI is a recently developed spectral index representing the forest likelihood based on the image statistics (Huang et al., 2008). IFI value is calculated by its normalized distance to the center of forest training pixels within that image, while the training forest pixels were identified using local histogram spectral windows (equation 4).

$$IFI_p = \sqrt{\frac{1}{NB}\sum_{i=1}^{NB}\left(\frac{b_{pi} - \overline{b}_i}{SD_i}\right)^2} \quad (4)$$

Where $\overline{b}_i$ and SD_i are the mean and standard deviation of selected forest training pixels for band *i*, b_{pi} is the band *i* spectral value for pixel *p*, and NB is the number of spectral bands (Huang et al., 2008). In this study, the IFI was calculated from red (Landsat band 3) and mid-infrared bands (Landsat bands 5 and 7). The smaller the pixel's IFI value, the more likely that it is a forest pixel. If the forest pixels performed a normal distribution on a spectral band histogram, statistically over 99% of forest pixels have single band derived IFI values of less than 3. Assuming the IFI value calculated using the multiple bands is statistically equivalent to a single band calculation, the pixels with IFI values of less than 3 are high confident forest pixels (Huang et al., 2008).

Considering the pre-burn situation, 40 of 71 plot-based CBI data were confident forest with an IFI value of less than 3 in the pre-burn image of 2000, and these plots were separated for analysis to compare with the total plots. In addition, the distribution of the plot values is shown in Figure 3 based on three range classes. The values of 11 CBI plots were lower than 1; 27 plots ranged from 1 to 2; and 33 CBI plots ranged from 2 to 3. This indicated the field CBI plots covered a wide range of burn severity from low, medium, to high.

Single variable linear regression analysis was examined between the correlation of individual spectral index and field CBI data. Multiple variable regression was also used for exploring two-year differences of pre/post-burn indices to estimate burn severity defined by the field-based CBI. The goal of the multiple variable regression was to examine the relationship between CBI and all eight independent variables of the indices' differences two years post-burn. The regression parameters are estimated using the least squares method.

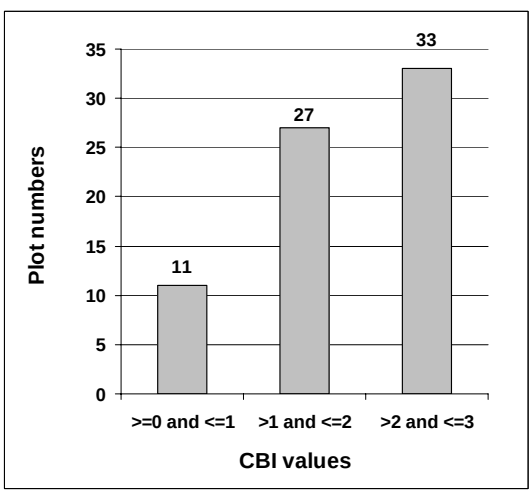

Figure 3. The distribution of CBI values among 71 field plots.

ANALYSIS AND RESULTS

Post-fire ecological impacts are well known. The first-order fire effects, also called immediate or direct effects, are the direct consequences of the fire combustion, such as injury and death of animals and plants, fuel consumption, heating of soil, and production of smoke and ash (Reinhardt et al., 2001; Eidenshink et al., 2007). The first-order effects usually present in the short-term after fire. The second-order effects are the indirect results of fire, such as soil erosion, vegetation succession, habitat changes, and local climate change (Reinhardt et al., 2001, Eidenshink et al., 2007). The second-order effects may present from a few hours to many decades after a fire and are a long-term result. Fire effects can be observed from remote sensing data if these effects resulted in significant changes of surface radiative characteristics.

After a fire, the radiative characteristics of a land surface may change due to the consumption of fire fuels and the presence of ash on the surface. In addition, vegetation transpiration is reduced and the surface temperature is increased after a fire. These effects can cause a significant reduction of surface reflectance in near-infrared (e.g., Landsat band 4) and increased reflectance in mid-infrared (e.g., Landsat band 7). The difference of pre/post-burn spectral index calculated from these burn sensitive bands could reflect the surface change magnitude and provide burn severity information. Considering the fire effects, the first year post-burn after a growing season is a good time to investigate the ecological significance of first-order fire effects. The second year post-burn is another time period to capture vegetation and soils delayed by first-order effects (e.g., delayed tree mortality) and the dominant second-order effects (e.g., soil erosion and vegetation succession). In this study, we focus on the first and second year pre/post-burn spectral indices to provide comprehensive indication of burn severity using remote sensing data and field CBI data.

The single variable linear regressions of the first year and second year pre/post-burn index differences with CBI data were shown in Table 1. In the first post-burn year, both NDVI and EVI had good correlation with all CBI data with R^2 values of 0.69s. NBR had slightly a lower R^2 value of 0.63. If only considering the 40 confident forest plots, the correlations are improved to 0.79, 0.79, and 0.76 for NDVI, EVI, and NBR, respectively. In the second year, the R^2 values were all reduced. NBR contained the best correlation in the second year with R^2 value of 0.60 for all CBI data and 0.74 for confident forest plots. These results are consistent with Epting et al. (2005) who found that NBR was highly correlated to burn severity in forested classes than in all vegetation types.

The first year pre/post-burn difference of IFI data had low correlation with CBI data. The second year pre/post-burn difference of IFI data contained good correlation with all CBI data with R^2 value of 0.62, which is higher than the other three indices in 2002 (Table 1). The correlation of IFI data and confident forest CBI data were 0.66. Unlike the above three spectral indices, IFI is an integrated statistical index on spectral performance and was designed for automated forest detection. In the first post-burn year, reflectance of red band (Landsat band 3) may be reduced significantly due to the dark soil background and ash on the surface. Therefore, some young forest plots with low burn severity may present a low IFI value and have no significant changes between pre- and first year post-burn IFI values. In the second year post-burn, the dark soil background might be covered with re-grown understory vegetation, and rain might have flushed out the ash. Most IFI values of burn plots increased significantly in 2002, and the difference of IFI had the highest correlation with field CBI data compared with other three spectral indices.

Table 1. The linear regressions (R^2) between field-based Composite Burn Index (CBI) and the pre/post-burn differences of spectral indices

	Indices difference of 2001 and 2000		**Indices difference of 2002 and 2000**	
	all plots	confident forest plots	all plots	confident forest plots
NDVI	0.69	0.79	0.56	0.67
EVI	0.69	0.79	0.58	0.71
NBR	0.63	0.76	0.60	0.74
IFI	0.16	0.34	0.62	0.66

To consider all the advantages of the four spectral indices, including both first-order and second-order fire effects information within the two-year post-burn period, multiple variable regressions with all differences of the four spectral indices in two years pre/post-burn were examined. Table 2 lists the coefficients for the multiple variable regressions using all 71 CBI plots and 40 confident forest plots. The comparison of field-collected CBI data with the predicted CBI using multiple variable regression in all 71 plots is shown in Figure 4. The linear correlation R^2 value of these two

datasets was 0.81, which indicated a good correlation between the predicted CBI and the field CBI data. If only considering the 40 confident forest plots, the R^2 value was improved to 0.87 (Figure 5), which demonstrated that spectral indices could provide more accurate burn severity estimation for confident forest plots than other plots.

Table 2. Coefficients of multiple variable regressions using two-year pre/post-burn differences of spectral indices for CBI estimation

$$CBI = b_0 + b_1 \bullet NDVI(1) + b_2 \bullet NDVI(2) + b_3 \bullet EVI(1) + b_4 \bullet EVI(2) + b_5 \bullet NBR(1) + b_6 \bullet NBR(2) + b_7 \bullet IFI(1) + b_8 \bullet IFI(2)$$

	Intercept b_0	NDVI(1) b_1	NDVI(2) b_2	EVI(1) b_3	EVI(2) b_4	NBR(1) b_5	NBR(2) b_6	IFI(1) b_7	IFI(2) b_8
All plots	0.48	-3.43	-0.76	-0.83	-0.09	-1.17	2.22	-0.15	0.10
Confident forests	0.81	-4.95	3.70	6.65	-12.10	-3.43	4.32	-0.24	0.13

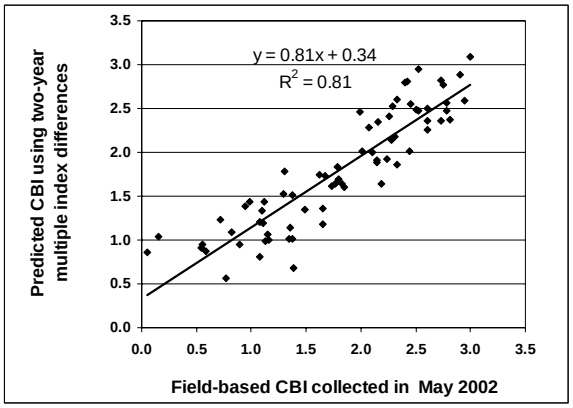

Figure 4. Comparison of all 71 field-based CBI data collected in May 2002 and the predicted CBI data using multiple variable regression of two-year index differences indicated in Table 2.

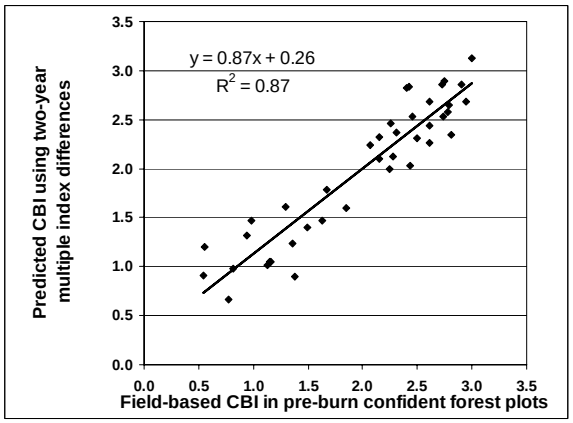

Figure 5. Comparison of 40 field-based CBI data collected in pre-burn confident forest plots and the predicted CBI data using multiple variable regression of two-year index differences indicated in Table 2.

CONCLUSIONS

Our study indicated that all four spectral indices have the capability to evaluate burn severity and vegetation damage in a short period after fire. Three spectral indices, NDVI, EVI, and NBR, contained good correlation with all CBI data in the study burned areas in the first post-burn year with R^2 values of 0.69, 0.69, and 0.63, respectively. Their correlations with pre-burn confident forest plots were significant and R^2 values were 0.79, 0.79, and 0.76, respectively. In the second post-burn year, all correlations were decreased, but NBR still contained a good correlation in confident forests ($R^2 = 0.74$). Pre/post-burn difference of IFI data had no correlation with field CBI data in the first year post-burn but had good correlation in the second year post-burn for all plots ($R^2 = 0.62$) and for confident forest plots ($R^2 = 0.66$). No index was identified as the highest R^2 for both two-year analyses. Multiple variable regressions using all indices in the two-year post-burn data provided high correlations of predicted CBI with field CBI. The R^2 values were 0.81 for all plots and 0.87 for the confident forest plots. By applying the multiple variable regression functions, scientists could estimate burn severity CBI values with high accuracy using remote sensing data at the Jasper Fire site.

In addition, these spectral indices could be examined for long-term monitoring of post-burn vegetation dynamics, which present second-order fire effects.

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