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# Quantifying burn severity in a heterogeneous landscape with a relative version of the delta Normalized Burn Ratio (dNBR)

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**Abstract**

Multi-temporal change detection is commonly used in the detection of changes to ecosystems. Differencing single band indices derived from multispectral pre- and post-fire images is one of the most frequently used change detection algorithms. In this paper we examine a commonly used index used in mapping fire effects due to wildland fire. Subtracting a post-fire from a pre-fire image derived index produces a measure of absolute change which then can be used to estimate total carbon release, biomass loss, smoke production, etc. Measuring absolute change however, may be inappropriate when assessing ecological impacts. In a pixel with a sparse tree canopy for example, differencing a vegetation index will measure a small change due stand-replacing fire. Similarly, differencing will produce a large change value in a pixel experiencing stand-replacing fire that had a dense pre-fire tree canopy. If all stand-replacing fire is defined as severe fire, then thresholding an absolute change image derived through image differencing to produce a categorical classification of burn severity can result in misclassification of low vegetated pixels. Misclassification of low vegetated pixels also happens when classifying severity in different vegetation types within the same fire perimeter with one set of thresholds. Comparisons of classifications derived from thresholds of dNBR and relative dNBR data for individual fires may result in similar classification accuracies. However, classifications of relative dNBR data can produce higher accuracies on average for the high burn severity category than dNBR classifications derived from a universal set of thresholds applied across multiple fires. This is important when mapping historic fires where precise field based severity data may not be available to aid in classification. Implementation of a relative index will also allow a more direct comparison of severity between fires across space and time which is important for landscape level analysis. In this paper we present a relative version of dNBR based upon field data from 14 fires in the Sierra Nevada mountain range of California, USA. The methods presented may have application to other types of disturbance events.


*Keywords:* Wildland fire; Burn severity; Change detection; Disturbance; Relative change; dNBR; Landsat TM

## 1. Introduction

Multispectral satellite data have become a common tool to aid in the detection of changes to ecosystems. Differencing is the most common technique used in multi-date change detection and has been used extensively to assess fire severity (Brewer et al., 2005; Cocke et al., 2005; Epting et al., 2005; Key & Benson, 2005a; Miller & Yool, 2002; Singh, 1989). Differencing can result in a measure of absolute change that is correlated to the pre-change image. For example, if a pixel where a small amount of photosynthetically active vegetation is measured in a pre-change image experiences complete mortality before the acquisition of the second image, a small change in living biomass within the pixel will be measured by differencing vegetation indices calculated from the two images. In contrast, a large change in live biomass will be measured in a pixel experiencing complete mortality that contained a large amount of photosynthetically active vegetation in the pre-disturbance image. However, both pixels experienced stand-replacing events. Confusion between high and moderate severity classes due to differing amounts of pre-fire cover in maps produced with a differenced index has been noted as a problem by researchers (Kokaly et al., in press). Measuring absolute change

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through techniques such as vegetation index differencing may therefore not provide a complete ecological picture of the disturbance event.

In the fire ecology literature burn severity is defined as the effect of fire on an ecosystem (Agee, 1993; Sugihara et al., 2006). Often burn severity is mapped in broad categories such as low, moderate and high representing the sum of effects in all structural strata in the ecosystem (DeBano et al., 1998). For a forested system those strata could include soil, surface fuels, herbaceous layer, understory shrubs, intermediate trees, and dominant and co-dominant trees. Fire regime types of surface, mixed lethal, and stand-replacing fire are commonly used as descriptive definitions for burn severity categories of low, moderate, and high (Arno & Fiedler, 2005; Brown & Smith, 2000). Returning to the example above, if all vegetation in the two pixels with small and large amounts of pre-fire vegetation experience complete mortality of live vegetation, i.e. stand-replacing fire, both pixels would be categorized as having experienced high severity fire. Thus the degree of severity experienced by vegetation in each pixel is not dependent upon the amount of vegetation present prior to the fire, but is dependent on the percent of the vegetation that was affected, making severity a relative measure. The same logic applies to heterogeneous landscapes with multiple vegetation types. Using an absolute measure of change could lead to incorrectly characterizing burn severity in pixels which contain less pre-disturbance chlorophyll on average than the surrounding landscape due not only to differences in the amount of cover but differences in the type of vegetation present. Correctly mapping spatial patterns of severity is crucial however to predict post-disturbance recovery since patch size and severity control the number of surviving individuals and distance to seed sources, which in turn influences succession processes (Pickett & White, 1985; Turner et al., 1998).

Little discussion exists in the remote sensing literature about relative indices although the issue of heterogeneous landscapes affecting change detection classification accuracies is well known (Coppin & Bauer, 1996). Projects that use a single post-disturbance image to map landscape change must make assumptions about the homogeneity of the pre-disturbance landscape (Coppin & Bauer, 1996; Jakubauskas et al., 1990; Vogelmann & Rock, 1988). Heterogeneous landscapes may be accounted for through the use of reference data detailing pre-disturbance conditions. Researchers have used various methodological approaches to include pre-disturbance conditions during classification. Pre-classification stratification by vegetation or cover type is a strategy that has been successfully employed to create homogeneous landscapes out of heterogeneous ones (Brewer et al., 2005; Ekstrand, 1994; Franklin & Wulder, 2002; Miller & Yool, 2002; Strahler, 1981; White et al., 1996). Image classification techniques utilizing multi-date imagery, such as principal components, artificial neural networks, etc., account for pre-disturbance conditions but training classifiers is inherently more difficult to implement operationally than thresholding single indices, especially for projects where the landscape of interest crosses many images in space or time (Brewer et al., 2005; Collins & Woodcock, 1996). However, thresholding absolute change images would require assessing each fire individually to derive properly calibrated thresholds that would be unique to each fire (Key & Benson, 2005a).

The purpose of this study was to determine how to derive thresholds that could be used to characterize severity resulting from hundreds of fires occurring across a heterogeneous landscape beginning with the 1984 launch date of Landsat TM through present. Most fires did not have any field sampled severity data to use in training a classifier, nor could expert knowledge of each fire be gathered even if it still existed. Vegetation maps of sufficient detail, scale, and timing would not be available for stratification of all fires. The products of this project will be used for subsequent future analysis at both site and landscape levels. We therefore required a continuous dataset from each fire that: 1.) correlated to severity experienced by vegetation in each fire, 2.) was on the same scale such that the same data value measured in each fire represented the same level of severity, and 3.) resulted in categorical maps of severity with satisfactory accuracy, though possibly not the highest accuracy possible. The methodology used to produce the severity data would have to be independent of any a-priori knowledge of each fire. Due to these requirements we felt that using a severity index derived from an absolute differencing algorithm was not desirable for our application.

Our supposition was that a relative severity index that was on the same scale for each fire and resulted in categorical maps of severity with satisfactory accuracy could be developed by incorporating pre-fire information in the form of a pre-fire image with an absolute change image. In this paper we present the methodology used to produce a relative burn severity index and the results from 14 fires that occurred from 2002 through 2004 in the Sierra Nevada, California, USA.

## 2. Methods

### 2.1. Study area

All 14 fires included in this study fall within the Sierra Nevada, California, USA (Fig. 1). The area ranges in elevation from 60 m adjacent at the Sacramento River in the foothills to 4418 m at Mount Whitney. The study area encompasses 11.5 million acres of National Forest land, five National Parks and National Monuments, and all or part of 32 counties in California and Nevada. The study area includes parts of seven ecological subregions of California (Miles & Goudy, 1997): the Sierra Nevada, Sierra Nevada Foothills, Southern Cascades, the Modoc Plateau, the Northwestern Basin and Range, and a small portion of the Mono. The fires were greater than 400 ha in size and cover a wide range of vegetation types and elevations (Table 1).

### 2.2. Data

#### 2.2.1. Field data

Field data quantifying severity were collected during the summer field season after each fire occurred. This project used

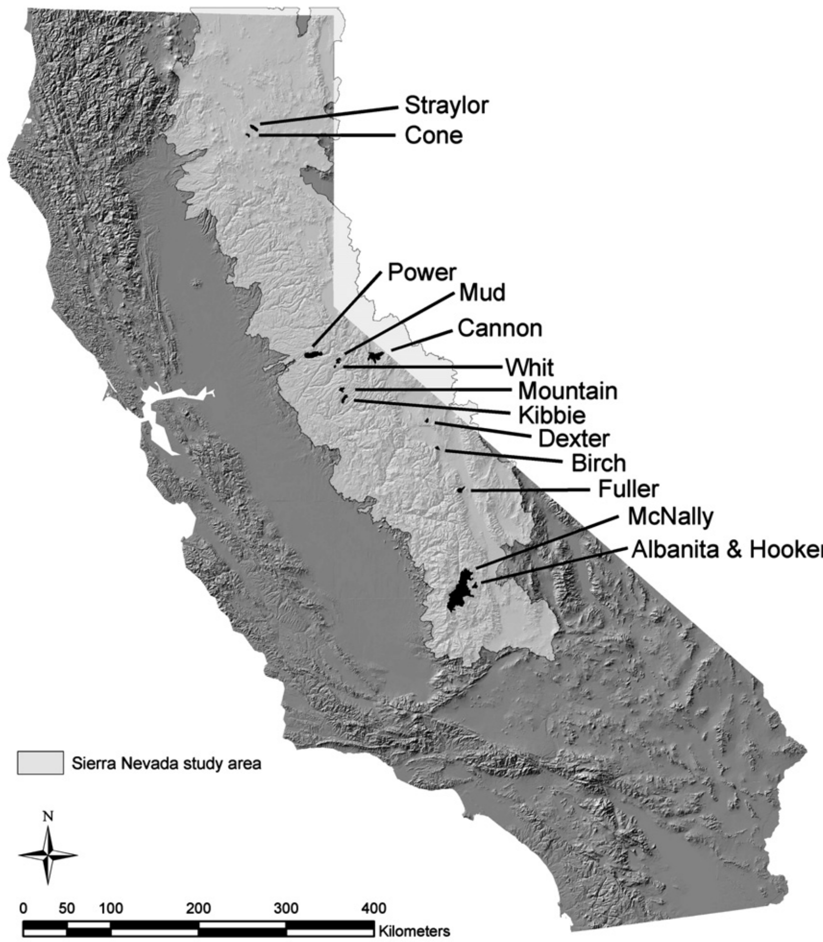


Fig. 1. Location of study area fires within the Sierra Nevada of California, USA.

the Composite Burn Index (CBI) field protocol (Fig. 2) developed by Key and Benson (2005b) as a field measure of the average burn condition found in a plot. The CBI protocol records fire effects in five strata: 1) surface fuels and soils; (2) herbs, low shrubs and trees less than 1 m; (3) tall shrubs and trees 1 to 5 m; (4) intermediate trees; and (5) big trees. Each stratum incorporates four or five variables that are visually estimated and ranked between zero and three. Values for all

Table 1
Fires used in the study

| Fire | Year | National forest | Fire type | Alarm date | Fire size (ha) | Elevation (m) | Vegetation type |
|---|---|---|---|---|---|---|---|
| Birch | 2002 | Inyo | Wildfire | 7/1/2002 | 1091 | 1870–2549 | Singleleaf pinyon pine, Sagebrush |
| Cannon | 2002 | Humboldt-Toiyabe | Wildfire | 6/15/2002 | 10973 | 1621–3117 | Singleleaf pinyon pine, Sagebrush, Mixed Conifer, Jeffrey Pine |
| Cone | 2002 | Lassen | Wildfire | 9/26/2002 | 824 | 1772–1952 | Jeffrey pine-ponderosa pine, Mixed Conifer, Jeffrey pine |
| Fuller | 2002 | Inyo | Wildfire | 7/12/2002 | 2719 | 1419–3355 | Sagebrush |
| McNally | 2002 | Sequoia | Wildfire | 7/21/2002 | 61491 | 1033–3061 | Interior live oak, Scrub oak, Foothill pine, Black oak, Canyon live oak, Ponderosa pine, Mixed conifer, Jeffrey pine, White fir |
| Albanita | 2003 | Sequoia | Fire Use | 9/3/2003 | 899 | 2371–2866 | Mixed Conifer, Jeffrey pine, Lodgepole pine, Red fir |
| Dexter | 2003 | Inyo | Fire Use | 9/2/2003 | 995 | 2330–2787 | Aspen, Jeffrey pine, Lodgepole pine |
| Kibbie | 2003 | Stanislaus | Fire Use | 7/29/2003 | 2752 | 1443–2475 | Mixed conifer, Jeffrey pine-ponderosa pine, Jeffrey pine, White Fir |
| Hooker | 2003 | Sequoia | Fire Use | 9/3/2003 | 997 | 2381–2803 | Mixed Conifer, Jeffrey pine, Lodgepole pine, Red fir |
| Mountain Complex | 2003 | Stanislaus | Fire Use | 7/20/2003 | 1709 | 2022–2535 | Mixed conifer, Jeffrey pine, Lodgepole pine, White fir, Red fir, Western white pine |
| Mud | 2003 | Stanislaus | Fire Use | 8/31/2003 | 1762 | 2010–2639 | Mixed conifer, Jeffrey pine, Lodgepole pine, White fir, Red fir |
| Whit | 2003 | Stanislaus | Fire Use | 8/31/2003 | 424 | 2007–2364 | Mixed conifer, Jeffrey pine, Lodgepole pine, White fir, Red fir |
| Power | 2004 | Edorado | Wildfire | 10/6/2004 | 6812 | 936–2098 | Black oak, Ponderosa pine, Mixed conifer, Jeffrey pine, White fir |
| Straylor | 2004 | Lassen | Wildfire | 7/22/2004 | 1385 | 1377–1785 | Ponderosa pine, Jeffrey pine, Western juniper |

**BURN SEVERITY --COMPOSITE BURN INDEX (BI)**

| | | | | | |
|---|---|---|---|---|---|
| **PD -Abridged** | Examiners: | | | Fire Name: | |
| Registration Code | | Project Code | | Plot Number | |
| Field Date mmddyyyy | / / | Fire Date mmyyyy | / | | |
| Plot Aspect | | Plot % Slope | | UTM Zone | |
| Plot Radius Overstory | | UTM E plot center | | GPS Datum | |
| Plot Radius Understory | | UTM N plot center | | GPS Error (m) | |
| Number of Plot Photos | | Plot Photo IDs | | | |

| **BI – Long Form** | % Burned 20 m Plot = | | | %Burned 30 m Plot = | | Fuel Photo Series = | | |
|---|---|---|---|---|---|---|---|---|
| **STRATA RATING FACTORS** | **BURN SEVERITY SCALE** | | | | | | | **ACTOR SCORES** |
| | **No Effect** | **Low** | | **Moderate** | | **High** | | |
| | **0.0** | **0.5** | **1.0** | **1.5** | **2.0** | **2.5** | **3.0** | |
| **A. SUBSTRATES** | | | | | | | | |
| **% Pre-Fire Cover: Litter =** | **Duff =** | | **Soil/Rock =** | | **Pre-Fire Depth (inches): Litter =** | **Duff =** | **Fuel Bed =** | **Σ= N = X̄ =** |
| Litter/Light Fuel Consumed | Unchanged | -- | 50% litter | -- | 100% litter | >80% light fuel | 98% Light Fuel | |
| Duff | Unchanged | -- | Light char | -- | 50% loss deep char | -- | Consumed | |
| Medium Fuel, 3-8 in. | Unchanged | -- | 20% consumed | -- | 40% consumed | -- | >60% loss, deep ch | |
| Heavy Fuel, > 8 in. | Unchanged | -- | 10% loss | -- | 25% loss, deep char | -- | >40% loss, deep ch | |
| Soil Cover/Color | Unchanged | -- | 10% change | -- | 40% change | -- | >80% change | |
| **B. HERBS, LOW SHRUBS AND TREES LESS THAN 1 METER:** | | | | | | | | |
| **Pre-Fire Cover =** | | **Enhanced Growth Factor =** | | | | | | **Σ= N = X̄ =** |
| %Foliage Altered (blk-brn) | Unchanged | -- | 30% | -- | 80% | 95% | 100% + branch loss | |
| Frequency % Living | 100% | -- | 90% | -- | 50% | < 20%N | None | |
| Colonizers | Unchanged | -- | Low | -- | Moderate | High-Low | Low to None | |
| Spp. Comp. -Rel. Abund. | Unchanged | -- | Little change | -- | Moderate change | -- | High change | |
| **C. TALL SHRUBS AND TREES 1 TO 5 METERS:** | | | | | | | | |
| **Pre-Fire Cover =** | | **Enhanced Growth Factor =** | | | | | | **Σ= N = X̄ =** |
| % Foliage Altered (blk-brn) | 0% | -- | 20% | -- | 60-90% | > 95% | Signifcant branch loss | |
| Frequency % Living | 100% | -- | 90% | -- | 30% | < 15% | <1% | |
| % Change in Cover | Unchanged | -- | 15% | -- | 70% | 90% | 100% | |
| Spp. Comp. -Rel. Abund. | Unchanged | -- | Little change | -- | Moderate change | -- | High Change | |
| **D. INTERMEDIATE TREES (SUBCANOPY, POLE-SIZED TREES)** | | | | | | | | |
| **Pre-Fire Cover =** | **Pre-Fire Number Living =** | | | | **Pre-Fire Number Dead =** | | | **Σ= N = X̄ =** |
| % Green (Unaltered) | 100% | -- | 80% | -- | 40% | < 10% | None | |
| % Black (Torch) | None | -- | 5-20% | -- | 60% | > 85% | 100% + branch loss | |
| % Brown (Scorch/Girdle) | None | -- | 5-20% | -- | 40-80% | < 40 or > 80% | None due to torch | |
| % Canopy Mortality | None | -- | 15% | -- | 60% | 80% | %100 | |
| Char Height | None | -- | 1.5 m | -- | 2.8 m | -- | > 5 m | |
| **Post Fire: %Girdled=%** | | **Felled =** | | **%TreeMortality =** | | | | |
| **E. BIG TREES (UPPER CANOPY, DOMINANT, CODOMNANT TREES)** | | | | | | | | |
| **Pre-Fire % Cover =** | **Pre-Fire Number Living =** | | | | **Pre-Fire Number Dead =** | | | **Σ= N = X̄ =** |
| % Green (Unaltered) | 100% | -- | 95% | -- | 50% | < 10% | None | |
| % Black (Torch) | None | -- | 5-10% | -- | 50% | > 80% | 100% + branch loss | |
| % Brown (Scorch/Girdle) | None | -- | 5-10% | -- | 30-70% | < 30 or > 70% | None due to torch | |
| % Canopy Mortality | None | -- | 10% | -- | 50% | 70% | %100 | |
| Char Height | None | -- | 1.8 m | -- | 4 m | -- | > 7 m | |
| **Post Fire: %Girdled =** | | **%Felled =** | | **%Tree Mortality** | | | | |

| **Community Notes/Comments:** | **BI = Sum ofScores / N Rated:** | **Sum of Scores** | **N Rated** | **CBI** |
|---|---|---|---|---|
| | **Understory (A+B+C)** | | | |
| | **Overstory(D+E)** | | | |
| | **Total Plot (A+B+C+D+E)** | | | |

% Estimators: **20 m Plot**: 314 $m^2$ 1% = 1x3 m 5% = 3x5 m 10% = 5x6 m
**30 m Plot**: 704 $m^2$ 1% = 1x7 m (<2x4 m) 7% = 5x7 m 10% = 7x10 m

*After, Key and Benson 1999, USGS NRMSC, Glacier Field Station.*
Versiersion 3.0 May 18, 2004

Strata and Factors are defined in FIREMON Landscape Assessment, Chapter 2, and on accompanying BI "cheat sheet". www.fire.org/firemon/lc.htm

Fig. 2. Composite Burn Index (CBI) field data form from Key and Benson (2005b).

strata were averaged to create a severity index value for the whole plot ranging between zero (unburned) and three (highest severity). Although CBI includes fire effects to soils, the index is heavily weighted to measuring fire effects to vegetation.

Choosing which CBI values to use as thresholds between severity categories is somewhat of a value judgment. Similar but distinct severity maps could be produced depending on management objective, analysis criteria, etc. For this project we chose to place the thresholds halfway between the values listed on the CBI data form shown in Fig. 2 for adjacent categories to create four severity categories; unchanged, low, moderate, and high. For example, the CBI data form indicates a "moderate" severity occurs when CBI ranges between 1.5 and 2.0, and "high" severity occurs between 2.5 and 3.0. We therefore chose 2.25 as the threshold between "moderate" and "high" severity categories. The exception to the mid-point rule was the threshold between unchanged and low for which we chose

Table 2
CBI severity category definitions

| Severity category | Field measured severity value | Definition |
|---|---|---|
| Unchanged | 0–0.1 | One year after the fire the area was indistinguishable from pre-fire conditions. This does not always indicate the area did not burn. |
| Low | 0.1–1.24 | Areas of surface fire occurred with little change in cover and little mortality of the structurally dominant vegetation. |
| Moderate | 1.25–2.24 | The area exhibits a mixture of effects ranging from unchanged to high. |
| High | 2.25–3.0 | Vegetation has high to complete mortality. |

0.1. Table 2 lists the CBI values that were used to define severity categories for this study. We labeled the lowest severity class “unchanged” instead of “unburned”. Since we measure severity after one growing season, it is therefore difficult sometimes to distinguish areas which have recovered after very low severity fire from unburned areas via satellite imagery.

The field protocol used in this project measured fire effects in a 90 m diameter circular plot. It is often difficult to visually assess a whole 90 m diameter plot from the center. In addition to the CBI protocol, field measurements were made for other purposes that are not presented here, but in acquiring those measurements the whole 90 m plot was visited and CBI estimates were made after visiting the entire plot. Plots were randomly located between 300 m and 400 m along randomly placed transects. Steep slopes were avoided for personnel safety reasons.

### *2.2.2. Imagery and preprocessing*

Imagery used in this study (Table 3) was chosen such that pre- and post-fire dates were as close to anniversary dates as possible to minimize differences in phenology and sun angle (Singh, 1989). All post-fire images were acquired the year following the fire and were smoke-free. All images were orthorectified using a terrain correction algorithm. To reduce storage and image processing times, each image was clipped to include an unburned area around each fire. All subsequent processing was performed only on the subset. The pre- and post-fire subset images for each fire were co-registered to within a pixel. All Landsat 5 images were converted to reflectance as described by Chander and Markham (2003). The change detection algorithm incorporates only the near-infrared and mid-infrared wavelengths measured by Landsat TM channels 4 and 7. Atmospheric scattering is negligible in the infrared bands (Avery & Berlin, 1992). Therefore we chose not to perform any atmospheric corrections. All image processing was performed using ERDAS Imagine version 8.7 on a Windows 2000 workstation.

## *2.3. Change detection algorithm*

Vegetation indices have been shown to enhance detection of vegetation (Tucker & Sellers, 1986). Ratio-based vegetation indices also minimize topographic-induced variance (Avery & Berlin, 1992). Vegetation index differencing has been shown to outperform other multi-date methods such as image differencing and ratioing (Lyon et al., 1998; Nelson, 1983). Recently the normalized burn ratio (NBR) has gained consideration, mostly in the United States, for detecting fire scars (Key & Benson, 2005a). NBR is formulated like the normalized difference vegetation index (NDVI) except Landsat TM mid-infrared band 7 is used in place of the red band as follows:

$$\mathrm{NBR} = \left(\frac{\mathrm{band4}-\mathrm{band7}}{\mathrm{band4}+\mathrm{band7}}\right)$$

Band 7 is employed due to the band 4 band 7 difference showing the largest change between pre- and post-fire images, especially in forested landscapes (Key & Benson, 2005a; Lopez Garcia & Caselles, 1991; Miller & Yool, 2002). Band 4 encompasses near-infrared 0.76–0.90 μm wavelengths primarily sensitive to the chlorophyll content of live vegetation. Band 7, which records middle infrared 2.08–2.35 μm wavelengths, is sensitive to water content in both soils and vegetation, the lignose content of non-photosynthetic vegetation, and hydrous minerals such as clay, mica, and some oxides and sulfates (Avery & Berlin, 1992; Elvidge, 1990). Band 7 wavelengths have been shown to be sensitive in separating non-photosynthetically active (dead) wood from soil, ash, and charred wood in a post-fire environment (Jia et al., 2006; Kokaly et al., in press). As a result of using these two bands, NBR is particularly sensitive to the changes in the amount of live green vegetation, moisture content, and some soil conditions which may occur after fire. We used the delta NBR (dNBR) in this study since it has been shown to perform at least as well if not better than other index differencing change detection methods in capturing the spatial complexity of severity within fire perimeters (Brewer et al., 2005; Epting et al., 2005; Thode, 2005). NBR values were multiplied by 1000 and converted to integer format to follow the convention established by Key and Benson (2005a). A focal mean algorithm was used to average pixel values in a 3 × 3 pixel window to match the 90 m diameter field plots. The dNBR for each fire was normalized to account

Table 3
Imagery used for each fire

| Fire | Alarm date | Landsat path/row | Pre-fire image date | Post-fire image date | Sensor |
|---|---|---|---|---|---|
| Birch | 7/1/2002 | 42/34 | 6/7/2002 | 6/10/2003 | Landsat 5 |
| Cannon | 6/15/2002 | 43/33 | 6/14/2002 | 7/3/2003 | Landsat 5 |
| Cone | 9/26/2002 | 44/32 | 9/25/2002 | 9/12/2003 | Landsat 5 |
| Fuller | 7/12/2002 | 42/34 | 7/9/2002 | 7/12/2003 | Landsat 5 |
| McNally | 7/21/2002 | 41/35 | 6/16/2002 | 6/16/2003 | Landsat 5 |
| Albanita | 9/3/2003 | 41/35 | 8/22/2003 | 8/8/2004 | Landsat 5 |
| Dexter | 9/2/2003 | 42/34 | 7/12/2003 | 7/30/2004 | Landsat 5 |
| Kibbie | 7/29/2003 | 42/34 | 7/12/2003 | 7/30/2004 | Landsat 5 |
| Hooker | 9/3/2003 | 41/35 | 8/22/2003 | 8/8/2004 | Landsat 5 |
| Mountain Complex | 7/20/2003 | 43/33 | 7/3/2003 | 7/5/2004 | Landsat 5 |
| Mud | 8/31/2003 | 43/33 | 7/3/2003 | 7/5/2004 | Landsat 5 |
| Whit | 8/31/2003 | 43/33 | 7/3/2003 | 7/5/2004 | Landsat 5 |
| Power | 10/6/2004 | 43/33 | 7/5/2004 | 8/25/2005 | Landsat 5 |
| Straylor | 7/22/2004 | 44/32 | 9/12/2003 | 9/1/2005 | Landsat 5 |

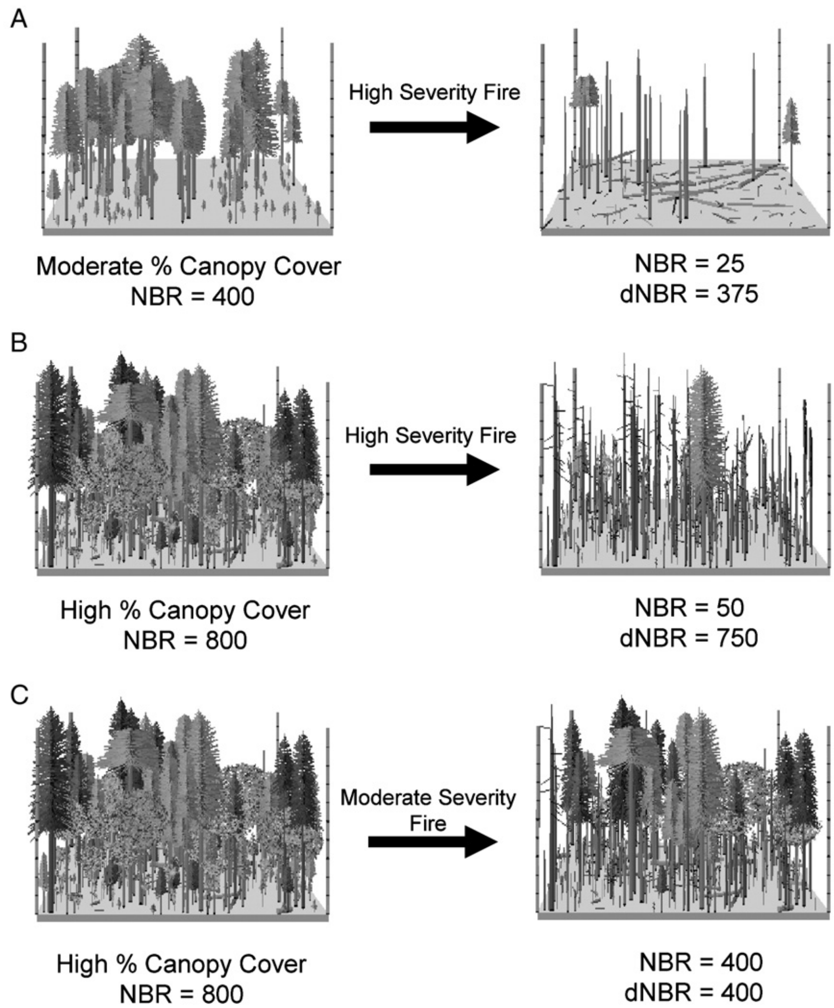


Fig. 3. Typical NBR and dNBR values in two plots with moderate (A) and high (B and C) percent canopy cover before and after experiencing high (A and B) or moderate severity fire (C). An NBR value of 25 indicates little to no live vegetation exists, where as a value of 800 indicates dense vegetation.

for inter-annual differences in precipitation by subtracting the average dNBR value sampled from an unburned area outside the fire perimeter.

### 2.4. Relative index development

Examining an example of a heterogeneous landscape, Fig. 3 depicts three scenarios within a fire perimeter in a conifer forest environment. Represented are two plots, one with moderate (Fig. 3A) and another with high (Fig. 3B) amount of pre-fire vegetation, both experiencing high severity fire and almost complete vegetation mortality. The resulting dNBR value of the more densely vegetated pixel is twice that of the moderately vegetated plot. If the more densely vegetated plot (Fig. 3C) had experienced moderate severity fire with only half of the vegetation experiencing mortality though, the resulting dNBR value would be around 400, higher than the dNBR value of 375 measured in the moderately vegetated plot experiencing high severity fire. Thus thresholding a dNBR image to create severity categories in this case would result in a misclassification error.

If burn severity is a relative measure, then when the vegetation in a pixel experiences stand-replacing fire, the result is high severity despite the amount of vegetation pre-fire. Therefore severity should be uncorrelated to the amount of pre-fire vegetation cover. Fig. 4A confirms that field measured burn severity is uncorrelated with pre-fire NBR values ($r$=.17). This is the relationship that we want to emulate with a satellite measured index of severity. Plotting dNBR values against pre-fire NBR values (Fig. 4B) on the other hand, results in a moderately high correlation of $r$=.53. Thresholding dNBR in Fig. 4B to create severity categories would most likely result in never correctly classifying a high severity plot that had low to moderate pre-fire vegetation cover (low pre-fire NBR). We therefore examined relativizing dNBR by dividing dNBR with the pre-fire NBR to eliminate the correlation to the pre-fire NBR and so that the relationship of resulting satellite derived severity index to pre-fire NBR would emulate the relationship of field measured severity to pre-fire NBR.

Regression models of CBI field measurements to dNBR and Relative dNBR were developed to determine whether

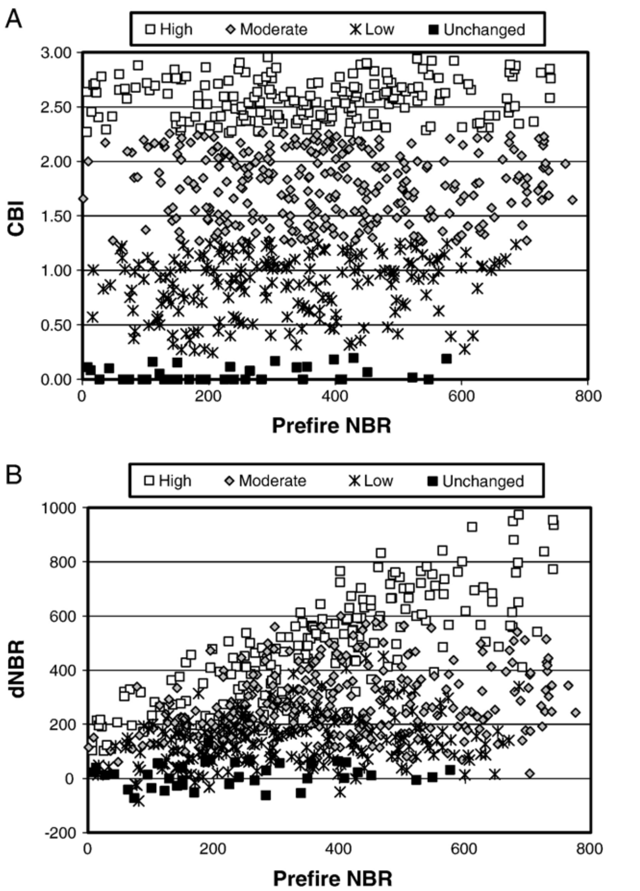


Fig. 4. CBI and dNBR values for all plots in all 14 fires colored by CBI severity category plotted against pre-fire NBR values: (A) field measured CBI severity values, $r$ = .17; (B) Landsat derived dNBR values, $r$ = .53.

relativizing dNBR would on average, over all fires, improve map accuracies over dNBR. Threshold values were computed using the regression models and confusion matrices computed using all field plots as an indicator of model improvement.

## 3. Results and discussion

### 3.1. Relative index

Our goal is to develop a relative index derived from satellite acquired data which when plotted against pre-fire NBR values emulates the shape of field-measured severity values against pre-fire NBR values (Fig. 4A). The customary mathematical formulation of a relative change index is to divide the change value by the pre-disturbance index value. The absolute change index is therefore converted to a percent and the resulting relative change index varies linearly with the variable of interest, which is severity in our case.

Fig. 5A shows the result of dividing dNBR by pre-fire NBR. The shape of the resulting data space does not emulate very well the data space of field measured severity against pre-fire NBR values shown in Fig. 4A. Locations with low to moderate pre-fire NBR values may result in exceptionally large values. It appears that the “boosting” effect only occurs within fire perimeters; increases with severity and decreasing amounts of pre-fire vegetation, and in some locations may be enhanced with certain soil types. Key and Benson (2005a) states that NBR is sensitive to char, mineral soil, ash, and changes in soil color. Experiments relativizing NDVI did not exhibit the same elevated values at low pre-fire values. We therefore hypothesize that the effect is caused by the use of Landsat mid-infrared band 7 in NBR. Since band 7 wavelengths are sensitive to water content in both soil and vegetation, hydrous minerals, iron oxides, lignose in non-photosynthetic vegetation, ash, and char, more than one mechanism may be involved (Avery & Berlin, 1992; Jia et al., 2006; Kokaly et al., in press). Another complicating factor is that CBI is a linear combination of up to 23 factors, only one of which is soil related. The remaining factors are all vegetation related (Fig. 2). As a result, CBI reaches a maximum value when there is complete vegetation mortality as opposed to dNBR which varies in value after complete vegetation mortality resulting in a nonlinear relationship of dNBR to CBI (van Wagtendonk et al., 2004). As a first order

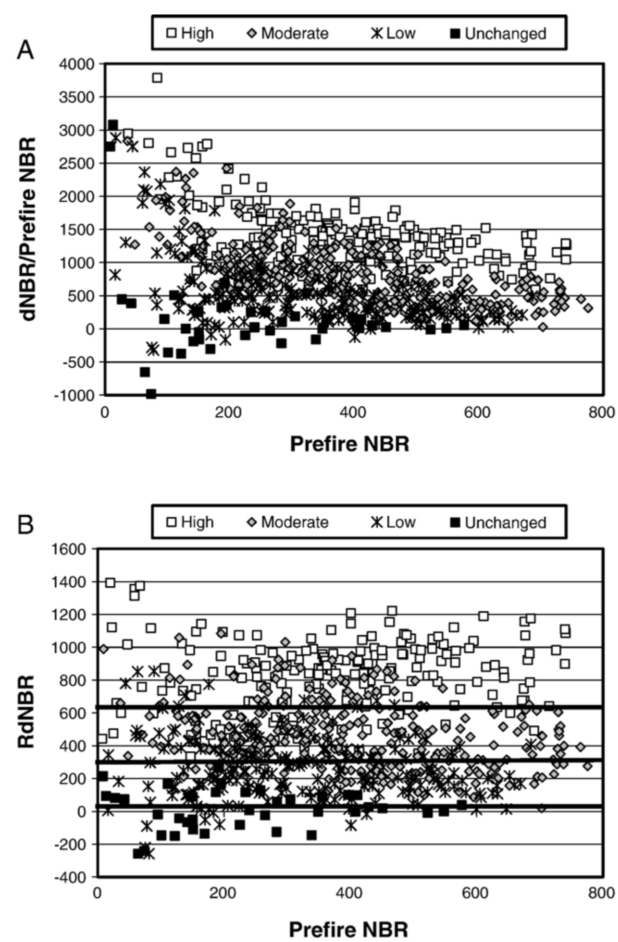


Fig. 5. Pre-fire NBR values for all plots in all 14 fires versus: (A) dNBR divided by pre-fire NBR values colored by CBI severity category; (B) RdNBR = dNBR divided by the square-root of pre-fire NBR values colored by CBI severity category. Horizontal lines represent low (69), moderate (316), and high (641) RdNBR thresholds derived from nonlinear regression model.

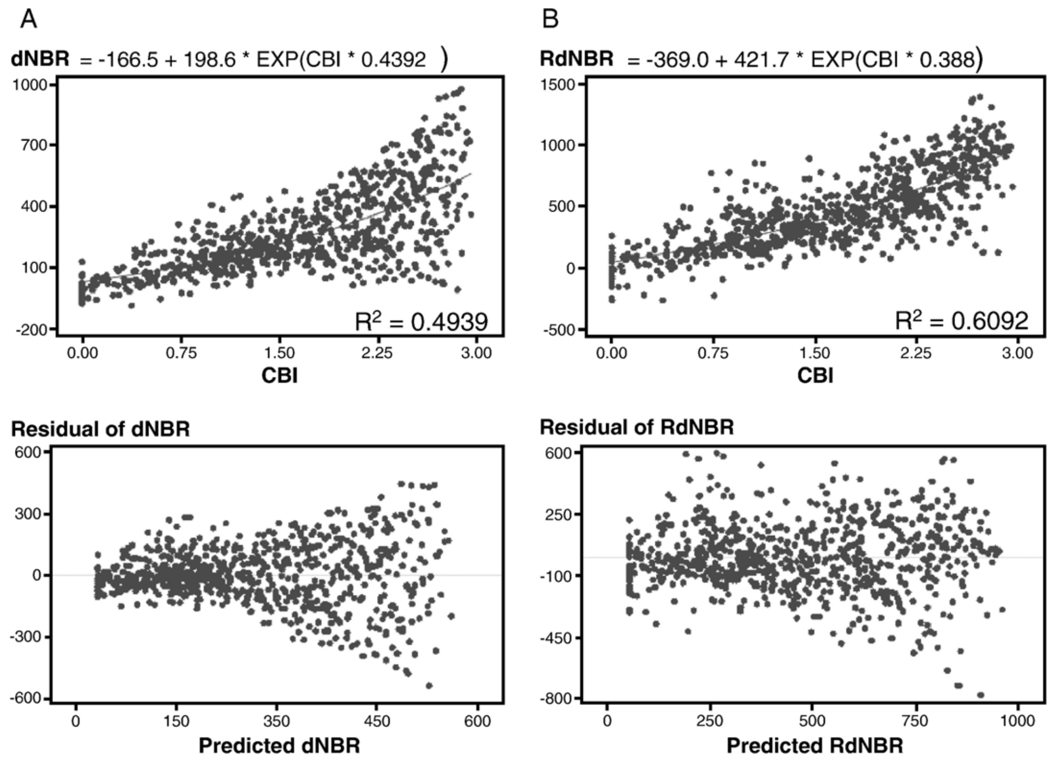


Fig. 6. Nonlinear regression models using CBI measured in 741 plots on 14 fires to (A) dNBR $R^2=0.4939$ and (B) RdNBR $R^2=0.6092$. The heteroscedasticity exhibited by the residuals in the dNBR model is reduced in the RdNBR model.

correction we chose to take the square root of the pre-fire NBR divisor to produce a data space as shown in Fig. 5B that more closely resembles the field data versus pre-fire NBR in Fig. 4A. We therefore used the following equation as our relative dNBR (RdNBR) change index:

$$\mathrm{RdNBR} = \left(\frac{\mathrm{PreFireNBR} - \mathrm{PostFireNBR}}{\mathrm{SquareRoot}(\mathrm{ABS}(\mathrm{PreFireNBR}/1000))}\right)$$

NBR values generally range between 1 and −1 just like NDVI. We scale NBR by 1000 to transform the data to integer format; therefore the pre-fire NBR must be divided by 1000 in the RdNBR formula. Taking the absolute value of the pre-fire NBR in the denominator allows computing the square-root without changing the sign of the original dNBR. Positive RdNBR values remain representing a decrease in vegetation just like dNBR while negative values represent increased vegetation cover. The absolute value function in the denominator is required since the square root of a negative number mathematically results in an imaginary number. Strongly negative NBR values would indicate a larger reflectance in band 7 than band 4. This case only occurs over areas that are not vegetated. If the area is not vegetated then fire cannot occur which would result in a zero value in the numerator. Operationally, negative pre-fire values do occur due to sensor noise, miss-registration, etc. However, negative pre-fire NBR values resulting from sensor noise and miss-registration fall within two standard deviations of the average unburned pixel value. Therefore the absolute function has the effect of putting those pixels into the unburned category as opposed to an undefined category.

There is a great deal of classification confusion between severity categories in the dNBR especially at low pre-fire NBR values (Fig. 4B). The Relative dNBR does not correct for this confusion (Fig. 5B). There is an inherent problem

Table 4
dNBR and RdNBR regression modeled thresholds

| Severity category | Field measured CBI severity value | Predicted dNBR | Predicted RdNBR |
|---|---|---|---|
| Unchanged | 0–0.1 | <41 | <69 |
| Low | 0.1–1.24 | 41–176 | 69–315 |
| Moderate | 1.25–2.24 | 177–366 | 316–640 |
| High | 2.25–3.0 | >=367 | >=641 |

Table 5
Confusion matrix of CBI (columns) vs. dNBR classified data (overall Kappa=0.411)

| Class name | Unchanged | Low | Moderate | High | Total | User's accuracy (%) |
|---|---|---|---|---|---|---|
| Unchanged | 23 | 34 | 5 | 5 | 67 | 34.3 |
| Low | 5 | 127 | 68 | 21 | 221 | 57.5 |
| Moderate | | 47 | 154 | 51 | 252 | 61.1 |
| High | | 4 | 66 | 131 | 201 | 65.2 |
| Total | 28 | 212 | 293 | 208 | 741 | |
| Producer's accuracy (%) | 82.1 | 59.9 | 52.6 | 63.0 | | 58.7 |

Table 6
Confusion matrix of CBI (columns) vs. RdNBR classified data. (Overall Kappa = 0.421)

| Class name | Unchanged | Low | Moderate | High | Total | User's accuracy (%) |
|---|---|---|---|---|---|---|
| Unchanged | 21 | 27 | 2 | | 50 | 42.0 |
| Low | 7 | 116 | 79 | 9 | 211 | 55.0 |
| Moderate | | 61 | 157 | 49 | 267 | 58.8 |
| High | | 8 | 55 | 150 | 213 | 70.4 |
| Total | 28 | 212 | 293 | 208 | 741 | |
| Producer's accuracy (%) | 75.0 | 54.7 | 53.6 | 72.1 | | 59.9 |

trying to derive a fire severity index from satellite imagery in forested systems. There is a limit to the sensitivity of passive sensors to observe under forested canopies. Since CBI is a linear combination of variables from all structural strata, some fire effects under the tree canopy may be hidden from the sensor. Errors in ocular estimates of severity variables in the field most likely also contribute to confusion errors. Since we are analyzing fire from multiple Landsat path/row combinations and multiple years, all image values were converted to reflectance at the sensor and we tried to normalize variations in dNBR values from fire to fire. Despite these efforts, variations in sensor calibration, sun angle and annual weather patterns may contribute to confusion errors seen in Fig. 4.

### 3.2. Regression analysis

To determine whether RdNBR produces a better relationship than dNBR to ground based severity measurements, nonlinear regression analysis was performed on dNBR and RdNBR values against field measured CBI data. Regression analysis was performed using data collected on 14 fires that occurred in multiple vegetation types within the Sierra Nevada Framework study area during 2002 through 2004 (Table 1). The dNBR nonlinear regression model (Fig. 6A) resulted in an $R^2$ of .4939 while the RdNBR model (Fig. 6B) achieved a higher $R^2$ of .6092. The heteroscedasticity characteristic exhibited by increasing variance in the residuals for the dNBR regression model is also reduced with the RdNBR model. Table 4 details the threshold values computed from the dNBR and RdNBR regression models corresponding to the CBI thresholds for each severity category.

### 3.3. Model assessment

To evaluate whether RdNBR thresholds derived from the above regression analysis produced more accurate results than the dNBR thresholds, we computed confusion matrices using all field plots (Tables 5 and 6). Comparing the two confusion matrices, overall accuracies and Kappa statistics were not significantly different. As expected, the high severity class producer and user accuracies for RdNBR

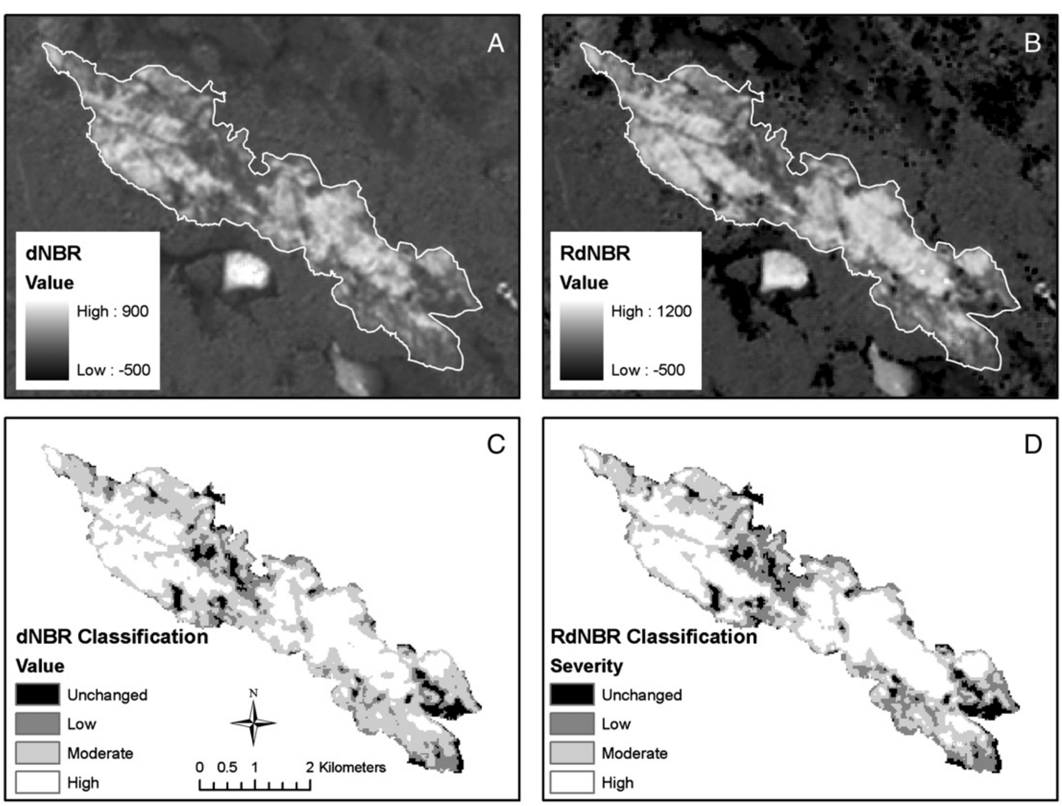


Fig. 7. Straylor Fire (A) continuous dNBR, and (B) continuous RdNBR. Increasing dNBR and RdNBR values indicate increasing severity. Negative values represent areas that exhibited increased greenness post-fire. High severity patches in the RdNBR are more homogeneous than those in the dNBR. Bright areas south and southwest of the fire perimeter are shallow lakes that had water pre-fire but were dry post-fire. (C) dNBR classification, and (D) RdNBR classification.

were significantly improved over dNBR. The accuracy of the moderate category remained about the same. Accuracies for both unchanged and low categories generally decreased with the exception of the user accuracy for the unchanged category which improved.

Overall accuracy should never be the only criteria for evaluating a classification. One should always examine why values do not fall on the diagonal of the error matrix (Congalton & Green, 1999). Classification accuracies of the unchanged and low classes decrease since low pre-fire NBR areas are more often classed as unchanged to low regardless of the actual severity with dNBR. Relativizing the dNBR increases the severity on some areas with low to moderate pre-fire NBR values so that some high severity areas become correctly classed as high and some low severity areas are miss-classified as moderate and high as shown in Fig. 5 and Tables 5 and 6. It appears that about as many areas shift from being correctly classified to being miss-classified thereby resulting in similar overall classification accuracies. However, the user and producer accuracies for the high severity category increase.

### 3.4. Results for selected fires

A detailed examination of dNBR and RdNBR classifications derived from the above regression based thresholds is presented below for three fires in various vegetation types. In the first example, the Straylor fire occurred in coniferous forest on the east side of the Sierra Nevada with heterogeneous percent cover and species adapted to xeric conditions. The second example, the Power fire, occurred on the more mesic west side of the Sierra Nevada in coniferous forest with denser and more homogenous percent cover. The final example is also from the east side of the Sierra Nevada but at lower elevation in a mixture of Pinyon pine and sagebrush.

#### 3.4.1. Straylor fire — heterogeneous percent cover

The 2004 Straylor fire occurred on the east side of the Sierra Nevada in Ponderosa pine, Jeffrey pine, and Western juniper vegetation types (Table 1). Pre-fire percent canopy cover derived from pre-fire digital orthophotos averaged 36% in field plots where post-fire effects were measured. The continuous dNBR and RdNBR data and resulting classifications using the regression derived thresholds are shown in Fig. 7. Comparing the continuous dNBR and RdNBR data (Fig. 7A and B) RdNBR values appear to be more uniform within areas mapped as high severity. The variability in dNBR values in areas of high severity is related to the amount of live pre-fire vegetation in each pixel. dNBR and RdNBR values plotted against pre-fire NBR values coded by field sampled CBI severity category for 48 field plots are provided in Fig. 8. Examining Fig. 8, the threshold between moderate and high severity categories could be optimally placed to minimize commission and omission errors for the high severity category. It appears that the optimum RdNBR threshold would be around 641 as listed in Table 4. The optimum threshold for the dNBR is a little less obvious due to the correlation of dNBR to

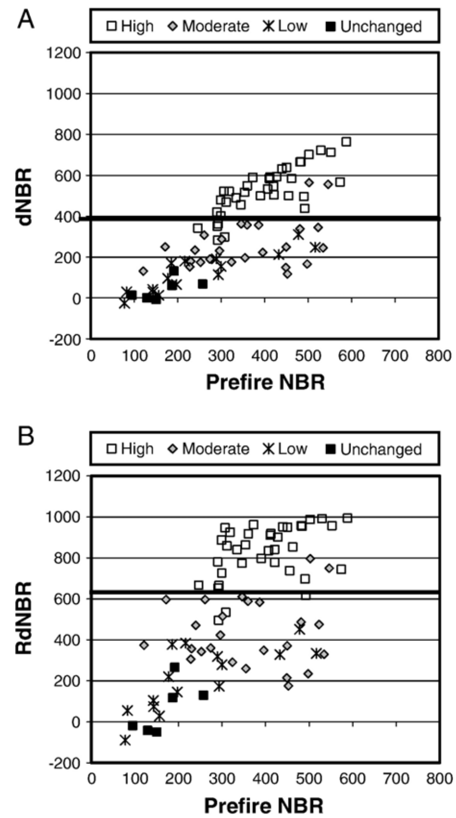


Fig. 8. Straylor Fire (A) dNBR and (B) RdNBR values plotted against pre-fire NBR values coded by field sampled CBI severity category. Horizontal lines indicate the optimal RdNBR threshold between moderate and high around 640 and dNBR around 400.

pre-fire NBR values. It may be around a value of 400 which is higher than the modeled high dNBR threshold listed in Table 4. Separation between moderate and high severity pixels in the RdNBR case appears to be more linear allowing more moderate and high severity plots to be correctly classified, therefore minimizing classification errors for the high severity class.

#### 3.4.2. Power fire — homogeneous percent cover

The 2004 Power fire occurred in predominately coniferous forest on the west side of the Sierra Nevada. Vegetation types within the fire range from Black oak and Ponderosa pine at the lower elevations to Mixed conifer, Jeffrey pine and White fir at the higher elevations (Table 1). Pre-fire percent canopy cover was denser on average than that seen in the Straylor fire, averaging 52% in field plots. The continuous dNBR and RdNBR data and resulting classifications using the regression derived thresholds are shown in Fig. 9. Differences between the continuous dNBR and RdNBR are minor except that it would appear that RdNBR data are scaled differently and therefore classifications derived from either dataset would most likely be similar. However, the two classifications in Fig. 9C and D are very different since the dNBR classification was derived using thresholds derived from a regression model using data collected in plots from 14 fires in various vegetation types. dNBR and RdNBR plotted against pre-fire

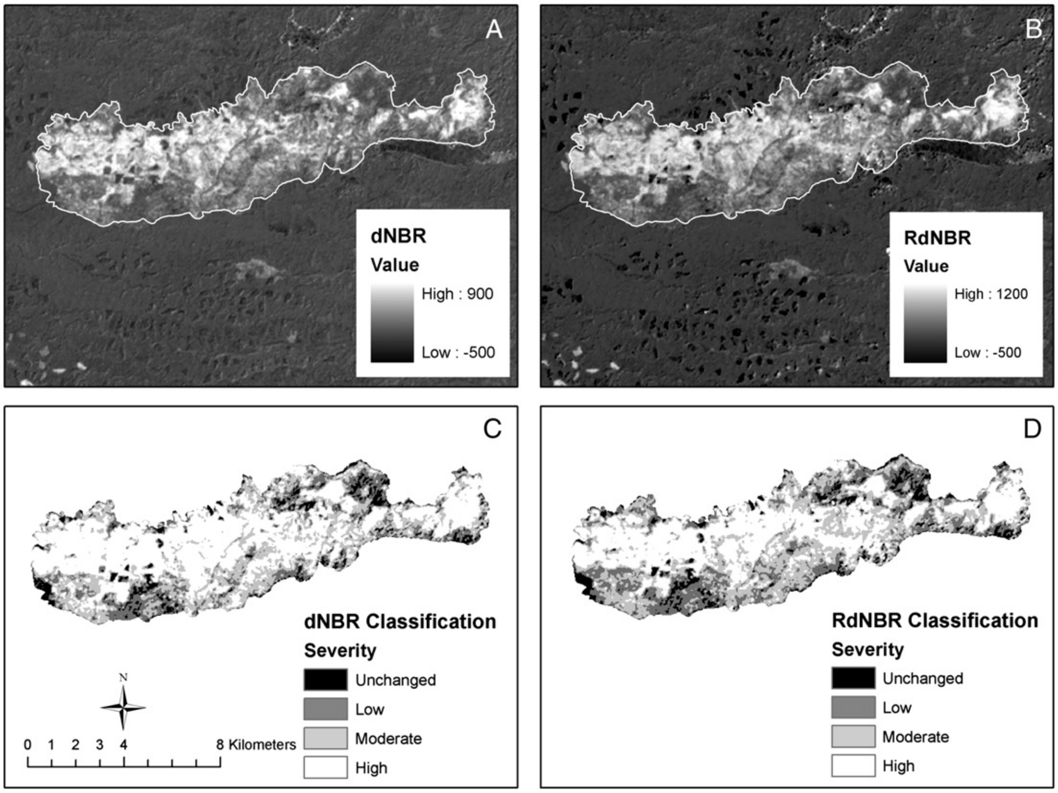


Fig. 9. Power Fire (A) continuous dNBR, and (B) continuous RdNBR. Increasing dNBR and RdNBR values indicate increasing severity. Negative values represent areas that exhibited increased greenness post-fire. The variation in the continuous dNBR and RdNBR data looks similar except the RdNBR values have a larger range. (C) dNBR classification, and (D) RdNBR classification. Classified data are different since they were derived using the regression based thresholds from all 14 fires.

NBR values coded by field sampled CBI severity category for 93 field plots are provided in Fig. 10. Pre-fire NBR values are on average higher than those in the Straylor since the average pre-fire canopy cover was higher pre-fire in the Power fire than the Straylor fire. It appears that the optimum RdNBR threshold would be around 641 just like the Straylor while the dNBR optimum may be around a dNBR value of 470 which is higher than the modeled high dNBR threshold listed in Table 4. The separation between severity classes in the dNBR and RdNBR data appears to be similar and again indicates that optimum classifications of the two would result in similar accuracies. Even though similar accuracies could be achieved, the RdNBR produces continuous data on the same scale across fires, allowing the use of common thresholds. However, as Key and Benson (2005a) indicate, thresholding dNBR requires assessing each fire individually to derive properly calibrated thresholds that will be unique to each fire.

### 3.4.3. *Birch fire — heterogeneous vegetation types*

The 2002 Birch fire occurred on the Inyo National Forest (Table 1). Before the fire occurred, Singleleaf pinyon dominated the upper elevations while sagebrush dominated the lower elevations. The continuous dNBR and RdNBR data and resulting classifications using the regression derived thresholds listed in Table 4 are shown in Fig. 11. RdNBR produced higher values in areas dominated by sagebrush than did dNBR, resulting in most sagebrush being classed as high severity by RdNBR as opposed to low to moderate by dNBR. Almost all of the Birch fire was high severity as shown in Fig. 11D. Thirty-one out of 33 post-fire field plots were high severity. Photos from three representative plots are included and the plot locations are displayed on each of the maps in Fig. 11. dNBR values of plots 112 and 98 are similarly low with both plots being classified as low severity (Fig. 11A and C). The dNBR value for Plot 116 is high resulting in a high severity classification. However, plot 98 has a high RdNBR value causing it to be assigned a high severity classification (Fig. 11B and D). Plots 112 and 116 retain the same severity category in both dNBR and RdNBR classifications. The post-fire photo of Plot 112 dominated by Pinyon pine shown in Fig. 11E indicates that the plot suffered little effect from the fire. The Pinyon pine stand in Plot 116 experienced complete mortality as shown in Fig. 11F. Plot 98 plot, dominated by sagebrush before the fire, also experienced complete mortality as shown in Fig. 11G and was therefore correctly classified in the RdNBR classification. Some areas where pre-fire cover was dominated by sagebrush on the east side of the fire exhibited RdNBR values greater than 2000 (Fig. 11B). These high RdNBR values appear to be a function of the sensitivity of Landsat band 7 to soil characteristics and only occur in areas where pre-fire vegetation is sparse and severity is high. They are higher than those normally seen in high severity areas that were densely vegetated pre-fire. Although the values were very high, they were correctly classified as high severity. Thus, RdNBR appears to

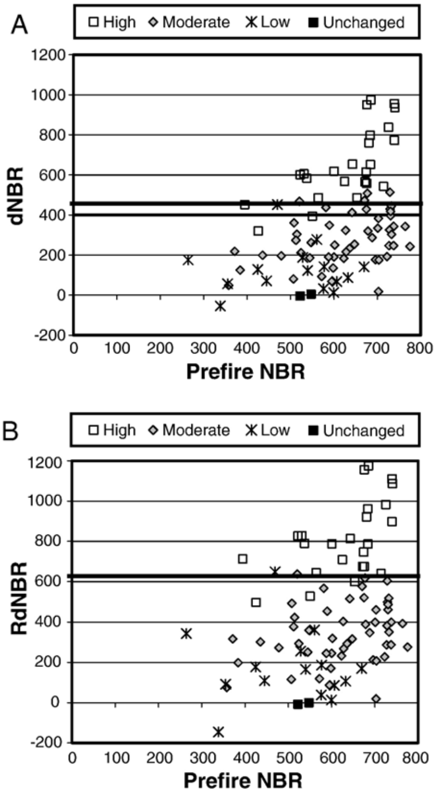


Fig. 10. Power Fire (A) dNBR and (B) RdNBR values plotted against pre-fire NBR values coded by field sampled CBI severity category. The delineation between severity categories is similar with RdNBR and dNBR which would result in classifications with similar accuracies. Horizontal lines indicate the optimal RdNBR threshold between moderate and high around 640 just like the Straylor in Fig. 9, and dNBR around 470 which is higher than for the Straylor.

do an acceptable job of producing severity data across vegetation types on the same scale.

## 4. Conclusions

We have demonstrated in this paper that thresholding a relative change detection image may be more appropriate than an absolute change image for mapping burn severity when severity is defined as the effects of fire primarily to vegetation. Using a relative index instead of an absolute index to map severity has two primary advantages: 1.) a relative index provides a more consistent definition of severity allowing comparison of fires across space and time, and 2.) classification of a relative index should result in higher accuracies for the high severity category in heterogeneous landscapes over those resulting from classifying an absolute index. In homogenous landscapes, absolute and relative indices could produce classifications with similar accuracies. The absolute index may require very different thresholds though. Fires in homogeneous sagebrush communities will have much lower thresholds than fires in coniferous forest for example. Direct comparison of severity maps between fires derived from different thresholds, however, can only be accomplished by using categorical data.

Severity is often lumped into categories so that we can easily communicate ideas and concepts though severity actually occurs on a continuum. The ability to compare a continuous severity index across time and space is a requirement for the successful analysis of landscape level processes, such as habitat models. These models can then be calibrated from one or multiple fires and be applied across the landscape. Lumping severity data on each fire into broad categories such as low, medium and high, can compensate for data from each fire being scaled differently. The problem with developing models with thematic data occurs when the process being modeled is driven by thresholds that differ from those used to create the severity classification. For example, if an animal species is dependent on at least 50% cover and the severity classification thresholds are based upon 25 and 75% cover, the analysis does not match. All severity data used as input to the model would then need to be reclassified so that the thematic categories match the processes thresholds. If the continuous data from each fire are on different scales then that reclassification process could be prohibitive. In addition, precise knowledge of fire effects on each fire required for optimum classification may not even be available.

Overall accuracy was not improved by the relative index. However, overall accuracy should never be the only criteria for evaluating a classification. There will always be confusion in the unchanged, low, and moderate categories since it is difficult to see under tree canopies using passive sensors. Additionally, many different combinations of effects can result in the same CBI score. Stand-replacing fire, i.e. high severity, should be easiest to map and result in high user and producer accuracies.

Accurately mapping the spatial size and extent of severity patches is important for site level recovery projects and for understanding overall landscape patterns created by fire. Thresholding an absolute index such as dNBR in heterogeneous landscapes may lead to under-representing high severity patches. In this study smaller commission and omission errors in the high burn severity class resulted from using RdNBR. Ecologically, severely burned patches are of interest since patch size and severity control the number of surviving individuals and distance to seed sources, which in turn influences succession processes. Severely burned areas are a focus for land managers after wildfire due to the slower vegetation responses of some species, higher erosion potential, issues of invasive species, changes in wildlife habitat components, reduced recreation potential, and concerns with the wildland urban interface. Minimizing classification errors for the high severity class will prove beneficial to land managers since it allows identification of more areas that are severely burned. Implementation of a relative index in the form of RdNBR would appear to achieve that goal for fire severity mapping.

There may be no one perfect index for mapping fire effects. A combination of both the dNBR and RdNBR may provide more complete information than either one alone. Since dNBR is correlated to the amount of pre-fire photosynthetically active vegetation, it provides an indication of how much vegetation was killed. In contrast, RdNBR measures the amount of

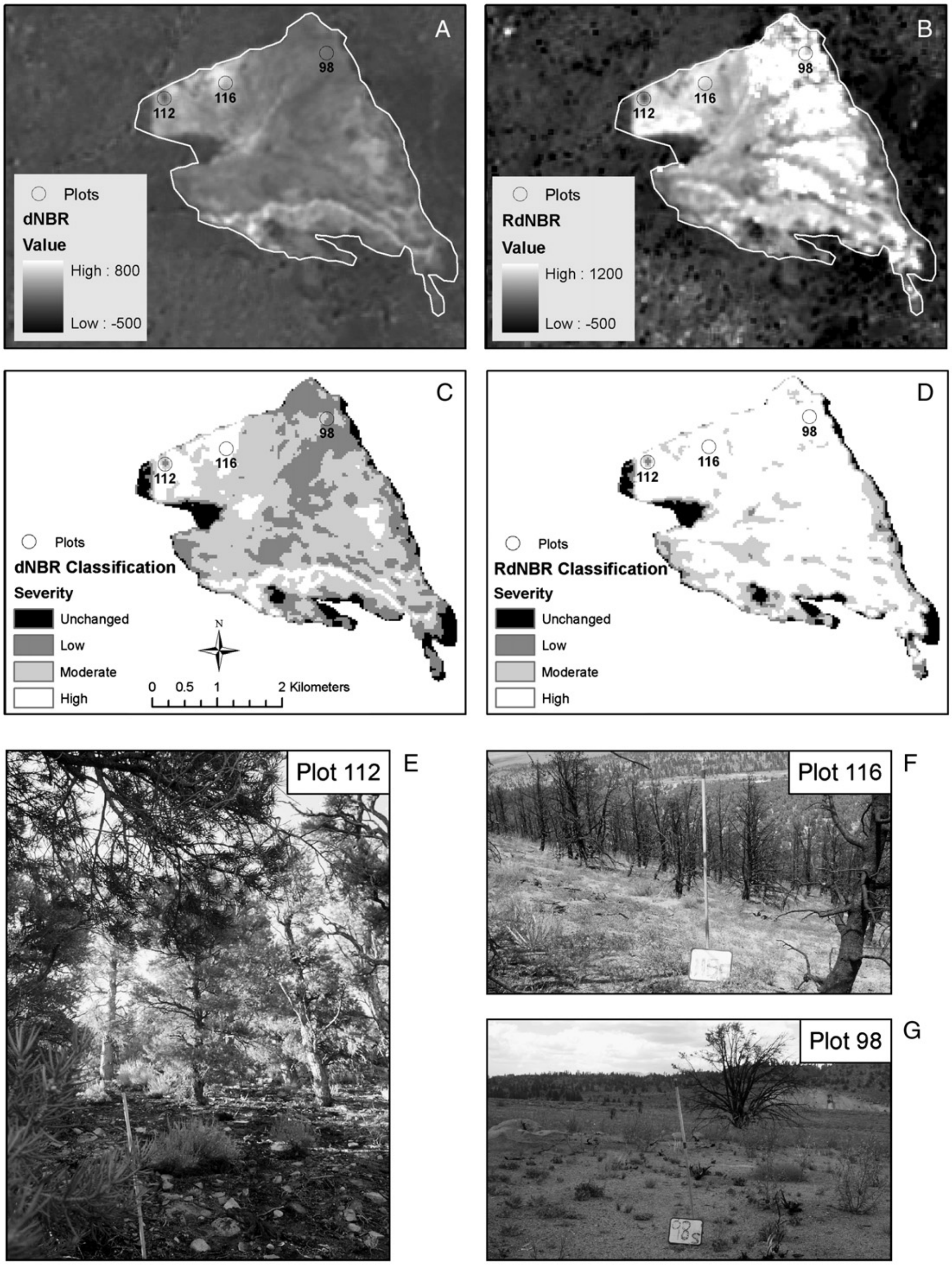


Fig. 11. Birch Fire (A) continuous dNBR, (B) continuous RdNBR, (C) dNBR classification, (D) RdNBR classification, (E) photo of plot 112, (F) photo of plot 116, and (G) photo of plot 98. Locations of plots 98, 112, and 116 are indicated on the continuous and classified dNBR and RdNBR data. Plots 112 and 116 exhibiting low and high severity respectively in Pinyon pine are correctly classified by both dNBR and RdNBR. Plot 98 with severely burned sagebrush is incorrectly classified as low to moderate severity by dNBR and correctly as high severity by RdNBR.

vegetation killed in relationship to the amount of pre-fire vegetation.

The formulation of RdNBR derived in this project with the square root of the pre-fire NBR divisor was influenced by the manor in which locations with low to moderate pre-fire NBR values may become exceptionally large. It appears that the "boosting" effect seen in the RdNBR increases with severity and decreasing amounts of pre-fire vegetation. The effect is most likely due to the inclusion of Landsat band 7 in NBR which is sensitive to not only vegetation but also soil characteristics. Applying the square root in the denominator appears to have been mostly successfully in correcting for the "boosting" effect that was seen in the data used for this study. It is possible that the square root function is not optimal or even required in other environments. That remains to be tested. It is likely however that some transformation is required when a relative dNBR is used to model CBI since NBR is sensitive to soil conditions and CBI is primarily a vegetation severity measurement.

The data used in this study came primarily from conifer and live oak systems in the Sierra Nevada. We feel confident that the methods presented here will translate to other ecosystems but further exploration is needed. The thresholds we have derived here reflect how we defined our CBI thresholds. Any other definition of severity will most likely result in different thresholds.

We have demonstrated in this paper that thresholding a relative change detection image may be more appropriate than an absolute change image when assessing the relative impact of fire to vegetation. Fire is just one form of disturbance however. It is logical that the use of relative versus absolute indices would extend to mapping severity due to other disturbances. This relative concept should be considered when an ecological change perspective is desired.

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