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Mapping forest post-fire canopy consumption in several overstory types using multi-temporal Landsat TM and ETM data

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Abstract

To facilitate the identification of appropriate post-fire watershed treatments and minimize erosion effects after socio-economically important fires, Interagency Burned Area Emergency Rehabilitation (BAER) teams produce initial timely estimates of the fire perimeter and classifications of burn severity, forest mortality, and vegetation mortality. Accurate, cost-effective, and minimal time-consuming methods of mapping fire are desirable to assist rehabilitation efforts immediately after containment of the fire. BAER teams often derive their products by manually interpreting color infrared aerial photos and/or field analysis. Automated classification of multispectral satellite data are examined to determine whether they can provide improved accuracy over manually digitized aerial photographs. In addition, pre-fire vegetation data are incorporated to determine whether further gains in accuracy of mapped canopy consumption can be made. BAER team classifications from the Cerro Grande Fire were compared to estimates of overstory consumption produced using a pre-fire vegetation classification, and a change detection algorithm using bands 4 and 7 from July 1997 pre-fire Landsat Thematic Mapper (TM) and July 2000 post-fire Enhanced Thematic Mapper (ETM) data. BAER team classifications are highly correlated to overstory consumption and should produce high Kappa statistics when verified using the same dataset. Our three-class supervised classification of the change image incorporating a pre-fire vegetation classification yielded the highest Kappa at 0.86. A three-class unsupervised classification of the change image yielded a lower Kappa of 0.72. BAER team classifications yielded Kappas ranging from 0.38 to 0.63 using the same verification dataset.

1. Introduction and background

Wildland fire is an ecologically important disturbance factor in many ecosystems. While providing many benefits in fire-adapted systems, catastrophic fire can cause severe ecosystem and watershed damage. Catastrophic fires modify ecosystems by removing vegetative cover and altering soil characteristics which increase the risk of severe erosion and the time required for ecosystem recovery. With increasing encroachment of human populations into wilderness areas there is also an increased threat to private and public infrastructure from wildfire effects. Not only are natural view sheds and recreational areas at risk of disappearing for decades or even centuries, but human lives, property, and livelihoods are at risk.

Interagency Burned Area Emergency Rehabilitation (BAER) teams are dispatched to potentially socio-economically significant fires in the USA to minimize post-fire erosion effects (mitigation) and shorten ecosystem recovery times (rehabilitation). Post-fire mitigation and rehabilitation treatments can be immensely costly undertakings due to the large areal extents of these fires and complex terrain in which they occur. Often treatments must be completed within weeks after containment of a fire due to the seasonality of the fire season and impending rainy period or onset of winter. Treatments therefore need to be targeted at strategic locations to cost effectively reduce erosion risks and they must be applied quickly. Not only are fire map products produced by BAER teams used for short-term rehabilitation and mitigation efforts, but they become part of the fire record and form baseline data for long-term recovery monitoring projects and future ecological studies. Consequently, BAER-derived maps must accurately represent fire severity patterns.

On the most critical fires, BAER teams employ color infrared aerial photography to map fire effects. Aerial

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photography has long been used by land management agencies and is well understood by most managers. Though the near-infrared wavelengths in color infrared photographs are useful in mapping vegetation mortality and soil moisture, it has been shown that mid-infrared bands (band 5 = 1.55–1.75 μm and band 7 = 2.08–2.35 μm) of Landsat Thematic Mapper (TM) contribute new information for classifying burn severity (White, Ryan, Key, & Running, 1996). Both mid-infrared bands are sensitive to moisture content of soil and vegetation. Mid-infrared bands also penetrate thin clouds and smoke better than visible bands, with band 7 to the greatest degree since its wavelengths are larger than most water vapor and smoke particles (Avery & Berlin, 1992). The advantages of multispectral satellite data have not overcome the traditional use of color infrared photography because satellite data have been expensive, over-flight schedules may be untimely, and the data are perceived as complicated to use. Although the 16-day over-flight schedule may limit chances of cloud-free scenes, as Landsat 5 remains in service along with Landsat 7, the combined over-flight schedule is 8 days. Further, the cost of Landsat data has decreased significantly. Terrain-corrected Landsat 5 is currently US\$650 and Landsat 7 is US\$600. Maps produced from aerial photography are assumed by some users to be more accurate than those produced from satellite imagery because the resolution of the photography is typically greater than satellite imagery. The minimum mapping unit of hand drawn polygons is however usually on the order of 20 ha, whereas Landsat data are about 0.6 ha.

A major reason why satellite imagery is perceived to be difficult to use for mapping fire severity is that previous studies have implemented many different techniques to derive features used in classification schemes that may or may not improve results (e.g., band ratios, linear transforms, vegetation indices) without presenting any error analysis, making a choice of the best technique difficult. Turner, Hargrove, Gardner, and Romme (1994) mapped burn severity in Yellowstone National Park using all seven bands of single date Landsat TM data to examine burn severity in relationship to disturbance history. No error analysis was performed, but they determined their map agreed well with existing maps by visual inspection and it passed inspection of local experts. While examining whether satellite data could detect fire severity and vegetation recovery, White et al. (1996) compared several classifications of different band combinations, band ratios, and modified band data. They found a single date classification of band 7 yielded the best results with an overall accuracy of 0.63. No details of the comparisons were given. Single date and multitemporal Kauth–Thomas transforms were found to produce more accurate maps (Kappa = 0.73 and 0.66) of vegetation mortality due to fire than principal components analysis (PCA) when resulting error matrices were compared (Patterson & Yool, 1998; Rogan & Yool, 2001). Clark (2000) compared difference images of pre- and post-fire images enhanced by PCA, Kauth–Thomas transform (Kauth & Thomas, 1976), Normalized Difference Vegetation Index (NDVI),

$$\frac{(\mathrm{Band4}-\mathrm{Band3})}{(\mathrm{Band4}+\mathrm{Band3})} \tag{1}$$

Modified Soil Adjusted Index (MSAVI) (Qi, Chehbouni, Huete, Kerr, & Sorooshian, 1994),

$$\frac{(\mathrm{Band4}-\mathrm{Band3})}{(\mathrm{Band4}+\mathrm{Band3}+L)}(1+L) \tag{2}$$

a band 7/band 4 ratio, and a simple differencing of band 4. Differencing the band 7/band 4 ratios was found to produce the best representation of fire severity based upon visual inspection and field knowledge. Key and Benson (1999b) coined a new index, the normalized burn ratio (NBR), formulated like the NDVI except using TM band 7 in place of the red band as follows:

$$\frac{(\mathrm{Band4}-\mathrm{Band7})}{(\mathrm{Band4}+\mathrm{Band7})} \tag{3}$$

They determined that the NBR difference performed best compared with a post-fire band 7, pre- and post-fire difference of band 7, and a pre- and post-fire NDVI difference.

Fire effects have been defined in terms of severity and intensity. These factors determine how well plants survive during fire or reproduce after a fire. It is apparent that there is no single, standardized classification system for quantifying wildland fire effects. Most likely, some ambiguity arises from different definitions. The BAER team (2000) defines fire severity based on soil characteristics, which are controlled by the temperature and amount of duff and surface fuels consumed. Fire intensity, as defined by the BAER team, is controlled by temperature, flame length, heat of combustion, and total amount and size of fuel consumed, transferring convective heat into the overstory. Chappell and Agee (1996) define fire severity as a percentage of tree basal area mortality. Some researchers define a combination of soil and overstory effects as fire severity (Ryan & Noste, 1985; Turner et al., 1994), while others call this burn severity (BAER, 2000; Key & Benson, 1999b). This discrepancy of terminology makes comparing map products potentially ambiguous. However, most researchers agree that fire severity is a measure of the amount of soil organic matter lost due to burning, decrease in surface cover, and volatilization or transformation of soil components to soluble mineral forms (Wells & Campbell, 1979). Severity is generally measured post-fire by examining the depth of char. Vegetation is usually able to regenerate in lightly charred soils but not deeply charred soils (Ryan & Noste, 1985). Fire intensity is generally defined as a measure of flame length and temperature conveyed into the overstory (Ryan & Noste, 1985). Flame length is difficult to measure during a fire but can be estimated post-fire from observed crown scorch. While fire intensity and fire severity can be correlated in most cases, in some forest types under some weather conditions, crown fires can completely consume the overstory without severely damaging the soil (Ryan & Noste, 1985).

BAER teams are tasked with minimizing post-fire erosion effects and shortening ecosystem recovery times. The removal of vegetative cover is the single most influential factor in increasing erosion risk (Diaz-Fierros, Rueda, & Moreira, 1987; Renard, Foster, Weesies, & Porter, 1991). Fire severity is the factor which most influences how well vegetation recovers (Lyon & Stickney, 1976; Ryan & Noste, 1985). Therefore, BAER teams are interested in mapping both factors. While all vegetation is usually removed in areas of high fire severity, not all areas with total vegetative cover removed are the most severely burned.

Landsat data record only surface reflected values, and cannot detect subsurface characteristics or how deep heat has penetrated. Soil color and texture can be changed by severe fire, but often ash covers the surface for several weeks after the fire, obscuring the soil surface. It has yet to be shown that Landsat data acquired immediately after a fire can distinguish between fire severity classes where all vegetation is removed and the soil has not been deeply charred, and where the soil has been deeply charred. Some researchers have assessed fire severity by examining vegetation recovery one and more years post-fire (Jakubauskas, Lulla, & Mausel, 1990; Key & Benson, 1999b; White et al., 1996). Flame length or fire temperature cannot be measured with post-fire Landsat data but how much of the overstory is consumed during the fire can be determined.

The work presented in this paper was accomplished within the first year after the fire and did not consider multi-year post-fire data. The post-fire image date was 6 weeks after containment of the fire and prior to summer rains that would promote vegetation growth. Potential vegetation recovery therefore cannot be quantified and only vegetation removal or short-term mortality due to fire could be quantified in this study. Since over 70% of the study area was covered by coniferous forest prior to the fire, “canopy consumption” most accurately describes the fire effects mapped during this project.

This paper has two objectives: (a) determine whether an unsupervised classification of canopy consumption derived from the differencing of pre-fire and post-fire indices from multispectral satellite data can be more accurate than digitizing from color infrared photography, and (b) show that accuracy of the canopy consumption map may be improved by incorporating a pre-fire vegetation classification.

2. Data and methods

2.1. Study area

The approximately 17,500-ha Cerro Grande Fire of May 6–31, 2000 occurred on the eastern slopes Jemez Mountains, approximately 40 km northwest of Santa Fe, NM, USA (Fig. 1). The fire encompassed the western portions of Los Alamos County on the east, including portions of Los Alamos National Laboratory (LANL), northern portions of Bandelier National Monument (BNM) on the south, the Santa Fe National Forest to the crest of the Sierra de los Valles on the west bordered by the Valles Calderas National Preserve (VCNP), and the Santa Clara Indian Reservation on the north. Precipitation levels range from about 46 cm/year at the Los Alamos town site to 76 cm/year at the highest elevations in the Sierra de los Valles, with 40% occurring during monsoon thunderstorms in July and August (Bowen, 1990).

Pinyon–juniper woodlands are the dominant vegetation community at the lower elevations of the study area between 1700 and 2100 m. Primary tree species are one-leaf pinyon (*Pinus edulis*) and one-seed juniper (*Juniperous monosperma*). Ponderosa pine (*Pinus ponderosa*) forests extend from 1900 m in protected canyons to 2400 m on the lower slopes of the Sierra de los Valles. Mixed conifer forest intergrades with ponderosa pine communities above 2100 m, and extends to the top of the Sierra de los Valles. Douglas-fir (*Pseudotsuga menziesii*), white fir (*Abies concolor*), and limber pine (*Pinus flexilis*) are the dominant trees at the lower mixed confier range with Englemann spruce (*Picea engelmannii*) and subalpine fir (*Abies lasiocarpa*) occurring at the higher elevations. Aspen (*Populus tremuloides*) occurs at the same elevations, and may be intermingled with mixed conifer forest, or may be dominant in previously burned areas (Balice, 1998; Foxx & Tierney, 1980).

2.2. Pre-fire to post-fire change image

Multi-temporal change detection of remotely sensed data is a common method for determining how biophysical systems change through time (Singh, 1989). Fire can produce significant changes to forested ecosystems. Change detection algorithms provide for quantification of the pattern and extent of fire effects. We had in our image catalog a July 3, 1997 Landsat TM image that could be used as a pre-fire image. This image was cloud-free over the fire scar, and matched the phenology of post-fire images. There had been negligible change in the landscape within the fire perimeter during the 3 years prior to the Cerro Grande Fire (e.g., construction of houses in Los Alamos, and fuels treatments on US Forest Service (USFS) and LANL property along State Highway 501). We felt these minor changes would produce fewer errors in the change detection algorithm than clouds and/or snow appearing in images acquired immediately before the fire. A Landsat ETM image from July 17, 2000 that had been terrain corrected by USGS was used as the post-fire image. This scene was the first image available that was smoke and cloud-free over the entire fire scar. The date was optimal in that it occurred more than 6 weeks after the fire (allowing unburned killed vegetation to drop leaves) but before the green-up due to the summer monsoon rains.

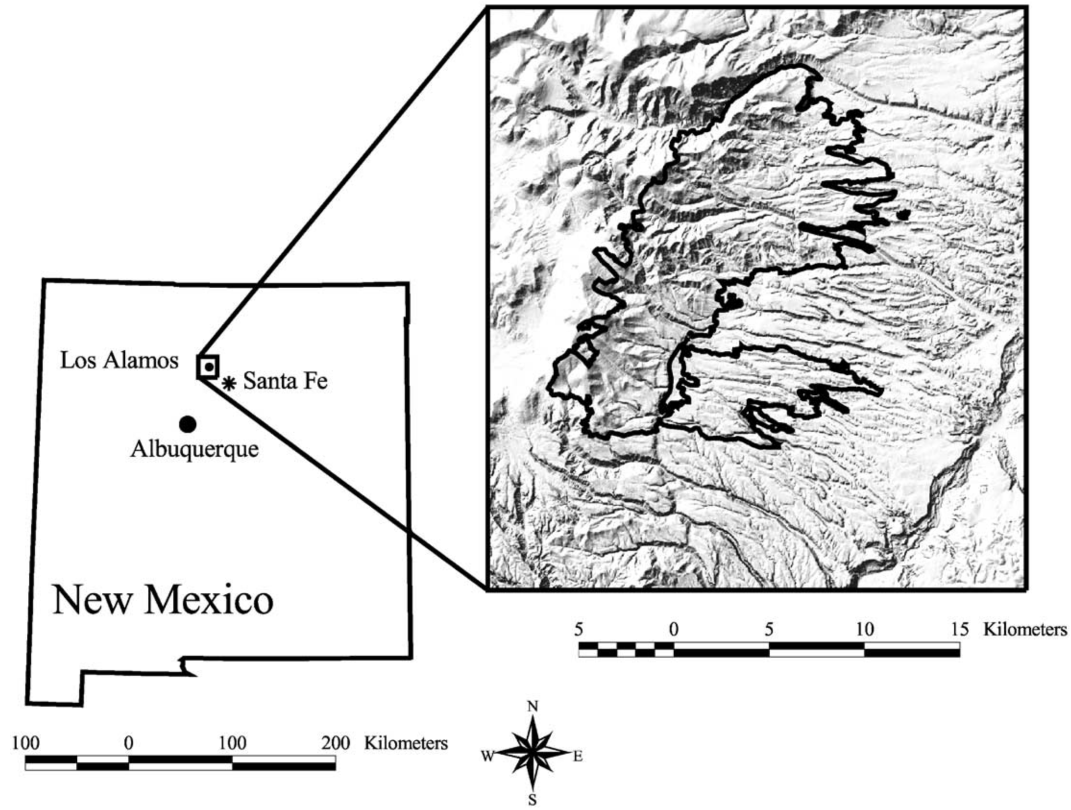

Fig. 1. Location of Cerro Grande Fire study site. The fire perimeter is outlined in black.

Some post-fire watershed treatments in severely burned areas however are visible in the image. The 1998 Oso Complex Fire, occurring between our pre- and post-fire image dates, was visible in the post-fire image, but did not overlap the Cerro Grande Fire.

Change detection methods require that images be co-registered, compensated for atmospheric effects, and scaled to the same units (Jensen, 1996). The processing steps to co-register images, transform the values in both images to reflectance, and calculate the change image are described below.

2.2.1. Image preprocessing

All image processing was performed using ERDAS Imagine version 8.3.1 on a Windows NT workstation. The July 3, 1997 pre-fire image was orthorectified to the July 17, 2000 ETM image using a terrain correction algorithm. A digital elevation model (DEM) matching the base image is required for this algorithm. The USGS 7.5-min National Elevation Dataset for New Mexico was acquired and subset to match the 2000 image. Orthorectification was accomplished using 23 ground control points, producing a 0.48-pixel RMSE. The change detection algorithm incorporates only the near-infrared and mid-infrared wavelengths. Atmospheric scattering is negligible in the infrared bands (Avery & Berlin, 1992). Therefore, we chose not to perform any atmospheric corrections. Digital numbers of the pre-fire Landsat 5 image were converted to reflectance as described by Markham and Barker (1985). Preprocessing of the July 17, 2000 Landsat ETM post-fire image consisted of converting to reflectance as specified in the Landsat 7 Science Data User's Handbook (NASA, 1998).

2.2.2. Change detection algorithm

Research by Clark (2000) has shown that pre- and post-fire differences of mid-infrared to near-infrared ratio (TM band 7/TM band 4) provided the highest contrast fire scar in comparison to TM band 4, PCA, Kauth–Thomas, NDVI, and MSAVI and, therefore provides the best enhancement for classifying changes due to fire. Previous researchers have shown that up to a year after fire the near-infrared (TM band 4) decreases the most in reflectance and the mid-infrared band 7 increases the most in comparison to pre-fire values (Lopez Garcia & Caselles, 1991; White et al., 1996). This relationship was true also for the Cerro Grande Fire immediately after the fire (Fig. 2). A normalized ratio of these two bands will be more sensitive (i.e., produce greater dynamic range) to fire effects (desiccated vegetation, soil moisture, etc.) than either of the two individual bands. Lopez Garcia and Caselles (1991), and Key and Benson (1999b) both derived a normalized ratio to exploit this relationship (Eq. (3)). NBR values range between -1 and 1 as does the NDVI. In pre-fire images, vegetated areas have values greater than zero and areas of bare ground or rock have values less than zero. In post-fire images, increasing fire severity is associated with decreasing values.

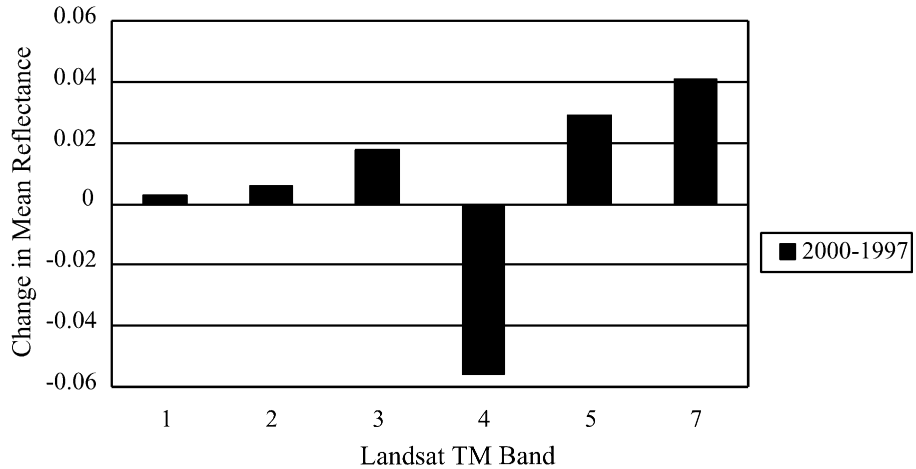

Fig. 2. Change in mean reflectance by Landsat band number pre-fire to post-fire within Cerro Grande Fire perimeter.

The NBR was calculated for both pre-fire and post-fire images and rescaled so that the values ranged between 0 and 2. The post-fire NBR was subtracted the from the pre-fire NBR to obtain the change image. The resulting image shown in Fig. 3 is overlain with the Cerro Grande Fire perimeter. Increasing degrees of change in the image are represented by increasingly lighter shades of gray ranging from black, no change, to white, maximum change. Clouds and cloud shadows from both the pre- and post-fire images were masked out and appear black outside the fire perimeter. The area of extreme change directly north of the Cerro Grande Fire is the Oso Complex Fire that occurred in 1998, between the pre- and post-fire image dates.

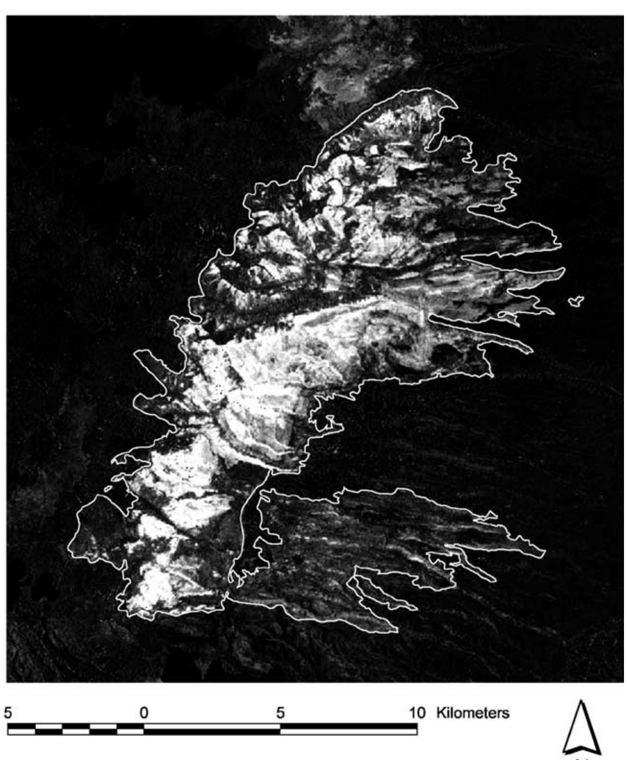

Fig. 3. Pre-fire to post-fire change image with Cerro Grande Fire perimeter overlain. Unburned areas appear dark, most severe white. 1998 Oso Complex Fire appears north of the Cerro Grande Fire. Masked clouds and cloud shadows appear black.

2.3. Fire perimeter

The fire perimeter was mapped to mask the change image so that only change within the fire perimeter would be included during later analysis of the change image. The change image was used in addition to post-fire true color aerial photos and pre-fire USGS digital orthophoto quarter quadrangles (DOQQs) to identify the fire perimeter. The post-fire 1:12,000 true color aerial photos contracted by the USFS were taken on May 30, 2000 over the entire fire scar. The perimeter was digitized onto DOQQs using the change image as the primary cue and verified with the aerial photographs. The area within the digitized perimeter was computed within a GIS and compared with BAER team fire perimeter. There were only minor differences between the two perimeters, with the new perimeter resulting in an area 70 ha (0.4%) larger than the BAER perimeter.

2.4. Pre-fire vegetation classification

One of our objectives was to determine whether post-fire canopy consumption classes exhibit unique ranges of change in different vegetation types. In detecting moderate levels of forest damage due to defoliation in spruce forests, Ekstrand (1994) was able to increase classification accuracies by pre-classification stratification of uniform areas of forest structure. Kushla and Ripple (1998) increased the accuracy in a classification of post-fire canopy survival by incorporating pre-fire Kauth–Thomas wetness with post-fire Landsat TM band transformations. Kauth–Thomas wetness has been shown to be correlated to forest structure (Cohen & Spies, 1992). Although they did not implement it, White et al. (1996) hypothesized they could improve a classification of fire severity by stratifying with pre-fire vegetation type before classifying.

The Cerro Grande Fire area encompassed predominately four forest types: (1) dry open pinyon–juniper woodlands; (2) ponderosa pine; (3) moist, mostly closed canopy mixed conifer; and (4) aspen. These overstory types typically have distinct spectral characteristics due to differences in site moisture and chlorophyll absorption characteristics (i.e., vegetation density, leaf area index, etc.). The change image was derived from the near- and mid-infrared bands, which are especially sensitive to these characteristics (Avery & Berlin, 1992). The change image should reflect how much change occurred in each overstory type, from unburned conditions to complete canopy removal, since a full range of canopy consumption classes occurred in each forest type. We expected the range of change in each overstory type to be unique. For example, fire intensity and severity should be less in the pinyon–juniper woodlands in comparison to the mixed conifer due to smaller pre-fire fuel loads.

A maximum likelihood classification was performed on the July 3, 1997 Landsat TM image using the six non-thermal bands and topography (Fig. 4). Training sites were chosen based upon field knowledge, DOQQs, and USFS true color 1:15,840 aerial photographs acquired on September 22, 1992. Error analysis was performed using 186 global positioning system (GPS) located plots where fuels data had been sampled before and after the Cerro Grande Fire (Balice, 2001; Balice, Miller, Oswald, Edminster, & Yool, 2000; Balice, Oswald, & Martin, 1999). Data gathered in these plots included identification of vegetation type, percent canopy cover, and dead and down fuels components as per standard USDA Forest Service procedures (Brown, Oberheu, & Johnston, 1982).

2.5. Fire effects maps

2.5.1. Definition of class categories

Most prior research in fire severity mapping have used either four severity categories (e.g., unburned, low, moderate, high) (Turner et al., 1994) or three categories, combining the low and unburned into one class (Jakubauskas et al., 1990; Patterson & Yool, 1998). Previous researchers have shown that understory components can be detected through satellite remote sensing only when canopy cover is sparse (Franklin, 1986). Stenback and Congalton (1990) found for example that Landsat TM data were sensitive to understory response under canopies with 30–70% crown closure in the Sierra Nevada of northern California but insensitive with canopies over 70% closure. Most of the Cerro Grande study

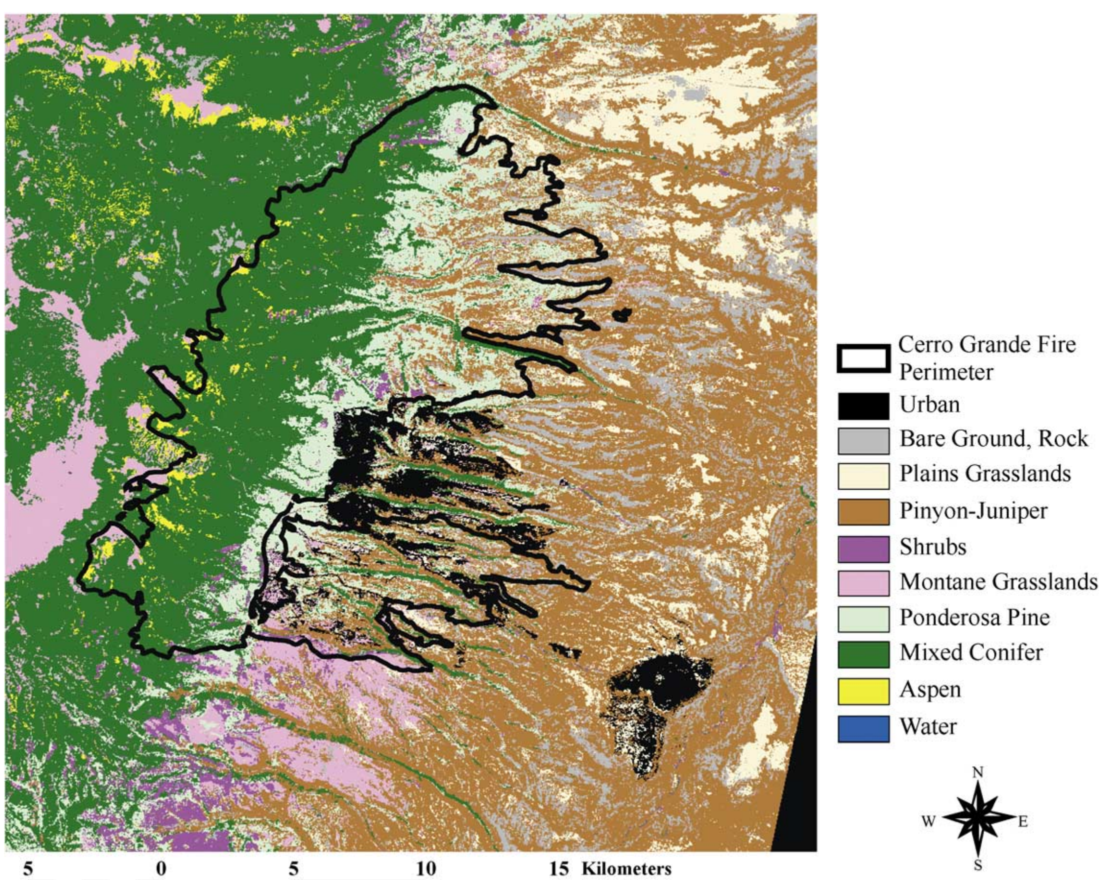

Fig. 4. Pre-fire vegetation classification. Maximum likelihood classification of July 3, 1997 Landsat TM image.

Table 1
Overstory consumption class definitions from Key and Benson (1999a)

	Unburned	Low	Moderate	High
Intermediate trees: 5–20 m tall				
% Green	100%	80%	40%	None
% Brown	None	5–20%	40–80%	None
% Black	None	5–20%	60%	100%
Char height	None	1.5 m	2.8 m	>5 m
Large trees: >20 m tall				
% Green	100%	95%	50%	None
% Brown	None	5–10%	30–70%	None
% Black	None	5–20%	50%	100%
Char height	None	1.8 m	4 m	>7 m

area is composed of mixed conifer and ponderosa pine forest with closed canopy. Pre-fire fuels plots in the study area indicated the average canopy cover was about 80% (Balice et al., 2000). The study area also included montane and plains grasslands, and pinyon–juniper woodlands with less than 70% canopy closures. Therefore, in this study canopy consumption was mapped in four classes (unburned, low, moderate, and high) to allow delineation of unburned and low classes in low canopy cover classes.

The definition of severity classes has not been consistent among previous remote sensing studies. Some definitions have been vague and used terms such as "mostly" or "partially" while others have included soil effects in their definitions (Jakubauskas et al., 1990; Turner et al., 1994; White et al., 1996). While definitions used by these researchers are not wrong, they are not precise and therefore may cause some confusion between classes, or they are difficult to implement with aerial photography. We have chosen to use the overstory component of the composite burn index (CBI) defined by Key and Benson (1999a) (Table 1). While Landsat data do contain information about the understory and substrate in non-closed canopy situations, they are integrated over 30 m so it is difficult to attribute whether the understory, overstory, or both were burned using Landsat data alone. Advantages to the overstory class definitions include: (1) they are precisely defined; (2) they describe overstory effects that are indicative of flame length, which are correlated with understory mortality; and 3) they provide consistent criteria which can be estimated from either aerial photography or the ground for developing training data and error analysis. The exceptions are low intensity surface fires, which in montane grassland systems (no overstory exists) fire severity is low by definition, and under closed canopies surface fires are difficult to detect from either satellite or aerial photography.

2.5.2. Change image classification

Unsupervised and supervised classifications were performed of the pre- vs. post-fire "change" image, with and without stratifying by pre-fire vegetation type. Since BAER team maps were all derived with three classes, our unsupervised classifications were performed with three classes (unburned/low, moderate, and high) in addition to four classes (unburned, low, moderate, and high). Four categories of canopy consumption were delineated in the supervised classifications (unburned, low, moderate, and high). The resulting "unburned" and "low" classes were combined in the supervised classifications to create three classes, per the BAER protocol for a total of eight classification trials (Table 2). Prior to classification, the change image was restricted to the fire perimeter to eliminate confusion with spectral signatures of change outside the fire. All unsupervised classifications were performed using an Iterative Self-Organizing Data Analysis Technique (ISODATA). The algorithm employed a minimum distance K-means formulation to organize pixels into a cluster for each canopy consumption class (i.e., a total of three clusters delineating unburned/low, moderate, and high canopy consumption classes). A maximum likelihood algorithm was used for the supervised classifications. Training sites were identified from post-fire true color 1:12,000 aerial photos to develop signatures for the supervised classifications.

2.5.3. Accuracy assessment

Eighty-seven plots were surveyed after the fire to determine post-fire effects and recovery (Balice, 2001). These plots were insufficient in number to perform a statistically significant error analysis of the canopy consumption maps. Congalton (1991) recommends that 50 verification points in each class is adequate for areas of less than 1/2 million ha, or classifications with less than 12 classes. Ground data are usually the most reliable source of reference data for accuracy assessment. When sufficient ground data are not available however, aerial photos may be used to assess the accuracy of maps derived from Landsat TM data. Large-scale aerial photos are generally considered to be one step closer to the ground than satellite data (Congalton & Green, 1999). To obtain a sufficient verification data set, 372 random points were selected. These points were stratified by canopy consumption class so at least 50 points were in

Table 2
Canopy consumption classification combinations

Classification	Description
UV3	Three class unsupervised classification with vegetation stratification
UV4	Four class unsupervised classification with vegetation stratification
UN3	Three class unsupervised classification without vegetation stratification
UN4	Four class unsupervised classification without vegetation stratification
SV3	Three class supervised classification with vegetation stratification
SV4	Four class supervised classification with vegetation stratification
SN3	Three class supervised classification without vegetation stratification
SN4	Four class supervised classification without vegetation stratification

the smallest class by area. The points were overlain on pre-fire DOQQs to aid in visually identifying the locations on post-fire 1:12,000 true color aerial photos. The canopy consumption class for each point was estimated from the aerial photos using categories listed in Table 1.

Accuracy assessment of all classifications was accomplished through the use of error matrices detailing producer's and user's errors and an overall Kappa statistic (Congalton & Green, 1999). The Kappa statistic, which ranges between 0 and 1, is a conservative measure of the difference between the *actual* agreement between reference data and an automated classifier, and the *chance* agreement between the reference data and a random classifier (Congalton & Green, 1999). A Kappa of 0.76 thus means that the classification accuracy was 76% greater than chance.

Error matrices of all classifications were compared using a *Z*-test to determine whether the overall Kappa values, and therefore two error matrices, were significantly different.

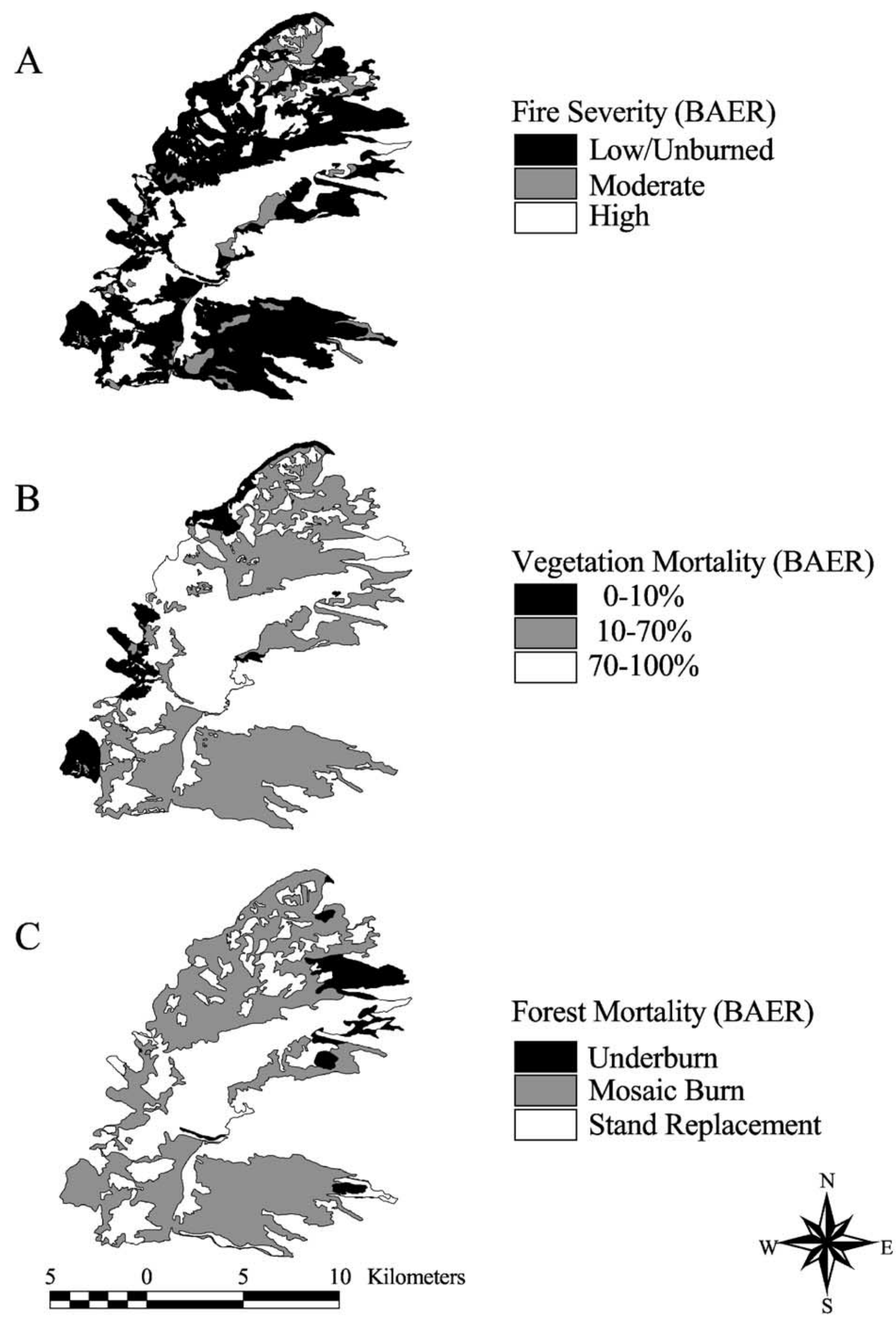

Fig. 5. Cerro Grande Fire BAER team fire effects maps. (A) Fire severity, (B) vegetation mortality, and (C) forest mortality in three classes. Vegetation mortality classes 10–40% and 40–70% were combined in panel (B).

Table 3
Error matrix for the pre-fire vegetation classification verified with plot data

Class name	Reference									User's accuracy (%)
	1	2	3	4	5	6	7	8	Total	
1. Urban	4		2						6	66.7
2. Plains grassland			1						1	0.0
3. Pinyon–Juniper	1		11		1	5	1		19	57.9
4. Shrubs						1			1	0.0
5. Montane grasslands	1				5		1		7	71.4
6. Ponderosa pine			1			49	5		54	88.9
7. Mixed conifer						5	82	1	88	93.2
8. Aspen					1		2	6	9	66.7
Total	6	0	15	0	7	60	91	7	186	
Producer's accuracy (%)	66.7		73.3		71.4	81.7	90.1	85.7		84.3
Overall Kappa	0.76									

The statistic for testing whether error matrices are significantly different is:

$$Z = \frac{|\mathrm{Kappa1} - \mathrm{Kappa2}|}{\sqrt{var(\mathrm{Kappa1}) + var(\mathrm{Kappa2})}} \tag{4}$$

where Z is standardized and normally distributed. Given the null hypothesis H_0: Kappa1 − Kappa2 = 0, H_0 is rejected if $Z > Z_{\alpha/2}$, where $\alpha/2$ is the confidence level of the two-tailed Z-test (Congalton & Green, 1999).

2.5.4. BAER team derived maps

The Cerro Grande BAER team produced three maps relating to fire effects: (1) burn severity, (2) vegetation mortality, and (3) forest mortality (Fig. 5). Digital color infrared aerial photography acquired on May 20–21 with a pixel resolution of 3 m was used to create these three maps. Individual tree canopies in closed canopy conditions cannot easily be identified at this scale. The photographs were georeferenced and mosaicked by a contractor and delivered to the BAER team on May 22. While total fire containment did not occur until May 31, the fire perimeter did not change after May 18 (BAER, 2000). A final fire perimeter was derived from daily operational fire progression maps and the post-fire color infrared photography.

Post-fire photography is not available to all BAER teams and few fires even have BAER teams assigned. The Cerro Grande fire is an example of best case methods employed for mapping fire effects by BAER teams, and thus provided a "best" case for testing alternative methods. For most fires a perimeter may be the only map product produced.

The following descriptions of the map products derived by the Cerro Grande BAER team are summarized from the BAER (2000) report.

2.5.4.1. Burn severity. The BAER burn severity map was created by digitizing polygons of unburned/low, moderate, and high severity on digital color infrared aerial photographs and verified by ground observations. The mapping criteria included "soil hydrophobicity (water repellency), ash depth and color (fire severity), size of residual fuels (fire intensity), soil texture and structure, and post-fire effective ground cover" (BAER, 2000, p. 276). Digitized polygons were no less than 40 acres (16 ha), leaving the possibility of small areas of non-homogenous burn severity within the polygons.

2.5.4.2. Vegetation mortality. Vegetation mortality was mapped to aid in evaluating impacts to wildlife habitat, the recovery ability of native plant associations, watershed stability, and potential treatments. The burn severity map, aerial and ground surveys were used by the BAER team to map mortality of grass, herb, shrub, and all tree species. Mortality was mapped in four categories: 0–10%, 10–40%, 40–70%, and 70–100%. Most high severity burn areas experienced greater than 70% vegetative loss. The majority of moderate burn severity areas experienced a 10–40% loss although some had mortality of up to 70%. Low burn severity areas were characterized primarily as having less than 10% vegetation mortality (BAER, 2000). The 10–40% and 40–70% vegetation mortality classes (Fig. 5B) were combined to facilitate comparison to canopy consumption maps derived in this study.

2.5.4.3. Forest mortality. The BAER team mapped forest mortality to determine where forest rehabilitation was required and potential salvage could occur. Classes of mortality were mapped by digitizing polygons on the color infrared photography. Helicopter and ground surveys served to refine and verify the degree of tree mortality within each digitized polygon. All previously forested areas within the burn perimeter were classified into one of three forest burn categories; understory, mosaic, or stand replacement. Understory burn consisted of areas that lost less than 25% of standing tree volume. Mosaic burn areas were where between 25% and 80% of standing trees were killed. Mortality was rated as stand replacement where greater than 80% of standing volume was killed or expected to die within 3 years (BAER, 2000). Although not explicitly stated by the BAER report, the minimum mapping unit of this map is assumed to be about 16–20 ha, as are the other BAER-derived maps.

Table 4
Change value statistics by overstory type from pre-fire vs. post-fire within the fire perimeter

Overstory category	Mean	Standard deviation	Range
Aspen	0.38	0.28	1.15
Mixed Conifer	0.52	0.03	1.22
Ponderosa Pine	0.37	0.25	1.08
Pinyon–Juniper	0.21	0.15	0.79

Larger values indicate a larger degree of change.

3. Results and discussion

3.1. Vegetation classification

The 158 plots where fuels data had been collected prior to the Cerro Grande Fire and 28 fire severity monitoring plots established post-fire were used to validate the vegetation classification. These plots were concentrated in aspen, mixed conifer, ponderosa pine, and pinyon–juniper communities, leaving most classes with minimal or no verification points. Mixed conifer and ponderosa pine were the only two classes with more than 50 verification points (Table 3). These plot data, however, were the best source of GPS-located points for verifying the pre-fire vegetation classi-

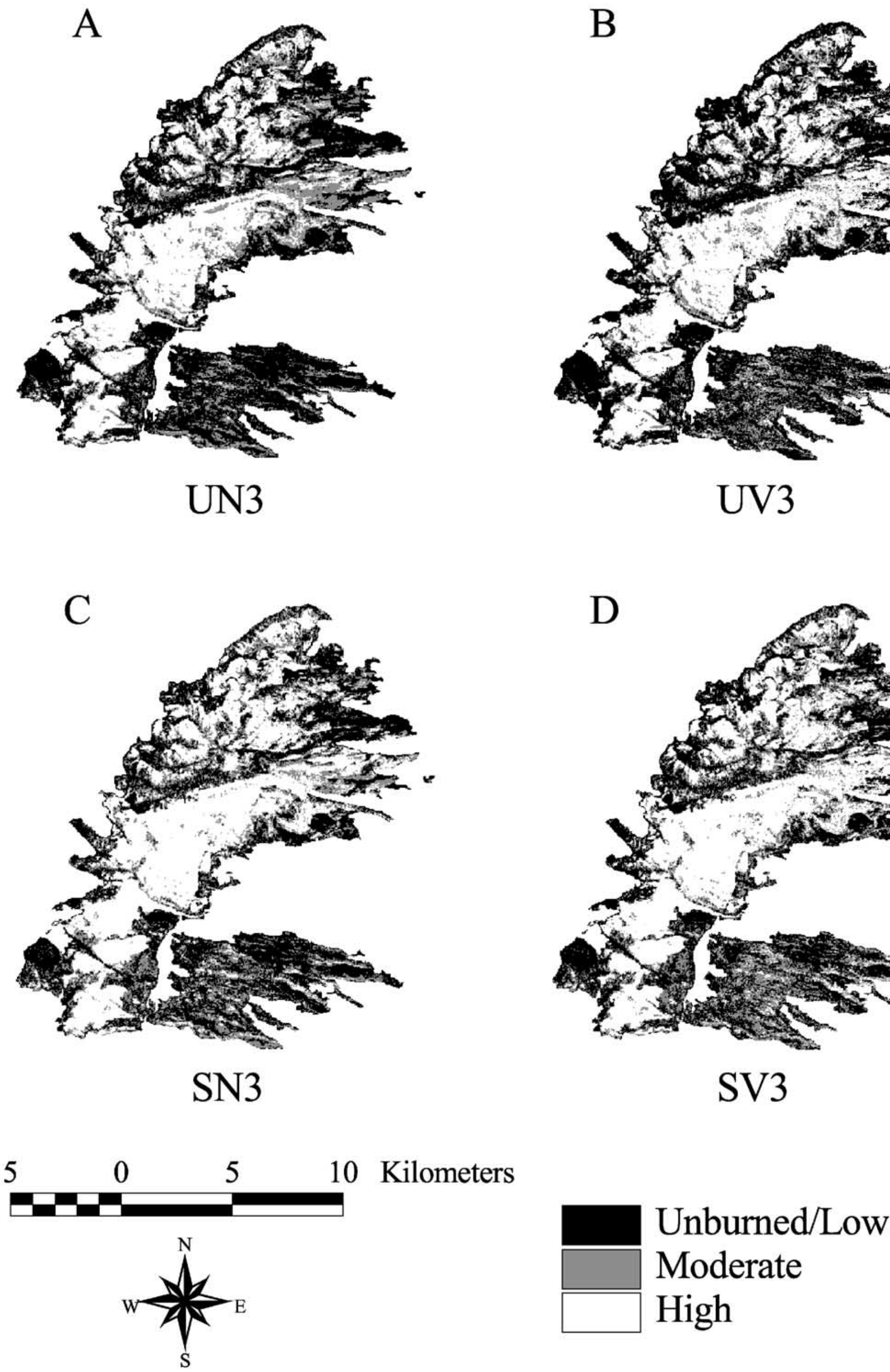

Fig. 6. Maps of three classes of canopy consumption using supervised and unsupervised classifications. See Table 2 for a description of canopy consumption classification definitions.

fication. The resulting overall Kappa for the vegetation classification was 0.76.

One of the objectives of this paper was to determine whether stratification of the change image by pre-fire vegetation type would improve the accuracy of a canopy consumption map. Average change values and most notably the range of change values were different by overstory type (Table 4). This would seem to indicate that stratification by vegetation type may improve classification accuracy.

3.2. Canopy consumption maps

The canopy consumption classifications are shown in Figs. 6 and 7. The number of hectares in the High class of the supervised classifications agreed fairly well with the BAER team burn severity map. Supervised classifications consistently classified more pixels as High and fewer pixels as Unburned or Unburned/Low compared to the unsupervised classifications (Fig. 8). The classifications with vege-

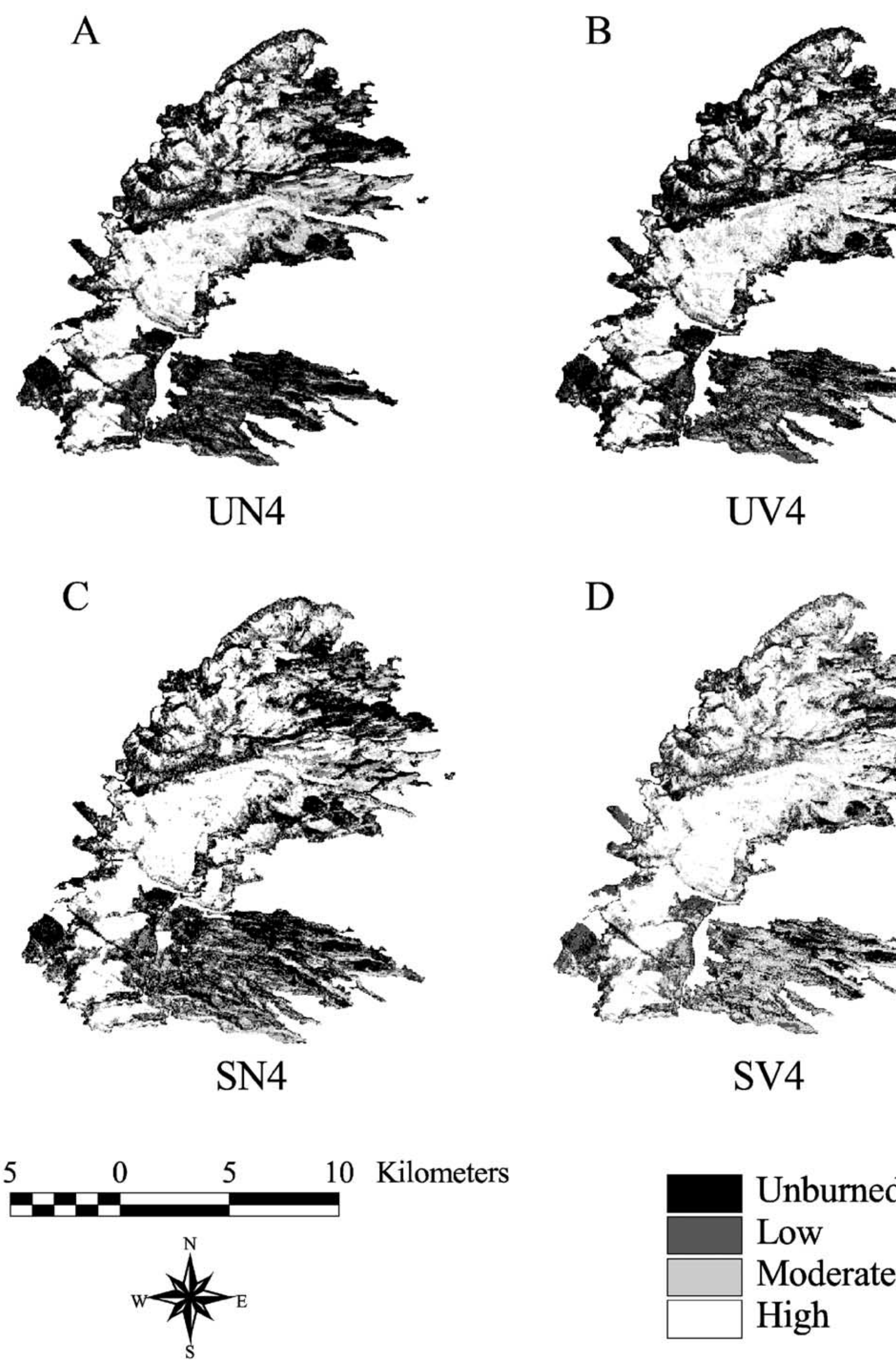

Fig. 7. Maps of four classes of canopy consumption using supervised and unsupervised classifications. See Table 2 for a description of canopy consumption classification definitions.

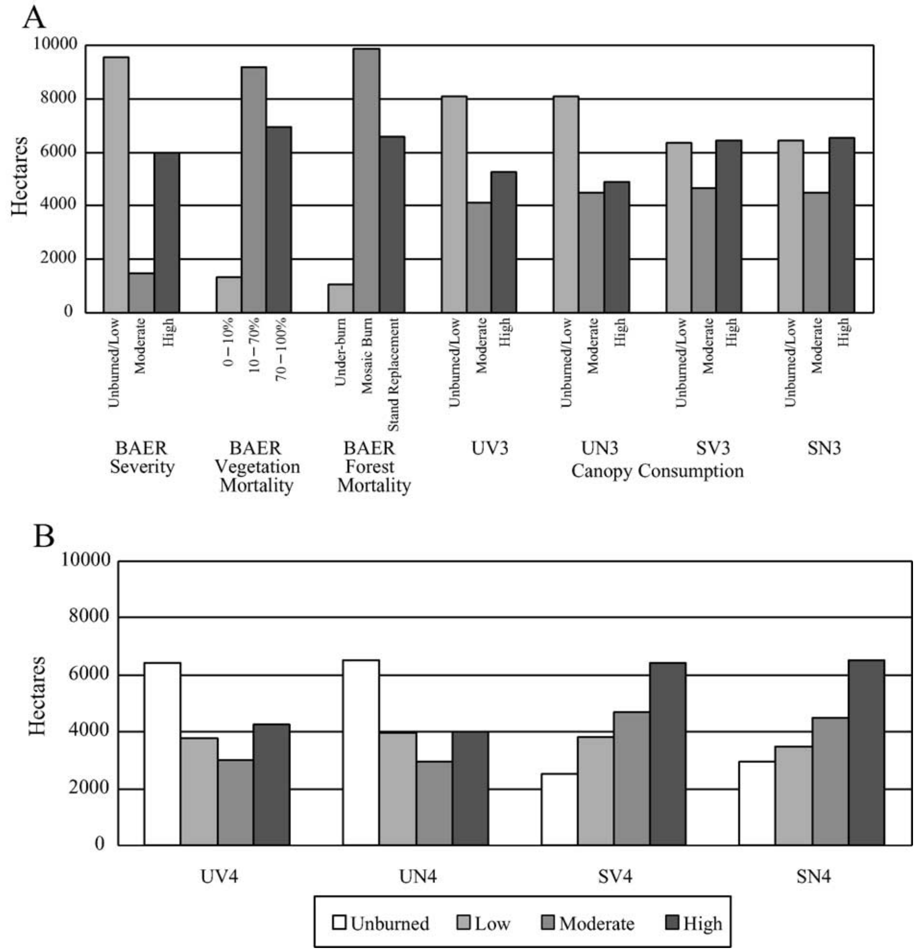

Fig. 8. Bar graph of the number of hectares burned. (A) Three fire effect classes by the BAER team and three classes of canopy consumption using supervised and unsupervised classifications. (B) Four canopy consumption classes using supervised and unsupervised classifications. See Table 2 for a description of canopy consumption classification definitions.

tation stratification tended to move pixels from the lower canopy consumption classes to the higher consumption classes to a lesser degree than the classifications without vegetation stratification. For example, the SV4 had more area classified as Low and Moderate, and less as Unburned compared to SN4. UV4 had more pixels classified as Moderate and High in comparison with UN4 (Fig. 8B). The four-class unsupervised classifications had fewer pixels in the Moderate and High classes in comparison with the three-class unsupervised classifications. This was not surprising because the clustering algorithm should reallocate pixels to create a fourth class. The ISODATA algorithm only had a one-dimensional space to separate pixels into classes. There tended to be only two modes in the frequency of values in the pre- vs. post-fire image, making it difficult for the *K*-means algorithm to pick break points between three and four classes. The means of the classes therefore tended to be uniformly distributed along the one-dimensional space. This is a common feature of *K*-means classifiers (Schowengerdt, 1997). The three-class supervised classifications (SV3 and SN3) were generalized from the four-class classifications (SV4 and SN4). The Unburned and Low classes were combined to create a single class and therefore did not yield a similar reallocation in the other classes as above. UN4 exhibited the least severe fire conditions, while SV4 and SV3 displayed the most severe in terms of area per class.

Contingency matrices and Kappa statistics were generated for all canopy consumption maps (Table 5). Random points ($n = 327$) were selected and photo-interpreted for analysis of the mapping error. These points were stratified by canopy consumption class using the SV4 classification, so at least 50 points were in the Unburned class which was the smallest class by area (Table 6). In general, classifications with three classes of canopy consumption were significantly better than the four-class classification when comparing Kappa values (Tables 5 and 7). SV3 did not however have a significantly larger Kappa than SV4. The user's accuracies of the Low and Unburned consumption classes were low, as expected since pre-fire fuels plots indicated average canopy cover was about 80%, making detection of understory effects difficult (Stenback & Congalton, 1990).

Table 5
Results for classifications verified with aerial photos

Classification	Overall kappa		Classification accuracy (%)			
			Unburned/Low		Moderate	High
UN3	0.72	User's	78.4		59.3	100.0
		Producer's	92.0		60.0	83.8
UV3	0.73	User's	76.2		64.1	100.0
		Producer's	94.9		51.3	88.3
SN3	0.78	User's	89.8		64.2	95.3
		Producer's	82.6		76.3	92.9
SV3	0.86	User's	94.4		72.3	100.0
		Producer's	84.8		91.3	95.5
BAER burn severity	0.63	User's	66.8		54.8	94.0
		Producer's	92.7		21.5	90.9
			Unburned	Low	Moderate	High
UN4	0.30	User's	24.8	26.2	24.0	100.0
		Producer's	100.0	20.8	15.0	70.8
UV4	0.32	User's	23.9	27.1	29.6	100.0
		Producer's	100.0	17.9	20.0	74.0
SN4	0.66	User's	44.4	81.8	64.2	95.3
		Producer's	100.0	42.5	76.3	92.9
SV4	0.80	User's	62.7	91.8	72.3	100.0
		Producer's	100.0	63.2	91.3	95.5
			0–10%	10–70%	70–100%	
BAER vegetation mortality	0.43	User's	9.3	37.6	78.8	
		Producer's	20.4	81.0	87.0	
			Under-burn	Mosaic burn	Stand replacement	
BAER forest mortality	0.38	User's	89.5	31.6	82.3	
		Producer's	12.4	74.7	87.7	

See Table 2 for a description of canopy consumption classification definitions.

Vegetation stratification did not significantly improve the unsupervised classifications (UV3 and UV4) over the non-stratified classifications UN3 and UN4 (Table 7). This lack of improvement was perhaps due to the uniform distribution of class means in the one-dimensional space by the K-means algorithm not representing the actual distribution of severity classes. The stratification did however significantly improve the supervised classifications (SV3 and SV4) over the non-stratified classifications (SN3 and SN4).

The SV3 classification (Kappa = 0.86) had a significantly higher Kappa than all but the SV4 classification (Kappa = 0.80). The SV4 classification posted a significantly higher

Table 6
Area burned within Cerro Grande Fire perimeter by vegetation class. Canopy consumption classes derived from supervised classification with vegetation stratification (SV4)

Vegetation class	Unburned (ha)	Low (ha)	Moderate (ha)	High (ha)	Total area within fire perimeter (ha)	% of total area
Water	2	0	0	0	2	0.0
Urban	327	0	141	4	472	2.7
Bare ground, rock	246	0	0	0	246	1.4
Plains grasslands	130	41	0	0	172	1.0
Pinyon–Juniper woodlands	641	547	770	647	2606	14.9
Shrubs	89	103	102	62	355	2.0
Montane grasslands	68	371	132	43	614	3.5
Ponderosa pine	228	1184	1644	1504	4559	26.1
Mixed conifer	777	1430	1825	4073	8105	46.4
Aspen	10	138	65	116	329	1.9
Total	2519	3813	4679	6448	17459	100.0

Table 7
Kappa analysis comparing canopy consumption error matrices[a]

Classification	UN3	UV3	UN4	UV4	SN3	SV3	SN4	SV4
UN3		0.32	6.23	6.05	1.46	3.67	1.04	1.65
UV3	NS		6.45	6.27	1.14	3.36	1.29	1.39
UN4	S	S		0.27	7.23	8.66	4.72	6.96
UV4	S	S	NS		7.07	8.54	4.52	6.80
SN3	NS	NS	S	S		2.22	2.15	0.46
SV3	S	S	S	S	S		3.76	1.25
SN4	NS	NS	S	S	S	S		2.28
SV4	NS	NS	S	S	NS	NS	S	

See Table 2 for a description of canopy consumption classification definitions.

S = significant, NS = not significant.

[a] $Z = 1.96$ significant at $\alpha = 0.05$.

Table 8
Results for the classifications verified with ground plot data

Classification	Overall kappa		Classification accuracy (%)			
			Unburned/Low		Moderate	High
SV3	0.76	User's	80.0		62.5	97.6
		Producer's	85.7		62.5	93.0
			Unburned	Low	Moderate	High
SV4	0.65	User's	0.0	63.0	62.5	93.0
		Producer's	0.0	73.9	62.5	97.6

See Table 2 for a description of canopy consumption classification definitions.

Kappa than all other four-class classifications. The SV4 classification had a higher Kappa than all three-class varieties, but was not significantly different from any of them. Table 6 lists the number of hectares burned by canopy consumption class as identified with the SV4 classification.

Although the number of post-fire field plots were not sufficient to perform a sound error analysis of the canopy consumption classifications, we generated error matrices for the supervised four consumption class maps (Table 8). Only one of the plots revisited after the fire within the fire perimeter was unburned, perhaps unrealistically lowering the accuracy of the four consumption class classification (SV4) from 0.80 to 0.65 (Tables 5 and 8). Comparing the error matrices for the three consumption classes (SV3) the overall Kappa fell from 0.86 to 0.76 (significant at $\alpha = 0.2$, not significant at $\alpha = 0.1$). The principal change was the drop in producer's accuracy of the Moderate class from 91% to 62% due to confusion with the Low class. This may suggest that the Moderate class was overestimated and Low class underestimated in the classification process, however the number of plots is low (16) and any conclusions are suspect.

3.3. BAER team-derived maps

The 372 verification points used in the error analysis of the canopy consumption maps were recycled in an error analysis of the BAER team fire effects maps. The best BAER map produced an overall Kappa of 0.63 (Table 5). All three-class trials (UN3, UV3, SN3, and SV3) produced significantly higher Kappa statistics than the BAER team maps (Table 9). The 30 m mapping unit of the canopy consumption maps vs. 20 ha or larger for the BAER team maps is one reason for the higher Kappa values. Many areas of moderate severity occurred in small patches and in the margins of high to low severity. The BAER burn severity map differed most by area from the UN3 and UV3 maps in the Unburned/Low and Moderate classes (Fig. 8). Fewer hectares were classified as Low and High and more as Moderate in the UN3 and UV3 trials, due most likely to the manner in which the unsupervised classification tended to uniformly distribute the means of the classes. While all classifications used remotely sensed data to delineate burned areas, the BAER team mapped fire severity accounting for soil conditions through ground observations as opposed to canopy consumption. In addition, the BAER team definition of Low vs. Medium vs. High classes may have differed from ours, influencing the error analysis. (The BAER team did not publish their definition.) The High BAER class agreed fairly well with the SV3 classification, both having high producer's accuracies of over 90%. All unsupervised classifications underestimated the High class in comparison to the BAER maps as shown by the smaller producer's accuracies (Table 5). This may be significant since mitigation efforts need to be targeted at those severely burned areas.

The BAER forest mortality map should agree favorably with SV3 (the best canopy consumption map) because the primary feature mapped was overstory consumption. The forest mortality map had the smallest overall Kappa of the three BAER team maps, however (Table 9). While the High mortality classes were virtually identical in size to the best supervised classification (SV3), the Mosaic class of the forest mortality map was much larger than the Moderate class of SV3 (Fig. 8). This result may be attributed to different definitions of the class labels, as "Mosaic" implies an all-encompassing class containing areas of varying mortality, whereas "Moderate" defines a specific range of mortality.

The vegetation mortality map had a low Kappa of 0.43. This may be due to the class categories not agreeing

Table 9
Kappa analysis comparing BAER team maps and three class canopy consumption error matrices[a]

Classification	UN3	UV3	SN3	SV3	BAER severity	BAER vegetation mortality	BAER forest mortality
UN3		0.32	1.46	3.67	2.04	6.00	7.07
UV3	NS		1.14	3.36	2.36	6.33	7.40
SN3	NS	NS		2.22	3.51	7.47	8.57
SV3	S	S	S		5.76	9.69	10.85
BAER severity	S	S	S	S		4.00	5.04
BAER vegetation mortality	S	S	S	S	S		0.98
BAER forest mortality	S	S	S	S	S	NS	

See Table 2 for a description of canopy consumption classification definitions.
S = significant, NS = not significant.
[a] $Z = 1.96$ significant at $\alpha = 0.05$.

with the class limits of the canopy consumption maps. The BAER classes were based upon percent of mortality by area, whereas the consumption maps were based primarily on average tree crown scorch (Table 1). The BAER team indicated that most of the low burn severity class areas fell primarily in the 0–10% mortality class, and moderate severity burn classes in the 10–40% and 40–70% mortality classes (BAER, 2000, p. 372). However, upon examining their map it appears that a significant area of low burn severity was placed in the 10–40% class which was combined with the 40–70% class for this project (Fig. 5).

4. Conclusions

Wildland fire effects mapping has become a standard practice for post-fire resource management by Federal land management agencies. Fire researchers and managers require standard, reliable techniques for efficient mapping and monitoring of wildland fire effects. We have demonstrated in this paper a straightforward algorithm for mapping fire effects at increased accuracy over methods currently in use for BAER. Additionally, these techniques may be useful for applications other than BAER, such as long-term monitoring projects. This algorithm can be implemented by land management personnel with little additional training.

We have shown that three-class unsupervised classifications using multi-date multispectral satellite data can produce maps of higher accuracy than maps produced using airphoto interpretation. Gains in accuracy were achieved primarily through the addition of middle infrared bands and a finer mapping unit. Differences in mapped fire effects and class categories between our maps and BAER team maps were minor, but may have contributed to differences in classification accuracies. It is difficult however to ascertain how such factors contributed to the gains in accuracy we attained. Some producer's accuracy in mapping the most severe fire effects may be sacrificed to gain an increased overall Kappas as shown by the lower producer's accuracies of all unsupervised classifications.

Incorporating post-fire severity in a supervised classification favors accurate mapping of the most severe fire effects while preserving the fine spatial resolution. Supervised classifications all achieved higher Kappas over the BAER team severity map, with three-class classifications producing the highest Kappas. We have also shown that if pre-fire vegetation data are available, stratifying training sites by vegetation type further improves the Kappas of supervised classifications when the fire occurs in multiple vegetation types with unique spectral signatures. What defines an acceptable classification accuracy is a management decision, although it is always best to achieve the highest accuracy possible. If a pre-fire vegetation classification does not exist or cannot be derived in time for application, then the stratification does not have to be applied to achieve improved accuracies.

Not all fires are supported by BAER teams, and not all BAER supported fires are able to afford aerial photography. While the 8-day over-flight schedule of Landsat satellites may reduce the likelihood of cloud-free scenes, the relatively cheap cost of the data may provide an opportunity for accurately mapping those fires. For non-BAER supported fires the 8-day limitation may not be as much of an issue, allowing for establishment of baselines for long-term ecological monitoring. For high socio-economic impact fires the higher classification accuracies achievable through the use of satellite-derived data may be desirable for operational planning of erosion mitigation and watershed rehabilitation efforts.

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