EVALUATING THE RELATIONSHIPS BETWEEN FIRE INDUCED CANOPY MORTALITY AND PRE-FIRE MULTISPECTRAL PATTERNS

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Abstract

Statistical tools were used to evaluate the relationships between observed fire effects and characteristics identifiable in pre-fire multispectral and terrain data. Random points were placed within field delimited polygons representing areas of high and low canopy mortality. Each point was then used to extract Landsat TM based pre-fire spectral characteristics and DEM derived terrain characteristics. The values for these random points were subjected to a multivariate discriminant analysis to ascertain whether specific spectral bands, indices, terrain characteristics, or specific combinations of these, could be effectively associated with the observed fire effects. Data values for high and low mortality points were found to be significantly different for all the pre-fire data sets. The normalized difference vegetation index (NDVI) and tasseled cap greenness values provided the highest magnitude of direct differentiation between high and low mortality points. Discriminant analysis revealed that NDVI had the highest correspondence to degree of future canopy mortality, while the combined effect of the pre-fire spectral response provided a prediction of observed fire effects with 87% accuracy, and the addition of terrain data improved accuracy to 90%.

Introduction

Mapping the effects of large forest fires is a reasonable application of remote sensing techniques. Such fires leave significant changes in the landscape that can be mapped even with space-borne sensors (Jakubauskas 1990, Turner et al. 1994, White et al. 1996, Medler and Yool 1997, Paterson and Yool 1998, Kushla and Ripple 1998). Such post-fire maps are quite valuable for fire management activities ranging from soil and watershed protection to evaluating impacts on timber supplies and wildlife habitat. However, modeling and anticipating the spatial patterns of fires before they occur is clearly more difficult. Many traditional fire models are mechanistic, requiring extensive spatially explicit input data, which is then subjected to mathematical or spatial approximation of the physical processes involved in fire or fire fighting (Rothermel 1972, 1983, Andrews 1986, Albini and Reinhardt 1995, Carapella 1996, Finney 1998). These models can offer critical insight into the potential behavior of fires under specific conditions. However, these models rely on a functional understanding of all the relevant processes and interactions involved. Problems such as inaccuracy in input data, error propagation, error multiplication, and the complex and chaotic feedbacks and relationships of fire make it very difficult to predict fire behavior across entire landscapes.

As an alternative methodology, which avoids some of the intermediate steps involved in mechanistic approaches, other previous research projects have used integrated Geographic Information Science (GIS) techniques that require less complete specification of all pertinent interactions that determine fire behavior (Burgan and Shasby 1984, Yool et al. 1985, Medler 1999). This paper supports continued research into these synthetic approaches by introducing a set of specific correlations that indicate it may be possible to produce some degree of spatial understanding of the possible ramifications of future fires, without first detangling all pertinent variables or understanding how such variables interact. The research reported here specifically provides evidence that basic correlations may exist between **pre-fire** spectral and terrain conditions and the patterns of canopy mortality observed in later fires.

Our statistical evaluation of pre-fire data sets indicated that certain characteristics in multispectral remotely sensed data and Digital Elevation Models (DEMs) can be directly associated with the spatial patterns of canopy mortality observed later in a specific forest fire. If the limited results presented here prove to be similar to correlations being examined for other fires, these local relationships could be used as the basis of a simple and cost efficient remote sensing based technique for large area mapping of likely canopy mortality in the case of similar future fires.

The statistical results presented in this paper are an essential component of a larger overall project developing a method to produce descriptive maps of potential canopy mortality patterns in specific areas. Such a system would not produce predictive models of expected fire behavior. Rather, this method would create descriptive maps showing the distribution of individual pixels that share spectral and terrain characteristics with areas that underwent complete canopy mortality in specific local historical fires. While obviously limited geographically, and constrained by the occurrence of historical fires that correspond to the types of fires to be modeled, such maps could provide valuable broad scale indications of future problems.

This paper identifies a close relationship between areas of observed canopy mortality caused by the 2000 Cerro Grande fire at Los Alamos, New Mexico, and the spectral and terrain characteristics present in the same areas before the fire. In pre-fire data sets, areas that later experienced complete canopy mortality were statistically separable from areas with similar vegetation communities that only underwent light surface fire. This finding indicates that we may be able to use multispectral and terrain data to identify general landscape patterns of expected canopy mortality despite the complicated and chaotic processes that determine fire behavior.

As part of the initial activities of this ongoing project, field data were gathered immediately after the Cerro Grande fire, identifying two sets of field polygons. One set of polygons represented areas that experienced complete canopy mortality. The other set of polygons represented areas with similar vegetation communities that had experienced only light fire with limited canopy mortality. Fire records and interviews with fire officials were used to assure that all polygons were placed in areas that had been subjected to little or no direct fire fighting activities. One thousand points were selected randomly within these polygons. These points were used to extract spectral and terrain characteristics of each individual pixel from pre-fire Thematic Mapper (TM) and DEM data sources. The values of these thousand points were subjected to a multivariate statistical analysis to ascertain whether specific spectral bands, indices, or terrain characteristics could be associated with the observed fire effects. Despite the complexities and influences of complicating factors during the fire, such as erratic weather and high winds, it was found that a combination of pre-fire TM bands 3 and 4, together with terrain data could provide a prediction of observed canopy mortality with 90% accuracy.

Background

The complexity of fire

Forest fires are complex phenomena. Many factors interact to determine fire behavior. For example, vegetation patterns, terrain, fuel, moisture, and weather all intersect to influence each fire as it unfolds through time. The complex spatial arrangement of each of these determinants, and others, influences the spatial pattern of changes each fire leaves on the landscape (Pyne et al. 1996). Additionally, even a small fire initiates a complex set of feedbacks between determinants. For example, the heat of a fire may produce convective lift drawing air into the fire, leading to locally chaotic changes in wind speed and direction. Heated air may also preheat fuels uphill from a burning front, changing fuel moistures enough to influence the behavior of the fire once it arrives. As Stephen Pyne observes in *Fire in America*,

> "Wildland fire behavior multiplies probability with probability. Unlike Astronomy, where it is possible to predict the position and velocity of individual objects with great precision, fire behavior deals with statistical ensembles - the limitless nuances of fuel complexes, the restless variety of topographic forms, and the maddening vagaries of weather." (Pyne 1982, p. 21)

Models that attempt to predict the patterns of future fires face these "limitless nuances" that blend and combine fire and weather, even while a fire is moving through complex associations of live and dead fuel, and across complex terrain. Therefore, deterministic models intended to predict even just the spatial extent of a fire with a given ignition point and duration, which do not account for these complex feedbacks and interactions, are likely to misrepresent a fire's complicated responses to terrain, wind patterns, and the extremely fine scale and complex microclimatic effects that result from fire itself.

Despite these complexities, a fire fighter familiar with a region's recent fires might walk into a patch of unburned forest and comfortably anticipate which areas might undergo complete canopy mortality, and which areas will probably only sustain light understory fire. This expert opinion involves extensive experience and the human ability to quickly synthesize large numbers of phenomena and recognize the most significant patterns. This fire fighter is recognizing areas that "look like" other areas that have experienced similar fire behavior. This implies that there are combinations of phenomena that can be identified on the ground that are likely to lead to particular outcomes in the case of certain fire conditions. This paper presents evidence that a similar synthesis of variables may also be recognizable in spectral patterns and terrain characteristics before a fire occurs.

Many recent fire hazard modeling projects are actually based on a very similar assumption. For example, recent efforts have used remote sensing data as input to map "Fire Behavior Fuel Models" (Keane et al. 1998, 1999; Wagtendonk and Root 1999). As the name implies, these fire behavior fuel models represent complex associations of fuels that are categorized by expected fire behavior and are based on Rothermel's initial models of fire propagation (Rothermel 1972, 1983, Anderson 1982). Therefore, attempts to map these fuel models with remote sensing assume that the complex association of physical variables that determine fire behavior are integrated within remotely sensed pixels in a way that allows analysts to categorize satellite data into classes of expected fire behavior. Once identified and mapped, these fuel models are often used as inputs to mechanistic computer models such as the FARSITE fire area simulator, which model the physical processes that determine the spatial behavior and propagation of a given fire (Finney 1998).

As an alternative to such mechanistic systems, this paper presents evidence that supports developing techniques that take advantage of a more direct path from satellite data to spatial information about fire hazards. The results presented here strongly suggest that spectral and terrain data capture patterns that can be associated directly with future canopy mortality without first identifying and deconstructing the nature of all the relevant determinants. Such relationships do not change the importance or relevance of mechanistic models, or efforts to understand the underlying principles governing fire behavior. Rather these results provide additional evidence that spectral data capture elements that are important in the behavior of fire.

Similar previous work

Previous work indicates there is good reason to explore the possibilities of extracting fire hazards directly from remotely sensed imagery and terrain data (Medler 1999). In this previous study, field data and satellite data were used to map the internal severity patterns for two similar 9,000-hectare fires that occurred over 300 kilometers apart. The severity maps from one fire were used to identify polygons of complete canopy mortality, and polygons of light surface fire. Once identified, these polygons were used to determine the pre-fire spectral and terrain data values associated with each of these classes of canopy mortality. These two sets of data values were then used as training data to effectively classify pre-fire imagery of the entire mountain range containing the second fire. The research reported here extends these findings by identifying the statistical relationship between pre-fire data and observed canopy mortality.

Field site

In May of 2000, the Cerro Grande Fire was intentionally ignited as a prescribed fire. Eventually the fire went out of control and burned into the town of Los Alamos as well as the Los Alamos National Laboratory (LANL), with total costs estimated at over a billion dollars. Such prescribed fire projects are undertaken because of the recognized risks associated with continued accumulation of fuels. However, this fire offers a chilling indication of the complex problems and risks faced by a growing number of other communities with similar urban-wildland interface areas and similar fuel accumulation. Other previous fires in the area had indicated that the area faced a particularly high danger from future fires (Easthouse 1999).

Like many other western communities, the area surrounding the town and LANL consisted of mixed conifer communities with interspersed aspen groves and alpine meadows at elevations up to approximately 3300 meters. Large expanses below these elevations contained forest of predominantly ponderosa pine (*Pinus ponderosa*). Further down slope, pinyon juniper communities eventually blend into desert grass and scrub (Touchan et al. 1994, Ribe 1997).

Exploratory multivariate approach: discriminant analysis

We used a multivariate discriminant analysis to evaluate whether pre-fire spectral and terrain characteristics can be related to the observed patterns of canopy mortality. Regression identifies linear combinations of variables that maximize the regression relationship between a continuous dependent variable and the regressing variables. Alternatively, with discriminant analysis the dependent variable is categorical and the objective is to maximize its separation based on the linear transformation of discriminating variables (Walker 1998). Discriminant analysis is often accompanied by multiple analyses of variance (MANOVA) to test whether or not the differences among these groups are significant.

The approach used here evaluates a given set of independent variables and computes weighted combinations of these variables that best discriminate the dependent variable. These combinations are referred to as "**canonical functions**." These functions are the weighted linear combinations of the original variables as expressed below:

$$Y = variable_1 weight_1 + variable_2 weight_2 + \ldots + variable_N weight_N + constant$$

The inferential mode of discriminant analysis provides outputs that are related to the discriminating variable relationship and the underlying gradient of variation. Among them, four relevant parameters are enumerated and discussed below.

The first discriminant analysis output gives an assessment of the statistical significance of the functions. This is an expression of whether the differences among the group means are significant. This is expressed by **Wilk's Lambda**. It is the likelihood ratio statistic for testing the hypothesis that group means are equal in the population.

Secondly, the **canonical correlation** provides the relationship between the functions and the original variables. A high correlation indicates that a large amount of variance in those variables is explained by the function.

Thirdly, the **standardized canonical coefficients** can be interpreted as weights. These quantify the relative importance of each discriminating variable. Therefore, the larger the coefficient, the greater the variable's contribution. However, when the correlation structure is complex and there are several significant coefficients (> 1.0), interpretation can be difficult. In such cases, individual coefficients reflect not only the influence of their corresponding discriminating variables, but also the influence of the other variables.

Finally, the **total canonical coefficient** is a matrix of the correlations between the discriminating variables and the functions. This explains the product-moment correlations between the canonical functions and the individual variables. These bivariate correlations are not affected by relationships with other variables, and therefore reflect the actual statistical relationships between each variable and the canonical function.

Methods

Field data

To associate TM and DEM data values with specific observed canopy mortality, field teams visited the site of the Cerro Grande fire in June and August of 2000. These teams identified and mapped a set of representative plots that had undergone complete and homogeneous canopy mortality, and another set of plots that had undergone light surface fire without significant canopy mortality. Because the fire was still burning during the June visit, access was limited to a small portion of the total area of the fire. During the August visit, the field teams were able to expand the total area visited, and increase the size of some of the plots. DEMs, vegetation maps, and United States Forest Service fire effects maps were used to insure that plots represented a wide variety of slopes, aspects and elevations, as well as each of the major vegetation community types.

Target areas were identified through examination of the available information sources. Field reconnaissance visits then identified suitable areas. Once an area was selected, a Global Positioning System (GPS) unit was used in conjunction with post-processed differential correction techniques to identify the exact location of a linear transect walked by a field technician. Other field technicians walked parallel transects with continuous visual contact with the GPS controlled transect. These outer team members recorded their distance from the GPS controlled transect at the beginning and end of each leg of the transect. Each outer team member ended their section of the transect if they observed fire effects not intended to be included in the polygon, either between themselves and the GPS controlled transect or within 30 meters on the outer edge of their transect. In some cases, much larger areas were clearly identifiable on either side of the GPS controlled transects. In these cases, topographic maps were used to delimit the area observed in the field. The complete field data set was entered into ArcView ™ Geographic Information System software, and the specific configuration of each polygon was mapped.

These efforts resulted in a set of GPS controlled and delimited polygons (Figure 1). Nine polygons were identified as areas with complete homogeneous canopy mortality, while eleven polygons were identified with low levels of canopy mortality despite evidence of surface fire. Each of these polygons represents an area of homogeneous fire effects visited by a field team, and each polygon has at least a 30 meter outside buffer area to insure that any TM pixel registered to these polygons falls within the appropriate mortality class.

TM, DEM, and other derived data sets

The field polygons were registered to a geo-rectified pre-fire Landsat TM scene acquired about a month before the fire, on 14 April 2000. Additionally, a geo-rectified DEM was used to derive values indicating elevation, slope and aspect. A subset of these data sets was created capturing the entire eastern half of the Jemez Mountains. Moreover, additional data sets were derived from the TM data, including the normalized difference vegetation index (NDVI), the normalized burn ratio index (NBRI), and the brightness, greenness and wetness dimensions that result from the Tasseled Cap (TC) transformation. NDVI ([TM4-TM3]/[TM4+TM3]) was selected as result of its long historical use in mapping and quantifying vegetation (Lillesand and Kiefer 1994). The NBRI ([TM7-TM4]/[TM7+TM4]) is a recently developed index that distinguishes between burned and unburned areas (Key and Benson 2000). The TC transformation was included because it was developed to specifically relate spectral response patterns to more specific phenomena in the field (Kauth and Thomas 1976, Crist and Cicone 1984a and 1984b). This transformation has also been used effectively in both mapping and anticipating fire effects (Patterson and Yool 1998, Medler 1999).

A random stratified set of one thousand points was selected from the plots described above. For each of these points, the category of high or low canopy mortality was recorded as the dependant variable for each point. Then independent variable values were extracted for each point from the TM and DEM based data sets described above. This total data set was then exported into the SPSS ™ (version 8.0) statistical analysis software package.

Discriminating areas of canopy mortality in pre-fire spectral and terrain dataset

Four discriminant analysis models were used in this analysis. The first model includes the seven bands of TM, indices such as the NBRI and NDVI, and the TC brightness, TC greenness and TC wetness. The second model includes the previous variables and adds elevation, slope, and aspect. The third model is a compilation of only the seven TM bands, while the fourth model segregates all the derived indices and transformed data.

The first two models are intended to evaluate the predictive power of spectral response patterns in isolation and the additional predictive power provided by inclusion of terrain variables. The third and fourth models were intended to evaluate the exclusive use of the original bands of TM and the effectives of derived indices, which have been previously used in fire investigations.

Discriminant analysis uses a forward stepwise procedure to enter each independent variable, evaluating both the differences in mean and the correlation to those variables already entered in the process. Thus, redundant variables were identified while the overall understanding of data relationship became more straightforward. In this stepwise procedure, the observed increment in the calculated canonical correlation for every variable included in the analysis indicates its amount of contribution in improving the amount of variation being expressed by the canonical function.

Results and Discussion

Before running the discriminant analysis, a preliminary analysis of normality was conducted for each of the discriminating variables for all the points collected for both high and low categories. This analysis examined both the underlying structure of the data and inter-variable relationships. A majority of the infrared bands (bands 4,5, and 7) were normally distributed while extremely bright outlier pixels were observed in bands 1 and 2. A very narrow range of values was recorded for both NBRI and the thermal band.

The visible channels of the pre-fire TM (bands 1, 2, and 3) showed higher responses in the low canopy mortality points than in the high mortality points. Additionally, high canopy morality points tended to have higher values in mid-infrared bands (TM bands 5 and 7). The strong positive correlation that exists among the visible TM bands indicates the low canopy mortality category exhibited higher reflective values than the high mortality category (see Table 2).

The TC greenness values correlated with the infrared bands. Alternately, the decreasing NDVI values were inversely related to the NBRI and TC brightness. The TC wetness and TM band 6 (surface temperature) were observed to be similar in sites of either high or low canopy mortality.

Higher values in the infrared bands indicate larger amounts of green vegetation in the high canopy mortality points. This strongly suggests that high canopy mortality generally occurred in areas with high pre-fire NDVI and TC greenness values. There is also a trend observable in Table 1 that unsurprisingly suggests that larger volumes of green vegetation indicate high future canopy mortality.

Discriminant Analysis

A simple comparison of mean (*t statistics*) for all the spectral and terrain data sets indicated that high and low canopy mortality points were 95% significantly different for all the data sets except TM band 5. This analysis also showed that the NDVI and the TC greenness values provided the highest magnitude of differentiation between high and low mortality points, while TM bands 7 and 3 also showed significant variation.

Discriminant analysis was then used to provide more detailed and quantitative information beyond the results of the bivariate analysis above. Discriminant analysis was initially conducted on Model 1, which included the entire range of TM spectral bands and both TM-derived indices and the TC transformations. The discriminant analysis results for Model 1 indicated that the entire range of spectral data is multicolinear. The occurrence of four spectral variables with standard canonical coefficients of more than 1.0 (see Table 3), suggests that there is a complex correlation that exists among them. As previously shown in Table 2, a strong relationship was noted among visible bands and the infrared bands. The presence of multicolinearity in the data sets offers the possibility of using other techniques (e.g. principal component analysis) that summarize data redundancy. However, discriminant analysis was chosen in this case to better determine which spectral bands of TM are most effective for differentiating the two categorical response variables. Data sets that are related or redundant are being omitted in the process, to improve modeling efficiency.

The total canonical coefficients of band 3 and NDVI pointed out these data set's high level of discriminatory capability between the two classes of field points. The NDVI of high canopy mortality points is significantly different from the average NDVI of the limited canopy mortality. The coefficients displayed the relationship between individual variables and the canonical functions. Band 3 and NDVI are equally related (total canonical coefficient = -0.78 and 0.78, respectively) to the canonical function that best discriminates the two sets of canopy mortality points. The overall discriminating capability of Model 1 can be largely attributed to the fifty percent (49.4%) variation between high and low mortality points in the value of Band 3. This band (0.63 – 0.69 μm) is traditionally related to the red chlorophyll absorption of healthy vegetation (Lillesand and Kiefer 1994).

Though the NDVI is linked to the strong discriminatory power of band 3, band 4 is also a component of this ratio based vegetation index. The relevance of band 4 emerged in Model 3 where only the original TM bands were included (Table 4). In Model 1, band 4 showed little discriminating power as this band is already incorporated as an essential parameter of NVDI, and is positively related to the other infrared bands.

Aside from band 3, the combined effect of NDVI, TC brightness, TM bands 1, 7, and 5 contributed to the overall discriminating power of Model 1 of 0.588. The inclusion of these variables in the model is due to the 95% likelihood that their group mean is different between the high and low mortality categories yet less linear for other variables already considered in the model (*Wilk's lambda statistics*). Consequently, redundant variables such as bands 2, 4, 7, and 5 along with the NBRI, TC greenness and TC wetness were identified as not contributing to the model's overall discriminatory ability. Each of these variables offered little additional capability as band 4 is a constituent of NDVI, TC greenness is strongly related to the NDVI, NBRI is similar to TC brightness, and the highly skewed band 2 was initially found to be highly correlated with band 3.

In Model 2, these results were extended to evaluate the potential contribution of the terrain data sets. The canonical correlation of 0.65 for Model 2 improved slightly over the value of 0.59 for Model 1(see Table 3). The discriminating capabilities of band 3 and NDVI were still evident in Model 2, while elevation was found to be more important than slope or aspect. Tables 3 and 4 also include a percentage classification accuracy statistic quantifying the proportion of cases that were predicted against the observed value for each point in each model (McGarigal et al. 2000). By including the terrain in Model 2, the classification accuracy was increased from the already high 86.7% obtained for Model 1, to 90.0%. This statistic indicates the two sets of field points can be classified with a 90.0% accuracy using the variables identified in Model 2. This result is remarkable when we consider that the data used to in this discrimination is spectral and terrain data from before the fire that produced the effects mapped by the 1000 points.

In Model 3, which contains only the original TM bands, band 3 was found to explain the major variation that distinguishes between high and low mortality points. The combined effect of bands 1, 4, and 6 contributed only (4%) to the model as compared to the dominant role of band 3 (49.4%). In the Model 4 grouping of TM derived indices and the TC dimensions, NDVI was identified as contributing most of the discrimination capability. With a canonical correlation of 0.493, the discriminating capability of NDVI could be slightly improved by the contribution of the NBRI, TC greenness and TC wetness (0.05). As NDVI is highly related to green above ground biomass, this result indicates that degree of overall green above ground biomass is generally a good indicator of the observed patterns future canopy mortality. NDVI is also a ratio-based index as compared to the linearly transformed TC greenness, and therefore compensates for changing illumination and slope conditions (Lillesand and Kiefer 1994).

Model 4 also specifies that band 6 and NBRI, which were earlier identified as having narrow ranges of values, showed little discriminatory potential in this model. Nevertheless, the examination of the percentage correctly classified statistics indicates similar discriminatory capability of either the original multi-band Model 3 or the derived bands of Model 4. However, by taking into account the integral properties of NDVI and its significance to several vegetation variables (amount, type and seasonality), this ratio based on TM bands 3 and 4 can reveal much of the pattern of future canopy mortality.

Conclusion

Data values for high and low canopy mortality points were significantly different for all the pre-fire data sets, while NDVI and TC greenness values provided the highest magnitude of direct differentiation between high and low mortality points. Discriminant analysis revealed that NDVI values were the paramount spectral value corresponding to degree of future canopy mortality. As NDVI is highly related to the amount of green aboveground biomass, these results indicated that high levels of such biomass were a good indicator of the future patterns of canopy mortality of the Cerro Grande. Discriminant analysis also indicated that the pre-fire spectral response patterns predicted far more of the observed canopy mortality than the terrain patterns. Spectral response patterns alone rendered 86.7% accuracy in the prediction of canopy mortality while the addition of terrain data improved accuracy to 90.0%.

The use of discriminant analysis in this case has provided valuable information on the correlation of individual spectral bands and derived data sets with the effects of the

Cerro Grande fire. However, these relationships and the methodology employed must be subjected to evaluation in other ecological areas. In addition, the set of statistical and field techniques presented in this paper are limited to recognizing the best combination of discriminating variables, and the full explication of the complex relationships between pre-fire conditions and future fire behavior is beyond the capability of such analytical techniques.

While in the field, many areas of the Cerro Grande fire could not be clearly placed in either the high or low mortality category, as various combinations of burned and unburned canopy could be observed at many different scales. The polygons used here were selected to represent the two clearly definable extremes of this continuum of fire effect, to facilitate clear evaluation of statistical separability. As the results presented here indicate a remarkably high level of correspondence between pre-fire characteristics and areas of high canopy mortality, a more advanced examination would evaluate the full range of the fire effects continuum. Nevertheless, these results indicate that it may be possible to extract considerable spatial understanding about future fires directly from widely available multispectral and terrain data sets. More efforts to extend our knowledge of the direct relationships between pre-fire conditions and future fire effects will help in the development of new techniques for fire hazard mapping.

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Figure Captions

Figure 1. Pre-fire TM scene acquired on April 14 2000, with the May 2000 Cerro Grande fire perimeter. Red polygons are surveyed field areas indicating total canopy mortally and blue polygons are areas lightly affected by fire. On the right are histograms showing the distribution patterns of band 3 and NDVI for points in high (left) and low (right) mortality categories.

Table Captions

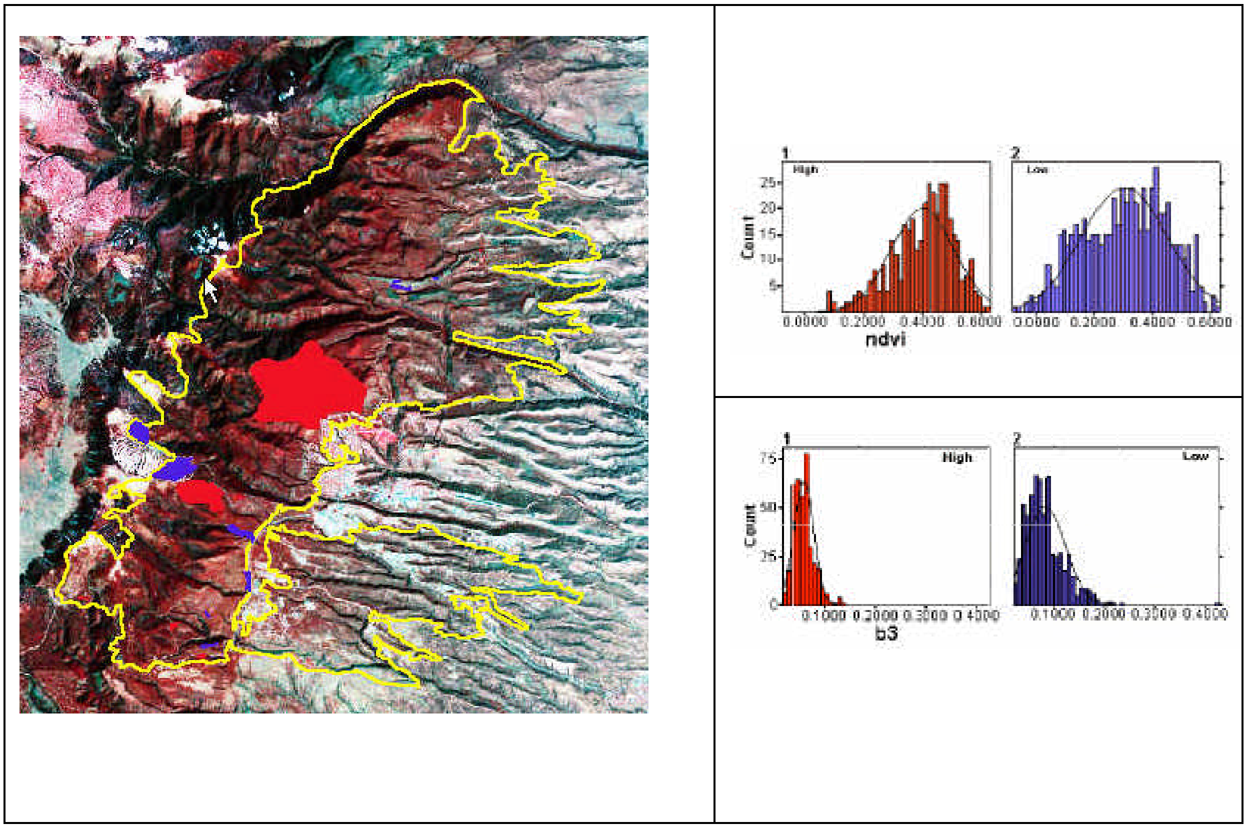
Table 1. Statistical summary (mean, standard deviation, comparison of mean) of the values for pre-fire TM data, TM derived indices, and DEM derived elevation, slope aspect at the 1000 points placed in the high and low canopy mortality polygons surveyed in the area burnt by the Cerro Grande fire.

Table 2. Correlation coefficients of pre-fire TM derived and DEM derived data at all the 1000 points placed in both the high and low canopy mortality polygons surveyed in the area burnt by the Cerro Grande fire.

Table 3. Standardized Canonical Coefficients and Total Structure Coefficients (*stepwise selection of variables).*

Table 4. Standardized Canonical Coefficients and Total Structure Coefficients (*stepwise selection of spectral variables*).

Figure 1



1
High
Count
0.0000 0.2000 0.4000 0.6000
ndvi
2
Low
0.0000 0.2000 0.4000 0.6000
1
High
Count
0.1000 0.2000 0.3000 0.4000
b3
2
Low
0.1000 0.2000 0.3000 0.4000

Table

	High Canopy Mortality n = 837	**Low Canopy Mortality** n = 163	**Pr(t)**	**Total (Burnt)** n = 1000
TM 1	0.0383 (± 0.0097)	0.0662 (± 0.0418)	0.0000	0.0428 (± 0.0216)
TM 2	0.0492 (± 0.0127)	0.0827 (± 0.0476)	0.0000	0.0547 (± 0.0256)
TM 3	0.0591 (± 0.0198)	0.1048 (± 0.0586)	0.0000	0.0665 (± 0.0342)
TM 4	0.1419 (± 0.0171)	0.1615 (± 0.0311)	0.0000	0.1451 (± 0.0213)
TM 5	0.1415 (± 0.0476)	0.1692 (± 0.0781)	0.8674	0.1460 (± 0.0546)
TM 6 (C^0)	52.2 (± 3.1)	50.5 (± 7.0)	0.0000	51.9 (± 4.1)
TM 7	0.0863 (± 0.0351)	0.1131 (± 0.0584)	0.0288	0.0907 (± 0.0411)
Tasseled Cap (Brightness)	0.2301 (± 0.0583)	0.3054 (± 0.0925)	0.0000	0.2424 (± 0.0708)
Tasseled Cap (Greenness)	0.0220 (± 0.0255)	-0.0031 (± 0.0459)	0.0002	-0.0179 (± 0.0312)
Tasseled Cap (Wetness)	-0.0210 (± 0.0145)	-0.0067 (± 0.0983)	0.0000	-0.0165 (± 0.0430)
NBRI	-0.2746 (± 0.1429)	-0.2077 (± 0.2561)	0.0000	-0.2637 (± 0.1683)
NDVI	0.4292 (± 0.0984)	0.2572 (± 0.1658)	0.0000	0.4011 (± 0.1288)
Elevation (m)	2499.4.0 (± 149.1)	2722.3 (± 247.1)	0.0000	2535.6 (± 187.9)
Slope (%)	106.0 (± 39.1)	95.1 (± 36.9)	0.0037	104.2 (± 38.9)
Aspect	132.4 (± 78.5)	105.3 (± 68.2)	0.0000	128.0 (± 77.5)

Table 2

	TM 2	TM 3	TM 4	TM 5	TM 6	TM 7	Bright	Green	Wet	NBRI	NDVI
TM 1	0.98	0.95	0.70	0.28	-0.06	0.33	0.50	-0.25	0.43	0.10	-0.63
TM 2	-	0.97	0.76	0.38	0.01	0.41	0.56	-0.31	0.36	0.17	-0.67
TM 3	-	-	0.77	0.52	0.12	0.55	0.66	-0.42	0.25	0.29	-0.73
TM 4	-	-	-	0.46	0.21	0.43	0.60	-0.18	0.13	0.18	-0.46
TM 5	-	-	-	-	0.69	0.99	0.78	-0.78	-0.51	0.79	-0.61
TM 6	-	--	-	-	-	0.65	0.52	-0.55	-0.58	0.63	-0.28
TM 7	-	-	-	-	-	-	0.77	-0.79	-0.47	0.79	-0.63
Bright	-	-	-	-	-	-	-	-0.83	-0.21	0.76	-0.85
Green	-	-	-	-	-	-	-	-	0.51	-0.94	0.76
Wet	-	-	-	-	-	-	-	-	-	-0.68	-0.07
NBRI	-	-	-	-	-	-	-	-	-	-	-0.63

Table 3

	F value	Model 1: Spectral Data *Canonical correlation = 0.59* *% Correctly classified = 86.7*		Model 2: Spectral + Terrain *Canonical correlation = 0.65* *% Correctly classified = 90.0*	
		Std. Canonical Coefficient	**Total Structure Coefficient**	**Std. Canonical Coefficient**	**Total Structure Coefficient**
TM 1	292.9	1.13	-0.75	-0.70	0.63
TM 2	303.5	x	x	x	x
TM 3	322.5	-1.56	-0.78	1.11	0.66
TM 4	129.4	x	x	x	x
TM 5	36.3	2.22	-0.26	-1.49	0.22
TM 6	23.7	0.38	0.21	0.40	-0.18
TM 7	61.7	-1.74	-0.34	1.02	0.29
Brightness	182.2	-0.41	-0.59	x	x
Greenness	96.7	x	x	x	x
Wetness	59.7	x	x	x	x
NBRI	22.0	x	x	x	x
NDVI	320.8	0.37	0.78	-0.48	-0.66
Elevation	237.7	-	-	0.75	0.57
Slope	10.6	-	-	-0.30	-0.12
Aspect	17.0	-	-	-0.21	-0.15

Note: x = excluded variable

Table 4

	Model 3: Spectral Data (multi-band) *Canonical correlation = 0.54* *% Correctly classified = 85.7*		Model 4: Spectral +Derived Data *Canonical correlation = 0.54* *% Correctly classified = 84.7*	
	Std. Canonical Coefficient	**Total Structure Coefficient**	**Std. Canonical Coefficient**	**Total Structure Coefficient**
B1	-0.97	0.85	-	-
B2	X	x	-	-
B3	2.04	0.90	-	-
B4	-0.21	0.57	-	-
B5	X	x	-	-
B6	-0.50	-0.24	-	-
B7	X	x	-	-
Brightness	-	-	x	X
Greenness	-	-	0.67	0.48
Wetness	-	-	0.38	-0.38
NBRI	-	-	1.49	-0.23
NDVI	-	-	1.33	0.88

Note: x = excluded variable