MODELING FIRE HAZARDS WITH REMOTELY SENSED DATA FROM RECENT FIRES

Michael J. Medler
Department of Geography, Rutgers University,
54 Joyce Kilmer Avenue,
Piscataway, NJ, 08854-8045
Phone: (732) 445-2707
E-mail: mmedler@rci.rutger.edu

ABSTRACT

Many factors effect the behavior of forest fires, resulting in complex spatial patterns after each fire. To manage growing fuel loads and associated fire hazards, as well as prioritize prescription efforts, it is essential to improve our understanding of the spatial patterns of potential fire effects. The study presented here models forest fire hazards directly from remotely sensed spectral response and digital terrain models, without first mapping each specific determinant of fire behavior. Remotely sensed satellite data are first used to map the internal burn patterns of historic fires. These maps are used in conjunction with fire records to identify polygons that underwent complete canopy mortality while burning at the height of afternoon fire conditions. These polygons are then used to extract spectral and terrain patterns from pre-fire satellite data and terrain models. Once extracted, these signatures are used as the basis of a maximum likelihood classification of the entire southwestern mountain range surrounding the historic fire. This classification identifies pixels with spectral response and terrain similar to those that burned in known ways during the historic fire. The effectiveness of the model is tested against the historic fire, and the spectral and terrain patterns are also used to classify another nearby mountain range to determine whether results from one area can be applied to another region. Preliminary results are promising.

INTRODUCTION

This paper presents a technique for quickly mapping fire hazards directly from remotely sensed spectral response and digital terrain models, without first mapping a set of specific determinants of fire behavior. Many traditional techniques of fire modeling and fire hazard mapping, instead, strive to integrate accurate spatial representation of the determinants of fire behavior, with mathematical models of fire behavior (Rothermel 1972, 1983, Andrews 1986, Finney 1995). While these techniques have great promise, they require very accurate high-resolution spatial data. Even if remote sensing is used to map variables such as canopy cover or fuel models, much time and energy must be devoted to gathering the field data necessary for accurate classification of the remotely sensed data. Once accurate spatial data is assembled for an area it must be integrated with mathematical models of fire behavior, ignition points and climatic conditions.

Such systems can offer valuable tactical and strategic tools for evaluating potential fire hazards. The spatial patterns of forest fires, however, are influenced by a host of complex factors such as soil, wind, terrain, and vegetation. Accurate quantification of all these relevant determinants is prohibitively difficult. Microclimate and winds, for example, change quickly and chaotically even while fires burn. Also, such deterministic models of dynamic systems can be extremely sensitive to initial conditions and subject to possible error propagation.

To address some of the complexity inherent in fires, the system presented here maps and models fire through pattern analysis of the synthetic combinations of determinants that is represented in spectral response and terrain models. These techniques use remote sensing and field data to first map the complex internal structure of historic fires, then those same patterns are used to extrapolate and model a potential pattern of canopy mortality in the larger region surrounding the historic fires. This method is intended to maximize efficiency and accuracy through modeling only potential canopy mortality. Such a system is not intended to be a true predictive model of expected fire effects. Rather, this system indicates which areas share spectral response and topographic characteristics with areas that experienced complete canopy mortality under known conditions in a previous fire. Such spatial information could be quickly produced and applied to a host of planning and public information needs. As the products are based on the patterns of recent fires, it is also intuitively easy for mangers and the public to understand that the maps are spatial extrapolations of a fire they may have recently experienced themselves.

STUDY AREA

The study areas featured here are the San Mateo Mountains in New Mexico and the Chiricahua Mountains of Arizona. These rugged mountains are typical Southwestern "sky islands." Specifically, the areas of higher elevation have cooler temperatures and higher precipitation than the surroundings. Mixed conifer communities occupy the highest elevations. *Pinus ponderosa* (Ponderosa pine) dominates the middle range. The lower elevations contain *Pinus edulis* (pinion) and *Juniperus* (juniper) communities, surrounded by semi-arid grass lands (Alexander et al. 1987).

Each range was the site of a major fire in 1994. The Coffee Pot Fire burned over 20,000 acres in the San Mateos, while the Rattle Snake Fire burned a similar area of the Chiricahuas. Both fires burned with unexpected severity. Of particular concern to the Forest Service was the large size of some patches of complete canopy replacement and associated soil deterioration (Macdonald 1996). For future fire planning in both ranges the Forest Service would like to understand potential spatial patterns of other future fires. The fires studied here can offer models of what might be expected from similar future fires that might occur in similar meteorological conditions.

TECHNIQUES

Field Data

In the summer of 1996 an automated terrain stratification procedure was used to place 8 transects involving nearly 500 individual circular plots (Medler and Yool Forthcoming). Plots were placed along these transect lines at constant intervals. To link the DEM-generated terrain models and the TM data with ground observations, a global positioning system (GPS) was used to obtain coordinates of ground samples, permitting accurate correlation of observed vegetation mortality with the geocoded TM and terrain data sets.

Each transect point defined the center of a circular plot with a 20 meter diameter and simultaneously, the reference point for placement of four neighboring plots placed 30 meters out in the four cardinal directions. Fire and vegetation data were recorded at each of these plots. The resulting five-plot sample design compensated for GPS errors and minor misregistration between the ground reference data and the 30 meter raster data sets (Jensen 1996).

Satellite Data

Many effects of wildfire, such as vegetation mortality and soil discoloration, are detectable with satellite remote sensing (Jakubauskas 1990, White et al. 1996, Kaufman et al. 1998). The spatial burn patterns of both the Coffee Pot and Rattle Snake fires are clearly visible in satellite data collected shortly after the fires. (Figure 1)

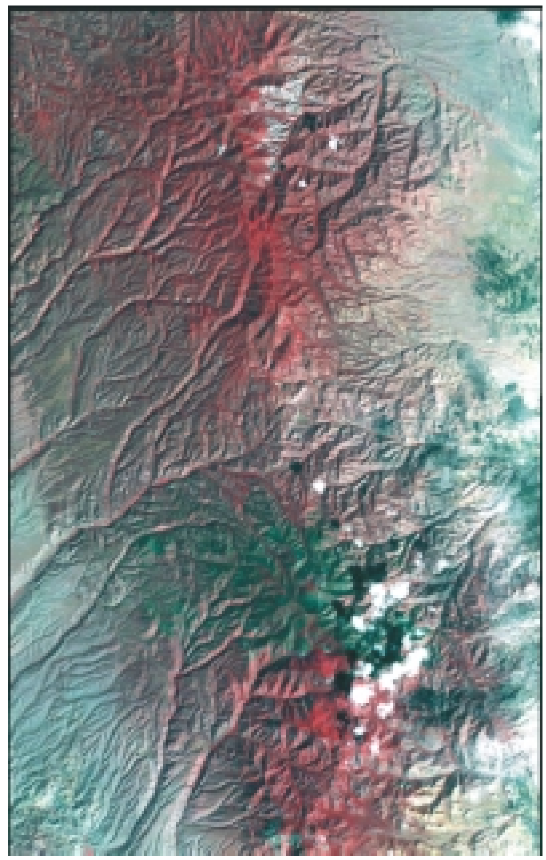

Figure 1. Landsat Thematic Mapper satellite image of the Coffee Pot Fire. False color infrared image shows vegetation in redder tones. The effects of the fire can be seen in the lower section of the image. Clouds can also be seen obscuring some of the areas.

TM data was acquired for the regions of both fires. Images were selected from before and after each fire to determine changes associated with the fires. The images were also selected on or near annual anniversary dates to minimize seasonal differences. Both sets of pre-fire imagery were geo-referenced to the USGS 30 meter DEM mosaic, (used latter for the terrain modeling component of this project), with less than 15 meter (0.5 pixels) root-mean-square (RMS) error (Lillesand and Kiefer 1994).

The post-fire images were co-registered to the pre-fire image using on-screen control points. The RMS error for the post-fire image was also less than 15 meters. All images were resampled using a nearest neighbor algorithm (Lillesand and Kiefer 1994). Each image was also corrected for atmospheric scattering. Because of the extensive cloud cover in the post-fire images, image regression was undesirable, and lack of open water limited the utility of dark body subtraction techniques (Lillesand and Kiefer 1994, Jensen 1996). Therefore, a histogram-offset technique was used to adjust all bands through linear subtraction to bring the minimum value of each band to zero (Campbell 1996, Jensen 1996).

Tasseled Cap Transformation

To reduce atmospheric effects, compress the TM data, and relate TM spectra to fire phenomena, both pre-fire and post-fire images were subjected to a Tasseled Cap (TC) linear transformation (Kauth and Thomas 1976, Crist and Cicone 1984 a, b, Collins and Woodcock 1996, Patterson and Yool 1998). This transformation converts the six highly correlated spectral bands of TM data to six nearly orthogonal bands of data. Much of the variance of the data is captured in the first three TC bands, while noise and atmospheric effects are concentrated in the last three bands (Kauth and Thomas 1976, Crist and Cicone 1984 a, b). Unlike many other linear transformations used in remote sensing, the coefficients for TC are predetermined, and not derived from the data sets themselves. The first three derived TC bands have been related to brightness, greenness, and wetness respectively (Figure 2)

Terrain Model

Two mosaics of 30 meter resolution United States Geologic Survey (USGS) DEMs were assembled for the respective study areas. Standard ERDAS Imagine™ protocols were applied to the mosaics to produce elevation, slope, and aspect images. Slope and aspect values were computed for each pixel, from the information in the surrounding three-by-three pixel window. These protocols produced three spatially co-registered terrain data sets.

Define Known Polygons

Pre-fire and post-fire TC images were subjected to image subtraction to create three individual images representing fire associated change in brightness greenness and wetness respectively. Values from the field data were used in conjunction with these change images, to identify contiguous areas of complete canopy mortality as well as areas that underwent no significant change. Fire records from the Coffee Pot Fire were also examined and personal interviews were conducted with fire managers present during the fire to assure polygons were placed in areas that received minimal fire suppression efforts (Macdonald 1996). In particular, it was necessary to exclude areas of the fire purposefully "back-burned," with fire backing down-hill at night. Once identified, areas that best represent each of these two classes were digitized on screen. (Figure 3)

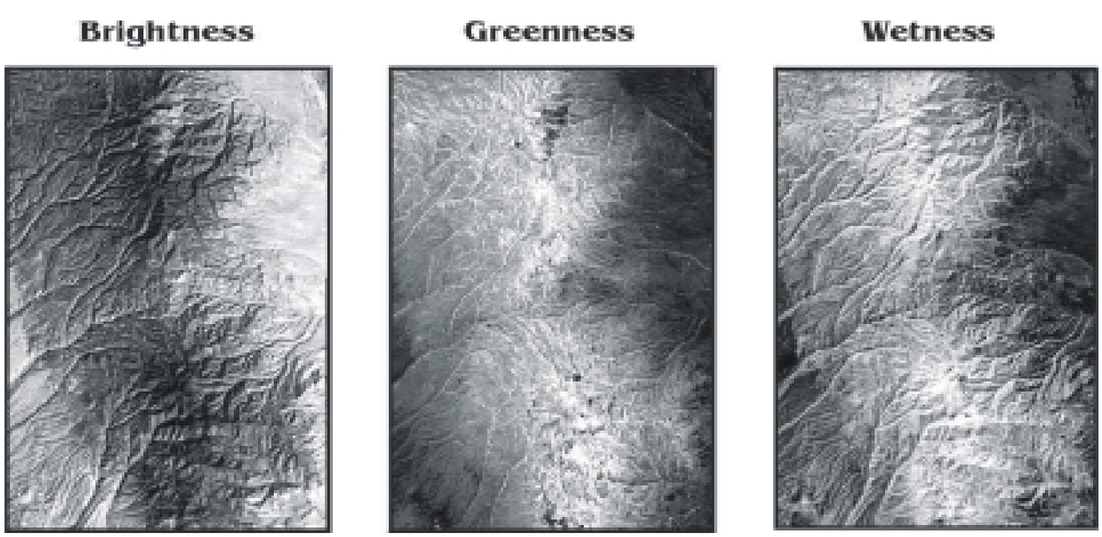

Figure 2. Pre-fire TM data is transferred into Tasseled Cap Brightness, Greenness, and Wetness images.

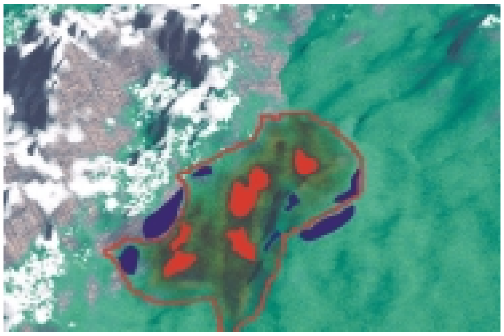

Figure 3. Polygons are defined from burned and unburned areas in order to compute training statistics.

Generate Training Statistics

Once the polygons are digitized for each of the two fire effects classes, training statistics are extracted for each of the three TC images, as well as for each of the three terrain model images. For each of the two fire severity classes, values of the pixels in the training polygons are recorded for each of six images. These values were used to calculate the maximum, minimum, mean and standard deviation of each severity class for each of the six images. (Figure 4)

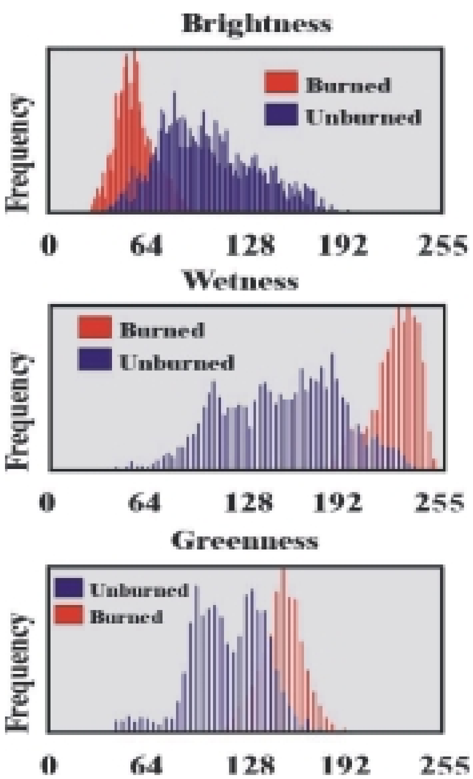

Figure 4. Extracted polygons are used to create training statistics for image wide classification. These graphs show the separability of burned and unburned pixels in the training polygons. Similar separability is seen in the data sets for elevation, slope, and aspect.

Classify San Mateos

Once the set of training statistics are developed for each fire effects class, these statistics are used as the basis of a maximum likelihood classification of the entire San Mateo range. In Figure 5 we can examine the results of this classification. For comparison, Figure 5 also includes a change detection image to illustrate the actual patterns of complete canopy mortality associated with the Coffee Pot Fire. As with any model designed to predict possible future conditions, these images are difficult to test. As the Coffee Pot Fire was the source of the burn patterns as well as the genesis of the field data used for these classifications, using the patterns of this same fire to test the effectiveness of the classification represents circular logic. Other fires would better test the images. Such fires may not, however, burn the entire range at the height of fire conditions any more than did the Coffee Pot Fire. The hazard image in Figure 5, therefore, is not intended to represent actual expected burn patterns. Rather, this image is intended to represent the degree to which each pixel shares reflective and topographical characteristics with areas of the Coffee Pot Fire that burned in known ways under extreme fire conditions.

Classify Chiricahuas

Without further fire in the San Mateos, it is difficult to assess the accuracy of the hazard model presented above. The technique described above can be tested, however, by examining whether it predicts the spatial patterns of similar fires in similar mountain ranges. The training statistics developed for the Coffee Pot Fire were therefore used as the basis for a maximum likelihood classification of the Chiricahuas. Such a classification identifies pixels in the Chiricahuas that share spectral and terrain characteristics with pixels that burned in known ways in the San Mateos. In Figure 6, this classification can be visually compared to the actual burn patterns of the Rattle Snake Fire.

It is interesting to note that at first glance this model does a better job of capturing the rough spatial pattern of the Rattle Snake Fire than it does the spatial patterns of the Coffee Pot Fire, upon which the training data is based. However, the Rattle Snake Fire burned a much larger proportion of the likely firescape than did the Coffee Pot Fire. The San Mateo mountains are more dissected with areas that impede fire contagion, and suppression efforts at the Coffee Pot Fire were able

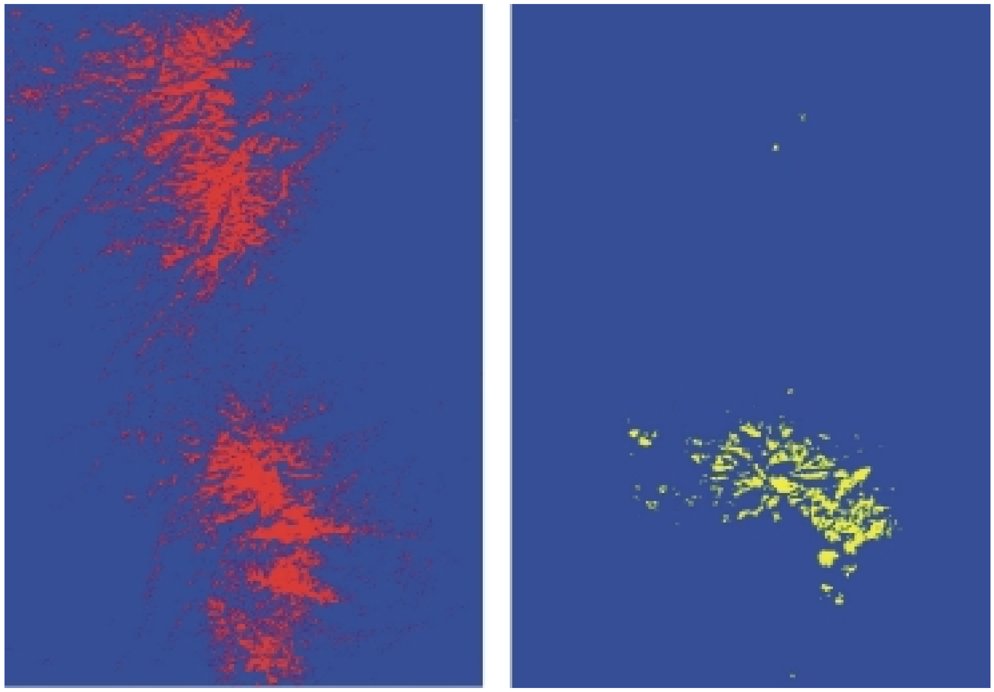

Figure 5. Training statistics are used to classify the entire mountain range. Red areas on the left indicate pixels with spectral response and terrain patterns that are similar to the areas that experienced complete canopy mortality in the Coffee Pot Fire. The yellow areas on the right indicate the actual burn patterns of the Coffee Pot Fire.

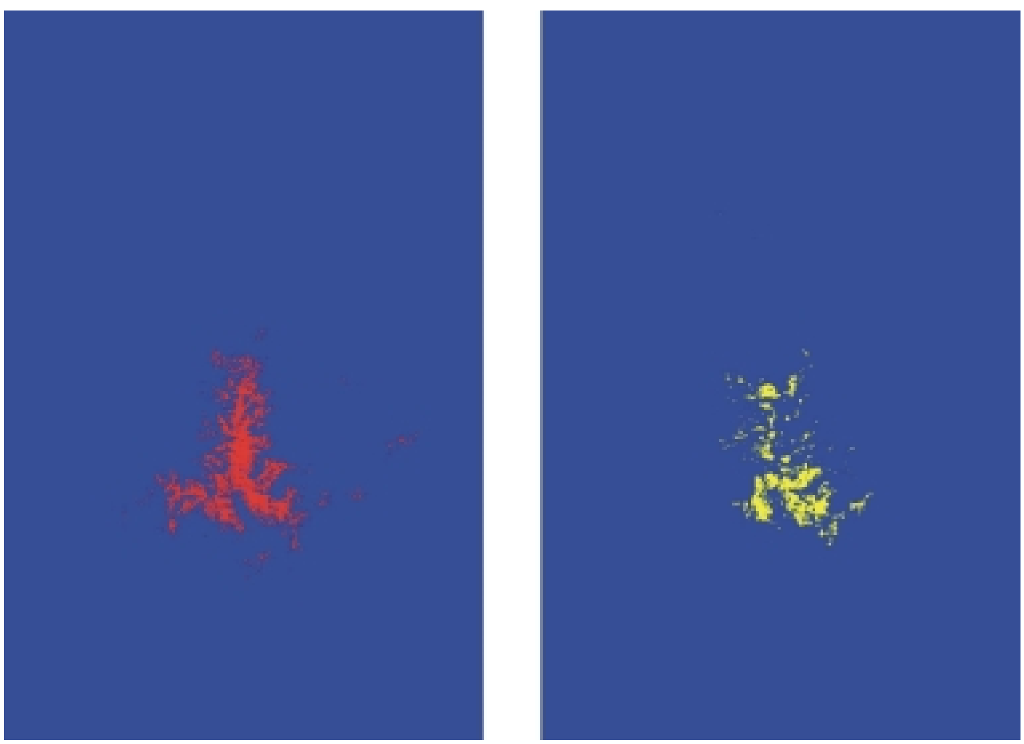

Figure 6. The training statistics from the San Mateos are used to classify the Chiricahuas. Red areas on the left indicate pixels in the Chiricahuas that are similar to the areas of complete canopy mortality in the Coffee Pot Fire. The yellow patterns on the right indicate the actual burn patterns of the 1994 Rattlesnake Fire that burned in meteorological conditions similar to those found at the Coffee Pot Fire.

to keep the fire from reaching into other flammable areas. Another means of analyzing the effectiveness of the hazard model generated for the Chiricahuas, is a standard error matrix. 100 randomly placed points were selected in the area of the Rattle Snake Fire. The results are shown in Table 1.

Historic Fire Map

		Burned	Unburned
MODEL	Burned	**50**	**25**
	Unburned	**0**	**25**

Table 1.

The results in Table 1 indicate that the model accurately predicted all 50 points that underwent complete canopy mortality during the Rattle Snake Fire. 25 points that were unburned by the actual fire were modeled however as burned areas. Another 25 points that did not undergo complete canopy mortality were modeled correctly. It is significant to note that the model was created by defining training areas from a set of pixels that represent areas burned by the Coffee Pot Fire at the peak of afternoon burning conditions, under minimal suppression efforts. Many of the areas within the perimeter of the Rattle Snake Fire would not fit these criteria, and so would be expected to undergo less sever fire behavior than this “worst case” model is intended to capture. Of more significance is that the model correctly identified the test pixels that did in fact undergo complete canopy mortality.

Fuzzy Classification

Traditional set theory requires that all individual units in a set either are, or are not, members of any given set. A pine tree, for example would either be, or not be, a member of the set of tall pine trees. The work presented here could also be based instead on Fuzzy Set Theory (Zadeh 1965, 1973). This alternative to traditional set theory allows individuals “fuzzy” or partial memberships in several categories.

A moderately tall pine tree, for example, may have only partial membership in the set of tall pine trees, or a pixel may be classified as only somewhat a member of the set of pixels likely to undergo complete canopy mortality.

A classification scheme based on fuzzy logic can overcome some of the long-standing problems associated with using remote sensing to classify continuous phenomena (Kosko and Isaka 1993, Jensen 1996). A traditional maximum likelihood classifier, for example, uses the statistical distribution of spectral response patterns of known areas to assign unknown pixels to the most likely classification. By contrast fuzzy classification determines each pixel’s relative membership in any number of classes, presumably avoiding the loss of relative class membership information (Robinove 1981, Richards and Kelly 1984, Campbell 1996, Jensen 1996). Fuzzy classification techniques may also be better suited to relating natural phenomena in a way similar to the imprecise nature of most human thinking (ACM. 1984, Jensen 1996).

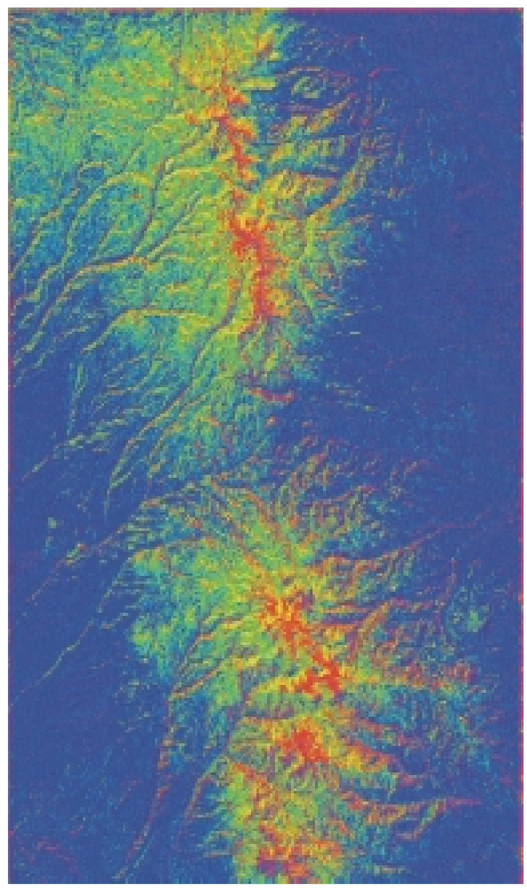

Figure 7. Fuzzy classification techniques and color shading are used to display the degree to which each pixel shares spectral and terrain conditions with areas that underwent known degrees of canopy mortality. The image above therefore represents a fuzzy range-wide extrapolation of the effects of the Coffee Pot Fire.

Fuzzy classification has been applied effectively to the estimation of forest parameters such as forest type and vegetation (Foody 1992, Maselli et al. 1995). It has also been applied effectively to mapping historic wildfire (Medler and Yool in review). Like many other spatial phenomena, wildfire occurs with a continuum of characteristics (Turner et al. 1994, Pyne et al. 1996), and because factors determining burn patterns are fuzzy and continuous in nature, the spatial patterns of these complex phenomena may be represented better with fuzzy classification.

The techniques presented above were also used to produce fuzzy classifications of the fire hazards of the entire San Mateo range (Medler in Review). In the exercise presented here, each set of training data is used to define fuzzy membership functions that assign each pixel full or partial membership in the fire hazard classes.

Like the other images shown in Figures 5 and 6, Figure 7 indicates which pixels share spectral and terrain characteristics with the pixels that burned in known ways during the Coffee Pot Fire. Unlike the previous images, this fuzzy classification uses color shade to actually indicate the relative degree to which each pixel shares those characteristics. Such a display can also be valuable way to help elucidate the relative certainty of each pixel's classification. The redder pixels are the ones that are closest to the mean values for the pixels that underwent complete canopy mortality in the Coffee Pot Fire, and therefore are the pixel's classified with the most certainty.

Visualization

Figure 8 is a visualization of the fuzzy hazard model draped over the DEM of the mountain range. Such a display offers a more intuitive understanding of the spatial distribution of the relative hazard information presented. This three-dimensional model can also be animated to allow a more complex or even interactive exploration of the location of contiguous patches of likely canopy replacement in relation to the terrain and familiar physical features. Such imagery or animations can also be placed directly on web-sites and thereby made available for land managers or the public.

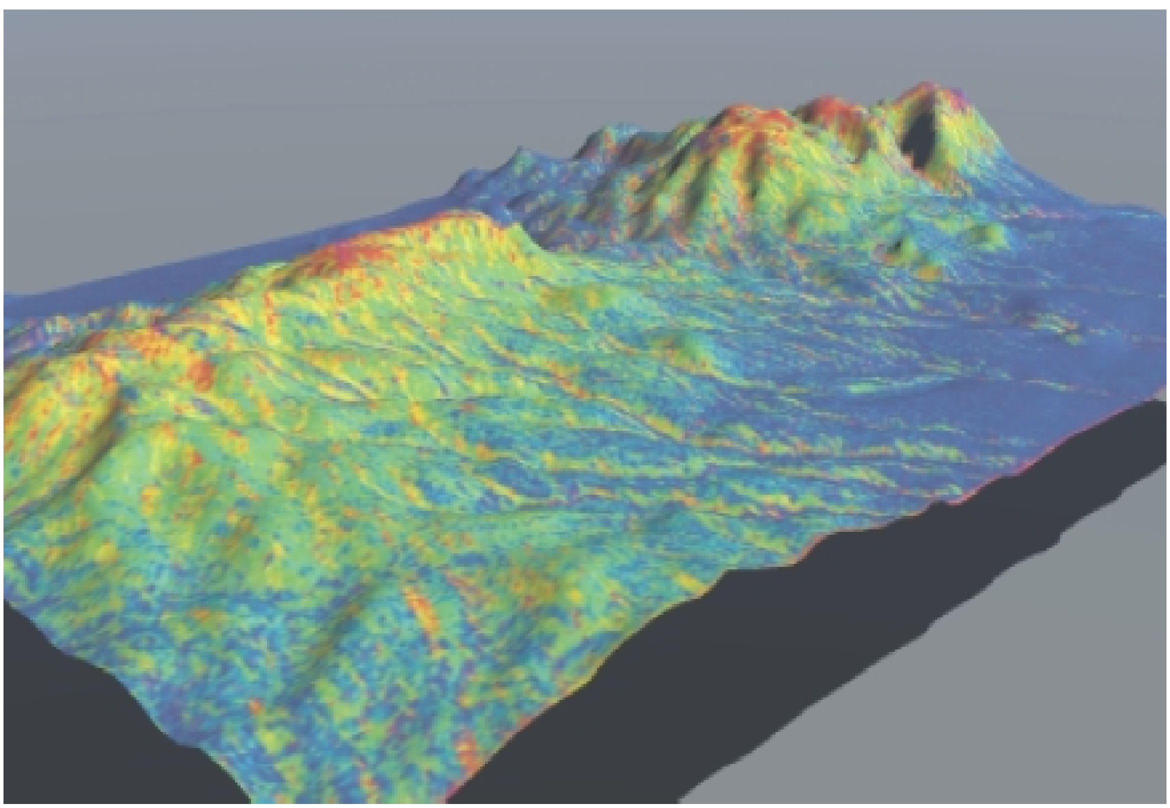

Figure 8. Imagery such as shown in Figure 7 can be draped over a digital elevation model to create intuitively interpretable displays. The figure above can also be animated or even displayed as an animated fly-though over the Internet. Such tools could have great potential for public education, as they represent extrapolations of fires many people still remember in their area.

Such tools may be particularly useful for public outreach efforts aimed at educating the public about urban-wildland interface fire hazard issues. Because the model is based on the patterns of a recent historic fire, many people will remember that recent fire and can easily imagine the ramifications of a similar fire burning through other similar areas, or perhaps their own neighborhood.

CONCLUSION

The techniques presented here are not offered as a replacement for current fire modeling or fire hazard mapping efforts. Rather, this set of techniques offers a quick and efficient way to display a model of fire hazards that is both intuitive and tied to events that have already captured the public's attention. Rather than displaying a predictive surface that maps how the next fire will burn, these techniques promote an understanding of the spatial distribution of synthetic combinations of the complex variables that determine multispectral imagery, and the complex biophysical phenomena that are captured by terrain models. It is hypothesized and left for further investigation, that beside the pervasive effects of meteorology, the spatial patterns of fire are in fact determined by a similar set of complex variables to those that determine multispectral response, or are captured in terrain models.

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