Appears in *Imaging Notes* Sept/Oct 2001.

VISUAL LEARNING SYSTEMS

CLASSIFYING & MAPPING WILDFIRE SEVERITY

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A forest fire roars in the valley just over a ridge from your home. Critical response teams are quickly positioning fire crews to attack the fire and deter it from your structure and other neighborhoods that are nestled among the trees. You hope those in charge know how to deploy the fire crews optimally to increase your chances of keeping your home and life-long belongings. The skill is there to make these decisions, however, their decisions are critically based on a database of fuel load information derived from previous fires and the intensity at which they burned. You now hope they have this database of knowledge.

Fire is an important and inevitable ecological process operating in many landscapes around the world. With increasing human population, the importance of mapping wildfires and their severity grows each year. In the short-term, detailed and accurate information about the geographic extent of wildfire is critical, not just for deploying resources to protect people and their property, but also for planning and prioritizing rehabilitation and restoration efforts once the fires are extinguished. In the longer term, knowing where and how past fires have burned should improve our ability to understand and respond more effectively to future fires.

Prior to the relatively recent availability of satellite imagery, as well as powerful computer hardware and software to process these data, wildfires were traditionally mapped using labor intensive manual methods, or not at all. In the western US, this legacy has left the land management agencies with relatively little detailed information about the extent and severity of wildfires that have occurred on public lands prior to the 1990s.

To address this need, an investigation was conducted on the utility of three state-of-the-art image classification methods for mapping the severity of wildfires. This study was done for the USDA Forest Service Northern Regional Office in response to the aftermath of the wildfires that burned millions of acres in the western US during the summer of 2000. All three methods involved a change-detection analysis between a pre- and post-fire Landsat Thematic Mapper (TM) imagery. One method was based on temporal image differencing (Key and Bensen MS, Coppin, White et al.); the second on principal component analysis (Fung and LeDrew 1988), and the third using the hierarchical machine learning technology of the **Feature Analyst™** (www.vls-inc.com) from Visual Learning Systems, Inc. We selected TM imagery for its multispectral characteristics and 30 m resolution; this imagery was well suited for detecting change in forest canopy conditions across large geographic areas. The general methodological approach should also work well with finer resolution, multi-spectral imagery, like Carterra 25 m multi-spectral images, especially for smaller wildfires that occur in more complex landscapes dominated by non-forest vegetation.

Shown here are the key findings from analyses of the Fort Howes wildfire complex that burned during the last week in July, 2000, south of Ashland, Montana USA. Because the areas burned actually spanned portions of two Landsat

TM scenes, Path 35/Row 28 and Path 35/Row 29, two TM images were required for each date. For the pre-fire images, we settled on a July 5, 2000 overpass by the Landsat 5 satellite; whereas the two post-fire images were collected by the Landsat 7 satellite on August 27, 2000.

GENERAL METHODS

All imagery was ortho-rectified and corrected for atmospheric scattering. Two ratios were calculated for each image date -- a Normalized Difference Vegetation Index (NDVI) based on the ratio of (TM4-TM3)/(TM4+TM3), and a Normalized Burn Ratio (NBR) based on (TM4-TM7)/(TM4+TM7) (Key and Bensen, MS). Ground-reference data was obtained by manual interpretation of aerial photographs (1:15840 scale) that were taken on August 17, 2000. To minimize subjectivity in the collection of these data, one person carried out all the photo-interpretation after being shown examples of each class type on the photos by Forest Service ecologists. A minimum of 10 points for each class was set aside and used only for accuracy assessment; the remaining points were used as training points.

BURN/SEVERITY CLASSES

Four classes of burned vegetation were mapped, along with three unburned classes. Fire severity was limited to forest vegetation as follows:

Lethal Tree -- The crowns of most if not all trees in the pixel or patch were burned, such that tree mortality was presumed to be high.
Mixed Tree -- Fire burned extensively in the understory, but the crowns of at least the larger trees in the pixel or patch were not burned.
Shrub -- The predominant vegetation in the pixel or patch was comprised of shrubs that were extensively burned by the fire.
Grass -- The predominant vegetation in the pixel or patch was comprised of grasses and forbs that were extensively or completely burned by the fire.

To these we added four unburned classes based primarily on lifeform: Forest, Shrub, Grass, and Other.

CLASSIFICATION METHODS

The **Feature Analyst** turned out to be a powerful general-purpose feature-extraction tool, usable by any novice within the popular ArCView GIS software platform. The hierarchical machine learning method from the **Feature Analyst** involved the application of inductive learning algorithms through a series of iterative classifications of a 12 band multi-temporal image -- eight from the pre-fire image (the seven original TM bands, plus NDVI ratio), and four from the post-fire image (bands 4, 6, and 7, plus NBR). Setting up the problem and spawning learning is done using simple menu options found within the Feature Analyst. The learning option of choice was the Feature Analyst's Learning Approach 1.

The image differencing method used thresholding to discriminate burned from unburned pixels that were associated with grass, shrub, and tree lifeforms; pixels associated with burned forest vegetation were subjected to a second threshold to classify fire severity. Frequency histograms of the difference between post- and pre-fire NBR images were plotted for each lifeform, and separate burn thresholds were determined by visual inspection for each lifeform. Classification of fire severity for forest pixels was based on linear interpolation between the burn/unburn threshold (0 % canopy change) and a second threshold, again manually set, that was thought to represent 100% canopy loss. Once these thresholds were set, along with the cut-offs for each severity class, the process of assigning each pixel to one of the seven burn classes was run as a model in ERDAS Imagine.

In the last method investigated, the principal components from a 14-band image (7 bands each for two image dates) were converted to image files, and visually inspected in relation to the fire perimeter and the false-color composites of the two original image dates. It turned out that low values of the second principal component (PC2) and high values of the fifth (PC5) matched the general fire perimeters quite well. From a scatterplot of these values, a line was drawn manually to separate burned from unburned pixels. Then a first level index was derived by calculating, in spectral space, the distance to the line for each pixel. To this index was added 1) the difference between the pre- and post-fire brightness values for TM band 4, 2) PC5, and 3) the negative value of PC2. At this point, the index values were split into burned and unburned classes according to the lifeform (tree, shrub, grass). Burned tree pixels were further subdivided into two classes, lethal tree and mixed burn, by splitting the frequency histogram of index values.

RESULTS

Overall the **Feature Analyst** classified the image into thematically correct classes substantially better than either the PCA or image-differencing classifiers (80.6% versus 55.6% for the other two). The Feature Analyst was the only technique that distinguished between burn and non-burn 100% of the time; the other two were 89% correct. When classifying non-burn vegetation, the **Feature Analyst** classified 83% of the forest, 60% of the shrub, and 100% of the grass correctly; the other two had classification accuracies of only 70%, 25%, and 38% respectively.

The **Feature Analyst** also had clearly superior results within the burn perimeter. The most important classification for determining future fuel loads is to adequately distinguish between lethal and mixed-tree burns The **Feature Analyst** was 100% correct in determining these classes, while the other two techniques obtained an accuracy level of about 85%. The Feature Analyst was substantially better in predicting burned grass and shrub as well (67% and 84% respectively, versus 0% and 44%). Finally, in terms of usability, the **Feature Analyst** provided the easiest and most straight forward technique, while involving much less subjectivity from the user.

CONCLUSIONS

The advent of quality satellite imagery, high-performance computing, and powerful feature extraction software such as the **Feature Analyst**, should provide the Forest Service with the heretofore unattainable ability to quickly and accurately map the intensity of fires. This will create for future generations a legacy of detailed information about the extent and severity of wildfires that have occurred on public lands. In the future, when a fire is raging near your home, you can rest assured that not only are there capable people in charge of the critical response effort, they also have the requisite database of knowledge upon which to make their decisions.

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