HYPERSPECTRAL ANALYSIS OF MULTI-TEMPORAL LANDSAT TM DATA FOR MAPPING FUELS IN YOSEMITE NATIONAL PARK

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ABSTRACT

We used multi-temporal Landsat Thematic Mapper imagery for developing a technique for identifying fuel types based on seasonal changes in plant phenology. Six ortho-corrected and registered TM scenes representing approximately one-month intervals during the 1992 growing season are being examined using hyperspectral analysis techniques. With accurate fuels information in hand, fire managers should be able to make informed decisions about ongoing wildland fires and fuels treatments. These decisions will result in safer conditions for fire fighters and less resource damage.

Keywords: fuel mapping, satellite imagery, temporal analysis, hyperspectral analysis

INTRODUCTION

In recent years, wildland fires have become more intense, resulting in increased loss of life and resource damage. Critical to resolving this problem is better information on the amount and condition of fuels on the ground. Traditional approaches have been to analyze aircraft and Landsat MSS data collections. For example, single-scene TM images have been used in the past to classify fuels (van Wagtendonk 1999). Maps produced from that analysis have been used to predict the behavior of two large wildland fires that were being allowed to burn to meet resource objectives, plan for extensive prescribed fires set by managers, and to make tactical decisions on a wildland fire that was being actively suppressed. In each case, operations were enhanced by the availability of accurate information on fuels.

In order to enhance the single-scene map, we decided to try a new approach using multi-temporal TM data. Such an analysis would allow us to discriminate fuels based on both spectral and temporal characteristics. Using temporal sequences, changes in annual grasslands, for instance, can be traced as the grasses green up in the spring and cure during the summer. This fuel type can thus be distinguished from alpine meadows which cure at a different rate. Similarly, deciduous hardwood fuels which drop to the ground in the fall are differentiated from evergreen hardwoods which retain their leaves.

METHODS

Six ortho-corrected and registered TM scenes representing approximately one-month intervals from April through November during the 1992 growing season were examined using hyperspectral analysis. The first step was to get all six scenes to overlay as closely as possible. We found that “standard” terrain correction was not sufficient and ended up using custom orthorectification to 1:24,000 digital elevation models.

After the scenes were georectified, we applied a “vegetation-only” mask created from a maximum NDVI layer from all 6 scenes using a value of 0.09 to distinguish vegetated areas from barren areas.

Hyperspectral processing techniques were then applied to TM bands 2, 3, 4, 5, and 7 for a total of 30 bands. This process involves several steps beginning with looking at changes in spectral signatures in both space and time (RSI 1997). The spectral data are then reduced using a minimum noise fraction function which determines the inherent dimensionality of the image data and segregates the noise in the data. Spatial data reduction is then accomplished using the pixel purity index function which finds the most “spectrally pure” pixels that typically correspond to mixing end members. These functions, in conjunction with the n-dimensional visualizer, help to locate, identify, and cluster the purest pixels and the most extreme spectral responses in the data set. Finally, mixture tuned matched filtering is used to find the abundances of user defined end members.

RESULTS

Initially, we tried to perform the analysis on a dedicated machine for the entire data set encompassing Yosemite National Park and the surrounding environs. After two months of run time, we prudently decided to segment the area and make multiple runs. Three subsets were selected; El Portal on the west edge of the Park, Yosemite Valley, and Tuolumne Meadows on the east edge. We will illustrate the process with data from Yosemite Valley.

Data Browsing

Data browsing is a technique used to look at spatial and spectral changes in reflectance over time. For example, Figure 1 shows band 3 (the red band) for the May, 1992, scene of Yosemite Valley. The black areas are devoid of vegetation and were masked out by the NDVI screen. Different areas of the scene show different values for band 3 based on varying reflectances. Grassy vegetation, such as that in El Capitan Meadow indicated by the arrow, has a high reflectance value in comparison to surrounding conifer vegetation. Areas in the shadow of the sheer valley walls show up as darker grays, as do some north-facing conifer stands.

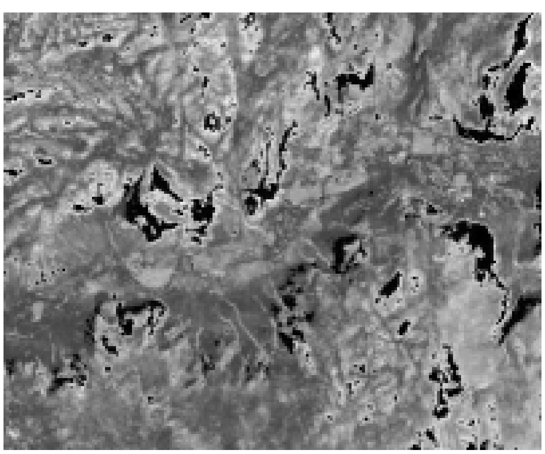

Figure 1. Calibrated reflectance, May 1992 Band 3 (red). The white arrow indicates the position of the grassy meadow pixel.

Shrubs in a large burned area in the lower left portion of the scene are a light shade of gray.

If we follow the grassy meadow pixel through the season, we can see how each spectral band varies with time. In Figure 2 the values for each band are displayed by month. For example, the near-infrared band (labeled as bands 4, 9, 14, 19, 24, and 29 in Figure 2) shows a slight increase between May and September and then decreases the remainder of the year. Similar spectral profiles of the other bands can elucidate differences between vegetation types and resulting fuels.

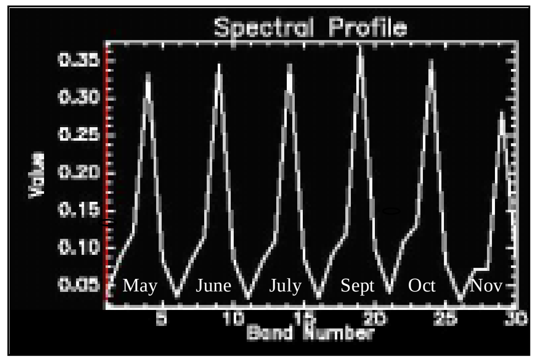

Figure 2. Spectral profile of raw data, grassy meadow pixel.

Data Reduction

The data reduction phase of the analysis strives to identify end members in the data set by separating noise from information and reducing the data set to its true dimensionality by applying the minimum noise transform and then determining spectrally pure (extreme) pixels using the pixel purity index function on the minimum noise fraction results. Figure 3 shows the spectral profile of the grassy meadow pixel resulting from the minimum noise fraction transform. As can

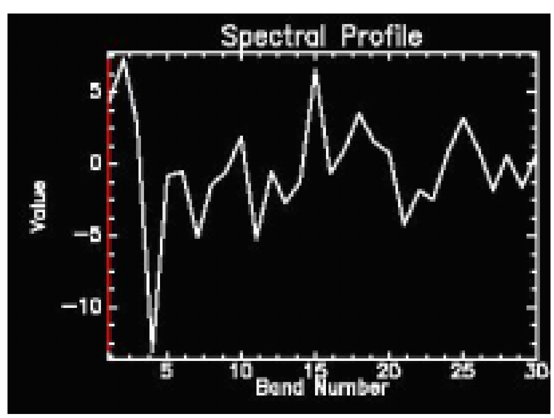

Figure 3. Minimum noise fraction, grassy meadow pixel.

be seen from the plot, most of the variation had been removed after five reprojections of transformed data. If the transformed data are redisplayed, the result is a "fuzzy" data set with little distinction between the classes (Figure 4). It is useful to remember that the

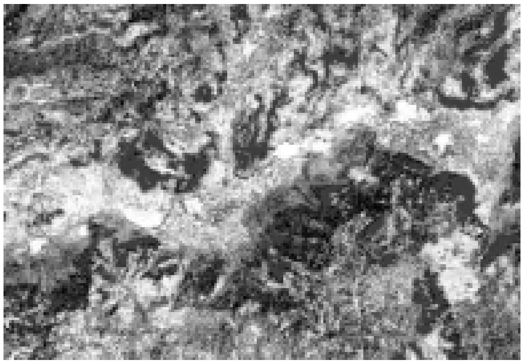

Figure 4. Map of minimum noise fraction transform with resultant "fuzzy" classes.

map now displays minimum noise data, with the lightest areas having the least noise. For example, the meadow areas still appear as the whitest areas in the map. The shadow and conifer areas come out as a mixture of grays, indicating that more noise is present in those pixels. These areas can be accentuated by doing a contrast stretch which refines the gray scale goodness of fit as shown in Figure 5.

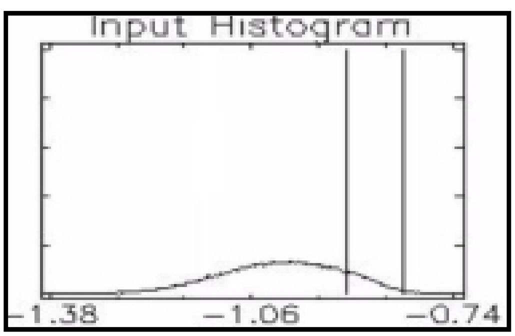

Figure 5. Contrast stretch function.

A replot of the stretched data clearly contrasts the areas with minimum noise from those with mixed signatures (Figure 6). In this case, the stand of open ponderosa pines (*Pinus ponderosa*) and some dry areas in El Capitan Meadow show up in gray. Meadows without trees in them appear as white while most of the other previously gray areas are black. The burned area still has a gray appearance.

The pixel purity index was then used to identify the purest pixels by projecting the first 15 minimum noise fraction bands onto a random unit vector (RSI 1997).

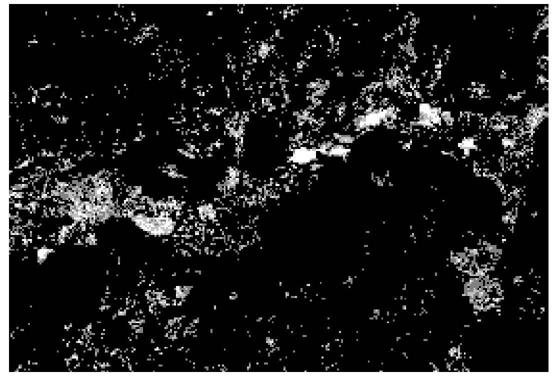

Figure 6. Map of contrast stretched minimum noise fractions.

The function then tallies the number of pixels that exceed a user specified threshold and fall into the tails of the distribution of the projected data. The result of thousands of iterations of the pixel purity index function is a plot of the total number of times that a pixel fell into a tail of the randomly projected distributions (Figure 7). Although an asymptote was not yet achieved, the rate of increase had started to decline after 5,000 iterations and 6,000 pixels, indicating that most of the pure pixels had been found.

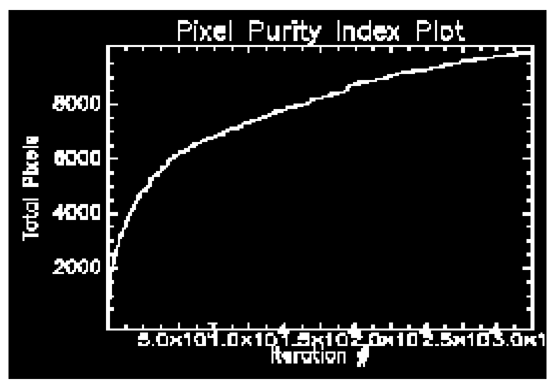

Figure 7. Pixel purity index.

Visualization and Identification

The intersections of the randomly projected vectors in the PPI analysis define projections or "bulges" in the n-dimensional data cloud which represent the component space characteristics of spectrally pure end-members. The results of the PPI analysis are thresholded to emphasize extreme pixel selection (i.e. the apex of the bulges) to the extent of 2 to 3 times the noise level in the data. The resulting data then can be viewed graphically by an animated n-dimensional viewer (Figure 8) where consistent clustering of points represents the presence of pure end-members in component space.

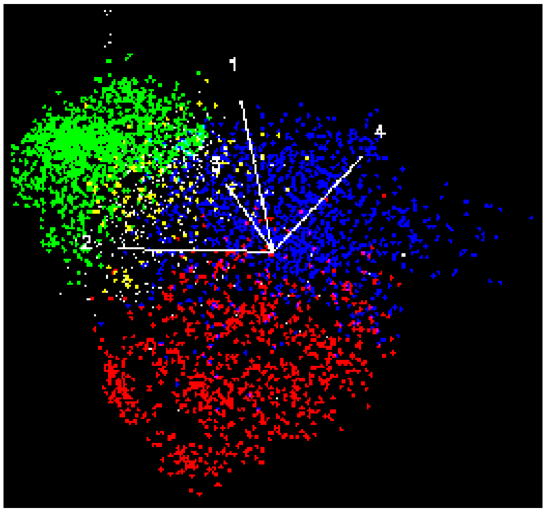

Figure 8. N-dimensional visualizer.

Individual clusters can be interactively delineated by "heads-up" digitizing of polygons around clusters in the n-d visualizer which can then be exported as "regions of interest" for input into classifications, unmixing, matched filtering, or other types of analyses (RSI, 1977).

Distribution and Abundance of End Members

Mixture tuned matched filtering (MTMF) was the technique used to develop a map of distribution and abundance of end-members defined in the process described above. This process is designed to maximize the response of known end-members and suppress the results of the complex unknown background. Because the technique may sometimes find some "false positives", an infeasibility image is also output (Figure 9) which can be divided into the MTMF output and normalized (using the NDVI algorithm) to substantially reduce the number of false positives found.

Two additional end-members, evergreen hardwood (mostly on the north side of the valley) and shadowed

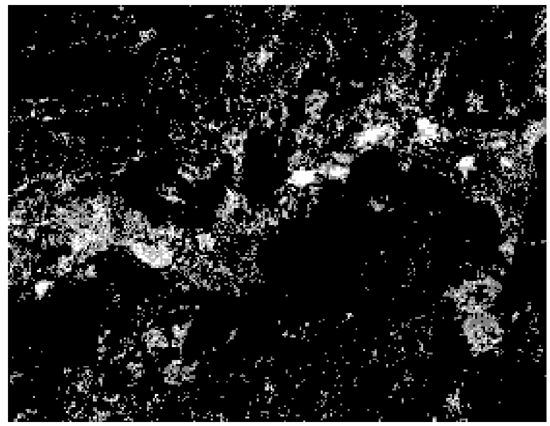

Figure 9. Mixture tuned matched filtering output for the herbaceous end-member, divided and normalized by the infeasibility image and contrast stretched for display.

areas (mostly on the south side of the valley) were similarly mapped. All 3 of these can be visualized simultaneously via color compositing. Figure 10 shows the herbaceous as green, evergreen hardwood as blue, and

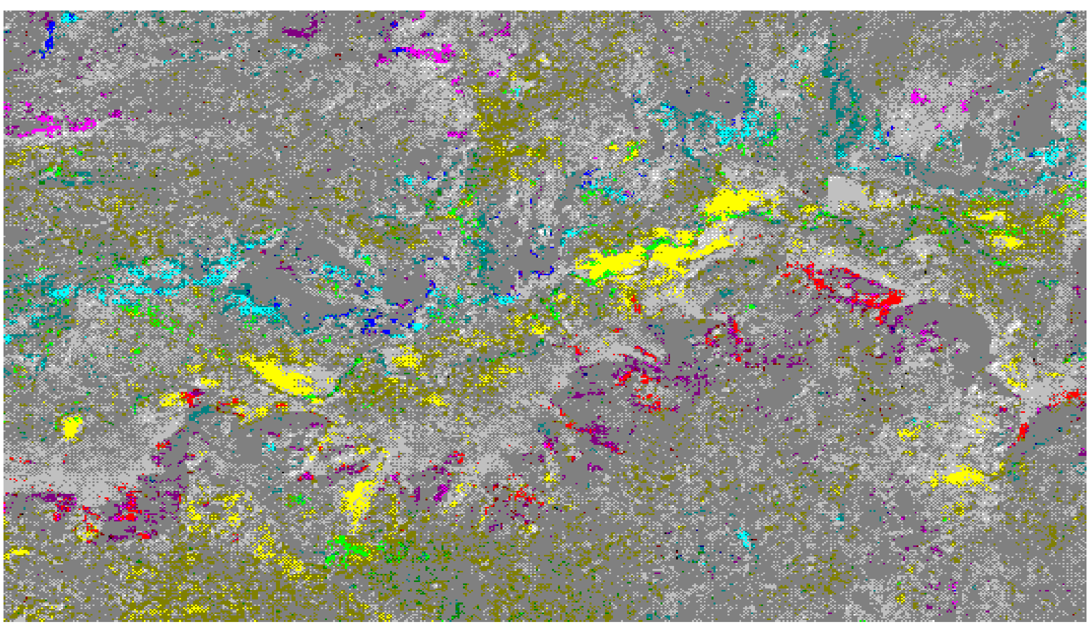

Figure 10. Herbaceous (green), evergreen hardwood (blue), and shadowed area (red) end-members viewed simultaneously as a color composite.

shadowed areas as red. Mixtures of herbaceous and evergreen hardwood (greens and blues) form complex patterns on the valley floor, especially in areas of mixed forest which did not express itself as an end-member.

CONCLUSIONS

End member classes mapped by the hyperspectral techniques described in this study successfully identified herbaceous and evergreen hardwood vegetation types, which had distinctive phenology. Other end members often represented areas of extreme spectral and temporal contrast such as clouds, patches of snow, and shadow. Only those areas with simple or highly contrasting characteristics were defined by this process as end members. Many vegetation types showed too little variation either spectrally or temporally to be discriminated. Mixtures of some end members may help define other fuel types.

Hyperspectral processing tools look promising for extracting information about herbaceous and evergreen hardwood fuel types from TM data at a level of detail not achieved by more conventional algorithms. The next steps will include refinements of the technique to improve results (e.g., removal of cloud and shadow effects), concentration on spectrally mixed areas including those dominated by conifers, evaluation of seasonal changes in NDVI values for more sensitivity to phenological variation, and exploration of the potential of neural net classifiers.

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