MAPPING FOREST CHANGE WITH LANDSAT 7 SLC-OFF DATA

Mutlu Ozdogan[1] and Curtis Woodcock[2]

[1]Department of Forest and Wildlife Ecology, University of Wisconsin-Madison
[2]Department of Geography and Environment, Boston University

1. INTRODUCTION

Landsat 7 experienced a Scan Line Corrector (SLC) problem on May 2003. The SLC problem causes individual scan lines to alternately overlap and then leave large gaps at the edges of the image. While it is now determined that the problem cannot be corrected, data in SLC-off mode maintain expected radiometric and geometric fidelity and a number of different approaches have been tried to extract useful information related to forest change from available image data. Two major approaches to date include interpolation and mosaic of overlapping scenes from subsequent acquisitions to "gap fill" missing data pixels.

One of the major application areas of Landsat data is monitoring forest change. A number of pilot studies have investigated the usability of Landsat 7 SLC-off data for monitoring forest change and concluded that the SLC-off data still has a large value in this regards [1]. In the research presented here, an alternative approach is proposed to monitor forest change with the Landsat 7 SLC-off data. The proposed method is based on the idea of generalization across time and space. The primary advantage of the new approach is to directly find forest change pixels, bypassing the need to "fill in" gaps before forest monitoring can commence.

2. PROPOSED METHOD

For the preliminary analysis reported here, the proposed method has been applied to an "end-point" forest change exercise where a pair of Landsat images - one pre- and one post-deforestation event – are used. The basic requirement of the proposed approach is two SLC-off data in the post-event period. The test area is Northern California (Landsat WRS2 path 46 row 31) and characterized by extensive logging as well as forest regrowth (Figure 1). The current analysis concentrates only on two classes (forest change and no-forest change) and involves 3 images: one pre-event [1989] and two post-event [2002] Landsat 7 SLC-off. The post-event SLC-off Landsat 7 data has "simulated" gaps, identical in shape and extent to the actual SLC-off gaps and are artificially introduced into the image. The value of working with data that have simulated gaps is that the original image without gaps is available and the results from the image with gaps can be compared "head-on" to results from non-gap images.

In the first step, all three images (one pre-event SLC-on and two post-event SLC-off) are atmospherically corrected using the image-based Dark Object Subtraction (DOS) method [2]. Note that atmospheric correction is critical as signatures from two different dates with different atmospheric compositions are used. Next, the pre- and post-event forest change image pairs are transformed into multi-temporal Kauth-Thomas (MKT) data, representing change in Brightness (B), Greenness (G), and Wetness (W) across dates [3]. The pre-event data is transformed into a single date BGW image.

The crux of the proposed method is to train a non-parametric classifier - decision trees in this case - on one pair of pre- and post-event images with examples of forest change and no-change categories and apply this trained classifier to the second pair of pre- and post-event data. The training examples are taken from the non-gap areas of the first image pair. A total of 50 training sites, each drawn on the first image pair, were selected as training samples. The trained classifier was first applied to the first image pair to map forest harvest. In this map, gap areas are not classified. Then, the same trained classifier was applied to the second pair to map forest harvest. The final step in this analysis is to fill the gap areas of the first map with the classified data from the second pair. To test the effectiveness of the post-classification gap filling approach, the trained classifier was also applied to the original image. Here the original image is a 2002 Landsat 7 data that does not have the simulated gaps. Any errors of omission or commission between the two maps can be interpreted as the cost of generalization.

3. RESULTS

Figure 1 shows the input image data used in the analysis. Already in 1989 (A), the area is characterized by logging tracts. Panels B and C show the locations of simulated gaps in two post-harvest Landsat 7 data while Panel D shows their time sequence: black lines show the locations of gaps in the August 30 image and the grey lines in the November 2 image. For the November image the gaps occupy roughly 25% of the image. Simply put, these numbers indicate the unavailable area of each image to map forest harvest on its own.

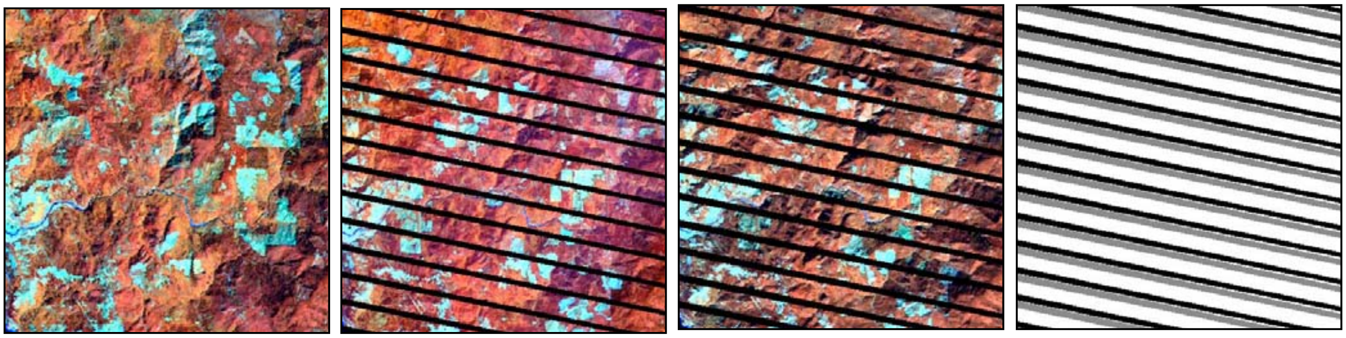

Figure 1. Pre-harvest (A) and post-harvest (B and C) Landsat images displayed as 4-5-3 band combination (RGB). The gaps are simulated in both B and C. Panel D shows the non-overlapping nature of the gaps from two different acquisitions.

Figure 2 shows the results of the approach proposed here. The left panel is the post-classification gap-filled map showing forest harvest between 1989 and 2002. The red areas indicate forest harvest mapped from the first pair and the magenta areas indicate forest harvest mapped from the second pair. Note that no training process was involved in mapping forest harvest from the second pair. Results were achieved simply by applying the trained classifier, trained from the first pair, to the second pair of data. To test the effectiveness of the proposed post-classification gap-filling approach, the trained classifier was also applied to the original image (one without the gaps) and the right panel on Figure 2 shows these results. In general, there is very little difference between gap-filled and the original image results. Most errors are in the form omission, trained classifier simply not being able to find areas of forest harvest in the new (generalized) pair.

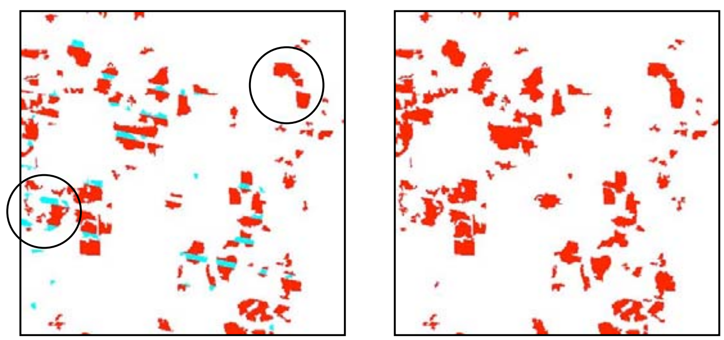

Figure 2. The left panel shows post-classification gap filling approach (in magenta) where forest change was mapped by classifying the second pair of pre- and post-harvest images with a trained classifier from the first pair. Circled areas indicate locations of omission errors.

No rigorous accuracy assessment was performed for either map at this time. However, visual comparison and overlay of the map generated form the original (no-gap) image indicate a high degree of confidence. Assuming that the map made from the original, non-gap image is correct and represent all of the forest harvest in this window area, the SLC-off data by itself recovers ~80 percent of forest harvest. This estimate is within 20 % of the estimate made with the SLC-on data. However, this uncertainty is primarily a function of size, pattern, and intensity of forest harvest tracts and results from different environments remains to be seen. When gaps are filled in post-classification fashion more than 93% of forest harvest is recovered. At this point, the uncertainty of just 7 percent is probably within the uncertainty range of any forest harvest mapping attempt, with or without SLC anomaly.

4. REFERENCES

[1] USGS, 2003, Preliminary Assessment of the Value of Landsat 7 ETM+ Data following Scan Line Corrector Malfunction, Compiled and summarized by the staff of the U.S. Geological Survey, EROS Data Center, Sioux Falls, SD 57198, 16 July 2003.

[2] Chavez, P. S. Jr., 1989, Radiometric calibration of Landsat Thematic Mapper multispectral images. Photogrammetric Engineering and Remote Sensing, 55 (9), 1285– 1294.

[3] Collins, J.B. and Woodcock, C.E., 1996, An assessment of several linear change techniques for mapping forest mortality using multi-temporal Landsat TM data, Remote Sensing of Environment, 56, 66-77.