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REGIONAL TO CONTINENTAL MONITORING OF CHANGE IN TEMPERATE CONIFER FORESTS

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ABSTRACT

The successful launch of Landsat 7 promises a dramatic change in the availability and affordability of high resolution optical imagery. One result will be the opportunity to pursue regional to continental scale mapping and monitoring of natural resources while maintaining the high degree of spatial detail in the landscape observable at Landsat resolutions. We are developing methods for monitoring change in temperate conifer forests applicable at these scales. At the heart of our approach is an effort to process previously unseen images, which requires careful atmospheric correction of images and application of classification algorithms in different places and/or times than where they were trained. The Fuzzy ARTMAP artificial neural network is the classification algorithm being used.

The USDA Forest Service recently produced a map of forest change in the Cascade Mountains of Oregon based on more conventional methods in which each pair of images is analyzed individually (Cohen et al., 1998). To test our new methods we produced a map of the same area for one time period. Our initial results for the Cascade Mountains in Oregon which cover portions of six Landsat scenes are very similar to those reported by Cohen et al., which is encouraging and indicates the potential of more automated methods to expand the capability of using Landsat data for monitoring large geographic areas.

INTRODUCTION

A global perspective on forests and forest change indicates several prominent themes, including widespread conversion of forests to other land uses, increasing demand for forest and wood products, and an increasingly important role for ecosystem services, including the sequestration of accumulating atmospheric CO2. However, the nature, causes and rates of change vary from biome to biome and often between geographic regions within biomes. Similarly, the fates of deforested lands vary dramatically, from areas immediately replanted with trees to those converted to other land uses. Temperate forests, and the change processes occurring in them, differ in many respects from tropical and boreal forests. For example, temperate forests occur in many of the most highly developed and industrialized countries in the world, where the history of use of forest resources is long and well established. One result is that there are few large tracts of previously untouched land being opened to use. In fact, more frequent is the opposite case in which areas used in the past for timber resources are now being added to preserves. These factors greatly influence the manner in which forest change occurs. Forest clearing in temperate forests tends to occur in many small sites scattered across landscapes where patterns due to past land use are readily apparent (see Figure 1). From a remote sensing perspective this poses a significant challenge, which is: *how to monitor large geographic areas of temperate forest with sufficient spatial detail to capture the many small sites of forest change.*

An alternative approach which holds great potential is to develop methods which rely upon *generalization* of training/calibration data in space and/or time. To illustrate this idea of generalization and its importance to the use of Landsat data to study large areas, let's take the example of image classification. The traditional approach to image classification requires training data for examples of the desired classes from within the image in question. These examples are used to train a classifier which is used to assign the pixels in the image to classes. The generalization in this case is *within image*, in the sense that samples from within the image are applied to the rest of the image. Almost all processing of Landsat data to date, as described above, follows this paradigm of *within image* generalization. A next level of generalization is *within scene*, where we use the term *scene* to refer to a geographic area and *image* to refer to a single acquisition by a sensor. (For example, Landsat scenes are indexed by WRS Path and Row numbers, while images also require a date.) For this level of generalization, training from one image would be applied directly to another image of the same scene. Another level of generalization which involves space is *within region*, in which training from one scene is applied to other neighboring scenes within the same geographic region. A higher level of generalization would be *across regions*, where training from one geographic region is applied to another. Similarly, we can define *across continents* as the case where training from one continent is applied in a different continent. Very little has been done to date to test the ability to exploit generalization past the level of *within images* using Landsat data. We find this surprising, as this sort of generalization is routinely done using other satellite data, such as from the AVHRR, for example.

There is a history to the idea of generalization (often referred to as "signature extension") that dates to the initial launch of the Landsat satellites when there was the hope that the spectral signatures from various surface materials could be stored and then use to map, or classify, new unseen images (Bauer et al., 1979; Goetz et al., 1982). This approach was tested in LACIE and other efforts to use Landsat to monitor crops, without much success (Minter, 1978). The primary reasons are that the variability from image to image is large due to the effects of changes in sun angles, atmospheric composition, phenological stages of vegetation and high frequency variability in such factors as soil moisture or snow cover. In the intervening decades, much has been learned about these effects in images and how to minimize their impact on the analysis of satellite imagery.

For the purposes of improving the monitoring of large geographic areas using Landsat imagery, we have been working on the development of analysis methods that rely on higher levels of generalization, including both *within scene* and *within region*. This approach allows for a more automated approach to analysis of Landsat imagery which will make the study of large geographic areas more feasible as well as more easily repeated through time. The purpose of this paper is to present initial results of a test of our new methods based on image generalization for detecting clear cuts in the Cascade Mountains of Oregon.

COMPARISON WITH THE MAP OF COHEN ET AL.

To test the ability of automated classification methods based on generalization to identify forest change, we have produced a map of forest change in the Cascade Range of Oregon from 1991-1995. We selected this area as Cohen et al., (1998) have recently mapped this area using more conventional methods based on unsupervised classification where each image was classified and labeled separately by image analysts. This approach follows the traditional paradigm of relying on examples from each pair of images to calibrate the results and provides a "state-of-the-art" basis for comparison. The study area includes pieces of six Landsat scenes, so Cohen et al. ran six separate classifications. Overall, their study included four time periods, so 24 separate classifications were required.

METHODS

To match their result we needed to produce a map of forest change (areas that were forest in 1991 but are no longer forest in 1995) where any changes smaller in size than 2 hectares are ignored. The main intent is to find the clear cuts, which are the dominant form of forest change in this area and range is size from 2 to 40-50 hectares. Our methods involve training of an artificial neural network (Fuzzy ARTMAP, Carpenter et al, 1997), with examples of *forest change* and *no forest change*. The training was done using areas identified in our prior field work in the region on a pair of Landsat 5 images from 1992 and 1995 for a single scene in the Cascades. The trained neural network was then applied to pairs of Landsat images from 1991 and 1995 from each of the six scenes required to map the area.

One of the key issues involved in this approach is atmospheric correction, as it is essential for the units of measurement to match between the images used for training the classifier and those used for mapping forest change. Our experience to date indicates that it is essential to correct images for atmospheric effects to the level where image values correspond to surface reflectances (Pax-Lenney et al., 1999). In two separate analyses involving generalization, we have found that among the readily available methods for correcting images that simple dark object subtraction methods (Chavez, 1989) work as well as any of the more recent innovations (such as Liang et al., 1997; Kaufman et al., 1997; Wen et al., 1999). This answer results from studying land use change in China (Song et al., 1999) and identification of conifer forests in the Pacific Northwest (Pax-Lenney et al., 1999). Thus, we used simple dark-object-subtraction to correct the images.

Pixel based classifications to identify change are often speckled and noisy due to effects like minor misregistration. To overcome this limitation, we segmented a two-date Landsat TM Band 5 composite into an image of homogeneous landscape patches, or polygons (Woodcock and Harward, 1992). The pixel based classification was merged with the polygon image and the label of each patch was labeled *forest change* or *no change* based on the proportion of forest change pixels within it.

Post classification editing was used to correct some obvious errors which occurred on places such as mountain peaks due to different amounts of snow cover between dates. Polygons at or near the threshold of *forest change* and *no change* were also reviewed. The time devoted to editing the images was about one day per scene, which varied somewhat depending on the fraction of the scene that was included in the analysis. Editing of this nature is also necessary for maps produced by more conventional methods such as those of Cohen et al. (1998). Finally, the six separate scenes were merged into a single forest change map of the Cascade Range in Oregon. A small portion of the map and the images for the two dates is shown in Figure 1.

RESULTS

An accuracy assessment of the map was performed based on visual inspection by two examiners of a sample of 538 3-by-3 pixel sites. The *forest change* class covered 1.3% of the image within which 146 sites were randomly selected. However, within the *no change* class we biased the sample to try to find the areas of forest change which might have been missed by our change detection methods. The area mapped as *no change* was divided into areas where change was *most likely* and *least likely* through the use of a threshold in a simple change indicator, or the change in Band 5 between the two dates of images. The *most likely* change areas within the *no change* class covered 16.3% percent of the image, and 172 random samples were drawn this area. The *least likely* change areas covered 82.4% percent of the image, and 220 random samples were drawn from this area. The results of the accuracy assessment are presented in Table 1, with the results for both the *most* and *least* likely areas of the *no change* class merged for ease of interpretation.

The accuracies are very similar to those reported by Cohen et al. (1998) and demonstrate the viability of these automated methods relying upon generalization. Sites falsely identified as *forest change* (errors of commission) were primarily due to two effects. The first cause was due to misregistration of images. Our problems with respect to registration were inherited from Cohen's study, as we used their registered images so that we could more easily compare the resulting maps. Our experience indicates that we can do a better job with image registration than the images we received from Cohen, so we don't expect significant problems with this issue in future studies.

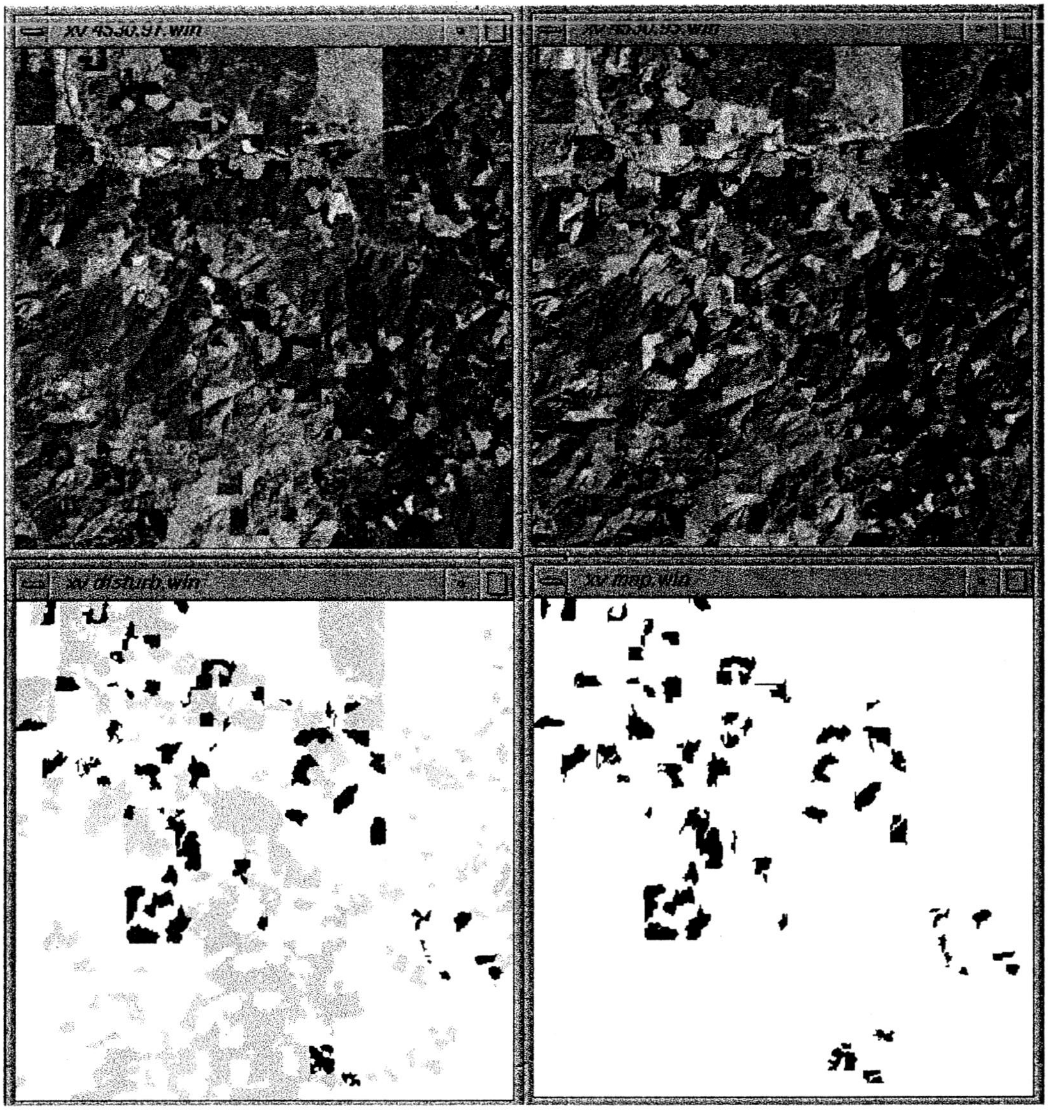

Figure 1. This figure shows the results of the automated change detection methods. The two top images are Landsat 5 TM images from 1991 (L) and 1995 (R) 15 km^2 region in the southern Cascades of western Oregon. The lower left image is a map of forest change produced with traditional change detection methods (Cohen et al, 1998); black represents forest change during 1991-1995, grey represents forest change from earlier time periods. The lower right image is a map of forest change produced with our more automated methods; black represents forest change during 1991-1995. The new methods produce results clearly comparable to those from the more traditional methods.

Table 1. Accuracy Assessment of the Forest Change Map

	Sites Labels:			
Map Labels:	Forest Change	No Change	Total	Percentage
Forest Change	137	9	146	93.84%
No Change	16	376	392	95.92%
Total	153	385	538	
Percentage	89.54%	97.66%		

The second cause of errors of commission in the *forest change* class was due to including areas of change which were not forest to begin with, such as sites from surrounding agricultural fields and areas of shrubs and other non-forest natural vegetation. Cohen et al. eliminated this problem in their map by overlaying a map of forested lands. We did not anticipate this problem and expect to be able to solve (or at least greatly reduce) it in future mapping efforts by providing examples of changes of these kinds for the *no forest change* class during training of the neural network. One of the strengths of the Fuzzy ARTMAP neural network is the "many-to-one" mapping capability, meaning that any single output map class can have many spectral manifestations, each of which is preserved internally within the neural net.

The errors of omission are somewhat more significant than the errors of commission (see Table 1). Many of these errors result from the post-processing step to generate change polygons which relies upon image segmentation. At times, large polygons were produced which included both areas of change and no change which were identified as *no change* in the map. Thus, some of the 3-by-3 pixel blocks sampled in the accuracy assessment are best characterized as having changed but occurred in *no change* polygons. We believe we can minimize this problem by using a slightly different version of the segmentation algorithm which includes a thematic map layer along with the original spectral bands in the segmentation process (Woodcock et al., 1993). The thematic map layer to be used is the per-pixel based *change/no change* output from the neural network.

CONCLUSIONS

There are three key points that emerge out of this effort. First, in our first attempt to use more automated methods based on generalization to map forest change we got results of comparable accuracies to those derived from using more time consuming approaches which require new training for each new pair of images. This encouraging result indicates we may eventually be able to improve the utility of Landsat data for monitoring large areas for forest change. To illustrate this point, we plan to update Cohen et al.'s maps for the 1995-1998 time period. Theoretically, we could process the images for this new time period using our existing trained neural network without any new training or local area calibration. In practice, we have learned of a few ways to improve our analysis and thus will probably retrain a new neural network with some slight changes based on the discussion of the results presented above. However, the key point is that adding a new time period to an analysis such as the one done by Cohen et al. becomes much easier when using methods based on generalization.

The second point is that there is still much to be learned about how to improve approaches based on generalization. There is about a quarter of a century worth of work devoted to the dominant paradigm for processing Landsat imagery in which training and calibration of methods is required for each image processed. To support the use of Landsat imagery for processing large areas more research is needed to understand the limitations of what can be accomplished and to refine the methods to be used.

Third, the launch of Landsat 7 is a necessary ingredient in the process of monitoring temperate forests at regional to continental scales, as the size of the areas of forest change are too small to be reliably detected using MODIS and other coarse resolution sensors. We do not yet know enough about how much effect the improved signal-to-noise ratio of the ETM+ will have, but the improved amount of imagery being collected, its reduced cost, and improved speed of accessibility all will dramatically improve the utility of Landsat imagery for monitoring environmental change over large areas.

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