A QUANTITATIVE COMPARISON OF CHANGE-DETECTION TECHNIQUES

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Six change detection techniques to study land cover change associated with tropical forest (El Rawashda forest reserve, Gedaref State, Sudan) were examined. Landsat 7 Enhanced Thematic Mapper (ETM+) data acquired on March 22, 2003 and Aster data acquired on February 26, 2006 were used. The change detection techniques employed are supervised change detection using pixel post-classification comparison (PCC), image differencing of different vegetation indices (Normalized Difference Vegetation Index NDVI, Soil-Adjusted Vegetation Index SAVI and Transformed Difference Vegetation Index TDVI), principal component analysis (PCA), multivariate alteration detection (MAD), change vector analysis (CVA) and tasseled cap analysis(TCA).

As field validation data is not available for 2003, an extensive visual assessment; a manual classification was performed, then a change map was conducted to locate and identify change in vegetation. This change map was used as a reference to quantitatively assess the accuracy of each change-detection techniques. Based on accuracy assessment, the most successful technique was the PCC technique with accuracy assessment of 94%. This was followed by the MAD technique with calculated accuracy assessment of 88.8%. However, among vegetation indices techniques, TDVI stood out as better than NDVI and SAVI in its ability to accurately identify vegetation change.

1. INTRODUCTION

In Sudan, there are large and diverse forest resources (Figure 1), which are the result of highly varied climate, topography, and soils.

Forests are considered among the most important natural features in the Sudan where they form, with other varying intensities of plant cover, the base for the terrestrial ecosystems of the country. Their indirect role in supporting agriculture through ameliorating an otherwise harsh climate, combating soil erosion and conserving water is well recognized by both government circles and rural societies. In spite of this unchallenged importance, accurate information on the extent and composition of the forest cover is neither complete nor reliable.

Change detection is the process in which temporal differences in the state of an object or phenomenon are identified (Singh 1989). It is important in monitoring natural resources as it can quantify the spatial distribution of land cover change in the area of interest. During the past 20 years, it has become a major application in remote sensing because of increasingly consistent image quality and repetitive coverage at short intervals (Mas 1999). Singh (1984; 1986) used image differencing to monitor change due to shifting cultivation in a tropical forest environment.

In this research, Landsat ETM and ASTER data were used to compare temporal change methods for detection of deforestation and reforestation over 3 years in the east region of Sudan.

2. METHODOLOGY

2.1. Study area

The Gedaref State is located in the eastern part of the Sudan. It covers area between longitudes 33–36° E and latitudes 14–16 °N with an area of approximately 78,000 km². It lies between two major tributaries of the Blue Nile: the Atbara river on the east and the Rahad river on the west. Climatologically (natural forest reserve in Gedarif State) Elrawashda lies in the semiarid zone, with summer rains and warm winters, characterized by a unimodal rainfall pattern ranging from 400 to 800 mm with an annual average of 600 mm. A study carried out in the Gedaref State reported that the rainfall pattern in the area is characterized by its variability from one year to another. Gedaref State experiences a dry season for about eight months of the year. Rainfall in the state is markedly seasonal in character; the length of the rainy season fluctuates around the four months between June and September reaching its peak in August. Most of the rains fall from June/July to October/November. Gedaref State lies in the zone of low rainfall woodland savanna on clay. El Rawashda forest is located near the transition between two main vegetation types of low-rainfall woodland savanna on clay: Acacia mellifera thorn land and Acacia seyal-Balanites aegyptiaca woodland.

2.2. Satellite Data

Landsat 7 Enhanced Thematic Mapper (ETM+) data acquired on March 22, 2003 and Aster data acquired on February 26, 2006 were used for analysing an area covering approximately 1.101.789 km² as area of interest.

2.3. Image pre-processing

For the geometric correction, the 2006 scene was co-registered to the 2003 scene, which had been acquired in UTM projection. Nearest neighbor re-sampling was applied when assigning pixel values to the aligned raster for the 2006 scene. Radiometric correction was necessary to reduce or eliminate differences due to atmospheric or a sensor variation between the two dates; atmospheric modeling was conducted by the software Geomatica. The thermal band was excluded because of its lower resolution and because principal component analysis (PCA) showed that it did not contribute significantly to the data variance in any of the components.

2.4 **Change detection analysis**

Six commonly applied methods of temporal analysis, image differencing, post-classification, principal component analysis (PCA), multivariate alteration detection (MAD) and change vector analysis (CVA), were selected to provide capability for comparison with reference data.

2.4.1. Image Differencing

Image differencing was applied to vegetation enhanced images that were derived using three vegetation indices: NDVI SAVI, and TDVI. In all cases, the 2003 transformed data were subtracted from 2006 transformed data, resulting in new images. The Tasseled Cap transformation (Roy *et al*. 1991; Guild *et al*. 2004) was applied to both scenes to produce brightness, greenness and moistness indices.

The greenness index (Mather 1989; Huang *et al*. 2002, as cited in IDRISI Kilimanjaro 2004 help guide) was used in image differencing analysis. A series of threshold values based on standard deviations from the mean were used on the new images to determine the changed from unchanged pixels. A visual assessment on the no-change/change pixels was performed to determine the threshold value with the highest accuracy.

2.4.2 Principal component Analysis

For change detection PCA was performed in two ways:
Multitemporal PCA: which was performed using the 10 reflective bands of the images of the two dates. All PCAs were applied to standardized data (i.e. using the correlation matrix) according to the recommendations of FUNG and LEDREW (1987).
Band wise PCA: which was performed on pairs of band, and then each pairs was examined for change detection (Chavez and Kwarteng, 1989).

2.4.3 Multivariate Alteration Detection (MAD)

The Multivariate Alteration Detection transformation (MAD), introduced by Nielsen et al. (1998), is based on a classical statistical transformation referred to as canonical correlation analysis to enhance the change information in the difference images. In past studies this method has been successfully applied to multispectral images (Canty and Niemeyer, 2002), (Niemeyer et al., 1999), (Nielsen, 1996). We applied the algorithm to all bands to test the usefulness of this method. The MAD bands were then examined to identify the quantity and the quality of changes.

2.4.4. Change Vector Analysis

The CVA uses any number of spectral bands from multi -date satellite data to produce change images that yield information about both the magnitude and direction of differences in pixel values (which are proportional to radiance) (Michalek *et. al*, 1993). The CVA was applied to the bands of the two images. With this method, two images are computed: one image for the vector intensity and another for the vector direction. The first image contains the information of change, while the second contains information on the type of change. In this analysis, only the image for the intensity of the change vector was computed, since we were only looking for vegetation change.

2.4.5. Post classification comparison (PCC)

PCC consisted of cross tabulation of forest / non-forest maps to determine the pixels that had changed from one class to the other. Supervised maximum likelihood classification of the 2003 and 2006 scenes was conducted to create the maps. Training data were selected in easily identifiable areas of the following four classes: closed forest; open forest; grass land and bare land.

2.5. Accuracy Assessment

From the outset of this project, it was known that accurate field or remote sensing based validation data for 2003 would be unavailable. As an alternative, validation was conducted by visually identifying areas of change or no-change in magnified displays of the RGB composites. This analysis was conducted for the original images to determine the best data transform. To accomplish this, a manual supervised classification was conducted to a subset of each image, and then change detection was conducted by computing image difference. Hereafter the result map was used as a reference. The change detection was conducted with the transformed images to assess its completeness in spatially detecting vegetation change.

3. RESULTS

Figure 1 and table 2 show the assessment of overall vegetation change using different change detection methods. The software eCognition was used for manual generated classification to develop a reference map.

Land cover changed map with a higher accuracy produced by Post classification comparison (PCC), the method detected the presence of reforestation and deforestation in most areas in a very accurate manner. Land cover changed maps with lowest accuracy were all produced with VI differencing technique.

Table 2 and figure 2 illustrate the accuracy assessment for change detection techniques from the 2003 and 2006 dates. The highest accuracy was also obtained by PCC (87%) Accuracy of the change image was estimated at change/no change detection level (Fig. 1) the accuracy assessments were 59.2% (NDVI), 59.9% (SAVI), 60.1% (TDVI), 62.2% (TCA), 68.6% (PCA), 60.09% (MAD) and 71.6% (CVA) respectively.

4. DISCUSSION AND CONCLUSION

There is no simple way to evaluate the errors in the classification associated with change detection. In addition to the errors generated in the single-date classification process, the analyst must contend with the propagation of errors in the second-date classification and the change-detection algorithm between the two dates. Congalton (1994) details the possible propagation of errors in both single-date classifications and change-detection studies. The analysis with multiple layers, change-detection studies are difficult to assess the accuracy because of the large number of variables associated with the process.

The highest accuracy was obtained using the post-classification comparison based on supervised classification of the two images. The good performance of this approach can be attributed to the high classification accuracy of 2003 and 2006 classified images and to the fact that accuracy has been improved by grouping classes which presented the most common spectral confusion such as grasses, bushes and agricultural crops.

Some authors carried out comparative studies of change detection techniques and generally found that post- classification comparison was less effective than image differencing and PCA (Muchoney and Haak 1994).

Vegetation indices procedures were not able to differentiate accurately the variations of soil moisture and vegetation phonology from variations due to land cover changes. The use of classification techniques avoided this problem. When carrying out independent supervised classifications, classes which present very different spectral signatures at the different dates can be classified into the same land cover. When using unsupervised multi-date classification, classes which present spectral variation between both dates, but where change is not occurring, can also be identified although, in the present study spectral classes corresponded to different classes of changes and, multi-date unsupervised classification did not allow the accurate classification of the land cover changes. Thus the procedure based on the comparison of independent supervised classifications was found less sensitive to radiometric variations between the scenes and is more appropriate when dealing with data captured at different dates. Post-classification comparison also presents the advantage of giving information about the nature of the changes. Results suggest that the principal land cover changes in the study area can be monitored accurately by remote sensing.

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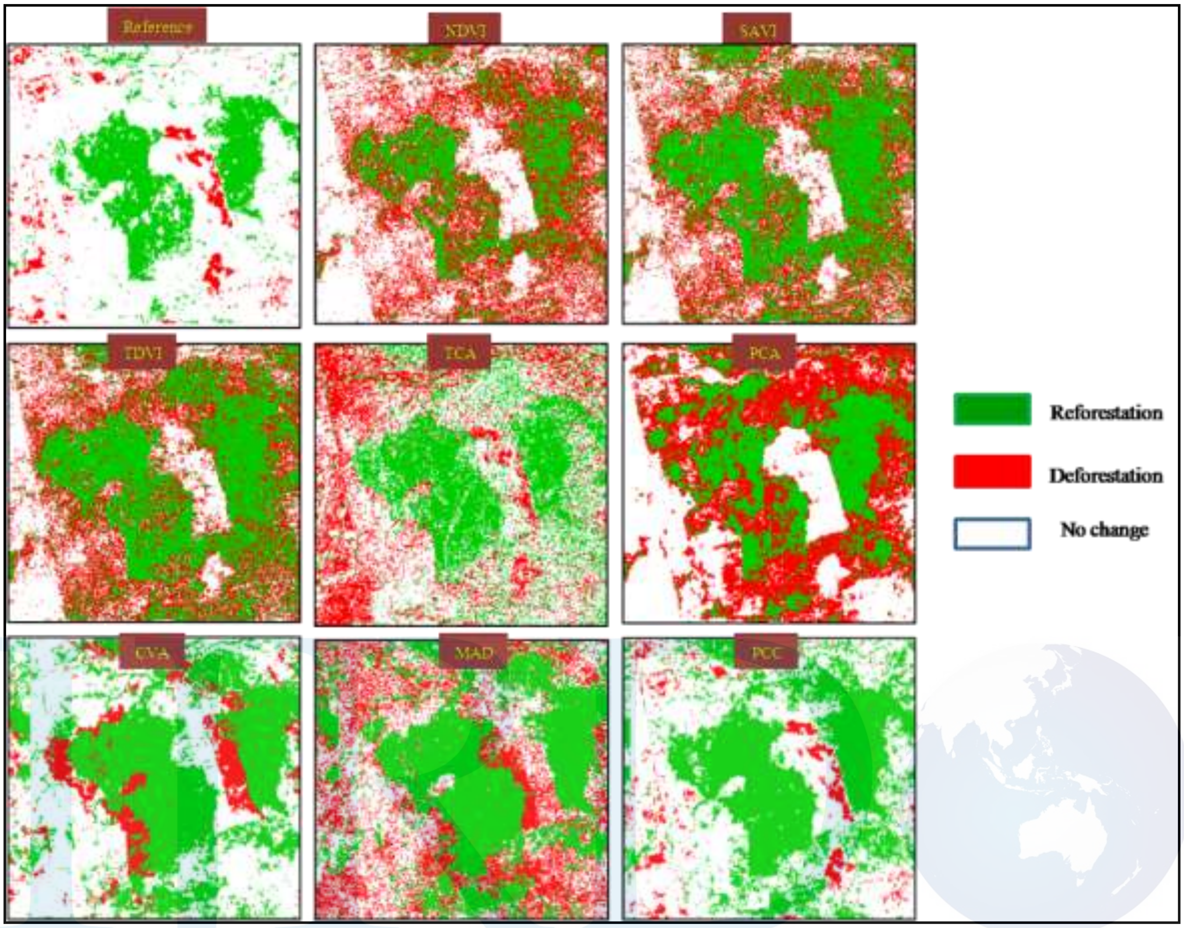

Figure 1 Change / no change map given by different change detection techniques (2003-2006)

Table 1: Percentages of Reforestation, Deforestation and No change (2003-2006)

Method	***Reforestation***	***Deforestation***	***No change***
Reference	20.0	4.9	75.1
NDVI	23.1	33.4	43.5
SAVI	28.0	34.9	37.1
TDVI	28.3	32.2	39.5
TC	22.3	28.2	49.5
CVA	34.2	17.0	48.8
PCA	26.0	39.8	34.2
MAD	32.1	26.5	58.6
PCC	31.8	7.8	60.4

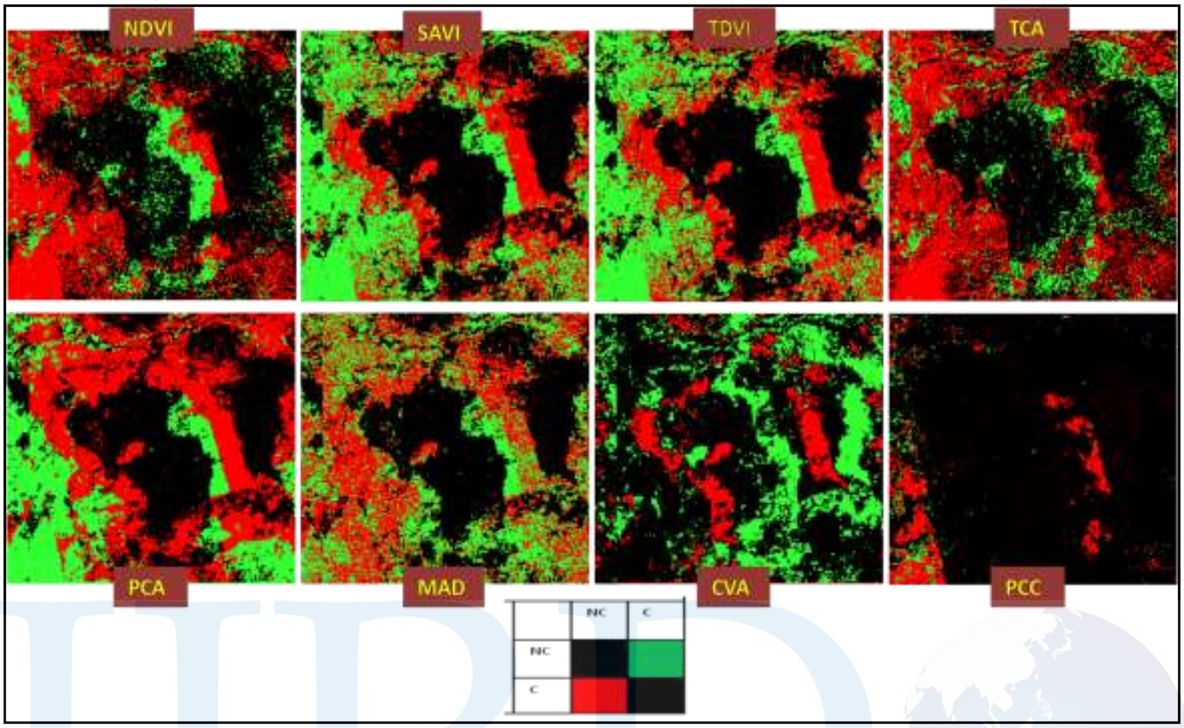

Figure 2: Accuracy map given by different change detection techniques (2003-2006)

Table 2 Comparison between different change detection techniques and its overall accuracy [%] (2003-2006)

NDVI 59.2	Reference			
		NC	C	∑
	NC	20752	17186	38516
	C	8975	17215	26190
	∑	29727	34401	64128

CVA 71.6	Reference			
		NC	C	∑
	NC	30926	11209	45910
	C	7609	14984	22593
	∑	38535	26193	64128

SAVI 59.2	Reference			
		NC	C	∑
	NC	21334	17301	38535
	C	8997	17096	26193
	∑	30331	34397	64128

PCA 68.6	Reference			
		NC	C	∑
	NC	22921	15614	38535
	C	5113	21080	26193
	∑	28034	36694	64128

TDVI 60.1	Reference			
		NC	C	∑
	NC	20014	17989	38003
	C	8204	18521	26725
	∑	28218	36510	64128

MAD 60.1	Reference			
		NC	C	∑
	NC	21259	12421	33680
	C	13772	17276	31048
	∑	28034	36694	64128

TC 65.2	Reference			
		NC	C	∑
	NC	21421	8169	29605
	C	17114	20379	37511
	∑	30331	43397	64128

PCC 87.0	Reference			
		NC	C	∑
	NC	36490	539	37029
	C	7774	19325	27089
	∑	44364	19864	64128