DETECTION OF LAND COVER CHANGES USING MULTI-TEMPORAL SATELLITE IMAGERY

Wafa Nori[1], El Nour Elsiddig[2], Irmgard Niemeyer[1]

[1] Institute for Mine-Surveying and Geodesy, TU Bergakademie Freiberg, D-09599 Freiberg, Germany
wafanori@yahoo.com, Irmgard.Niemeyer@tu-freiberg.de
[2] Faculty of Forestry, University of Khartoum, Khartoum, Sudan- elnour_elsiddig@yahoo.com

Commission WG: VII/5

KEY WORDS: Multi-temporal Data, Change Detection, Pixel-based Techniques, Land Cover Changes.

ABSTRACT:

In this study, two different change detection techniques were applied in order to assess land cover changes in El Rawashda forest, Sudan: comparison of classification and multivariate alteration detection. Firstly, two satellite imagery, acquired in 2003 by Landsat ETM+ and by ASTER in 2006, were classified into four main land cover classes namely grass land, close forest, open forest and bare land. A change matrix was created in order to map the land cover changes from 2003 to 2006. Generally, the results show a noticeable increase in area on both close forest and open forest areas with decrease in grass lands within the period 2003-2006. More than one third of grassland (36%) was converted to close forest, one fourth (24%) to open forest areas. In the three-year period, 9079 hectares of open forest, (8% of the investigation area), were transformed to close forest. Secondly, we perform linear transformation by applying the multivariate alteration detection (MAD), the MAD components were then examined to identify the quality of changes.

1. INTRODUCTION

This paper, which reviews the methods and the results of digital change detection primarily in tropical forest ecosystems, has two major components. First, we focus on change detection based on post-classification comparison, in the second part; we investigate the usefulness of a change detection procedure, the so-called multivariate alteration detection (MAD) technique. Both change detection procedures were applied to case study in tropical forest (east Sudan, El Rawashda forest reserve).

Change detection is the process of identifying differences in the state of an object or phenomenon by observing it at different times (Singh, 1989). A variety of digital change detection techniques has been developed in the past three decades. Basically, the different algorithms can be grouped into the following categories: algebra (differencing, rationing, and regression), change vector analysis, transformation (e.g. principal component analysis, multivariate alteration detection, Chi-square transformation), classification (post-classification comparison, unsupervised change detection, expectation-maximization algorithm) and hybrid methods. Reviews on the most commonly used techniques are given by i.e. Coppin et al. (2004), Lunetta and Elvidge (1998), Lu et al. (2004), Maas (1999), Singh (1989).

2. METHODOLOGY

2.1 Research site

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 semi-arid 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 (Eltayeb, 1985). 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. Elrawashda 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* a*egyptiaca* woodland. *Acacia mellifera* thornland alternates with semi-desert grassland and occurs northward from the 400-500 mm isohyets; *A. mellifera* thickets dominate the vegetation. *Acacia seyal – Balanites aegyptiaca* woodland emerges with a sharp clear ecotone south of *Acacia mellifera* thornland and with an increase in the annual rainfall to more than 500 mm. The most dominant grass of the forest is *Cymbopogon nervatus*. (Harrison and Jackson, 1958)

2.2 Satellite Data

Landsat 7 Enhanced Thematic Mapper (ETM+) data acquired on March 22, 2003 and Aster data acquired on February 26, 2006 was used for analysing an area covering Elrawashda forest. A subscene covering approximately 1.101.789 square km was extracted 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 Classification

In order to enhance the image features a PCA fusion technique was applied by using the panchromatic and multispectral bands of Landsat ETM and Aster data. Following, supervised maximum likelihood classification of PCA 2003 and 2006 scenes was conducted, classifying four classes: grassland, close forest, open forest and bare land.

2.5 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 and briefly described as follows: If multispectral images of a scene acquired at times t_1 and t_2 are represented by random vectors **X** and **Y**, which are assumed to be multivariate normally distributed, the difference D between the images is calculated by $D=a^TX - b^TY$.

Analogously to the principal component transformation, the vectors a and b are sought subject to the condition that the variance of D is maximized and subject to the constraints that var (a^TX)=var(b^TY)=1. As a consequence, the difference image D contains the maximum spread in its pixel intensities and - provided that this spread is due to real changes between t_1 and t_2 - therefore maximum change information. Determining the vectors a and b that way is a standard statistical procedure which amounts the so-called generalised eigenvalue problem. For a given number of bands N, the procedure returns N eigenvalues, N pairs of eigenvectors and N orthogonal (uncorrelated) difference images, referred to as to the MAD variates.

Since relevant changes of man-made structures will generally be uncorrelated with seasonal vegetation changes or statistic image noise, they expectedly concentrate in the higher order components (if sorted according to the increasing variance). Furthermore, the calculations involved are invariant under affine transformation of the original image data. Assuming that changes in the overall atmospheric conditions or in sensor calibrations are approximately equivalent to affine transformations of the pixel intensities, the method is insensitive to both of these effects.

The decision thresholds for the change pixels could be set by standard deviations of the mean for each MAD.

3 INVESTIGATIONS

3.1 Classification and Change Detection Accuracy

Results of supervised classification of ETM and Aster imagery were evaluated for the study area. Overall classification accuracy and Kappa Coefficient were computed to provide measures of the accuracy of the classification. The user's and producer's accuracy as well as elements of the error matrix were calculated to assess error patterns of the respective classification. For this study a total number of 151 reference samples were used.

Landsat ETM: Figure 1 shows the result of supervised classification of Landsat ETM data of the year 2003. The Kappa coefficient came up to 0.89 and the overall accuracy was 91.9%. The sample pixels for most classes showed more or less high spectral variability which facilitated difficulties in separating each class from other. Areas highlighting grass class appeared with a user's accuracy of 92.6% and producer's accuracy of 97.4%, closed forest displayed high user's accuracy of 97.4% and producer's accuracy of 90.4%. The lowest user's accuracy and producer's accuracy were obtained in open forest classes which were both 76.9%, the spectral reflectance of the open forest training data was heterogeneous. Thus the problem in separating these classes was the major source of misclassification. Bare land showed a user's accuracy and producer's accuracy of 93.3%.

Aster: Figure 2 shows the result of supervised classification of Aster data of the year 2006. The Kappa Coefficient took a value of 0.89 and overall accuracy 92.1%. In this classification, grassland, close forest and open forest showed a balanced producer's and user's accuracy and also the producer's accuracy was relatively low for open forest (88.8) and confusion may be result from the presence of low height open forest stands in the forest as well as in the class boundaries. Bare land sample data appeared to be well defined with producer's accuracy of 96.8% and also with a user's accuracy of 93.9%.

3.2 Post Classification Change Detection

A map of the major land cover types and the changes from 2003 to 2006 is shown in Figure 3.

There are several ways to quantify the land cover change results. One basic method is to tabulate the totals for each land use cover type and examine the trends between the years. Table 1 and 2 show the comparison of classification from Landsat (2003) classification and Aster (2006) classification, i.e. absolute number of pixels and relative number of pixels (in percent of all image pixels). Grassland, close forest, open forest and bare land are the four major land covers classes. In 2003, 38% of all image pixels were classified as grassland, 30% as close forest, 24% as open forest and 8% as bare land. Three years later, the distribution of land cover classes changed in the following way: 19% grassland, 39% close forest, 33% open forest, 9% bare land. The percentage of unchanged pixels in the two classification maps was 496.361 (41%).

The tables demonstrate the kind of land cover changes, namely "from-to" information, that occurred during this period, note that the pixels without change are located along the major diagonal of this matrix. If the classes defined for 2003 are taken as basis (Table 3), the changes for each class turned up as follows: More than one third of grassland (36%) was converted to close forest, one fourth (24%) to open forest areas. Only one third (36%) of the pixels classified as grassland in 2003 do have the same class membership in 2006. The class close forest implied fewer changes. Half of the class pixels (47%) remained close forest; one third (33%) was converted to open forest. For open forest, almost half of the class pixels (45%) were assigned to the same class in 2006, one third (35%) shifted to the class close forest. The class bare land includes the largest changes: One third (32%) of the class pixels were transformed to close forest, more than one third (39%) to open forest. Only one fourth of the class pixels (24%) did not change.

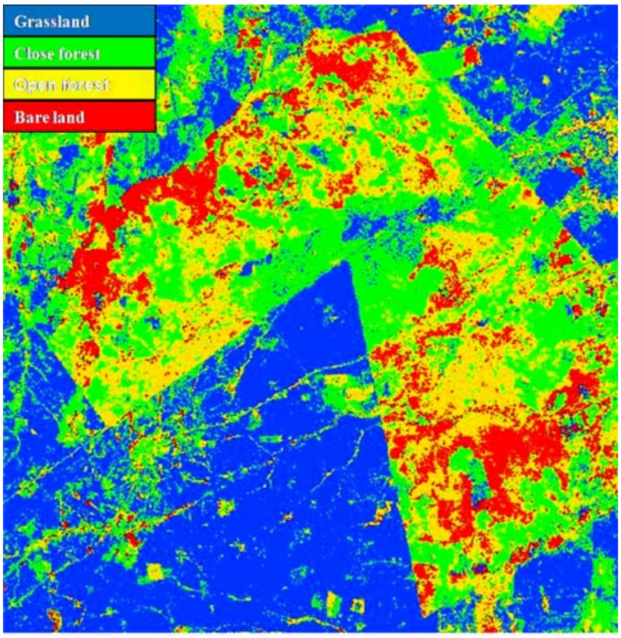

Figure 1: Supervised classification of Landsat ETM data of the year 2003

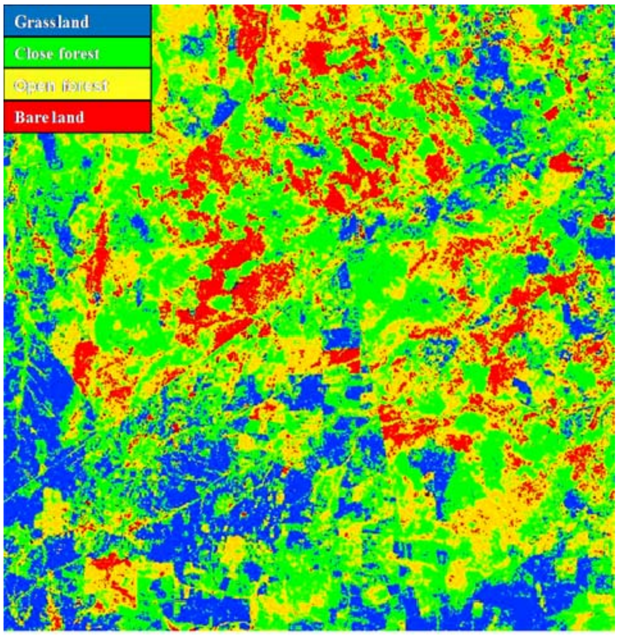

Figure 2: Supervised classification of Aster data of the year 2006

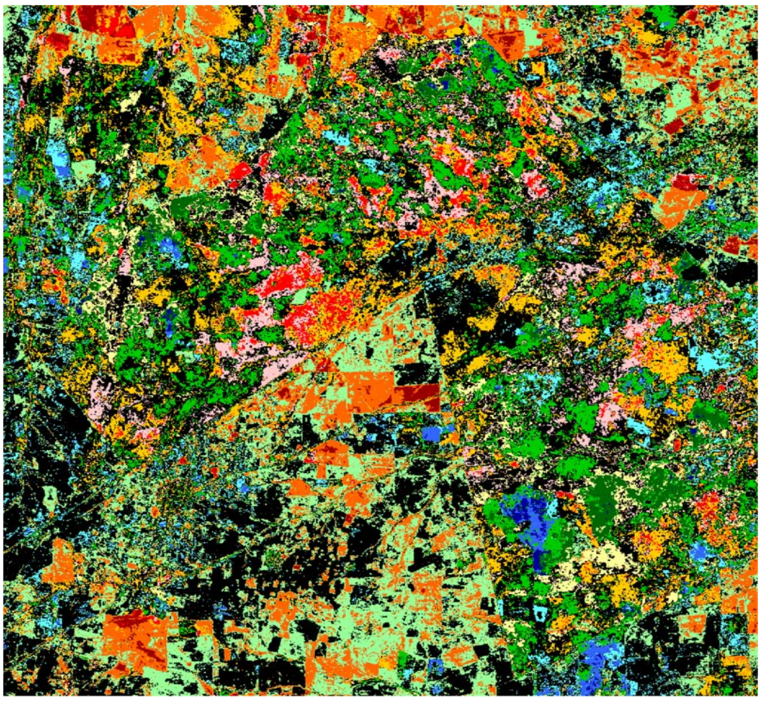

Figure 3: Change Map

		Classification 2006			
		GL	CF	OF	BL
Classification 2003	GL				
	CF				
	OF				
	BL				

3.3 Multivariate Alteration Detection (MAD)

The results of the MAD transformation (first 5 components) are shown in Figure 4. Maximum change areas are shown as white (positive changes) and black (negative changes) pixels. Gray areas indicate no change.

Correlations between the change areas of the MADs and the original bands (wavelength regions) are shown in Table 4. The correlation of MAD 3 and MAD 5 have highest correlation in all channels, with negative correlation in ETM image and positive correlation in Aster image. Therefore MAD 3 and MAD 5 are probably indicators of vegetation changes.

Actually, if we consider MAD 3 and MAD 5 (Figure 4) we can identify positive and negative changes more clearly than in other MAD components. MAD 2 shows small areas of changes in vegetation and has slightly low correlation with the original bands. MAD 1 and MAD 4 are uncorrelated with all bands in both years, MAD 1 shows image noise.

		Classification 2006				
		GL	CF	OF	BL	∑
Classification 2003	GL	168,688	170,228	111,153	16,595	466.664
	CF	44,171	173,488	120,876	28,561	367.096
	OF	14,833	100,845	129,620	43,718	289.016
	BL	4,525	32,502	39,842	24,565	101.434
	∑	232,217	477,063	401,491	113,439	

Table 1. Comparison of classifications, absolute number of pixels. (GL= grassland, CF = close forest, OF = open forest, BL = bare land)

		Classification 2006				
		GL	CF	OF	BL	∑
Classification 2003	GL	13.78	13.91	9.08	1.36	38.12
	CF	3.61	14.17	9.87	2.33	29.99
	OF	1.21	8.24	10.59	3.57	23.61
	BL	0.37	2.65	3.25	2.01	8.29
	∑	18.97	38.97	32.80	9.27	100

Table 2. Comparison of classifications, relative number of pixels in percent (basis: all image pixels).

		Classification 2006				
		GL	CF	OF	BL	∑
Classification 2003	GL	36.15	36.48	23.82	3.56	100
	CF	12.03	47.26	32.93	7.78	100
	OF	5.13	34.89	44.85	15.13	100
	BL	4.46	32.04	39.28	24.22	100

Table 3. Comparison of classifications, relative number of pixels in percent (basis: image pixels of each class in 2003).

Original bands	MAD 1	MAD 2	MAD 3	MAD 4	MAD 5
ETM 2	0.01	-0.18	-0.35	-0.19	-0.33
ETM 3	-0.13	-0.19	-0.33	-0.15	-0.36
ETM 4	-0.09	-0.2	-0.28	-0.05	-0.4
ETM 5	-0.07	-0.22	-0.14	-0.17	-0.39
ETM 7	0.06	0.56	0.23	-1.31	0.23
Aster 1	-0.05	0.04	0.61	0.14	0.23
Aster 2	0.09	0.06	0.63	0.1	0.24
Aster 3	0.06	0.04	0.61	0.02	0.3
Aster 4	0.01	0.31	0.36	0.13	0.39
Aster 6	0.02	0.16	0.24	0.22	0.38

Table 4: Correlation matrix of the MAD components with the original bands.

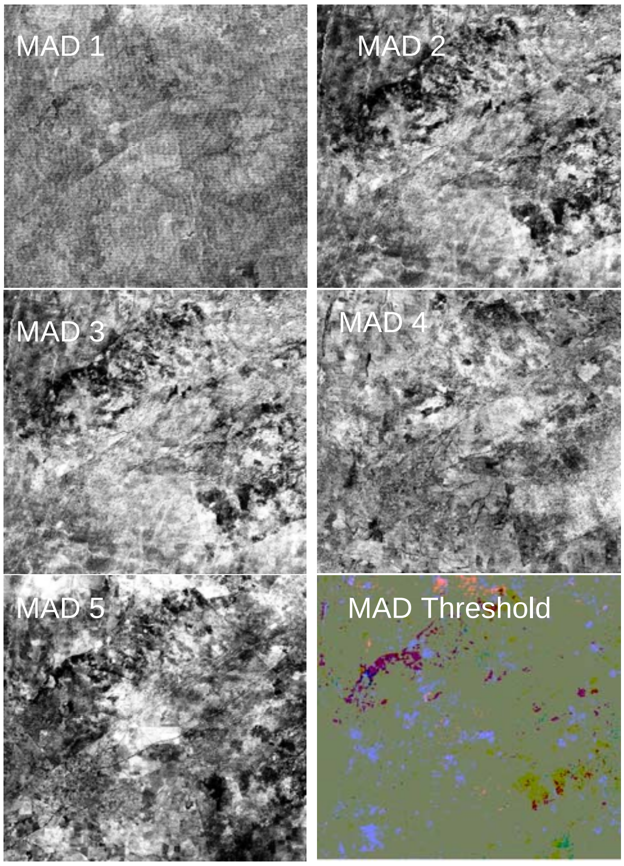

Figure 4: MAD components (1-5) and RGB view of MADs 3, 4, 5 with thresholds.

4 CONCLUSIONS

Information from satellite remote sensing can play a useful role in understanding the nature of changes in land cover/use, where they are occurring, and projecting possible or likely future changes. Such information is essential to planning for development and preserving our natural resources and environment, and is needed by urban planners and citizens.

Satellite remote sensing approaches provide a cost-effective alternative when more information is needed, but budgets are declining. Our continuing work includes adding satellite imagery from other acquisition times, before and after the dates reported here, and classifications to the temporal series.

The purpose of this study was to detect vegetation change using supervised and unsupervised change detection approaches. The applicability of maximum likelihood classification and the MAD method in multi-temporal satellite imagery change detection studies was demonstrated and an interpretation approach based on change matrix and correlation matrix was given. The study proved that maximum likelihood classification provided an accurate way to quantify, map and analyze changes over time in land cover. It has also been found the MAD transformation to be good unsupervised change detection method for satellite images and it can be applied on any spatial and/or spectral subset of the full data set.

The study concluded that remote sensing can be used to support some criteria and indicators for sustainable forest management.

Specifically, the study aimed at using optical satellite remotely sensed images (i.e. Landsat-ETM and Aster data) to detect change in vegetation in protected area The study was successfully able to detect vegetation change and concluded that the area of the grass land has decreased whereas the area of close forest and open forest has increased within the period 2003-2006. Future work with more satellite images and ground truth data may help to map the land cover changes with maximum level of accuracy.

REFERENCES

Coppin, P. Jonckheere,I.Nackaerts, K. Muys, P and Lambin, E. 2004. Digital Change Detection in Ecosystem Monitoring. A Review, *International Journal of Remote Sensing* 25(9), pp. 1565-1596.

Eltayeb, G. E. (ed.) 1985. Environmental management in the Sudan: Gedaref district study area. Institute of Environmental Studies, University of Khartoum, Sudan.

Harrison, M. N. & Jackson, J. K. 1958. Ecological classification of the vegetation of the Sudan. *Forest Bulletin* No. 2. Ministry of Agriculture, Khartoum.

Lu, D. Mausel, P. Brondizio, E and Moran, E. 2004.Change Detection Techniques, *International Journal of Remote Sensing* 25(12),pp. 2365-2407.

Lunetta, R.S and. Elvidge, C.D. 1998. *Remote Sensing Change Detection. Environmental Monitoring Methods and Applications.* Taylor & Francis, London.

Mas, J. F. 1999. Monitoring land-cover changes: a comparison of change detection techniques, *International Journal of Remote Sensing* 20(1), pp.139-152.

Nielsen, A. Conradsen, K. Simpson, J, 1998 Multivariate Alteration Detection (MAD) and MAF Postprocessing in Multispectral, Bitemporal Image Data: New Approaches to Change Detection Studies, *Remote Sensing of Environment* 64, pp. 1-19.

Singh, A. 1989. Digital change detection techniques using remotely-sensed data. *Int. J. Remote Sens.*, 10(6), pp.989-100.