Environ Monit Assess (2008) 145:227–235
DOI 10.1007/s10661-007-0031-6

Change vector analysis to categorise land cover change processes using the tasselled cap as biophysical indicator

Description: Implementing Landsat TM and ETM to detect land cover and land use changes in the mount Cameroon region using the CVA technique with the tasselled cap as biophysical indicator

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Received: 22 March 2007 / Accepted: 30 October 2007 / Published online: 12 January 2008

Abstract The continuous extraction of wood and the conversion of forest to small- and large-scale agricultural parcels is rapidly changing the land cover of the mount Cameroon region. The changes occur at varying spatial scales most often not more than 2ha for the small-scale subsistence farms and above 10ha for the extensive agricultural plantations of cocoa and palm. Given the importance of land use and land cover data in conservation planning, accurate and efficient techniques to provide up-to-date change information are required. A number of techniques for realising the detection of land cover dynamics using remotely sensed imagery have been formulated, tested and assessed with the results varying with respect to the change scenario under investigation, the information required and the imagery applied. In this study the Change Vector Analysis (CVA) technique was implemented on multitemporal multispectral Landsat data from the Thematic Mapper (TM) and Enhanced Thematic Mapper (ETM) sensors to monitor the dynamics of forest change in the mount Cameroon region. CVA was applied to multi-temporal data to compare the differences in the time-trajectory of the tasseled cap greenness and brightness for two successive time periods – 1987 and 2002. The tasseled cap was selected as biophysical indicator because it optimises the data viewing capabilities of vegetation, representing the basic types of land cover – vegetation, soil and water. Classes were created arbitrarily to predict the technique‘s potential in monitoring forest cover changes in the mount Cameroon region. The efficiency of the technique could not be fully assessed due to the inavailability of sufficient ground truth data. Assessment was based on the establishment of an error matrix of change versus no-change. The overall accuracy was 70%. The technique nevertheless demonstrated immense potentials in monitoring forest cover change dynamics especially when complemented with field studies.

Keywords Change vector analysis · Tassled cap · Mount Cameroon · Forest cover change · Deforestation · Agriculture extension · Wood extraction

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Introduction

Agricultural expansion (that is, the conversion of forest to large scale agricultural plantations and/or smallholder food crop farms), and wood exploitation (logging or fuelwood extraction) have been identified as the most dominant causes of deforestation in

Cameroon. Smallholder agriculture alone is allegedly responsible for 85–95% of deforestation in Cameroon (Essama Nssah and Gokowski 2000). On the other hand, Van Dorp (1995) reports that Cameroon has the highest percentage of forest exploited for logging of any African nation with large rain forest. Commercial logging plays a primordial role in wood extraction and small-holder farm establishments as it creates roads in formerly inaccessible areas. Except for the case of large scale agricultural establishments, which leads to the conversion of large forest areas, logging and fuelwood extraction are very selective while smallholder agricultural plantations are established in the midst of lowland forest trees, making it difficult to monitor these activities using optical remote sensing imagery. Various multi-spectral data sets and tools are now available for mapping forest cover and forest cover changes. Similarly, algorithms for automatic derivation of forest cover change information from multi-spectral data have advanced in robustness. An array of techniques is available to detect land cover changes from multi-temporal remote sensing data sets. They include methods that use the original images (differencing, ratioing), methods that use mathematical transformations of the original images (principal component analysis [PCA] and Normalised Difference Vegetation Index [NDVI]), and methods that create thematic maps and identify changes from the different thematic classifications through time, and combinations of these techniques. A detailed review of change detection techniques as well as comparative studies can be obtained from: Jensen (1996), Singh (1989), Deer (1995), Coppin and Bauer (1996), and Coppin et al. (2004). Most change detection studies in the tropics have been implemented using conventional post classification comparison or image differencing approaches. These techniques have proven to be efficient in depicting changes in land cover categories (from one land cover category to another) but the detection of changes within land cover categories leaves much to be desired. This paper reviews the implementation of the change vector analysis in monitoring changes within land cover classes as well as changes from one land cover category to another.

Materials and methods

This study was carried out using a bi-temporal series of Landsat images, 1987 and 2002. The images were processed using SILVICS™ and ERDAS Imagine 8.6™ software.

Study area

The mount Cameroon is located in the southwest of Cameroon bordering the Atlantic ocean (Fig. 1). The test area for this study is approximately 5,000ha and is located on the west slope of the mountain. It comprises four small, sparsely populated village settlements with the predominant activity being small-holder and large scale agriculture. The small-holder agricultural farms are basically of food crops: yams, cassava, cocoyams, plantains and bananas; while the large scale agricultural projects consists primarily of oil palm and cocoa plantations. This site was selected due to landscape disturbances occurring at various scales and rates. Deforestation and degradation are occurring in the surrounding area due to fuel wood extraction, illegal wood exploitation and agricultural expansion (food crop and plantation agriculture).

Data

Landsat images of the mount Cameroon corresponding to path 187 and row 057 from two different time periods were analysed in this study. The images were acquired in March 1987 and December 2002 respectively. A digital elevation raster was calculated prior to digitising contour lines from the topographic map of the region. (TIN interpolation to 30m GRID cells sizes). The digital elevation raster was resampled using the nearest neighbour polynomial to 30m to match the resolution of the ETM image. The 28.5m TM band was also resampled to 30m.

Image preprocessing

The images were geometrically corrected and topographically normalised to carter for variations in reflection due to sun angle and topography. The C-Factor non-Lambertian method, which is based on using a Digital Elevation Model (DEM) of the same resolution as the image to be corrected, was used to model illumination conditions (McCormick 1999).

Fig. 1 Location of the mount Cameroon

Modified change vector analysis

Multi-spectral remote sensing data can be represented as coordinates of a vector in multidimensional space, that is many axes or dimensions as there are spectral components (bands) associated with the pixel. A particular pixel in an image is represented by a point in such a space.

A change vector can be described by a magnitude (vector length) of change from date 1 to date 2 (Jensen 1996) and an angle of change (vector direction). If a pixel's grey-level values in two images on dates t1, t2 are given by $G = [g_1, g_2, g_3, \ldots\ldots g_n]^T$ and $H = [h_1, h_2, h_3 \ldots h_n]^T$, respectively, and n is the number of bands, a change vector is defined as shown in Eq. 1.

$$\Delta G = H - G = \begin{matrix} h_1 - g_1 \\ h_2 - g_2 \\ h_3 - g_3 \\ \ldots\ldots\ldots \\ h_n - g_n \end{matrix} \tag{1}$$

where ΔG includes all the change information between the two dates for a given pixel, and the change magnitude //ΔG// is computed as the Euclidean distance in multidimensional space based on the Pythagorean theorem (Eq. 2):

$$//\Delta G// = \sqrt{(h_1 - g_1)^2 + (h_2 - g_2)^2 + \ldots.(h_n - g_n)^2} \tag{2}$$

When the CVA is applied to multi-temporal data, it compares the differences in the time-trajectory of a biophysical indicator for successive time periods (Lambin and Strahler 1994). In this study CVA was applied using the tassled cap as biophysical parameter. The tassled cap transformation rotates the Landsat data such that 95% or more of the total variability is expressed in the first two bands: brightness and greenness (Lillesand and Kiefer 2000). Brightness is defined in the direction of the principal variation in soil reflectance and greenness is strongly related to the amount of green vegetation present in the scene.

Overview of procedure

First, tassled caps were calculated from bands 1,2,3,4,5,and 7 of the 1987 and 2002 images respectively. Using the first two bands of the tassled cap images, brightness and greeness, difference images were determined for the interval. Next, the magnitude and direction of the difference images were calculated.

Magnitude was calculated from the difference images as indicated in Eq. 3:

$$|\Delta G| = \sqrt{(\text{brightness diff.})^2 + (\text{greenness diff.})^2} \tag{3}$$

Change magnitude is measured as the Euclidean distance or length of the change vector from a pixel measurement at time 1 to the corresponding pixel measurement at time 2 (Kuzera et al. 2005). Thresholds were determined for the magnitude image to separate change from no-change pixels. Conventionally, the threshold of the change magnitude is empirically determined. After examining the histogram and statistical values of the magnitude image, three categories were arbitrarily assigned to represent the intensity (amount) of the change that occurred between the time periods. The assigned categories were low (30 to 66), medium (66 to 102) and high (102 to 126). Two standard deviations from the mean were considered as threshold. Values below 30 and above 126 were considered as outliers. These ranges indicate the length of the change vector in measurement space.

Finally, the directions were determined as in Eqs. 4 and 5:

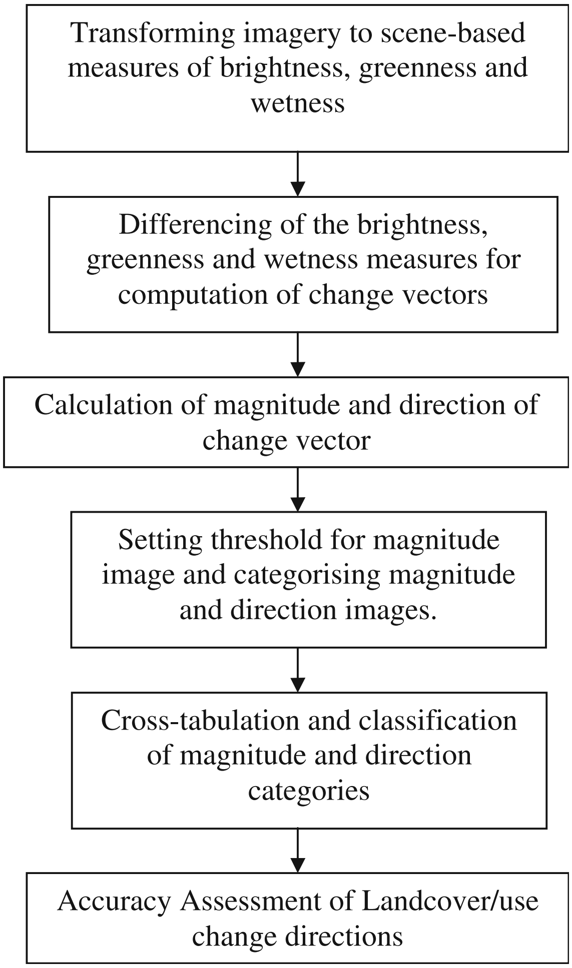
$$Cos\theta 1 = \text{brightness diff./magnitude} \tag{4}$$

$$Cos\theta 2 = \text{brightness diff./magnitude} \tag{5}$$

The direction images facilitated the discrimination of the change types. Change direction is measured as the angle of the change vector from pixel measurement at t1 to the corresponding pixel measurement at t2. Since two bands were used in this case the resultant change direction classes are 2^2 which is 4; depending on the change directions within pixels in the brightness and greenness bands. Angles measured between 90 and 180 indicate an increase in greenness and a decrease in brightness. Angles measured between 270 and 360 indicate a decrease in greenness and an increase in brightness. Angles measured between 0 to 90 indicate increase in greenness and increase in brightness. 180 to 270 indicate decrease in greenness and decrease in brightness.

The change direction and magnitude values were cross-tabulated and classified into 13 categories. Three categories of regeneration (low, medium, high), three categories of regrowth (low, medium, high), three categories of forest clearing (low, medium, high) three categories of biomass loss (low, medium, high) and persistence.

Workflow of the CVA Procedure



Results

The direction of change was determined from the brightness and greenness direction images. Table 1 shows the four possible direction classes and their respective descriptions obtained from the two bands:

Table 1 Possible change direction classes from brightness and greenness components and related types of change

Classes	Brightness	Greenness	Description
Class 1	+	+	Biomass loss
Class 2	+	−	Forest clearing
Class 3	−	+	Biomass gain
Class 4	−	−	Regrowth

brightness and greenness. Figure 2 illustrates the direction changes between 1987 and 2002.

Sector 1 changes (increase in brightness and greenness) represent areas of significant loss of biomass.

Sector 2 changes (brightness increases while greenness decreases) indicate cleared forest areas.

Sector 3 changes (brightness decreases while greenness increases) show areas of increase in forest vegetation. These changes are annotated as biomass gain within this study and simply identifies areas where the amount of vegetation increased during the study period.

Sector 4 changes (decrease in brightness and greenness) represent areas of forest regrowth.

Total area of change for each category obtained by cross-tabulating and classifying the direction and magnitude images is displayed on Table 2. The relative percentages of each class with respect to the entire study area and with respect to the direction category were determined. The majority of the area has experienced some change as just 5% of the landscape is classified as persistence. 76.75% of the landscape is gaining biomass. Combining this with the 1% of forest regrowth area means that 77.75% of the study area is experiencing a positive vegetation trend. On the other hand the total percentage of biomass loss area is 21.7%. This added to the 0.5% forest clearing sums up the percentage of negative vegetation trend to 22.3% of the total landscape.

To ease interpretation of the final CVA image, the classes biomass loss and forest clearing were collated, likewise were the classes regrowth and regeneration. Figure 3 shows the study area classified into 7 categories: Regeneration (high, medium and low), forest loss (high, medium low) and persistence.

Historical reference data for the study area were either inexistent or incomplete. Consequently, the visual interpretation method reported in Cohen et al. (1998) was adapted and used to develop reference data for error matrices. Random sample points were selected from ground truth data collected in 2003 and displayed on the TM, RGB colour composite imagery of 1987. The points were then labelled as change or no change by visual interpretation and comparison. Interviews on land use history carried out during field studies were used to complement the data (“from” information). An error matrix was subsequently devel-

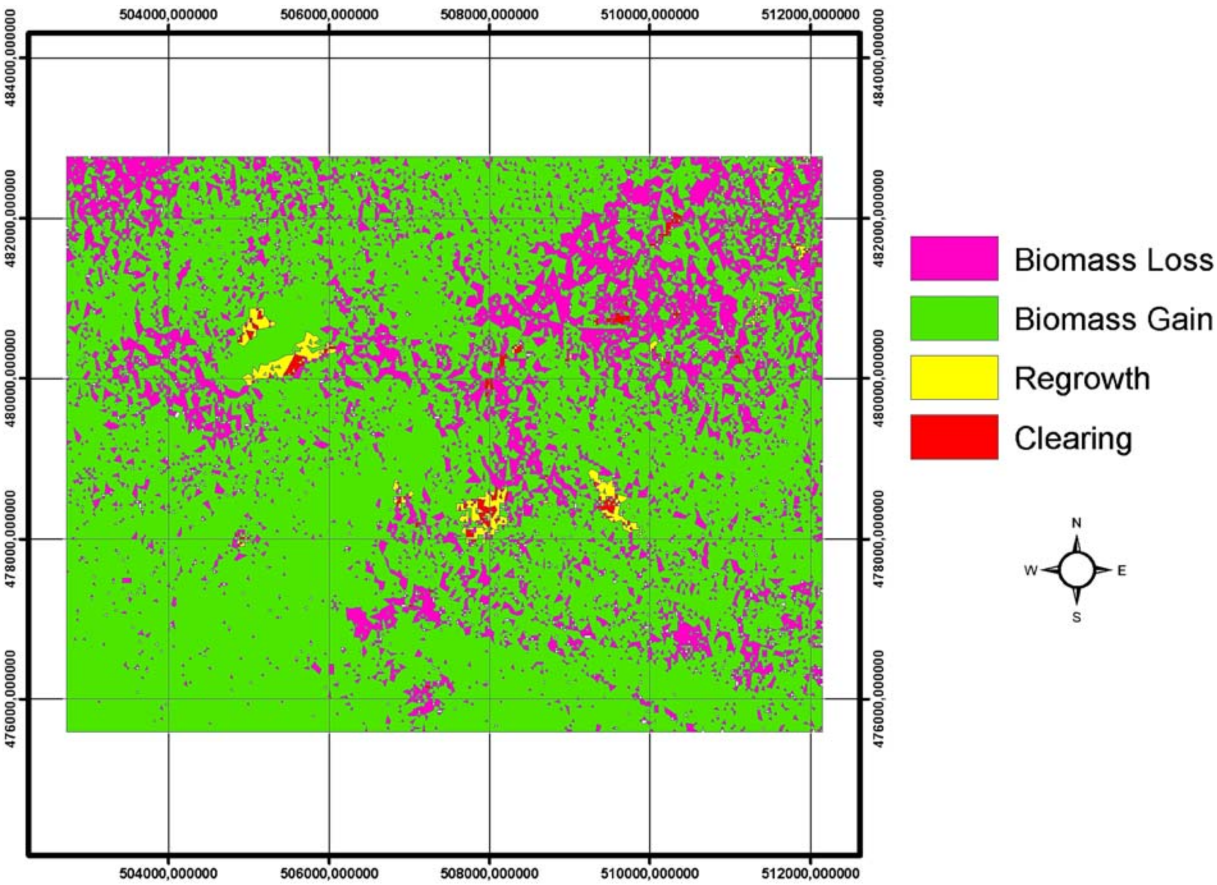


Fig. 2 CVA direction image from tassled cap brightness and greenness between 1987 and 2002 showing four classes; biomass loss, biomass gain, regrowth and forest clearing

oped and plotted against the values of change images. The overall accuracy was 70% with a Kappa Coefficient of 0.36.

Discussions

The potential of the technique in monitoring forest cover dynamics could not be fully evaluated due to inadequate field surveys. The classes were established using arbitrary threshold values that were not related to any field measurements. Field survey was carried out prior to the image analysis consequently the resultant direction and magnitude images were not validated. Validation was thus based on the creation of an error matrix of change versus no-change (that is change from one forest cover category to another). This accounted for the relatively low overall accuracy of 70% when compared to other approaches like the post classification comparison, band 4 differencing and NDVI differencing which perform better. The accuracy of the changes occurring within land cover categories, which are generally represented by the intensity maps could not be assessed. This negatively affected the users accuracy as most areas that were identified as change on the map were not reflected by the ground data (accuracy assessment dataset). The accuracy assessment data was thus bias to the technique as it was established based on changes from one land cover category to another.

Nevertheless, the majority of the clearcut areas were detected. These are mostly forest areas cleared for the establishment of agricultural plantations.

Most of the regrowth areas lie adjacent to these areas. This is principally due to the fact that the forest is cleared to be subsequently cultivated and to a lesser extent the high rate of natural regeneration in this landscape.

The biomass loss areas are either close to the villages or lie along the main road of the area. These areas are characterised by small-holder agricultural

Table 2 CVA analysis results between 1987 and 2002 classified into 13 categories of biomass loss, biomass gain, regrowth, forest clearing and persistence

	Area (in hectares)	Percent of landscape	Percent of Category
Biomass loss			
Low	587	9%	42%
Medium	703	11%	50.6%
High	99	1.6%	7%
Total	1390	21.7%	100%
Biomass gain			
Low	1314	20.5%	26.75%
Medium	2491	39%	50.7%
High	1107	17.3%	22.5%
Total	4912	76.75%	100%
Regrowth			
Low	39	0.6%	58%
Medium	26	0.4%	39%
High	1.6	0.03%	3%
Total	66	1%	100%
Forest Clearing			
Low	18	0.27%	56.3%
Medium	11	0.17%	35.4%
High	3	0.04%	8.3%
Total	32	0.5%	100%
Persistence	354	5.53%	
Total	6400		

activities, which range from 0.5 to 2 ha. These farms are established after a few dominant tree species have been felled and most often the complete under-storey. Burning sometimes precedes planting.

The biomass gain class theoretically indicates the area contained more vegetation in 2002 than it did in 1987. Practically, this can also be a conversion of the vegetation to other vegetative classes with higher

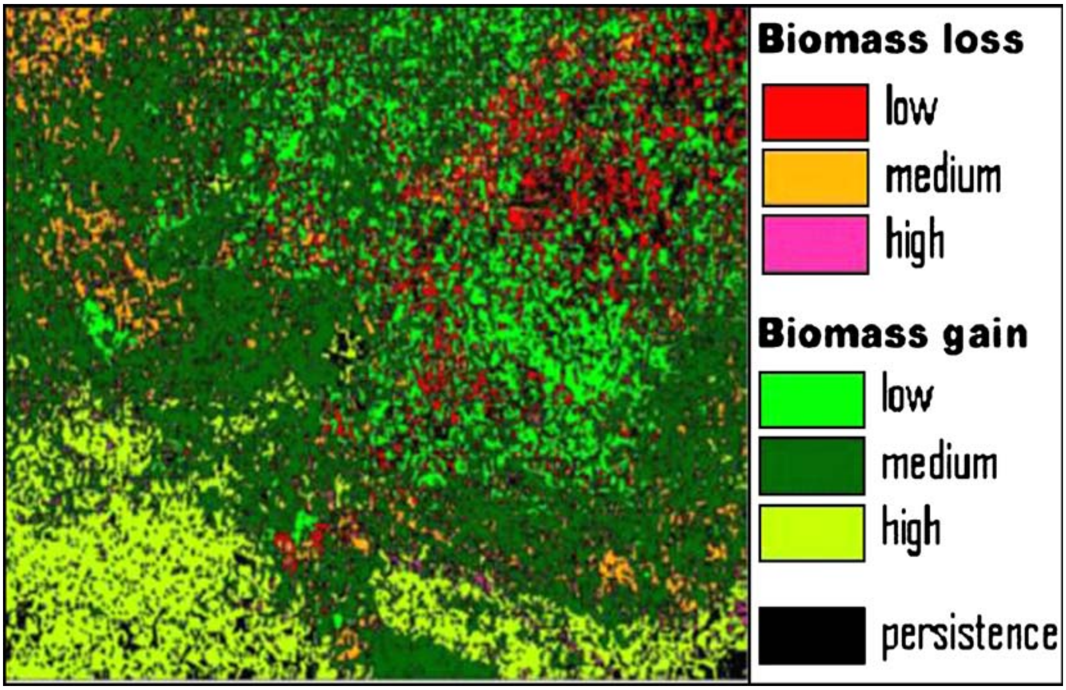


Fig. 3 CVA between 1987 and 2002 compressed in two directions with three intensity classes; low, medium and high respectively

spectral reflection and not necessarily an increase in vegetative biomass. More than 3-quarter of the study area falls in this category. This is probably due to the fact that most of the area still remain inaccessible. The poor infrastructure coupled with the low population means that the pressure on the environment is limited. Nevertheless, the establishment of large agricultural plantations of palm, cocoa and Musa species leads to the opening of new forest trails and the fragmentation of forest. These conditions are ideal for the creation of small-holder agricultural parcels and also encourage fuel wood exploitation.

Generally, the CVA approach demonstrates great potentials in monitoring tropical vegetation change. The direction images provide qualitative information, which indicate the trend of evolution of the vegetation. Sohl (1999) analysing change in United Arab Emirates reported the excellence of the CVA technique in providing rich qualitative details about the nature of change. A major advantage of this technique is its capability to analyse change concurrently in all data layers or in selected bands. Rather than employing all the bands as was the case in this study, the CVA can be applied to the near infrared and short wave infrared bands to minimize the effect of atmospheric scatterring.

A main limitation of this approach was stated by Johnson and Kasischke (1998), in that the vectors contain dynamic information and not state information. For example, the vector representing deforestation (increase in brightness and decrease in greenness) neither indicates that the change area was previously forest nor that it has changed to non-forest. Nevertheless, the direction and intensity classes enables the monitoring of changes within land cover and land use classes. A good understanding of the change processes in the area is required to improve on the interpretation of the direction and intensity maps obtained. Another reproachful aspect of the methodology is the determination of threshold values, which remains a subjective approach.

Conclusion

The CVA technique's effectiveness in detecting forest cover change was tested. This technique is fully automated and the approach employed in this study made use of all the bands of Landsat image time series. The conversion of the bands to Tassled Cap greenness and brightness reduced the dimensionality of the bands and at the same time highlighted vegetative properties of the landscape. The technique eschewed the use of training sites and land cover categorisation. Nevertheless, a priori information is needed if the CVA change image is to be interpreted correctly. Also, the technique fails to provide concise from–to information (which land use class was there before and what land use class is present afterwards). Instead it offers qualitative information concerning the direction in which the vegetation is evolving and the intensity of the change.

The technique's full extent in monitoring changes within land cover categories could not be assessed due to the absence of historic land cover change information. To exploit the full potential of the technique and simultaneously evaluate its accuracy, it would be necessary to continuously monitor the landscape and obtain precise data that would enable the assessment of changes occurring within and between forest cover classes.

The technique has great potentials in monitoring changes within and between forest cover categories. These changes are characteristic of the mount Cameroon region where small scale changes are prevalent within various forest cover categories. It is important to complement this approach with field studies to fully exploit its monitoring potentials. The technique serves as a tangible alternative in monitoring forest cover dynamics in the tropics.

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