MAPPING DEFORESTATION IN THE CONGO BASIN FOREST USING MULTI-TEMPORAL SPOT-VGT IMAGERY FROM 2000 TO 2004

Donatien Njomo

University of Yaounde I, Environmental Energy Technologies Laboratory (EETL),
PO Box 812, Yaounde, Cameroun; dnjomo(at)usa.net

ABSTRACT

Time-series of SPOT-VEGETATION S10 imagery for the African continent for the period January 2000 to December 2004 have been analysed. A region of interest has been extracted using the CROP-VGT software package for a Central African region (15°S - 15°N; 5°E - 35°E). Clouds and cloud shadows were masked using information from the associated Status Maps distributed with the S10 images. Hence, a set of cloud free annual composites was produced using the ENVI band math function, extracting the maximal Normalised Difference Vegetation Index (*NDVI*) value for 36 decadal syntheses for each year from 2000 to 2004. Subsequently, an unsupervised ISODATA classification with 11 classes was performed using annual *NDVI* composites. Finally, new vegetation maps for Central Africa were produced. An *RGB-NDVI* change detection strategy to detect and quantify major decreases or increases in green biomass - associated with forest harvest or regeneration - was developed as well and applied for the years 2000 till 2004. The *NDVI* analysis will - in the near future - be applied to study reflectance behaviour in single channels to obtain a better accuracy for our classification results. The use of the Red (B2) and Near-Infrared (B3) channels, for example, provides complementary information to make a distinction between bright soil with high reflectances in both the B3 and B2 bands and vegetation, where reflectance is low in the B2 band.

Keywords: Congo Basin forest; SPOT-VGT imagery; *RGB-NDVI* change detection; deforestation

INTRODUCTION

The Congo Basin's tropical forest, which, in 1995, covered more than 198 million ha, is the second largest contiguous rain forest in the world after that of the Amazon Basin. Between 1990 and 2000, on average, an area the size of 0.852 million hectares was cleared every year in the region (1). The Congo Basin forests span six countries: Equatorial Guinea, Cameroon, the Central African Republic, the Democratic Republic of Congo, the Republic of Congo, and Gabon.

Clearing of tropical forest, known as deforestation, involves cutting down, damaging, and burning of forest. Actually, an estimated 100 million ha of Central African forests are under logging leases (2). Logging in the tropics is often characterised by a cut-and-remove attitude in logging companies. The removal of high volumes per hectare has led to an aggravation of degradation of dipterocarp forests. In extreme cases, these practices even cause death and destruction, especially where clearcutting has been applied. Logging roads are among the most important means of access facilitating deforestation (3). The construction of new roads opened up millions of hectares of previously inaccessible forest to human settling. The globally most important actors of deforestation are the slash-and-burn farmers who live in tropical forest or at their margins. It is estimated that small farmers account for nearly 2/3 of all deforestation (4). Bringing deforestation in the tropics to a halt has become an international movement with the important objective to stop the loss of rain forest.

The actual rate of deforestation in the Congo Basin forest is difficult to determine. The initiative *Tropical Ecosystem Environment Observation by Satellite* (TREES) recently produced estimates of the deforestation rate in the humid tropical domain being 23 percent lower than those developed by FRA 2000 (The Global Forest Resources Assessment 2000 of the U.N. Food and Agriculture Organization) for the same time period and forest type (5). Accurate estimates of deforestation rates and associated locations are necessary to develop land-use and forest management policies that reflect local, national and international interests and concerns. In the Congo Basin, deforestation estimates are hampered by the lack of reliable time-sequence land use maps, the lack of varying standards for forest and non-forest classification, inadequate ground truthing of satellite imagery, and the institutional weakness of governmental forest departments in the Central Africa region.

All types of Central African tropical forest taken together cover about 2.2 million km². The Congo basin moist deciduous forest covers approximately 1.14 million km², nearly one-fifth of the world's remaining area of this type of biome. An estimated 50% of Central African forests are now under logging leases. Vegetation maps of the region have recently been produced using imagery from satellites and forest classification routines for forest mapping. Forest maps have subsequently been compared with older maps (6;5;7). Very seldomly, studies have addressed the dynamics of land-use and land-cover change in the region (8,5,9,10). The most recently published estimates of land-cover change for the 1990-2000 period for the Central African region suggest an annual rate of deforestation ranging from 0.1 (Congo and Central Africa Republic) to 0.9% (Cameroon) with an average value of 0.4% (1).

Many techniques are available to detect land-cover change with multi-temporal remote sensing data (11;12). The goal of forest change detection is to identify areas on digital images depicting change features of interest (e.g. forest clearing or land-cover / land-use change) between two or more images taken. Widely used change detection methods in land-cover / land-use change studies are based on image differencing techniques, the Normalised Difference Vegetation Index (*NDVI*) image differencing method, the principal component analysis (PCA) technique and the Red, Green, Blue *RGB-NDVI* projection method (13).

Deforestation is a major source of carbon emissions to the atmosphere. Tropical forests play an important role in the global carbon cycle and hence in the global climate (14,15). Recently published estimates, however, differ significantly for areas affected by tropical deforestation, and for the resulting flux of carbon to the atmosphere and the impact of this flux on climate (16,17,18,5,19). Estimates of the global anthropogenic deforestation flux amounting to 1.6 Gt C/yr were considered realistic in the past (20,21). A re-analysis of the spatial extent of tropical forest cover from long-term satellite time-series (19) challenges previous estimates as unrealistically high, claiming only 0.6 Gt C/yr to be more probable for the 1980s and 0.9 Gt C/yr for the 1990s. Using different sensors and methods, Achard *et al.* (5) found a value of similar magnitude (0.64 ± 0.21 Gt C/yr for 1990-1997). These large differences are not easily explained.

SPOT-VGT digital imagery, e.g. S-10 products, were acquired for the ROI previously defined in Africa and for five years (2000 to 2004) with the objective of applying a change detection algorithm to monitor and map annual variations in deforestation for the Central African forest. The specific long-term objectives of the study are:

- to produce more accurate and timely information on the location and magnitude of deforestation in the Congo Basin;
- to provide vegetation maps indicating the spatial variation of the deforestation patterns in our ROI in Central Africa and;
- to assess the seasonal and interannual variability of CO_2 fluxes between the atmosphere and different land-cover / land-use types and from the Congo Basin region as a whole.

DATASET DESCRIPTION

Region of interest

The study presented focuses on the moist tropical forest in the Congo Basin, and covers six countries: Equatorial Guinea, Cameroon, the Central African Republic, the Democratic Republic of Congo, the Republic of Congo, and Gabon (Figure 1a). Central Africa contains the largest remaining contiguous expanse of the moist tropical forest on the African continent and the second largest in the world after the Amazon forest. The Democratic Republic of Congo is by far the largest country of this sub-region, with more than 226 million hectares of land. An important characteristic of this sub-region is its zonal climate distribution inducing a gradient of ecosystems and hence biodiversity. The lowland evergreen broadleaf rain forest including swamp forests is localised for the greatest part in eastern Congo and the western part of the Democratic Republic of Congo. Semi-deciduous broadleaf forest in these areas dominates this sub-region and counts among the richest in Africa. The montane forests in Cameroon and the Democratic Republic of Congo are of lower biodiversity but often have a larger number of endemic species (22). Central Africa also possesses dry forests in the northern Central African Republic and Cameroon. The uses of these forests are multiple, including the collection of non-woody forest products; furthermore the use of wood may vary from low-impact harvesting to high-intensity commercial logging.

Figure 1a: Location of the ROI of this study.

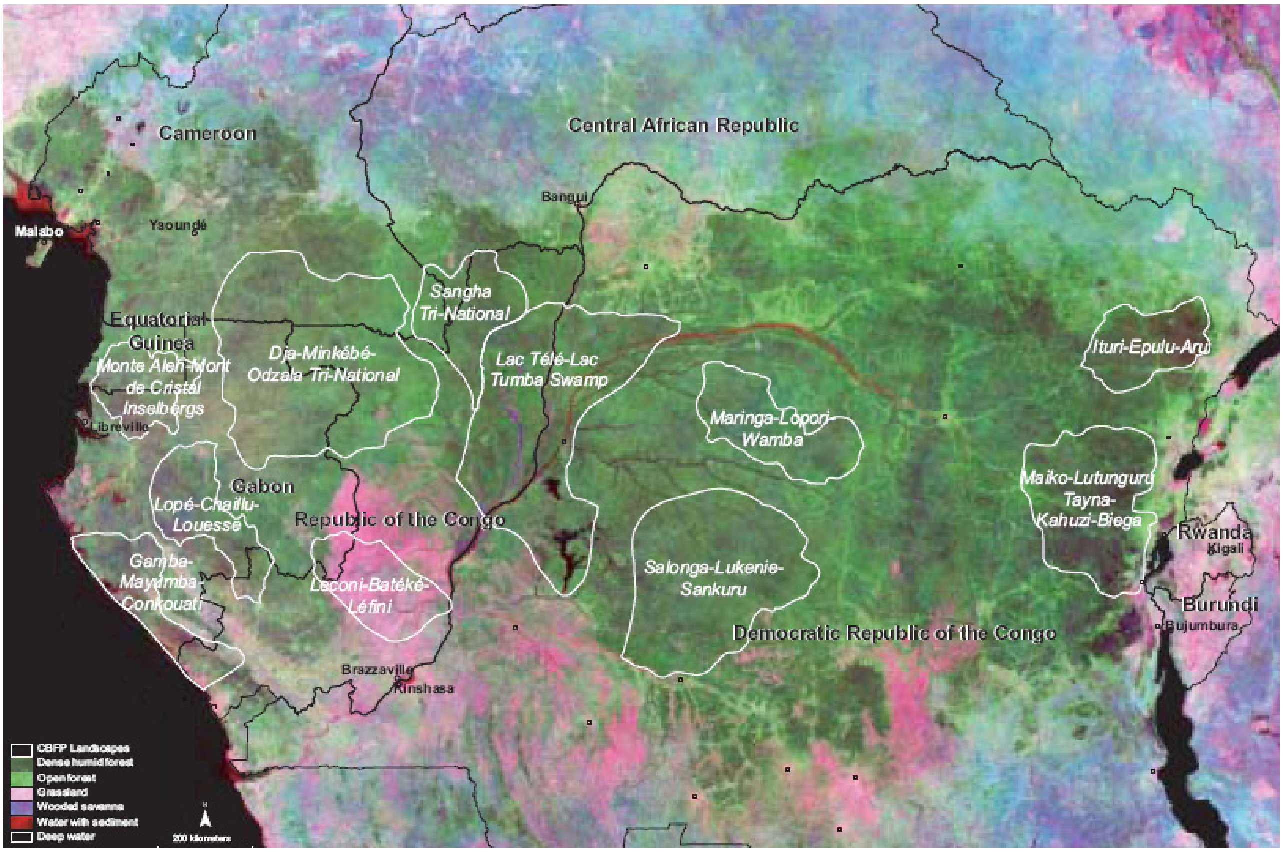


Figure 1b: A view from space of Central Africa from MODIS satellite images collected between 1999 and 2002 (courtesy: http://carpe.umd.edu/)

Forests undergo a tremendous human pressure in Central Africa. Unsustainable timber exploitation, shifting cultivation practices, and urban expansion pose an increasingly stronger threat to this globally significant forest resource; moreover, information concerning distribution, function and level of disturbance is very limited, scattered, often out of date, and sometimes erroneous. The mapping of these ecosystems is of critical importance for natural resources management, agricultural planning and biodiversity assessment. Frequent monitoring is required due to the high anthropogenic change rate and the highly dynamic phenology and sensitivity of these forests and savannas to climate variations. Despite the lack of accurate statistical material, it is clear that the forests of the Congo Basin have experienced relatively low annual rates of clearing compared to other tropical forests and to Africa as a whole (9). Nevertheless, they have been subjected to a progressive degradation, difficult to estimate. With its vast forest reserves, Central Africa is also the most important sub-region of Africa for carbon sequestration and mitigation of carbon dioxide emissions.

SPOT-VEGETATION data used

The VEGETATION instrument onboard SPOT 4 and SPOT 5 has four spectral bands B0 (Blue channel), B2 (Red channel), B3 (NIR channel) and SWIR (MIR channel) as given in Table 1 below.

Table 1: SPOT-VEGETATION main characteristics

Field of view	101°
Ground swath	2250 km
Altitude	830 km
Orbital inclination	98.72°
Instantaneous Field Of View (IFOV)	1.15 km at nadir; 1.3 km at 50° off-nadir
Absolute pixel positioning	350 m
Pixel geometric superposition	< 0.5 km
B0 (Blue channel)	0.43 – 0.47 μm
B2 (Red channel)	0.61 – 0.68 μm
B3 (Near Infrared channel)	0.78 – 0.89 μm
MIR (Short Wave Infrared channel)	1.58 – 1.75 μm

The B2, B3 and SWIR bands are well adapted for the observation of plant and crop cover, while B0 is used for atmospheric correction. The instrument can discriminate surfaces with reflectances differing just 0.001 to 0.003, meaning that subtle changes in plant cover and crops can be detected. The onboard calibration system ensures target reflectance accuracies of 3% for inter-band and multi-date measurements, and close to 5% for absolute measurements. The VEGETATION instrument is dedicated to the daily observation of terrestrial ecosystems and the biosphere, particularly to address global change and environmental issues. The principal characteristics of the sensor are optimised for global scale vegetation monitoring. Though VEGETATION has some similarity compared with AVHRR, both sensors differ due to some fundamental characteristics.

Firstly, the acquisition is based on a push-broom system which limits the off-nadir pixel-size increase. Secondly, the presence of a Short Wave Infrared channel (SWIR) permits the study of vegetation water content. Finally, the ground segment is organised to acquire, process and archive all daily data over land surfaces at the full 1×1 km² resolution.

SPOT-VEGETATION S10 product time-series were downloaded for the African continent from the VEGETATION internet site for the period January 2000 to December 2004. A subset coinciding with the ROI mentioned before was created using the CROP-VGT programme for the window 15°S to 15°N latitude and 5°E to 35°E longitude. It was also decided to mask clouds and cloud shadows in the *NDVI* bands. The information on cloudy pixels was derived from the associated status maps distributed with S10 imagery. A pixel is classified as cloudy if its radiance B0≥720 and the radiance MIR≥320. Alternatively, a pixel is considered as clear if its radiance B0<493 or the radiance MIR<180 and uncertain in all other cases. VGT-S products are compiled by stitching data strips for the region of interest acquired over a time period yielding imagery that is largely cloud-free. The stitching process involves mosaicking portions of data strips selected according to their *NDVI* value. Hence, VGT-S10 products are composites of data strips acquired over a period of 10 days. These products have a low spatial resolution (1×1 km²), but provide a very effective source for the examination of intra- and inter-annual climatic variations because of a high temporal resolution. Pre-processing of the data done by the Flemish Institute for Technological Research (VITO) consisted of atmospheric correction with SMAC (23) and compositing with ten-day intervals based on the Maximum Value Compositing (*MVC*) criterion. The *MVC* selects individual pixels with the highest *NDVI* over a ten-day period. This procedure eliminates most clouds (24). VGT-S10 products provide information for all spectral bands, e.g. B0, B2, B3, MIR, the *NDVI* and auxiliary data on image acquisition parameters.

METHODS AND RESULTS

The vegetation index *NDVI* is a very commonly used index to monitor vegetation presence and properties. The *NDVI* varies between -1.00 and 1.00 and is computed as follows:

$$NDVI = \frac{NIR - Red}{NIR + Red}$$

where *NIR* and *Red* are the reflectances measured in the near infrared and red channels, respectively. A bitscale is used to represent the *NDVI* pixel value in a range form 0 to 255 which is more convenient to be used on 8-bit gray tone displays.

The presence of dense green vegetation implies that the *NDVI* has a large bit value, due to high concentrations of chlorophyll resulting in a low reflectance in the red band as well as to high stacking of leaves. Sparse vegetation on the other hand, as in desert and semi-desert areas, implies that *NDVI* values are low due to less or even no chlorophyll and leaves at all (Figure 2). Bright and dark bare soils elicit spectral characteristics in the *Red* and *NIR* bands resulting in *NDVI* values close to the *NDVI* values of sparse vegetation and can create some confusion when classes are labelled. An advantage of *NDVI* use is that since it is a ratio, it cancels out a large proportion of signal variations due to calibration, noise, and changing irradiance conditions caused by varying sun angles, topography, clouds, shadows and atmospheric conditions.

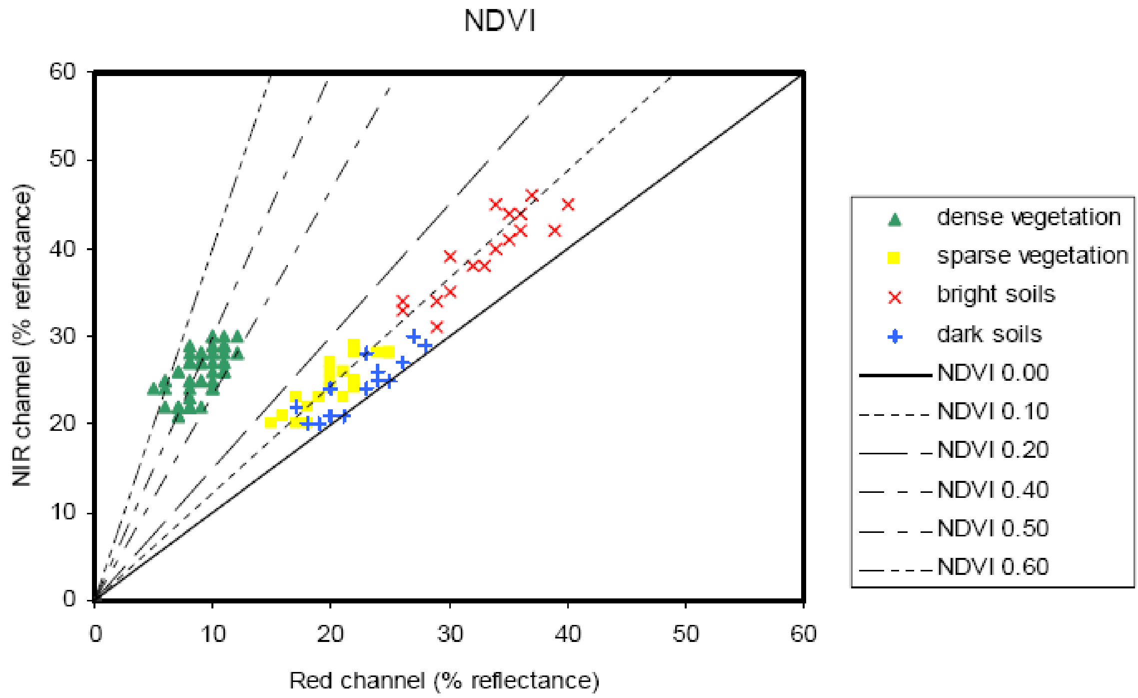


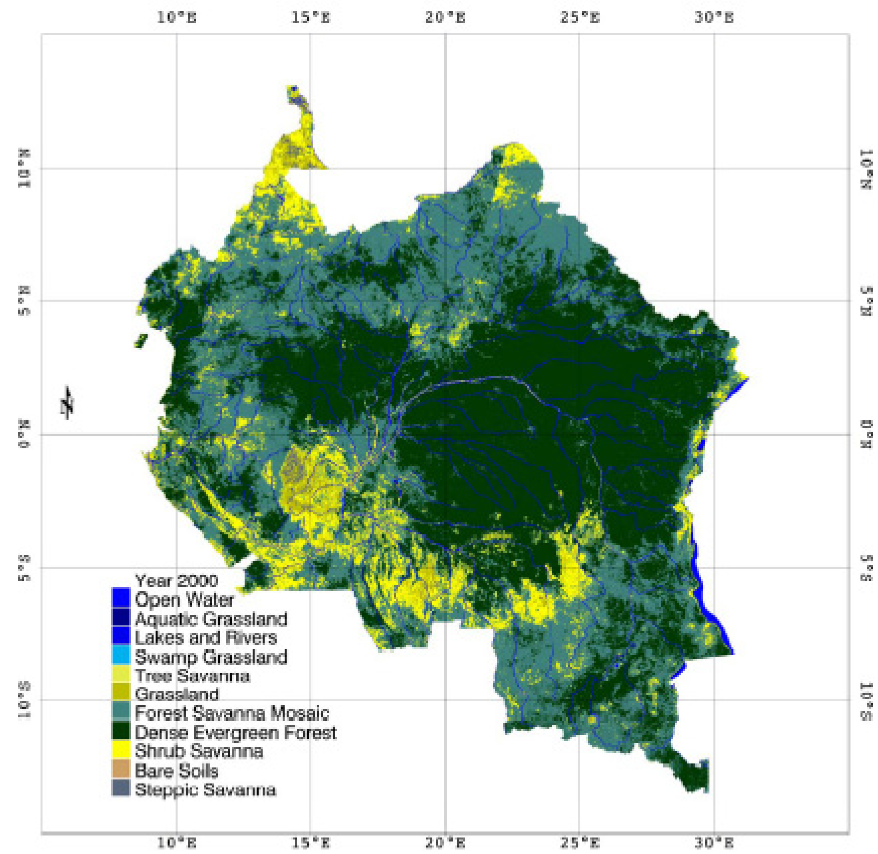
Figure 2: Scatter plot of Red and NIR channel values showing the NDVI isolines and different types of vegetation and bare soil values.

For each single image, the documentation file of CROP-VGT provides information from which ENVI image headers are built, enabling the data to be viewed in ENVI and subsequently geo-located. We used the ENVI band math function to produce annual *NDVI* composites based on the maximum *NDVI* value extracted from all 36 decadal *NDVI* syntheses for each year of the period 2000 to 2004. Because of the cloud filter initially applied to each cropped image synthesis we were able to obtain completely cloud-free annual *NDVI* composites. An unsupervised ISODATA classification with 11 classes was performed on each annual *NDVI* composite. Unsupervised classification is a multivariate method where a classifier identifies distinct spectral groupings among unknown pixels in an image and aggregates them into a specified number of cluster classes (25).

The vegetation maps shown in Figure 3 were obtained as a first result of the classification. When compared with the GLC2000 forest cover map of Mayaux *et al.* (8), these vegetation maps elicit an underestimation of forest cover in the western region of Central Africa and an overestimation for the forest cover in the eastern zone of this region. This classification error indicates the limits of the classification strategy based on the annual maximum *NDVI* composite. Probably, this is due to the effect of the greening seasons being masked by cloudiness for some decadal syntheses in the western zone of Central Africa.

Three annual *NDVI* composites for the years 2000, 2002 and 2004 were projected on a RGB axis following the *RGB-NDVI* change detection strategy of Sader *et al*. (13). The map shown in Figure 4 was obtained in this way. This change detection method incorporates multi-date *NDVI* values to detect and quantify major decreases or increases in green biomass associated with forest harvest or regeneration (26,27,28).

Clearly, high resolution data (e.g. SPOT HRV, LANDSAT ETM or ASTER) are needed to obtain more detailed imagery on the western and eastern zones of our ROI, to be able to assess the extent and intensity of land-cover changes in these regions more in detail. Land-use change estimates can then be combined with estimates of carbon sequestration and parameters related to cleared vegetation. This should enable the production of datasets enabling the calculation of carbon fluxes emitted due to deforestation.



(a)

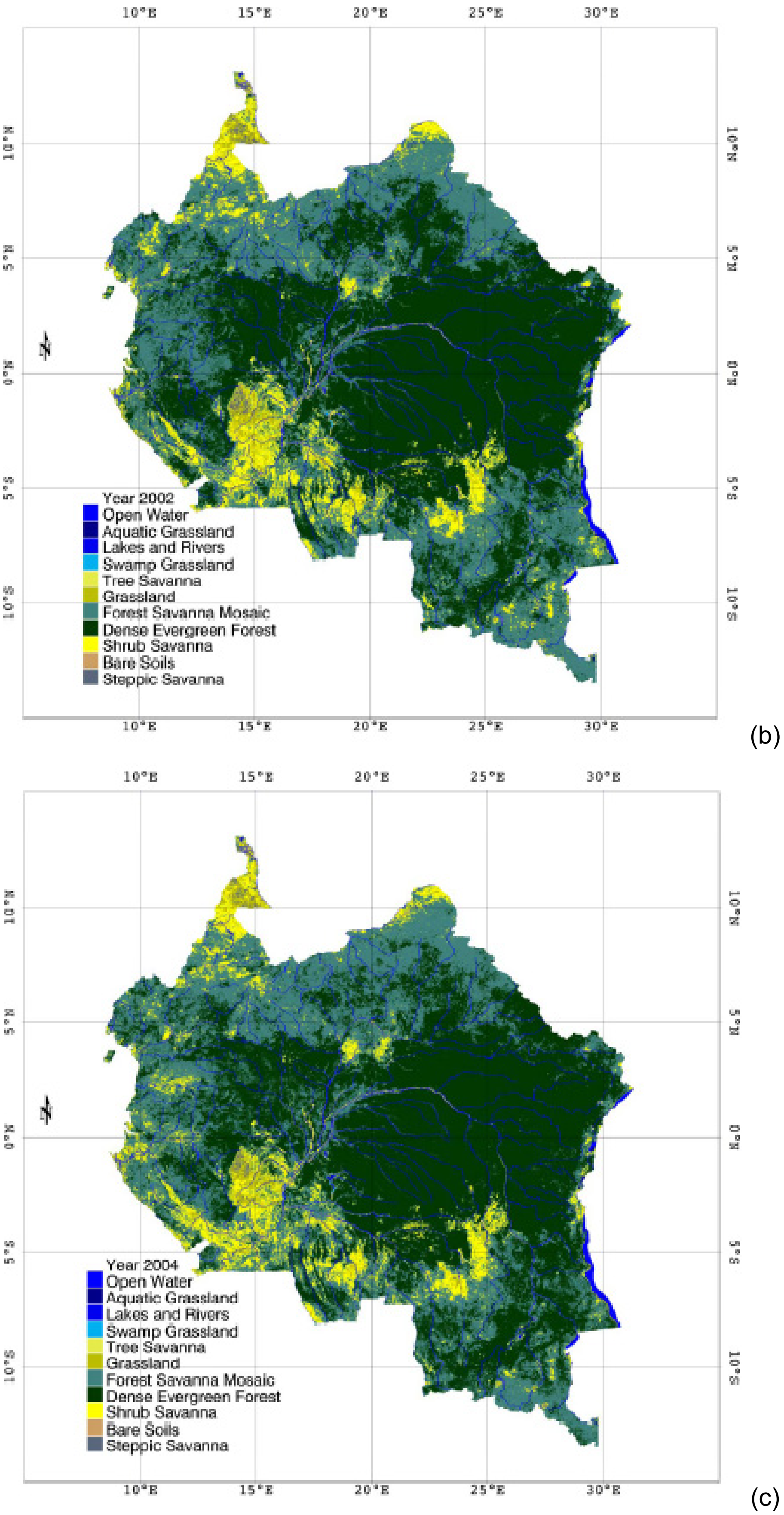


Figure 3: Vegetation maps of Central Africa for the years 2000 (a), 2002 (b), and 2004 (c).

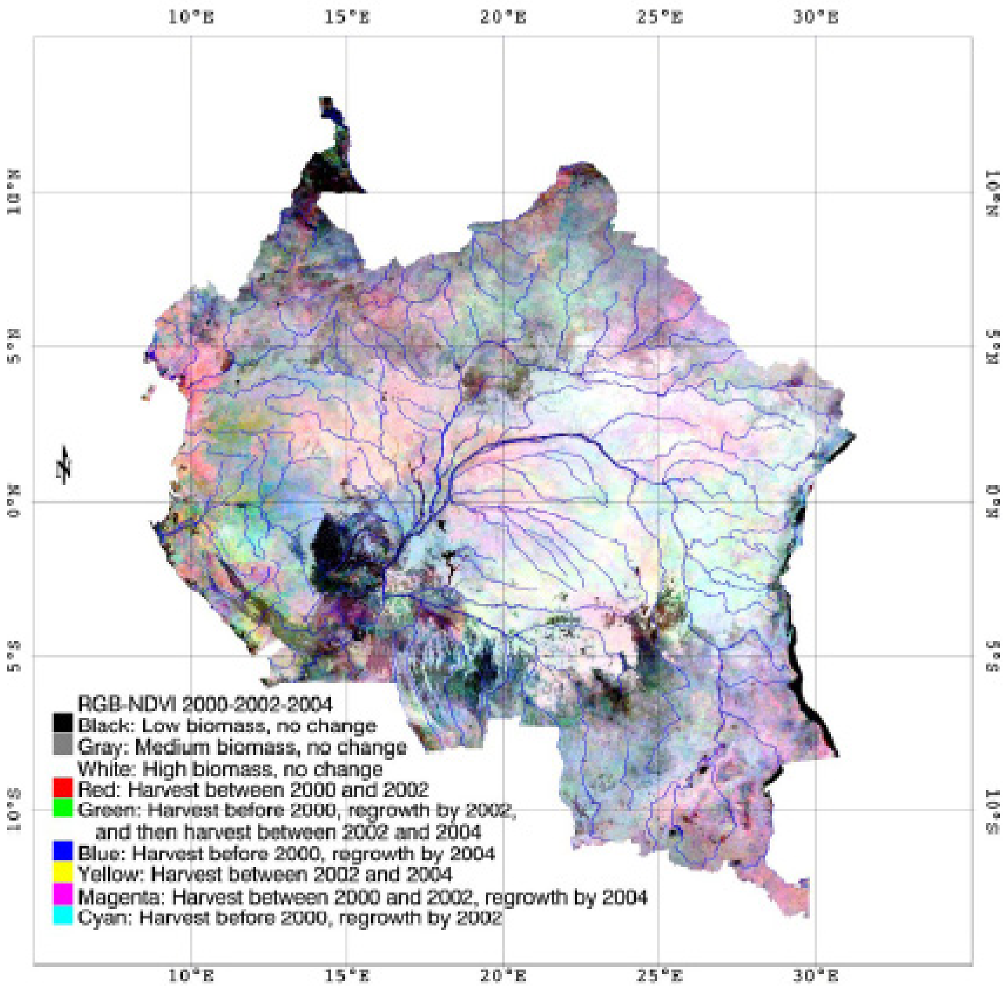


Figure 4: RGB-NDVI change detection in the Congo Basin forest for the years 2000, 2002 and 2004 with the colour legend used to depict changes in forest cover.

CONCLUSIONS

SPOT-VEGETATION *NDVI* time-series for Central Africa (15°S - 15°N ; 5°E - 35°E) covering the period January 2000 to December 2004 have been extracted from S10 products of the African continent. Clouds and cloud shadows in NDVI imagery were masked by using the information from associated Status Maps distributed with the S10 images. A set of cloud-free annual *NDVI* composites was then produced using the ENVI band math function to extract the maximum *NDVI* value from all the decadal syntheses of a year under consideration. An unsupervised ISODATA classification with 11 classes was applied for each annual *NDVI* composite. Classified vegetation maps of Central Africa were thus obtained. These vegetation maps underestimate forest cover in the western region of Central Africa and overestimate forest cover in the eastern zone of this region. This error also affected our *RGB-NDVI* change detection strategy so that we could not derive valid estimates of carbon fluxes emitted from the Congo Basin forest during the period 2000-2004. Clearly, this work needs to be pursued further, to improve the quality of our results. We plan to refine our *NDVI* analysis by analysing reflectance in single VGT channels. The use of the Red (B2) and Near-infrared (B3) channels, for example, provides complementary information to distinguish between bright soil with high reflectances in both the B3 and B2 bands and vegetation where reflectance is low in the B2 band. High resolution data (SPOT HRV, LANDSAT ETM or ASTER) are also required to zoom in on the western and eastern zones of our ROI, to assess the extent and intensity of land cover changes in these regions. The estimates of land use change will then be combined with the estimates of carbon storage and the parameters concerning the fate of cleared vegetation to produce datasets needed for the calculation of carbon fluxes emitted due to deforestation.

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