CONGO BASIN FOREST COVER CHANGE ESTIMATE FOR 1990, 2000 AND 2005 BY LANDSAT INTERPRETATION USING AN AUTOMATED OBJECT-BASED PROCESSING CHAIN

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KEY WORDS: Congo Basin, forest cover, REDD, land cover, land cover change, object-based validation, high spatial resolution

ABSTRACT:

Central Africa contains the second largest area of contiguous moist tropical forest of the world. In the framework of the Observatory of Forests in Central Africa (OFAC) and the Forest Resources Assessment (FRA-2010) led by Food and Agricultural Organization of the United Nations (FAO), each country is invited to provide an estimation of forest cover change for years 1990-2000-2005 (and later 2010). In this context, developing efficient methods to detect forest changes by processing remote sensing data is more than ever a challenging need. At the moment, only satellite images can provide enough information on processes such as deforestation at the scale of Congo basin. An automatic method has been designed to map and quantify forest change in Central Africa. 1168 subsets of 20 x 20 km of 30 m resolution Landsat or Aster are required to cover the different countries. The different steps of the method are a (1) multi-date segmentation, applied on each extracts triplet (1990-2000 and 2005), (2) an unsupervised classification and an (3) automatic pre-labeling. (4) Change is detected by a statistical object-based method. (5) The involvement of national experts is an essential part of the intepretation process. The OFAC team together with Joint Research Centre (JRC-EU) and FAO invited in Kinshasa (September 2009) 13 national experts from the 6 countries of the Congo Basin to validate the land cover mapping and change maps. National experts check, and change if needed, the pre-interpretation of each sample using an object-based validation tool developed by the JRC. This unique exercise estimates not only deforestation and reforestation but also degradation and regeneration which are particularly important in Central Africa. These results are expected to contribute to the discussion on the reduction of CO2 emissions from deforestation and forest degradation (UN-REDD).

1. INTRODUCTION

Although they covering less than 10% of the total land surface of the Earth, tropicals forests include the most biodiverse of terrestrial ecosystems (Myers *et al.*, 2000). Congo Basin hosts the second-largest contiguous block of tropical forest after the Amazon (FAO, 2009) and has been in the spotlight for several decades as one of the world's most threatened ecosystems. In spite of their strategic importance in global climate change and biodiversity richness, forests have been grappling with both historical and contemporary issues like commercial logging, clearing for subsistence agriculture, poaching for bush meat, including civil strife and influx of refugees in some of the countries in the region, as well as an upsurge in resources exploitation for reconstruction after civil wars like in the Democratic Republic of Congo (CoFCCA, 2009). Quantifying rates of humid tropical forest cover clearing is critical for many areas of earth system and sustainable science (Hansen *et al.*, 2008) and to assist policy decision making. However, it has been difficult to collect reliable data to map and monitor the deforestation of Central Africa because of the inaccessibility of its massive land area and very low in-country forest monitoring capacities (Zhang *et al.*, 2005).

The Observatory for the Forests of Central Africa, an initiative of multiple members of the Congo Basin Forests Partnership, aims to pool the knowledge and available data necessary to monitor the ecological, environmental, and social aspects of Central Africa's forests. Congo Basin is composed by six countries: Cameroon, Central African Republic (CAR), Congo, Democratic Republic of Congo (DRC), Equatorial Guinea and Gabon. Today, optical earth observations approaches are operational for forest monitoring. Furthermore, they offer a unique and valuable information source for large volume data acquisition and management and a mass volume processing in a repeatable way. In this context OFAC and FRA-2010 led by FAO, invited each country to work together to provide forest cover changes for years 1990, 2000 and 2005.

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This paper presents all the essential steps in the elaboration of forest cover changes at regional level: multi-date segmentation, automated pre-labeling, national expert validation, statistics computation and first results.

2. OBJECTIVES

Object methods have been used for change detection whether for temperate forests (Desclée *et al.*, 2006) or tropical forests (Duveiller *et al.*, 2008). Automation of the method made possible by study of Verhegghen *et al.* (this issue), opens new horizons. The paper aims to demonstrate reproducibility of figures produced by Duveiller et al. (2008) for Central Africa forests by an automated object-based method and a national expert validation. The second objective is to apply the method to 2000 – 2005 satellite imagery.

3. SELECTION AND PRE-PROCESSING IMAGERY

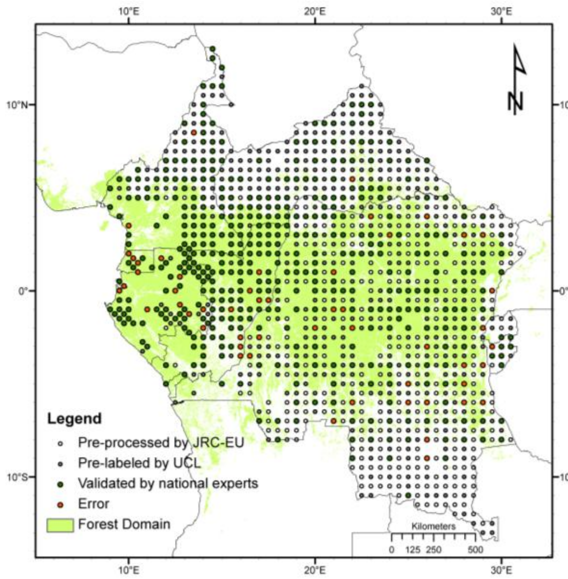

Figure 1: Data status

1168 subsets of Landsat or Aster imagery (30m resolution), 20 km x 20 km and systematically distributed on Central Africa have been extracted (Figure 1). For every sample site, two (pair) or three (triplet) co-registered Landsat or Aster imagery were available. Each pair is composed by a high resolution Landsat TM imagery acquired around 1990 and by a Landsat ETM+ acquired around 2000. Each triplet is composed by a high resolution Landsat TM imagery acquired around 1990, by a Landsat ETM+ acquired around 2000 and by a Landsat ETM+ or Aster imagery acquired around 2005. The grid system selected for the systematic sampling is a rectilinear grid based on 0.5° degrees of geographical latitude and longitude. Due to the lack of data on cloudy regions, Equatorial Guinea and Gabon have been over-sampled every 0.25°. Five important steps have been realized: (1) imagery selection (visual assessment), (2) multi-temporal image registration, (3) data calibration, (4) clouds and shadow masking and (5) haze correction.

4. OPERATIONAL STUDY

Based on recent studies (Desclée *et al.*, 2006; Duveiller *et al.*, 2008; Verhegghen *et al.*, this issue) we have developed an automated object-based pre-interpretation to map and quantify changes in forests of Central Africa.

4.1 Multi-date segmentation

Following method proposed by Desclée *et al.* (2006), we used a multi-date segmentation for object delineation. This method, based on multi-resolution segmentation (Baatz & Schäpe, 2000), partitions multi-year image into homogeneous regions. These regions regroups pixel which are spectrally homogeneous and have a similar land cover change trajectories. Multi-date segmentation using bands red, near-infrared (NIR), short wavelength infrared (SWIR) (5) and SWIR (7) has been applied to each pair or triplet of satellite images at two different levels. The two levels of segmentation have been implemented making sure that the smaller level is included in the largest one. Spectral bands all have the same weight. Thanks to a loop implemented on the scale parameter in the rule set, smaller level contains 95% of objects which have a minimum mapping unit (MMU) of 1 ha. This level is used for the automated pre-labeling and the interactive interpretation by experts. As the coarser level (95% of objects have a MMU of 5 ha) is used for change processes and statistics computation. To hone objects delineation and to avoid heterogeneous polygons, a spectral difference segmentation followed by four consecutive multi-resolution segmentations have been applied.

4.2 Automatic pre-labelling and change detection

Objects (1 ha MMU) delineated by the segmentation step are classified in 20 clusters by an unsupervised classification (k-means classification). Classification is performed independently on each image of the pair or the triplet.

Based on a reference land cover map (i.e. Africover or Globcover), objects occupied by more than 95 % of forest land cover are selected. In order to select forest training set, objects that didn't prove a spectral signature typical of forests are eliminated by iterative trimming on mean (within objects) of band 3, 4, 5 and standard deviation of band 4 (confidence level of 0.99). Trimming is defined as the removal of extreme values that behave like outliers (Desclée *et al.*, 2006). Based on three spectral bands (red, NIR, SWIR), the Mahalanobis distance is calculated between forest training set and other objects. Object with a signature within the confidence interval (0.95) are classified as tree cover. A cluster occupied by more than 70% of forest object is classified as tree cover. Other clusters are classified as non forest. Among these, four classes are differentiated: water, cloud/shadow, shrub cover and other land cover. The two first are computed with spectral signature in E-Cognition software. The shrub label is computed by extracting information from a reference map and adapted through decision rules (mean object size and Mahalanobis distance).

The resulting land cover legend is the following: (1) tree cover (the canopy density of the tree layer should be at least 10% and tree height 5 m or more), (2) shrub cover (any woody vegetation layer of less than 5 m height), (3) other vegetation cover (land cover other than tree or shrub cover), (4) water, (5) cloud and shadow and finally (6) no data.

The automated change detection is based on an object method over two-time interval: 1990-2000 and 2000-2005. Under the forest mask, which is the result of the union of forest classification of both dates, the reflectance difference is computed. The trimming procedure highlights objects considered as outliers with a confidence level 1-α equal to 0.99.

4.3 Participative approach and expert validation

Involvement of national experts is an essential part of the process. In order to enhanced capacity building in the six countries of the Congo Basin for monitoring, assessing and reporting on forests and land use changes, the OFAC team together with FAO and JRC-EU invited in Kinshasa (DRC) 13 national experts with profound knowledge on regional context.

The workshop participants had to validate the automatic pre-interpretation land cover mapping and the change detection. Thanks to an object-based validation tool developed by the JRC-EU, two validation steps were proposed. At first, national experts had to check and recode (if needed) the label assigned to each cluster by the automated labeling. This step had to be done independently for the two or three dates (year 1990, year 2000 and year 2005). Secondly, they had to check objects highlighted as change between 1990 and 2000 and between 2000 and 2005 by verifying if change was marked or not in a label difference and vice versa. 897 samples (two or three dates) were pre-labeled by the automated processing and available for the national experts (Figure 1). 443 samples have been validated by national experts id est 4.8 samples sites a day by expert. Few extracts have been validated in some areas (south of DRC, north-west of CAR) due to the complexity of the landscape and lack of time.

4.4 Statistics computation

This last steps leads to the final assignment of land cover labels. The land cover information of small objects (MMU of 1 ha) is aggregated to coarser object (MMU of 5 ha) using decision rules taking into account the proportion of the different land cover classes. This step creates two additional vegetation classes: (1) tree cover Mosaic High (the ratio of tree cover area within the object is between 40 and 70%), (2) tree cover Mosaic Low (the ratio of tree cover area within the object is between 10 and 40%). These classes will be used to define four forest cover dynamics: (1) deforestation, (2) reforestation, (3) degradation and (4) regeneration (Table 1). Deforestation is the sum of three distinct processes. The conversion of tree cover (TC) to other vegetation cover (NTC) or water, the conversion of tree cover mosaic high (MH) to NTC or water and the conversion of tree cover mosaic low (ML) to NTC or water.

Land cover class for the oldest image	Forest cover change processes	Land cover class for the latest image	Weight
TC	Deforestation 1	NTC or Water	1
MH	Deforestation 2	NTC or Water	0.55
ML	Deforestation 3	NTC or Water	0.25
TC	Degradation 1	ML	0.75
TC	Degradation 2	MH	0.45
MH	Degradation 3	ML	0.30
NTC or Water	Reforestation 1	TC	1
NTC or Water	Reforestation 2	MH	0.55
NTC or Water	Reforestation 3	ML	0.25
ML	Regeneration 1	TC	0.75
MH	Regeneration 2	TC	0.45
ML	Regeneration 3	MH	0.30

Table 1 : Forest cover dynamics

In order to reflect actual loss of forest area, weights are given to each process according to the forest cover portion in polygons. Reforestation is the inverse process of deforestation. Degradation is the sum of three processes. The conversion of TC to MH, the conversion of TC to ML and the conversion of MH to ML. Each process receives a specific weight depending on loss of forest cover area. Regeneration is the counterpart of degradation. Degradation and regeneration are based solely on significant detected change in forest cover and not in qualitative terms (i.e. change in species composition).

For each sample site, the change transition matrix is calculated for the two time interval 1990-2000 and 2000-2005 (if available).

	1990 - 2000			2000 - 2005		
Country	*n*	Annual Gross deforestation	Annual Gross reforestation	*n*	Annual Gross deforestation	Annual Gross reforestation
Cameroon	*39*	0. 16% ± 0.08%	0.07% ± 0.03%	*10*	0.21% ± 0.21%	0.11% ± 0.11%
Congo	*51*	0.09% ± 0.04%	0.06% ± 0.04%	*33*	0.30% ± 0.20%	0.16% ± 0.13%
Gabon	*47*	0.13% ± 0.07 %	0.06% ± 0.03%	*7*	0.18% ± 0.18 %	0.10% ± 0.13%
Equat. Guinea	*2*	0.10% ± 0.09 %	0.02% ± 0.04%	*0*		
CAR	*11*	0.19% ± 0.12 %	0.11% ± 0.09%	*9*	0.27% ± 0.11 %	0.23% ± 0.13%
DRC	*222*	0.20% ± 0.04 %	0.09% ± 0.03%	*161*	0.56% ± 0.16%	0.23% ± 0.08%
Central Africa	*372*	0.17% ± 0.03 %	0.08% ± 0.02%	*220*	0.48% ± 0.12 %	0.21% ± 0.06%

Table 2 : PRELIMINARY RESULTS - National figures for annual gross deforestation and annual gross reforestation between 1990 and 2000 and between 2000 and 2005. The number of processed samples (n), the change rates and their confidence interval are given for each country, each time interval and each process.

	1990 - 2000			2000 - 2005		
Country	*n*	Annual Gross degradation	Annual Gross regeneration	*n*	Annual Gross degradation	Annual Gross regeneration
Cameroon	*39*	0. 04% ± 0.03%	0.03% ± 0.01%	*10*	0.25% ± 0.23%	0.05% ± 0.05%
Congo	*51*	0.05% ± 0.03%	0.03% ± 0.02%	*33*	0.15% ± 0.09%	0.08% ± 0.06%
Gabon	*47*	0.03% ± 0.02 %	0.02% ± 0.01%	*7*	0.03% ± 0.04 %	0.10% ± 0.19%
Equat. Guinea	*2*	0.02% ± 0.04 %	0.01% ± 0.02%	*0*		
CAR	*11*	0.06% ± 0.03 %	0.04% ± 0.02%	*9*	0.14% ± 0.07 %	0.14% ± 0.08%
DRC	*222*	0.09% ± 0.02 %	0.03% ± 0.01%	*161*	0.30% ± 0.09%	0.11% ± 0.03%
Central Africa	*372*	0.07% ± 0.01 %	0.03% ± 0.01%	*220*	0.26% ± 0.07 %	0.10% ± 0.02%

Table 3: PRELIMINARY RESULTS - National figures for annual gross degradation and annual gross regeneration between 1990 and 2000 and between 2000 and 2005. The number of processed samples (n), the change rates and their confidence interval are given for each country, each time interval and each process.

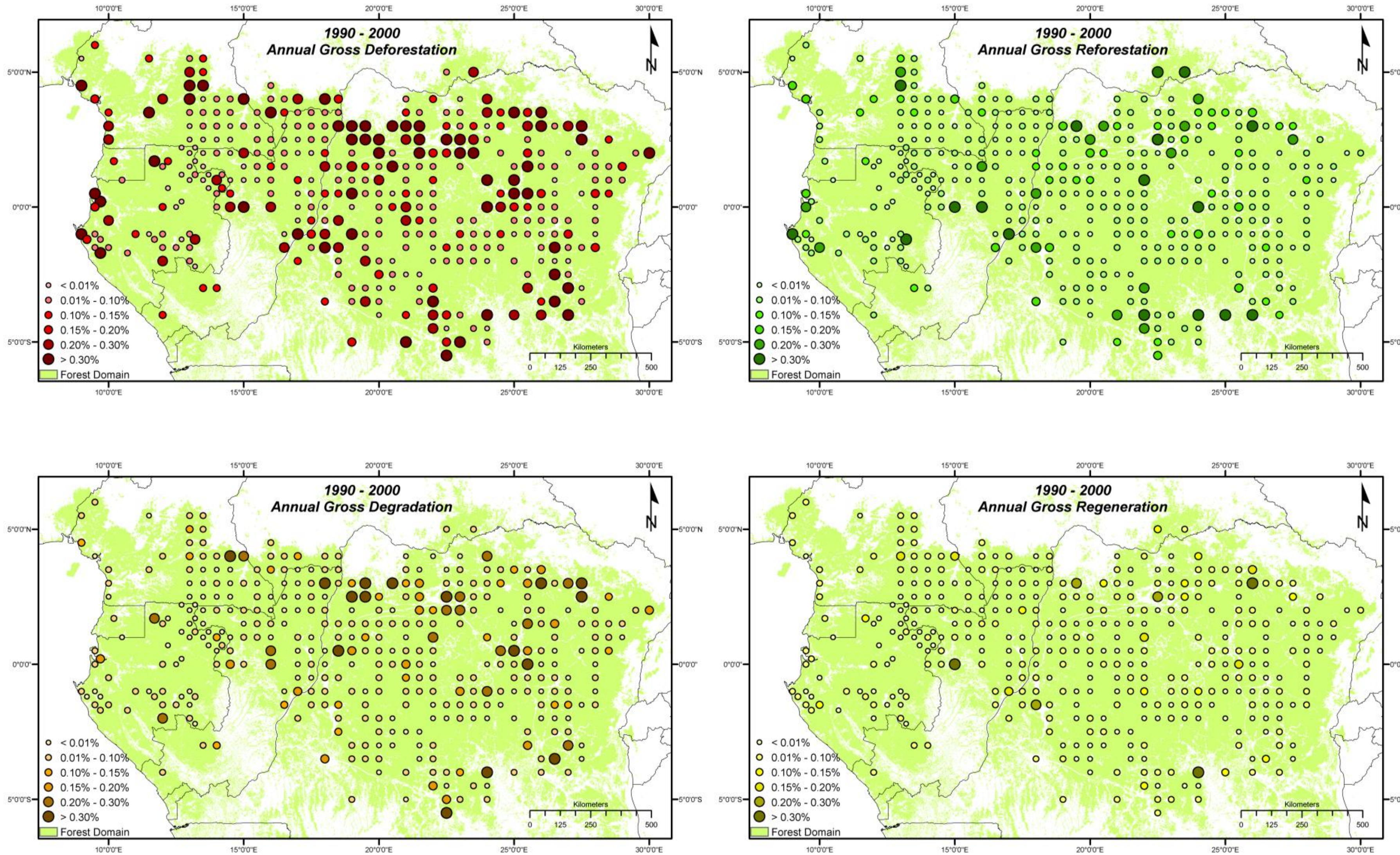

Figure 2: Spatial distribution of forest change dynamics (deforestation, reforestation, degradation and regeneration) between 1990 and 2000 over forest domain in Central Africa. The circle size is proportional to the phenomenon intensity.

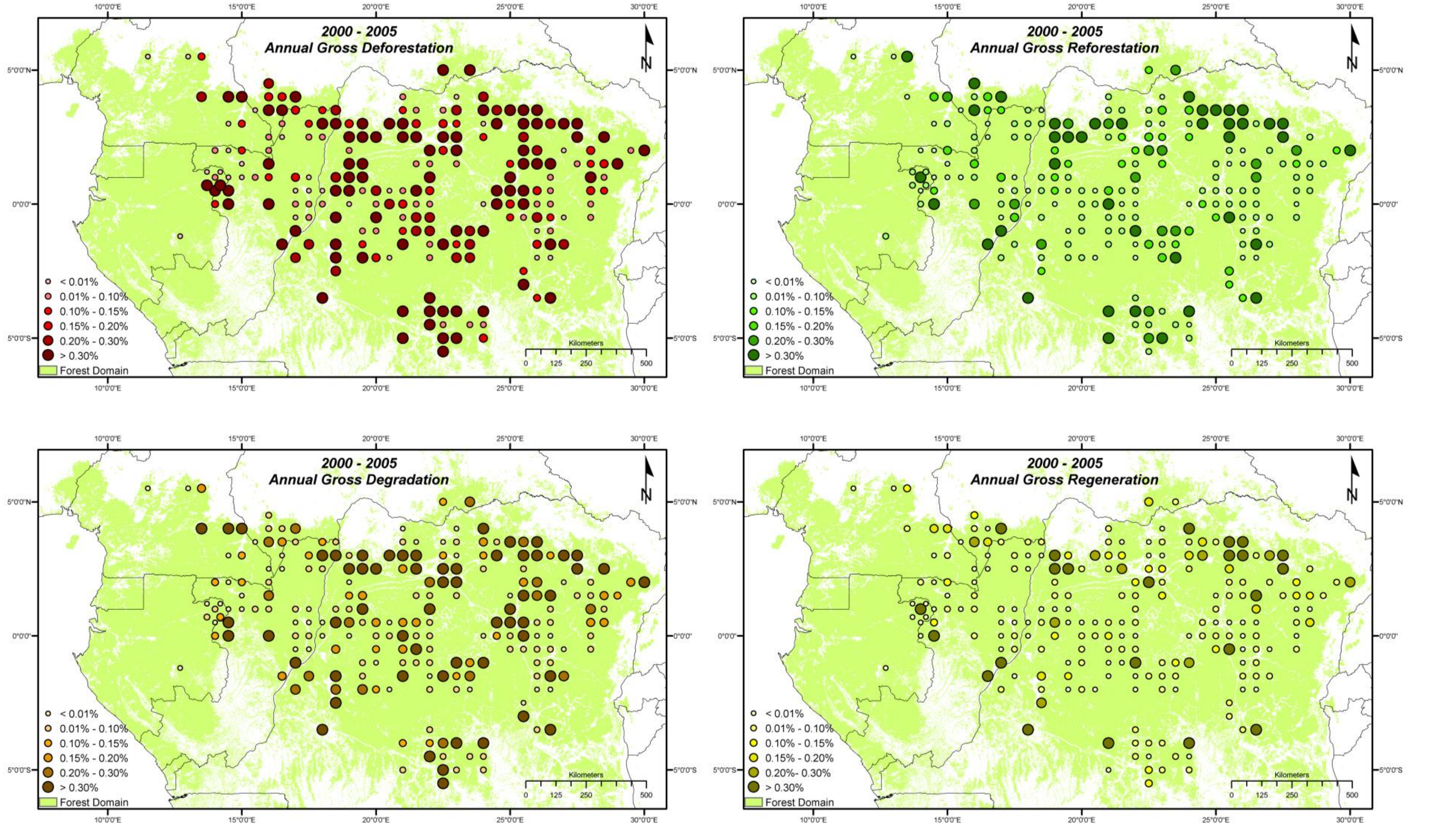

Figure 3 : Spatial distribution of forest change dynamics (deforestation, reforestation, degradation and regeneration) between 2000 and 2005 over forest domain in Central Africa. The circle size is proportional to the phenomenon intensity.

5. PRELIMINARY RESULTS

Since each satellite image are not acquired at the same date but around the first of June 1990, 2000 and 2005, land cover area and change transition matrix are linearly extrapolated to these pivot dates. Statistics of forest cover change processes are calculated. Each process is characterized by an annual rate. This rate is computed by dividing the total changed surface by the time period between the two images (typically 10 for change between 1990 and 2000 and 5 for 2000 - 2005) and by the estimated total forest area between these two dates (the sum of forest area between 1990 and 2000 divided by 2 or the sum of forest area between 2000 and 2005 divided by 2). The variance is estimated by the classical formula used for random sampling, even though the design of this current study is systematic. The calculation can be considered as conservative since it provides higher figures for variance than the real one (Duveiller *et al*., 2008). The total number of validated samples was 443. But only 372 of these 443 samples were located in forest domain and have been used for the forest cover change estimation. 220 samples of the 372 samples were 3 dates. For 1990-2000, by comparing these preliminary results (Table 2, Table 3) with those published by Duveiller *et al.* (2008), we note confidence interval coincides, apart from Equatorial Guinea and annual gross reforestation in DRC. Results differ slightly more for annual gross degradation and annual gross regeneration. Approach developed in both studies might explain the inconsistency of some figures. Duveiller *et al.* (2008) uses a manual interpretation and labeling whereas we developed an automated pre-labeling completed by national expert validation. Secondly, the land cover classes used in both studies are different. Furthermore, in this study, specific weights have been given to each sub-process in order to reflect area forest cover loss. Finally, the survey of Duveiller *et al.* (2008) was composed of 10 x 10 km sampling sites while 20 x 20 km sampling sites was used in this case.

For 1990-2000, the deforestation phenomenon remains relatively modest in the Congo Basin overall but tends to increase sharply for 2000-2005 especially in CAR, Congo and DRC. Due to missing data in 2000-2005, national figures of some countries (i.e. Cameroon or Gabon) are not representative and additional survey are necessary.

For each time-interval, the spatial distribution of deforestation (Figure 2 and Figure 3), reforestation, degradation and regeneration processes is illustrated. Between 1990 and 2000, we notice that deforestation, reforestation and degradation phenomena are more important in accessible areas such as forest fringe or along the Congo River. This seems to be less pronounced with the annual regeneration rate. Between 2000 and 2005, deforestation and degradation processes tend to worsen and reach less accessible areas.

6. CONCLUSIONS

The forests of the Congo Basin are a world treasure that provides crucial ecosystem services to forest-dependent communities and that stores enormous quantities of carbon (Dkamela *et al.*, 2009). Quantifying the temporal and the spatial deforestation, reforestation, degradation and regeneration rates is crucial.

Contribution of object based automated method is undeniable and allows a large data processing and an easily expert validation. Additional investigate would be interesting to analyze the reason of some inconsistency between Duveiller *et al.* (2008) and this study, to test the reproducibility of the method and to consolidate annual rates. However, this paper demonstrates the importance of capacity building and technology transfer to countries in the Congo Basin, a necessary step to national ownership. Central African countries have the technological and scientific maturity for forest change assessment.

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