# AUTOMATED LAND COVER MAPPING AND INDEPENDENT CHANGE DETECTION IN TROPICAL FOREST USING MULTI-TEMPORAL HIGH RESOLUTION DATA SET

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# **ABSTRACT:**

An automatic method for land cover mapping and for detecting forest change has been designed for high resolution couples of image. The work is done on 20x20 km samples of 30 m resolution Landsat imagery. The methodology has been developed for two dates extracts but several couple of images can be compared. An automatic multi-date segmentation is applied on extracts pairs. Segmentation parameters are tuned, thanks to an iterative procedure, in order to provide image-objects of 1 hectare. In dense moist forest areas, 1 hectare guarantees a pure land cover for each object-segment. These image-objects will be the units of the classification and change detection work. An unsupervised classification is performed for each image, grouping image-objects into clusters. For each image, a tree cover mask is made based on a land cover map of reference with a coarser scale. Each cluster is then automatically labelled with this tree cover mask. Small image-objects are aggregated into image-objects with a minimum mapping unit of 5 hectares thanks to a second segmentation level. Two independent things are then produced, a land cover map for each date of interest and a set of objects flagged as changed between the two dates. The forest change detection is obtained by running a statistical outlier detection method on the difference of both images. The detection is done under the union of the tree cover mask of both dates in order to work with an homogeneous set of objects. The accuracy of this methodology is assessed for ten pairs of images, visually validated by experts.

# 1. INTRODUCTION

The free-release of Landsat images gives the opportunity to process large amount of multi-temporal high resolution images and to follow during time ecosystems such as the tropical forest. Still, competitive methodologies have to be developed to extract accurate information from this data.

This study aim at developing an automatic method for the land cover mapping and the detection of forest change of a large dataset of multi-temporal high resolution optical imagery for the semi-(evergreen) extension of the forest domain. The potential of an automatic labelling and change detection will be assessed for a simple land cover legend in the (semi-)evergreen domain, where the absence of seasonality makes the change detection easier. The aim of this method is also to be more accurate in the characterization of the dynamics of the forest change. Therefore, we will try to establish a method that assesses not only deforestion and reforestation but also intermediate processes such as degradation and regeneration. These phenomenons are very representative of the forest change that occurs in Central Africa. The expected final products are two land cover maps, a map of the forest changed zones and four rates of forest dynamics changes (deforestation, reforestation, degradation and regeneration).

# 2. DATA AND STUDY AREA

The study focus on the (semi-)evergreen tropical forests. The images used for the development of the method have been selected in the data provided by two different research projects, 250 test sites for the JRC-FAO remote sensing survey of the Forest Resources Assessment 2010 programme (FRA 2010) and

665 sites of the Democratic Republic of Congo for the FORAF project; the initiative of Europe for the establishment of the Observatory for Forests of Central Africa. The FORAF survey in global consists of +/- 1200 sampling sites separated by 0.5° intervals and regularly distributed in Central Africa (Burundi, Cameroon, Central African Republic, Congo, Democratic Republic of the Congo, Equatorial Guinea, Gabon and Rwanda). In both case, only the images from the biome of interest have been taken into consideration, which represents still 80 sites in South America and South East Asia and around 400 in DRC.

For every sample site, two co-registered high spatial resolution imagery extracts are available. Each pair is composed of an image extract acquired around 1990 and a second acquired around 2000. These image extracts consists of samples of 20x20 km size of Landsat TM and ETM+ images at a spatial resolution of 30 m or 28.5 m. The resolution is depending on the origin of the original Landsat scenes (Global Land Cover Facility of University of Maryland or National Center for Earth Resources Observation and Science). Six spectral channels are available for TM and ETM+; band 1 (0.45-0.515 um), 2 (0.525-0.605 um), 3 (0.63- 0.690 um), 4 (0.75-0.90 um), 5 (1.55-1.75 um) and 7 (2.09-2.35 um) in UTM (Universal Transverse Mercator) coordinates. A thermal channel corresponding to band 6 has been used in the pre-processing.

The selection of Landsat imagery have been done by the JRC-GEM as well as the pre-processing steps, registration of multitemporal image, radiometric calibration of data, masking of clouds and clouds shadows and correction of haze.

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# 3. METHODOLOGY

In remote sensing surveys like the one of the FAO for the FRA 2010, thousands of images have to be processed. A good compromise have to be found between the automation of the process to reduce the processing time and the capitalization on the knowledge of regional experts in order to enhance the final quality of the products. The first assumption of this study is that it would be possible to automatically label high resolution images if the land cover legend is reduce to a minimum, the majority of the image is covered by forest and the seasonality is not consequent. Although the aim is to be as automatic as possible, the method have been designed in a perspective of facilitating the visual validation work of the final products. The entire method for (semi-)evergreen forests will be described, focusing on the automatic aspect of it. Different alternatives were tested for the labelling of the classification but only the most efficient will be presented here. A visual validation effort realised on ten images in Central Africa allows to get a first characterization of the precision of the labelling method. The methodology has been developed for two dates extracts but several couple of images can be compared.

#### 3.1 Pre-processing and segmentation

The object delineation has been achieved here using a general segmentation algorithm based on homogeneity definitions, in combination with local and global optimisation techniques, as implemented in the Defininens commercial software (Desclee et al., 2006). The segmentation algorithm is a region-merging technique which fuses the objects according to an optimisation function (Baatz & Schape, 2000). An automatic multi-temporal segmentation is applied to the two-date (1990 - 2000) (Duveiller et al., 2008). Four bands from both TM and ETM+ are used with equal weights: 3 (Red), 4 (NIR), 5 (SWIR) and 7 (SWIR)). Bands 1 and 2 are not used because they have a high susceptibility to aerosol contamination (Krueger & Fischer, 1994). The product of this segmentation is a set of spectrally and spatially coherent objects and identical for both images. Multi-temporal segmentation relies not only on spatial and spectral information but also on temporal dimension of the images. This approach allows to extract group of adjacent and spectrally homogenous pixels that are representative of the landcover change between the two dates (Desclée, 2007). This approach has been used previously to detect changes in forest cover (Duveiller et al., 2008; Desclee et al., 2006).

Thanks to an iterative procedure, segmentation parameters are tuned for two levels of segmentation, micro and macro objects. The first level contains image-objects with a minimum mapping unit of 1 hectare (or 11 pixels). In dense moist forest areas, 1 hectare guarantees a pure land cover for each object-segment. These image-objects will then be the working units for the mapping process (classification and automatic labelling) and for the automatic change detection algorithm. Micro image-objects are aggregated, into macro image-objects with a minimum mapping unit of 5 hectares (55 pixels). The smaller level is therefore included in the largest one. The macro-objects layer constitutes the final elements of work and can be used for calculating statistics and for the definition of changes dynamic between the two dates. For the Definiens software, the Minimum Mapping Unit (MMU) or the minimum image-object size can be approximated through the selection of an appropriated "scale parameter", corresponding to the threshold of heterogeneity (Desclee et al., 2006).

Besides this, the Normalized Difference Vegetation Index (NDVI) is calculated for TM and ETM+ imagery. In order to compare the multi-date evolution of the spectral signal, the reflectance of the two sequential satellite image TM and ETM + was subtracted pair-wise. For each object delineated by the previous multi-date segmentation, the distribution of the reflectance difference values was summarized by a multi-date signature. This signature includes two descriptive statistics, i.e., the mean and the standard deviation, corresponding respectively to a measure of surface reflectance difference and heterogeneity. (Desclee *et al.*, 2006). A cloud mask is provided by the JRC when required. Water masks are created after the segmentation when necessary.

# 3.2 Tree cover mask production

For each TM and ETM+ image, a tree cover mask is derived from a land cover map of reference with a coarser scale than Landsat, typically Globcover 300m (or Africover for DRC). These masks allow to adapt the information of a land cover map of a different spatial resolution or from a different date to the Landsat image of interest, using the spectral information of the imagery. This binary mask will be used in the automatic labelling process and for the automatic change detection in order to work with a homogeneous set of objects.

The tree cover mask method is based on the procedure developed by Desclée (2007). Masks are produced in three major steps. (i) A forest training set is created with the objects covered by 95% of forest in the reference map. (ii) This first training set has to be updated. Based on their mean spectral signatures, non-forest objects are eliminated by iterative trimming. Trimming is defined as the removal of extreme values that behave like outliers. This rely of course on the assumption that the forest have experienced minor changes. Objects with signature within the confidence interval of the last iteration are selected as forest training areas. (iii) The forest mask is complemented by looking for a spectral similarity derived by the Mahalanobis distance (Richards, 2006) computed for 3 spectral bands between the forest training set and the other image-objects.

# 3.3 Automatic pre-labeling of TM and ETM+ micro image-objects

To facilitate a further manual validation work and to deal with coarser reference map, an unsupervised classification is performed for each image, grouping the 1ha micro imageobjects into clusters which will be subsequently labeled to produce a full thematic land cover classification for both extract dates (Duveiller et al., 2008). The strong inter-sample heterogeneity (due to sensor radiometric differences and atmospheric perturbations) renders supervised classification too time-consuming since training zones would have to be collected for every individual image (Duveiller et al., 2008). The unsupervised classification algorithm is a k-means. The object clustering is based on the band 3 (Red), 4 (NIR) and 5 (SWIR) reflectance values averaged at the micro-object level and on the standard deviation of band 4 (NIR) reflectance. These statistics were chosen because they represent, in simple and robust terms, the essential information for each object. (Duveiller et al., 2008).

The alternative chosen for the automatic pre-labeling of the clusters of each imagery relies on the land cover information of a reference map instead of a landcover spectral signatures database. This reference map information is however corrected thanks to the spectral information of the imagery. The external reference maps often have a coarser scale (e.g. Globcover). The reference map is used to build the tree cover mask for both imagery (TM and ETM+). Each methodology is first applied on the most recent imagery (ETM+) and then on the TM imagery. Each of the clusters is automatically labelled based on the appropriate (TM or ETM+) tree cover mask A cluster is labeled forest or non forest depending of the class of the mask that covers the majority of its area. A spatial intersection of the cluster-image and the tree cover mask is performed and the proportion in terms of area is set to 70% to label the cluster with the class of the tree cover mask.

The water and clouds/clouds shadow masks are used to label the appropriate clusters. To avoid omission errors, these masks are used to label clusters and not objects. Indeed, clouds and clouds shadows masks do not integrate small clouds but these small clouds can be gathered together with bigger ones in the same cluster.

At this stage, the labels of the micro-objects (using the cluster classification) can be corrected by an expert in a visual quality control exercise (Ernst *et al.*, this issue).

#### 3.4 Aggregation

The micro image-objects labels are aggregated into macro image-objects thanks to the second segmentation level. This step will result in the production of final forest cover maps for each date at 5 ha level. Decision rules for determining the label of the macro object are based on the majority or the proportion of labels into the object resulting in respectively 'pure' or mosaic labels (Ernst *et al.*, this issue2010).

# 3.5 Change detection

Besides the two Landcover maps, an independent change detection is operated, producing a set of objects flagged as changed between the two dates. A multivariate iterative statistical ('iterative trimming') outlier detection method is used to distinguish "changed objects", corresponding to areas with (land cover) change, from "unchanged objects" based on theirs object difference signatures; mean of the difference of band 3, 4 and 5 and standard deviation of the difference of band 4. This statistical algorithm assumed that unchanged objects exhibit similar reflectance differences while changes induce large surface reflectance variation and abnormal reflectance differences. The algorithm measures for each object the surface reflectance variation over time and compares it between objects. Object exhibiting abnormal reflectance change over time can thus be statistically identified and labelled as changed areas. The algorithm relies also on the assumption that changes are rare and concern a small part of the total study area. This assumption is verified for most forested areas, where changes between the observations are not too important (Desclee et al., 2006). In order to work with an homogeneous set of objects, the tree cover mask is used to delimit the objects that will be compared. The detection is done under the union of the tree cover mask of both dates. The trimming is done for three different thresholds.



Figure 1: Flowchart of the main steps in the processing chain

#### 3.6 Land cover classes and change processes

The land cover of the study zone can be characterized with 7 classes. The micro-objects (processing units) will be labeled only with 5 land cover classes. The mosaic labels are only used for the aggregated macro-objects

- Tree cover (the canopy density of the tree layer should be at least 10% and tree height 5 m or more);
- Mosaic (High) : Tree Cover Other (tree cover proportion 40 -70 %)
- Mosaic (Low) : Other –Tree cover (tree cover proportion 10 -40 %)
- Other vegetation cover (land cover other than tree or shrub cover);
- Water;
- Cloud/shadow
- No data.

# 4. FIRST RESULTS AND DISCUSSION

## 4.1 Implementation of the automatic chain

The steps of the automatic chain are written in a Python script integrating ArcGis (ESRI) and Matlab commands. The multi-temporal segmentation is done with the Definiens software (Baatz and Scape, 2000) and cannot yet be integrated in the Python script but the Definiens Server allow to process a large amount of data within the same process sequence.

#### 4.2 Results and Validation exercise in Central Africa

The method have been tuned on the 450 sites located in the (semi-)evergreen forest. More analysis of these pairs of imagery extended to the whole regional region, are done in Ernst *et al.* (this issue). We will focus on the validation of some imagery. A pilot validation study has been realized in February 2009 at the SPIAF (Service Permanent d'Inventaire et d'Aménagement forestier), Kinshasa, DRC. Ten pairs of TM and ETM+ imagery, randomly distributed among the dense forest (Figure 2), have

been visually corrected. The resulting validated land cover maps comes from the dialogue of three experts. This pilot study has lead to a Central Africa validation workshop with 15 experts in September 2009 (Ernst *et al.*, this issue).



Figure 2: Distribution of the validated extracts

As the methodology has been designed in order to facilitate the validation by experts, the revision of the clusters of each imagery lead to a complete validated land cover map. The interpretation has been made at a scale of 1:50 000. To characterize the accuracy of the land cover maps, confusion matrices for each pair of ETM+ and TM imagery have been calculated with the area of each land cover classes. Table 1, 2 and 3 present the accuracy indexes averaged for the ten images. The total accuracy is high for both dates, the area automatically labelled with the right label is important. But the high proportion of tree cover in each imagery makes it necessary to study Tree Cover and No Tree Cover separately.

	ETM+	TM
Total accuracy	95,21 %	94,99 %
Table 1 : Total mean accuracy	y of the classification	(area proportion

Table 2 and 3, shows that for tree cover class, the omission and commission errors are low and are compensated. For the no tree cover class, the commission errors are largest than the omission errors with the lower user accuracy for ETM+, indicating that the no tree cover class has to be checked more attentively by the validator. An accurate detection of the no tree cover class is clearly crucial in term of change detection. Besides this, the subjectivity of the interpretation of each experts has to be considered. Especially in Central Africa where

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the distinction between tree cover and no tree cover vary sometimes a lot between experts due to intermediary processes of the deforestation, such as regeneration and degradation of the tree cover.

	ETM +	TM
Manual interaction	7,00%	6,00%
Table 4 : Mean pror	portion of the cluste	rs with a wrong label

Table 4 shows the proportion of clusters that have been edited by the experts, averaged for the ten images. It indicates the importance of the manual interaction necessary to correct the land cover maps automatically produced. For ETM+ and TM, this variable is lower than ten percent, justifying the use of an automatic method combined with a visual interpretation.

## **4.2.1** Reference map for the Tree cover mask

A reference map is used in the production of the tree cover mask. For the DRC samples, a high resolution land cover map, Africover, was available. But we have seen that the use of a reference map of a coarser resolution (e.g. Globcover 300 m) is not deteriorating the quality of the final output as far as the forest is the majority class on the Landsat imagery. In zones were tree cover is a minority, a risk of confusion is possible when the choice of the tree cover mask training set objects is made. As tropical forest is quite homogenous, the training set does not need to contain a lot of objects. In Figure 3, we can see that even with a different set of forest objects in the beginning and a different training set of objects, we end up with the same tree cover mask.

An important limitation of the tree cover mask is the limitation to a binary tree cover-no tree cover mask which do not allow to work in areas were more land cover classes are necessary.

#### **4.2.2** Change detection

Even if the tree cover mask is used in both process, the change detection is independent from the labeling. This allows to avoid error propagation of a post-classification approach. Three different threshold are considered for the change detection ouputs. These thresholds should be flexible for each pair of imagery in order to get the most appropriate change detection. As we are working in (semi-)evergreen forest, the seasonality do not influence the change detection, reducing commission errors. In the future development of the work, the same accuracy analyze than for the land cover maps should be made for the change detection.

			User	Errors of
TC	NTC	Total	accuracy	commission
339,70	6,88	346,58	97,97	2,03
12,30	41,52	53,82	78,53	21,47
352,00	48,40			
96,56	90,39			
3,44	9,61			
	339,70 12,30 352,00 96,56	339,70 6,88   12,30 41,52   352,00 48,40   96,56 90,39	339,70 6,88 346,58   12,30 41,52 53,82   352,00 48,40   96,56 90,39	TC NTC Total accuracy   339,70 6,88 346,58 97,97   12,30 41,52 53,82 78,53   352,00 48,40 96,56 90,39

Table 2 : Confusion matrix for ETM +. Mean value for area (km<sup>2</sup>)

				User	Errors of
Method\Validation	TC	NTC	Total	accuracy	commission
TC	346,93	5,48	352,42	98,46	1,54
NTC	14,57	33,55	48,12	81,79	18,21
Total	361,50	39,04			
Method accuracy	95,81	86,51			
Errors of omission	4,19	13,49			

Table 3 : Confusion matrix for TM. Mean value for area (km<sup>2</sup>)







Figure 3: Tree cover mask process for a Landsat ETM+ image in DRC with two different resolution reference map (up = Africover, down = Globcover)..

# 5. CONCLUSIONS AND PERSPECTIVES

The implication and participation of national experts is an essential element of a forest change detection survey. With this automatic method, the expert can focus on a small proportion of the image, saving thereby time and permitting the validation of a large dataset.

This method has a potential to be tested for the following of tentral African forest in the FRA-2010 initiative of the FAO and by the Observatory for the Forests of Central Africa.

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