TROPICAL FOREST MONITORING BY OBJECT-BASED CHANGE DETECTION : TOWARDS AN AUTOMATED METHOD IN AN OPERATIONAL PERSPECTIVE

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ABSTRACT:

Deforestation still nowadays occurs at an alarming rate in tropical regions. Forest monitoring is required to delineate the extents of deforested areas based on high resolution satellite images (SPOT). But classical change detection techniques have failed to detect small clearing spread over the landscape as occurring in African forests. Developed initially for temperate forests, the automated object-based change detection method using segmentation and statistical algorithm was extended to tropical regions. This approach consists in three phases: (1) multidate segmentation and object signature computation, (2) forest/non-forest classification and (3) forest change detection. First, the multidate image was partitioned into objects using segmentation and several summary statistics were derived from the within-object reflectance differences. Second, a automated forest/non-forest classification was applied on the first image to define the initial forest mask. Finally, focused on these regions, the forest change detection algorithm detected deforestation thanks to a statistical test using a multivariate iterative trimming procedure. Tested over a protected area located at the eastern border of the Democratic Republic of Congo, this method produced a deforestation map with an overall accuracy of 84 % as assessed by an independent aerial survey. Given its efficiency to detect complex forest changes and its automated character, this method is seen as adequate operational tool for tropical forest monitoring.

1. INTRODUCTION

Despite the efforts of government and conservation organizations, tropical deforestation - mainly conversion of forest to agricultural land - continues to proceed at an alarmingly high rate, estimated at 9.2 million hectares per year from remote sensing survey. However, forest planting, landscape restoration and natural forest expansion have significantly reduced the net loss of forest area over the years 2000–2005 (FAO, 2006). Conservation of these tropical forests is very crucial for species diversity, climate stability and carbon cycle. Forest monitoring is thus required to provide timely and reliable information on forests condition, composition, and extent for making good decision in forest management and planning at a large scale.

Remote sensing is probably the most adequate tool for monitoring tropical forests. Satellite imageries cover large forested regions that are often difficult to access. Thanks to the increasing availability of remote sensing data and the fast evolution in change detection techniques (Lu et al., 2004), forest extent and its dynamic can be assessed. Precise measurement of deforestation requires high spatial resolution images from satellite sensors such as Landsat TM, ASTER or SPOT. Among the variety of change detection methods, the post-classification comparison is widely used to detect detailed change trajectories. The classifications are either based on visual delineation and interpretation (Roy and Tomar, 2001; Achard et al., 2002) or on digital techniques (Tucker and Townshend, 2000; Sanchez et al., 2001; Zhang et al., 2005). Other change detection techniques also based on classification have been developed and evaluated over tropical forests. Multidate classifications using NDVI (Hayes and Sader, 2001) or tasseled cap (Guild et al., 2004) are more straightforward to detect changes. However, they still require time-consuming procedures and image interpretation such as definition of a preliminary forest mask and visual interpretation for labelling classes. Other methods such as image differencing, principal component analysis have been assessed by Mas (1999) and Lu et al. (2005) but they require precise radiometric normalizations and histogram thresholding to distinguish change/no-change classes, which are scene-dependent procedures. Moreover, when applied over tropical forests, these techniques - also referred to as pixel-based change detection - suffer from important "pepper and salt" effects. Indeed, hazy atmospheres, very frequent in tropical regions, introduce temporal variability not related to surface changes. The spatial variability of high resolution images is also dependent on canopy roughness and geometry of observation (de Wasseige and Defourny, 2002). Object-based methods based on segmentation could thus help reducing these local spectral variations when combined to a statistical object-based change detection method developed by Desclée et al. (2006), that has proved its efficiency to detect forest changes in temperate regions. To the best of our knowledge, such kind of change detection methods has not been applied on tropical forest yet.

Forest change detection require a preliminary forest delineation to mask irrelevant features and focus the analysis only on forest changes (Coppin and Bauer, 1996). This forest mask can be derived from a preliminary classification (Hayes and Sader, 2001; Guild et al., 2004). Based on the first satellite image of the image pair, a land cover classification is performed and classes are merged to produce forest/non-forest mask. In order to reduce the time-consuming interpretation required for these classifications, forest limits are sometimes derived from other data sources such as existing forest maps (Häme, 1998). However, this forest delineation is often not accurate enough or outdated compared to the satellite images used for change detection.

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This study aims at delineating tropical deforestation from high resolution satellite images (SPOT). Due to its efficiency to detect forest changes in temperate forests, the statistical object-based change detection method developed by Desclée et al. (2006) was extended to tropical forests. An automated forest/non-forest classification was developed based on the first satellite image of the images pair to focus the change detection only over deforested areas. This methodology was applied to monitor forests degradation in the Virunga National Park, a protected area, at the eastern border of the Democratic Republic of Congo (DRC).

2. STUDY AREA AND DATA

The Virunga National Park is a site of exceptional biological and ecological value due to its considerable altitudinal range (from 800 m to up to 5100 m in the Ruwenzori Mountains) over a restricted region (790,000 ha). It is located on the border between Democratic Republic of Congo, Uganda and Rwanda. This area is crucial for the conservation of a large range of ecosystems (afro-alpine vegetation, savannah, swamps, lowland forest, lacustrine and volcanic successional gradients and even snow field) and the protection of numerous endemic species (birds, flora, mammals, invertebrates, etc). Although it is the first national park created in Africa (1925) and one of the biologically richest parks in central Africa (it was declared as a World Heritage Site by UNESCO in 1979), it is at the same time one of the most threatened ones. The study area is the Semliki sector located at the north of the Virunga National Park. It is nearly exclusively composed of low land tropical forest on both side of the Semliki river including very different forest degradations. The extension of the agricultural activities of the people living near the park leads to progressive degradation distributed in small patches inside the forest domain. In contrast with shifting cultivation practices where forests recover after several years by natural regeneration, the cut parcels are not abandoned and forest does not regenerate.

Two SPOT images were acquired respectively on April 1, 2000 and May 6, 2004 over the Semliki sector. The first image at 20 m spatial resolution was resampled at 10 m resolution using bilinear interpolation in order to match the 10 m resolution of the second image. The preprocessing includes three steps, namely geometric correction, cloud masking and image differencing. Orthorectification was first applied on each image based on the SRTM DEM (90 m resampled at the image resolution) and a set of 6 to 14 GCP's. For both images, the Root Mean Square Errors (RMSE) were below pixel size. Clouds and their shadows were systematically removed afterwards by visual interpretation. Finally, pairs of successive images were subtracted for each spectral band, including Green, Red, NIR and SWIR bands. One image difference was produced (May 2004 minus April 2000). From an airborne video recorder linked to a GPS, aerial photographs were acquired by the WWF team on April 6 and 7, 2004. Sixty aerial photographs were randomly selected for the change detection accuracy assessment. These images were coregistred using 4-5 GCP's as derived from the GPS location and the interpretation of the SPOT image acquired in May 2004.

3. METHODOLOGY

The method proposed here for tropical deforestation mapping includes 3 steps, namely (1) the multidate segmentation and object signature computation, (2) the forest/non-forest classification and (3) the forest change detection. Based on the change detection method developed by Desclée et al. (2006) over temperate forests, the methodology was generalized to solve the remote sensing tropical difficulties such as high reflectance variability due to canopy roughness and strong atmospheric effects. Moreover, an automated forest/non-forest classification was developed to focus the subsequent change detection analysis only on deforested areas. This deforestation mapping technique assumes that the satellite image covers large forest areas with small surfaces of deforestation. This general assumption should be respected to ensure the efficiency of this method.

3.1 Multidate segmentation and object signature

The multidate segmentation consists in partitioning an image into objects which group pixels that are spatially, spectrally and temporally similar. Including two satellite images over the same location at two different dates, the multidate image is segmented into multidate objects (Desclée et al., 2006) using the eCognition software (Baatz and Schäpe, 2000). The segmentation is based on an optimization function which involves three parameters, namely the spectral, the compactness and the scale parameters. The spectral parameter w_{sp}, trading spectral homogeneity vs. object shape, is included in order to obtain spectrally homogenous objects while irregular or branched objects are avoided. The compactness parameter w_{cp}, trading compactness vs. smoothness, adjusts the object shape between compact objects and smooth boundaries. Finally, the scale parameter h_{sc}, controlling the object size, is selected in order that the minimum object size matches the Minimum Mapping Unit (MMU). Depending on this scale parameter, different segmentation levels can be produced, each characterized by their own mean object size.

Two segmentation levels of objects were produced from the multidate image in this study. The first level delineates "small objects" for the change detection analysis. Spectral w_{sp} parameter was set to 0.9 to obtain very spectrally homogeneous objects. Compactness parameter w_{cp} was set to 0.5 to equally balance between smoothness and compactness. To obtain objects down to the smallest forest change size (about 0.25 ha), scale parameter h_{scale} was set to 20. The second segmentation level contains "large objects" (mean size of 2000 ha) and was produced for the forest/non-forest classification and the simplification of the change detection results at coarser scale. The spectral w_{sp} and the scale h_{scale} parameters were set respectively to 1.0 and 500 in order to obtain large areas by focusing on the spectral homogeneity.

Based on this object delineation, object signatures (OS) were computed for each small object. These signatures include several objects features or summary statistics derived from the groups of pixels inside the object. These statistics were selected to characterize each object for the subsequent analyses, namely the forest/non-forest classification and the change detection. The classification between forest and non-forest requires the object mean (M) of each spectral band over image 1 (OS1). The change detection algorithm which compares images thanks to image differencing requires the object Mean (M) and object

Standard deviation (S) of each spectral band of the difference image (OS21).

3.2 Forest/Non-forest classification

An automated object-based classification was developed to separate forest from non-forest areas on the first image of the satellite image pair, hereafter named image 1. Two classes, namely forest and non-forest, were discriminated. Forest corresponds to forested land with closed canopy. Non-forest includes agricultural fields, savanna, fallow land and water bodies. Only applied on image 1, this classification is based on two steps, namely (1) the automated identification of forest training sets and (2) the stratified forest/non-forest classification.

The identification of forest training sets aims at defining automatically a representative sample of forest small objects for the subsequent classification. Two statistical analyses based on multivariate iterative trimming procedure were performed. Whereas trimming is defined as the removal of extreme values that behave like outliers, this statistical test is used in a multivariate way for detecting changed objects having abnormal multitemporal behaviour. The first statistical analysis is a severe change detection performed on the whole set of multidate objects in order to keep only "unchanged" objects, this including mainly forest objects but also some non-forest objects. Based on the object signatures from the image difference (OS21), the iterative trimming procedure was performed with a confidence level equal to 90 %. Objects having signatures inside the confidence interval of the last iteration were classified as unchanged objects. Because visible spectral bands were very sensitive to haze, only infrared bands were used. These object signatures (OS21) include object means and object standard deviations on NIR and SWIR difference bands. Afterwards, a second statistical analysis aims at extracting forest objects among the selected "unchanged" objects, considering only image 1. As "unchanged" non-forest objects are less numerous and spectrally very different compared to "unchanged" forest objects, they can be considered as outliers based on the object signatures of image 1 (OS1). Iterative trimming was applied on these signatures which include object means on Green, Red, NIR and SWIR spectral bands with a confidence level of 99.9 %. Objects with signature values inside the confidence interval of the last iteration are considered as forest training sets.

The forest/non-forest classification distinguishes forest from non-forest objects based on the spectral signature of forest training sets. As non-forest objects include many different land-cover classes such as savanna, agricultural field, fallow and water bodies, they have very different spectral signatures which is time-consuming to modelize. Instead of comparing the object probability of belonging to each land-cover class, as done in maximum likelihood classification, this classification selects objects having spectral signatures similar to forest training sets. To measure this similarity and distinguish forest from non-forest, a confidence interval is computed based on the object signatures of forest training sets in the 4-dimensional space corresponding to the object means on Green, Red, NIR and SWIR spectral bands. Among all multidate objects, the objects with signature outside the interval defined with a confidence level of 99 % were considered as non-forest and were then masked for the subsequent analysis. Over the whole study area, several forest types are present and their spectral signatures are very heterogeneous. In order to increase the classification performance and reduce the forest spectral heterogeneity, this process was repeated at local scale over each "large object" as produced by the second segmentation level. This "stratified" classification allows us to take into account local forest types characterized by specific spectral signatures.

3.3 Forest change detection

In order to identify deforestation areas, the change detection method based on multivariate iterative trimming was applied on the multidate objects classified as forest in image 1. This statistical analysis was performed based on object means from the image difference over NIR and SWIR bands (OS21) with a confidence level set at 99%. The resulting changed objects are classified as deforestation giving that they were initially forest. The generalization of this result at coarser scale was done by measuring the rate of deforestation in terms of surface for each "large object" of the second segmentation level. The area of the small objects detected as deforested was summarized over large object to obtain surfaces and rates of deforestation.

3.4 Accuracy assessment

The change map based on this methodology was assessed using reference data set including objects selected by stratified random sampling. These objects were photo-interpreted based on satellite images as well as on aerial photographs when available. Four performance indices were derived from the confusion matrix: overall accuracy, overall kappa and, for the change class, the omission and commission errors. 180 objects were selected by stratified random sampling based on the zone covered by aerial photographs and the land cover change classes. 120 objects were photo-interpreted using the two SPOT images (April 2000 and May 2004) and 60 objects based on the georeferenced aerial photographs of April 2004. The forest/non-forest classification (forest/non-forest) and the change detection (change/no-change) were separately assessed.

4. RESULTS

4.1 Deforestation maps

Over the years 2000 and 2004, deforested areas were identified based on this methodology applied on the corresponding SPOT images. The simplification of these results at coarser scale leading to the generalized change map is presented in figure 1. Over the whole area, deforestation rates ranged from 0 to 10 % depending on the zones. From a forest extent of 160,000 ha on the satellite image of April 2000, about 3,100 ha were deforested in May 2004. Inside the Park, about 800 ha of forest were clear-cut, the majority of them in the south-western part (figure 2). Around the Park, about 2,300 ha of forest were degraded and converted into agricultural fields.

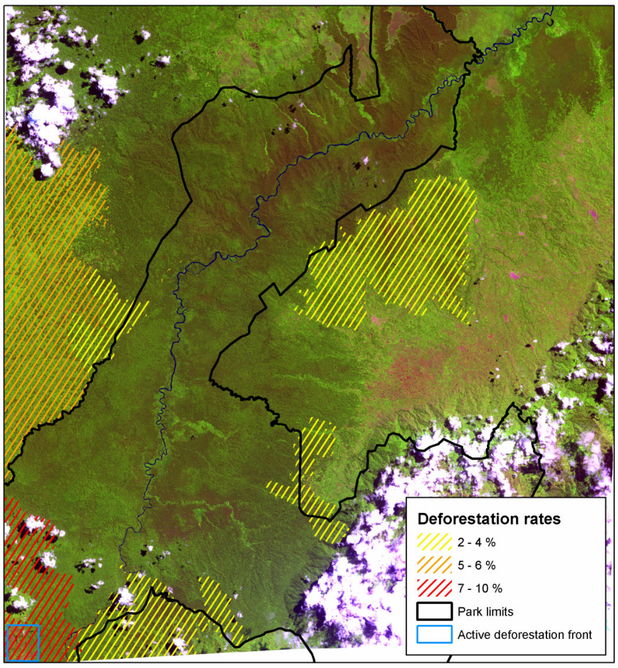
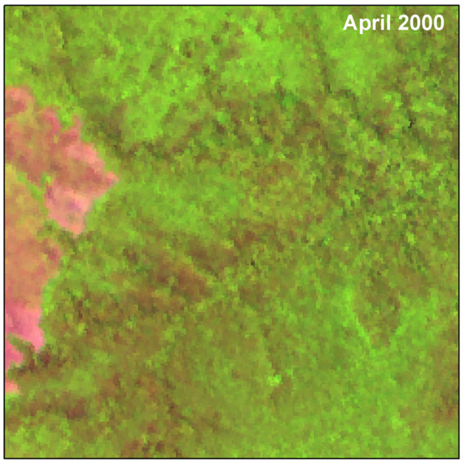
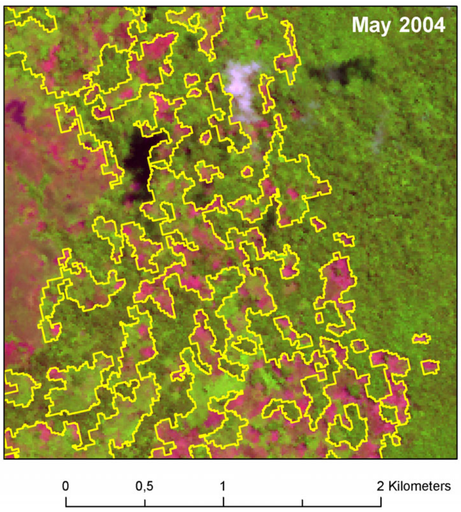


Figure 1. Generalized deforestation map over the Semliki sector overlaid on the whole SPOT image of May 2004.



(a)



(b)

Figure 2. Image subsets over the Semliki sector over the active deforestation front, acquired respectively (a) in April 2000, b) in May 2004 overlaid by the detected deforested regions between 2000 and 2004.

4.2 Method assessment

Table 1 summarizes the accuracy assessment results of the deforestation mapping method. This was done for the whole method and separately for its two steps, namely the automated forest/non-forest classification and the change detection. The method's overall accuracy and the overall kappa were respectively 84 % and 0.75. The automated forest/non-forest classification achieved an overall accuracy of 88 % whereas the same index reached 93 % for the change detection. Taking into account only the change class, the rates of omission errors was 23 %. However, these errors were due to the change detection (3 %) but mainly to the forest/non-forest classification (19 %). The change class commission errors due to the change detection are numerous (16 %) and combined with the 9 % due to the forest/non-forest classification, the whole method achieved 25 % commission errors.

	Whole Method	F/NF Classif.	Change Detection
Overall Accuracy (%)	84.2	87.6	93.3
Overall Kappa	0.75	0.75	0.84
Change: Omissions (%)	22.6	19.4	3.2
Change: Commissions (%)	25.0	9.4	15.6

Table 1. Accuracy assessment results (n=180) of the deforestation mapping method and its two steps, namely the forest/non-forest (F/NF) classification and the change detection over the Semliki sector.

5. DISCUSSIONS

This study proposes an automated method to map deforestation areas over complex tropical regions. The change detection based on image objects has the advantage of reducing the spectral noise due to canopy roughness and strong atmospheric effects, but also to overcome the tropical landscape complexity. Moreover, time-consuming radiometric corrections are not required in this method due to its robustness as it makes use of reflectance differences by the way of a statistical test, the iterative trimming. On the other hand, this method requires a forest mask before performing the change detection analysis. Often this mask is derived from time-consuming land cover classification or from other forest maps which are outdated and sometimes not accurate enough. This method automatically produces its own up-to-date forest/non forest mask, from the first image of the image pair. Because this step is based on the same satellite image as for change detection, the resulting deforestation map should be more accurate. Another difficulty coming from the diversity of forest types and their different spectral signatures was solved by stratifying the classification based on the large objects. It is worth noting however that a limitation of object-based methods is that small deforested areas are not taken into account. Indeed, the scale parameter required for the segmentation defines the minimum object size. In spite of this limitation, this methodology was proved flexible giving that the different case studies of deforestation were successfully mapped. Indeed, both small encroachments and large clear-cuttings occurred in the study area.

The change map based on this methodology reached an overall accuracy of 84 %. This result is quite good given the complexity of forest changes and the lack of up-to-date forest map. Moreover, this method can also be considered as efficient when compared with other tropical deforestation studies assessed by independent reference data, which are rare. Assessing different pixel-based change detection method over tropical regions, Mas (1999) achieved the highest results with the post-classification comparison with an overall accuracy of 87 %. Using the RGB-NDVI technique, Hayes et Sader (2001) have obtained an overall accuracy of 86 % to detect forest change. Guild et al. (2004) have tested three change detection techniques using tasseled cap and have obtained as best results a 79 % overall accuracy. However, change map produced by this study have still omission and commission errors. Whereas omission errors are mainly due to the forest/non-forest classification, the commission errors are due to the change detection algorithm. These errors are also linked to the difficulties to map tropical forests. Indeed, this mapping is a difficult task due to technical and conceptual problems pointed by Foody (2003). Tropical landscapes are very complex to analyze. Forest edges are sometimes difficult to delineate due to the continuum between vegetation types. Moreover, the rapid forest regeneration renders the visual interpretation difficult between the forest succession states.

This change detection method can be considered as operational given its efficiency to detect different forest change types and its automated character. Indeed, its good overall performance over both temperate and tropical forests proved its ability to identify small clearing spread over the landscape as well as large cut parcels. Moreover, whereas high cost, large data volume and low frequency of data acquisition were a problem in the past, the current large variety of easy-to-access satellite imageries renders fine spatial resolution images very promising to apply this automated forest monitoring technique in an operational framework.

In addition to assessing our method over tropical regions, this study brought a solution to the Congolese authorities and conservation NGO requiring information about the evolution of deforestation fronts. Three crucial information were provided with respect to this (i) the delineation of the forest degradation front, (ii) the quantification of deforestation rates for big blocks of homogenous degradation patterns, and (iii) the quantification of all forest surfaces affected by human activities. The simplification of these results at coarser scale as done in the generalized change map is also needed for field actors. Indeed, this kind of map is required to evaluate the global situation and focus the most sensitive regions of these protected areas.

6. CONCLUSIONS

Tropical deforestation was successfully delineated from high resolution satellite images acquired from SPOT sensor. Developed initially for temperate forests, the automated object-based change detection method using segmentation and statistical algorithm was extended to tropical regions. An automated forest/non-forest classification was developed to delineate the reference forest mask. This methodology was applied to monitor the forest degradations and assessed in the Virunga National Park in the east border of the Democratic Republic of Congo (DRC). The produced deforestation map reached an overall accuracy of 84 % as assessed by an independent aerial survey. Deforestation map of better accuracy could even be achieved by improving the preliminary forest/non-forest classification or using up-to-date forest map. This change detection method combining object-based techniques and statistical tests has also proved its efficiency to detect complex tropical forest changes such as small clearing spread over the landscape. Moreover, its automated character renders this method appropriate for operational tropical forest monitoring.

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