Detecting forest degradation patterns in Southeast Cameroon

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Abstract. The objective of this study was to evaluate the use of a spectral index and a contextual classifier for detection of forest degradation associated to selective logging in Southern Cameroon. This methodology, already applied in the Amazon, builds the Normalized Difference Fraction Index (NDFI) to enhance the forest canopy damage signal. A contextual classification algorithm (CCA) applied later to the NDFI image enables the separation of anthropogenic disturbance. These methods were tested in a certified forest concession area of Southern Cameroon, in the Congo Basin. The results show that the NDFI is able to detect infrastructure associated to most selective logging operations in the study area. The additional CCA was able to accurately discriminate human-caused forest degradation from natural occurrences.

Keywords: fragmentation, spectral mixture models, normalized difference fraction index,REDD+.

1. Introduction

Cameroon is a country located in the Congo Basin, the second largest area of continuous rainforest in the world. Tropical evergreen forests cover an estimated 17 million hectares, 36 per cent of the national territory, mostly in the southern regions. A major threat to these forests is the degradation due to fires, agricultural encroachment and selective logging activities (Sayer et al., 1992).

The rapid growth of the logging industry in recent years is of growing concern (Essama-Nssah and Gockowski 2000) in the country. Annually, 350,000 ha of concessions are logged, making it the African nation with the largest percent of forest exploited among those with substantial rainforest.

A common practice of the logging industry is the selective harvesting of a limited number of high-value tree species. This selective logging, which causes widespread damage to remaining trees and the surrounding landscape, is hard to monitor by using satellite observation. Differences in reflectances between forest and degraded forest are more subtle than in the case of deforestation, and degradation patches are generally small compared with clearings. Temporal dynamics of regrowth is another factor to consider. For these reasons, methods for monitoring degradation are not as well established as those for monitoring deforestation (GOFC-GOLD 2009).

The present study assesses the application of a methodology proposed by Souza et al (2005 b) to detect and monitor forest degradation in Southern Cameroon.

2. Study area

Currently more than 55,000 km^2 of forest are under logging concessions in Cameroon (Mertens et al., 2007). Together with Equatorial Guinea, Cameroon has the highest logging road density (0.09 km km^{-2}) in the Congo Basin (Laporte et al. 2007).

The study area was established in the vicinity of a recently harvested timber extraction area near the town of Lomié in the East province of Cameroon (**Figure 1**). The core area corresponds to the planned annual exploitation target (4690 hectares) inside a larger forest management unit (i.e., forest concession block UFA 10 044) assigned to the PALLISCO company.

Dense evergreen forest is the predominant vegetation in the study region. Logging activities in the concession follow sustainable forest management practices, mechanized operations and harvesting is selective to only high quality timber species. Additionally to the core area, known for having being harvested in 2008, a buffer area is included to compare forest degradation dynamics from previous years inside and outside the forest concession.

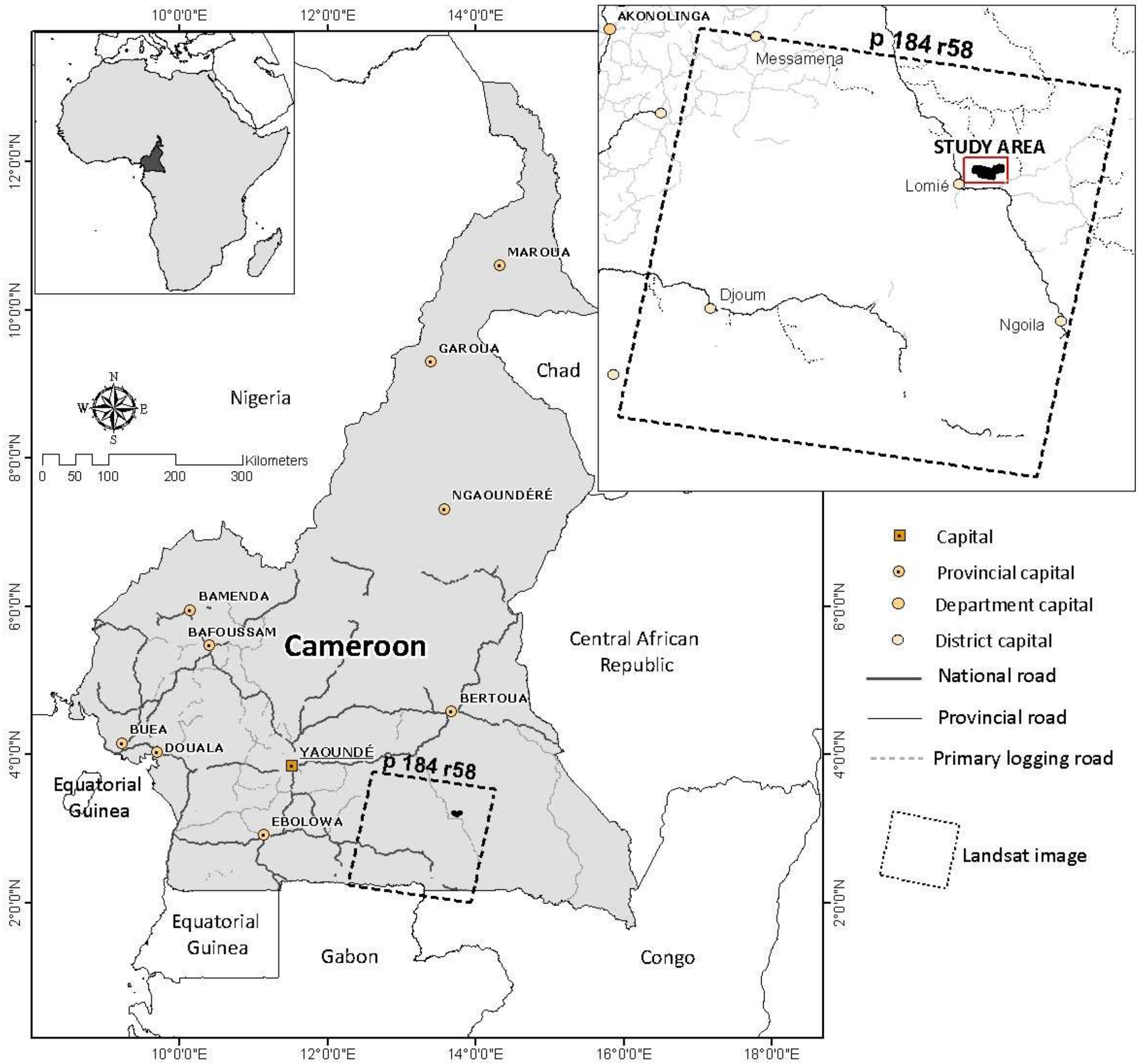

Figure 1. Location of the study area in Cameroon.

2. Methodology

2.1. Data

2.1.1. Data acquisition and gap filling

The study makes use of non-thermal bands of Landsat 7 ETM+ (*Enhanced Thematic Mapper*) sensor. Images corresponding to year 2002, 2004, 2005, 2006, 2007, 2008 and 2009 were acquired for scene location 184/058 (see Figure 1) from the United States Geological Survey satellite database. All images were co-registered to orthorectified images from the NASA Geocover 2000 dataset (Tucker et al., 2004).

A methodology adapted from USGS (2003) was applied to account for the missing data that all ETM+ imagery present since May 2003. Through a triangulation method, an additional set of images were used to fill the gap in the base image (Pringle, Schmidt and Muir 2009) using the ENVI 4.7 software environment. This method is similar in principle to the local linear histogram matching technique of Scaramuzza (2004) and USGS (2003).

2.1.2. Atmospheric correction and cloud masking

To account for the spatially variable atmospheric contamination, a technique proposed by Carlotto (1999) was applied. This method is an improvement over other haze equalization methods in that it preserves subtle detail between pixels and maintains spectral integrity among image bands (Souza, Roberts and Cochrane 2005b, Carlotto 1999).

The images were radiometrically corrected using the gains and offset values provided in the image metafile. An atmospheric correction was later performed using physics-based technique in FLAASH module available in ENVI software. Visibility and water vapor parameters of the atmospheric correction model were determined by a trial-and-error sensitivity analysis of a dark object reflectance (i.e., a lake). The final parameters were estimated when the expected reflectance values of the dark object were found. The fixed water vapor was 40 mm, and image atmosphere visibility was 25 km (Souza, Roberts and Monteiro 2005a).

Clouds and cloud shadows were masked using a semi-automatic bagging decision tree algorithm (Xu et al. 2005). The resulting cloud/shadow extent was slightly expanded to cover possible omission errors. Quality assessment was performed visually and the automatic cloud masks were manually enhanced when necessary.

2.2. Spectral mixture analysis and Normalized Difference Fraction Index

A spectral mixture analysis (SMA) was applied on the Landsat ETM+ reflectance data to decompose each pixel into fractions of photosynthetic vegetation (GV), non-photosynthetic vegetation (NPV) and soil (**Figure 2**). This analysis required a selection of pure spectra pixels (i.e., endmembers) extracted from the reference reflectance image (Adams et al, 1993).

The Normalized Difference Fraction Index (NDFI) was calculated from fraction images obtained from SMA. This spectral index proposed by Souza et al (2005b) allows enhancing the forest degradation signal caused by selective logging. High NDFI values indicate the presence of intact forest, whereas a degraded forest shows high NPV and soil values, making NDFI values to decrease.

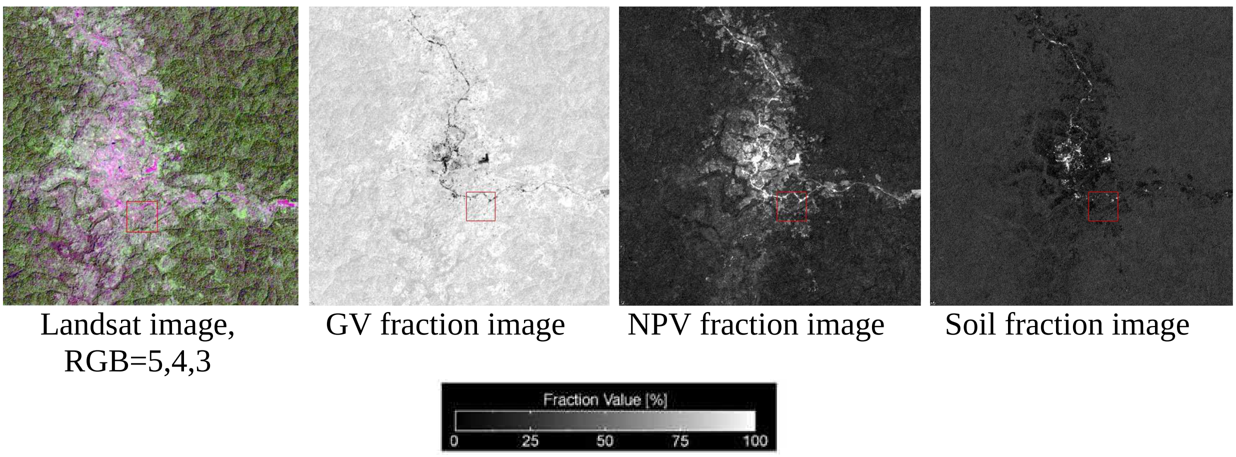

Figure 2. Original image and fraction images resulting from Spectral Mixture Analysis.

2.4. Contextual Classification Algorithm – CCA

As a next step, the Contextual Classification Algorithm (CCA) was applied to separate canopy changes due to selective logging and forest fires from those caused by other natural disturbances. The CCA combines the spatial information on log landing and roads, detected by the fraction images, with the degradation areas identified by the NDFI image.

Log landings and timber harvesting locations are extracted using the soil fraction values (>10%). This step is achieved with the image segmentation (Feature Extraction) module in ENVI, applying the form and surface rules. Then CCA algorithm looks, in a two-dimensional space, for a specific range of values in the NDFI image associated with canopy damages due to selective logging and burning (Souza et al. 2003, GOFC-GOLD 2009). Starting from a previously identified canopy disturbance (e.g., log landing) area, the search program checks NDFI values in the surrounding pixels. If a pixel has an NDFI value within the forest degradation range it is assigned a “canopy damage” class, otherwise it is classified as “intact forest”.

3. Results and discussion

3.1. Forest degradation detection

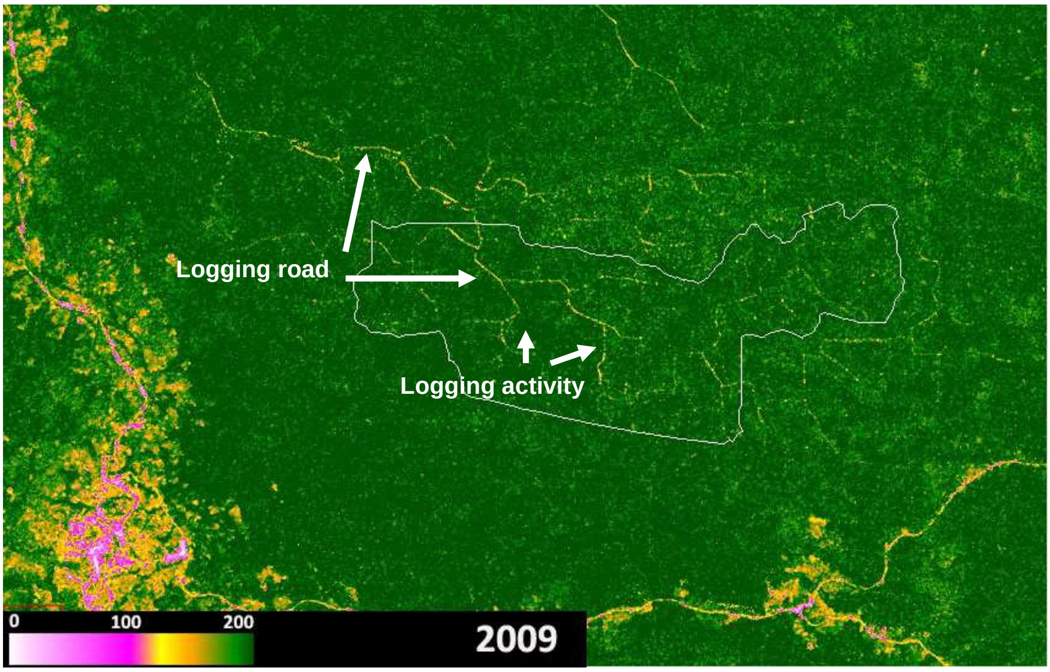

Figure 3. Forest degradation (lighter tones of green) detected by the NDFI index.

A study in the Brazilian Amazon found out the NDFI values associated to forest degradation tend to fall in a range from 150 to 175 (Souza et al. 2005b). This is the range applied in the present study of Cameroon (lighter tones of green in Figure 3). A minor variation on this range was found for an area of the Bolivian Amazon, supported by very-high resolution imagery validation (Rodriguez, Hinojosa and Seifert 2009).

The NDFI computation for the entire time series (years 2002, 2004, 2006-2009) allowed to highlight some forest disturbance events. A first selective logging event was detected for year 2006 inside the core area of PALLISCO concession (white boundary in Figure 3). This forest disturbance, extended until year 2008, was characterized as a group of log landing areas and logging roads that connect them.

The accelerated forest regeneration in the area is also visible in the log landing sites as bare soil recovers very fast its vegetation. In year 2009 the image no longer depicts the logging areas because the NDFI signal falls outside the forest degradation range.

NDFI image

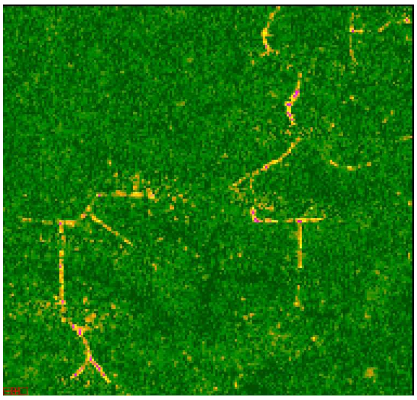

Figure 4a. Logging area

Degradation forest

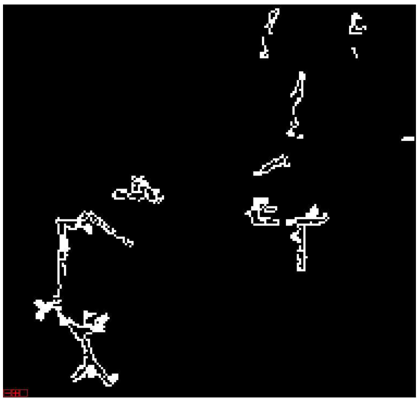

Figure 4b. Canopy damage in a logging area

Forest logging activities are characterized by timber extraction in the vicinity of roads. This regular spatial pattern is especially evident for satellite imagery acquired in a date near the forest disturbance (figure 4)(Asner, Keller and Silva 2004). The rapid tropical forest regeneration, as much as 10% per year depending of the exploitation type (Asner 2002), poses the challenge of picking the appropriate temporal window to detect forest disturbance.

To enhance the detection of log decks a texture analysis was applied on the soil fraction image. This analysis was used to detect neighbor variations in the forest structure, as depicted in the NDFI image. The filter size was defined as 3x3 pixels (figure 5b) to avoid a smoothing effect that would hinder the detection of small gaps in forest canopy (Asner 2002).

In comparison to the visual analyses described above, the 3x3-pixel textural filtering provided increased sensitivity to a broader range of canopy damage (Asner 2002). It is possible to observe log landings and infer the location and shape of the primary logging roads connecting the log landings.

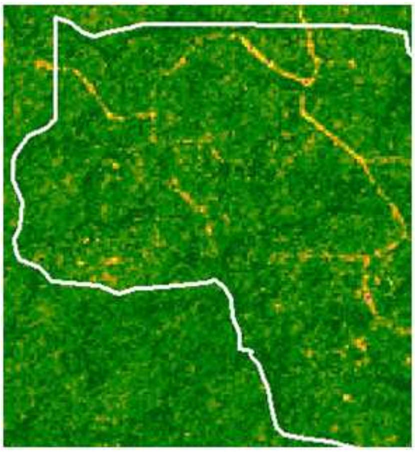

Figure 5a - Disturbance as detected by the NDFI index

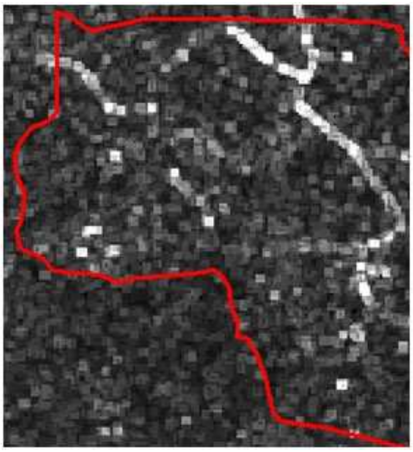

Figure 5b. Applied texture analysis filter (3x3 pixel)

The NDFI, CCA and NDFI texture analysis values were later compared to ancillary GIS layers (roads and skid yards) in the forest exploitation extent (Asner 2002). Visual interpretation suggests that areas near roads exhibit higher NDFI values. This spatial correlation and the observation that associated NDFI values fall in the forest degradation range, confirm that the index is correctly detecting forest logging activities.

It is important to remember that in Central Africa the timber extraction activities make for intensified forest degradation because of the high road density in logging concessions. In Cameroon, this degradation extends to 15% of forest (Laporte et al. 2007), supporting the use of road coverage as a control parameter (figure 6c, 6d).

Figure 6c. Log landings (in red) and canopy damage (in white).

6d. GIS ancillary layer: roads (in black)

The selective logging produces a landscape mosaic, with areas of intact forest that do not experience timber extraction or canopy damage. These areas present no roads or log landing sites (figure 6c,d). The calibration and validation of forest degradation indices that make use of Landsat data call for a visual inspection of increased resolution imagery (Stone and Lefebvre 1998). Very-high resolution (i.e., < 5 m pixel size) sensors are the most suitable source to understand the subtle spatial patterns of selective logging.

4. Conclusions

This study has shown that the Normalized Difference Fraction Index (NDFI) is a valid technique to detect forest degradation associated to selective logging in Southern Cameroon. The NDFI was built with high spatial resolution imagery (i.e., Landsat ETM+) openly available to the country, even though constant cloud coverage may be a cause of concern.

Our results show that the NDFI is able to detect infrastructure associated to most of selective logging operations (roads, skid yards) in the PALLISCO area, a certified timber concession. The additional Contextual Classification Algorithm (CCA) was able to correctly discriminate human-caused degradation from natural occurrences.

Acknowledgements

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