Radiometric detection of selective logging in tropical forest using UAV-borne hyperspectral data and simulation of satellite imagery

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Abstract

The aim of this research is to assess the detectability of small spatial scale tropical forest disturbances implying partial removal of the forest canopy cover, with optical high spatial resolution remote sensing imagery.

Among the forest change processes contributing to the global greenhouse gasses emissions, the degradation processes like selective logging represent the most challenging ones to be detected and quantified due to its partial forest canopy removal and their small scale. Furthermore selective logging events are considered as precursor of deforestation and important drivers for reduction of ecosystem services provided by tropical forests. In this research an Unmanned Airborne Vehicle (UAV) with a hyperspectral camera with 101 bands was used to detect and quantify small scale canopy gaps originating from selective logging. The UAV-based radiometric detection analysis provides the possibility to calibrate and validate a selective logging radiometric detection method based on airborne or satellite-borne very high spatial resolution data. Using the UAV's ultra-high (20cm) resolution data the canopy gaps were identified visually in Kalimantan, Indonesia. The SMACC linear spectral unmixing algorithm was used to derive abundance maps for three endmembers (Green Vegetation, Non Photosynthetic Vegetation and Shadow) in order to compare a pre-harvest and a post-harvest dataset where a single valuable tree was removed. The removed trees create increase in the shadowed area, hence the shadow abundance was used as the main endmember for detection of canopy changes occurred between pre- and post-harvest imagery.

Introduction

In rainforests, there are multiple drivers pushing forests to degrade such as: shifting cultivation, fuel wood collection, wood extraction for charcoal production, legal and illegal selective logging (Miettinen et al., 2014). When selective logging is practiced in an unsustainable way it leads to forest degradation (Mon et al., 2012a), and according to Kissinger et al. (2012) is the leading driver of forest degradation in these areas. In Southeast Asia the main reasons for forest degradation are shifting cultivation, fire and selective logging (Stibig et al. 2007b). Particularly, in the islands of Southeast the logging activities are more impacting than in other tropical regions because in these countries the Reduced Impact Logging (RIL) is seldom practiced (FAO, 2011b), (Miettinen et al., 2014). Moreover, short rotational logging times such as 20 years (Wilcove et al., 2013) are adding to the unsustainable logging practices resulting in a biomass reduction cycle (Miettinen et al., 2014).

Literature Review: Logging detection

Various remote sensing techniques have been developed to map forest degradation from selective logging. Visual interpretation using images from Landsat Thematic Mapper (TM) to characterize selective logging was tested by (Stone and Lefebvre, 1998). The authors managed to measure the logged areas under the condition that the image is acquired in a short period after the logging. Due to Landsat's TM coarse resolution (30x30m), this method is feasible only when the logging areas are at least as big as the pixel size (Souza et al., 2005). However, visual interpretation is subjective and labor intensive when it comes to large areas (Mietinen et al., 2014). Negron-Juarez et al. (2011) and Asner et al. (2004) also used Landsat images to map selective logging but with the 30x30m area limitation to remain.

Minimum distance and maximum likelihood classification (Stone & Lefebvre, 1998) was used in Amazonia to classify selectively logged areas using Landsat Thematic Mapper satellite data. This approach was not capable to define a different spectral class for selectively logged areas due to the complexity of the forest's structure, the coarse resolution of the sensor and the cloud coverage in the area. The authors stated that an automated classification procedure to detect the logging areas is unlikely to be developed under this setting. Reflectance and texture analysis (Asner et al., 2002a) have also been used for mapping selective logging but without robust results due to Landsat's spectral and spatial limitations. The difficulty lies due to the fact that gaps that are formed by selective logging are small and therefore very difficult to detect with Landsat.

Franke et al (2012), used multi-temporal Rapid Eye satellite data in Southern Kalimantan, Indonesia and they were able to apply MTMF, a partial spectral unmixing technique to detect unplanned (illegal) logging. Malahlela et al (2014) used WorldView-2 (WV-2) data to detect gaps in a subtropical forest with dense vegetation in South Africa. They used two classification techniques, the pixel based (Maximum likelihood, Support Vector Machine and Random Forest) and the object-based image analysis. Both methods succeed higher accuracy compared to sensors with the conventional visible and NIR bands. However this paper outlines that these methods are still inferior to the methods that are using LiDAR technology and this is because laser scanners can also capture tree height where the traditional optical sensors cannot (Dubayah and Drake 2000; Harding et al. 2001; Nelson, Oderwald and Gregoire 1997).

However, the costs and the data dimensionality of the LiDAR technology are high (Mutanga, Adam and Cho 2012) and therefore its application especially in large areas is limited. Gong, Biging and Standiford 2000, Swellengrebel 1959 and Green 2000, used digital aerial photography and digital surface models to map canopy gaps with success. Depending on the application, aerial photography has some disadvantages because it is time consuming and their availability for tropical areas is limited (Asner et al., 2002b). Canopy gaps where also derived using synthetic aperture radar (SAR) interferometry (Ferrazoli and Guerriero 1994; Imhoff 1995) but with the same practical limitations as LiDAR scanners (Malahlela et al., 2014).

Some methods that were developed for the Amazon basin could possibly be used in other tropical regions like the insular Southeast Asia. Some examples of these methods are: segmentation based automated statistical method for gap detection (Pithon et al., 2013) and combination of spectral mixture analysis (SMA) information into one band, using the Normalized Difference Fraction Index (NDFI) to detect forest areas with canopy damage (Souza et al. 2005).

Problem Definition

In the tropical rainforest region, forests in their non-affected state have closed canopies. A forest with closed canopy makes simpler the degradation monitoring because areas with gaps and reduced canopy cover can be counted as a sign of degradation (Miettinen et al., 2014). Furthermore, the climate conditions result in small yearly variations of forest features (Miettinen et al., 2014). However, even with the aforementioned detection advantages of the tropical forests, the mapping of selective logging using optical remote sensing remains hard since the cloudy climatic conditions and atmospheric disturbances make the acquisition of suitable satellite images difficult (Miettinen et al., 2014). Moreover, the scale of the disturbance is small and variates between distinct gaps and shadowed gaps and thus hard to detect with conventional sensors. The fast regrowth of those forests make the detection problematic because the gaps are fading resulting in low variation between gap and vegetated pixels (Miettinen et al., 2014).

Objectives

This on-going research is focusing on the radiometric detection of canopy gaps that are created by selective logging in the tropics. The main objective is to develop a method to radiometrically detect gaps caused by selective logging that is possible to apply in high-very high (5-10m) resolution satellite sensors. A spectral unmixing algorithm approach is adopted and the sensitivity of the method will be evaluated. A secondary objective is the exploration of the spectral characteristics of the materials. This exploration will assist to correctly distinguish the endmembers that are going to be used for the spectral unmixing.

Specific research questions are:

- What are the characteristics of the spectral signature related with canopy gaps?
- What methodology can be used in order to radiometrically detect canopy gaps caused by selective logging and how big should be this gap in order to be detected?
- How well is the developed method performing when applied to hyperspectral data simulated in a way that match the spatial and spectral resolution of a satellite with multispectral sensor?

Materials

Study Area

The study area (Figure 1) is in Central Kalimantan Indonesia and it lies between Latitude -2.404727° and Longitude 113.13°. The study area is composed of peat swamp forests which are moist forests with difficult access due to their density and soil condition. These forests are well-known for their abundance in valuable trees. This leads to fast deforestation caused by legal or illegal logging (Nurhayati, 2015).

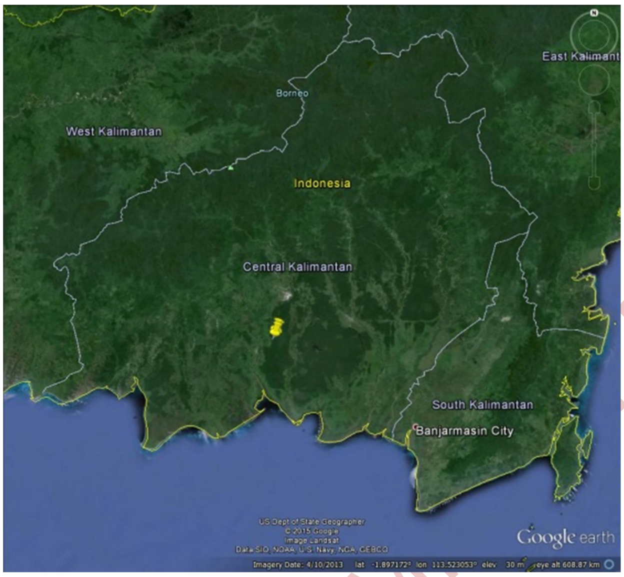

Figure 1. Study area in Southern Central Kalimantan, Indonesia.

Data

The data was acquired with an hyperspectral camera which was mounted on a Unmanned Airborne Vehicle (UAV). This hyperspectral camera carries 101 bands (450nm-950nm) with 5 nm intervals between each band. Two flights were performed, a pre-harvest and a post-harvest flight (Figure 2). Between these flights a single valuable tree were harvested. The altitude of the flights defined the resolution in 0.197cm pixels.

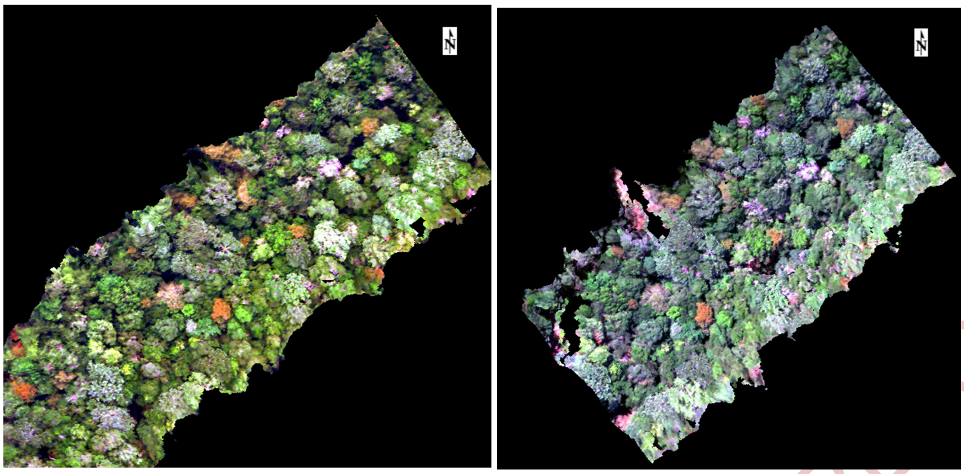

Figure 2. Pre-Harvest (left) and Post-Harvest (Right) datasets in Red, Green and Blue bands.

More information about the platform and the camera are provided through the link below. You will be directed to the web page of Wageningen UR Unmanned Aerial Remote Sensing Facility (UARSF).

Contents

- Available platforms
- Camera types
- Projects that currently use this facility
- Publications

http://www.wageningenur.nl/en/Expertise-Services/Chair-groups/Environmental-Sciences/Laboratory-of-Geo-information-Science-and-Remote-Sensing/Research/Integrated-land-monitoring/UARSF.htm

Methods

Spectral characteristics of gaps caused by selective logging

To investigate the spectral characteristics of a gap there is the need to differentiate between distinct gap and shadowed gap. For the scope of this research, distinct gap is defined as an area that a mixture of soil, shadow and non-photosynthetic vegetation can be spotted after logging, whereas shadowed gap is an area that only the shadow fraction was increased after a logging event. In the tropics the vegetation is dense and there are occasions which a single valuable tree is removed and a distinct gap is not visible. This can be attributed to the sun angle and the understory that is uncovered after the logging. In the study area, the gap that created after the logging event is a shadowed gap. The change most prominent that can be spotted is the difference in shadow abundance. The characteristics of these gaps are not differentiating from the characteristics of shadows that are introduced by the canopy structure and the sun angle.

To explore the spectral characteristics of the gaps, an issue to take into consideration is the different scale in reflectance values between the pre- and post-harvest datasets. This is demonstrated in Figure 3, where the spectral signatures of the same object, in this case, a tree crown reflecting differently in terms of magnitude. This difference in reflectance value can be attributed to different illumination conditions between the two flights. To overcome this issue, separate spectral signatures were collected. The distinct and shadowed gaps were identified visually using ENVI/IDL (ITT Visual Information Solutions, Boulder, CO, USA). Regions of interest used to extract the mean reflectance of each target.

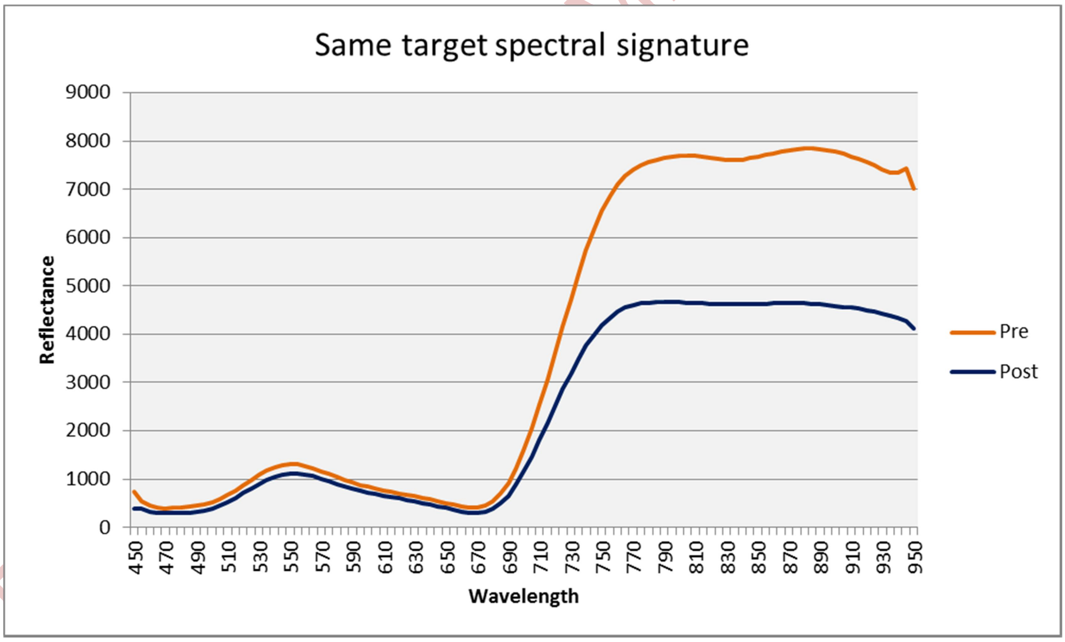

Figure 3. Difference in illumination conditions between pre- and post- harvest flights demonstrated by the spectral signature of a tree crown.

Radiometric Gap Detection

Endmember Selection

The Sequential Maximum Angle Convex Cone (SMACC) is used to derive abundance maps with a unity to one constraint. SMACC derives the endmembers automatically based on a Convex Factorization. For the scope of this research, three endmembers were identified. Green Vegetation (GV), a mixture of Non-Photosynthetic Vegetation (NPV) and Soil and Shadow. Figures 4 and 5 show the handpicked (observed) endmembers and the SMACC derived endmembers for the pre- and the post-harvest datasets.

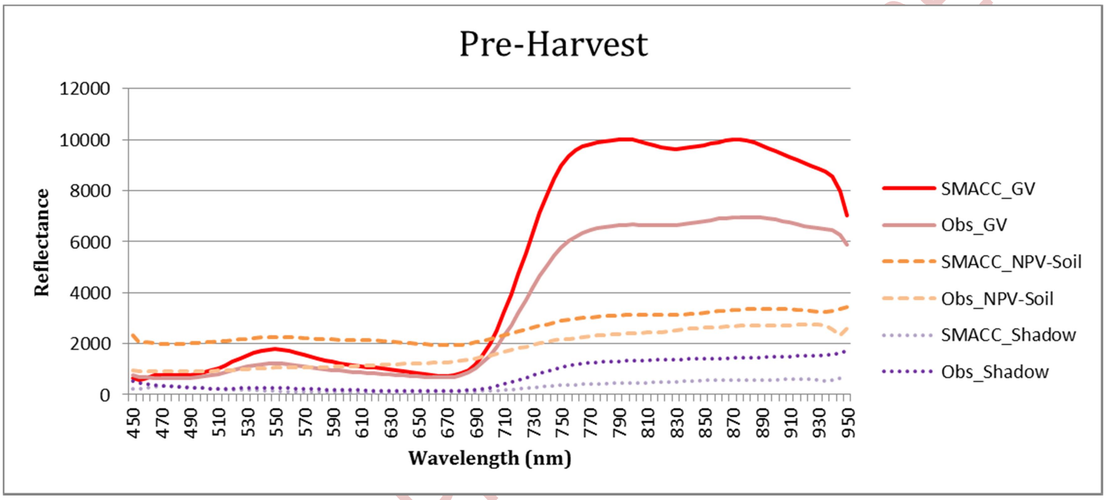

Figure 4. Graph showing the match between the observed and SMACC endmembers of the pre-Harvest dataset.

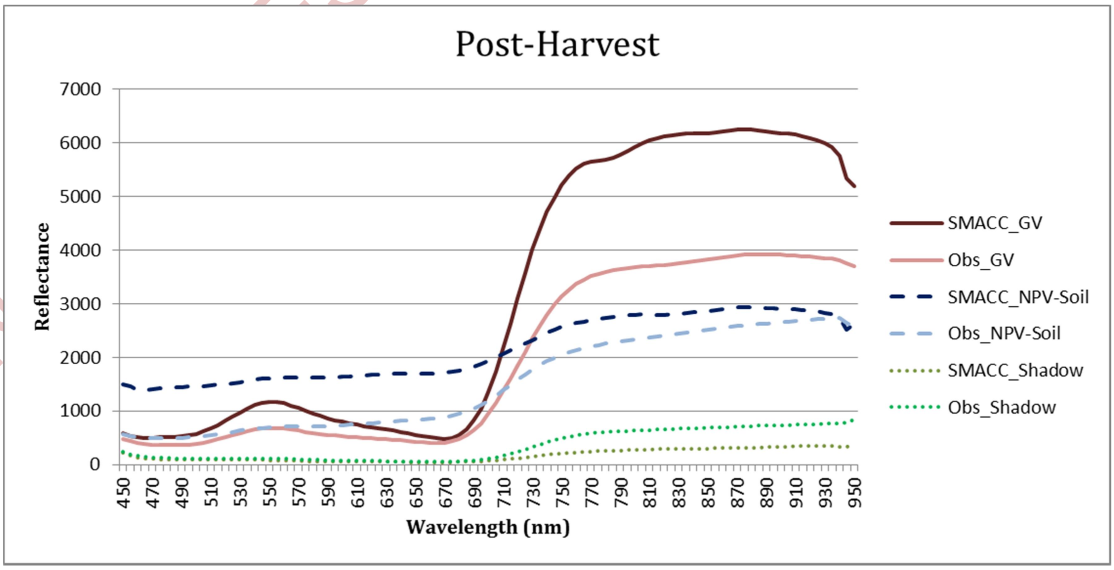

Figure 5. Graph showing the match between the observed and SMACC endmembers of the post-Harvest dataset.

Abundance Maps

The SMACC algorithm using the aforementioned endmembers, returned abundance maps with 3 bands, one for each endmember (Figure 6).

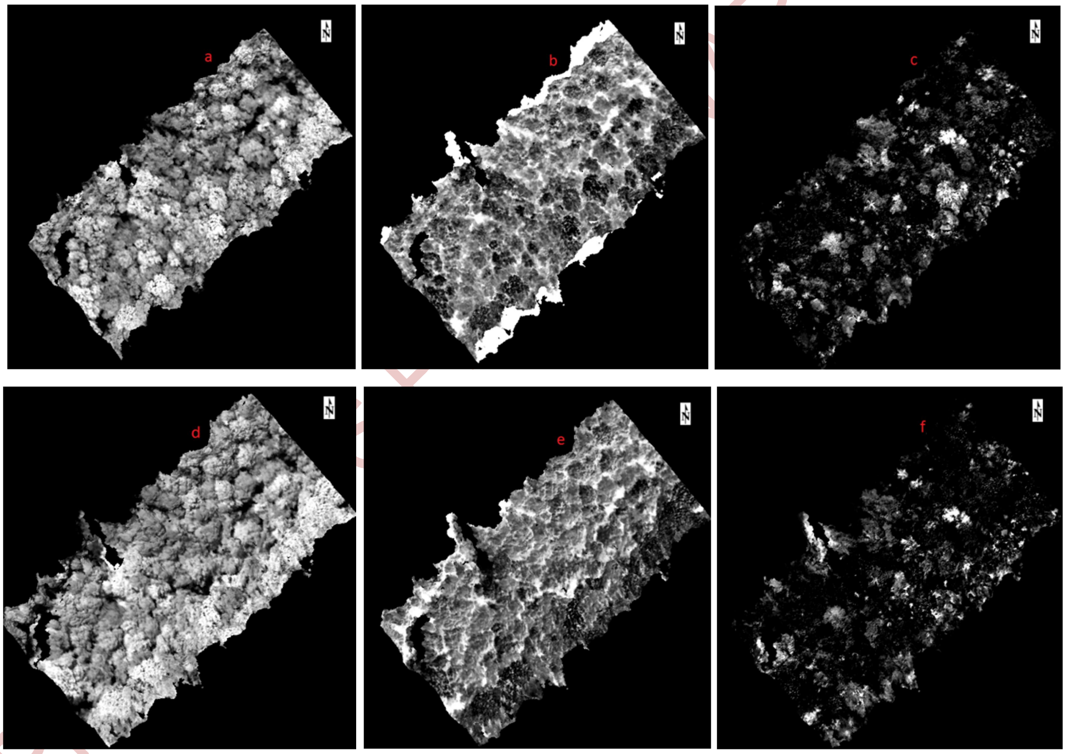

Figure 6. a) pre-harvest GV, b) pre-harvest Shadow, c) pre-harvest NPV-Soil, d) post-harvest GV, e)post-harvest Shadow, f) post-harvest NPV-Soil.

Preliminary results

Subtracting the pre-harvest shadow abundance band from the post-harvest shadow abundance map (Figure 7) is possible to identify the area where the change (logging) occurred. In the figure the bright white color area depicts areas that have biggest difference in shadow abundance between pre- and post-harvest. The large increase in shadow is used as indicator of location of logging event.

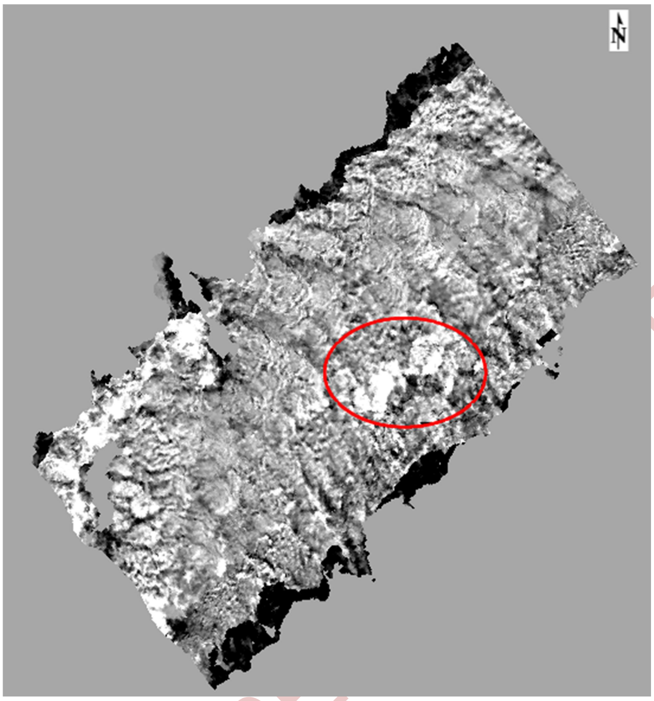

Figure 8. The bright pixels inside the red ellipse depict the area where a logging event occurred.

This research is still in progress. Results for all the plots are not yet available.

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