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Improving tropical deforestation detection through using photosynthetic vegetation time series – (PVts-β)

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ABSTRACT

This paper proposes a new approach of change detection that reduces seasonality in time series by using Photosynthetic Vegetation Time Series (PVTS) from satellite images. With this approach, each pixel value represents at the subpixel level a fraction of the photosynthetic forest's activity. Our hypothesis is based on an assumption that photosynthetic vegetation fractions will remain constant until a disturbing agent (natural or anthropic) occurs. Using Landsat data, we compared our approach with the Carnegie Landsat Systems Analysis-Lite (CLASlite) approach and with the national reports of the Ministry of the Environment of Perú (MINAM). After reducing seasonal variations in Landsat data, we detected deforestation events with a new detection method. Our approach (which was called PVts-β) of detection is a simple method that does not model the seasonality and it only requires as inputs: i) the average and standard deviation of the time series of a pixel and ii) a threshold magnitude (β) that was calibrated to detect deforestation events in tropical forests. For the PVts-β approach, the results of calibration show that deforestation was optimally detected for β = (5,6), higher or lower than this range, the biases favor to false detections and favor the omission of deforestation too. On the other hand, the overall accuracy for the PVts-β approach was 91.1%, with an omission and commission of 8.3% and 0.5% respectively, while for CLASlite the overall accuracy was 79.2%, with an omission and commission of 20.8% and 0.0% respectively. The differences in the overall accuracy between the PVts-β and CLASlite approach were significant, being atmospheric noise a main problem which CLASlite usually does not work optimally. The strength of our PVts-β approach is the early detection at the subpixel level of deforestation events that, added to our new method of change detection explain the little omission obtained in the results. Therefore, the PVts-β approach -that we propose here- provides the opportunity to monitoring deforestation events in tropical forests at sub-annual scales using Landsat data, and it can be used for near-real-time change detection monitoring without a doubt.

1. Introduction

Rapid changes in tropical forest ecosystems worldwide have had tremendous environmental impacts in recent decades, contributing significantly to climate change (Gullison et al., 2007) and biodiversity loss (Laurance et al., 2012). In response to these threats, international level discussions, frameworks and initiatives have been set up to combat anthropogenic forest loss. One such initiative, the "Reducing Emissions from Deforestation and forest Degradation" (REDD+) programme, features results-based payments to mainly tropical countries that implement activities to stem CO_2 emissions arising from deforestation and forest degradation (Corbera et al., 2010). The importance of including remote sensing data in Measuring, Reporting and Verification (MRV) for REDD+ has been widely recognized among the scientific community (De Sy et al., 2012; Goetz & Dubayah, 2011).

Mapping deforestation using medium spatial resolution satellite data (e.g. Landsat, Sentinel-2) is increasingly shifting from decadal (Achard et al., 2014) and annual scales (DeVries et al., 2015a; Griffiths et al., 2012; Kennedy et al., 2010; Souza et al., 2013) to sub-annual scales (Dutrieux et al., 2015; Reiche et al., 2015) mainly because of increased temporal availability of medium spatial resolution satellite data in recent years. Mapping deforestation from medium spatial resolution satellite data at sub-annual scales is beneficial because it provides opportunity for timely detection of small deforestation events that

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cannot be detected from coarse spatial resolution data (Hamunyela et al., 2016).

Currently, however, detecting deforestation from medium spatial resolution satellite data at sub-annual scales is challenging especially in forests that exhibit strong seasonality in their photosynthetic activity. Satellite images from medium spatial resolution satellite sensors are often not acquired regularly in all parts of the globe. Methods, which are used to detect deforestation at sub-annual scales from satellite image time series, account for seasonality in the time series using a seasonal model (e.g., DeVries et al., 2015a; Verbesselt et al., 2012; Zhu and Woodcock, 2014). The use of a seasonal model is based on an assumption that there is an identifiable seasonal pattern in the time series which can be described mathematically (Cleveland et al., 1990). However, this assumption may not always hold if the time series is for satellite images which are not acquired at regular interval, or have wide temporal gaps due to persistent cloud cover (Asner, 2001). Oftentimes, however, a seasonal model is still used to account for seasonality in such image time series (DeVries et al., 2015a; Zhu and Woodcock, 2014).

Change detection methods increasingly make use of Landsat Time Series (LTS) data, signaling a shift away from conventional bi-temporal change detection methods (Coppin et al., 2004). This shift is due in part to the opening of the Landsat archive to the public in 2008, which was followed by the development of methods which make maximal use of the data contained in the Landsat archive (Wulder et al., 2012). Following the opening of the Landsat archive, the pre-processing of imagery to derive surface reflectance and mask clouds became operationalised (Masek and Vermote, 2006; Zhu and Woodcock, 2012), facilitating the use of these data for a wide range of applications, including change detection.

A wide range of change detection methods has been proposed (Table 1) based on dense LTS either by creating annual composite time series (e.g., Griffiths et al., 2013; Kennedy et al., 2010; Huang et al., 2010) or by exploiting all data available in the archive (e.g., Broich et al., 2011; DeVries et al., 2015a; Dutrieux et al., 2015; Reiche et al., 2015; Zhu et al., 2012). A well-known and frequently used method is Breaks for Additive Seasonal and Trend (BFAST) developed by Verbesselt et al. (2010). It integrates the decomposition of time series into its trend, seasonality components, and the random effect to detect changes. Similarly, Continuous Change Detection and Classification (CCDC) by Zhu and Woodcock (2014) is an algorithm for detecting land cover changes using all available Landsat data based on a time series model that has seasonality and tendency components.

However, unlike the seasonality captured with images of strong temporality (e.g., Moderate Resolution Imaging Spectroradiometer (MODIS)), the seasonal patterns of LTS vegetation are not fully captured due to temporal resolution. To try to minimize this problem recently, time series from coarse resolution sensors (e.g., MODIS) have been used to derive the seasonal patterns when mapping deforestation at sub-annual scales from medium spatial resolution satellite data (Dutrieux et al., 2015).

The approach of using time series from coarse resolution sensors to address the problem of seasonality in medium spatial resolution satellite data is known and can be viewed as a synergistic way of using satellite data (De Sy et al., 2012; Reiche et al., 2015; Zhang, 2010). The weakness of this approach, however, is its reliance on data from another sensor to account for seasonality in Landsat data. If the sensor producing data that are used to derive the seasonal pattern fails, the approach would also not work anymore. To avoid such situations, methods that can address the issue of seasonality in image time series without using data from other satellite sensors to derive the seasonal pattern are critically needed and should be developed (Hamunyela et al., 2016).

Most approaches that use the components of time series to detect changes use complex models based on mathematical harmonics that model the seasonality and the tendency. In this sense, recent efforts to minimize the seasonal component within the time series (e.g., Landsat, MODIS) were developed by Hamunyela et al. (2016). However, these recent efforts in the detection of changes while minimizing the seasonal effect still makes use of solutions that model the seasonality in the time series. Therefore, we believe that after minimizing the seasonal component, it is also necessary to propose new approaches in the detection of changes without the need to use complex harmonic models accounting for the seasonal component. In this sense, our objectives were: (i) to investigate how the photosynthetic vegetation time series can be used to reduce seasonal variations in satellite images series, (ii) to propose a change detection approach (called PVts-β) that does not model the seasonality and that is based on the average, standard deviation and magnitude threshold (β) of the temporal values of the pixels, and iii) to evaluate if the use of PVts-β improves the precision in the detection of deforestation events regarding to the use of historical series of vegetation indexes, even when using CLASlite (Asner et al., 2009). Normalized Difference Vegetation Index (NDVI) (Tucker, 1979) and Enhanced Vegetation Index (EVI) derived from Landsat Thematic Mapper (TM5), Enhanced Thematic Mapper Plus (7 ETM+) and Operational Land Imager (8 OLI) images spanning from 1990 to 2016 were used as an indicator of vegetation temporal dynamic. The fraction of live vegetation, technically called Photosynthetic Vegetation (PV) because it maintains unique spectral properties associated with leaf photosynthetic pigments and canopy water content (Roberts et al., 1993), is obtained from CLASlite under an Automated Monte Carlo Unmixing approach (AutoMCU), which provides quantitative analysis of the fractional or percentage cover (0–100%) of live vegetation (PV), dead vegetation (technically called Nonphotosynthetic Vegetation (NPV)) and bare substrate (called S) within each satellite pixel (e.g., within each 30 × 30 m pixel in a Landsat image) (Asner et al., 2009).

2. Data and methods

The methods used in this study are shown in Fig. 1. Each step will be discussed in the following sections.

Table 1
Selection of forest change detection methods using LTS data (modified from DeVries et al., 2015b).

	Method	References
1	LandTrendR – temporal segmentation on annual LTS	Griffiths et al. (2013), Kennedy et al. (2010)
2	Continuous Monitoring of Forest Disturbance Algorithm (CMFDA) – temporal trajectory-based method for all available LTS data based on modeled historical time series	Zhu et al. (2012), Zhu and Woodcock (2014)
3	Vegetation Change Tracker (VCT) – change detection on annual Integrated Forest Z-scores (IFZ) derived from LTS data	Huang et al. (2010)
4	Breaks For Additive Season and Trend (BFAST) – temporal trajectory based method for all available LTS data based on monitoring structural changes in a monitoring period	DeVries et al. (2015a), Dutrieux et al. (2015), Reiche et al. (2015), Verbesselt et al. (2012)
5	Global forest change mapping using thresholding and bagged decision tree classifiers	Hansen et al. (2013)
6	Time series of forest probabilities for forest change monitoring	Broich et al. (2011)
7	Continuous Change Detection and Classification (CCDC)	Zhu and Woodcock (2014), Zhu et al. (2015)