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Monitoring forest cover loss using multiple data streams, a case study of a tropical dry forest in Bolivia

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ABSTRACT

Automatically detecting forest disturbances as they occur can be extremely challenging for certain types of environments, particularly those presenting strong natural variations. Here, we use a generic structural break detection framework (BFAST) to improve the monitoring of forest cover loss by combining multiple data streams. Forest change monitoring is performed using Landsat data in combination with MODIS or rainfall data to further improve the modelling and monitoring. We tested the use of the Normalized Difference Vegetation Index (NDVI) from the Moderate Resolution Imaging Spectroradiometer (MODIS) with varying spatial aggregation window sizes as well as a rainfall derived index as external regressors. The method was evaluated on a dry tropical forest area in lowland Bolivia where forest cover loss is known to occur, and we validated the results against a set of ground truth samples manually interpreted using the TimeSync environment. We found that the addition of an external regressor allows to take advantage of the difference in spatial extent between human induced and naturally induced variations and only detect the processes of interest. Of all configurations, we found the 13 by 13 km MODIS NDVI window to be the most successful, with an overall accuracy of 87%. Compared with a single pixel approach, the proposed method produced better time-series model fits resulting in increases of overall accuracy (from 82% to 87%), and decrease in omission and commission errors (from 33% to 24% and from 3% to 0% respectively). The presented approach seems particularly relevant for areas with high inter-annual natural variability, such as forests regularly experiencing exceptional drought events.

1. Introduction

Getting spatially and timely accurate information about land cover change is essential as change in forest cover is likely to affect aspects of the biosphere such as carbon cycle and biodiversity (Malhi et al., 2008). Remote sensing, especially in recent years, with large amount of data becoming freely available offers great opportunities to monitor forest at relatively high spatial resolution and in a systematic and objective way. However, there is a challenge that consists in extracting the desired information from large amounts of spatio-temporal data containing natural variability (seasonality and exceptional events such as droughts) and noise. The scientific community has reacted to this growing need and a variety of methods and products has appeared in the last few years, with a trend moving from bi/multi-temporal to hyper-temporal approaches (Lu et al., 2014). This trend can be explained by the opening of the Landsat archive, which allowed researchers to take full advantage of all the Landsat data that have been acquired since the beginning of the program in the 70s. In addition to being widely available at no cost, Landsat data, thanks to their spatial (30 m resolution) and temporal characteristics (16 days revisit period) are well suited to monitor processes such as deforestation and forest degradation (Asner et al., 2004a,b; de Wasseige and Defourny, 2004; Souza et al., 2005). Hence, by mining the entire Landsat archive for a given area, Zhu et al. (2012) were able to detect forest disturbances in temperate forests of the western United States. In a following paper Zhu and Woodcock (2014) extended their method to include land cover mapping following disturbance detection. Using super geo-computing facilities, Hansen et al. (2013) were able to globally map annual forest cover loss. From a methodological point of view, the existing multi-temporal methods differ slightly, depending on their intended use. For instance, in order to investigate land trajectories, Kennedy et al. (2010) developed LandTrendr, a temporal segmentation method capable of reconstructing recent land use history. LandTrendr works by identifying, using a time-series of annual image composites, segments of stable land use trajectories (stable

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forest, agriculture, regrowing forest, etc). For producing annual estimates of forest cover loss, Hansen et al. (2013) also worked on a year by year basis, computing differences between forest cover percentages produced annually from regression trees calibrated with Very High Resolution (VHR) images, such as Quickbird imagery. However, aiming at producing forest cover loss information with precise timing of disturbances requires approaches that work directly on the entire time-series. Working on the entire time-series, which means using all data available has two main advantages. First it allows to capture not only inter-annual differences, but also intra-annual variation. For instance vegetation, particularly in temperate regions is well known for having an intra-annual seasonal signal, which we call phenology. A time-series approach that uses full time-series can account for the phenology and identify changes in the phenological patterns (Verbesselt et al., 2010a). Second, using all data allows a higher precision in the timing of the events being detected. An example of method which uses the full time-series is the Continuous Monitoring of Forest Disturbances Algorithm (CMFDA), proposed by Zhu et al. (2012), which uses Fourier series and a threshold based deviation from the model mechanism to detect abnormal behaviours in newly acquired images. CMFDA requires three consecutive observations exceeding the threshold for a change event to be confirmed, which in an optimal setting with two Landsat satellites (8 days revisit period) can be as short as 16 days (Zhu et al., 2012). Similarly, approaches proposed by Brooks et al. (2013), Verbesselt et al. (2012), and DeVries et al. (2015) use all pixels available within the time-series and identify change based on statistical hypotheses of stability and confidence intervals. An intermediate approach, using all data from cloud free Landsat scenes, rather than all pixels, is proposed by Huang et al. (2010) for their Vegetation Change Tracker, which uses spectral distances to a set of reference pixels to derive forest likelihood. All these methods have been successful in detecting on a pixel basis events of forest cover loss soon after they occur in temperate forests at Landsat scales (Zhu et al., 2012; Brooks et al., 2013; DeVries et al., 2015) and forest disturbances and droughts from Moderate resolution time-series (Verbesselt et al., 2010a,b, 2012). However, an additional challenge, which has not been much investigated yet, consists in detecting in a similar way forest cover loss in highly variable forest environments. Seasonality in some environments may vary in amplitude from year to year, making the use of traditional seasonality models inappropriate since they cannot model differences among years. The challenge therefore consists in discriminating what is natural from what is anthropogenic in a temporal signal.

We identified two mechanisms potentially capable of discriminating human induced from anthropogenic variations. The first consists in taking advantage of the spatial context, since natural variations occur at regional scales, while human induced change (excluding climate change) tend to be much more localized. The second mechanism is to use an additional independent variable capable of predicting the observed variable. When interested in vegetation, or more specifically the Normalized Difference Vegetation Index (NDVI), time-series, the two above mentioned strategies can be translated as (1) including an extra NDVI time series at a different spatial resolution and (2) using a climatic index, since climatic conditions are known to be an important driver of vegetation greenness (Jong et al., 2013; Nemani et al., 2003). Previous studies taking advantage of contextual information or external data sources in a change detection context include Huang and Friedl (2014) and Kleynhans et al. (2011). Huang and Friedl (2014) developed a method capable of detecting sub MODIS pixel land cover change with context based calibration, while Kleynhans et al. (2011) developed a change metric at MODIS pixel level, using information from a 3 × 3 pixels window, hence using spatial context as a way to discriminate anthropogenic change from natural variability. Although the above mentioned studies illustrate ways of using the spatial context for change detection the level of spatial detail they provide is not sufficient for tracking small forest disturbances.

The proposed approach is an extension of the Break detection For Additive Season and Trend (BFAST) concept. BFAST has been developed as a generic change detection framework for disturbance detection. It is fully statistically based and has been validated for forest change detection (Verbesselt et al., 2010a), phenological change (Verbesselt et al., 2010b) and optimised for near real-time detection (Verbesselt et al., 2012). The framework has recently been evaluated for forest change monitoring in the tropics on Landsat time series for continuous forest change tracking in Ethiopia (DeVries et al., 2015), and for disturbance monitoring using fused radar-Landsat time-series (Reiche et al., 2015). In this study we further test and improve the BFAST framework by including extra data sources to improve the discrimination of anthropogenic changes from natural variability. Monitoring is performed using Landsat data. We tested two candidate variables to be used as external regressors; NDVI from the Moderate Resolution Imaging Spectroradiometer (MODIS) and the Standardized Precipitation Index (SPI). The proof of concept is done over a tropical dry forest of lowland Bolivia and the accuracy of the method is assessed using a set of visually interpreted Landsat time-series in combination with recent Very High Resolution imagery. Further insights on the approach performances and applicability are gained by experimenting with the different parameters combinations of the method, as well as via qualitative assessment of spatio-temporal patterns and single time-series profiles.

2. Material and methods

2.1. Change detection algorithm

In the BFAST framework, techniques for break detection (Chu et al., 1996; Leisch et al., 2000; Zeileis et al., 2005, 2010) which have been optimised for linear regression frameworks by Zeileis (2005), are combined with a seasonal-trend model for detecting change in vegetation dynamics (Verbesselt et al., 2012). The method consists in fitting a model to the data by Ordinary Least Square (OLS) fitting on a period defined as stable history, and to check for stability of that same model during a period defined as monitoring period. Discrepancy between the model predictions and the data during the monitoring period is estimated using a moving sums of residuals (MOSUM) approach (Chu et al., 1996), and when observed data significantly deviate from the model, a break is detected.

2.1.1. Seasonal-trend model with an external regressor

The additive seasonal trend model used by Verbesselt et al. (2012) to detect change within satellite image time-series is the following:

$$y_t = \alpha_1 + \alpha_2 t + \sum_{j=1}^{k} \gamma_j \sin\left(\frac{2\pi jt}{f} + \delta_j\right) + \epsilon_t \quad (1)$$

where the dependent variable y at a given time t is expressed as the sum of an intercept α_1, a slope α_2 for potential temporal trend in the data, a sum of different frequency harmonic components representing seasonality $\left(\sum_{j=1}^{k}\gamma_j \sin\left(\frac{2\pi jt}{f} + \delta_j\right)\right)$, and an error term ϵ_t. For the harmonic component of the model, $j = 1$ corresponds to the 1 year cycle, k is the chosen harmonic order, γ_j and δ_j correspond respectively to the amplitude and phase of the harmonic order j, and f is