Near Real-Time Tropical Forest Disturbance Monitoring Using Landsat Time Series and Local Expert Monitoring Data

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ABSTRACT

In this paper, we present an integrated near real-time forest disturbance monitoring system which utilizes temporally dense Landsat time series in combination with a continuous local expert based system in a tropical forest ecosystem in southern Ethiopia. Landsat time series were analyzed using the Break detection For Additive Season and Trend Monitor (BFAST Monitor) method and *in situ* local expert data was in turn facilitated by the use of mobile devices programmed to be able to classify land use changes. BFAST Monitor was found to be able to describe forest change dynamics using irregular Landsat time series data with frequent cloud and SLC-off gaps. Disturbance data collected by local experts enhanced the BFAST Monitor results by providing contextual information such as the specific area and local drivers of disturbance events.

Index Terms— REDD+, near real-time monitoring, time series, Landsat, tropical deforestation

1. INTRODUCTION

With deforestation in the tropics accounting for nearly 20% of global carbon emissions [1], tropical forests are known to play a key role in the mitigation against global climate change. For this reason, efforts as the Reduction of Emissions from Deforestation and Degradation in developing countries (REDD+) require the establishment of robust forest monitoring systems, for which remote sensing data are an important component.

As remote sensing data such as imagery from the Landsat satellite missions become increasingly available under open data policies, methods are needed to utilize these data to their maximum potential. Time series based methods such as BFAST Monitor [2] represent an improvement in the ability to describe land cover changes compared to commonly used bi-temporal change detection methods. With the recent launch of Landsat 8 and the OLI sensor [3], these time series based methods are poised to play an important role in ongoing remote sensing based monitoring methods. Importantly, ongoing image acquisition allows for near real-time detection of changes [2], an ability which will play a key role in monitoring and alert systems, such as those required by REDD+.

A key component of a local monitoring system is the incorporation of ground-based data to ensure accuracy of the results and sustainability of the system. To this end, community-based or local expert based monitoring data can greatly enhance the efficiency of data collection. In this paper, we present an integrated forest disturbance monitoring system in the Kafa Biosphere Reserve of Southwest Ethiopia, where remote sensing time series data is integrated with local expert based monitoring data towards continuous near real-time forest disturbance detection.

2. DATA AND METHODS

2.1. Study Area

This study was carried out in the UNESCO Kafa Biosphere Reserve (http://www.kafa-biosphere.org), located in the afro-montane forests in Southern Nations Nationalities and People's Region (SNNPR) state of southern Ethiopia. Approximately half of the Biosphere Reserve is covered with moist evergreen forests with relatively high disturbance rates, and the rest of the area is characterized by patchy cropland-forest matrix landscapes. Smallholder agriculture is the major driver of forest loss with coffee being a major crop for both smallholder farmers and investors alike [4].

2.2. Remote Sensing Data Pre-Processing

All Landsat ETM+ data from p170r55 with cloud cover below 70% were downloaded from the USGS GloVis server (http://glovis.usgs.gov). Atmospheric and coarse topographical correction was carried out using the LEDAPS method [5]. Clouds and cloud shadows were detected using the FMASK algorithm [6] and subsequently masked from the Landsat images. The Normalized Difference Vegetation Index (NDVI) was calculated for all images and resulting NDVI images were assembled into a time series stack. A forest mask based on a supervised classification of a 2005 Landsat image was used to determine which pixels to include in the disturbance monitoring algorithm.

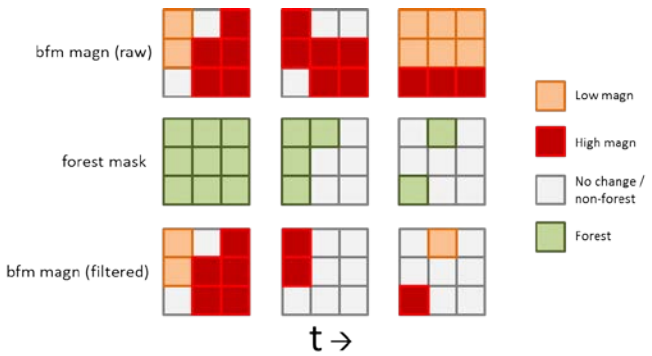

Figure 1 – Simulation of a dynamic forest mask. Forest pixels (green) are monitored using BFM in sequential monitoring periods. High-magnitude changes (dark red) result in the exclusion of that pixel in subsequent monitoring periods, whereas low-magnitude changes (orange) are continually monitored.

2.3. Forest Disturbance Detection

The Bfast Monitor (BFM) method [2] was applied to each pixel of the Landsat time series stacks to determine locations of possible forest disturbances. Briefly, BFM detects breakpoints in time series by applying a statistical test to observations in a defined monitoring period to determine if these observations deviate from a time series modeled after a determined stable history period. By detecting breaks at the tail of a time series, BFM can be used to detect changes in near real-time [2]. In addition to the presence of a breakpoint in the pixel time series, another important output of BFM is the change magnitude per pixel, which is defined as the median difference between expected and observed values during the monitoring period.

2.4. Dynamic Forest Mask for Sequential Monitoring

To exploit the change magnitude parameter in mapping forest disturbances, 1-year sequential monitoring periods were defined from 2005 to 2011 and BFM was run in succession using these monitoring periods. The change magnitude could thus be used to assess disturbance 'intensity' within a consistent monitoring time-frame (one year in this case of this study). To avoid redundant change pixels, a dynamic forest mask approach was adopted (Figure 1), whereby pixels where change magnitude values less than a predetermined threshold value were encountered were assumed to represent forest clearings and were accordingly masked from subsequent monitoring periods. For this study, a change magnitude threshold of -0.03 was adopted based on comparisons with high resolution images and field observations. After applying the sequential monitoring method, near real-time forest disturbance monitoring was carried out using BFM on a monthly basis, using the updated forest mask to ensure that changes detected by BFM were indeed new changes.

2.5. In Situ Disturbance Monitoring Using Smart Phones

Local expert based disturbance data related to deforestation and forest degradation were collected by local experts, together with forest communities, using mobile devices. It has been previously shown that mobile devices with integrated GPS and camera functionality can enhance the capacity of communities in collecting, entering and managing data [7]. Methods and techniques were developed such that the data collected by local experts can be sent and stored in a database system in an efficient and cost-effective way for further usage in monitoring.

These methods and techniques were realized by several component-based software architecture principles. First, data collection forms were designed based on existing monitoring activities and requirements of national REDD+ programmes. These forms were based on a decision-tree based design, optional input constraints, flow depending on previous answers and icon based user-friendly graphics. Second, the forms were deployed on android-based smart phones. These phones stored the data asynchronously and transferred to servers over GPRS, Wi-Fi or USB depending on connectivity. Finally, these local data were processed and analysed in an integrated environment with the results of the BFM analysis described above. These local data included several parameters of the change event, including location, type, timing, scale and drivers of the reported change. The local expert data allowed the user to classify Land Use, Land Cover and Land Cover Change. Near real-time disturbance data received from local experts was used to evaluate the change results obtained from the BFM analysis.

3. RESULTS AND DISCUSSION

3.1 Forest Disturbance Detection Using Irregular Time Series Data

BFM has previously been shown to be effective in detecting time series breaks in regular MODIS time series data [2]. In this study, we show that BFM is also applicable to Landsat time series data, which are characterized by cloud and cloud shadow gaps especially over tropical forest ecosystems. In the case of Kafa, Ethiopia, 129 ETM+ scenes were available for analysis, with many of the scenes subject to data loss due to clouds, cloud shadows and SLC-off gaps. However, despite frequent data loss, BFM was still shown to be able to detect changes without having to rely on gap-filling methods.

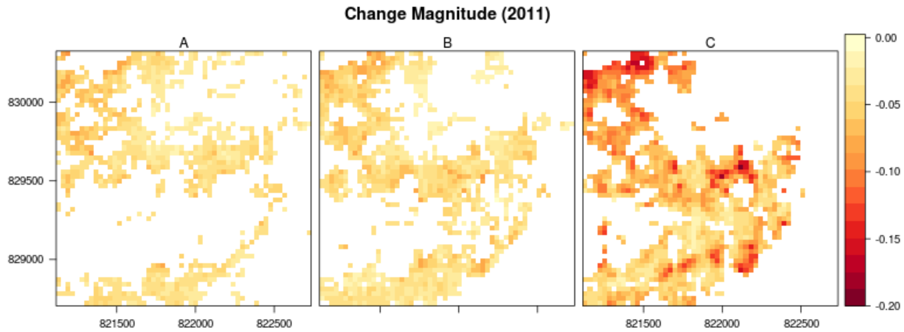

Figure 2 – Change magnitude in 2011 for an area experiencing extensive forest disturbance. Changes detected using a simple 2011 monitoring period (C) allow for discrimination of change types based on magnitude compared to a 2009-2011 monitoring period (A) or a 2010-2011 monitoring period (B).

3.2 Monitoring of Change Dynamics

Change magnitude, defined as the median NDVI change during the monitoring period between expected values (based on the stable history period) and observed values, was hypothesized to be related to the intensity of disturbance event (for example, degradation versus deforestation). The length of the monitoring period was found to have an impact on the change magnitude, since spectral dynamics before and after the change (due to crop phenology after forest conversion, for example) can effectively dampen the magnitude signal. This phenomenon is demonstrated in Figure 2, where changes in 2011 were assessed using three monitoring periods: 2009-2011, 2010-2011, and only 2011. When only 2011 was considered as a monitoring period, it was possible to discriminate types of forest disturbances based on the magnitude values.

Given the effect of the monitoring period length, a sequential monitoring approach using monitoring periods of consistent length was adopted to enable interpretation of the change magnitude parameter. As such, pixels with high magnitude changes were found to be representative of clear-cutting events, whereas low magnitude changes were often associated with gradual canopy clearing due to ongoing forest degradation. Adopting a sequential monitoring approach (shown in figure 1) allowed for the characterization of incremental changes leading to deforestation, which was found to be characteristic of the small-holder agriculture related changes taking place in the Kafa Biosphere Reserve.

3.3 Near Real-Time Monitoring Using BFM and Local Expert Monitoring Data

From January to April 2013, 134 forest disturbance reports were collected on smart phones and transmitted by local forest rangers in the Kafa Biosphere Reserve. These reports were facilitated by the use of smart phones with GPS and photography capabilities. These local data not only provided the estimated area of change (including GPS coordinates of the boundary of the changed area) but also provided a complete history of the change process via local interviews with farmers. Including these data with systematic photographic evidence (taken in all directions as shown in figure 3) enhanced the understanding of the forest change process.

An important observation reported by local experts was the local driver for change events, which can be very difficult to assess using remote sensing data alone. The majority of reports during this time pointed to fuel wood consumption as a major driver of forest degradation. Since this driver is known to drive low-level degradation which usually does not affect the forest canopy [8], these observations can thus be considered complementary to an optical remote sensing based data stream where understory changes are not detected.

These data are part of an ongoing effort to systematically capture forest disturbance events from the ground on a near real-time basis. By combining these observations with continually updated BFM results, including change magnitude as a descriptor of change type, an integrated monitoring system is envisioned, where a variety of change processes are documented. Independent validations are still needed to ascertain the full potential and roles of these data streams in a local monitoring system.

4. CONCLUSIONS

In this study we have shown that Bfast Monitor (BFM) can be applied to irregular Landsat time series data to detect forest disturbance in a tropical forest ecosystem. By measuring the change magnitude over sequential monitoring periods, complex change dynamics could be captured by BFM. Integration of this change information with *in situ*

Date	14-3-2013
Woreda	Gesha
Kebele	Atta wedity
Distance To Road	More than 3 Km
DistanceToNearestVillage	1-2 Km
DistanceToCoreForest	2-3 Km
Topography	Medium slope
Is forest?	yes
Forest Type	Degraded forest
CanopyCover	Very open (1 - 15% canopy cover)
CanopyHeight	Medium (10 - 25m tall)
CanopyStructure	Monoplane (trees mostly same height)
UnderstoryType	GRASS
DominantTreespecies	Chago
Is Disturbance?	yes
Date Of Disturbance	14-2-2013
Calendar	EUROPEAN
EvidenceOfDisturbance	Selective Logging, Grazing, DeBarking
ApproximateAreaAffected	2 Ha
DriverOfDisturbance	Charcoal, FirewoodCollection
NoOfTreePresence	17

Figure 3 – Forest disturbance data captured by local experts compared with a change polygon detected by BFM in 2013. The change area demarcated by the local expert is indicated as a solid line while the BFM change polygon is indicated as a dotted line. Photos taken in all directions are shown around the polygon, and the attribute table attached to the geo-data are shown on the right.

disturbance data collected by local experts and communities was shown to enhance the monitoring capability of this method. Follow-up research will address the need for validation of both the change magnitude parameter returned by BFM, as well as the quality of the *in situ* data collected by local experts.

To support such initiatives as local Measuring, Reporting and Verification (MRV) for REDD+, an integrated and interactive monitoring system composed of both remote sensing time series based methods and ground-based monitoring methods described in this paper is proposed. Such an integrated approach will enhance the near real-time disturbance monitoring capability of these monitoring and MRV systems.

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