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Tracking disturbance-regrowth dynamics in tropical forests using structural change detection and Landsat time series

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ABSTRACT

Increasing attention on tropical deforestation and forest degradation has necessitated more detailed knowledge of forest change dynamics in the tropics. With an increasing amount of satellite data being released to the public free of charge, understanding forest change dynamics in the tropics is gradually becoming a reality. Methods to track forest changes using dense satellite time series allow for description of forest changes at unprecedented spatial, temporal and thematic resolution. We developed a data-driven approach based on structural change monitoring methods to track disturbance-regrowth dynamics using dense Landsat Time Series (LTS) in a tropical forest landscape in Madre de Dios, southern Peru. Whereas most existing post-disturbance regrowth monitoring methods rely on annual or near-annual time series, our method uses all available Landsat data. Using our disturbance-regrowth method, we detected annual disturbance from 1999 to 2013 with a total area-weighted accuracy of $91 \pm 2.3\%$. Accuracies of the regrowth results were strongly dependent on the timing of the original disturbance. We estimated a total area-weighted regrowth accuracy of $61 \pm 3.9\%$ for pixels where original disturbances were predicted earlier than 2006. While the user's accuracy of the regrowth class for these pixels was high ($84 \pm 8.1\%$), the producer's accuracy was low ($56 \pm 9.4\%$), with markedly lower producer's accuracies when later disturbances were also included. These accuracies indicate that a significant amount of regrowth identified in the reference data was not captured with our method. Most of these omission errors arose from disturbances late in the time series or a lack of sensitivity to long-term regrowth due to lower data densities near the end of the time series. Omission errors notwithstanding, our study represents the first demonstration of a purely data-driven algorithm designed to detect disturbances and post-disturbance regrowth together using all available LTS data. With this method, we propose a continuous disturbance-regrowth monitoring framework, where LTS data are continually monitored for disturbances, post-disturbance regrowth, repeat disturbances, and so on.

1. Introduction

Rapid changes in tropical forest ecosystems worldwide in recent decades have had tremendous environmental impacts globally, 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 who implement activities to stem CO_2 emissions arising from deforestation and forest degradation (Corbera, Estrada, & Brown, 2010). A key requirement for the successful implementation of REDD+ is the Measuring, Reporting and Verification (MRV) of forest-related emissions and emission reductions (DeVries & Herold, 2013; Herold & Skutsch, 2011; Joseph, Herold, Sunderlin, & Verchot, 2013). The importance of including remote sensing data in MRV for REDD+ has been widely recognized among the scientific community (De Sy et al., 2012; Goetz & Dubayah, 2011).

A range of tropical forest monitoring systems and initiatives have been developed in recent years to support national and international efforts to stem tropical forest loss. With an increase in the availability of free satellite imagery, large-area mapping of forest disturbances has been operationalised in several key instances in the tropics. First, the Brazilian Space Agency (INPE) launched the PRODES and DETER monitoring databases to provide data on annual forest change and near real-time disturbance detection, respectively (INPE, 2014a, 2014b). Second, a global map of annual forest change made at 30 m resolution (Hansen et al., 2013) was recently made public under the banner of the Global Forest Watch (World Resources Institute, 2014). These systems represent an important development towards the operational monitoring of forest change, not only in support of REDD+ MRV, but

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also as a tool to raise public awareness of the scale and rate of tropical forest change.

Change detection methods increasingly make use of Landsat Time Series (LTS) data, signaling a shift away from conventional bi-temporal change detection methods (Coppin, Jonckheere, Nackaerts, Muys, & Lambin, 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, Masek, Cohen, Loveland, & Woodcock, 2012). Following the opening of the Landsat archive, the pre-processing of imagery to derive surface reflectance and mask clouds became operationalised (Masek & Vermote, 2006; Zhu & Woodcock, 2012), facilitating the use of these data for a wide range of applications, including change detection. Table 1 outlines a selection of some change detection methods based on dense LTS either by creating annual composite time series (e.g. (Griffiths et al., 2014; Kennedy, Yang, & Cohen, 2010; Huang et al., 2010)) or by exploiting all data available in the archive (e.g. (Broich et al., 2011; DeVries, Verbesselt, Kooistra, & Herold, 2015; Dutrieux, Verbesselt, Kooistra, & Herold, 2015; Reiche, Verbesselt, Hoekman, & Herold, 2015; Zhu, Woodcock, & Olofsson, 2012)).

While a wealth of forest disturbance methods and products based on LTS have been developed in recent years, disturbance-recovery dynamics are less well understood, especially in tropical forest systems. An understanding of the fate of forests after a disturbance is important in order to estimate net changes (Brown & Zarin, 2013) or to elucidate the drivers of forest change (Kissinger, Herold, & Sy, 2012). As in the case of disturbance monitoring, LTS data present an opportunity to describe forest dynamics with much more detail and certainty than is possible with bi-temporal comparison methods (Kennedy et al., 2014). A number of studies in temperate and tropical forests have used LTS to describe disturbance–regrowth dynamics, ranging from classification to temporal trajectory based methods. Carreiras, Jones, Lucas, & Gabriel (2014) monitored disturbance–regrowth dynamics at several sites in the Brazilian Amazon by classifying near-annual Landsat time series data into forest, secondary forest or non-forest classes, thereby shedding light on age classes and re-clearance rates of the forests. Schmidt, Lucas, Bunting, Verbesselt, & Armston (2015) measured regrowth in a forest-savanna landscape in Queensland, Australia by measuring trends in annual minimum NDVI. Czerwinski, King, & Mitchell (2014) monitored sudden and gradual positive and negative trends in a protected forest in Canada by applying the Theil-Sen slope estimator (Fernandes & Leblanc, 2005; Sen, 1968) paired with the Contextual Mann–Kendall test (Neeti & Eastman, 2011; Neeti et al., 2012) on annual LTS data. The LandTrendR method (Kennedy et al., 2010), which segments LTS into temporal trajectories, has been demonstrated in a number of contexts to be useful in describing historical forest disturbance–regrowth patterns (Main-Knorn et al., 2013; Neigh, Bolton, Diabate, Williams, & Carvalhais, 2014; Powell, Cohen, Kennedy, Healey, & Huang, 2013), an approach which has also proven valuable in predicting above-ground biomass using LTS (Frazier, Coops, Wulder, & Kennedy, 2014; Pflugmacher, Cohen, & Kennedy, 2012). Similarly, the Vegetation Change Tracker (VCT; (Huang et al., 2010)) monitors forest change and recovery using annual time series of spatially defined forest probability index derived from LTS. The most spatially comprehensive analysis of forest regrowth was undertaken by Hansen et al. (2013), who mined LTS data globally to produce a map of global forest loss and gain over the period 2000 to 2012 using a thresholding and bagged decision tree approach.

The spectral band or index used in the disturbance-regrowth method is an important determinant of the sensitivity of the method to forest change dynamics. The Normalized Difference Vegetation Index (NDVI) is one of the most commonly used indices in vegetation monitoring. While NDVI has been shown to be sensitive to forest change when used in a time series context (DeVries et al., 2015; Dutrieux et al., 2015; Reiche et al., 2015), it performs poorly as a measure of forest cover and structure (Freitas, Mello, & Cruz, 2005), and tends to saturate over dense forest (Gamon et al., 1995; Huete et al., 2002). A number of alternative metrics have been proposed in the forest disturbance monitoring literature, including the Normalized Burn Ratio (NBR) (Key & Benson, 2006), the Normalized Difference Moisture Index (NDMI; also known as the Normalized Difference Water Index, NDWI) (Gao, 1996; McDonald, Gemmell, & Lewis, 1998; Wilson & Sader, 2002), and a range of metrics derived from the Tasseled Cap transformation (Ahmed, Franklin, & Wulder, 2014; Crist & Cicone, 1984; Crist & Kauth, 1986; Healey, Cohen, Zhiqiang, & Krankina, 2005; Kennedy et al., 2010; Kennedy et al., 2012). Indices exploiting difference in reflectance between the SWIR and near infra-red (NIR) regions of the electromagnetic spectrum (e.g. NDMI or Tasseled Cap Wetness) have been found to be particularly useful in discriminating forest age classes (Fiorella & Ripple, 1993) due to their sensitivity to canopy moisture content (Hardisky, Klemas, & Smart, 1983; Hunt & Rock, 1989; Jin & Sader, 2005).

Most regrowth monitoring algorithms rely on annual or near-annual time series constructed either by selecting a representative image or composite of images for each time period (Carreiras et al., 2014; Czerwinski et al., 2014; Kennedy et al., 2012). As with disturbance monitoring, the reduction of the temporal resolution of the data can lead to losses of information as off-season images are excluded from the analysis (Zhu et al., 2012). The inclusion of all available data in a time series, on the other hand, gives a clear advantage for specific monitoring objectives, including near real-time disturbance monitoring, for example (Reiche et al., 2015; Verbesselt et al., 2012; Zhu et al., 2012). Other monitoring objectives such as post-disturbance regrowth can similarly benefit from the inclusion of all available data. Temporally dense time series with multiple observations per season can shed light on phenological dynamics in forests (Schmidt et al., 2015; Verbesselt, Hyndman, Zeileis, & Culvenor, 2010), potentially reducing the need for training data in separating permanent land use change (e.g. forest to cropland) from transient changes (e.g. forest harvest cycles).

Structural change monitoring methods rooted in the econometrics discipline have been shown to be useful in describing time series data in rich detail (Chu, Hornik, & Kuan, 1992; Leisch, Hornik, & Kuan,

Table 1
Selection of forest change detection methods using LTS data.

	Method	Study area	Reference(s)
1	LandTrendR — temporal segmentation on annual LTS	Temperate forests (U.S., Europe)	Griffiths et al. (2014), Kennedy et al. (2010)
2	CMFDA — temporal trajectory-based method for all available LTS data based on modeled historical time series	Eastern U.S.	Zhu et al. (2012), Zhu & Woodcock (2014))
3	VCT — change detection on annual Integrated Forest Z-scores (IFZ) derived from LTS data	U.S.	Huang et al. (2010)
4	BFAST monitor — temporal trajectory based method for all available LTS data based on monitoring structural changes in a monitoring period	Tropical forests	DeVries et al. (2015), Dutrieux et al. (2015), Reiche et al. (2015), Verbesselt, Zeileis, & Herold (2012)
5	Global forest change mapping using thresholding and bagged decision tree classifiers	Global	Hansen et al. (2013)
6	Time series of forest probabilities for forest change monitoring	Indonesia	Broich et al. (2011)