DETECTION OF FOREST DISTURBANCES BY TIME SERIES ANALYSIS OF NDVI FROM MODIS SENSOR FOR MICHOACAN STATE, MEXICO (2000 – 2014)

Alexander Quevedo[1], Yan Gao[1*]

[1] Centro de investigaciones en Geografía Ambiental, Universidad Nacional Autónoma de México, Antigua carretera a Patzcuaro 8701, col. Ex hacienda de San José de la Huerta, Morelia, 58190, México, Email: alexquevedo@gmail.com; ygao@ciga.unam.mx

*corresponding author

ABSTRACT

We present forest disturbance detection using time-series MODIS NDVI (2000-2014) data for Michoacán state, Mexico. First, we carried out a data preprocessing by applying a quality layer (QA), a spline interpretation and a Savitzky-Golay filter. Then we applied the method Bfast monitor (Verbesselt et al. 2012) for the detection of forest disturbance. Bfast monitor decomposes the time-series data into harmonic function, trend and remainder (noise). It works by first constructing a linear function using data from a presumably stable period. It applies a moving sum to detect a breakpoint where a change occurred, and calculates a change magnitude by the difference between the observed and the predicted NDVI values at the breakpoint. In our case, we manually defined the data from 2000 – 2007 as reference period, and data of 2007 – 2014 as change detection period, and forest disturbances were detected spatially and temporally by combining the maps of break points and change magnitude. We define a forest gain as a positive change magnitude larger the threshold 0.05 and a forest loss as a negative change magnitude smaller than -0.05. We compared the results with the changes derived from high spatial resolution land-cover maps (10 m) from 2007 and 2014. NDVI time-series detected less changes than the reference data, ranging from 46% - 48%. On one land, MODIS does not detect changes smaller than 6.25 ha, on the other hand, MODIS time-series detects more than land cover change, such as deforestation, but degradation as well, which is forest that remains as forest. However, the separation of both is still an unsolved problem, with no proved relation between magnitude and change categories.

1. INTRODUCTION

Forest disturbance affects forest structure, carbon budget, and forest ecosystem processes. Both natual and human induced disturbances have undesirable impacts on forest functions, leading to deforestation and forest degradation. Quantifying forest degradation with remote sensing data remains a challenge due to many factors ranging from the lack of agreed definition to the lack of data with sufficient spatial resolution and a proper methodology to quantify forest degradation in forest which remains as forest (Putz and Redford 2010; Morales-Barquero etal., 2014).

Time series analysis with dense satellite image product such as NDVI, can monitor the trajectory of forest changes and provide spatial and temporal forest disturbances data, which might shed light on the quantification of forest degradation with remote sensing data (Shimizu et al., 2016).

In this paper, we intend to detect and quantify forest disturbance with time series MODIS NDVI data for Michoacán, Mexico (2000 – 2014), with the assumption that forest disturbance is manifested in the value of NDVI, and positive change relates to the gain of forest and negative change relates to the loss of forest.

2. METHODOLOGY

2.1 The study area

The state of Michoacán is located in western Mexico (figure 1). It is rich in tree species: 37 species of genus Bursera in the tropical dry forest, 35 of genus Quercus, and 15 of genus Pinus in the oak and coniferous forest.
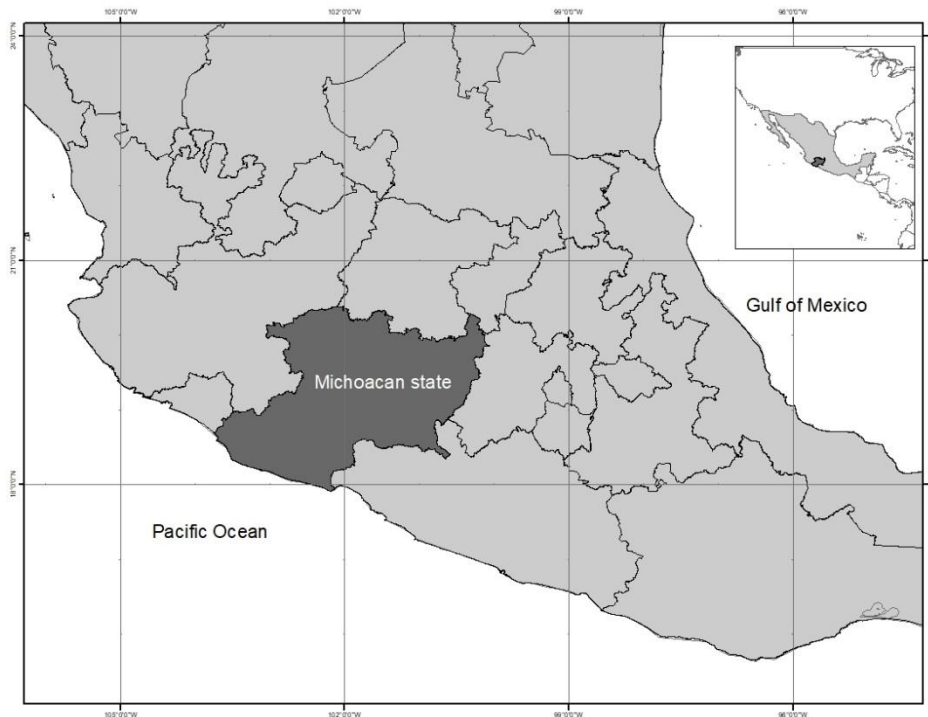
Figure 1. Map of location for the study area, in Michoacán state, Mexico.

2.2 Data:

We obtained time-series MODIS NDVI (2000 – 2014) from page http://e4ftl01.cr.usgs.gov. The NDVI data from the product MOD13Q1 is a composition of the best observations for a period of 16 days with a spatial resolution of 250m. Pixels contaminated by clouds and taken when the sensor is outside of the nadir position are considered as bad quality in comparison with the pixels that are free of clouds and atmospheric effects and are taken when the sensor is in nadir position. The applied algorithm conserves only the filtered data with good quality, however, not all the abnormalities are removed and for this, there exists a quality layer (QA-SDSs) which contains a summation of those abnormalities (Didan & Huete, 2006).

Land cover maps from 2007 and 2014 produced by using high spatial resolution images of SPOT were used as reference data (reference).

2.3 Data preprocessing

The preprocessing comprises two steps; the first is to apply QA-SDSs available for each time-series NDVI data, and the next is to fill the gaps where the pixels have been filtered out (Julien and Sobrino, 2010; Geng et al. 2014).

2.3.1. Data filtering by QA layer. The quality layer is a data of 16 bits, describing the quality of each pixel (https://www.ctahr.hawaii.edu/grem/mod13ug/sect0005.htm). The bits 0-5 describe the general quality, and the bits 6-15 describe the quality in a more specific manner. For this analysis, we consider the bits for general quality, utility, clouds, land/water mask and shadow. All the pixels that have bits for general quality of 00 are assigned as valid pixels, otherwise, they are further tested if the bits for general quality are 11, and if yes, those pixels are assigned as not valid pixels, otherwise, those pixels are considered for utility with bits combinations of 0000, 0001, 0010, 0011, 0100, 0101. The pixels with bits that do not fulfill with any of those combinations are assigned as not valid pixels, and those that are fulfilled continue with the test of clouds with bit 0, and land/water 001, and shadow 0. Fulfilled pixels are assigned as valid, otherwise not valid.

2.3.2. Interpolation and Salvinsky-Golay filtering. The processing with QA layer left gaps in the time-series data, and they were filled by a spine interpretation. Due to the clouds, atmospheric conditions, and bi-odirectional effects there were still noises even after the processing with QA (Chen et al. 2004), and a Savitzky Golay filter was applied (Wei et al. 2016).

The Savitzky Golay filter (1) applies a simplified least squares fit convolution (Chen et al 2004).This filter can be applied to any consecutive data with fixed data points and uniform interval.

$$Y_{j*} = \frac{\sum_{i=-m}^{i=m} C_i Y_{j+i}}{N} \qquad (1)$$

Where Y_j is the original NDVI value, Y_{j*} is the filtered value, C_i is the coefficient for the ith NDVI value of the filter, and N is the number of convolution integers and is equal to the smoothing window size ($2m$ +1). The *Index j* is the running index of the original ordinate data table, and m is the half-width of the smoothing window.

2.4 Bfast Monitor for time-series change detection

Bfast monitor is an algorithm to detect forest cover change (Verbesselt et al., 2012a, b), based on breaks For Additive Seasonal and Trend (BFAST, Verbesselt et al., 2010a, b). BFAST was designed to detect disturbances in the entire time-series data t = 1, …, n, while bfast monitor looks at if the new observations t = n, n+1, …continue the expected tendency of the historical data t = 1, …n. It works by identifying and modeling automatically a stable historical data, and then detect the changes in the new observations (Verbesselt et al. 2012b). The period of time-series data for change detection is named detection period. The abrupt changes are identified in function of historical period defined as the range of data before the detection period. The historical period may not represent a stable trend. A historical period that is representative or stable by definition are free of abrupt changes, and used as reference period for the change detection of the detection period. There are three steps involved in bfast monitor: 1) identify a stable reference period; 2) model the stable reference period; 3) analyze the data in the detection period for abrupt changes.

2.4.1. Seasonal and trend modeling. Bfast monitor models time series data with three components: a seasonal component, a trend component, and error (2),

$$Y_t = T_t + S_t + \varepsilon_t \qquad (2)$$

$$T_t = \propto_1 + \propto_2 t \qquad (3)$$

The equation (3) corresponds to trend, $\propto_1$ is the intercept, and $\propto_2$ is the slope of a linear model.

$$S_t = \sum_{j=1}^{k} \gamma \sin(\frac{2\pi jt}{f} + \delta_j) \qquad (4)$$

The equation (4) is harmonic function representing seasonal component, where γ is the amplitude, δ_j is the phase, f is the frequency by unit of time (e.g. f = 23 annual observations for a time-series of data every 16 days for a year) and k is a constant defined by the user.

ε_t is the error that cannot be explained by either the harmonic or trend function.

2.4.2 Change detection. Applying the equations (2, 3, 4), it is possible to estimate a trend and seasonality model. Being stable in an observed period of time, the point is to determine if the same trend maintain for the new observations (Verbesselt et al. 2012b). With this purpose in mind and considering that the data can be modelled in a linear regression, a structural change detection method was formed. Using moving sum of the residuals of the monitoring period t = n+1, …, when the result of the moving sum, depicted in equation 5, deviating from zero up to more than a significant level of 95%, bfast monitor identify this pixel as a breakpoint.

$$MO_t = \frac{1}{\sigma\sqrt{n}} \sum_{s=t-h+1}^{t} (Y_s - Y_{1s}) \qquad (5)$$

Where σ is the variance estimate, Y_s is the actual observation, Y_{1s} is the expected value, n is the number of the observations in the historical period and h is the band width of the moving sum defined as a fraction of n. Bfast monitor calculates the magnitude of change, regardless of when a change will be detected. The magnitude of change is defined as the subtraction between the value observed and the value expected.

2.4.3 Reference period. The assumption of the bfast monitor is that the observation in the historical period t=1,…, n, are free of change and can be used to model the expected behavior using the equation 2, 3 and 4. A illustration of bfast monitor is presented in figure 2. However, it is not always the case. Often they look at all the available observation and identify a stable historical period, right before the beginning of the monitoring period.

Bfast monitor allows identifying a stable historical period manually or automatically. Manual selection is recommended when there is expert knowledge (Verbesselt et al., 2012b). In the cases of no, or the time series

data is large (e.g. satellite images), bfast monitor can identify a stable historical period automatically based on the available data. To automatically define the detection period, a accumulating sum is used of the residuals in a reversed order (ROC), that it evaluates the error in the prediction using the equation 2 to retreat in time t=n, n-1, n-2, … until a disturbance is found.
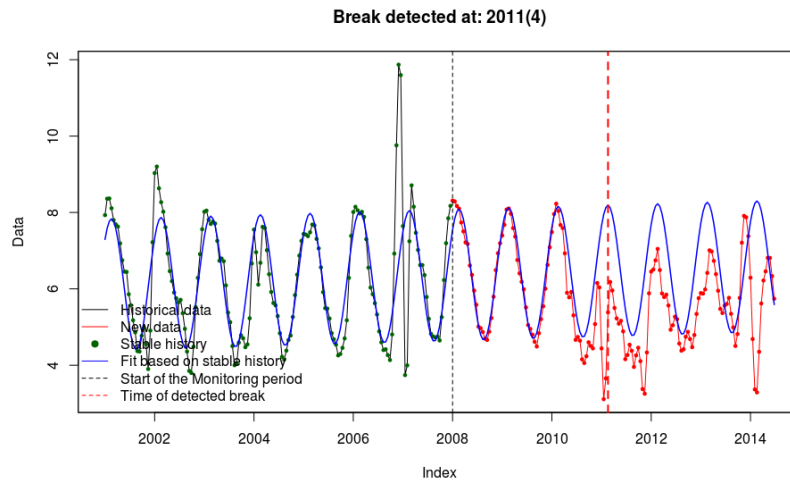

Figure 2. An illustration of change detection by bfast monitor.

2.4.4 Bfast spatial. Bfast spatial uses the algorithm of bfast monitor, in a context of satellite images, where potentially each pixel corresponds to a time series (Dutrieux, et al., 2016). The result of bfast spatial is a pile of data with three layers: 1) detected break points for each pixel, with information of the occurring dates in format of decimal year, 2) magnitude of change for each pixel, 3) error, with value of 1 when an error is found in a particular pixel or NA data where the algorithm was successful.

To detect forest cover change, it is considered only the magnitude of those pixels where breakpoints occurred, the negative magnitude is associated with deforestation or degradation, and the positive is associated with revegetation or reforestation. However, to define the changes, only by the presence or absence of the breakpoints is not enough, since it cannot be related directly to changes (Dutrieux et al., 2016, 2015). To avoid the false positive detection it is necessary to establish a threshold. This study applies a threshold of 0.05 following Dutrieux (2016).

2.5 Comparison of the results with two-times change results

A transition matrix and transition maps are calculated using land cover maps 2007 and 2014. The first 10 important transitions judged by the number of pixels are specified in the transition matrix to carry out the comparison with the changes detection by time-series NDVI data.

3.   RESULTS

3.1 Change detection by bfast monitor with mask of forests at 2007

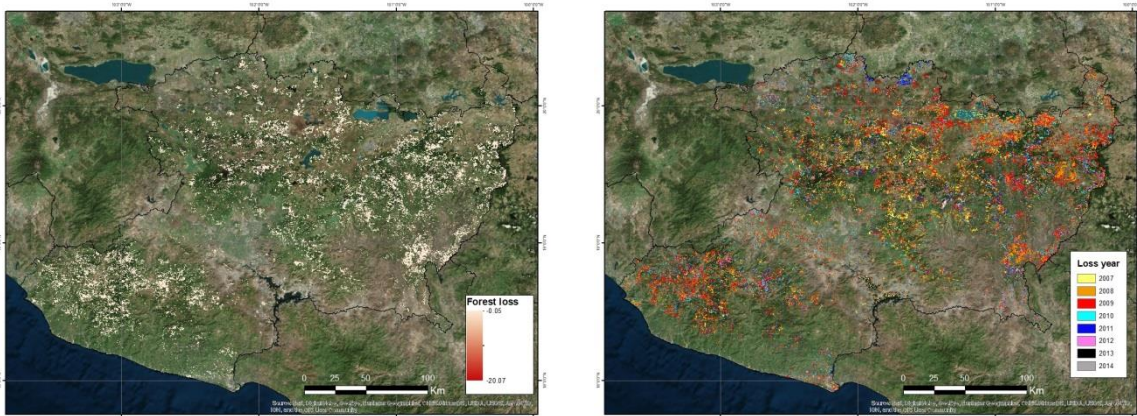**3.1.1. Forest loss by magnitude and by year of occurrence**

Figure 3. Forest loss (2007 – 2014) detected by bfast spatial applying forest mask (2007), by magnitude (left) and by year of occurrence (right).

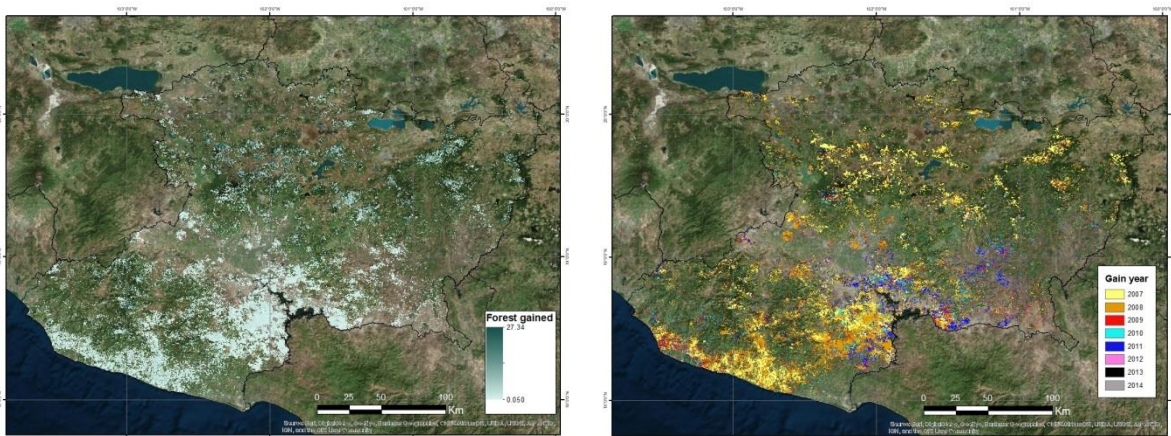### 3.1.2 Forest gain by magnitude and by year of occurrence

Figure 4. Forest gain (2007 – 2014) detected by bfast spatial applying forest mask (2007), presented by magnitude (left) and by year of occurrence (right).

3.2. Change detection without applying forest mask at 2007 (Global change)

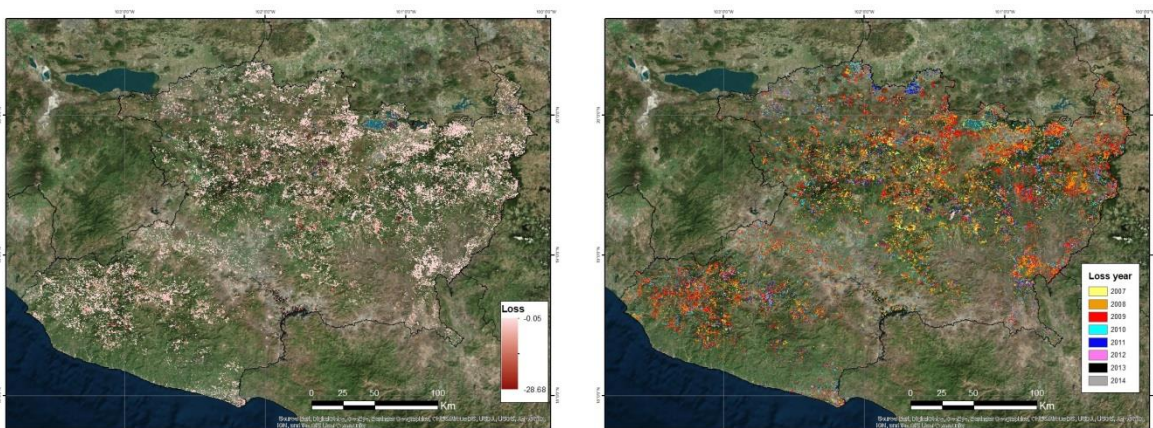### 3.2.1. Loss by magnitude and by year of occurrence

Figure 5. Forest loss (2007 – 2014) detected by bfast monitor without applying forest mask of 2007, presented by magnitude (left) and by year of occurrence (right)

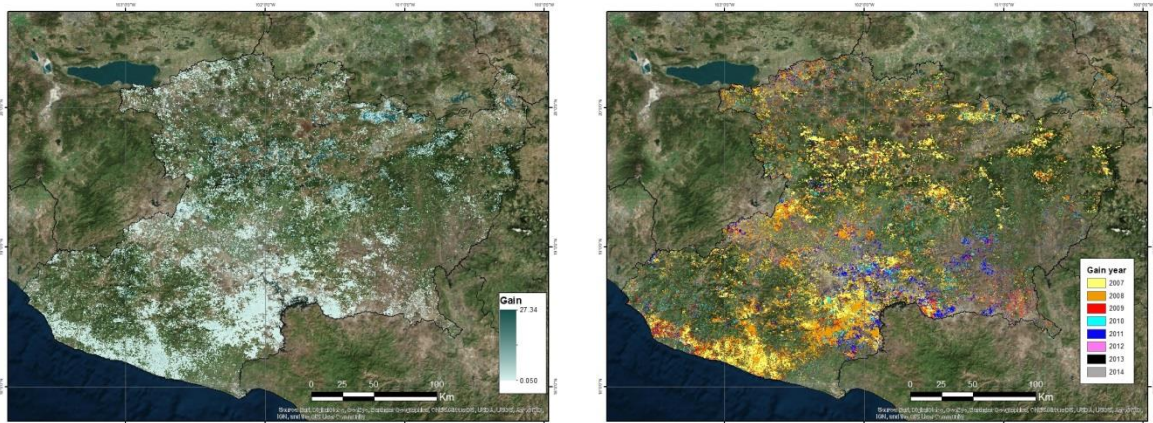### 3.2.2. Gain by magnitude and by year of occurrence

Figure 6. Forest gain detected by bfast spatial without applying forest mask of 2007, by magnitude (left) and by year of occurrence (right).

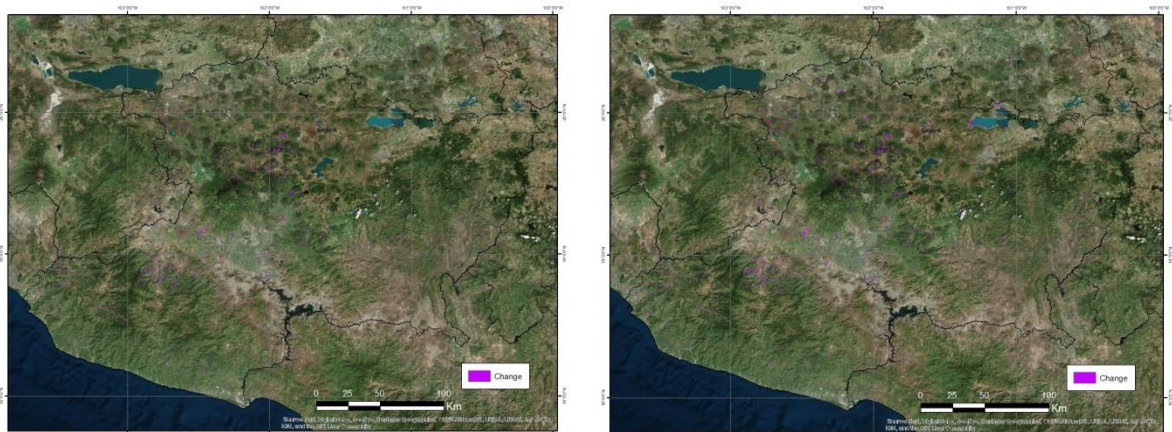### 3.3. Forest cover change from land cover maps of 2007 and 2014

Figure 7. forest cover change derived from land cover maps of 2007 and 2014, differentiated by applying forest mask (left) and without applying forest mask (right).

3.4. Comparison between changes by NDVI time-series and by land cover maps

For results with/without forest mask

Categories 2007	Categories 2014	With forest mask				Without forest mask			
		verification	Gain/bfast	Loss/bfast	Percentage	verification	Gain/bfast	Loss/bfast	percentage
Tropical dry forest / secondary	Induced / cultivated grassland	488	117	80	40.4 %	511	120	80	39.1 %
Tropical dry forest / primary	Induced / cultivated grassland	433	96	75	39.5 %	452	102	77	39.6 %
Tropical dry forest / primary	Tropical dry forest / secondary	279	95	70	59.1 %	288	101	75	61.1 %
Pine oak forest/primary	Pine oak forest / secondary	278	82	68	54.0 %	288	84	72	54.2 %
Oak forest/herbal secondary	Induced / cultivated grassland	277	78	59	49.5 %	287	78	60	48.1 %
Pine oak forest /secondary	Perennial crops	269	63	57	44.6 %	284	66	59	44.0 %
Oak forest/primary	Oak forest/secondary	248	60	55	46.4 %	253	60	58	46.6 %
Irrigated agriculture	Pine forest/ secondary	175	50	49	56.6 %	175	52	50	58.3 %
Pine oak forest /primary	Perennial crops	169	46	44	53.3 %	174	46	48	54.0 %
Pine oak forest /secondary	Induced / cultivated grassland	157	42	43	54.1 %	164	43	44	53.0 %
Total		2708	672	586	46.5 %	3879	1013	856	48.2 %

Table 1. Comparison of changes detected by bfast spatial and by land cover maps of 2007 and 2012. In which, the first two columns show the land cover categories in 2007 and 2014. The columns 3-6 show the scenario with application of forest mask, and columns 7-10 show the scenario without the application of forest mask. The column of verification data was derived by transition matrix with land cover maps of 2007 and 2014. The percentage is calculated by dividing the number of the change from the verification data with the sum of the gain and loss calculated by bfast spatial.

4. CONCLUSIONS

With time-series MODIS NDVI data for 2000 – 2014, by applying method of bfast spatial, we obtained results for the detection of forest disturbance data represented in forest loss and forest gain spatially and temporally. Time-series NDVI analysis can potentially detect vegetation trajectory change, the gain of NDVI value can be related to vegetation growth (e.g. reforestation and regrowth) and the loss of NDVI values can be related to vegetation decrease (e.g. deforestation, forest degradation). However, it is still a challenge to relate the change magnitude to change categories. A comparison of trajectory change results achieved by bfast spatial with traditional two-time period change analysis might shed light on relating the change magnitude with change categories.

In this paper, we tested the change detection in two scenarios: with and without the application of forest mask at year 2007. The results show that by applying the forest mask, bfast spatial detected less changes. By applying a forest mask using the land cover of year 2007, changes in forest cover can be underestimated, since it excluded changes such as reforestation and recovery, and especially those changes from non-forest to forest. However applying a forest mask is necessary in the cases of permanent cultivation areas (e. g. avocado, mango, and guava crops), since by the analysis of time-series NDVI, these areas will probably not present trends or seasonal changes, if their residence time exceeds the historical period of the analysis, which can generate noise in the estimation of deforestation and forest degradation by non-traditional methods such as time series analysis.

At last, we would like to state some possible limitations of this analysis; first, the analysis with Bfast spatial is based only on the value of time series NDVI data. Many factors could cause the change in NDVI values, such as climate factor. Further study is needed to precise this analysis. Second, we are aware that due to the spatial resolution of MODIS sensor, forest disturbances smaller than 6.25ha can not be detected, which implies that possibly the majority of disturbances (especially with scale smaller than the pixel size of MODIS) were not registered by NDVI time series analysis.

REFERENCE

Didan, K., Huete, A., (2006). MODIS Vegetation Index Product Series, Collection 5 Change Summary. https://landweb.modaps.eosdis.nasa.gov/QA_WWW/forPage/MOD13_VI_C5_Changes_Document_06_28_06.pdf.

Dutrieux, L. P., Jakovac, C. C., Latifah, S. H., and Kooistra, L. (2016). Reconstructing land use history from landsat time-series: Case study of a swidden agriculture system in brazil.International Journal of Applied Earth Observation and Geoinformation, 47:112-124.

Dutrieux, L. P., Verbesselt, J., Kooistra, L., and Herold, M. (2015). Monitoring forest cover loss using multiple data streams, a case study of a tropical dry forest in bolivia. ISPRS Journal of Photogrammetry and Remote Sensing, 107:112-125.

Geng, L., Ma, M., Wang, X., Yu, W., Jia, S., and Wang, H. (2014). Comparison of eight techniques for reconstructing Multi-satellite sensor time-series NDVI data sets in the Heihe River Basin, China. Remote sensing, 6(3): 2024-2049.

Julian, Y., and Sobrino, J.A., (2010). Comparison of cloud-reconstruction methods for time series of composite NDVI data. Remote sensing of environment, 114(3): 618-625.

Morales-Barquero, L., Skutsch, M., Jardel-Peláez, E., Ghilardi, A., Kleinn, C., Healey, J., (2014). Operationalizing the definition of forest degradation for REDD+, with application to Mexico. Forests, 5(7), 1653-1681.

Putz, F., Redford, K., H., (2010). The importance of defining 'forest': tropical forest degradation, deforestation, long-term phase shifts, and further transitions. Biotropica, 42(1), 10-20.

Shimizu, K., Ponce-Hernandez, R., Ahmed, O. S., Ota, T., Win, Z. Ch., Mizoue, N., Yoshida, S., (2016). Using Landsat time series imagery to detect forest disturbance in selectively logged tropical forests in Myanmar. Canadian Journal of Forest Research, 47(3), 289-296.

Verbesselt, J., Hyndman, R., Newnham, G., and Culvenor, D. (2010a). Detecting trend and seasonal changes in satellite image time series. Remote sensing of Environment, 114(1):106-115.

Verbesselt, J., Hyndman, R., Zeileis, A., and Culvenor, D. (2010b). Phenological change detection while accounting for abrupt and gradual trends in satellite image time series. Remote Sensing of Environment, 114(12):2970-2980.

Verbesselt, J., Kalomenopoulos, M., Souza, C., and Herold, M. (2012a). Near real-time deforestation monitoring in tropical ecosystems using satellite image time series. In Geoscience and Remote Sensing Symposium (IGARSS), 2012 IEEE International, pages 2020-2023.

Verbesselt, J., Zeileis, A., and Herold, M. (2012b). Near real-time disturbance detection using satellite image time series. Remote Sensing of Environment, 123:98-108.

Wei, W., Wu, W., Li, Z., Yang, P., and Zhou, Q. (2016). Selecting the Optimal NDVI TimeSeries Reconstruction Technique for Crop Phenology Detection. Intelligent Automation &Soft Computing, 22(2), 237-247.