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COMPARISON OF THE VEGETATION INDICES TO DETECT THE TROPICAL RAIN FOREST CHANGES USING BREAKS FOR ADDITIVE SEASONAL AND TREND (BFAST) MODEL

Yahya Darmawan[1*] and Parwati Sofan[2]
[1]Indonesian Meteorological Climatological and Geophysical Agency (BMKG), Region I, Medan; *e-mail: yahya.darmawan@bmkg.go.id
[2]National Institute of Aeronautics and Space (LAPAN), Jakarta

Abstract. Remotely sensed vegetation indices (VI) such as the Normalized Difference Vegetation Index (NDVI) are increasingly used as a proxy indicator of the state and condition of the land cover/vegetation, including forest. However, the Enhanced Vegetation Index (EVI) on the outcome of forest change detection has not been widely investigated. We compared the influence of using EVI and NDVI on the number and time of detected changes by applying Breaks for Additive Seasonal and Trend (BFAST), a change detection algorithm. We used MODIS 16-day NDVI and EVI composite images (April 2000-April 2012) of three pixels (pixels 352, 378, and 380) in the tropical peat swamp forest area around the flux tower of Palangka Raya, Central Kalimantan. The results of BFAST method were compared to the Normalized Difference Fraction Index (NDFI) maps and the maps were validated by the hotspot of the Infrastructure and Operational MODIS-Based Near Real-Time Fire (INDOFIRE). Overall, the number and time of changes detected in the three pixels differed with both time series data because of the data quality due to the cloud cover. Nonetheless, we found that EVI is more sensitive than NDVI for detecting abrupt changes such as the forest fires of August 2009-October 2009 that occurred in our study area and it was verified by the NDFI and the hotspot data. Our results demonstrated that the EVI for forest monitoring in the tropical peat swamp forest area which is covered by intense cloud cover is better than that NDVI. Nonetheless, further research with improving spatial resolution of satellite images for application of NDFI is highly recommended.

Keywords: *NDVI, EVI, BFAST method, NDFI, Forest Changes, Indonesia*

1 INTRODUCTION

The detection of forest changes is useful for many applications such as land-use changes, habitat fragmentation, rate of deforestation, etc. It is also important to identify the spatial and temporal trends in forest management (Healey *et al.*, 2005). Natural changes can be the result of fires, insect attack, and drought whereas anthropogenic disturbances results from human activities such as deforestation, urbanization and farming (Verbesselt *et al.*, 2010a). There is now an ever growing interest in information about the condition of ecosystems, especially it is caused by potentially devastating phenomenon such as global warming, biodiversity loss, and carbon accumulation in the atmosphere.

Satellite vegetation index products are generally applied in a wide variety of applications to observe and distinguish the Earth's vegetation cover from space (Jiang *et al.*, 2008). Vegetation properties predicted from remote sensing data are often employed as proxy indicator of land cover change. Sensor recorded radiances are transformed to vegetation indices that are known to possess a strong positive correlation to vegetative cover of the land surface. The key advantages of the vegetation indices over single-band radiometric responses in their ability to reduce appreciably the data volume for processing and analysis, and their innate capacity to provide information that are otherwise not available from any single-band (Coppin *et al.*, 2004). However, no single vegetation index exist that can summarize completely information in multidimensional spectral data space (Coppin *et al.*, 2004).

The most challenging task in the use of vegetation index is the choice of vegetation index models for the purpose of change detection. The suitability of any vegetation index for change analysis would seem therefore, to be case and purpose dependent (Wallace and Campbell, 1989). Although Normalized Difference Vegetation Index (NDVI) have started the most widely used vegetation index for change detection analysis, it is generally recognized to be vulnerable to changes in background reflectance and to saturate at medium to high leaf area index (LAI), resulting in insensitivity to seasonal changes (Sjostrom *et al.*, 2011). The introduction of Moderate Resolution Imaging Spectroradiometer (MODIS) produced the development of the Enhanced Vegetation Index (EVI) which can strengthen the vegetation signal by minimizing influences from the atmosphere and canopy background, and is able to improve sensitivity in high biomass regions (Sjostrom *et al.*, 2011). Nonetheless, comparative studies which assess the suitability of NDVI and EVI in change detection for different land cover types is lacking in the literature.

In this research, Breaks For Additive Seasonal and Trend (BFAST), which is a change detection algorithm proposed by Verbesselt *et al.* (2010a, 2010b), will be applied to MODIS 16-day NDVI and EVI composite images for a location of MODIS flux tower in Indonesia. Principally, BFAST combines the decomposition of time series into trend, seasonal, and remainder components with methods for detecting change within time series (Verbesselt *et al.*, 2010a, Verbesselt *et al.*, 2010b). BFAST method gives information about when the forest changes happen in those locations. It does not give information about the details information of the changes. BFAST method still needs to be optimized for deforestation monitoring by improving the capacity to deal with high cloud cover. The objective of this research was to compare the sensitivity between EVI and NDVI for analysing the tropical forest changes using the BFAST method. The result of BFAST method will be verified by the NDFI Landsat images and hotspot data in the Palangka Raya, Indonesia from April 2000 to April 2012.

2 MATERIAL AND METHODS

2.1 Study area

For supporting research, a micrometeo-rological tower (flux tower) in Palangka Raya, Central Kalimantan Province was chosen (Figure 1). This study was conducted in a tropical peat swamp forest area around Palangka Raya. A flux tower site in Palangka Raya was chosen based on the availability of clear Landsat images and its high potential of disaster hazard triggered by forest changes. The flux tower used eddy covariance methods to measure the exchange of carbon dioxide (CO^2), water vapour, and energy between terrestrial ecosystems and the atmosphere (NASA, 2012). Palangka Raya flux tower representing a tropical peat swamp forest area was selected for the study. The coordinate position of the Palangka Raya flux tower in UTM projection Zone 50 South is 170751 m and 9741010 m, respectively. The information about flux towers can be seen in http:// daac. ornl. gov/cgi-bin/ MODIS/ GR_col5_1/ corners. 1.pl?site= fn_idpalaya& res=250m.

2.2 Data descriptions

2.2.1 The MODIS EVI and NDVI (MOD13Q1 collection 5)

The 16-days NDVI and EVI composites with 250 m resolution (MOD13Q1 collection 5) for Palangka Raya site were acquired for the period covering 6 April 2000 to 6 April 2012 (277 series of data). The ASCII files of this site consist of NDVI and EVI data from 784 pixels of the study area. For applied the BFAST method, we focused on the 3 pixels in the centre 1 km pixels in Palangka Raya flux tower which were the pixels 352, 378, and 380 (Figure 2). Three pixels are chosen by randomly which would be used as a example of data extraction by BFAST Method. The BFAST method was only detect the abrupt changes of the forest based on a pixel. Three pixels of MODIS data will help us to decide when the abrupt changes happen. Hence, we do not need to process all of the Landsat images in the selected time period (12 years).

In other words, the forest changes in the study area will be determined based on all the pixels from the whole area by apply the NDFI method to the Landsat images.

The MODIS sensor was consisted of 36 spectral bands spreading from the visible to the thermal infrared wavelengths (from 0.405 to 14.385 μm). The MODIS data were available in real time as 16-day EVI and 16-day NDVI. The EVI and NDVI MODIS data can be downloaded in ftp:// daac. ornl. gov/ data/modis_ascii_subsets/ C5_ MOD13Q1/data/.

The NDVI (Rouse *et al.*, 1973) and EVI are formulated as (Hui Qing and Huete, 1995):

$$\mathrm{NDVI} = \frac{\rho_{\mathrm{NIR}} - \rho_{\mathrm{RED}}}{\rho_{\mathrm{NIR}} + \rho_{\mathrm{RED}}} \tag{1}$$

$$\mathrm{EVI} = \mathrm{G} \times \frac{\rho_{\mathrm{NIR}} - \rho_{\mathrm{RED}}}{\rho_{\mathrm{NIR}} + (\mathrm{C}_1 \times \rho_{\mathrm{RED}} - \mathrm{C}_2 \times \rho_{\mathrm{BLUE}}) + \mathrm{L}} \tag{2}$$

Where L is a soil adjustment factor, and C_1 and C_2 are coefficients used to correct aerosol scattering in the red band by the use of the blue band (Huete *et al.*, 1997). The ρ_{BLUE}, ρ_{RED} and ρ_{NIR} represent reflectance at the blue (0.45-0.52µm), red (0.6-0.7µm), and Near-Infrared (NIR) wavelengths (0.7-1.1µm), respectively. In general, G=2.5, C1=6.0, C2=7.5, and L=1 (Huete *et al.*, 1997).

2.2.2 Landsat images

For multi temporal analysis, a series of 10 (ten) images was obtained from Landsat-ETM+ L1T (Path-118/Row-062). The temporal images obtained were from the data in June 2001, May 2002, April 2004, July 2005, August 2006, July 2007, May 2008, June 2009, April 2010 and June 2011. The Landsat images can be downloaded from http://glovis.usgs.gov/.

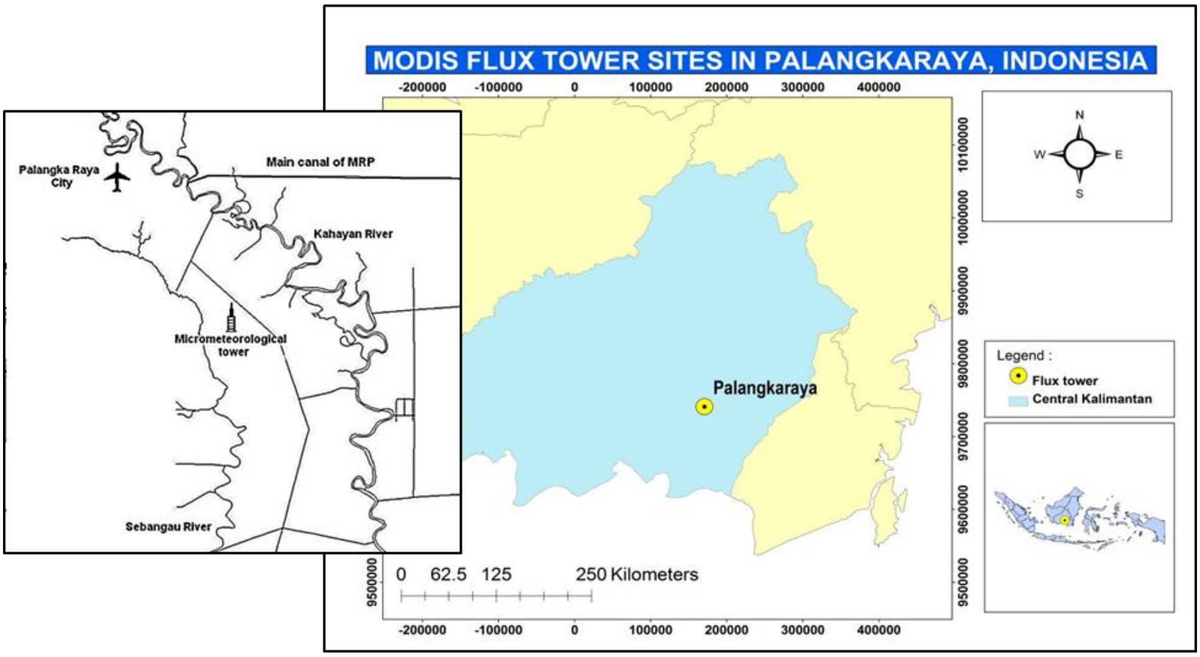

Figure 1. The location of the flux tower in Palangka Raya (Segah *et al.*, 2010).

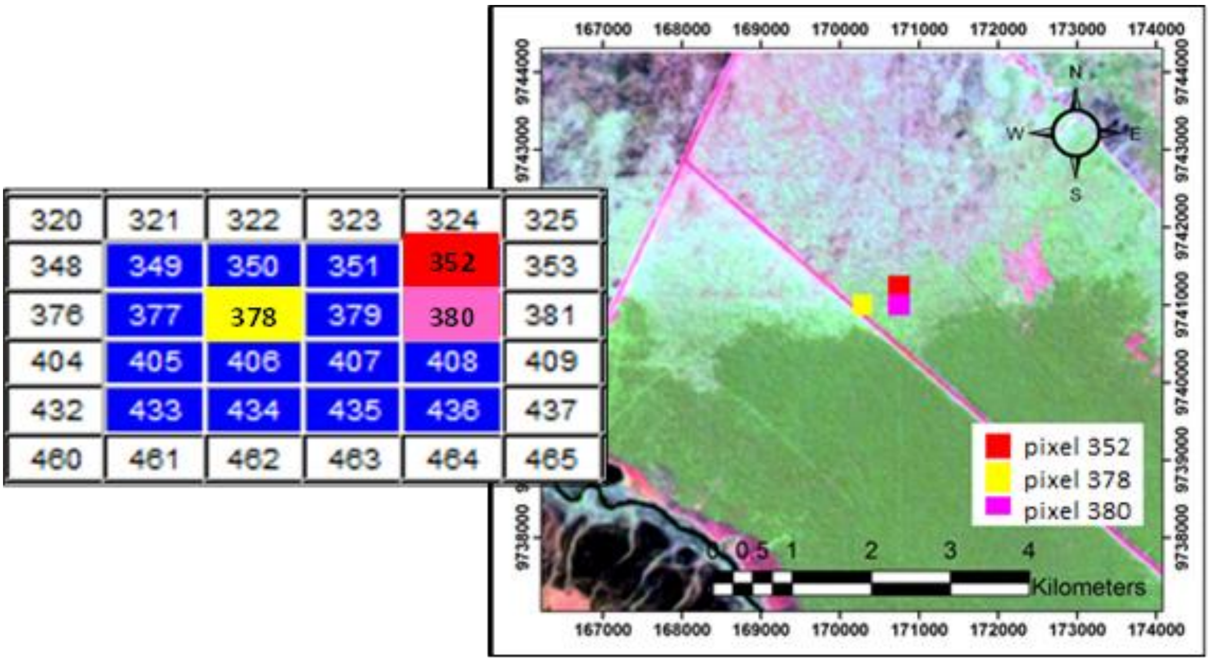

Figure 2. The 3 pixels in the centre 1 km pixels of Palangka Raya flux tower

2.2.3 The hotspot data

The hotspots data was produced by Indofire. Indofire was an operational near real-time (NRT) satellite-based monitoring system for fire monitoring and management which covers the whole of Indonesia and was accessed freely through the internet (Dawbina *et al.*, 2011). Indofire was an automatic real-time satellite processing of fire information based on the FireWatch MODIS-based fire hotspot detection system (http: //firewatch.landgate.wa.gov.au/) (Dawbina *et al.*, 2011). The validation of the hotspot was done in Central Kalimantan and it showed that the hotspots data had high correlation to the forest fires which detected through the satellite images (Vetrita *et al.*, 2012). Partners in the Indofire project included Indonesian National Institute of Aeronautics and Space (LAPAN), Ministry of Forestry (Kementerian Kehutanan/ Kemenhut), Ministry of Environment (Kementerian Lingkungan), Ministry of Education within Indonesia and the Western Australian Land Information Authority (Landgate) in Australia (Dawbina *et al.*, 2011). The data consisted of 12 years data from April 2000 to April 2012. The data can be accessed via internet from http:// indofire.landgate.wa.gov.au/indofire.asp.

2.3 The BFAST method for detecting the forest changes

Principally, BFAST was done by an additive decomposition model (Verbesselt *et al.*, 2010b). Decomposition models were generally used to define the trend and seasonal factors in a time series (PSU, 2012). The main objective of decomposition was to predict the seasonal effects which can be used to present seasonally adjusted values. The seasonal effect from a value will be removed during the seasonally adjusted values, so the trends will be seen more clearly. The additive model was useful when the seasonal variation was relatively constant over time (PSU, 2012).

Additive decomposition can be calculated by the general model (Verbesselt *et al.*, 2010b):

$$Y_t = T_t + S_t + e_t \quad (t = 1, \ldots, n) \tag{3}$$

Where Y_t is the observed data at time t, T_t is the trend component, S_t is the seasonal component, and e_t is the remainder component. The remainder component is the residual variation in the seasonal and trend components.

The trend component (T_t) is assumed as a linear function with break point: $t1^*, \ldots, t_m^*$ and define $t_0^* = 0$, so that (Verbesselt *et al.*, 2010a):

$$T_t = \alpha_t + \beta_j t \tag{4}$$

For $t^*_{j-1} < t \leq t_j^*$ and where j = 1. Intercept (α_j) and slope (β_j) can be used to calculate the magnitude of the abrupt change and slope of the gradual change between detected breaks points (Verbesselt *et al.*, 2010a). The magnitude of an abrupt change at a peak-points can be calculated by the difference between T_t at $t^*_{j-1}, \ldots, t_j^*$. So that:

$$Magnitude = (\alpha_{j-1} + \alpha_j) + (\beta_{j-1} + \beta_j)\, t \tag{5}$$

And slopes of the gradual changes before and after breakpoints are $((\beta_{j-1} + \beta_j)$.

A piecewise linear seasonal model was implemented based on seasonal dummy variables to fit the seasonal component (Verbesselt *et al.*, 2010a). The seasonal breakpoints was calculated by $\tau_1^{\#}, \ldots, \tau_p^{\#}$ and again express $\tau_0^{\#}$ and $\tau^{\#}_{p+1} = n$. S_t is a harmonic model for $\tau^{\#}_{j-1} < t \leq \tau_j^{\#}$ ($j = 1, \ldots, p$) and K the number of harmonic terms:

$$S_t = \sum_{k=1}^{K} a_{j.k} \sin\left(\frac{2\pi kt}{f} + \delta_{j.k}\right) \tag{6}$$

Where the unknown parameters are the segment-specific amplitude $a_{j.k}$ and phase $\delta_{j.k}$ and f is the (known) frequency (i.e. f = 23 annual observations for a 16-days' time series). The remainder component (also known as the residual) is what remains after the seasonal and trend components of a time series have been predicted and removed. In principle, the optimal position and number of breakpoints can be defined by minimizing the residual sum of squares linear of the regression model. The estimation of parameters will be performed by iterative procedure until the position and number of breakpoints is unchanged (Verbesselt *et al.*, 2010b).

The BFAST methods are available in the BFAST package for R from CRAN (http:// cran.r-project.org/package=bfast) (Verbesselt *et al.*, 2010b). In this research, the BFAST was used to process the satellite image time series from the MODIS 250 m 16-days composite gridded vegetation index products (MOD13Q1). The processing data in this research was divided into four parts. First, the BFAST method was applied based on the EVI and NDVI time-series data. The BFAST method decomposed the fits trend and seasonal change' stimeseries component. Second, the analysis of the phenological changes and abrupt changes was applied for the results of BFAST in all components. The number of phenology changes was displayed by seasonal components. The number of the abrupt changes was displayed by trend components. Third, the signal-to-noise ratio (Δc1) has an influence on the RMSE (Root Mean Square Error) for detecting the number of phenological changes (Verbesselt *et al.*, 2010b).

This implied that the higher seasonal amplitude (a) of the time series or lower noise level (σ) results indicated more accurate detection of the number of phenological changes. The signal-to-noise ratio (Δc1) can be derived by dividing the seasonal amplitude (a) from seasonal component to the noise level (σ). Fourth, evaluation of the sensitivity and reliability between the NDVI and EVI time-series data was the most crucial part in this study. Evaluation of sensitivity and reliability of data was conducted with an investigation upon quality of data which was used. This was related to the missing data that might be lost during the process of masking and cleaning the noise of the data in the BFAST before the data interpolation. The high number of the missing data was equal with the declining quality of interpolation results. The BFAST model was processed by using R programming.

2.4 NDFI for identifying of the forest degradations

In addition to the calculation of signal-to-noise ratio and number of gaps (NA), the accuracy of the BFAST was proven by using other image's satellites. The BFAST method provided estimation when the forest changes happen in a site for those periods of time. After the time of the disturbances was known, another set of data was compared to the result, to verify whether the detection was correct or not. The ground and aerial surveys as well as finer spatial and spectral resolution imagery can be detail investigation in estimated locations (Verbesselt *et al.*, 2010a). In order to achieve this objective, other satellite images i.e. Landsat data, were used to verify the BFAST results.

There were some steps to be performed in NDFI application. First, the pre-processing was done before the Landsat images were used for NDFI analysis. The pre-processing data aimed to reduce the atmospheric disturbance due to cloud cover. It consisted of stacking the Landsat images and removing the cloud cover from the images. Second, the candidate of Endmembers was derived from the Landsat images for three types of Endmembers: GV (Green Vegetation), NPV (Non-Photosynthetic Vegetation), Soil and Shade based on the Landsat images. Once the candidates of Endmembers were chosen for the four types of Endmembers, we calculated the average from these the candidates of Endmembers. Third, the fraction images for every Endmembers were calculated by using SMA (Spectral Mixture Analysis) model. Fourth, the GV shade was calculated by using fraction images GV and Shade. Finally, the calculation of NDFI was done by using the fraction image of GV shade, Shade and Soil. NDFI can be determined by using the following formula (Souza *et al.*, 2003):

$$NDFI = \frac{GVshade - (NPV + Soil)}{GVshade + NPV + Soil} \quad (7)$$

where GV shade, which is the shade normalized GV, is given by:

$$GVshade = \frac{GV}{100 - Shade} \quad (8)$$

The NDFI values range from -1 to 1. Ideally, the NDFI value in undamaged forest is expected to be high (i.e., about 1) because of the combination of high GV shade (i.e., high GV and canopy Shade) and low NPV and Soil values (Souza *et al.*, 2005). In the case of the forest degraded, the NPV and Soil fractions are expected to increase, lowering the NDFI values relative to intact forest. Therefore, the NDFI has the potential to enhance the detection of forest degradation caused by selective logging and burning (Souza *et al.*, 2005). The analysis of NDFI result was conducted by visual assessment the map as the whole area for every month and calculation of average NDFI for the subset of three pixels (352, 378 and 380). As the final part, the result of NDFI will be overlaid by the hotspots data of Indofire for validating the results.

3 RESULT AND DISCUSSION

3.1 Detection of forest changes using BFAST method

The application of BFAST method to the MODIS EVI and NDVI time series for the flux tower pixels generated estimates of the time, number and type of the significant changes. The only site with detected change in the seasonal component was in the pixel 352 and this was only found in the NDVI data (Figure 3). The seasonal changes were detected by NDVI in February 2008, August 2009, and January 2011. There were also divergences in the number and time of abrupt changes in the trend component from the EVI and NDVI data for pixel 352 (Figure 3). While the analysis of the EVI data estimated four the abrupt changes occurring in May 2002, November 2005, September 2007, and September 2009, the NDVI data characterized the changes in March 2004, March 2009, and May 2010 as abrupt changes.

The details of the abrupt changes at pixel 352 which detected in the trend component are shown in Figure 4. The highest magnitude of changes for EVI and NDVI, indicated by trend component (Tt), were - 0.40 (September 2009) and 0.20 (May 2010), respectively. According to trend component of EVI, there was a big decreasing of EVI in September2009. Other negative amplitudes of abrupt changes can be observed in May 2002, November 2005. For NDVI, it has only one negative abrupt change in March 2004. We can say that most of the abrupt changes in EVI have negative amplitude which represented to the decreasing of vegetation covers.

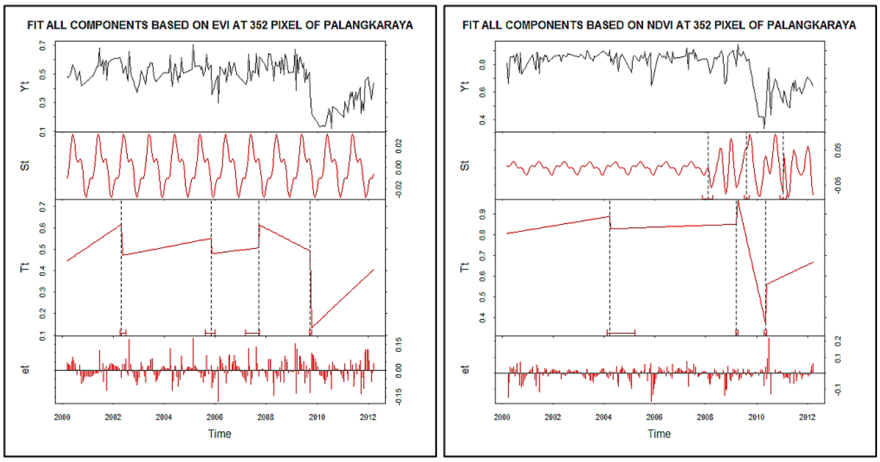

Figure 3. Detected changes (---) in Seasonal (St) and Trend components (Tt) of 16-days EVI (left) and NDVI (right) time series (data) extracted from a pixel 352 Palangka Raya flux tower.

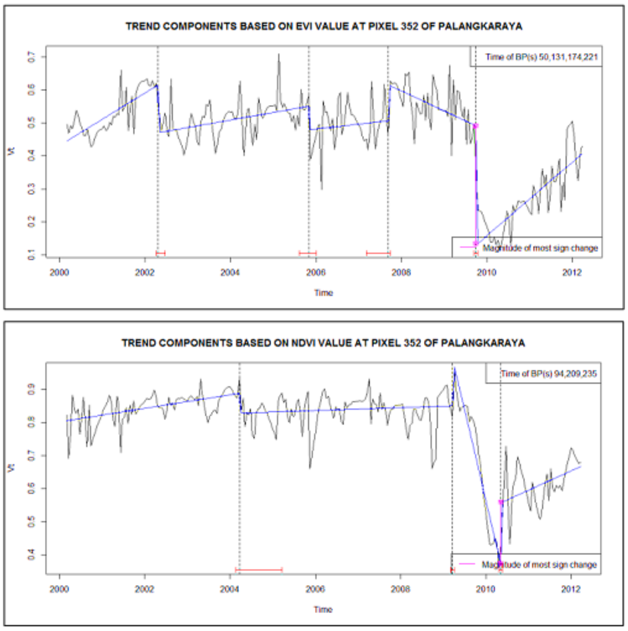

Figure 4. The abrupt changes which detected in the trend component of the pixel 352 for EVI (top) and NDVI (bottom)

In the pixel 378, there were six abrupt changes in the trend component of the EVI data (March 2001, September 2003, October 2004, March 2006, September 2007 and October 2009) as against four abrupt changes (August 2002, January 2004, September 2008, September 2010) estimated from the NDVI data (Figure 5). There was no seasonal change in both of datasets.

The highest magnitude of changes in EVI and NDVI were 0.20 (March 2001) and -0.10 (September 2010), respectively (Figure 6). The positive magnitudes of changes in EVI indicated the re-growth of vegetation in March 2010. NDVI produced a negative magnitude of changes which can be used to

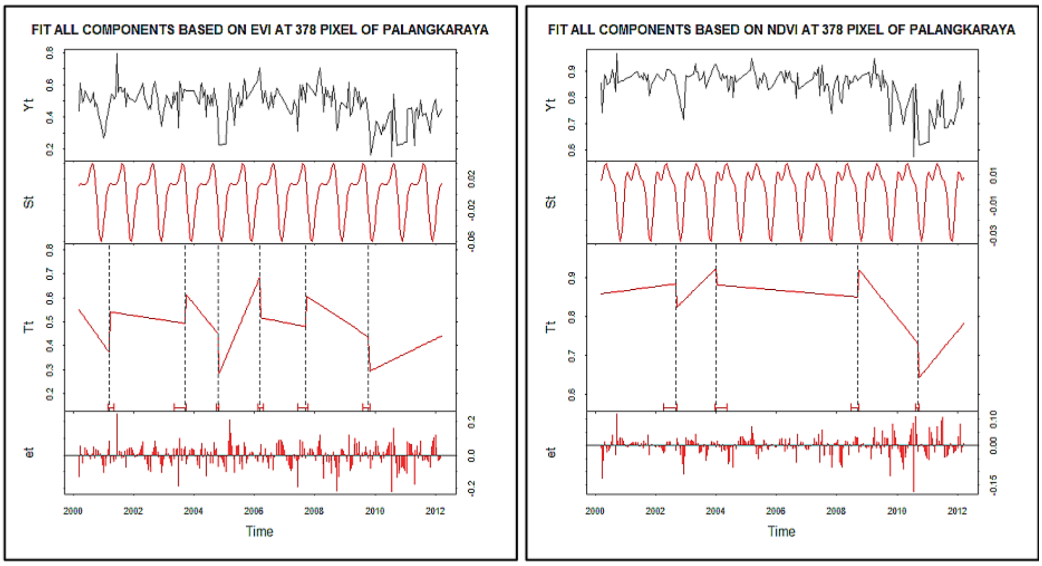

Figure 5. Detected changes (---) in trend components (Tt) of 16-days EVI (left) and NDVI (right) time series (data) extracted from the pixel 378 Palangka Raya flux tower

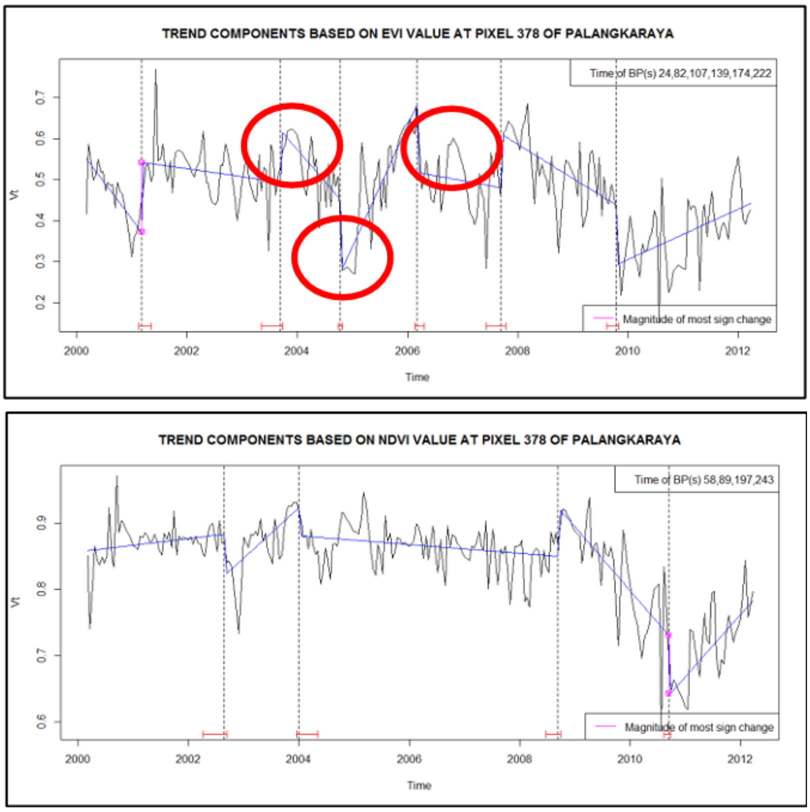

Figure 6. The abrupt changes in the trend component of the pixel 378 for EVI and NDVI; The red circle shows the interpolated data from the sequential series of missing data at pixel 378

indicate the forest degradation in September 2010. In the EVI result, there were three negative magnitudes of the abrupt changes which occurred in October 2004, March 2006 and October 2009. On the other hand, NDVI showed that three negative magnitudes of abrupt changes were occurred in August 2002, January 2004, and September 2010.

Based on the interpolated data of EVI and NDVI in pixel 378, the data quality was low here (Figure 6). As result of interpolation data, there were many gaps in the sequential series of data which can be indicated by the flat pattern of data (red circle in Figure 6). In pixel 380, there were difference in the number and time of the detected changes in the trend component of each site from both of EVI and NDVI. The BFAST analysis on the EVI indicated three abrupt changes in the trend component occurring in September 2007, April 2009 and June 2010 and revealed five abrupt changes which occurred in April 2008, October 2003, February 2005, August 2009 and August 2010 in NDVI (Figure 7). For pixel 380, there was no change in the seasonal components in both of the EVI and NDVI time series (Figure 7).

The highest magnitude of changes in the trend components were 0.10 for EVI (September 2007) and NDVI (February 2005) (Figure 8). Based on Figure 8, it can be observed that one positive of abrupt changes is detected in EVI (April 2009) and one positive of abrupt changes is detected in NDVI (August 2009).

For all the pixel (352, 378, 380), the seasonal amplitude and the noise level of the MODIS EVI data sets in the pixel 352, were found be lower than MODIS NDVI data sets (Table 1). Consequently, EVI of the pixel 352s had lower of signal-to-noise ratio than NDVI. For the pixel 378, EVI has higher seasonal amplitude and the signal-to-noise ratio than NDVI. The pixel 380 shows that EVI and NDVI had the same seasonal amplitude, the noise level and the signal-to-noise ratio. Both of datasets were observed in the number of missing data. In this case, EVI had a lower the number of missing data than NDVI.

For the abrupt changes, NDVI could not detect the abrupt changes from forest fire in 2009 at the pixel 352. On the other hand, EVI showed the occurrence of the abrupt changes in September 2009. In pixel 378, EVI can detect the forest fire event in September 2009. At pixel 380, there was disagreement of the abrupt changes in 2009 for EVI and NDVI. In pixel 380, the abrupt changes of EVI detected in April 2009 as a positive magnitude of change which indicates the vegetation growth. Conversely, NDVI detected a positive magnitude of changes which happens in 2009. The positive magni tude of changes indicated the growth of vegetation. In fact, the big forest fire occured in the study area from August 2009 to October 2009 (WWF, 2009). The forest fires of Palangka Raya can aslo be proved by hotspots data from Indofire of MODIS satelite (Figure 9). The BFAST result based on NDVI at pixel 380 showed

Table 1.SEASONAL AMPLITUDE (a), NOISE LEVEL (σ), SIGNAL-TO-NOISE RATIO (Δc1) AND NUMBER OF MISSING DATA (dg) OF THE EVI AND NDVI TIME SERIES DATA OF THE THREE PIXELS

PIXELS	a		σ		Δc1 = a/ σ		Missing data	
	EVI	NDVI	EVI	NDVI	EVI	NDVI	EVI	NDVI
352	0.05	0.10	0.15	0.20	0.33	0.50	119	129
378	0.10	0.05	0.20	0.15	0.50	0.33	111	127
380	0.05	0.05	0.15	0.15	0.33	0.33	126	135

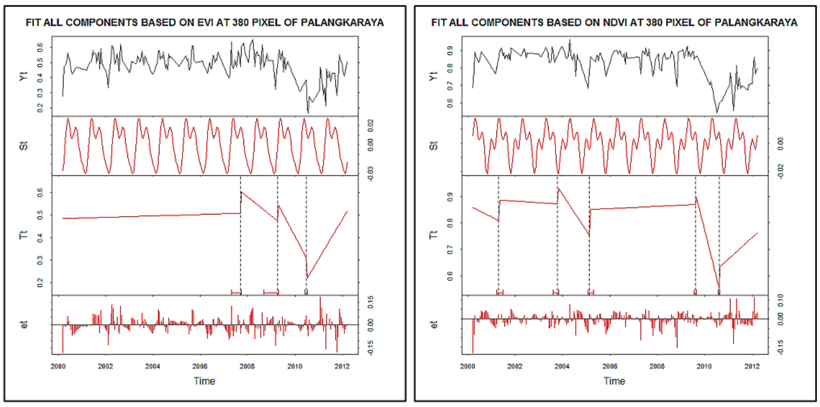

Figure 7.Detected changes (---) in trend components (Tt) of 16-days EVI (left) and NDVI (right) time series (data) extracted from the pixel 380 of Palangka Raya flux tower

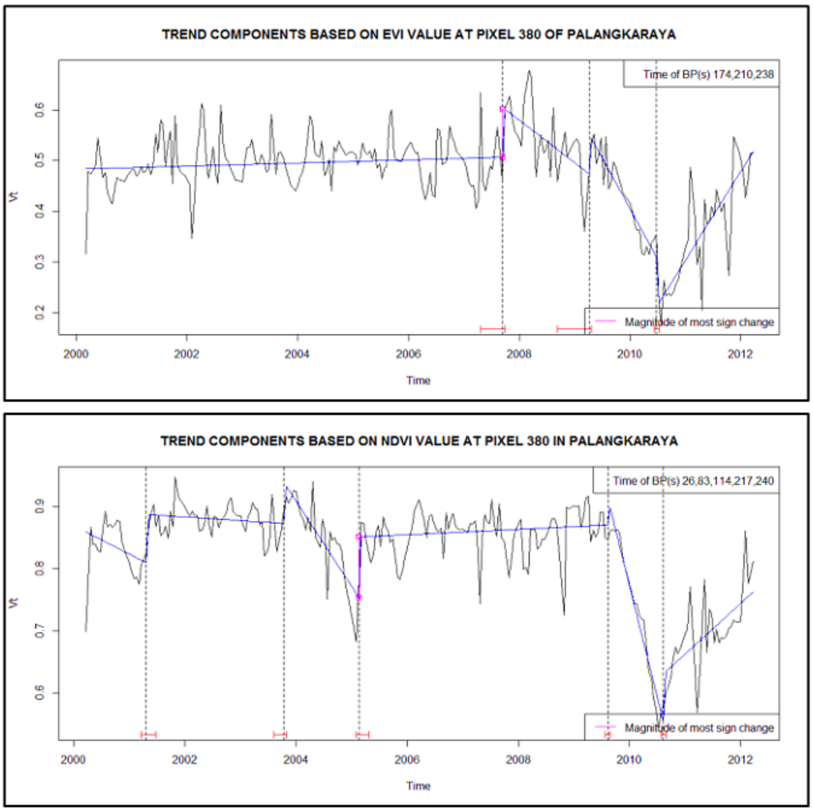

Figure 8. The abrupt changes in the trend component of the pixel 380 for EVI (top) and NDVI (bottom).

the discrepancy result to the hotspots data. Based on the pixel 380, the negative magnitude of changes should be found in September 2009 because of the forest fires, but BFAST result based on NDVI shows the opposites results.

The pixel 378 had the lowest of missing data after filtering process (Table 1). Removing the noise (e.g. clouds and sun angle) from the satellite images satellite needed more attention due to the data quality (Holben, 1986). Before application of BFAST method, filtering and cleaning of data was done by using the reliability information in the MODIS product. Consequently, some values were missing because of cloud removal. Missing data, after filtering process, was assumed to be zero. In this research, missing data were replaced by linear interpolation (Verbesselt *et al.*, 2006). Though pixel 378 had the lowest of the missing data, the quality of the interpolated data in pixel 378 was lower than others. Lower quality data of pixel 378 can be observed by few flat patterns within the data (see Figure 6). The flat pattern implied the limitation of linier interpolation method to fill the gaps due to the high missing data. One disadvantage of the linear interpolation was a tendency to force the data into a linear (straight line) (Meijering, 2002). The linier interpolation used the data which were located at before and after the data gaps for filling the data gaps. Consequently, the larger data gaps mean the lower accuracy of estimated data. The linier interpolation was applied on these pixels, but this method might be not applicable when the datasets had large missing data. Not only the large of missing data, but also the position of missing data could influence the accuracy of estimated data. When the data gaps consisted of large missing data and located in the sequential series, the linear interpolation might lead to low quality of the interpolated data. As a result, higher number of the abrupt changes to the trend component of BFAST did not guaranty more accurate the model. The further analysis of the data quality and other supported data are still needed to evaluate the accuracy of BFAST results.

A closer look at the number of missing data points indicates that the EVI had smaller number of missing data than the NDVI time series of three pixels (Table 1). Missing data can influence the result of model. Since the study area had high cloud cover and dense vegetation, EVI can reduce the effect of atmospheric disturbance and canopy by using blue band (Dietz *et al.*, 2007, Sjostrom *et al.*, 2011, Huete *et al.*, 1997). The fewer missing data may

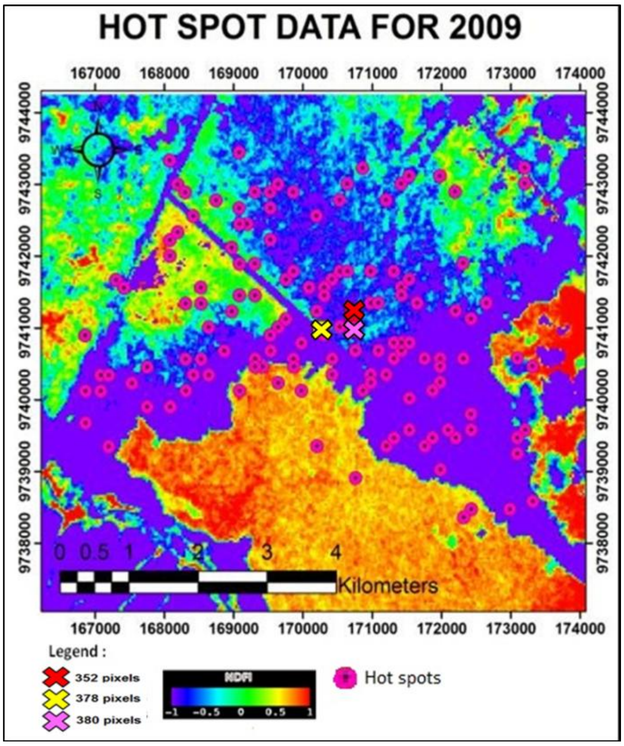

Figure 9. Overlay the hotspots data to the NDFI result for 2009

indicate that EVI data might be more accurate to reflect the condition of the forest in comparison with NDVI data. As a result, most of EVI analyses could detect the forest fire in 2009 as the abrupt changes in trend component of BFAST results.

3.2 NDFI for identifying the forest degradation

Because of the cloud cover problem in the study area, analysis of the NDFI for this area cannot be applied for every month continuously in 12 years period. In this research, the Landsat images were used to calculate NDFI, but the calculation was only done for one month to represent one year NDFI. The most crucial factor for the successful application of SMA models depends on the identification of the nature and number of pure spectra (i.e., Endmembers). Four types of Endmembers were derived for NDFI such as: GV, NPV, Soil and Shade. Next, these Endmembers will be used to calculate the fraction of images by using spectral mixture model. An example of results from SMA model can be seen in the Figure 10.

The NDFI results for every year are shown in Figure 11. If a pixel has a value of NDFI which close to one, it means that the pixel has high green vegetation and canopy shade but low in NPV and soil (Souza *et al.*, 2003). NDFI results show that the vegetation cover was decreased after May 2002. From the May 2003, it can be observed by the lower NDFI values in the middle part of study area (blue colour in Figure 11). April 2004 contained a lot of clouds and probably affects the quality of the result. Increasing of vegetation occurred in April 2004, especially in the northeast part of the study area. However, July 2005 and August 2006 show a quite similar pattern to map of May 2003. So it could be said that April 2004 had lower accuracy than others due to the cloud cover. The biggest forest changes occurred after June 2009. It can be seen based on comparison of maps from May 2008 to June 2011. However, April 2010 also had high cloud cover. Though April 2010 had lower quality to show this forest changes, we can observe in June 2011 whether there was the forest changes in 2009. April 2010 and June 2011 indicated that a big forest disturbance happened between June 2009 and April 2010.

Based on the results of BFAST and NDFI, it shows that the abrupt changes were occurred in the study area, especially in the month after June 2009. For the detail analysis about the results between BFAST and NDFI, the Indofire hotspots data were used to verify whether the fire forest disaster occurred in this area (Figure 11). It recorded that there were many hotspots in this area which were triggered by fire forest. It was occurred between August 2009 and October 2009.

The qualitative comparison among the NDFI results from May 2008 to July 2011 shows NDFI has the values close to -1 after June 2009 (Figure 10). A low of NDFI values (close to -1) related to a high of canopy damage and forest disturbance (e.g. deforestation, forest degradation) which occurs between June 2009 and October 2009 (Souza *et al.*, 2003). Based on the hotspot data, there was forest fire in the study area between August 2009 and October 2009. According to the EVI data, BFAST method estimated that there was a negative magnitude of the abrupt changes in September 2009 for the pixel 352 and a negative magnitude of the abrupt changes in October 2009 for the pixel 378. A negative magnitude of change in trend component of BFAST indicated the degradation of vegetation cover (Verbesselt *et al.*, 2010a). We can say that there was an agreement of the forest changes between NDFI and BFAST results because both NDFI and BFAST detected the forest fires in August 2009 – October 2009 as the abrupt changes.

Based on the number of gaps (Table 1) and verified by the hotspot data (see Figure 9), the use of EVI is more powerful than NDVI to detect the abrupt changes in the study area. Thouh the noise level was higher than 0.15 and seasonal amplitude lower than 0.10, EVI was proven to be able to detect the occurrence of the forest fires from August 2009 to October 2009 as the abrupt changes in trend component of BFAST. In addition to NDVI, EVI might be applied in application of BFAST method especially in the case of the tropical peat swamp forest area (dense vegetation) and intense cloud cover area, for instance in Indonesia.

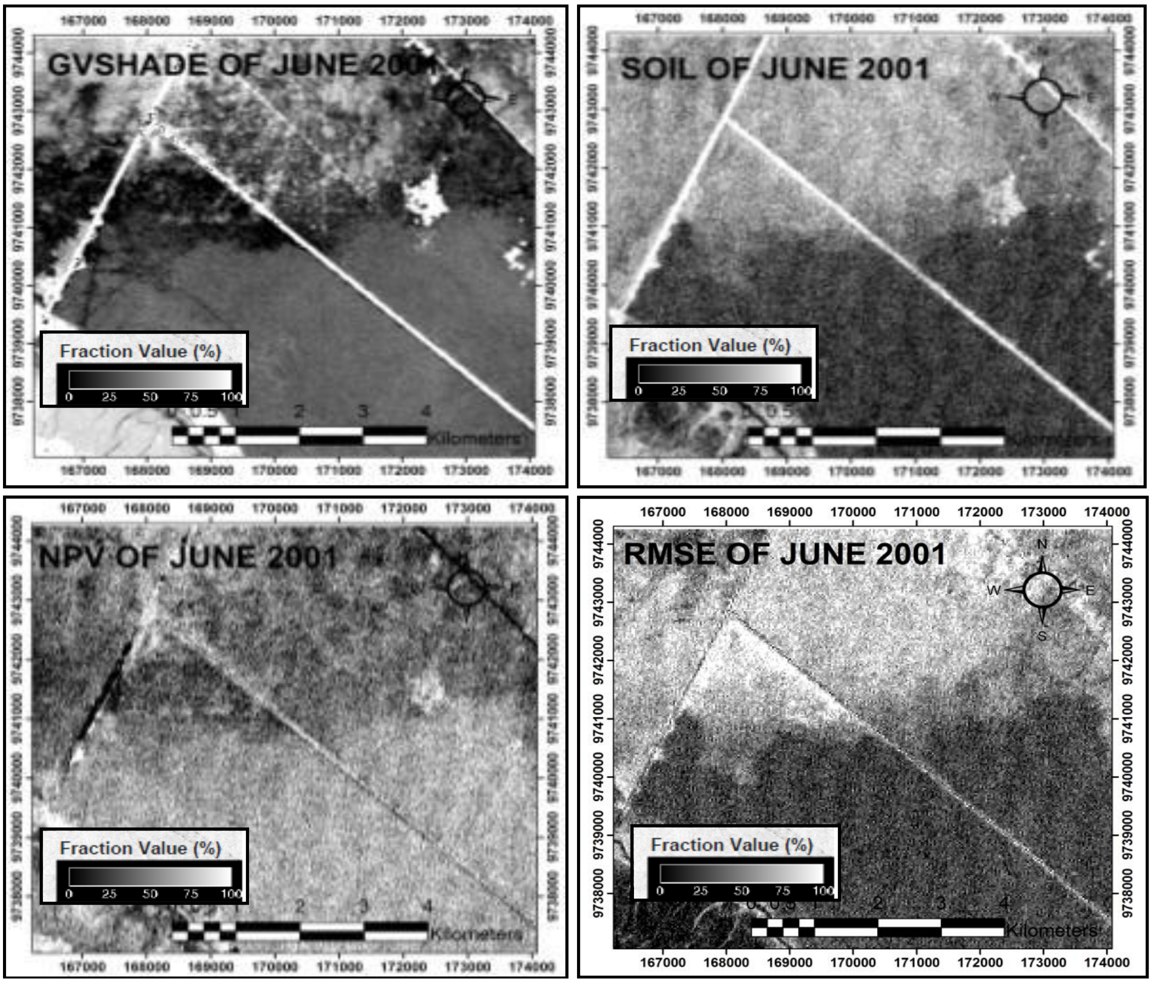

Figure 10.SMA results for Gvshade and NPV (left), soil and RMSE (right) result based on data from June 2001

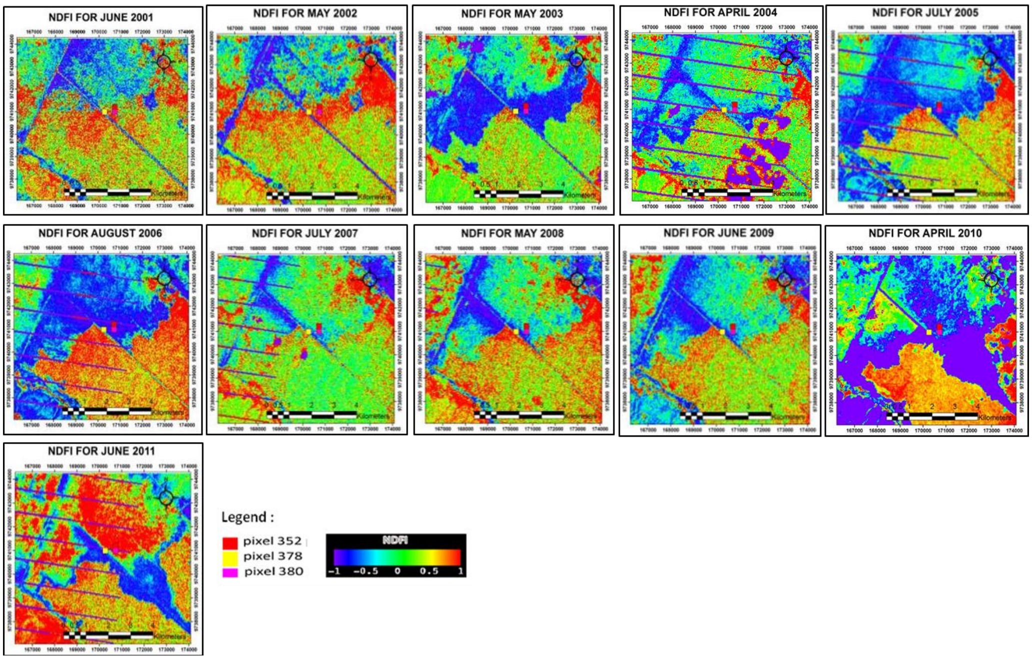

Figure 11. NDFI results for every year from Landsat images in 2001–2011

4 CONCLUSIONS

In the case of tropical peat swamp forest area and high cloud cover, EVI can minimize the influence of atmospheric disturbance and vegetation density resulting in the lower of the missing data during the data filtering. The sensitivity of the EVI has been proven to be able to detect the presence of abrupt changes than the NDVI does.

NDFI was found to be able to display the decreasing in NDFI values in that period as the forest degradation event or the canopy damage. There was a similar trend found among EVI, NDVI and NDFI values which shows the decreasing of vegetation cover in the study area during 12 years. The decreasing of vegetation cover indicates the increase of the forest damages in the study area. For the abrupt changes detection, NDFI can be used to support the BFAST result.

There were many data which removed during the filtering and cleaning data. Though the bilinear interpolation was applied to fill the gaps, the quality of BFAST detection was reduced by this problem. In the further research, a new development of BFAST method was proposed to use for near real-time disturbance detection using satellite image time series.

For the cloud cover, the result of the SMA model could be the important issues for NDFI analysis. Though we chose the correct spectral band for determining of the endmembers, the fraction images of SMA could be affected by the quality of satellite images. The increasing of spatial resolution of satellite images will improve the result of NDFI.

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