DETECTION THE VEGETATION CHANGES USING MODIS SATELLITE BASED ON THE CHOICE OF VEGETATION INDICES AND LAND COVER TYPES

Case Study: Australia

(Deteksi Perubahan Vegetasi Dengan Satelit MODIS Berdasarkan Pilihan Indeks Vegetasi dan Jenis Tutupan Lahan. Studi Kasus: Australia)

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ABSTRACT

Nowadays, Breaks for Additive Seasonal and Trend (BFAST) method based on time series of Moderate Resolution Imaging Spectroradiometer (MODIS) satellite data is increasingly used to monitor the temporal dynamics of vegetation changes. Nevertheless, sensitivity of the BFAST method for detecting the vegetation cover changes based on the choice of vegetation indices and land cover types has not been widely investigated. Breaks for Additive Seasonal and Trend (BFAST) method has applied to MODIS 16-day Enhance Vegetation Index (EVI) and Normalized Difference Vegetation Index (NDVI) composites images (2000-2014) of three land cover types (Urban and Built-Up, Evergreen Broadleaf Forest and Savannah) within Australia. Overall, the number and time of changes detected in the three land cover types differed with both time series data because of the data quality due to the cloud cover. As conclusion, the EVI is more sensitive than NDVI for detecting the seasonal and abrupt changes for the land cover which has the dense vegetation and large canopy background such as evergreen broadleaf forest. Furthermore, NDVI is more reliable to detect the seasonal and abrupt changes that occurred in land cover types which have sparse vegetation such as urban, built-up area and savannah.

Keywords: *Additive Model, BFAST, EVI, NDVI, MODIS*

ABSTRAK

Saat ini, Metode Breaks for Additive Seasonal and Trend (BFAST) berdasarkan data satelit Moderate Resolution Imaging Spectroradiometer (MODIS) telah banyak diaplikasikan untuk melakukan monitoring terhadap perubahan dinamis dari tutupan vegetasi. Namun, sensitifitas BFAST untuk mendeteksi perubahan vegetasi berdasarkan pilihan indeks vegetasi dan jenis tutupan lahan yang berbeda belum banyak dilakukan. Metode Breaks for Additive Seasonal and Trend (BFAST) telah diaplikasikan dengan menggunakan data Enhanced Vegetation Index (EVI) dan Normalized Difference Vegetation Index (NDVI) dari satelit MODIS 16-harian terhadap tiga jenis tutupan lahan (perkotaan dan lahan terbangun, hutan berdaun lebar dan padang rumput) di wilayah Australia untuk periode data tahun 2000 - 2014. Secara umum, hasil deteksi metode BFAST berbeda untuk setiap tutupan lahan baik dari segi jumlah dan waktu yang dipengaruhi oleh kualitas data karena adanya tutupan awan di lokasi penelitian. Dapat disimpulkan bahwa EVI lebih sensitif digunakan dalam mendeteksi adanya perubahan musiman dan mendadak pada tutupan lahan dengan vegetasi yang rapat dan berkanopi lebar seperti hutan tropis. Sedangkan NDVI lebih sensitif digunakan untuk mendeteksi komponen musiman dan perubahan mendadak terutama untuk tutupan lahan yang memiliki vegetasi jarang seperti perkotaan, lahan terbangun dan padang rumput.

Kata kunci: *Additive Model, BFAST, EVI, NDVI, MODIS*

INTRODUCTION

Ecosystems are in a state of continual change driven by anthropogenic and natural forces. Natural disturbances can be from fires, insect attacks, droughts, whereas anthropogenic disturbances results from human activities such as deforestation, urbanization and farming (Verbesselt et al, 2010a). As such, change in ecosystems can be divided into three classes: (1) seasonal change which triggered by annual temperature and rainfall variation which impact to the plant phenology or proportional of land cover; (2) gradual change such as inter-annual climate variability such as trends of mean annual rainfall; and (3) abrupt change which affected by disturbances such as deforestation, urbanization, floods, and fires (Verbeselt et al, 2010; Wilson et al, 2002). There is now an ever growing interest in information about the condition of ecosystems because of potentially devastating phenomenon such as global warming, biodiversity loss and carbon accumulation in the atmosphere.

The Vegetation Index (VI) from Moderate Resolution Imaging Spectroradiometer (MODIS) satellite signifies improved spatial, spectral, and radiometric capacity of surface vegetation environment (Tucker et al, 2005). The vegetation index (VI), defined as “the arithmetic combination of two or more bands related to the spectral characteristics of vegetation, has been widely used for the phenology monitoring, vegetation classification, and biophysical derivation of radiometric and structural vegetation parameters” (Matsushita et al, 2007). The choice of an appropriate VI for the purpose of change detection remains a challenging task. Some authors have reported differing results in change detection from the use of more than one vegetation index derived for the same land cover. In Indonesia, the sensitivity between Enhanced Vegetation Index (EVI) and Normalized Difference Vegetation Index (NDVI) has investigated for tropical forest in Palangkaraya Flux tower is investigated (Darmawan and Sofan, 2012). They found that EVI is more sensitive than NDVI for detecting the abrupt changes which occurred due to forest fire for August to October 2014 (Darmawan & Sofan, 2012). Moreover, Wilson and Sader (2002) found the Normalized Difference Moisture Index (NDMI) outperformed the widely used NDVI in detecting forest harvest in northern Maine forest in the USA (Wilson et al, 2002). Sonnenschein et al., (2011) reported NDVI to be relatively weaker than the Tasselled Cap Greenness in trend analysis of dry lands in Greece (Sonnenschein et al, 2011).

Currently, NDVI is the most frequently applied as a global-based vegetation index. NDVI enabled to cancel out a mostly proportion of the noise caused by shifting sun angles, topography, clouds, shadow, and atmospheric conditions (Matsushita et al, 2007). However, NDVI still has a risk to large sources of error and uncertainty over variable atmospheric and canopy background factors (Matsushita et al, 2007). The EVI was improved to enhance the vegetation signal by reducing influences from the atmosphere and canopy background and to improve sensitivity in high biomass regions (Sjöström et al, 2011). Several limitations of the NDVI have opened opportunities to use EVI for detecting trend and seasonal changes in time series data especially for forest vegetation. EVI has a higher sensitivity correlated with green leaf area index (LAI) and canopy background than NDVI (Dietz et al, 2007).

Moreover, Enhanced Vegetation Index (EVI) was found to be more linearly correlated with green Leaf Area Index (LAI) in crop fields, less prone to saturation in common and tropical forests and minimally responses to residual aerosol (Jiang et al, 2008). The EVI was improved to reduce soil and atmospheric sensitivity observed in the NDVI by including the blue band for atmospheric correction (Jiang et al, 2008). The EVI is more functional on Near Infra-Red (NIR) reflectance than on Red absorption, and therefore it does not “saturate" as rapidly as NDVI in dense vegetation. The EVI is increasingly used in phenological, productivity and evapotranspiration (ET) studies (Glenn et al, 2008).

Furthermore, several different techniques of change detection have been improved to extract some information from satellite image time series (Wallace and Campbell, 1989). Now, the BFAST (Breaks for Additive Seasonal and Trend) method iteratively predicts the dates and number of changes happening inside seasonal and trend components (Wallace & Campbell, 1989). The BFAST method improved by using a harmonic seasonal model which more effectively in number of observation, is more stable to reduce effect of noise, and of which the parameters is more compatible used to describe phenological change (Verbesselt et al, 2010b). The BFAST has been applied to any time series data and it is not limited to NDVI. Nevertheless, comparative studies which assess the respond of BFAST method using NDVI and EVI in change detection for different land cover types is lacking in the literature.

In this paper, Breaks for Additive Seasonal and Trend (BFAST), which is a change detection algorithm proposed by Verbesselt et al. (2010), was applied to MODIS 16-day NDVI and EVI composite images for three land cover types (Verbesselt et al, 2010a; Verbesselt et al, 2010b). BFAST combines the decomposition of time series into trend, seasonal, and remainder components with methods for detecting change within time series (Verbesselt et al, 2010). The specific objective of this paper was to explore the use of MODIS satellite data for detecting the vegetation changes based on the choice of vegetation indices and land cover types.

METHOD

Three flux towers in Australia representing three land cover types were selected for the study (**Table 1**). Australia has chosen as the study area because Australia has more various land cover types than Indonesia. Location of flux tower in Australia in **Figure 1.**

Table 1. Name, location (State), latitude and longitude (lat/long, decimal degrees), land cover types of the flux tower sites in Australia.

Flux tower	Lat	Lon	Land cover
Burdekin Delta	-19.57	147.40	Urban and Built-Up
Cape Tribulation	-16.10	145.45	Evergreen Broadleaf Forest
Daly River Savannah	-14.16	131.39	Savannah

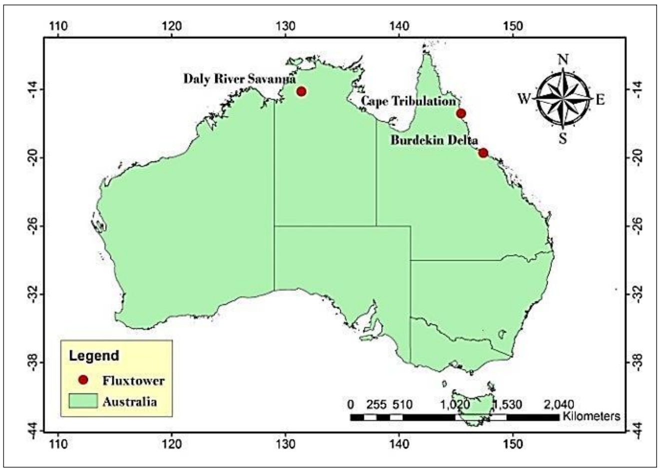


Figure 1. The map location of flux tower in Australia

Due to the size of the continent, there is not one single seasonal calendar for the entire continent. Instead there are six climatic zones and this translates as two main seasonal patterns such as temperate zone and tropical zone (Department of the Environment, Australia Government, 2014). Sixteenth-day NDVI and EVI composites with 250 m resolution (MOD13Q1 collection 5) for these sites were acquired for the period covering 06th of April 2000 to 30th of September 2014 (337 images). One pixel measuring 250 m x 250 m covering the flux tower was selected per land cover type. The binary MODIS Quality Assurance flags were used to choose cloud-free, optimum quality data. However, because the algorithm used to exempt clouds employ bands with coarse resolution (Verbesselt et al, 2010a). There is no absolute guarantee that the quality flags totally isolate cloud-corrupted data for the 250 m MODIS pixels. Missing values within the NDVI and EVI series were filled by using linear interpolation (Verbesselt et al, 2010a).

A change detection algorithm, Break for Additive Trend (BFAST) was used to decompose and detect changes within the NDVI and EVI time series. BFAST decomposes the time series data by iteratively fitting a piecewise linear model to the trend component and a harmonic model to the seasonal component (Verbesselt et al, 2010a; Verbesselt et al, 2010b). Anomalies or significant changes in the trend or seasonal components in the data will appear as breakpoints after fitting the model to the data. The principal advantages of BFAST are that it is more generic, independent of data type and change trajectory.

The methods are available in the BFAST package for R from CRAN (http://cran.r-project.org/package=bfast) (Verbesselt et al, 2010a; Verbesselt et al, 2010b). The processing data in this research divided into five parts. First, the BFAST method was applied for the EVI and NDVI dataset. Principally, the BFAST method will decompose the time series data to the seasonal, trend and noise component. Second, the phenological and abrupt changes will be analyzed for all components. The breaks of seasonal component are referring to the number of phenology changes. Furthermore, number of the abrupt changes is displayed by trend components. Fourth, the signal-to-noise ratio (Δc1) can be used as the control variable for quality control of BFAST result. It will be influenced on the RMSE for detecting the number of phenological changes (Verbesselt et al, 2010b). This infers that the higher seasonal amplitude (a) of the time series or lower noise level (σ) results means a more accurate detection of the number of phenological changes (Verbesselt et al, 2010b). The signal-to-noise ratio (Δc1) can be derived by dividing the seasonal amplitude (a) from seasonal component with the noise level (σ). Finally, evaluation of the sensitivity and reliability between the NDVI and EVI time series data is the most crucial part in this study.

Evaluation of sensitivity and reliability of data were done with an investigation of the quality of data that has been used. This is related to the number of data (NA) that may be lost during the process of masking and cleaning the noise of the data in the BFAST before the interpolation data. The high number of the missing data is equal with the declining quality of interpolation results. The BFAST model was processed by using R programming. Analyze has focused on the amplitude of the seasonal component, the magnitude of the changes in the trend component, the signal-to-noise ratio, and the number of gaps of missing data (dates without data probably due to cloud cover) for every land cover types.

RESULTS

Principally, application of BFAST 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. No one site which detected change in seasonal, even in the EVI and NDVI data (**Figure 2-4**). Nonetheless, urban and built-area in Burdekin Delta site has the highest of seasonal amplitude mostly for NDVI datasets (**Table 2**). Moreover, the EVI and NDVI seasonal amplitude for the evergreen broadleaf forest in Cape Tribulation is below the minimum limit of 0.1 VI considered adequate for BFAST to capture any phenological change in time series (Verbesselt et al, 2010a; Verbesselt et al, 2010b). There are also discrepancies in the number and time of abrupt changes in the trend component from the EVI and NDVI data for every site, except in Burdekin Delta Site (**Figure 2**).

In Burdekin Delta site, there are no abrupt changes detected for both of EVI and NDVI data. Moreover, BFAST analysis on the EVI and NDVI data for the Cape Tribulation site indicated one of negative amplitude of abrupt change in trend

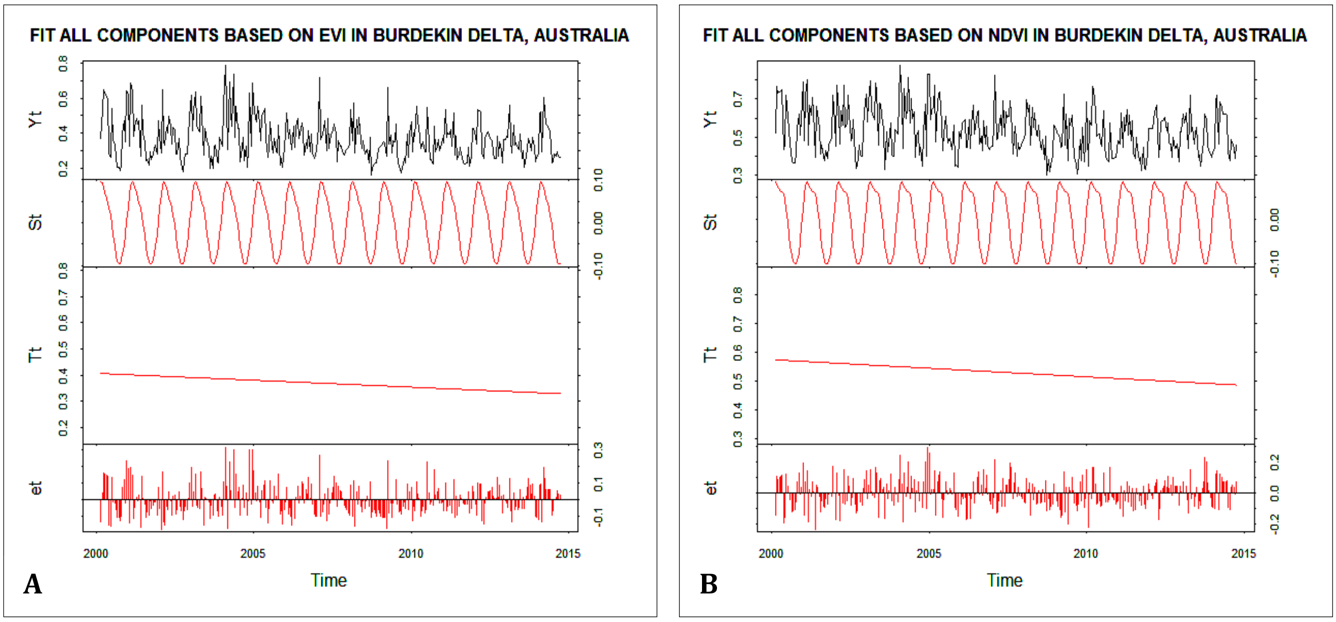
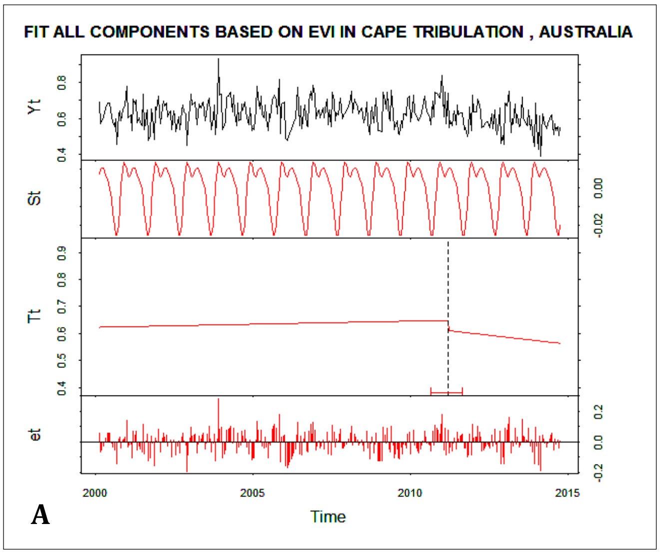


Figure 2. Detected changes (---) in seasonal and trend components (in red) of 16-day EVI (A) and NDVI (B) time series (data) extracted from a single pixel of Urban and Built-area in Burdekin Delta Site, Australia, with no abrupt change in both of the EVI and NDVI data.

component which occurred in 6th of March 2011 and 30th of September 2013 respectively (**Figure 4**). Furthermore, the Daly River Savannah site analysis indicated 7 (seven) of changes for the EVI data (2001, 2004, 2005, 2006, 2008, 2011 and 2013) and 4 (four) for the NDVI data (2001, 2006, 2011, 2013) which can be seen in trend component (**Figure 7**).

Ideally, results from a BFAST calculation over different of land cover types indicate the different wavelet characteristics of each land cover type (**Figure 2-4**). In the seasonal component, there are no seasonal changes found in the seasonal component for three kinds of land cover types. It is known that BFAST is more sensitive to detect the abrupt changes in the trend component than the seasonal component change (Verbesselt et al, 2010a). Although it was difficult to interpret the differences between each type of land cover without validation the observed data, but the characteristics for every land cover types were perfectly captured by the amplitude of seasonal component.

Figure 3. Burdekin Delta (Urban & Build up)
Source: Google earth, 10/2013.



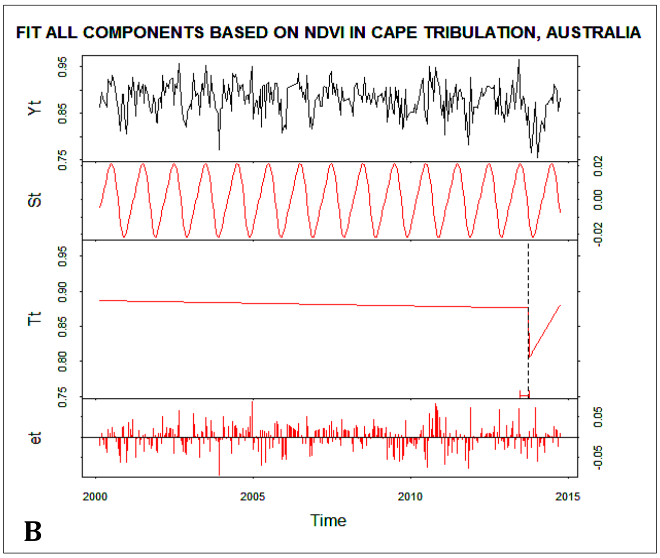


Figure 4. Detected changes (---) in the trend components (in red) of 16-day EVI (A) and NDVI (B) time series (data) extracted from a single pixel of an Evergreen Broadleaf Forest, Cape Tribulation Site, Australia, with one of abrupt change in both of the EVI and NDVI data.

Figure 5. Cape Tribulation (Evergreen Forest), *Source: Google earth, 11/2014.*

Figure 6. Daly River Savanna, *Source: Google earth, 07/2014.*

Overall, the seasonal amplitude of the MODIS NDVI data set was higher than that of the MODIS EVI data set for all land cover types (Table 2). When using NDVI data, the built-up area has the highest seasonal amplitude (**Figure 2 & 3**). This indicates that the NDVI data set captures more seasonal variability in phenology of the vegetation compared to the EVI data sets (Verbesselt et al, 2010a; Tsutsumida et al, 2013). Furthermore, urban and built-up area has a notably strong cyclic inter-annual variation with one peak in each year (Tsutsumida et al, 2013). This is not surprising, as vegetation closer to human settlements are generally disturbed (grazing, farming, fire) the most in Burdekin Delta site, hence high variation in seasonal NDVI. In this case, use of the NDVI time series, particularly by BFAST, is able to describe land cover changes (Tsutsumida et al, 2013).

Mostly, the abrupt changes are triggered by suddenly disturbances such as deforestation, urbanization, floods, and fires (Verbesselt et al, 2010a). Based on the number of abrupt changes, Burdekin Delta site did not show any abrupt changes in both of datasets (**Figure 2**). Since Burdekin Delta site consist of urban and built-up area (**Figure 3**), so that there is no significant abrupt changes which occurred in this location. Although there is vegetation in urban and built-up, but the vegetation grew sparse in some parts and not much disturbed by human.

In Cape Tribulation site, a closer look at the signal-to-noise ratio and the missing data indicates that the EVI had higher signal-to-noise ratio and smaller number of missing data than the NDVI time series of this grassland (**Table 2**). It would therefore appear that the EVI data might truly reflect the condition of the Evergreen Broadleaf Forest than the NDVI data (Darmawan and Sofan, 2012; Bhandaria et al, 2011).

For Daly River Savanna site, it consists of Savanna which has more sensitive of vegetation changes due to climatic factor and human intervention. In this case, NDVI has a lower missing data than using EVI and equal value of the signal-to-noise ratio with EVI datasets (Verbesselt et al, 2010a). It can be postulated that NDVI is better to detect the seasonal change and abrupt change in Savanna. Based on the results, it appears that EVI time series was more effective at capturing the changes than the NDVI especially for tropical forest. MOD13Q1 NDVI showed higher seasonal amplitude, but was less accurate at capturing phenology and disturbances compared to the EVI in tropical forest.

Finding from this research is relevant to the previous research which has done by Darmawan and Parwati (2012). They found that EVI is more powerful to apply in tropical forest of Palangkaraya, Indonesia which has similar type of vegetation with Evergreen Broadleaf Forest, Australia. This can be happened because EVI formulated by account the blue wavelength which can reduce the effect of aerosol and canopy background due to the dense vegetation (Darmawan and Sofan, 2012). The EVI was less affected by variable viewing and illumination geometry in terms of amplitude, but was affected in terms of time shift in periodicities providing erroneous information on phenology (Verbesselt et al, 2010a; Verbesselt et al, 2010a).

Apart from the seasonal amplitude, it cannot be infallibly stated whether the NDVI data was better than the EVI data. Though the seasonal amplitude of NDVI data was higher than the EVI data for all land cover types, the EVI had significant lower number of gaps of missing data especially for Evergreen Broadleaf Forest (Table 2). Generally, the number of missing data for both time series and all land cover types is quite low except for Evergreen Broadleaf Forest (**Table 2**). The choice of a single pixel (250 m) per land cover type may have been insufficient in capturing information of the land cover because of cloud contamination of the entire pixel. The effect of cloud cover will be minimized if averages of the vegetation indices are taken over a larger pixel (e.g 3 X 3) for the sites (Verbesselt et al, 2010a).

Table 2. Seasonal amplitude (a), Noise level (σ), Signal-to-noise ratio ($\Delta c1 = a/\sigma$) and number of missing data (DG) of the EVI and NDVI time series data of the land cover types.

Parameter		Urban and Built-up Area	Evergreen Broadleaf Forest	Savannah
a	EVI	0.10	0.03	0.10
	NDVI	0.20	0.02	0.15
σ	EVI	0.30	0.30	0.10
	NDVI	0.30	0.10	0.15
$\Delta c1$	EVI	0.33	0.10	1.00
	NDVI	1.5	0.10	1.00
DG	EVI	26	47	55
	NDVI	24	56	52

CONCLUSIONS

A challenge to change detection studies utilizing vegetation indices as a proxy indicator of the condition of land cover lies in the identification of the best vegetation index that suits a particular land cover type. To assess the influence of the choice of vegetation indices on the number and time of detected seasonal (or phenological) and abrupt changes, we applied BFAST, a change detection algorithm, to MODIS 16-day NDVI and EVI composites images (2000-2014) of three locations in Australia. The three land cover types (location) are: urban and built-up area, evergreen broadleaf forest, and savanna. Overall, the number and time of the detected changes in a particular land cover type differed in both NDVI and EVI time series data. Irrespective of the land cover type and the time series, the magnitude of the abrupt changes detected was small. The difference in detected of abrupt changes between the EVI and NDVI time series for every land cover types may be attributed to data quality, as the NDVI data had the higher seasonal amplitude and low missing data than the EVI especially for the land cover which has the sparse vegetation and small canopy (urban and built-up area, savanna). In opposition, EVI is better to capture the seasonal and abrupt changes for land cover which has the dense vegetation and large canopy such an Evergreen Broadleaf Forest.

Commonly, the NDVI had higher seasonal amplitude than the EVI time series for all land cover type, except for the evergreen broadleaf forest. Findings from this research confirm that BFAST is effectively applied by EVI and NDVI which depend on the land cover types. Because of the very limited time available to conduct this study and the dearth of field data to corroborate the findings from our study, we recommend further research that will incorporate field information or ground truth in assessing the influence of choice of vegetation indices in change detection in different land cover types.

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