Detecting trend and seasonal changes in satellite image time series

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Abstract

A wealth of remotely sensed image time series covering large areas is now available to the earth science community. Change detection methods are often not capable of detecting land cover changes within time series that are heavily influenced by seasonal climatic variations. Detecting change within the trend and seasonal components of time series enables the classification of different types of changes. Changes occurring in the trend component often indicate disturbances (e.g. fires, insect attacks), while changes occurring in the seasonal component indicate phenological changes (e.g. change in land cover type). A generic change detection approach is proposed for time series by detecting and characterizing Breaks For Additive Seasonal and Trend (BFAST). BFAST integrates the decomposition of time series into trend, seasonal, and remainder components with methods for detecting change within time series. BFAST iteratively estimates the time and number of changes, and characterizes change by its magnitude and direction. We tested BFAST by simulating 16-day Normalized Difference Vegetation Index (NDVI) time series with varying amounts of seasonality and noise, and by adding abrupt changes at different times and magnitudes. This revealed that BFAST can robustly detect change with different magnitudes (> 0.1 NDVI) within time series with different noise levels (0.01–0.07 σ) and seasonal amplitudes (0.1–0.5 NDVI). Additionally, BFAST was applied to 16-day NDVI Moderate Resolution Imaging Spectroradiometer (MODIS) composites for a forested study area in south eastern Australia. This showed that BFAST is able to detect and characterize spatial and temporal changes in a forested landscape. BFAST is not specific to a particular data type and can be applied to time series without the need to normalize for land cover types, select a reference period, or change trajectory. The method can be integrated within monitoring frameworks and used as an alarm system to flag when and where changes occur.

Key words: Change detection, NDVI, time series, trend analysis, MODIS, piecewise linear regression, vegetation dynamics, phenology

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1. Introduction

Natural resource managers, policy makers and researchers demand knowledge of land cover changes over increasingly large spatial and temporal extents for addressing many pressing issues such as global climate change, carbon budgets, and biodiversity (DeFries et al., 1999; Dixon et al., 1994). Detecting and characterizing change over time is the natural first step toward identifying the driver of the change and understanding the change mechanism. Satellite remote sensing has long been used as a means of detecting and classifying changes in the condition of the land surface over time (Coppin et al., 2004; Lu et al., 2004). Satellite sensors are well-suited to this task because they provide consistent and repeatable measurements at a spatial scale which is appropriate for capturing the effects of many processes that cause change, including natural (e.g. fires, insect attacks) and anthropogenic (e.g. deforestation, urbanization, farming) disturbances (Jin and Sader, 2005).

The ability of any system to detect change depends on its capacity to account for variability at one scale (e.g. seasonal variations), while identifying change at another (e.g. multi-year trends). As such, change in ecosystems can be divided into three classes: (1) *seasonal change*, driven by annual temperature and rainfall interactions impacting plant phenology or proportional cover of land cover types with different plant phenology; (2) *gradual change* such as interannual climate variability (e.g. trends in mean annual rainfall) or gradual change in land management or land degradation; and (3) *abrupt change*, caused by disturbances such as deforestation, urbanization, floods, and fires.

Although the value of remotely sensed long term data sets for change detection has been firmly established (de Beurs and Henebry, 2005), only a limited number of time series change detection methods have been developed. Two major challenges stand out. First, methods must allow for the detection of changes within complete long term data sets while accounting for seasonal variation. Estimating change from remotely sensed data is not straightforward, since time series contain a combination of seasonal, gradual and abrupt changes, in addition to noise that originates from remnant geometric errors, atmospheric scatter and cloud effects (Roy et al., 2002). Thorough reviews of existing change detection methods by Coppin et al. (2004) and Lu et al. (2004) have shown, however, that most methods focus on short image time series (only 2–5 images). The risk of confounding variability with change is high with infrequent images, since disturbances can occur in between image acquisitions (de Beurs and Henebry, 2005). Several approaches have been proposed for analyzing image time series, such as Principal Component Analysis (PCA) (Crist and Cicone, 1984), wavelet decomposition (Anyamba and Eastman, 1996), Fourier analysis (Azzali and Menenti, 2000) and Change Vector Analysis (CVA) (Lambin and Strahler, 1994). These time series analysis approaches discriminate noise from the signal by its temporal characteristics but involve some type of transformation designed to isolate dominant components of the variation across years of imagery through the multi-temporal spectral space. The challenge of these methods is the labeling of the change components, because each analysis depends entirely on the specific image series analyzed. Compared to PCA, Fourier analysis, and wavelet decomposition, CVA allows the interpretation of change processes, but can still only be performed between two periods of time (e.g. between years or growing seasons) (Lambin and Strahler, 1994), which makes the analysis dependent on the selection of these periods. Furthermore, change in time series if often masked by seasonality driven by yearly temperature and rainfall variation. Existing change detection techniques minimize seasonal variation by focussing on specific periods within a year (e.g. growing season) (Coppin et al., 2004), temporally summarizing time series data (Bontemps et al., 2008; Fensholt et al., 2009) or normalizing reflectance values per land cover type (Healey et al., 2005) instead of explicitly accounting for seasonality.

Second, change detection techniques need to be independent of specific thresholds or change trajectories. Change detection methods that require determination of thresholds often produce misleading results due to different spectral and phenological characteristics of land cover types (Lu et al., 2004). The determination of thresholds adds significant cost to efforts to expand change detection to large areas. Trajectory based change detection has been proposed to move towards a threshold independent change detection by characterizing change by its temporal signature (Hayes and Cohen, 2007; Kennedy et al., 2007). This approach requires definition of the change trajectory specific for the type of change to be detected and spectral data to be analyzed (e.g. short-wave infrared or near-infrared based indices). Furthermore, the method will only function if the observed spectral trajectory matches one of the hypothesized trajectories. Trajectory based change detection can be interpreted as a supervised change detection method while there is a need for an unsupervised, more generic, change detection approach independent of the data type and change trajectory.

The purpose of this research was to develop a generic change detection approach for time series, involving the detection and characterization of Breaks For Additive Seasonal and Trend (BFAST). BFAST integrates the iterative decomposition of time series into trend, seasonal and noise components with methods for detecting changes, without the need to select a reference period, set a threshold, or define a change trajectory. The main objectives are:

(1) the detection of multiple abrupt changes in the seasonal and trend components of the time series; and

(2) the characterization of gradual and abrupt ecosystem change by deriving the time, magnitude, and direction of change within the trend component of the time series.

We assessed BFAST for a large range of ecosystems by simulating Normalized Difference Vegetation Index (NDVI) time series with varying amounts of seasonal variation and noise, and by adding abrupt changes with different magnitudes. We applied the approach on MODIS 16-day image composites (hereafter called 16-day time series) to detect major changes in a forested area in south eastern Australia. The approach is not specific to a particular data type and could be applied to detect and characterize changes within other remotely sensed image time series (e.g. Landsat) or be integrated within monitoring frameworks and used as an alarm system to provide information on when and where changes occur.

2. Iterative change detection

We propose a method that integrates the iterative decomposition of time series into trend, seasonal and noise components with methods for detecting and characterizing changes (i.e. breakpoints) within time series. Standard time series decomposition methods assume that trend and seasonal components are smooth and slowly changing, and so these are not directly applicable to the problem of identifying change. For example, the Seasonal-Trend decomposition procedure (STL) is capable of flexibly decomposing a series into trend, seasonal and remainder components based on a LOcally wEighted regreSsion Smoother (LOESS) (Cleveland et al., 1990). This smoothing prevents the detection of changes within time series.

2.1. Decomposition model

We propose an additive decomposition model that iteratively fits a piecewise linear trend and seasonal model. The general model is of the form $Y_t = T_t + S_t + e_t$, $t = 1, \ldots, n$, 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 remaining variation in the data beyond that in the seasonal and trend components (Cleveland et al., 1990). It is assumed that T_t is piecewise linear, with break points $t_1^*, \ldots, t_m^*$ and define $t_0^* = 0$, so that

$$T_t = \alpha_j + \beta_j t \tag{1}$$

for $t_{j-1}^* < t \leq t_j^*$ and where $j = 1, \ldots, m$. The intercept and slope of consecutive linear models, α_j and β_j, can be used to derive the magnitude and direction of the abrupt change (hereafter referred to as magnitude) and slope of the gradual change between detected break points. The magnitude of an abrupt change at a breakpoint is derived by the difference between T_t at t_{j-1}^* and t_j^*, so that

$$\text{Magnitude} = (\alpha_{j-1} - \alpha_j) + (\beta_{j-1} - \beta_j)t \tag{2}$$

and the slopes of the gradual change before and after a break point are β_{j-1} and β_j. This technique represents a simple yet robust way to characterize changes in time series. Piecewise linear models, as a special case of non-linear regression (Venables and Ripley, 2002), are often used as approximations to complex phenomena to extract basic features of the data (Zeileis et al., 2003).

Similarly, the seasonal component is fixed between break points, but can vary across break points. Furthermore, the seasonal break points may occur at different times from the break points detected in the trend component. Let the seasonal break points be given by $t_1^\#, \ldots, t_p^\#$, and define $t_0^\# = 0$. Then for $t_{j-1}^\# < t \leq t_j^\#$, we assume that

$$S_t = \begin{cases} \gamma_{i,j} & \text{if time } t \text{ is in season } i,\ i = 1, \ldots, s-1; \\ -\sum_{i=1}^{s-1} \gamma_{i,j} & \text{if time } t \text{ is in season } 0, \end{cases} \tag{3}$$

where s is the period of seasonality (e.g. number of observations per year) and $\gamma_{i,j}$ denotes the effect of season i. Thus, the sum of the seasonal component, S_t across s successive times is exactly zero for $t_{j-1}^\# < t \leq t_j^\#$. This prevents apparent changes in trend being induced by seasonal breaks happening in the middle of a seasonal cycle. The seasonal term can be re-expressed as

$$S_t = \sum_{i=1}^{s-1} \gamma_{i,j}(d_{t,i} - d_{t,0}), \tag{4}$$

where $d_{t,i} = 1$ when t is in season i and 0 otherwise. Therefore, if t is in season 0, then $d_{t,i} - d_{t,0} = -1$. For all other seasons, $d_{t,i} - d_{t,0} = 1$ when t is in season $i \neq 0$. $d_{t,i}$ is often referred to as a seasonal dummy variable (Makridakis et al., 1998, pp.269-274); it has two allowable values (0 and 1) to account for the seasons in a regression model. The regression model expressed by Eq. 4 can also be interpreted as a model without intercept that contains $s-1$ seasonal dummy variables and where the sum of the coefficients, $\gamma_{0,j}, \gamma_{1,j}, \ldots, \gamma_{s-1,j}$, is exactly zero between breakpoints $t^{\#}_{j-1}$ and $t^{\#}_{j}$.

2.2. Iterative algorithm to detect break points

Our method is similar to that proposed by Haywood and Randal (2008) for use with monthly tourism data. Following Haywood and Randal (2008), we estimate the trend and seasonal components iteratively. However, we differ from their method by: (1) using STL to estimate the initial seasonal component ($\hat{S}_t$); (2) using a robust procedure when estimating the coefficients α_j, β_j and $\gamma_{i,j}$; (3) using a preliminary structural change test; and (4) forcing the seasonal coefficients to always sum to 0 (rather than adjusting them afterward). An alternative approach proposed by Shao and Campbell (2002) combines the seasonal and trend term in a piecewise linear regression model without iterative decomposition. This approach does not allow for an individual estimation of the seasonal and trend component. Moreover, Shao and Campbell (2002) used a sinusoidal function to fit seasonal variation whereas seasonal dummy variables (Eq. 4) are used in BFAST allowing for a more flexible estimation of the seasonal component.

Sequential test methods for detecting break points (i.e. abrupt changes) in a time series have been developed, particularly within econometrics (Bai and Perron, 2003; Zeileis et al., 2003). These methods also allow linear models to be fitted to sections of a time series, with break points at the times where the changes occur. The optimal position of these breaks can be determined by minimizing the residual sum of squares, and the optimal number of breaks can be determined by minimizing an information criterion. Bai and Perron (2003) argue that the Akaike Information Criterion usually overestimates the number of breaks, but that the Bayesian Information Criterion (BIC) is a suitable selection procedure in many situations (Zeileis et al., 2002, 2003; Zeileis and Kleiber, 2005). Before fitting the piecewise linear models and estimating the breakpoints it is recommended to test whether breakpoints are occurring in the time series (Bai and Perron, 2003). The ordinary least squares (OLS) residuals-based MOving SUM (MOSUM) test, is selected to test for whether one or more breakpoints are occurring (Zeileis, 2005). If the test indicates significant change ($p < 0.05$), the break points are estimated using the method of Bai and Perron (2003), as implemented by Zeileis et al. (2002), where the number of breaks is determined by the BIC, and the date and confidence interval of the date for each break are estimated.

The iterative procedure begins with an estimate of $\hat{S}_t$ by using the STL method, where $\hat{S}_t$ is estimated by taking the mean of all seasonal sub-series (e.g. for a monthly time series the first subseries contains the January values). Then it follows these steps.

Step 1 If the OLS-MOSUM test indicates that breakpoints are occurring in the trend component, the number and position of the trend break points $(t_1^*, \ldots, t_m^*)$ are estimated from the seasonally adjusted data, $Y_t - \hat{S}_t$.

Step 2 The trend coefficients, α_j and β_j for $j = 1, \ldots, m$, are then computed using robust regression of Eq. 1 based on M-estimation (Venables and Ripley, 2002). The trend estimate is then set to $\hat{T}_t = \hat{\alpha}_j + \hat{\beta}_j t$ for $t = t_{j-1}^* + 1, \ldots, t_j^*$.

Step 3 If the OLS-MOSUM test indicates that breakpoints are occurring in the seasonal component, the number and position of the seasonal break points $(t_1^\#, \ldots, t_p^\#)$ are estimated from the detrended data, $Y_t - \hat{T}_t$.

Step 4 The seasonal coefficients, $\gamma_{i,j}$ for $j = 1, \ldots, m$ and $i = 1, \ldots, s-1$, are then computed using a robust regression of Eq. 4 based on M-estimation. The seasonal estimate is then set to $\hat{S}_t = \sum_{i=1}^{s-1} \hat{\gamma}_{i,j}(d_{t,i} - d_{t,0})$ for $t = t_{j-1}^\# + 1, \ldots, t_j^\#$.

These steps are iterated until the number and position of the breakpoints are unchanged. We have followed the recommendations of Bai and Perron (2003) and Zeileis et al. (2003) concerning the fraction of data needed between the breaks. For 16-day time series, we used a minimum of one year of data (i.e. 23 observations) between successive change detections, corresponding to 12% of a 9 year data span (2000–2008). This means that if two changes occur within a year, only the most significant change will be detected. This also satisfies the requirement that the minimum number of observations must be greater than the number of seasonal dummy variables (i.e. $s-1$) used in the model to estimate S_t (Eq. 4) where $s = 23$ for 16-day time series.

3. Validation

The proposed approach can be applied to a variety of time series, and is not restricted to specific remotely sensed vegetation indices. However, validation has been conducted using Normalized Difference Vegetation Index (NDVI) time series, the most widely used vegetation index in medium to coarse scale studies. The NDVI is a relative and indirect measure of the amount of photosynthetic biomass, and is correlated with biophysical parameters such as green leaf biomass and the fraction of green vegetation cover, whose behavior follows annual cycles of vegetation growth (Myneni et al., 1995; Tucker, 1979).

We validated BFAST by (1) simulating 16-day NDVI time series, and (2) applying the method to 16-day MODIS satellite NDVI time series (2000–2008). Validation of multi-temporal change-detection methods is often not straightforward, since independent reference sources for a broad range of potential changes must be available during the change interval. Field validated single-date maps are unable to represent the type and number of changes detected (Kennedy et al., 2007). We simulated 16-day NDVI time series with different noise, seasonality, and change magnitudes in order to robustly test BFAST in a controlled environment. However, it is challenging to create simulated time series that approximate remotely sensed time series which contain combined information on vegetation phenology, interannual climate variability, disturbance events, and signal contamination (e.g. clouds) (Zhang et al., 2009). Therefore, applying the method to remotely sensed data and performing comparisons with in-situ data remains necessary. In the next two sections, we apply BFAST to simulated and real MODIS NDVI time series.

3.1. Simulation of NDVI time series

NDVI time series are simulated by extracting key characteristics from MODIS 16-day NDVI time series. We selected two MODIS NDVI time series (as described in 3.2) representing a grassland and a pine plantation (Fig. 1), expressing the most different phenology in the study area, to extract seasonal amplitude, noise level, and average value. Simulated NDVI time series are generated by summing individually simulated seasonal, noise, and trend components. First, the seasonal component is created using an asymmetric

Gaussian function for each season. This Gaussian-type function has been shown to perform well when used to extract seasonality by fitting the function to time series (Jönsson and Eklundh, 2002). The amplitude of the MODIS NDVI time series was estimated using the range of the seasonal component derived with the STL function, as shown in Fig. 2. The estimated seasonal amplitudes of the real forest and grassland MODIS NDVI time series were 0.1 and 0.5 (Fig. 1). Second, the noise component was generated using a random number generator that follows a normal distribution N($\mu = 0$, $\sigma = x$), where the estimated x values were 0.04 and 0.02, to approximate the noise within the real grass and forest MODIS NDVI time series (Lhermitte et al., submitted). Vegetation index specific noise was generated by randomly replacing the white noise by noise with a value of -0.1, representing cloud contamination that often remains after atmospheric correction and cloud masking procedures. Third, the real grass and forest MODIS NDVI time series were approximated by selecting constant values 0.6 and 0.8 and summing them with the simulated noise and seasonal component. A comparison between real and simulated NDVI time series is shown in Fig. 1.

Based on the parameters required to simulate NDVI time series similar to the real grass and forest MODIS NDVI time series (Fig. 1), we selected a range of amplitude and noise values for the simulation study (Table 1). These values are used to simulate NDVI time series of different quality (i.e. varying signal to noise ratios) representing a large range of land cover types.

Table 1: *Parameter values for simulation of 16-day NDVI time series*

Parameters	Values
Amplitude	$0.1, 0.3, 0.5$
σ Noise	$0.01, 0.02, \ldots, 0.07$
Magnitude	$-0.3, -0.2, -0.1, 0$

The accuracy of the method for estimating the number, timing and magnitude of abrupt changes was assessed by adding disturbances with a specific magnitude to the simulated time series. A simple disturbance was simulated by combining a step function with a specific magnitude (Table 1) and linear recovery phase (Kennedy et al., 2007). As such, the disturbance can be used to simulate, for example, a fire in a grassland or an insect attack on a forest. Three disturbances were added to the simulated seasonal, trend, and noise components using simulation parameters (Table 1). An example of a simulated NDVI time series with three disturbances is shown in Fig. 3. A Root Mean Square Error (RMSE) was derived for 500 iterations of all the combinations of amplitude, noise and magnitude of change levels to quantify the accuracy of estimating: (1) the number of detected changes, (2) the time of change, and (3) the magnitude of change.

3.2. Spatial application on MODIS image time series

We apply BFAST to real remotely sensed time series, and compare the detected changes with a spatial validation data set. BFAST provides information on the number, time, magnitude and direction of changes in the trend and seasonal components of a time series. We focussed on the timing and magnitude of major changes occurring within the trend component.

We selected the 16-day MODIS NDVI composites with a 250m spatial resolution (MOD13Q1 collection 5), since this product provides frequent information at the spatial scale at which the majority of human-driven land cover changes occur (Townshend and Justice, 1988). The MOD13Q1 16-day composites were generated using a constrained view angle maximum NDVI value compositing technique (Huete et al., 2002). The MOD13Q1 images were acquired from the February 24th of 2000 to the end of 2008 (23 images/year except for the year 2000) for a multi-purpose forested study area (*Pinus radiata* plantation) in South Eastern Australia (Lat. 35.5° S, Lon. 148.0° E). The images contain data from the red (620–670nm) and near-infrared (NIR, 841–876nm) spectral wavelengths. We used the binary MODIS Quality Assurance flags to select only cloud-free data of optimal quality. The quality flags, however, do not guarantee cloud-free data for the MODIS 250 m pixels since that algorithms used to screen clouds use bands at coarse resolution. Missing values are replaced by linear interpolation between neighboring values within the NDVI series (Verbesselt et al., 2006).

The 16-day MODIS NDVI image series were analyzed, and the changes revealed were compared with spatial forest inventory information on the 'year of planting' of *Pinus radiata*. Time of change at a 16-day resolution was summarized to a yearly temporal resolution to facilitate comparison with the validation data. The validation protocol was applied under the assumption that no other major disturbances (e.g. tree mortality) would occur that would cause a change in the NDVI time series bigger than the change caused by harvesting and planting activities.

4. Results

4.1. Simulated NDVI time series

Fig. 3 illustrates how BFAST decomposes and fits different time series components. It can be seen that the fitted and simulated components are similar, and that the magnitude and timing of changes in the trend component are correctly estimated. The accuracies (RMSE) of the number of estimated changes are summarized in Fig. 4. Only results for seasonal amplitude 0.1 and 0.5 are shown but similar results were obtained for 0.3 NDVI amplitude. Three properties of the method are illustrated. First, the noise level only has an influence on the estimation of the number of changes when the magnitude of the change is -0.1, and is smaller than the overall noise level. The noise level is expressed as 4 σ, i.e. 99% of the noise range, to enable a comparison with the magnitude (Fig. 4). Second, the noise level does not influence the RMSE when no changes are simulated (magnitude = 0), indicating a low commission error independent of the noise level. Third, the seasonal amplitude does not have an influence on the accuracy of change detection. In Fig. 5 only simulation results for an amplitude 0.1 are shown, since similar results were obtained for other amplitudes (0.3 and 0.5). Overall, Fig. 5 illustrates that the RMSE of estimating the time and magnitude of change estimation is small and increases slowly for increasing noise levels. Only when the magnitude of change is small (-0.1) compared to the noise level (> 0.15), the RMSE increases rapidly for increasing noise levels.

4.2. Spatial application on MODIS image time series

The application of BFAST to MODIS NDVI time series of a *Pinus radiata* plantation produced estimates of the time and magnitude of major changes. These results are shown spatially in Figs. 6 and 7. The time of change estimated by BFAST is summarized each year to facilitate comparison. Only areas for which we had validation data available were visualized in Figs. 6 and 7. The overall similarity between the time of planting and time of detected change illustrates how BFAST can be used to detect change in a forest plantation (Fig. 6). However, differences in the estimated time of change can be interpreted using differences in the magnitude of change estimated by BFAST. Fig. 7 shows that detected changes can have either a positive or a negative magnitude of change. This can be explained by the fact that planting in pine plantations in the study area corresponds with a harvesting operation in the preceding year (personal communication with C. Stone). Harvesting operations cause a significant decrease in the NDVI times series, whereas planting causes a more gradual increase in NDVI. Firstly, if planting occurred before 2002, the NDVI time series did not contain any significant decrease in NDVI caused by the harvesting operations, since the MODIS NDVI time series only started in early 2000. BFAST therefore detected change with a positive magnitude, indicating regrowth (Fig. 7), corresponding to a time of change during or later than the plant date (Fig. 6). Fig. 8 (top) illustrates detected changes within a NDVI time series extracted from a single MODIS pixel within a pine plantation with a planting activity during 2001. Secondly, if planting occurred after 2003, the time series contained a significant decrease in NDVI caused by the harvesting operations. Major change detected as a consequence are changes corresponding to harvesting preceding the planting operation, and are therefore detected before the planting date (Fig. 6) and have a negative magnitude (Fig. 7). Fig. 8 (middle) illustrates detected changes within a NDVI time series with harvesting operation activity during 2004. These points illustrate BFAST's capacity to detect and characterize change, but also confirm the importance of simulating time series in a controlled environment, since it is very difficult to find validation data to account for all types of change occurring in ecosystems.

Fig. 8 (bottom) shows an example of changes detected by BFAST in an area where harvesting and thinning activities were absent. Fig. 9 illustrates how BFAST decomposed the NDVI time series and fitted seasonal, trend and remainder components. In 2002 and 2006 the study area experienced a severe drought, which caused the pine plantations to be stressed and the NDVI to decrease significantly. Severe tree mortality occurred in 2006, since trees were drought-stressed and not able to defend themselves against insect attacks (Verbesselt et al., in press). This explains why the change detected in 2006 is bigger (magnitude of the abrupt change) and the recovery (slope of the gradual change) is slower than the change detected in 2003, as shown in (Fig. 9). This example illustrates how the method could be used to detect and characterize changes related to forest health.

5. Discussion and further work

The main characteristics of BFAST are revealed by testing the approach using simulated time series and by comparing detected changes in 16-day MODIS NDVI time series with spatial forest inventory data. Simulation of NDVI time series illustrated that the iterative decomposition of time series into a seasonal and trend component was not influenced by the seasonal amplitude and by noise levels smaller than the simulated change magnitude. This enabled the robust detection of abrupt and gradual changes in the trend component. As such, full time series can be analyzed without having to select only data during a specific period (e.g. growing season), or can avoid the normalization of reflectance values for each land cover type to minimize seasonal variability (Healey et al., 2005; Hilker et al., 2009). Seasonal adjustment by decomposing time series, as implemented in the BFAST approach, facilitates the detection of change in the trend component independent of seasonal amplitude or land cover type information. Considerations for further research fall into three main categories:

(1) Further research is necessary to study BFAST's sensitivity to detecting phenological change in the seasonal component. This research has focussed on the detection and characterization of changes within the trend component of 16-day NDVI time series. Changes in the seasonal component were not simulated, and BFAST's sensitivity to detecting seasonal changes using simulated data was not assessed. However, changes occurring in the seasonal component can be detected using BFAST. The application of BFAST to 16-day MODIS NDVI time series on a forested area (40000ha) revealed that seasonal breaks were detected in only 5% of the area. The small number of seasonal breaks occurring in the study area could be explained by the fact that a seasonal change is only detected when a change between land cover types with a significantly different phenology occurs. Time series with a higher temporal resolution (e.g. daily or 8-day) could increase the accuracy of detecting seasonal changes but might also impact the ability to detect subtle changes due to higher noise levels. Zhang et al. (2009) illustrated that vegetation phenology can be estimated with high accuracy (absolute error of less than 3 days) in time series with a temporal resolution of 6–16 days, but that accuracy depends on the occurrence of missing values. It is therefore necessary to study BFAST's capacity to detect phenological change caused by climate variations or land use change in relation to the temporal resolution of remotely sensed time series.

(2) Future algorithm improvements may include the capacity to add functionality to identify the type of change with information on the parameters of the fitted piecewise linear models (e.g. intercept and slope). In this study we have focussed on the magnitude of change, derived using Eq. 2, but the spatial application on MODIS NDVI

time series illustrated that change needs to be interpreted by combining the time and magnitude of change. Alternatively, different change types can be identified based on whether seasonal and trend breaks occur at the same time or not and whether a discontinuity occurs (i.e. magnitude > 0) (Shao and Campbell, 2002). Parameters of the fitted piecewise linear models can also be used to compare long term vegetation trends provided by different satellite sensors. Fensholt et al. (2009), for example, used linear models to analyze trends in annually integrated NDVI time series derived from Advanced Very High Resolution Radiometer (AVHRR), SPOT VEGETATION, and MODIS data. BFAST enables the analysis of long NDVI time series and avoids the need to summarize data annually (i.e. loss of information) by accounting for the seasonal and trend variation within time series. This illustrates that further work is needed to extend the method from detecting change to classifying the type of change detected.

(3) Evaluating BFAST's behavior for different change types (e.g. fires versus desertification) in a wide variety of ecosystems remains important. BFAST is tested by combining different magnitudes of an abrupt change with a large range of simulated noise and seasonal variations representing a large range of land cover types. BFAST is able to detect different change types, however, it remains important to understand how these change types (e.g. woody encroachment) will be detected in ecosystems with drastic seasonal changes (e.g. strong and variable tropical dry seasons) and severe noise in the spectral signal (e.g. sun angle and cloud cover in mountainous regions).

(4) The primary challenge of MODIS data, despite its high temporal resolution, is to extract useful information on land cover changes when the processes of interest operate at a scale below the spatial resolution of the sensor (Hayes and Cohen, 2007). Landsat data have been successfully applied to detect changes at a 30m spatial resolution. However, the temporal resolution of Landsat, i.e. 16-day, which is often extended by cloud cover, can be a major obstacle. The fusion of MODIS with Landsat images to combine high spatial and temporal resolutions has helped to improve the mapping of disturbances (Hilker et al., 2009). It is our intention to use BFAST in this integrated manner to analyze time series of multi-sensor satellite images, and to be integrated with data fusion techniques.

This research fits within an Australian forest health monitoring framework, where MODIS data is used as a 'first pass' filter to identify the regions and timing of major change activity (Stone et al., 2008). These regions would be targeted for more detailed investigation using ground and aerial surveys, and finer spatial and spectral resolution imagery.

6. Conclusion

We have presented an generic approach for detection and characterization of change in time series. 'Breaks For Additive Seasonal and Trend' (BFAST) enables the detection of different types of changes occurring in time series. BFAST integrates the decomposition of time series into trend, seasonal, and remainder components with methods for detecting multiple changes. BFAST iteratively estimates the dates and number of changes occurring within seasonal and trend components, and characterizes changes by extracting the magnitude and direction of change. Changes occurring in the trend component indicate gradual and abrupt change, while changes occurring in the seasonal component indicate phenological changes. The approach can be applied to other time series data without the need to select specific land cover types, select a reference period, set a threshold, or define a change trajectory.

Simulating time series with varying amounts of seasonality and noise, and by adding abrupt changes at different times and magnitudes, revealed that BFAST is robust against noise, and is not influenced by changes in amplitude of the seasonal component. This confirmed that BFAST can be applied to a large range of time series with varying noise levels and seasonal amplitudes, representing a wide variety of ecosystems. BFAST was applied to 16-day MODIS NDVI image time series (2000–2008) for a forested study area in south eastern Australia. This showed that BFAST is able to detect and characterize changes by estimating time and magnitude of changes occurring in a forested landscape.

The algorithm can be extended to label changes with their estimated magnitude and direction. BFAST can be used to analyze different types of remotely sensed time series (AVHRR, MODIS, Landsat) and can be applied to other disciplines dealing with seasonal or non-seasonal time series, such as hydrology, climatology, and econometrics. The R code (R Development Core Team, 2008) developed in this paper is available by contacting the authors.

7. Acknowledgements

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Figures

For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.

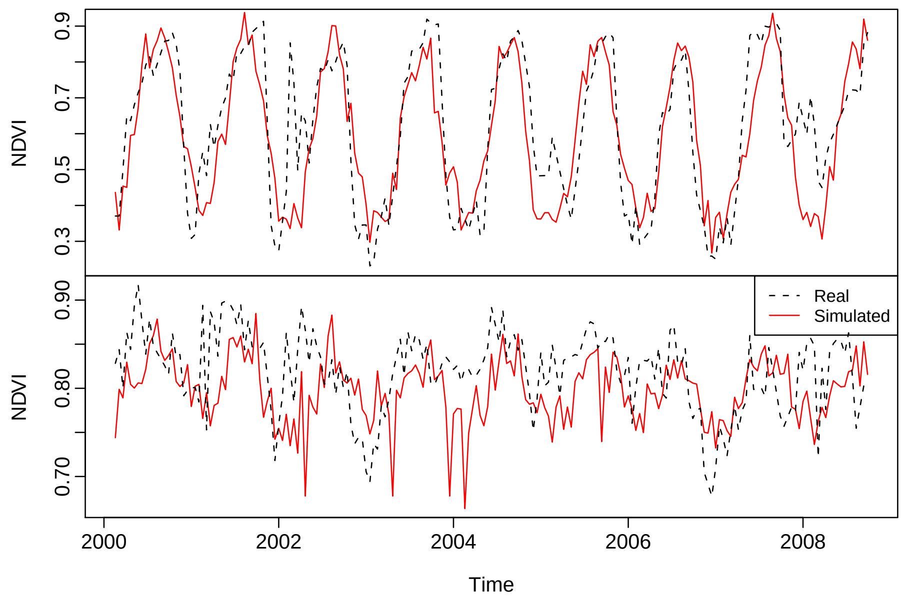

Figure 1: *Real and simulated 16-day NDVI time series of a grassland (top) and pine plantation (bottom).*

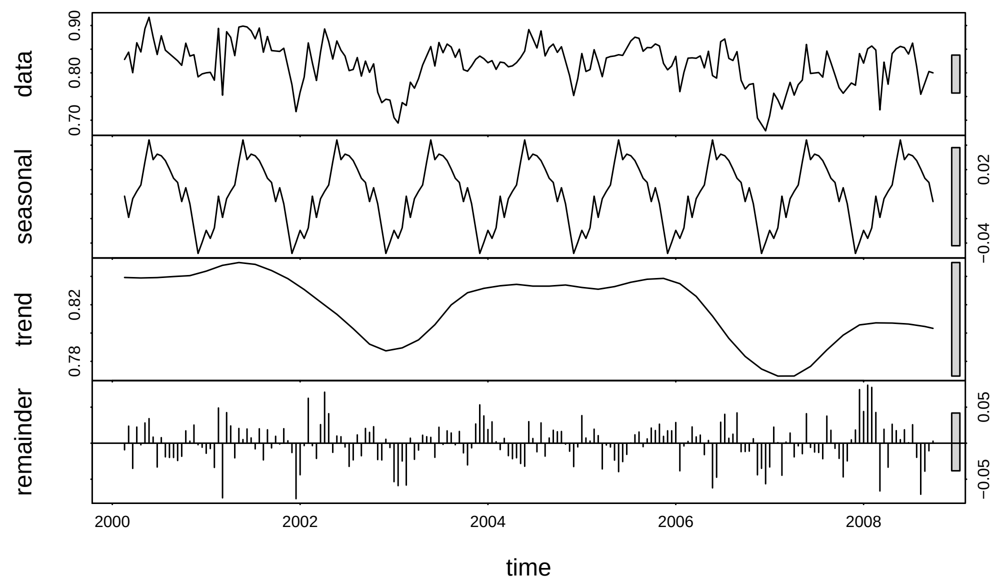

Figure 2: *The STL decomposition of a 16-day NDVI time series of a pine plantation into seasonal, trend, and remainder components. The seasonal component is estimated by taking the mean of all seasonal sub-series (e.g. for a monthly time series the first sub-series contains the January values). The sum of the seasonal, trend, and remainder components equals the data series. The solid bars on the right hand side of the plot show the same data range, to aid comparisons. The range of the seasonal amplitude is approximately 0.1 NDVI.*

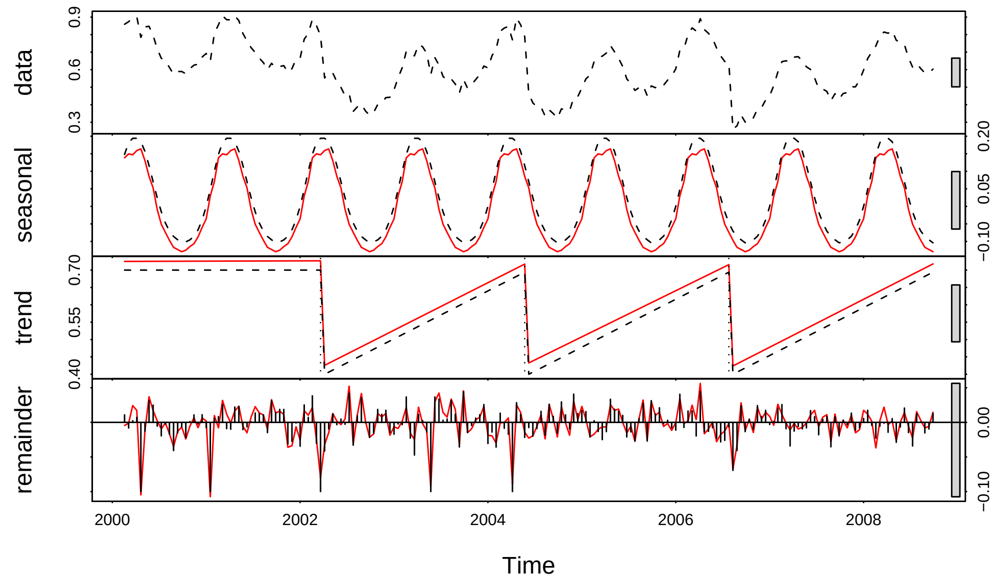

Figure 3: *Simulated 16-day MODIS NDVI time series with a seasonal amplitude = 0.3, σ = 0.02 and change magnitude = -0.3. The simulated data series is the sum of the simulated seasonal, trend and noise series (- - -), and is used as an input in BFAST. The estimated seasonal, trend and remainder series are shown in red. Three break points are detected within the estimated trend component ($\cdots$). The solid bars on the right hand side of the plot show the same data range, to aid comparisons.*

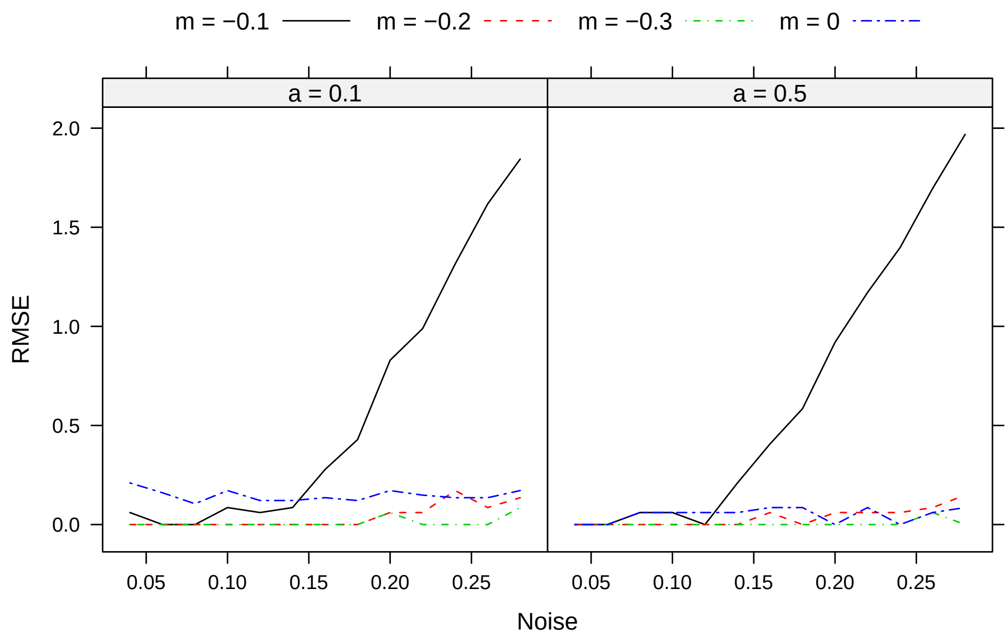

Figure 4: *RMSEs for the estimation of number of abrupt changes within a time series, as shown in Figure 3 (a = amplitude of the seasonal component, m = magnitude of change). The units of the x and y-axes are 4σ (noise) and the number of changes (RMSE). See Table 1 for the values of parameters used for the simulation of the NDVI time series. Similar results were obtained for a = 0.3*

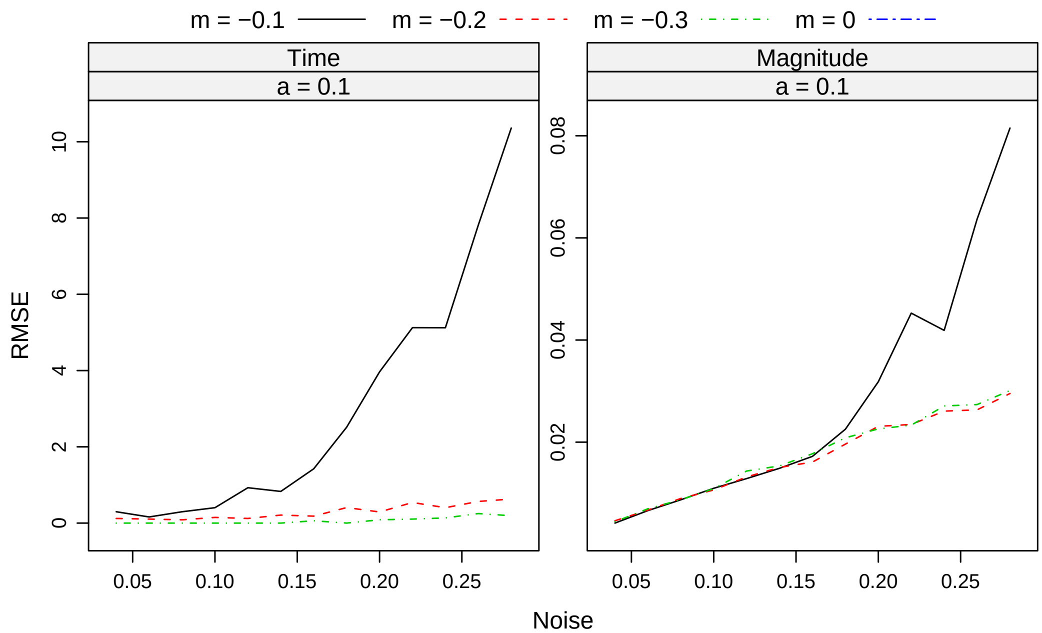

Figure 5: *RMSEs for the estimation of the time and magnitude of abrupt changes within a time series (a = amplitude of the seasonal component, m = magnitude of changes). The units of the x-axis are 4σ NDVI, and y-axis are relative time steps between images (e.g. 1 equals a 16-day period) (left) and NDVI (right). See Table 1 for the values of parameters used for the simulation of NDVI time series. Similar results were obtained for a = 0.3 and 0.5.*

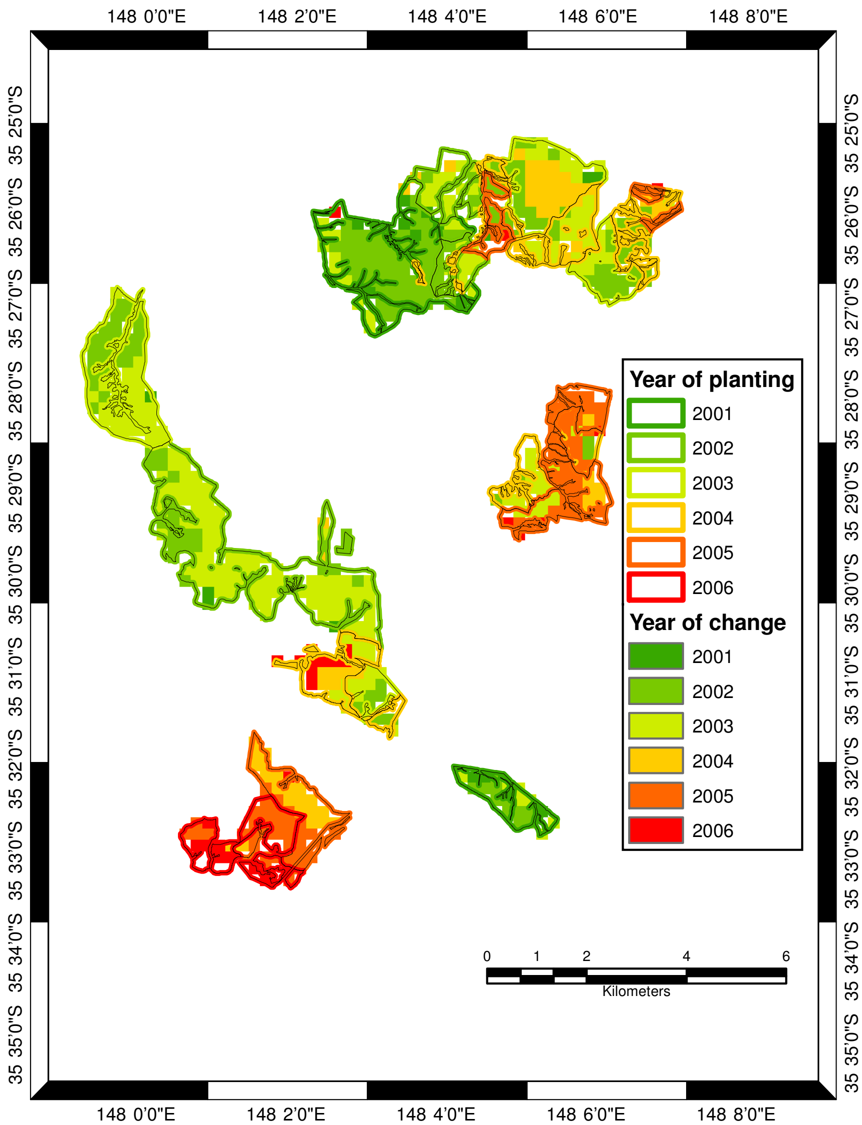

Figure 6: *Comparison between the year of Pinus radiata planting derived from spatial forest inventory data and the BFAST estimate of the year of major change occurring in MODIS NDVI image time series (2000–2008) for a forested area in south eastern Australia.*

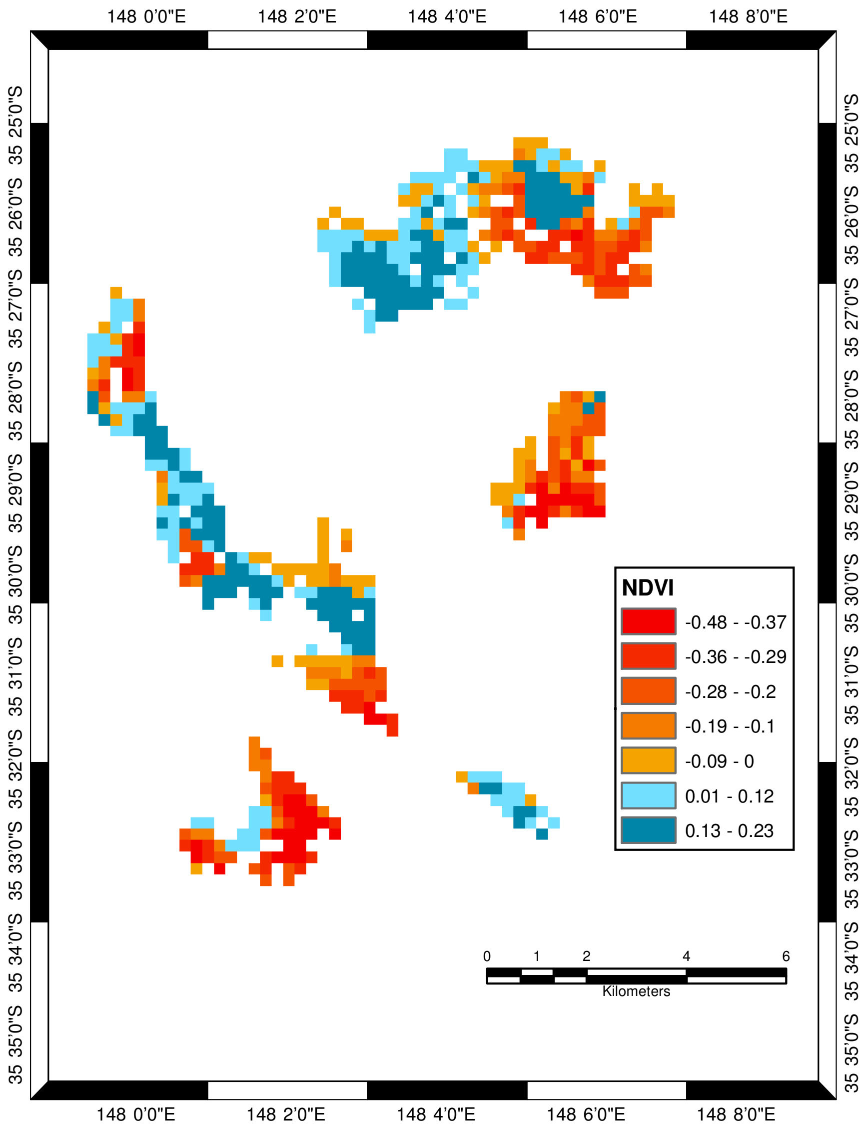

Figure 7: *BFAST estimated magnitudes of major changes occurring in MODIS NDVI image time series (2000–2008) for a forested area in south eastern Australia. Negative values generally indicate harvesting, while positive values indicate forest growth.*

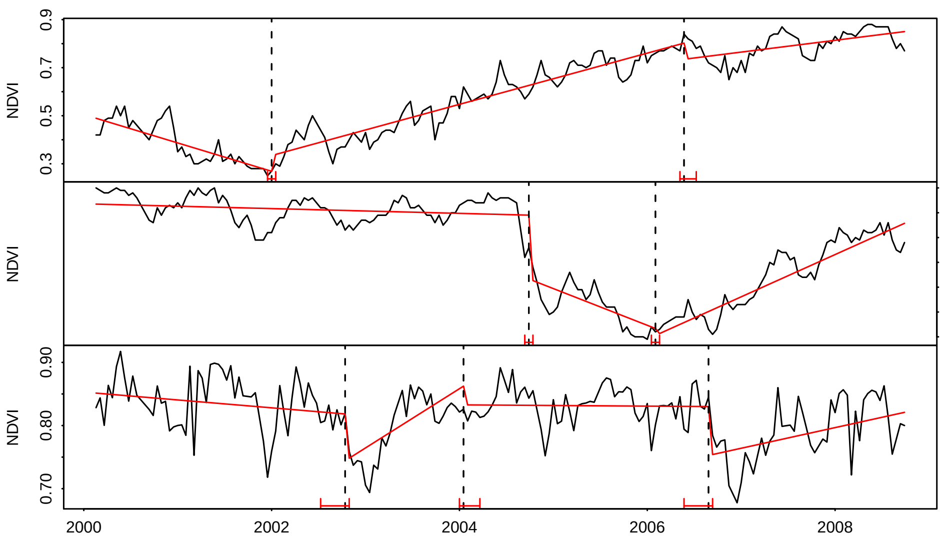

Figure 8: *Detected changes in the trend component (red) of 16-day NDVI time series (black) extracted from a single MODIS pixel within a pine plantation, that was planted in 2001 (top), harvested in 2004 (middle), and with tree mortality occurring in 2007 (bottom). The time of change (- - -), together with its confidence intervals (red) are also shown.*

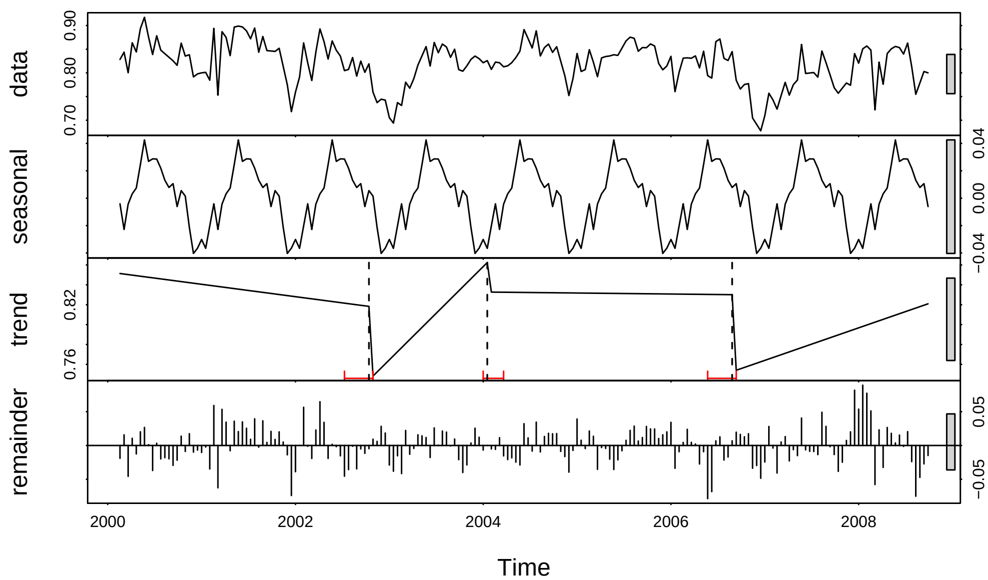

Figure 9: *Fitted seasonal, trend and remainder (i.e. estimated noise) components for a 16-day MODIS NDVI time series (data series) of a pine plantation in the northern part of the study area. Three abrupt changes are detected in the trend component of the time series. Time (- - -), corresponding confidence interval (red), direction and magnitude of abrupt change and slope of the gradual change are shown in the estimated trend component. The solid bars on the right hand side of the plot show the same data range, to aid comparisons.*