Real-time land cover disturbance detection
using satellite image time series

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Abstract

Real-time monitoring of forest and land cover disturbances are critical for addressing impacts on carbon storage, biodiversity, and socio-ecological processes. Satellite remote sensing enables cost-effective and accurate monitoring at frequent time steps over large areas. Yet, methods to detect disturbances in near real-time within newly captured satellite images are lacking.

We are proposing a time series analysis approach to detect disturbances in near real-time within recently captured satellite images by automatically identifying a stable history period to model normal expected behaviour and enable detection of abnormal changes (i.e. disturbances related to abnormal vegetation dynamics).

Validation and accuracy assessment of the real-time change detection method is done by (1) simulating 16-day MODIS NDVI time series with different amount of noise, seasonality and containing disturbances with different magnitudes, (2) using real MODIS satellite image time series.

Results illustrate the proof-of-concept of the proposed real-time monitoring method. Disturbances are successfully detected in real-time, i.e., at the end of a time series, while being robust (?)for seasonality and noise. However, the simulation experiment and application on satellite data was focussed on detecting changes in forested areas and further work is required to test the method for ecosystems with a dominant herbaceous cover.

The noise level of the time series being analysed for real-time change remains the most important driver of accuracy and potential to detect changes. As such, data pre-processing in order to improve the quality and reliability of time series remains essential to enable change detection in time series data.

The method is publicly available within the *bfast* package for R. This method is developed so that it can be used at a global scale since is fast, does not depend on vegetation type specific thresholds or definitions and does not require gap filling of time series. The method is flexible and can be applied for different purposes (e.g., drought or fire or detection) and to different types time series data (e.g., in-situ monitoring sensors or different types of satellite image time series).

Further work is needed for operational implementation of the method to enable a rapid response and alert system by applying it to time series data with a high temporal resolution (e.g., hourly or daily data).

Research Highlights

- A novel near real-time change detection approach within newly measured data using time series analysis.

- The method is validated by simulating time series and applying it on real satellite data.

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- The approach is robust, fast, and flexible to different data sets and does not require gap filling.

- The is freely available as a function in the *bfast* package for the open-source statistics system R.

Keywords: Early warning, real-time, disturbance detection, land cover and land use change, NDVI, time series, MODIS, vegetation dynamics, phenology

1. Introduction

Real-time forest and land cover disturbance monitoring is critical for tracking human-induced and natural disturbances promptly (Asner, 2011). Such information is needed for signalling abnormal developments, quickly raising awareness, and allow for prompt actions to intervene, relief efforts and reduce negative impacts to natural resources, humans, and infrastructure.

Key to approaches looking at forest and land cover disturbances is that many recent change events occur worldwide at unknown locations with unknown change magnitudes. In this sense, remote sensing tools can be in the first instance used to alert when things start to appear *abnormal*. For example, deviations from *normal* land surface phenology, defined as the seasonal variation in vegetated land surface from remote sensing (White et al., 2009), can indicate important changes in forest health (Stone et al., 2008; Morisette et al., 2009), carbon status, regional drought effects and even climate change (Cleland et al., 2007; Hargrove et al., 2009).

Satellite sensors are well-suited to provide consistent and frequent measurements over large areas which is appropriate for capturing the effects of many processes that cause change, including natural (e.g., insect attacks, droughts, fires, floods) and anthropogenic (e.g., deforestation, urbanisation, farming) disturbances (Jin & Sader, 2005).

Many types of ecosystem changes affecting the land surface range from diurnal cycles to long-term change in vegetation patterns. The ecosystem changes commonly observed with remote sensing approaches can be divided into three categories: (1) *seasonal or cyclic change*, driven by annual temperature and rainfall interactions impacting plant phenology resulting in distinct intra-annual patterns for different vegetation types; (2) *gradual trend change* such as trends in mean annual rainfall or gradual change in land management (e.g., forest regrowth after fire) that result in changes over several years; and (3) *abrupt trend change*, caused by events from human activities (e.g., deforestation) or natural causes (e.g., wind throw or an extreme drought event) that change land cover over short time frames (days or weeks) (de Beurs & Henebry, 2005a,b; Verbesselt et al., 2010b).

Estimating change from remotely sensed data is not straightforward, since time series contain a combination of seasonal, gradual and abrupt ecosystem changes occurring in parallel, in addition to noise that originates from the sensing environment (e.g., view angle), remnant geometric errors, atmospheric scatter and cloud effects (de Beurs & Henebry, 2005b; Roy et al., 2002; Wolfe et al.,

1998). The ability of any system to detect change depends on its capacity to differentiate normal phenological cycle from abnormal change (e.g., drought effects, degradation, deforestation).

Several change detection methods are available to detect disturbances within historical satellite image time series (de Beurs & Henebry, 2005a; Verbesselt et al., 2010a,b; White & Nemani, 2006) but generic methods to detect changes in real-time within newly captured satellite images are lacking. Three major challenges remain.

First, global scale change detection techniques need to be independent of vegetation-specific thresholds while being robust against the inherent noise and seasonality captured within time series. Most change detection methods require user designation of a threshold or change type definition separating real change from spectral changes caused by variability in illumination, seasonality, or atmospheric scattering (Lu et al., 2004). White & Nemani (2006) presented a method for real-time monitoring of land surface phenology but requires a region-specific threshold for detecting change. The determination of thresholds adds significant cost to efforts expanding change detection across regions or becomes complex when regions are changing. Trajectory-based change detection has been proposed to move towards a threshold-independent change detection by characterising change by its temporal signature (Hayes & Cohen, 2007; Kennedy et al., 2007). This approach requires the definition of the change trajectory specific to the type of change to be detected. Furthermore, the method will only function if the observed spectral trajectory matches one of the hypothesised trajectories. A historical analysis using archived satellite data is needed to model normal, expected behaviour against which abnormal behaviour in the near future can be described (Hargrove et al., 2009). This illustrates that there is a critical need to enable analysis of time series independent of vegetation specific thresholds to detect disturbances in near real-time.

Second, it is crucial to be able to detect disturbance in near real-time (i.e. within newly capture satellite images). In previous work, we proposed a generic and threshold independent method for change detection within time series (Verbesselt et al., 2010a,b). This method, BFAST (Break detection For Additive Seasonal and Trend), detects and characterises changes within historical time series but the method is developed to detect disturbances at the end of a time series (i.e. in near-real time). Methods to detect changes in near real-time, also called online monitoring methods, have been developed to monitor and detect in real-time, for example, abnormal stock exchange dynamics (Bai & Perron, 2003; Zeileis et al., 2010). These method have not been implemented for real-time monitoring and disturbance detection of climate driven vegetation dynamics using satellite image time series. This confirms the need to develop an approach that enable generic and near real-time disturbance detection at a continental or global scale.

Third, change detection methods need to deal with missing data (e.g., clouds or sensor defects) in time series. Most existing change detection methods smooth or interpolate data using one of many existing techniques (e.g., filtering, Fourier analysis) (Jönsson & Eklundh, 2002; Roerink et al.,

2000; Julien & Sobrino, 2010) when dealing with noisy times series of remotely sensed data. For a given date, these methods typically require looking both backwards and forwards in time, negating use in real-time or forecast applications (White & Nemani, 2006). Also, time series smoothing and interpolation techniques model data and fill gaps based on assumptions of normal data variation which inhibits the detection of disturbances. Therefore, methods able to analyse non-gap-filled time series are critical for real-time change detection.

We propose a generic approach for real-time change detection of disturbances using time series data that does not require specific thresholds and deals with missing data. The following major research questions are answered in this paper:

(1) Can a period, representing *normal* historical data variation representing both seasonal and gradual changes, be identified within a time series? (2) Is the model representing the *normal* historical data variation able to reliably and quickly differentiate between normal and abnormal changes (i.e. disturbances) within newly incoming observations (i.e., real-time)?

We assessed this approach for different ecosystems by simulating Normalised Difference Vegetation Index (NDVI) time series with varying amounts of seasonal variation and noise, and by adding changes with different magnitudes.

We applied the approach on MODIS 16-day image composites (hereafter called 16-day time series) to demonstrate its potential use in forested areas and detect real-time forest disturbances in a forested area in south eastern Australia.

The method described in this study is available in the *bfast* package for R (R Development Core Team, 2011) from the Comprehensive R Archive Network (CRAN) at `http://CRAN.R-project.org/package=bfast`.

It can be used for disturbance detection within other data sets (e.g. temperature, rainfall, CO_2 time series data) or be integrated within monitoring frameworks (e.g., `http://rapidfire.sci.gsfc.nasa.gov/`), and used as an alarm system to provide information on when and where significant disturbances occur.

2. Real-time change detection

The methods proposed here are based on a similar additive season and trend model as employed by Verbesselt et al. (2010b). However, while Verbesselt et al. (2010b) focussed on the question if and where structural breaks occur in the season and trend component of a given observed time series $t = 1, \ldots, n$, we want to investigate a different question: *Does the season-trend model for future observations $t = n, n + 1, \ldots$ still conform with the season-trend model established for the historical sample $t = 1, \ldots, n$?* Thus, we want to monitor potential abnormality at the end of a time series, in real-time, by comparing it with historical observations.

2.1. Season-trend model

For the observations y_t at time t, a season-trend model is assumed with linear trend and harmonic season:

$$y_t = \alpha_1 + \alpha_2 t + \sum_{j=1}^{k} \gamma_j \sin\left(\frac{2\pi j t}{f} + \delta_j\right) + \varepsilon_t, \tag{1}$$

where the intercept α_1, slope α_2 (i.e., trend), amplitudes $\gamma_1, \ldots, \gamma_k$, and phases $\delta_1, \ldots, \delta_k$ (i.e., season) are the unknown parameters, f is the known frequency (e.g., $f = 23$ annual observations for a 16-day time series), and ε_t is the unobservable error term at time t. The choice of k controls at which frequencies seasonal variations occur. In the applications below, we employ three harmonic terms (i.e., $k = 3$) to robustly detect phenological changes within MODIS NDVI time series, as components four and higher represent variations that occur on a three-month cycle or less (Geerken, 2009; Julien & Sobrino, 2010). More information about this season-trend model is provided by Verbesselt et al. (2010b).

It is more convenient to reparametrize the model so that it can be written as standard a linear regression model while still giving equivalent predictions (see e.g., Cryer & Chan, 2008, Chapter 3.3):

$$y_t = x_t^\top \beta + \varepsilon_t,$$
$$x_t = \{1, t, \sin(2\pi 1 t/f), \cos(2\pi 1 t/f), \ldots, \sin(2\pi k t/f), \sin(2\pi k t/f)\}^\top,$$
$$\beta = \{\alpha_1, \alpha_2, \gamma_1 \cos(\delta_1), \gamma_1 \sin(\delta_1), \ldots, \gamma_k \cos(\delta_k), \gamma_k \sin(\delta_k)\}^\top,$$

where the $p = 2 + 2k$ parameters are collected in the regression coefficients β which can be estimated and tested using ordinary least squares (OLS) techniques. In particular, if all season-trend parameters in β can be assumed to be stable for a given sample $t = 1, \ldots, n$, the OLS estimator $\hat{\beta}$ is consistent for the unknown parameters.

2.2. Monitoring structural change

Based on the season-trend model introduced above, the question raised in the introduction can be rephrased into a structural change framework: *Given that a stable season-trend model was estimated in an observed time period, does it remain stable for future incoming observations?* An abnormal structural change is detected when the model does not remain stable for new incoming observations.

As the season-trend model can be formulated as an OLS regression, we can leverage from the methods proposed in the structural change literature for linear regression models where this problem is known as *monitoring* of structural changes (Chu et al., 1996). The idea for monitoring techniques is simple. Given that the parameters β can be consistently estimated as $\hat{\beta}$ from a stable history period $t = 1, \ldots, n$, we want to check whether $\hat{\beta}$ still fits the data y_t for $t > n$. To do

so, some measure of discrepancy is needed, e.g., residuals, re-estimation of the parameters, or the score function of the model (see Chu et al., 1996; Leisch et al., 2000; Zeileis, 2005). Here, we simply use (suitably scaled) moving sums (MOSUMs) of the residuals in the monitoring period $t = n + 1, \ldots, N$:

$$m_t = \frac{1}{\hat{\sigma}\sqrt{n}} \sum_{s=t-h+1}^{t} (y_s - x_s^\top \hat{\beta}), \tag{2}$$

where h is the bandwidth of the MOSUM and is typically chosen relative to the size of the history sample, e.g., $h = n/4$ or $h = n$ (Zeileis, 2005; Zeileis et al., 2010). If the model remains stable, the MOSUM process m_t should be close to zero and fluctuate only randomly. However, if a structural change occurs, m_t will deviate systematically from zero. A structural break is declared if the absolute value $|m_t|$ exceeds some boundary that is asymptotically only crossed with 5% probability under structural stability. The technical details for the boundary are based on a so called functional central limit theorem. See Leisch et al. (2000) and especially their Table 1 for more details.

2.3. Selecting the stable history period

A crucial assumption for the monitoring approach proposed above is that the history period $t = 1, \ldots, n$ itself is free of structural changes, i.e., that the parameters β are stable during this time. Only in that case $\hat{\beta}$ is a consistent estimate (i.e., the season-trend structure can be sensibly estimated) against which incoming new observations for $t > n$ can be compared.

In practice, there are often long series of observations y_t available before the start of the monitoring process and it would be naive to assume that always all of these observations can be adequately captured by a single season-trend model. Hence, a natural idea is to not use all observations but only the last $\ell, \ldots, n$ observations with $\ell \geq 1$ so that a stable season-trend pattern can be established.

Ideally, there is prior subject-matter knowledge for a suitable size of the history period. If not, various data-driven techniques for determining ℓ have been suggested in the literature. One popular approach is to assume that there are multiple structural breaks already in the history period whose timing can be estimated using the methods of Bai & Perron (2003) (which was is also a core ingredient of the BFAST method of Verbesselt et al., 2010b). Then, ℓ is selected as the first observation after the last estimated breakpoint. This approach is straightforward and is known to work well if there are large abrupt shifts in the season-trend model in the history period. However, Pesaran & Timmermann (2002) show that, when smaller gradual changes occur, this breakpoint approach is less accurate due to a trade-off between bias and variance.

Hence, they suggest an alternative technique. By moving backward in time for $t = n, n - 1, n - 2, \ldots$ they consider cumulative 1-step ahead prediction errors until the season-trend model breaks down. The method is also known as reversed-ordered-cumulative sum (CUSUM) of residuals, or

ROC. The ROC method is based on similar ideas as the monitoring approach introduced above, but in reverse ordering. The season-trend model is estimated $\hat{\beta}^{(s+1:n)}$ based on observations $t = s + 1, \ldots, n$ and it is checked whether the last previous observation s conforms with this.

The suitably scaled residuals $\tilde{\varepsilon}_s$ are then cumulated (in reverse ordering):

$$\tilde{\varepsilon}_s = \frac{y_s - x_s^\top \hat{\beta}^{(s+1:n)}}{\sqrt{1 + x_s^\top \left(X^{(s+1:n)^\top} X^{(s+1:n)} \right)^{-1} x_s}},$$

$$r_i = \frac{1}{\tilde{\sigma}\sqrt{n}} \sum_{s=n-i+1}^{n} \tilde{\varepsilon}_s$$

where $X^{(s+1:n)}$ is the regressor matrix based on observations $s + 1, \ldots, n$ and $\tilde{\sigma}$ is an estimate of the residual standard deviation. For this ROC process r_i with $i = p + 1, \ldots, n$, there are again boundaries whose asymptotic crossing probability under structural stability can be controlled (see Zeileis et al., 2002).

If no boundary crossing occurs, there is no evidence for structural changes within the history period. Thus $\ell = 1$ can be chosen and the monitoring approach can be conducted as described above. However, if there is a boundary crossing, the last observation before the boundary crossing is chosen as ℓ, corresponding to the last point up to which there is no sufficiently large deviation from parameter stability. The remaining observations $1, \ldots, \ell - 1$ are pruned from the history period and then the monitoring is conducted as described above but with a reduced sample size of the history period (i.e., the stable history).

In summary, when using the method with real data three steps are being performed: (1) verify which part of the history period is stable by going back in time from the last of the history period, (2) fit the seasonal-trend model on the stable history period and (3) monitor and verify whether the stable history model is still valid for the new incoming data (i.e., real-time change detection).

3. Validation

We validated the real-time change detection approach by (1) a simulation experiment and (2) analysis of 16-day MODIS satellite NDVI time series. 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 (Kennedy et al., 2007). We simulated 16-day NDVI time series with different noise levels, seasonality, and disturbances in order to robustly test the real-time change approach in a controlled environment. However, it is challenging to create simulated time series that approximate remotely sensed time series, because these contain combined information on vegetation phenology, inter-annual climate variability, disturbance events, sensor conditions (e.g., viewing angle), and signal contamination (e.g., clouds) (Zhang et al., 2009). Therefore, applying the method to real remotely sensed data remains necessary. A similar validation strategy was proposed

by Verbesselt et al. (2010a,b) to validate the detection of phenological shifts, abrupt and gradual changes within time series. Here, we focus on the validation of detection of changes at the end of a time series, i.e., in real-time, when new images are recently captured. In the next two sections, the simulation of NDVI time series and application on real MODIS NDVI satellite image time series are explained.

3.1. Simulation experiment

The objective of the time series simulation experiment was to validate, how much new data is required to detect a disturbance, while varying the amount of noise, seasonal amplitude, and the magnitude of the disturbance in the simulated time series. NDVI time series were simulated using a similar approach as proposed by Verbesselt et al. (2010b). Simulated NDVI time series are generated by summing individually simulated seasonal, abrupt, and noise components (Fig. 1). First, the seasonal component is created using an asymmetric Gaussian function with a amplitude (a) for each season. Second, an abrupt change was added to the trend component to simulate an abrupt disturbance (e.g., fire, flood or harvest operation). This was simulated by combining a step function with a magnitude (m) and fixed gradient recovery phase. Third, the noise component was generated using a random number generator that follows a normal distribution $N(\mu = 0, \sigma = x)$. 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.

Table 1: Parameter values (a, σ noise and m) for simulation of 16-day NDVI time series while varying the amount of data available in the monitoring period (n i.e., 16-day time steps).

Parameters	Values
a	$0.1, 0.3, 0.5$
σ noise	$0.01, 0.02, \ldots, 0.08$
m	$0, -0.1, -0.2, \ldots, -0.5$
n	$1, 2, \ldots, 8$

Two periods within the simulated time series are selected to validate the real-time monitoring approach; (a) a *history period* i.e., data that already has been acquired and which will be analysed for stability in order to model normal vegetation dynamics, and (b) a *monitoring period* i.e., the period representing new data that recently has been captured that needs to be analysed for disturbances. Here, the history is defined as the period from 2000 until mid 2006 (i.e., the time step just before the simulated break), whereas the monitoring period is defined as the period from the simulated break onwards of which the length is gradually increased during the experiment (n) (Fig. 2 and Table 1).

The objective is to verify how much data (n) is required before the abrupt change in the monitoring period is detected while varying σ, a, and m (Table 1). The 16-day NDVI time series
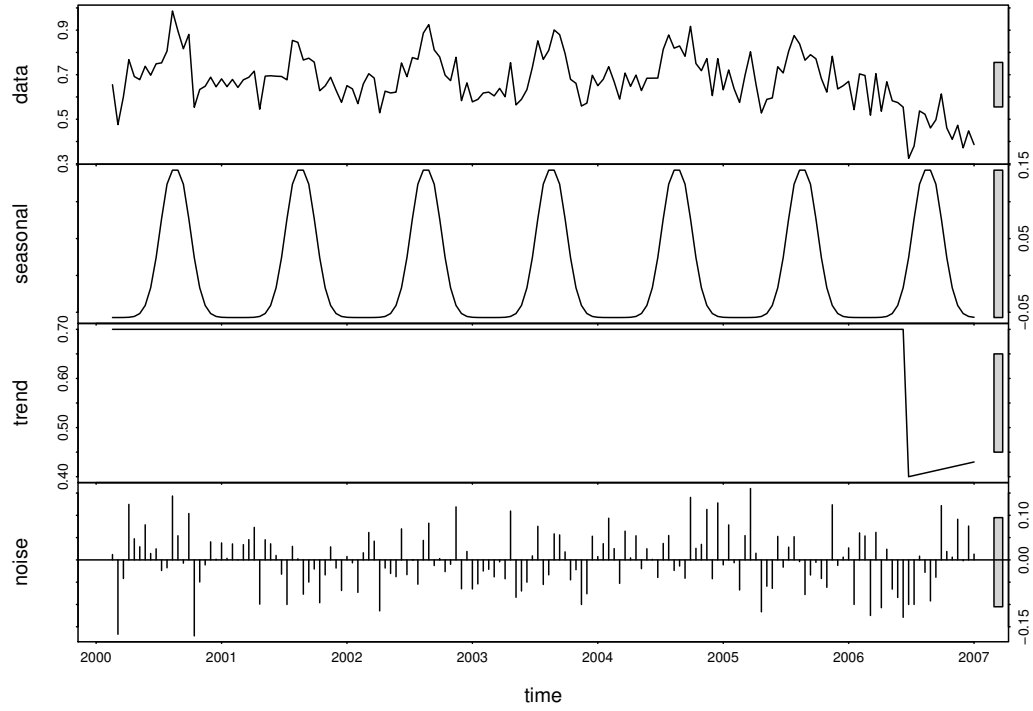
Figure 1: Simulated 16-day MODIS NDVI time series (data) with $a = 0.2$, $\sigma = 0.05$, containing one simulated abrupt change with $m = -0.3$) (Table 1). The simulated data series is the sum of the simulated seasonal, trend and noise series and is used as an input in real-time monitoring method and has a length of 7 years (i.e., 2000–2006) containing a simulated abrupt change in 2006. The solid bars on the right-hand side of the plot show the same data range, to aid comparisons.

are simulated by extracting key characteristics from MODIS 16-day NDVI time series within the study area (Verbesselt et al., 2010a). We selected a range of a, σ, and m values for the simulation study to represent a large range of land cover types of different data quality while varying the amount of data available in the monitoring period (Table 1). An example of the set-up of the simulation experiment is shown in Fig. 2. 1000 iterations of all the combinations of σ, a, n and m were performed to quantify the probability of detecting a disturbance in the monitoring period (i.e., recently acquired data).
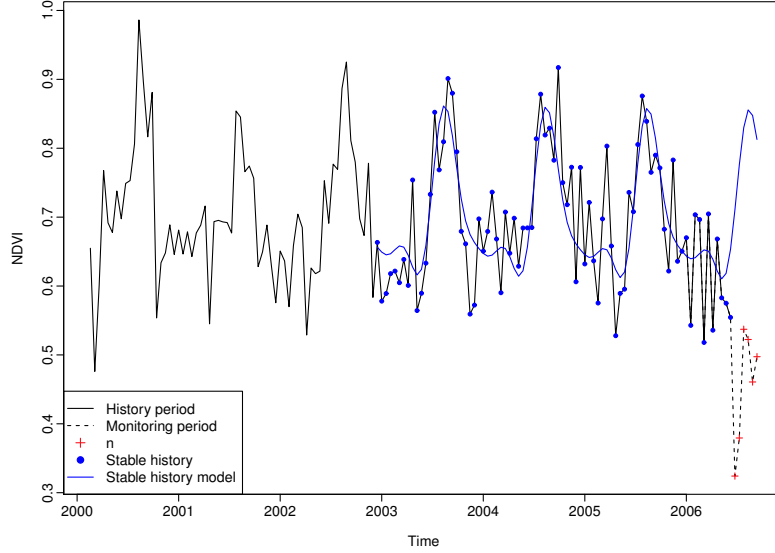

Figure 2: Simulated 16-day MODIS NDVI time series with $a = 0.2$, $\sigma = 0.05$, containing one simulated abrupt change with $m = -0.3$) (Fig. 1). During the simulation experiment the period from 2000 until mid 2006 (i.e., the time step just before the simulated break), is considered the *history period* and the period after the simulated break is the *monitoring period*. In this example, $n = 6$. The result of applying the monitoring approach on the simulated NDVI series is also shown. A stable history period is identified within the history period and used to model the normal data variation (i.e., stable history model) and predict normal data variation during monitoring period to enable the change detection (Section 2.2).

3.2. Spatial application on MODIS 16-day NDVI time series

The use of the real-time monitoring approach is demonstrated using real MODIS NDVI satellite image time series. To enable comparison with available in-situ forest inventory data, the period from 2000 until end of 2005 was considered as the history period and the year 2006 as the monitoring period. The timing of the detected abrupt changes in the monitoring period (i.e., 2006) revealed were discussed and interpreted using in-situ forest inventory data and expert knowledge (Stone et al., 2008; Verbesselt et al., 2009). The seasonal amplitude and noise level were also estimated to compare the performance of the method with the obtained results from the simulation experiment. The noise level is estimated by deriving the standard deviation of the residuals from the fitted seasonal-trend model (Section 2.1) of the stable history period, whereas the amplitude was estimated as the range of the seasonal component of the fitted model.

We selected the 16-day MODIS NDVI composites with a 250 m 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 & 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 24 February 2000 to 14 September 2009 for a multi-purpose forested study area (*Pinus radiata* plantation) in South Eastern Australia (Lat. 35.5° S, Lon. 148.0° E). The abrupt, gradual trend changes and phenological shifts occurring within the MODIS 16-day NDVI time series for this study area are described by Verbesselt et al. (2010a,b). We used the binary MODIS Quality Assurance flags to select only cloud-free data of optimal quality. Moreover, a pixel time series was only selected for analysis when it lacked less than 10% of the data (de Beurs et al., 2009).

4. Results

4.1. Simulation experiment

Fig. 3 illustrates the probability for detecting a break within the monitoring period of a time series (i.e., the newly acquired data) while varying the noise level (σ), magnitude of simulated disturbance in the monitoring period (m) and the amount of data available in the monitoring period (n). The seasonal amplitude (a) did not influence the probability for break detection and results shown in Fig. 3 are valid for the different simulated a's (Table 1). The length of the identified stable history period also did not influence the probability for break detection (results not shown).

Furthermore, Fig. 3 shows that a break with $m = -0.2$ can be detected when noise level (σ) is smaller than 0.04 and $n = 3$ (i.e., 3 images available). When the magnitude of the break is larger (e.g., $m = -0.3$), less data points ($n < 3$) are required in the monitoring period for a similar amount of noise (e.g., $\sigma < 0.04$) in the history period.

4.2. Spatial application on MODIS 16-day NDVI time series

The main purpose of applying the real-time monitoring approach to MODIS 16-day NDVI time series is to illustrate a proof-of-concept of real-time monitoring for forest areas. Fig. 4 shows the spatial variation of the noise level (σ) in the study area. The lower noise levels correspond to the forested area within the boundaries of the Pinus radiata plantation. Higher noise levels occur outside the plantation area and correspond to the different grassland types as shown in Verbesselt et al. (2010b). Higher noise levels in grasslands are caused by a large seasonal NDVI amplitude and inter-annual phenological shifts (e.g., shifts in the start and end of the growing season) due rainfall and temperature dynamics.

Therefore, results in Fig. 5 and Fig. 6 are shown for the region within the boundaries of the forest plantation, which approximately corresponds to the lower noise levels in Fig. 4 and the noise

range used in the simulation experiment illustrated in Fig. 3 (Table 1). Fig. 5 illustrates the time of the detected changes in 2006. Many changes are detected in 2006 due to a drought that occurred around that time in combination with ongoing harvest operations. Fig. 6 shows the length of the stable history period and illustrates where and when changes occurred in the history period (e.g., a recent harvest operation). Results shown in Fig. 5 and 6 are illustrated for three locations within the study area in Fig. 7 and 8.

Fig. 7 and 8 are examples for specific locations in the study area illustrating the detected (1) disturbance and (2) the identified length of the stable history period. First, drought stress in 2006 is the main driver of the disturbance detected in the top graph of Fig. 7, whereas a harvest operations explains the change detected in the bottom graph of Fig. 7. Second, a different length of the automatically identified stable history is also visible in Fig. 7 (top versus bottom). A larger impact of a drought period in 2003 on the NDVI time series of a Pinus radiata plantation (top versus bottom graph) could explain the shorter stable history period. Fig. 8 illustrates an ongoing harvests operation during the history period which explains the shorter identified stable history period. Nonetheless a change is still detected in 2006 due the ongoing effects of the harvest operation.

5. Discussion and further work

Results of the simulation experiment and application on 16-day MODIS NDVI time series illustrate a proof-of-concept of the proposed time series based real-time monitoring approach. The change detection approach is a generic, data driven approach based on statistical principles applicable to different types of time series (e.g., in-situ or satellite sensors). The method can be applied to time series with a higher temporal resolution (e.g., hourly, daily or 8-day time series) to enable rapid response to detected disturbances. Application of the proposed method to the MODIS rapid response data (e.g., http://lance.nasa.gov/) or data available from geostationary satellites (e.g., http://www.cmsaf.eu/) can enable fast and automated detection of disturbances.

The results from the simulation experiment illustrated that noise level, available data in the monitoring period (i.e., available newly acquired data), and the magnitude of the to be detected disturbances are the drivers of the real-time monitoring approach. As such, the accuracy of the method, i.e., the magnitude of breaks that potentially can be detected, can be determined when analysing other time series data (e.g., with a higher temporal resolution) by deriving the noise level and the available data in the monitoring period. While the data and methods used here are appropriate for proof-of-concept development (White & Nemani, 2006), other applications (e.g., deforestation monitoring in tropical forests or oil spill detection) will mandate further calibration and validation, as discussed below;

(1) Further testing is required to assess the impact of phenological shifts (e.g., changes in the start/end-of-season) on the real-time monitoring approach. We demonstrated the monitoring

approach for NDVI time series derived from forested areas where seasonal NDVI amplitude and the impact of phenological shifts are relatively small when compared to grassland areas, for example. Continuous modelling of the seasonality using the proposed real-time concept and seasonal-trend model allows for relating remote sensing to a continual process of land surface phenology change instead of a single date extraction (Verbesselt et al., 2010b; White & Nemani, 2006). Grasslands, for example, demonstrate large inter-yearly seasonal variation caused by a early or late start/end of the growing season which is more difficult to be fitted within multi-year time series data. This is illustrated by the higher noise levels (i.e., standard deviation of the residuals of the season-trend model used in this study) in the grasslands surrounding the forest plantations. Further testing is required for areas with a dominant herbaceous vegetation layer (e.g., grasslands, agriculture, and savannah areas). The proposed concept, however, has the potential to detect phenological shifts in near-real time (Verbesselt et al., 2010b) but still need to tested. The real-time monitoring approach is validated and tested for forested areas. It can be implemented in an operational framework for deforestation monitoring such as, the Brazilian real-time deforestation monitoring system (DETER, Shimabukuro et al., 2006) or (CLASLITE, Asner et al., 2009) and as an alert system in other regions in the world (e.g., Indonesia, Vietnam) where a real-time monitoring system is not implemented yet but deforestation is occurring at a fast rate (Asner, 2011).

(2) Further work is needed to explore the use of the identified stable history period when implementing the method within an operation framework. The length of the stable history is identified for modelling normal, stable data variation within the history period to enable differentiation from abnormal changes in the monitoring period. The method for identifying the stable history is based on the structural change detection methods (Bai & Perron, 2003; Zeileis et al., 2010) and is implemented to assess stability of the history period. The method is a basic and fast approach with the objective of verifying whether or not a structural change is occurring while stepwise going back in history. It is not implemented to determine accurately the time of change but for testing whether of not a change is occurring in the history period (Zeileis et al., 2002). The BFAST approach is developed to detect and characterise accurately the time and magnitude of change within time series (Verbesselt et al., 2010a). The approach to asses the stability of the history period can be used e.g., for identifying when and where in recent history disturbances occurred or to restrict detection of changes in the monitoring period to time series which have a stable history period e.g., longer than 2 years. Alternatively, a stable history with a fixed length can also be used based on expert knowlegde but is not recommended for regional or global scale analysis due to a loss in flexibility. In summary, the length of the stable history as such can be used to optimise the real-time change detection approach depending on the objectives of operational real-time disturbance system.

(3) The real-time monitoring could be further improved by; (a) including other explanatory variables in the monitoring model (e.g., temperature, rainfall) which will contribute to model the data and determine what is normal versus what is abnormal (GAM modelling references), (b) determining the magnitude of change from the fitted parameters of seasonal-trend model similar as implemented in the BFAST approach (Verbesselt et al., 2010a) and (c) the monitoring model proposed here can also be used as a forecasting model. Similar to current real-time monitoring approach, forecasting requires a profound understanding of vegetation dynamics and vegetation interaction with the atmosphere, combined with proper data analysis techniques (Ji & Peters, 2004).

(4) To be included in the above paragraph: Climate tipping points etc. might be an nice reference (Lenton, 2011) and illustration of current ideas and potential use of

(Achim could you double check whether I formulate the 2nd paragraph correctly.) README

6. Conclusion

Currently, real-time satellite images and their derivatives are routinely produced and published on the World wide Web (e.g., http://rapidfire.sci.gsfc.nasa.gov/ or http://www.dmcii.com/index.html) but methods for real-time monitoring and change detection are lacking. Here, we proposed a time series based real-time monitoring approach that enables the detection of changes within newly acquired images or data. The real-time monitoring approach is a generic data driven approach that can be applied to any type of time series data. Results from the simulation experiment demonstrated that the noise level within the time series together with the amount of data available in the monitoring period are the main drivers of the capacity to detect disturbances within newly acquired images. Results from the simulation experiment are also applicable for time series with a higher temporal resolution as noise level will also be a driver in these time series (e.g., daily). The simulation experiment and application on MODIS 16-day data was focussed on testing the method for detecting changes in forested areas. Further work is require to test and optimise the method for ecosystems with a dominant herbaceous cover (e.g., grassland, agriculture) .

The method has the following characteristics that make it appropriate for real-time change detection implementation at different spatial scales. The method (1) is fast and require a minimum a mount of processing time (e.g., 0.04 seconds to analyse 6 year long 16-day time series on a normal desktop computer), (2) does not require the definition of thresholds, change type or even minimum amount of data as required by the BFAST approach, (3) can analyse time series with data gaps (e.g., masked clouds or sensor defects) and does not require gap filling techniques, and 4) it analyses the full temporal detail of a time series and it not restricted to definition and time dependent phenological metrics. Furthermore, the real-time monitoring method is implement in open-source software environment and is freely available on http://bfast.R-Forge.R-project.org/

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. The methods are available in the *bfast* package for R (R Development Core Team, 2011) from http://CRAN.R-project.org/package=bfast.

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.)
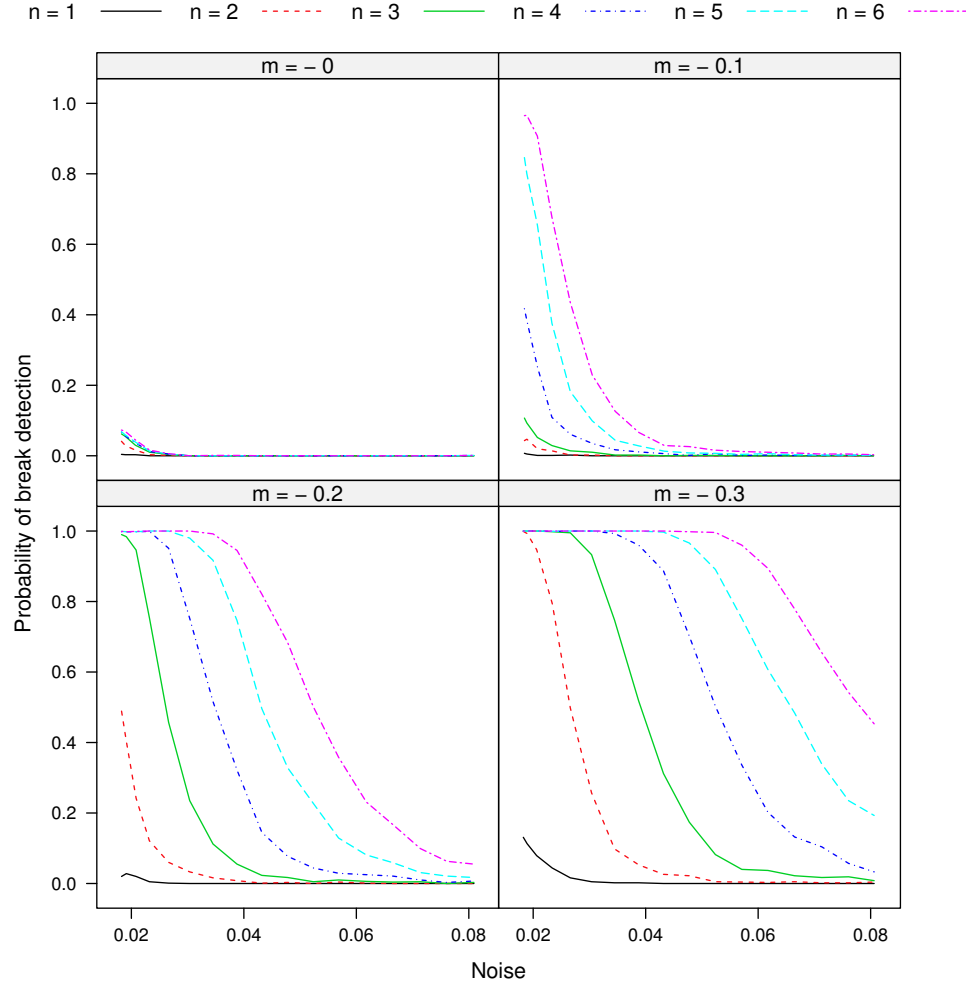

Figure 3: Results from the simulation experiment (1000 iterations) illustrating the probability for break detection in the monitoring period while varying the amount of noise (σ), magnitude of the simulated break (m), and amount of data available in the monitoring period (n). The units of the x and y-axis are noise (i.e., σ NDVI of the residuals of the fitted seasonal-trend model on the history period) and probability of detecting a break (i.e., proportion of detected breaks in 1000 iterations). See description of the simulation experiment for more details (Section 3.1).
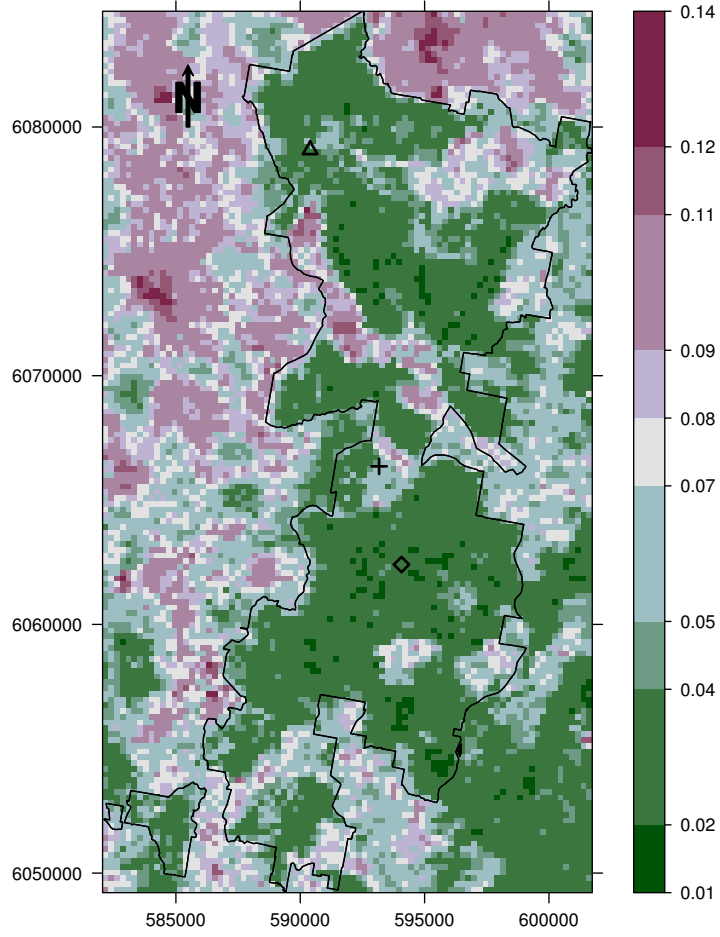
Figure 4: Spatial variation of the noise level (i.e., the standard deviation of the residuals of the stable history model) in the study area, a forested area in south eastern Australia. The black line indicates the boundary of the Pinus radiata plantation, which corresponds to the area with a lower noise level. The plantation is surrounded by grasslands. Examples of real-time change analysis for three locations ($\triangle$, $+$ and $\diamondsuit$) are shown in Fig. 7 and 8.
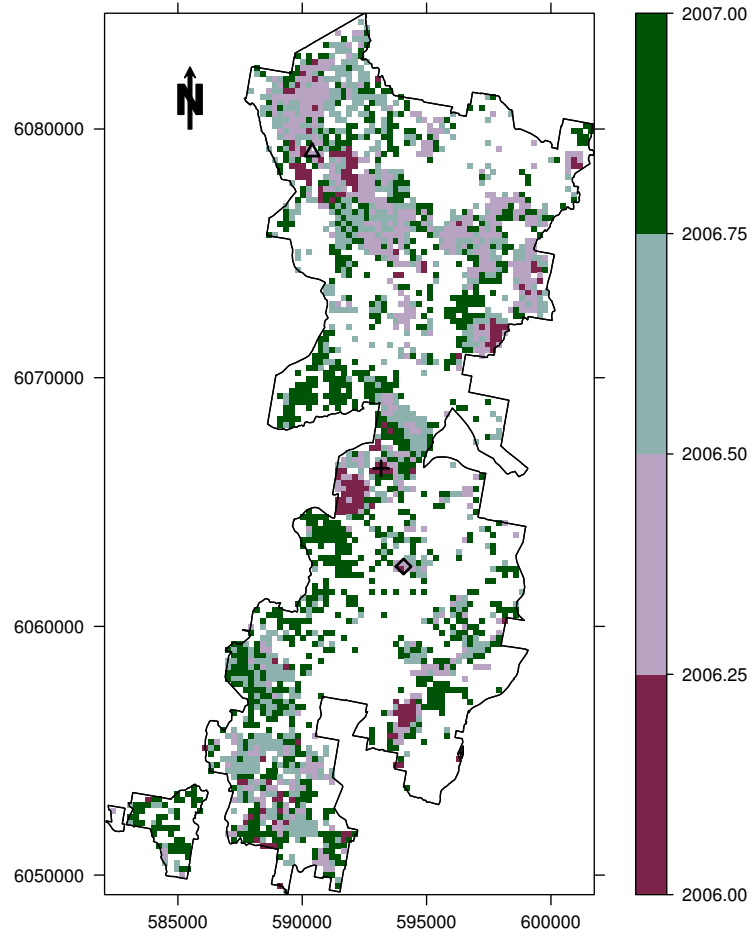
Figure 5: Time of detected changes within the study area in the monitoring period (i.e., 2006), where white indicates that no change is detected for a forested area in south eastern Australia. The black line indicates the boundary of the Pinus radiata plantation which is surrounded by grasslands. Examples of real-time change analysis for three locations ($\triangle$, $+$ and $\diamondsuit$) are shown in Fig. 7 and 8.
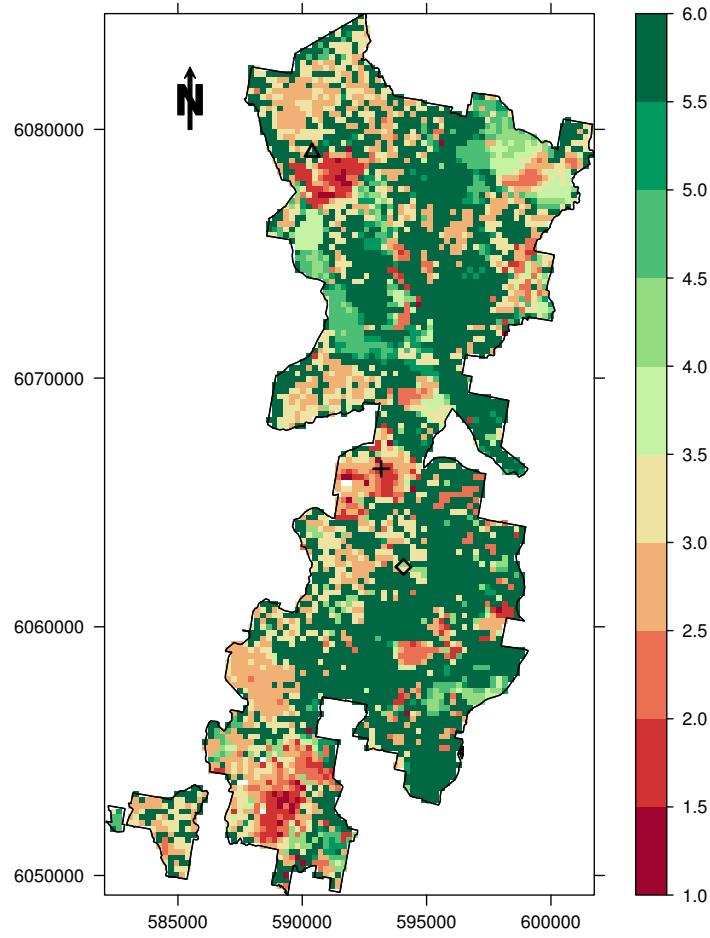
Figure 6: Spatial variation of the length the stable history period (expressed in years, i.e., 23 16-day images) of a forested area in south eastern Australia. The black line indicates the boundary of the Pinus radiata plantation, which is surrounded by grasslands. The length of the history period indicates when in the history period a potential disturbance occurred (e.g., shorter length indicates a more recent disturbance). Examples of real-time change analysis for three locations ($\triangle$, $+$ and $\diamond$) are shown in Fig. 7 and 8.
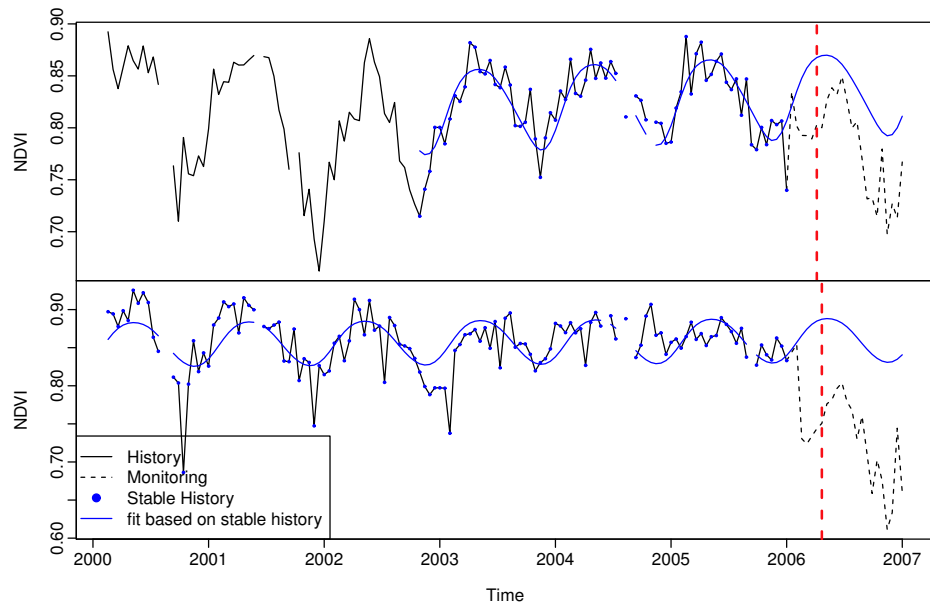
Figure 7: Results of real-time monitoring approach applied to 16-day MODIS NDVI time series for two locations, i.e., ◇ (top) and △ (bottom) on Fig. 4, 5 and 6), situated within the Green Hills study area. In both time series a break (vertical red dashed line in 2006) is detected in the monitoring period (i.e., 2006) while using 2000 until end of 2005 as a history period. A stable history period (blue dots) is automatically detected with the history period. The method is able to deal with time series with data gaps (e.g., after cloud removal) which is illustrated by data gaps within the data analysed and model fit based on the stable history period.
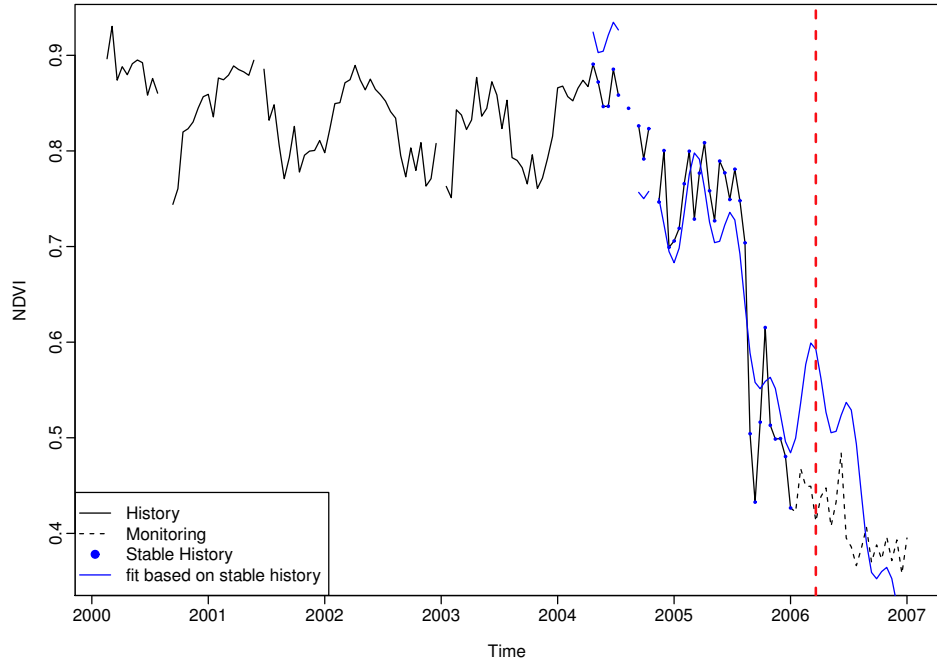
Figure 8: Results of real-time monitoring approach applied to 16-day MODIS NDVI time series for a location situated within the Green Hills study area (i.e., the + symbol on Fig. 4, 5 and 6). A break (vertical red dashed line in 2006) is detected in the monitoring period (i.e., 2006) while using 2000 until end of 2005 as a history period. A short stable history period (blue dots) is detected within the history period due to an ongoing harvest operation from 2005 onwards. The method is able to deal with time series with data gaps (e.g., after cloud removal) which is illustrated by data gaps within the data analysed and model fit based on the stable history period.