Verbesselt, Jan; Zeileis, Achim; Herold, Martin

Working Paper

Near Real-Time Disturbance Detection in Terrestrial Ecosystems Using Satellite Image Time Series: Drought Detection in Somalia

Working Papers in Economics and Statistics, No. 2011-18

Provided in Cooperation with:
Institute of Public Finance, University of Innsbruck

University of Innsbruck

Near Real-Time Disturbance Detection in Terrestrial Ecosystems Using Satellite Image Time Series: Drought Detection in Somalia

Jan Verbesselt, Achim Zeileis, Martin Herold

Working Papers in Economics and Statistics

2011-18

Research Platform eeecon
Empirical and Experimental Economics

University of Innsbruck
http://eeecon.uibk.ac.at/

University of Innsbruck
Working Papers in Economics and Statistics

The series is jointly edited and published by

Department of Economics

Department of Public Finance

Department of Statistics

Contact Address:
University of Innsbruck
Department of Public Finance
Universitaetsstrasse 15
A-6020 Innsbruck
Austria
Tel: + 43 512 507 7171
Fax: + 43 512 507 2970
e-mail: eeecon@uibk.ac.at

The most recent version of all working papers can be downloaded at
http://eeecon.uibk.ac.at/wopec/

For a list of recent papers see the backpages of this paper.

Near Real-Time Disturbance Detection in Terrestrial Ecosystems Using Satellite Image Time Series: Drought Detection in Somalia

Jan Verbesselt
Wageningen University

Achim Zeileis
Universität Innsbruck

Martin Herold
Wageningen University

Abstract

Near real-time monitoring of ecosystem disturbances is critical for addressing impacts on carbon dynamics, biodiversity, and socio-ecological processes. Satellite remote sensing enables cost-effective and accurate monitoring at frequent time steps over large areas. Yet, generic methods to detect disturbances within newly captured satellite images are lacking. We propose a generic time series based disturbance detection approach by modelling *stable* historical behaviour to enable detection of *abnormal* changes within newly acquired data. Time series of vegetation greenness provide a measure for terrestrial vegetation productivity over the last decades covering the whole world and contain essential information related land cover dynamics and disturbances. Here, we assess and demonstrate the method by (1) simulating time series of vegetation greenness data from satellite data with different amount of noise, seasonality and disturbances representing a wide range of terrestrial ecosystems, (2) applying it to real satellite greenness image time series between February 2000 and July 2011 covering Somalia to detect drought related vegetation disturbances. First, simulation results illustrate that disturbances are successfully detected in near real-time while being robust for seasonality and noise. Second, major drought related disturbance corresponding with most drought stressed regions in Somalia are detected from mid 2010 onwards and confirm proof-of-concept of the method. The method can be integrated within current operational early warning systems and has the potential to detect a wide variety of disturbances (e.g. deforestation, flood damage, etc.). It can analyse in-situ or satellite data time series of biophysical indicators from local to global scale since it is fast, does not depend on thresholds or definitions and does not require time series gap filling.

Keywords: early warning, real-time monitoring, global change, disturbance, time series, remote sensing, vegetation and climate dynamics.

1. Introduction

Real-time ecosystem disturbance detection is critical for tracking human-induced and natural disturbances promptly (Asner 2011). Such information is needed for signalling abnormal developments, quickly raising awareness and reducing negative impacts to natural resources, humans, and infrastructure. Ecosystem disturbances can also contribute to the current rise of carbon dioxide (CO_2) levels in the atmosphere due to the emission of CO_2 from terrestrial biomass loss (Potter *et al.* 2003; Schimel *et al.* 2001). Key to approaches looking at disturbances is that many recent change events occur worldwide at unknown locations. 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 satellite sensors (White *et al.* 2009), can indicate deforestation activities (Asner 2011), forest health issues (e.g. tree mortality) (Hargrove *et al.* 2009; Stone *et al.* 2008; Verbesselt *et al.* 2009), drought and climate anomalies (Funk and Budde 2009; Vrieling *et al.* 2011).

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 disturbances, including physical (e.g. droughts, fires, floods), biogenic (e.g. herbivorous insects and pathogens) and anthropogenic (e.g. deforestation, urbanisation, farming) disturbances (Jin and Sader 2005; Potter *et al.* 2003). A common way to derive indicators of ecosystem dynamics and disturbances is the use of spectral vegetation indices such as the Normalised Difference Vegetation Index (NDVI) related to the photosynthetic capacity of vegetation canopies (Myneni *et al.* 1995; Pettorelli *et al.* 2005; Potter *et al.* 2003). Although NDVI might be affected by soil background and a saturation effect at high biomass levels, it captures seasonal and inter-annual changes in vegetation status (Huete *et al.* 2002; Myneni *et al.* 1997).

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., long term drought, 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 and Henebry 2005a; Verbesselt *et al.* 2010a,b).

Detecting changes within time series is the first step towards understanding the acting processes and drivers (e.g. natural or anthropogenic). Estimating change from remotely sensed data series however 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 and Henebry 2005a; 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 anomalies, degradation, deforestation). Several change detection methods are available to detect disturbances within historical satellite image time series (de Beurs and Henebry 2005b; Verbesselt *et al.* 2010a,b; White and Nemani 2006) but generic methods to detect disturbances within newly captured satellite images are lacking. Three major challenges remain.

First, it is crucial to be able to detect disturbances within newly captured satellite images to enable a rapid response or early warning. In previous work, we proposed an approach, BFAST i.e. Break detection For Additive Season and Trend, for change detection within seasonal time series (de Jong *et al.* In Review; Verbesselt *et al.* 2010a,b). BFAST detects and characterises trend and seasonal changes within historical time series but the method is not developed to detect disturbances in recently acquired data. Methods to detect changes in near real-time, also referred to as monitoring techniques, have been suggested in the statistics and econometrics literature to assess the stability of linear regression models (Chu *et al.* 1996), e.g., for investigating exchange rate dynamics (Zeileis *et al.* 2010). However, these methods have not been optimised for real-time disturbance detection of terrestrial ecosystems using remotely sensed time series data.

Second, change detection techniques for global disturbance monitoring 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; Potter *et al.* 2003; Hayes and Cohen 2007). White and Nemani (2006) presented a method for real-time monitoring 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 the regions are changing. A historical analysis using archived satellite data is needed to model normal, expected behaviour against which abnormal behaviour, i.e. disturbance, in the near future can be described (Hargrove *et al.* 2009). There is a critical need to enable analysis of time series independent of specific thresholds or definitions to detect disturbances.

Third, change detection methods need to deal with missing data (e.g., clouds or sensor defects) in time series data. Existing change detection methods smooth or fill gaps (Jönsson and Eklundh 2002; Roerink *et al.* 2000; Julien and 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 and Nemani 2006). Furthermore, gap filling techniques model data based on assumptions of normal data variation which inhibits the detection of disturbances (Samanta *et al.* 2011). Hence, methods able to analyse and detect changes in non-gap-filled time series are urgently needed for global change monitoring.

We propose a multi-purpose approach for near real-time disturbance detection 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 stable (i.e. 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., near real-time)?

We assess this approach for different ecosystems by simulating NDVI time series with varying amounts of seasonal variation and noise, and by adding changes with different magnitudes representing a wide variety of terrestrial ecosystems. We demonstrate the proof-of-concept using the MODIS (Moderate Resolution Imaging Spectrometer) NDVI 16-day image composites from February 2000 until July 2011 for drought disturbance detection in Somalia. NDVI time series are also used by organisations like the European Research Centre (JRC), the United State's Warning System Network (FEWS-NET), and the United Nations Food and Agricultural Organisation (FAO) as an early warning of potential food production problems in African countries (Rojas *et al.* 2005).

2. Material and methods

2.1. Real-time disturbance detection

When investigating disturbances using satellite data, many approaches (e.g., de Jong *et al.* In Review; Potter *et al.* 2003; Verbesselt *et al.* 2010b; White *et al.* 2009) focus on the question if and where disturbances occur in the season and trend component of a given observed time series $t = 1, \ldots, n$. Here, we want to investigate a different question: *Do new observations* $t = n, n+1, \ldots$ *still conform with the expected behaviour of the historical sample* $t = 1, \ldots, n$? Thus, we want to detect disturbances at the end of a time series by comparison with representative, i.e. stable, historical observations. Here, a method is presented that is able to detect disturbances within newly acquired time series data by automatically identifying a stable history period (Section 2.4) to model normal expected behaviour (Section 2.2) against which disturbances can be detected (Section 2.3).

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). Thus, we simulated 16-day NDVI time series with different noise levels, seasonality, and disturbances in order to robustly test the disturbance detection approach in a controlled environment (Verbesselt *et al.* 2010a,b). It, however, 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). Hence, we tested the method by (1) a simulation experiment (Section 2.5) and (2) analysis of 16-day MODIS satellite NDVI time series for drought disturbance detection Somalia (Section 2.6).

2.2. Season-trend model

The method proposed here is based on a similar additive season and trend model as employed by Verbesselt *et al.* (2010b) to account seasonal and trend changes typically occurring within climate driven biophysical indicators derived from satellite data (e.g. NDVI) (de Beurs and Henebry 2005a). For the observations y_t at time t, a season-trend model is assumed with linear trend and harmonic season:

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

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 (with standard deviation σ). In the applications below, we employ three harmonic terms (i.e., $k = 3$) to robustly detect disturbances within MODIS NDVI time series, as components four and higher represent variations that occur on a three-month cycle or less (Geerken 2009; Julien and Sobrino 2010). The model (Eq. 1) can be written as standard a linear regression model (see e.g., Cryer and Chan 2008, Chapter 3.3):

$$
\begin{aligned}
y_t &= x_t^\top \beta \ + \ \varepsilon_t, \\
x_t &= \{1, t, \sin(2\pi 1t/f), \cos(2\pi 1t/f), \dots, \sin(2\pi kt/f), \cos(2\pi kt/f)\}^\top, \\
\beta &= \{\alpha_1, \alpha_2, \gamma_1 \cos(\delta_1), \gamma_1 \sin(\delta_1), \dots, \gamma_k \cos(\delta_k), \gamma_k \sin(\delta_k)\}^\top,
\end{aligned}
$$

containing the $p = 2 + 2k$ regression parameters β which can be estimated and tested using ordinary least squares (OLS) techniques. If there are gaps in the time series y_t, these observations are simply omitted prior to estimation of β which can then still consistently be identified (unless *all* observations at certain frequencies are missing). The season-trend model takes the underlying trend and seasonal variation within a time series into account so that season-trend patterns are removed in the resulting residuals. This corresponds to approaches where in multiple steps a time series is 'detrended' and 'deseasonalized' (Potter *et al.* 2003) whereas here the adjustment is done in a single step by OLS-fitting of the season-trend model.

2.3. Monitoring structural change

Based on the season-trend model introduced above, the question raised in the introduction can be rephrased: *Given that a stable season-trend model was estimated in an observed time period, does it remain stable for new observations?* A disturbance 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 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 $t = 1, \dots, n$, we want to check whether $\hat{\beta}$ still fits the data y_t for $t > n$ (i.e. for new data). To do so, some measure of discrepancy is needed (Chu *et al.* 1996; Leisch *et al.* 2000; Zeileis 2005). Here, we use moving sums (MOSUMs) of the residuals in the monitoring period $t = n + 1, \dots, N$:

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

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 MO_t should be close to zero and fluctuate only randomly. However, if a structural change occurs, MO_t will deviate systematically from zero. A structural break is declared if the absolute value $|MO_t|$ exceeds some boundary that is asymptotically only crossed with 5% probability under structural stability. If there are missing values in y_t in the monitoring period, these are again simply not included in the MOSUM MO_t, i.e. only reduce the number of observations available. The technical details for the boundary are based on a so called functional central limit theorem (see Leisch *et al.* 2000, for details). The boundary function employed here is taken from Zeileis *et al.* (2005, Eq. 7).

2.4. Selecting the stable history period

A crucial assumption for the monitoring approach proposed above is that the history period $t = 1, \dots, n$ itself is free of disturbances, that the parameters β are stable during this time,

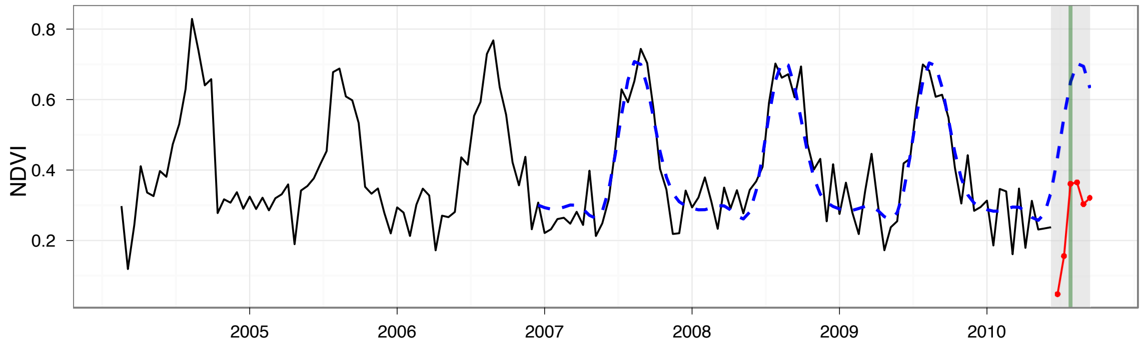


Figure 1: Simulated 16-day MODIS NDVI time series with $a = 0.4$, $\sigma = 0.05$, containing one simulated abrupt change with $m = -0.3$). The period from 2004 until mid 2010 (i.e., the time step just before the simulated break), is considered the *history period* and the period after the simulated break is the *monitoring period* (grey background). The monitoring period contains 6 observations ($d = 6$, red line). The result of the monitoring approach are shown. A stable history period is identified within the history period (i.e. 2007 until mid 2010) and used to model and predict the normal data variation (blue dashed line) to enable disturbance detection (Section 2.3). Here, a disturbance is detected (green vertical line).

and can be used to model normal expected behaviour. 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 $l, \dots, n$ observations with $l \geq 1$ so that a stable season-trend model can be fitted. Here, we implement a technique proposed by Pesaran and Timmermann (2002) that by moving backward in time for $t = n, n-1, n-2, \dots$ considers a cumulative prediction error until the season-trend model (Eq. 1) breaks down. The method is also known as reversed-ordered-cumulative sum (CUSUM) of residuals, or ROC. The CUSUM test (see Zeileis *et al.* 2002, for more details) is based on similar ideas as the monitoring approach introduced above and the ROC method simply applies it in reverse ordering.

Figure 1 provides an overview of the three steps that are being performed when applying the real-time disturbance detection approach. Two periods are defined within a time series; (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. The blue line illustrates the fit of the season-trend model on the identified stable part of the history period of an example NDVI time series (Section 2.2 and 2.4). This season-trend fit is used to model the normal expected behaviour in the *history period* and as such detect abnormal data variations, disturbances, within the *monitoring period* (Section 2.3). Here, a disturbance is detected with only a short delay.

2.5. Simulation experiment

The objective of the time series simulation experiment is to assess the *detection delay*, i.e. how much new data is required to detect a disturbance, while varying the amount of noise,

Parameters	Values
a	$0.1, 0.3, 0.5$
σ noise	$0.01, 0.02, \ldots, 0.15$
m	$0, -0.2, -0.4, \ldots, -0.8$
d	$1, 2, \ldots, 6$

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 (d, 16-day time steps units) to quantify the detection delay.

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) representing a wide range of ecosystem dynamics. Simulated NDVI time series are generated by summing individually simulated season, trend, and noise components (Figure 1).

First, the seasonal component is created using an asymmetric Gaussian function with an amplitude (a) for each season. Second, a disturbance was added to the trend component (e.g., fire or drought) 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 $\mathrm{N}(\mu = 0,\ \sigma = x)$. 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 (see Verbesselt *et al.* 2010b, for more details). Figure 1 shows a simulated 16-day MODIS NDVI time series with $a = 0.2$, $\sigma = 0.05$, containing one simulated abrupt change with $m = -0.3$.

In the simulation experiment the *history period* 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 (d) (Figure 1 and Table 1). 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, d, available in the monitoring period (Table 1). An example of the set-up of the simulation experiment is shown in Figure 1. 1000 iterations of all the combinations of σ, a, d and m were performed to quantify the probability of detecting a disturbance in the monitoring period in relation to the amount of data available (d).

2.6. Drought disturbance detection in Somalia

The use of the real-time monitoring approach is demonstrated using the 16-day MODIS NDVI composites with a 0.05° spatial resolution (MOD13C1 collection 5). This product provides NDVI corrected for the effect of atmospheric gases, thin cirrus clouds and aerosols as a proxy for global scale vegetation dynamics and disturbances (Huete *et al.* 2002). The MOD13C1 global satellite images were acquired from February 2000 to July 2011 and were analysed for disturbances from mid 2010 onwards covering Somalia in order to assess the impact of the 2010–2011 drought on the vegetation photosynthetic capacity. The MODIS quality assurance (QA) flags are used to select only cloud-free data of optimal quality. An NDVI time series is only analysed when either (1) it lacked less than 15% of observations masked out by the QA flags and (2) covering vegetated land; i.e. having a median of NDVI time series larger than 0.2 NDVI (de Beurs *et al.* 2009; de Jong *et al.* In Review; Vrieling *et al.* 2011). The noise level (σ)

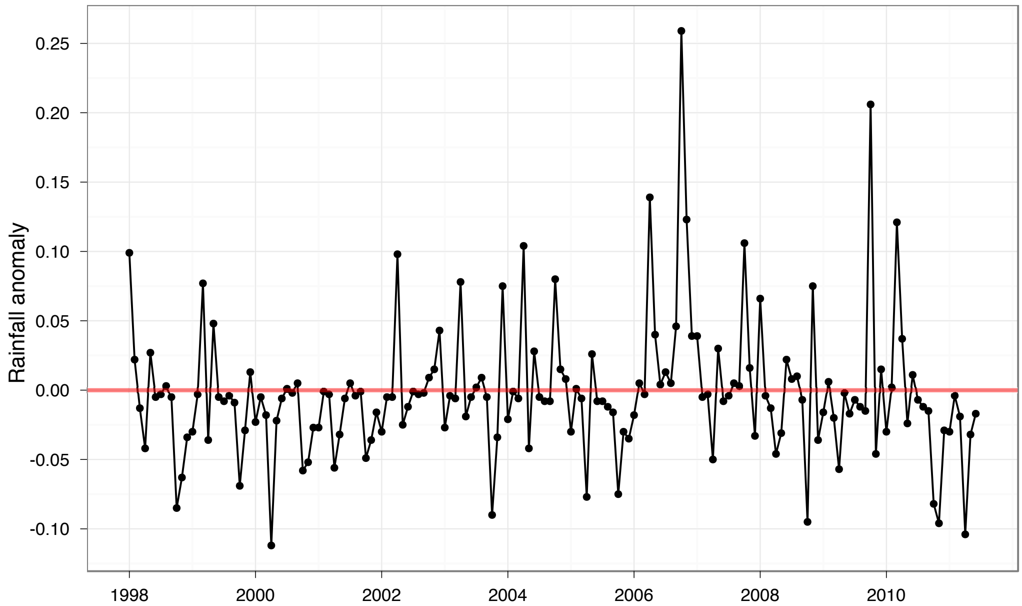
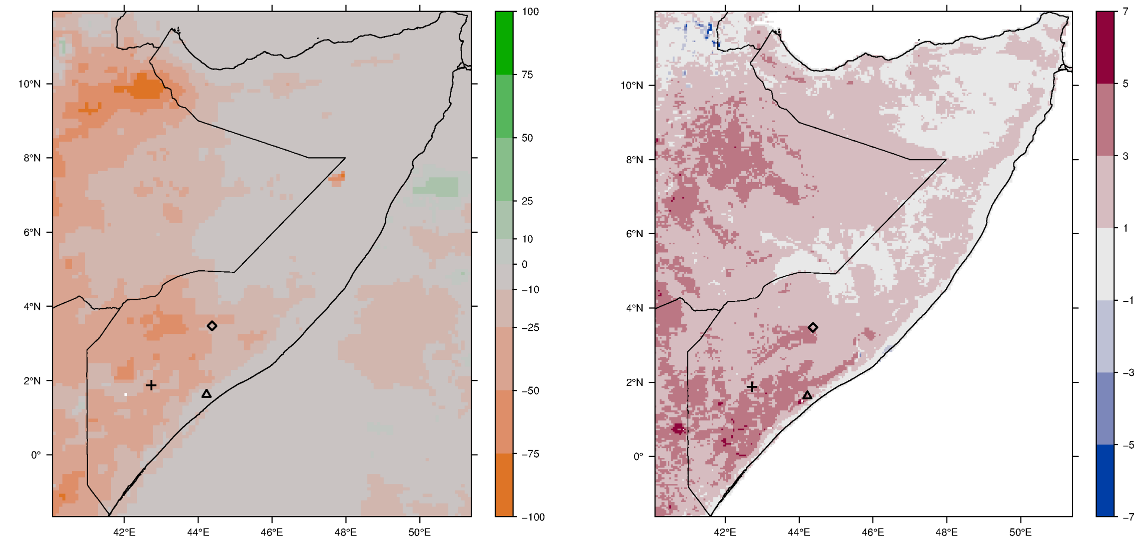


Figure 2: Monthly rainfall anomaly (mm/hr) for the period 1998–2011 measured by the tropical rainfall measuring satellite mission (TRMM) for an area in South Somalia (2° Lat. and 43° Long.). The time series was derived from the TRMM 3B43 climatology (version 6) data set using the online visualisation and analysis system (TOVAS). Anomalies are computed as the difference between the measured precipitation and the average climatology for the selected region (Acker and Leptoukh 2007).

of NDVI time series is estimated by deriving the standard deviation of the residuals from the fitted season-trend model (Eq. 1) on the stable history period. The magnitude and direction of the disturbance is estimated by deriving the difference between the median of the fitted season-trend model and the new observations during the monitoring period.

Somalia has a tropical but not torrid climate, and there is little seasonal change in temperature. In the low areas, the mean temperature ranges from about 24° C to 31° C. The plateau region is cooler, the southwest warmer. The periodic winds, the southwest monsoon (June–September), and the northeast monsoon (December–March) influence temperature and rainfall. Rain falls in two seasons of the year: heavy rains from March to May, and light rains from September to December. Average annual rainfall is estimated at less than 28 cm (`http://www.nationsencyclopedia.com/`). However, after a period of persistent poor rains during the past decade, the autumn 2010 rains were poor and the spring rains in 2011 failed completely (Funk 2011). The lack of rainfall combined with high food prices has weakened the population's resilience to food emergencies and are among most important factors explaining the severe and ongoing famine in Somalia today. The monthly rainfall anomaly time series shown in Figure 2 illustrates the lack of rainfall in the last decade and the severity of the rainfall anomaly occurring from mid 2010 onwards in Southern Somalia. The spatial extent of the drought severity is illustrated by the February–March 2011 rainfall (Xie and Arkin 1997) and land surface temperature anomaly for Somalia (Figure 3). Below normal rainfall and above normal temperatures occurred during February–March 2011 in south Somalia.



(a) (b)

Figure 3: Two-monthly rainfall estimates (RFE2) (a) and land surface temperature (LST) (b) anomaly are shown for Somalia illustrating the below normal rainfall and above normal land surface temperature during the February-March period in 2011. The RFE2 data is a merged satellite-gauge rainfall product produced by NOAA's Climate Prediction Centre at a 0.1°spatial resolution. The LST product is the land surface temperature measured by the MODIS satellite and is provided at a 0.05°spatial resolution. Individual observations are subtracted from the time series mean to produce anomaly data. MODIS NDVI time series (2000–2011) for three locations ($\triangle$, $+$ and $\diamondsuit$) are shown in Figure 6. The data was obtained using the Early Warning Explorer software tool available at `http://earlywarning.usgs.gov/`.

3. Results

3.1. Simulation experiment

Figure 4 illustrates the probability for detecting a break within the monitoring period of a time series while varying the noise level (σ), magnitude of simulated disturbance (m) and the amount of data available in the monitoring period (d). The seasonal amplitude (a) did not influence the probability for break detection and results shown in Figure 4 are valid for the different simulated a's (Table 1). Random and NDVI specific noise levels were introduced to simulate disturbances in the history period of the simulated time series and trigger identification of stable history periods with different lengths. The length of the identified stable history period also did not influence the probability for break detection (results not shown). We, however, recommend limiting the disturbance detection to time series with a stable history period longer than 2 years (i.e. 46 observations representing two seasons in this study) to enable a reliable estimation of the 8 season-trend model parameters. Furthermore, Figure 4 shows that a break with $m = -0.4$ can be detected when σ is smaller than 0.1 and $d < 3$. When the magnitude of the break is larger (e.g., $m = -0.6$), less observations ($d < 4$) are required for a similar amount of noise (e.g., $\sigma < 0.1$).

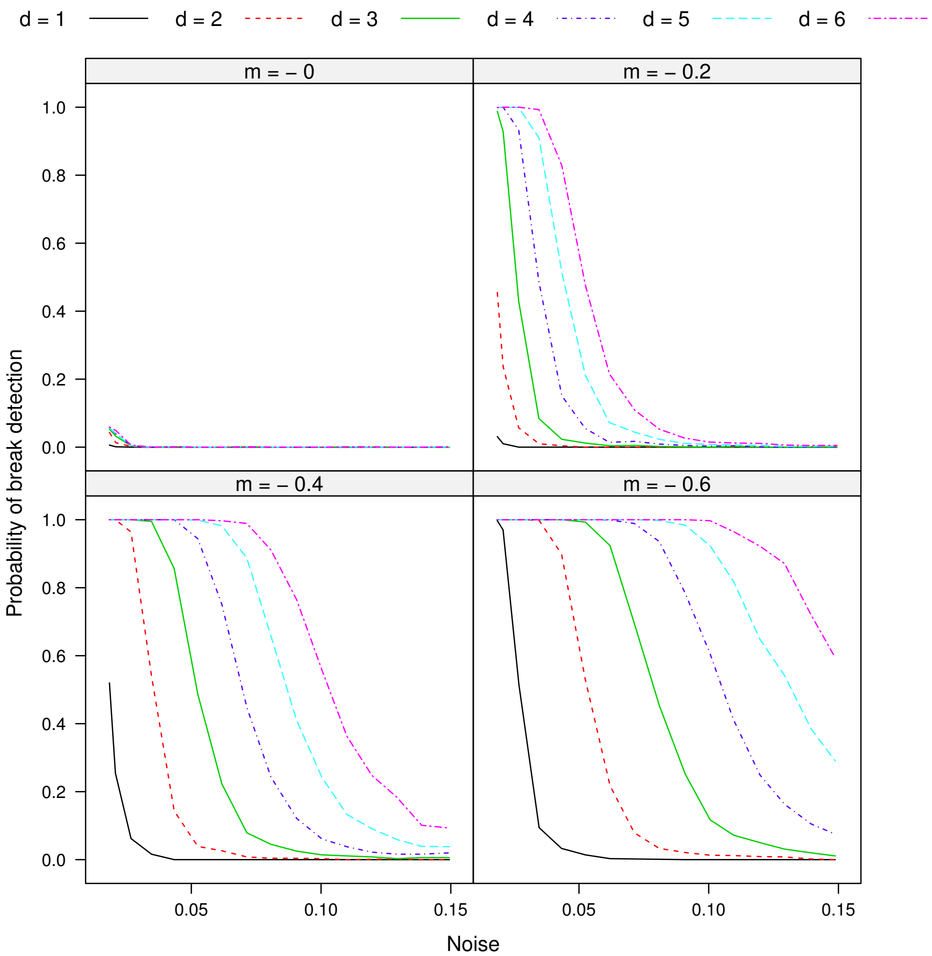


Figure 4: Results from the simulation experiment (1000 iterations) illustrating the probability for break detection in the monitoring period while varying the amount of noise (σ), magnitude of the simulated break (m), and amount of data available in the monitoring period (d). The units of the x and y-axis are noise (i.e., σ NDVI of the residuals of the fitted season-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 2.5).

3.2. Drought disturbance detection in Somalia

We demonstrate the proof-of-concept of a multi-purpose near real-time disturbance detection method by analysing MODIS 16-day NDVI image time series. Here, the disturbance detection is limited to areas (1) with a minimum amount of vegetation cover by restricting the analysis to time series with a median NDVI > 0.2 during the 2000–2011 period (Vrieling *et al.* 2011) and (2) with a stable history longer than two years (see Section 3.1);

(1) Figure 5a illustrates the median of an NDVI image time series (2000–2011) as a proxy for vegetation cover during the period of analysis. Areas with no or very low vegetation cover are occurring in the North East of Somalia whereas areas with higher vegetation

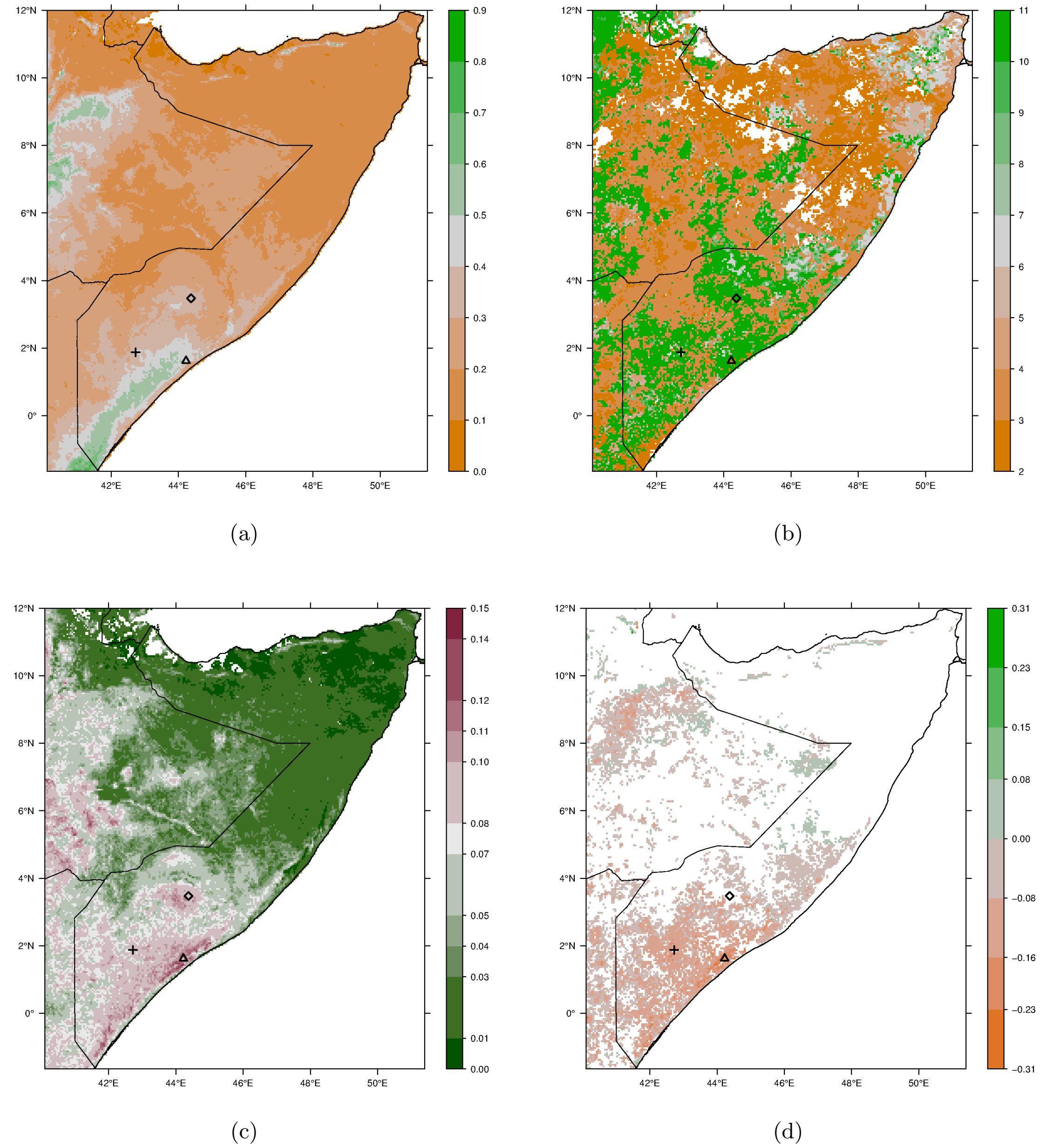


Figure 5: Results from the analysis of 16-day MODIS NDVI image time series from February 2000 until July 2011 covering Somalia; (a) median of all NDVI images as a proxy for vegetation cover during the 2000–2011 period, (b) length of the stable history period expressed in years where a shorter length is an indication of a more recent disturbance, (c) spatial variation of the noise level i.e. the standard deviation of the residuals of the stable history model, (d) the magnitude of the detected disturbances in the monitoring period (mid 2010 onwards) where white indicates that no disturbance is detected. The analysis of (d) was restricted to areas with minimum vegetation cover i.e. median NDVI 2000–2011>0.2 and length of the history period >2 years. Examples for three locations ($\triangle$, $+$ and $\diamond$) are shown in Figure 6.

cover are situated in the South of Somalia. Similar approaches have been used by Brown *et al.* (2010) and Vrieling *et al.* (2011) to study response of African land surface phenology. The NDVI time series with no or very low NDVI values do not show any seasonal climate related vegetation dynamics and are mainly influenced by irregular variations of the soil background. The areas with NDVI values above 0.2 correspond to the areas where below normal rainfall and above normal land surface temperature is occurring (Figure 3) which illustrates that a severe drought is impacting areas with a minimum amount of vegetation cover (NDVI > 0.2).

(2) Figure 5b illustrates the spatial variation of the length of the stable history period and is used to restrict the analysis to regions with a stable history longer than 2 years. The stable history is identified for modelling normal variation within the history period to enable differentiation from abnormal changes, i.e. disturbances, in the monitoring period (i.e. mid 2010 onwards). The ROC approach (Section 2.4) verifies whether or not a structural change is occurring while stepwise going back in history. The length of the stable history (Figure 5b) can be used as an approximation of the occurrence of the most recent large (enough) disturbance in the history period. (If a more precise estimate of the timing of this last major disturbance if of interest, more appropriate methods are available, e.g. Bai and Perron 2003, or Verbesselt *et al.* 2010a.) Analysed NDVI time series for specific locations are shown in Figure 6 where for time series in Figure 6a and c the whole history period and in Figure 6b a shorter stable history period is identified as stable. The short history period in Figure 6b can be explained by a lack of rainfall at the beginning of 2008 (Funk and Budde 2009).

Figure 5c shows the spatial variation of the noise level (i.e. $\hat{\sigma}$ of the residuals of the season-trend model) where low $\hat{\sigma}$ correspond to the low vegetated areas and the high $\hat{\sigma}$ correspond to the semi-arid ecosystems (e.g. woodland and savannah) (see Figure 5a). High $\hat{\sigma}$ in the semi-arid ecosystems can be explained by large inter-annual phenological shifts (e.g. shifts in the start and end of the growing season) and double growing seasons when compared to areas with low vegetation cover or forested areas (Verbesselt *et al.* 2010b; Brown *et al.* 2010). Forest ecosystems when compared to semi-arid ecosystems (herbaceous land cover types) are more resistant to seasonal climate variations in rainfall and temperature due to the deeper rooting system (Verbesselt *et al.* 2006). Furthermore, Vrieling *et al.* (2011) illustrated that vulnerability to food insecurity tends to increase when cumulated NDVI – used as a proxy for net primary productivity – shows high temporal variability.

Figure 5c also illustrates that the noise range, 0–0.15, corresponds to the noise range of the simulation experiment (Figure 4) which confirms that the range of terrestrial ecosystem NDVI dynamics occurring in the study area were appropriately simulated for testing the proposed method in a controlled environment. The noise range shown in Figure 5c can be used when interpreting Figure 5d, since the simulation experiment (Figure 4) illustrated that σ is one of the main drivers of the probability to detect disturbance. Figure 5d shows the magnitude of the disturbance when detected in the monitoring period. Only disturbances with large negative magnitudes are detected and illustrate the effect of the 2010–2011 drought on vegetation photosynthetic capacity as measured by the NDVI in Somalia and surrounding countries (Funk 2011). Due to the high seasonal variability (i.e. high σ levels) only severe disturbances with large magnitude can be detected with the method, as illustrated in the simulation experiment (Figure 4) and in Figure 5d. Again, these findings confirm the severity of the ongoing drought

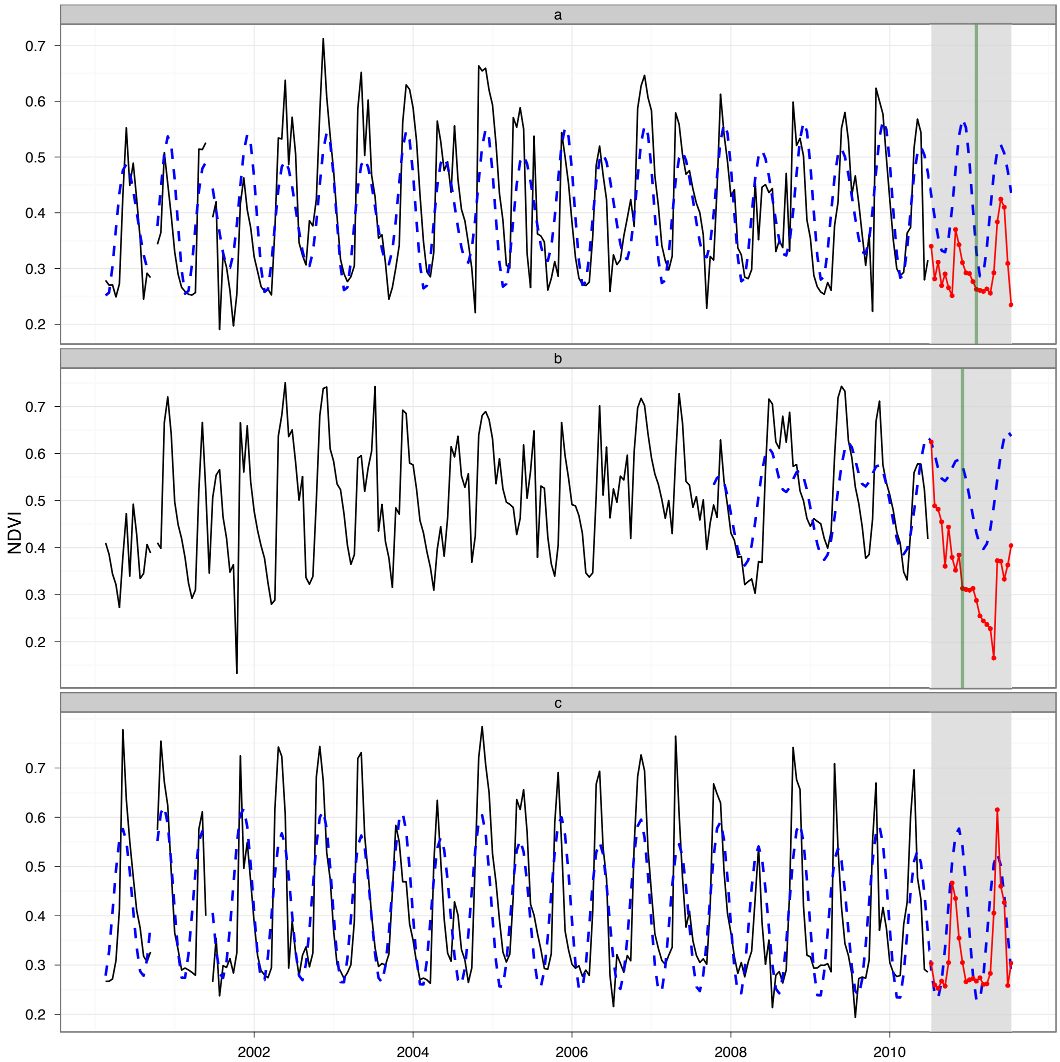


Figure 6: Results of real-time monitoring approach applied to 16-day MODIS NDVI time series for three locations a, b, and c, corresponding to symbols +, △ and ♢ shown in Figure 5. The period from 2000 until mid 2010, is considered the *history period* and the period after the simulated break is the *monitoring period* (grey background, red line). The stable history period within the history period (blue dashed line) is used to model and predict the normal data variation and enable disturbance detection in the monitoring period (Section 2.3). A disturbance is detected (green line) in Fig 5a and 5b.

and corresponds with the regions in South Somalia showing most intense drought anomaly (Figure 3).

Figure 6a and b illustrate to examples of NVDVI time series where a disturbance with a negative magnitude is detected in the monitoring period. The negative magnitude is clearly shown by the lack of seasonality and major decrease in NDVI from mid 2010 onwards. Statistical significant disturbances are detected early 2011 and confirm the early warning capacity of the proposed multi-purpose disturbance detection method. Hence, the method can contribute to existing early warning systems and be integrated in operational monitoring systems to automatically confirm abnormal events at the end of a time series (i.e. in near real-time).

4. Discussion

Real-time satellite images are routinely produced (e.g. http://www.fews.net/) but methods for disturbance detection within newly acquired images are lacking. Here, we propose a time series analysis approach that automatically identifies a stable *history period* within time series to model normal expected behaviour and enables detection of abnormal events (i.e. disturbances) within new observations (i.e. *monitoring period*).

The method is tested in a controlled environment by simulating time series containing disturbances and demonstrated by applying it to MODIS NDVI image time series covering Somalia. First, NDVI time series representing a wide range of terrestrial ecosystems are simulated and results illustrate that when more than two new observations are available in the *monitoring* period disturbance detection becomes possible. It is also shown that the noise level remaining after fitting the season-trend model is the main driver of the capacity to detect disturbances. Hence, data pre-processing in order to improve the quality and reliability of time series data remains essential to improve disturbance detection. Second, major disturbances are detected in southern Somalia in early 2011 illustrating the severity of the drought affecting the photosynthetic capacity of the vegetation. This illustrates the proof-of-concept of the method as a near real-time disturbance detection system that can be integrated within existing early warning systems for automated disturbance detection (e.g. drought or deforestation). Three items can be discussed in detail;

(1) Results confirm the importance of a simulation experiment when developing global change detection methods. Novel methods can be tested in a controlled environment while varying individual parameters. When detecting changes in real data at a global scale often accurate field data about disturbances and influencing factors (e.g. quality of the time series observations) are not available. However, it is challenging to create simulated time series that approximate remotely sensed time series (Zhang *et al.* 2009). For example, it is important to assess the effect of inter-yearly seasonal shifts in real satellite data (e.g. shifts in the growing season) as these can increase the σ and reduce the probability of disturbance detection. The inter-yearly seasonal variation is especially high in grasslands, savannah regions with a high herbaceous cover fraction and unpredictable rainfall (de Jong *et al.* In Review). The effect of inter-yearly seasonal variations have been simulated in this experiment by introducing high σ levels (i.e. up to 0.15 σ, Table 1). On the other hand, drought related anomalies cause major disturbances (e.g. magnitudes < -0.2 NDVI) in herbaceous ecosystems (i.e. large variations in NDVI) which enables drought disturbance detection in highly variable ecosystems (Section 3.2).

(2) The accuracy of estimating the time of disturbance was not assessed in the simulation experiment. The proposed method is developed as a fast, generic and globally applicable alert system for disturbances within newly acquired data of available time series observations. In previous work, the BFAST method was proposed to determine the number, type, and timing of trend and seasonal changes within historical time series (Verbesselt *et al.* 2010a) whereas, here, we focussed on disturbance detection in newly acquired observations. A possible operational workflow for disturbance monitoring could be to (a) verify

whether or not a disturbance is occurring in new observations using the method proposed here and then (b) if a disturbance is detected the timing, magnitude and direction of change can be determined when more data is available. Similarly, the accuracy of the estimated *stable history length* was not assessed. The validated ROC approach (Pesaran and Timmermann 2002) was used here as an automated approach to identify a history period without disturbances and is not developed for time estimation of disturbances in the history period. Again, in a second phase the BFAST approach can be used for a more accurate time of disturbance estimation. Alternatively, when expert knowledge is available the stable history period can manually be set but is not recommended for regional or global scale analysis due to a loss in flexibility. This functionality is available in the real-time monitoring function available in the *bfast* package for R (R Development Core Team 2011).

(3) Food security is not simply a function of NDVI dynamics, but also factors such as poverty, market forces, conflict, lack of infrastructure, and HIV/AIDS play an important role (Funk 2011; Vrieling *et al.* 2011). Still, analysis of climate and NDVI variability provides important input for food security analysis. Current operational food security monitoring by organisations as FEWS-NET, JRC, and FAO concentrate on mapping of NDVI anomalies deviating from a long term mean. Anomalies compared to a mean do not take into account gradual and seasonal variability (i.e. seasonal and trend related changes captured by the season-trend model in Eq. 1). Vrieling *et al.* (2011) has shown that temporal variability needs to be taken into account for anomaly-based food security monitoring. The method proposed here addresses this issue and models normal season-trend variation of an automatically identified stable history period to enable drought disturbance detection in the monitoring period.

The multi-purpose approach is 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 a more rapid response to detected disturbances and has the following characteristics that make it appropriate for real-time global scale disturbance detection: It (1) is fast and requires a minimum amount of processing time (e.g., 0.02 seconds to analyse 10 year long 16-day time series on a normal desktop computer), (2) does not require the definition of thresholds, (3) can analyse time series with data gaps (e.g., masked clouds or sensor defects) and does not require gap filling techniques, and (4) analyses the full temporal detail of a time series. Furthermore, the real-time monitoring method is implement in open-source software environment and is freely available in the *bfast* package for R (R Development Core Team 2011).

While the data and methods used are appropriate for proof-of-concept development for global scale disturbance monitoring, specific applications (e.g., drought or deforestation monitoring) mandates integration within an operational early warning framework (e.g. `http://www.fews.net/` or `http://earlywarning.usgs.gov/`). For example, further work is required to verify whether the real-time disturbance detection approach can be implemented in an operational framework for deforestation monitoring to complement existing systems such as the Brazilian deforestation monitoring system (DETER, Shimabukuro *et al.* 2006 or CLASLITE, Asner *et al.* 2009) or as an independent alert system in other regions in the world (e.g., Indonesia, Vietnam) where real-time monitoring systems are not implemented yet (Asner 2011).

5. Acknowledgments

This work was funded by a Marie-Curie IRG fellowship within the European Community's Seventh Framework Program to Jan Verbesselt (grant agreement 268423). Thanks to Glenn Newnham and Rogier de Jong whose comments greatly improved this paper and thanks to Molly Brown and Chris Funk for scientific support and data via the Famine Early Warning Systems Network (http://www.fews.net/) and the Early Warning Explorer (http://earlywarning.usgs.gov/). We also acknowledge the MODIS mission scientists and associated NASA and USGS personnel for the production of the data used in this research effort. TRMM rainfall data used in this paper are produced with the Giovanni online data system, developed and maintained by the NASA Goddard Earth Sciences Data and Information Services Centre.

References

Acker J, Leptoukh G (2007). "Online analysis enhances use of NASA Earth Science Data." *EOS*, **88**(2), 14–17.

Asner GP (2011). "Painting the world REDD: Addressing scientific barriers to monitoring emissions from tropical forests." *Environmental Research Letters*, **6**(2), 021002.

Asner GP, Knapp DE, Balaji A, Paez-Acosta G (2009). "Automated mapping of tropical deforestation and forest degradation: CLASlite." *Journal of Applied Remote Sensing*, **3**(1).

Bai J, Perron P (2003). "Computation and analysis of multiple structural change models." *Journal of Applied Econometrics*, **18**(1), 1–22.

Brown ME, de Beurs K, Vrieling A (2010). "The response of African land surface phenology to large scale climate oscillations." *Remote Sensing of Environment*, **114**(10), 2286–2296.

Chu CSJ, Stinchcombe M, White H (1996). "Monitoring structural change." *Econometrica*, **64**(5), 1045–1065.

Cryer JD, Chan KS (2008). *Time Series Analysis – With Applications in R*. 2nd edition. Springer-Verlag, New York.

de Beurs K, Wright C, Henebry G (2009). "Dual scale trend analysis for evaluating climatic and anthropogenic effects on the vegetated land surface in Russia and Kazakhstan." *Environmental Research Letters*, **4**(4).

de Beurs KM, Henebry GM (2005a). "Land surface phenology and temperature variation in the International Geosphere-Biosphere Program high-latitude transects." *Global Change Biology*, **11**(5), 779–790.

de Beurs KM, Henebry GM (2005b). "A statistical framework for the analysis of long image time series." *International Journal of Remote Sensing*, **26**(8), 1551–1573.

de Jong R, Verbesselt J, Schaepman ME, de Bruin S (In Review). "Trend changes in greening and browning detected from time series of global satellite data (1981–2006)." *Global Change Biology*.

Funk C (2011). "We thought trouble was coming." *Nature*, **476**(7358), 7.

Funk C, Budde ME (2009). "Phenologically-tuned MODIS NDVI-based production anomaly estimates for Zimbabwe." *Remote Sensing of Environment*, **113**(1), 115–125.

Geerken RA (2009). "An algorithm to classify and monitor seasonal variations in vegetation phenologies and their inter-annual change." *ISPRS Journal of Photogrammetry and Remote Sensing*, **64**(4), 422–431.

Hargrove W, Spruce J, Gasser G, Hoffman F (2009). "Toward a national early warning system for forest disturbances using remotely sensed canopy phenalogy." *Photogrammetric Engineering & Remote Sensing*, **75**(10), 1150–1156.

Hayes DJ, Cohen WB (2007). "Spatial, spectral and temporal patterns of tropical forest cover change as observed with multiple scales of optical satellite data." *Remote Sensing of Environment*, **106**(1), 1–16.

Huete A, Didan K, Miura T, Rodriguez EP, Gao X, Ferreira LG (2002). "Overview of the radiometric and biophysical performance of the MODIS vegetation indices." *Remote Sensing of Environment*, **83**(1-2), 195–213.

Jin SM, Sader SA (2005). "MODIS time-series imagery for forest disturbance detection and quantification of patch size effects." *Remote Sensing of Environment*, **99**(4), 462–470.

Jönsson P, Eklundh L (2002). "Seasonality extraction by function fitting to time-series of satellite sensor data." *IEEE Transactions on Geoscience and Remote Sensing*, **40**(8), 1824–1832.

Julien Y, Sobrino JA (2010). "Comparison of cloud-reconstruction methods for time series of composite NDVI data." *Remote Sensing of Environment*, **114**(3), 618–625.

Kennedy RE, Cohen WB, Schroeder TA (2007). "Trajectory-based change detection for automated characterization of forest disturbance dynamics." *Remote Sensing of Environment*, **110**(3), 370–386.

Leisch F, Hornik K, Kuan CM (2000). "Monitoring structural changes with the generalized fluctuation test." *Econometric Theory*, **16**, 835–854.

Lu D, Mausel P, Brondizio E, Moran E (2004). "Change detection techniques." *International Journal of Remote Sensing*, **25**(12), 2365–2407.

Myneni R, Keeling C, Tucker C, Asrar G, Nemani R (1997). "Increased plant growth in the northern high latitudes from 1981 to 1991." *Nature*, **386**(6626), 698–702.

Myneni RB, Hall FG, Sellers PJ, Marshak AL (1995). "The interpretation of spectral vegetation indexes." *IEEE Transactions on Geoscience and Remote Sensing*, **33**(2), 481–486.

Pesaran MH, Timmermann A (2002). "Market timing and return prediction under model instability." *Journal of Empirical Finance*, **9**, 495–510.

Pettorelli N, Vik JO, Mysterud A, Gaillard JM, Tucker CJ, Stenseth NC (2005). "Using the satellite-derived NDVI to assess ecological responses to environmental change." *Trends in Ecology and Evolution*, **20**(9), 503–510.

Potter C, Tan PN, Steinbach M, Klooster S, Kumar V, Myneni R, Genovese V (2003). "Major disturbance events in terrestrial ecosystems detected using global satellite data sets." *Global Change Biology*, **9**(7), 1005–1021.

R Development Core Team (2011). *R: A Language and Environment for Statistical Computing*. R Foundation for Statistical Computing, Vienna, Austria. ISBN 3-900051-07-0, URL http://www.R-project.org/.

Roerink G, Menenti M, Verhoef W (2000). "Reconstructing cloudfree NDVI composites using Fourier analysis of time series." *International Journal of Remote Sensing*, **21**(9), 1911–1917.

Rojas O, Rembold F, Royer A, Negre T (2005). "Real-time agrometeorological crop yield monitoring in Eastern Africa." *Agronomy for Sustainable Development*, **25**(1), 63–77.

Roy DP, Borak JS, Devadiga S, Wolfe RE, Zheng M, Descloitres J (2002). "The MODIS Land product quality assessment approach." *Remote Sensing of Environment*, **83**(1-2), 62–76.

Samanta A, Costa MH, Nunes EL, Vieira SA, Xu L, Myneni RB (2011). "Comment on "Drought-induced reduction in global terrestrial net primary production from 2000 through 2009"." *Science*, **333**(6046), 1093–1093.

Schimel D, House J, Hibbard K, Bousquet P, Ciais P, Peylin P, Braswell B, Apps M, Baker D, Bondeau A, Canadell J, Churkina G, Cramer W, Denning A, Field C, Friedlingstein P, Goodale C, Heimann M, Houghton R, Melillo J, Moore III B, Murdiyarso D, Noble I, Pacala S, Prentice I, Raupach M, Rayner P, Scholes RJ, Steffen W, Wirth C (2001). "Recent patterns and mechanisms of carbon exchange by terrestrial ecosystems." *Nature*, **414**(6860), 169–172.

Shimabukuro Y, Duarte V, Anderson L, Valeriano D, Arai E, Freitas R, Rudorff B, Moreira M (2006). "Near real time detection of deforestation in the Brazilian Amazon using MODIS imagery." *Revista Ambiente e Água–An Interdisciplinary Journal of Applied Science*, **1**(1).

Stone C, Turner R, Verbesselt J (2008). "Integrating plantation health surveillance and wood resource inventory systems using remote sensing." *Australian Forestry*, **71**(3), 245–253.

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

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

Verbesselt J, Jönsson P, Lhermitte S, van Aardt J, Coppin P (2006). "Evaluating satellite and climate data derived indices as fire risk indicators in savanna ecosystems." *IEEE Transactions on Geoscience and Remote Sensing*, **44**(6), 1622–1632.

Verbesselt J, Robinson A, Stone C, Culvenor D (2009). "Forecasting tree mortality using change metrics derived from MODIS satellite data." *Forest Ecology and Management*, **258**(7), 1166 – 1173.

Vrieling A, Beurs KM, Brown ME (2011). "Variability of African farming systems from phenological analysis of NDVI time series." *Climatic Change*.

White MA, de Beurs KM, Didan K, Inouye DW, Richardson AD, Jensen OP, O'Keefe J, Zhang G, Nemani RR, van Leeuwen WJD, Brown JF, de Wit A, Schaepman M, Lin X, Dettinger M, Bailey AS, Kimball J, Schwartz MD, Baldocchi DD, Lee JT, Lauenroth WK (2009). "Intercomparison, interpretation, and assessment of spring phenology in North America estimated from remote sensing for 1982–2006." *Global Change Biology*, **15**, 2335–2359.

White MA, Nemani RR (2006). "Real-time monitoring and short-term forecasting of land surface phenology." *Remote Sensing of Environment*, **104**(1), 43–49.

Wolfe RE, Roy DP, Vermote E (1998). "MODIS land data storage, gridding, and compositing methodology: Level 2 grid." *IEEE Transactions on Geoscience and Remote Sensing*, **36**(4), 1324–1338.

Xie P, Arkin P (1997). "Global precipitation: A 17-year monthly analysis based on gauge observations, satellite estimates, and numerical model outputs." *Bulletin of the American Meteorological Society*, **78**(11), 2539–2558.

Zeileis A (2005). "A unified approach to structural change tests based on ML scores, F statistics, and OLS residuals." *Econometric Reviews*, **24**(4), 445–466.

Zeileis A, Leisch F, Hornik K, Kleiber C (2002). "strucchange: An R package for testing for structural change in linear regression models." *Journal of Statistical Software*, **7**(2), 1–38.

Zeileis A, Leisch F, Kleiber C, Hornik K (2005). "Monitoring structural change in dynamic econometric models." *Journal of Applied Econometrics*, **20**(1), 99–121.

Zeileis A, Shah A, Patnaik I (2010). "Testing, monitoring, and dating structural changes in exchange rate regimes." *Computational Statistics and Data Analysis*, **54**(6), 1696–1706.

Zhang XY, Friedl MA, Schaaf CB (2009). "Sensitivity of vegetation phenology detection to the temporal resolution of satellite data." *International Journal of Remote Sensing*, **30**(8), 2061–2074.

Affiliation:

Jan Verbesselt, Martin Herold
Remote sensing team
Wageningen University
Droevendaalsesteeg 3
Wageningen 6708 PB, The Netherlands
E-mail: Jan.Verbesselt@wur.nl, Jan.Verbesselt@wur.nl
URL: http://www.grs.wur.nl/

Achim Zeileis
Department of Statistics
Universität Innsbruck
Universitätsstr. 15
6020 Innsbruck, Austria
E-mail: Achim.Zeileis@R-project.org
URL: http://eeecon.uibk.ac.at/~zeileis/

University of Innsbruck - Working Papers in Economics and Statistics
Recent Papers can be accessed on the following webpage:

http://eeecon.uibk.ac.at/wopec/

2011-18 **Jan Verbesselt, Achim Zeileis, Martin Herold:** Near Real-Time Disturbance Detection in Terrestrial Ecosystems Using Satellite Image Time Series: Drought Detection in Somalia

2011-17 **Stefan Borsky, Andrea Leiter, Michael Pfaffermayr:** Does going green pay off? The effect of an international environmental agreement on tropical timber trade

2011-16 **Pavlo Blavatskyy:** Stronger Utility

2011-15 **Anita Gantner, Wolfgang Höchtl, Rupert Sausgruber:** The pivotal mechanism revisited: Some evidence on group manipulation

2011-14 **David J. Cooper, Matthias Sutter:** Role selection and team performance

2011-13 **Wolfgang Höchtl, Rupert Sausgruber, Jean-Robert Tyran:** Inequality aversion and voting on redistribution

2011-12 **Thomas Windberger, Achim Zeileis:** Structural breaks in inflation dynamics within the European Monetary Union

2011-11 **Loukas Balafoutas, Adrian Beck, Rudolf Kerschbamer, Matthias Sutter:** What drives taxi drivers? A field experiment on fraud in a market for credence goods

2011-10 **Stefan Borsky, Paul A. Raschky:** A spatial econometric analysis of compliance with an international environmental agreement on open access resources

2011-09 **Edgar C. Merkle, Achim Zeileis:** Generalized measurement invariance tests with application to factor analysis

2011-08 **Michael Kirchler, Jürgen Huber, Thomas Stöckl:** Thar she bursts - reducing confusion reduces bubbles *modified version forthcoming in* *American Economic Review*

2011-07 **Ernst Fehr, Daniela Rützler, Matthias Sutter:** The development of egalitarianism, altruism, spite and parochialism in childhood and adolescence

2011-06 **Octavio Fernández-Amador, Martin Gächter, Martin Larch, Georg Peter:** Monetary policy and its impact on stock market liquidity: Evidence from the euro zone

- 2011-05 **Martin Gächter, Peter Schwazer, Engelbert Theurl:** Entry and exit of physicians in a two-tiered public/private health care system
- 2011-04 **Loukas Balafoutas, Rudolf Kerschbamer, Matthias Sutter:** Distributional preferences and competitive behavior *forthcoming in Journal of Economic Behavior and Organization*
- 2011-03 **Francesco Feri, Alessandro Innocenti, Paolo Pin:** Psychological pressure in competitive environments: Evidence from a randomized natural experiment: Comment
- 2011-02 **Christian Kleiber, Achim Zeileis:** Reproducible Econometric Simulations
- 2011-01 **Carolin Strobl, Julia Kopf, Achim Zeileis:** A new method for detecting differential item functioning in the Rasch model
- 2010-29 **Matthias Sutter, Martin G. Kocher, Daniela Rützler and Stefan T. Trautmann:** Impatience and uncertainty: Experimental decisions predict adolescents' field behavior
- 2010-28 **Peter Martinsson, Katarina Nordblom, Daniela Rützler and Matthias Sutter:** Social preferences during childhood and the role of gender and age - An experiment in Austria and Sweden *Revised version forthcoming in Economics Letters*
- 2010-27 **Francesco Feri and Anita Gantner:** Baragining or searching for a better price? - An experimental study. *Revised version accepted for publication in Games and Economic Behavior*
- 2010-26 **Loukas Balafoutas, Martin G. Kocher, Louis Putterman and Matthias Sutter:** Equality, equity and incentives: An experiment
- 2010-25 **Jesús Crespo-Cuaresma and Octavio Fernández Amador:** Business cycle convergence in EMU: A second look at the second moment
- 2010-24 **Lorenz Goette, David Huffman, Stephan Meier and Matthias Sutter:** Group membership, competition and altruistic versus antisocial punishment: Evidence from randomly assigned army groups
- 2010-23 **Martin Gächter and Engelbert Theurl:** Health status convergence at the local level: Empirical evidence from Austria *(revised Version March 2011)*
- 2010-22 **Jesús Crespo-Cuaresma and Octavio Fernández Amador:** Buiness cycle convergence in the EMU: A first look at the second moment
- 2010-21 **Octavio Fernández-Amador, Josef Baumgartner and Jesús Crespo-Cuaresma:** Milking the prices: The role of asymmetries in the price transmission mechanism for milk products in Austria

2010-20 **Fredrik Carlsson, Haoran He, Peter Martinsson, Ping Qin and Matthias Sutter:** Household decision making in rural China: Using experiments to estimate the influences of spouses

2010-19 **Wolfgang Brunauer, Stefan Lang and Nikolaus Umlauf:** Modeling house prices using multilevel structured additive regression

2010-18 **Martin Gächter and Engelbert Theurl:** Socioeconomic environment and mortality: A two-level decomposition by sex and cause of death

2010-17 **Boris Maciejovsky, Matthias Sutter, David V. Budescu and Patrick Bernau:** Teams make you smarter: Learning and knowledge transfer in auctions and markets by teams and individuals

2010-16 **Martin Gächter, Peter Schwazer and Engelbert Theurl:** Stronger sex but earlier death: A multi-level socioeconomic analysis of gender differences in mortality in Austria

2010-15 **Simon Czermak, Francesco Feri, Daniela Rützler and Matthias Sutter:** Strategic sophistication of adolescents - Evidence from experimental normal-form games

2010-14 **Matthias Sutter and Daniela Rützler:** Gender differences in competition emerge early in live

2010-13 **Matthias Sutter, Francesco Feri, Martin G. Kocher, Peter Martinsson, Katarina Nordblom and Daniela Rützler:** Social preferences in childhood and adolescence - A large-scale experiment

2010-12 **Loukas Balafoutas and Matthias Sutter:** Gender, competition and the efficiency of policy interventions

2010-11 **Alexander Strasak, Nikolaus Umlauf, Ruth Pfeifer and Stefan Lang:** Comparing penalized splines and fractional polynomials for flexible modeling of the effects of continuous predictor variables

2010-10 **Wolfgang A. Brunauer, Sebastian Keiler and Stefan Lang:** Trading strategies and trading profits in experimental asset markets with cumulative information

2010-09 **Thomas Stöckl and Michael Kirchler:** Trading strategies and trading profits in experimental asset markets with cumulative information

2010-08 **Martin G. Kocher, Marc V. Lenz and Matthias Sutter:** Psychological pressure in competitive environments: Evidence from a randomized natural experiment: Comment

2010-07 **Michael Hanke and Michael Kirchler:** Football Championships and Jersey sponsors' stock prices: An empirical investigation

2010-06 **Adrian Beck, Rudolf Kerschbamer, Jianying Qiu and Matthias Sutter:** Guilt from promise-breaking and trust in markets for expert services - Theory and experiment

2010-05 **Martin Gächter, David A. Savage and Benno Torgler:** Retaining the thin blue line: What shapes workers' intentions not to quit the current work environment

2010-04 **Martin Gächter, David A. Savage and Benno Torgler:** The relationship between stress, strain and social capital

2010-03 **Paul A. Raschky, Reimund Schwarze, Manijeh Schwindt and Ferdinand Zahn:** Uncertainty of governmental relief and the crowding out of insurance

2010-02 **Matthias Sutter, Simon Czermak and Francesco Feri:** Strategic sophistication of individuals and teams in experimental normal-form games

2010-01 **Stefan Lang and Nikolaus Umlauf:** Applications of multilevel structured additive regression models to insurance data

University of Innsbruck

Working Papers in Economics and Statistics

2011-18

Jan Verbesselt, Achim Zeileis, Martin Herold

Near Real-Time Disturbance Detection in Terrestrial Ecosystems Using Satellite Image Time Series: Drought Detection in Somalia

Abstract
Near real-time monitoring of ecosystem disturbances is critical for addressing impacts on carbon dynamics, biodiversity, and socio-ecological processes. Satellite remote sensing enables cost-effective and accurate monitoring at frequent time steps over large areas. Yet, generic methods to detect disturbances within newly captured satellite images are lacking. We propose a generic time series based disturbance detection approach by modelling *stable* historical behaviour to enable detection of *abnormal* changes within newly acquired data. Time series of vegetation greenness provide a measure for terrestrial vegetation productivity over the last decades covering the whole world and contain essential information related land cover dynamics and disturbances. Here, we assess and demonstrate the method by (1) simulating time series of vegetation greenness data from satellite data with different amount of noise, seasonality and disturbances representing a wide range of terrestrial ecosystems, (2) applying it to real satellite greenness image time series between February 2000 and July 2011 covering Somalia to detect drought related vegetation disturbances. First, simulation results illustrate that disturbances are successfully detected in near real-time while being robust for seasonality and noise. Second, major drought related disturbance corresponding with most drought stressed regions in Somalia are detected from mid 2010 onwards and confirm proof-of-concept of the method. The method can be integrated within current operational early warning systems and has the potential to detect a wide variety of disturbances (e.g. deforestation, flood damage, etc.). It can analyse in-situ or satellite data time series of biophysical indicators from local to global scale since it is fast, does not depend on thresholds or definitions and does not require time series gap filling.

ISSN 1993-4378 (Print)
ISSN 1993-6885 (Online)