Time series analysis and change detection techniques

Towards tropical forest resilience from remote sensing time series

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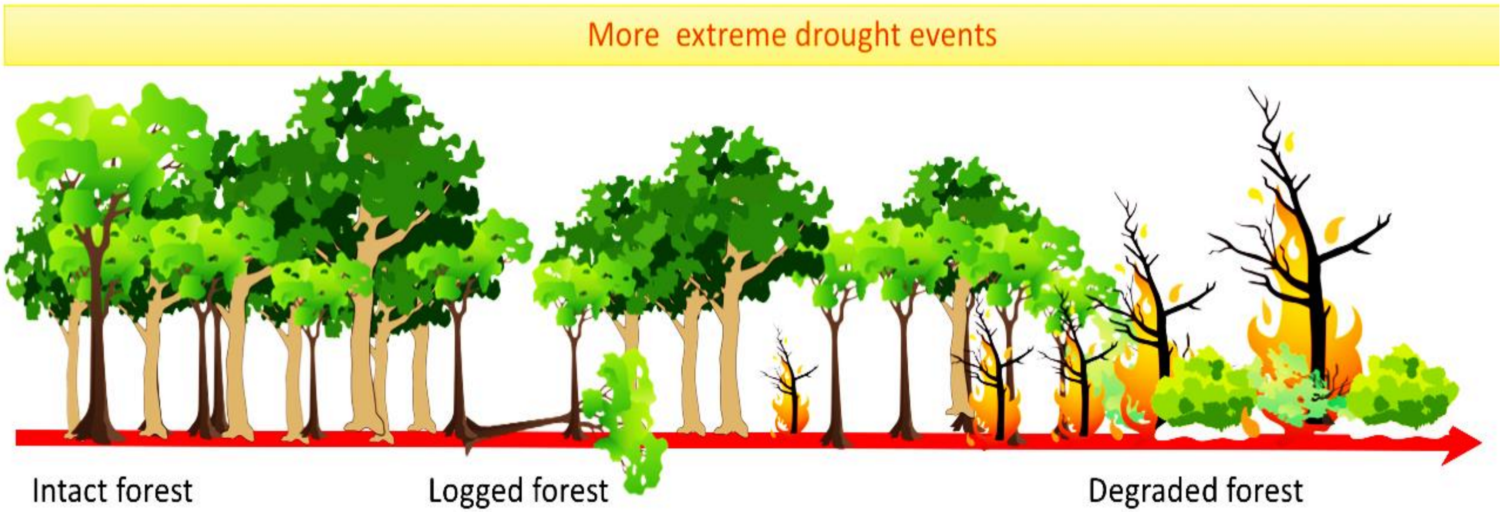
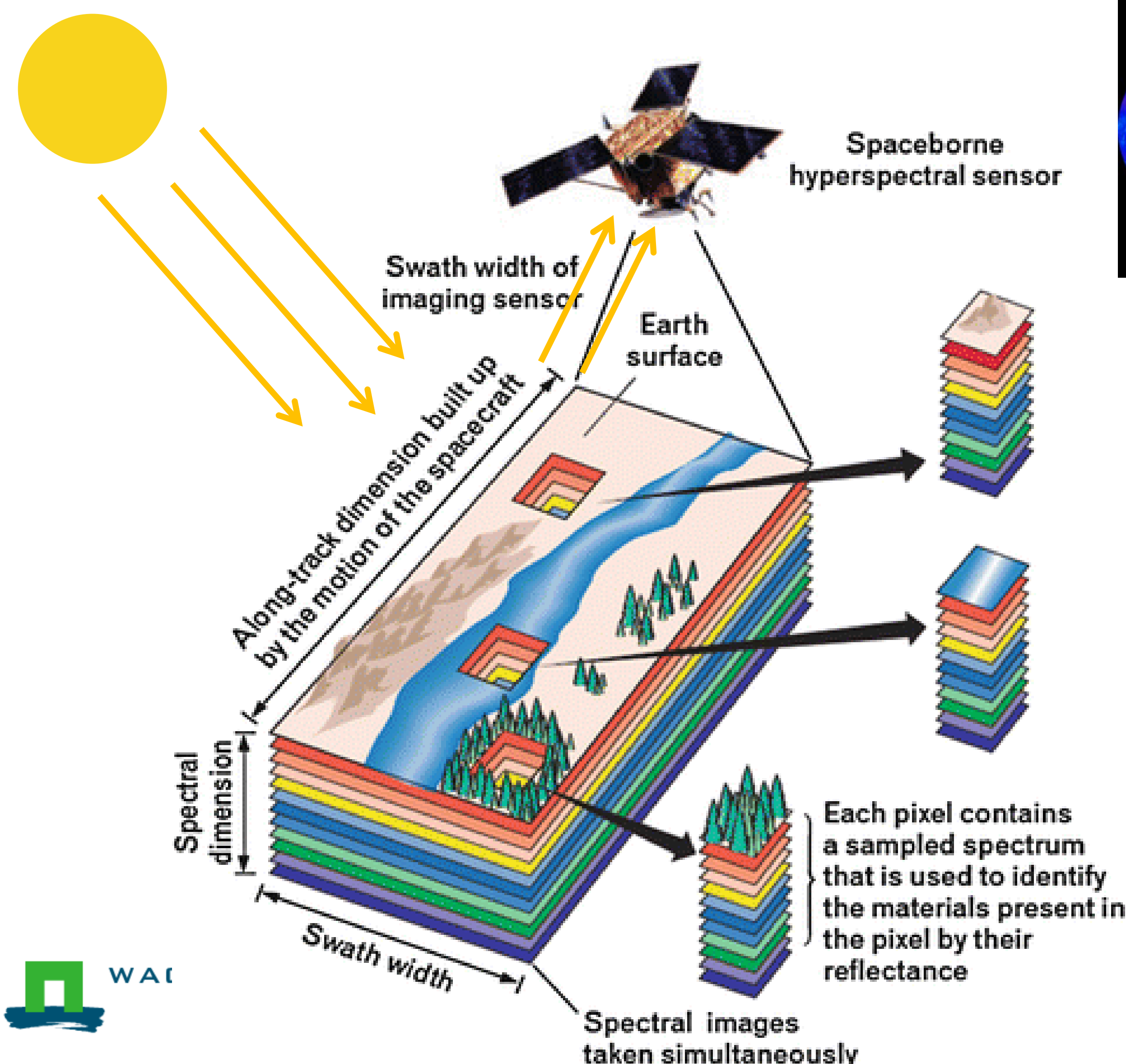
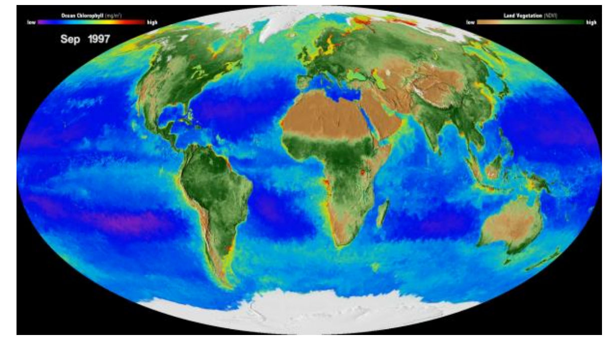
Framework

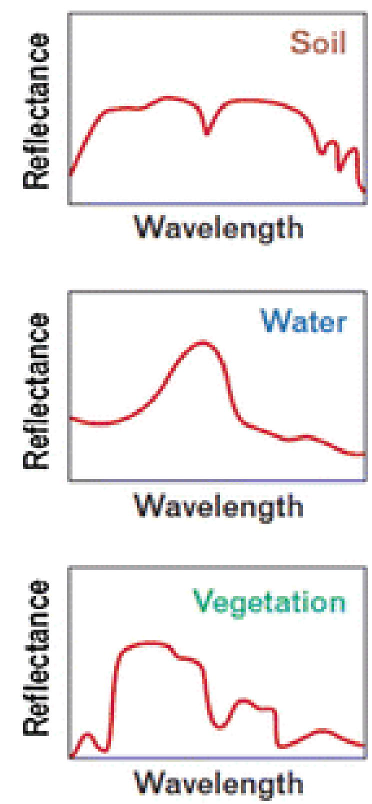


Urgent need to monitor the recovery capacity of tropical forests!

Remote sensing







Resilience of intact tropical forests

nature climate change
LETTERS
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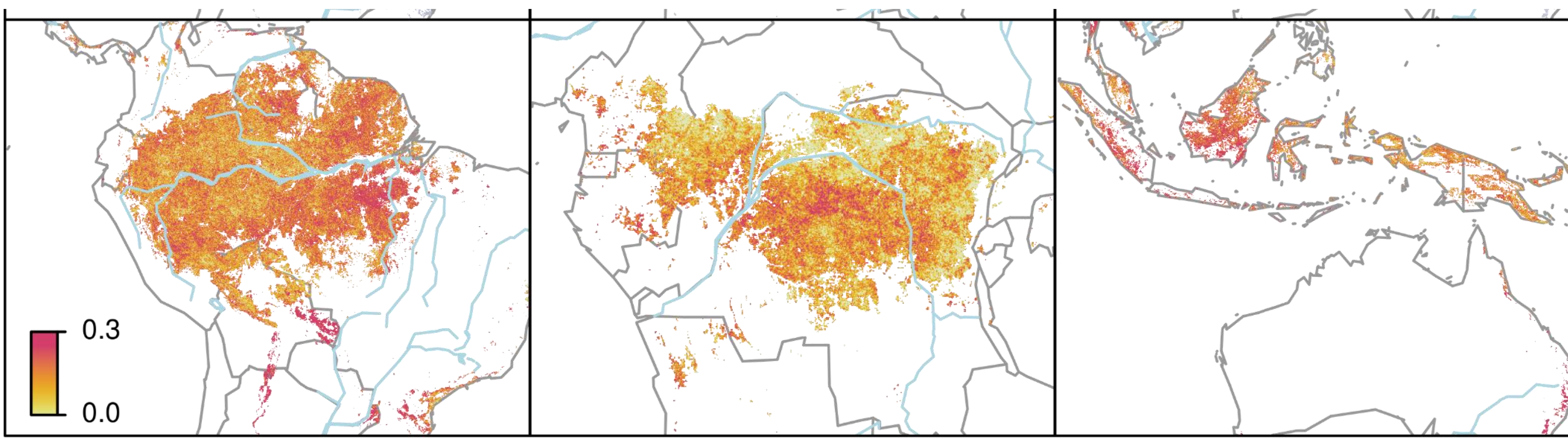
Remotely sensed resilience of tropical forests

Jan Verbesselt[1]*, Nikolaus Umlauf[2], Marina Hirota[3,4,5], Milena Holmgren[6], Egbert H. Van Nes[3], Martin Herold[1], Achim Zeileis[2] and Marten Scheffer[3]*

South America | Africa | Asia & Australia



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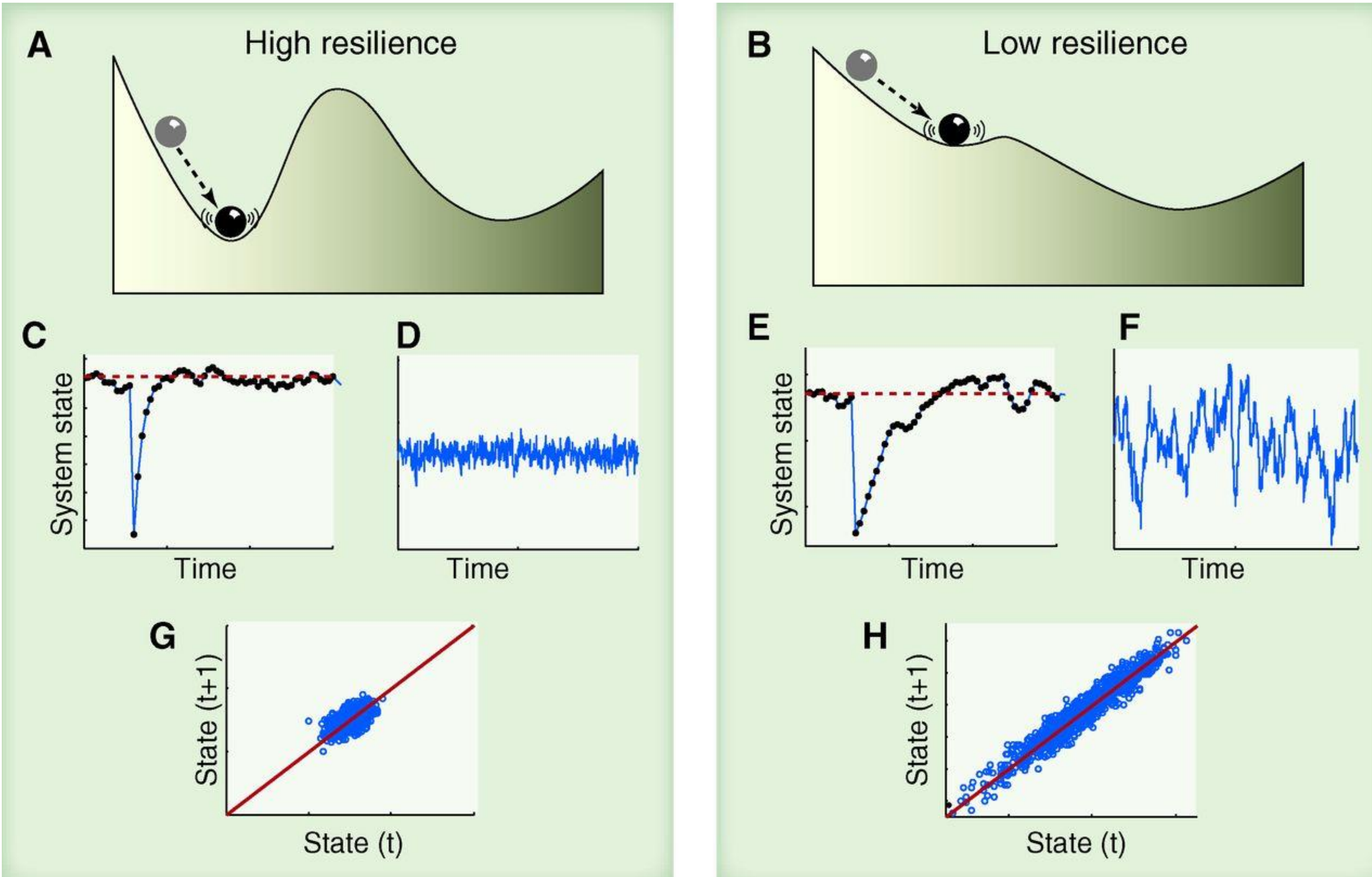
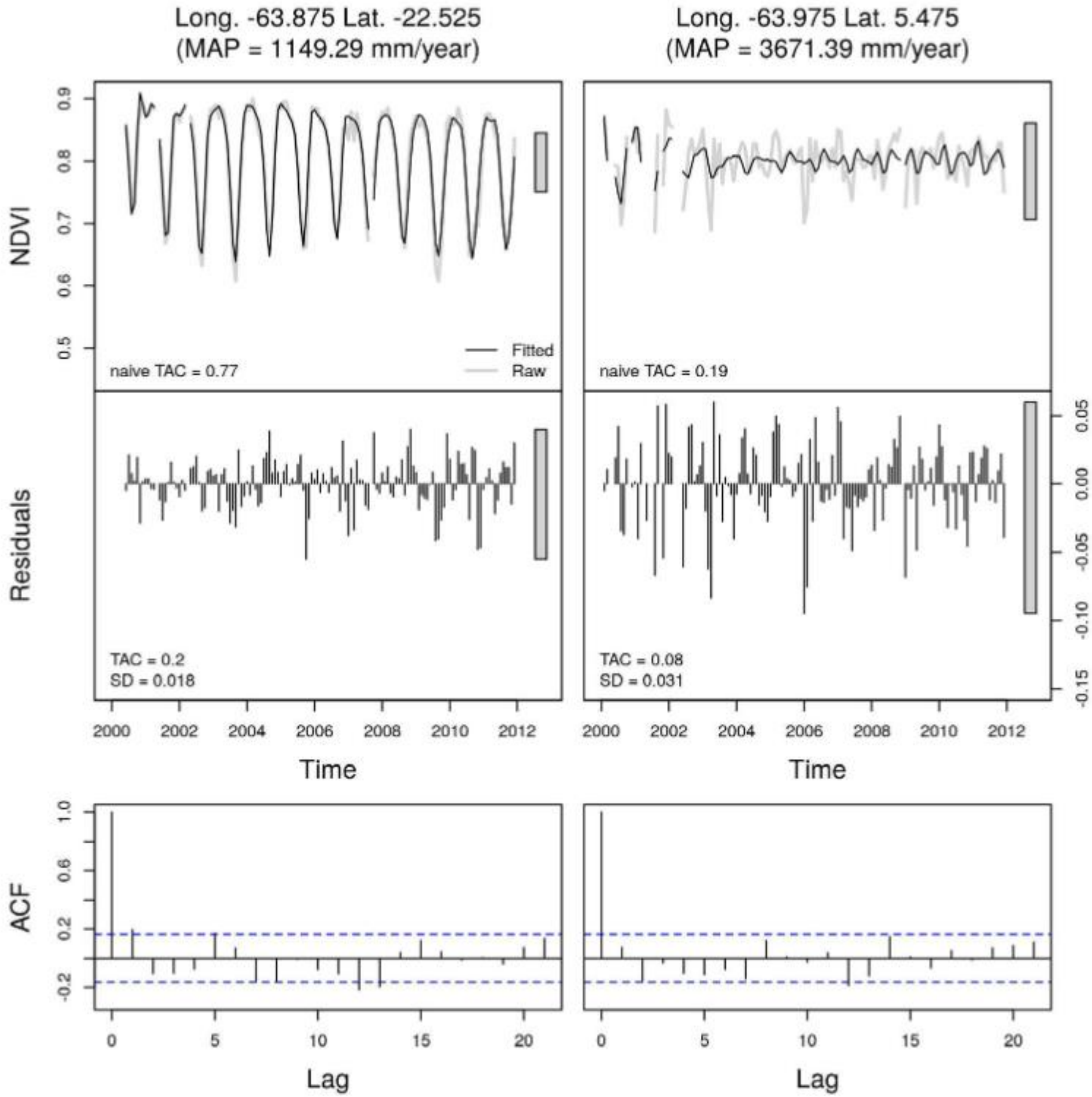
Verbesselt, J. *et al.* Remotely sensed resilience of tropical forests. *Nat. Clim. Chang.* (2016).

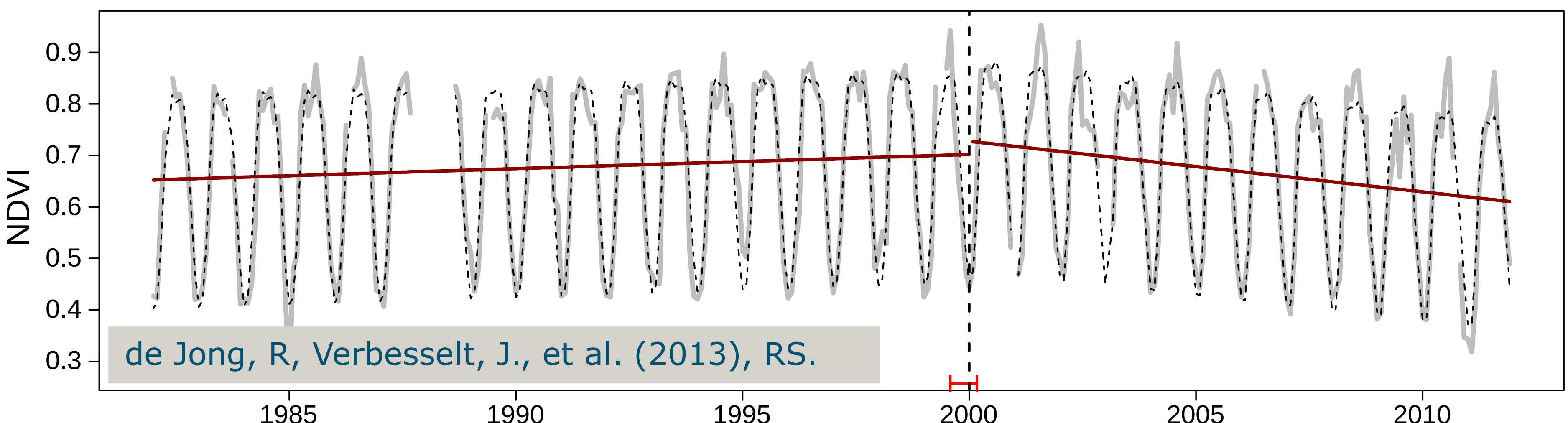

A
High resilience
B
Low resilience
C
System state
Time
D
Time
E
System state
Time
F
Time
G
State (t+1)
State (t)
H
State (t+1)
State (t)


Long. -63.875 Lat. -22.525
(MAP = 1149.29 mm/year)
Long. -63.975 Lat. 5.475
(MAP = 3671.39 mm/year)
NDVI
Fitted
Raw
naive TAC = 0.77
naive TAC = 0.19
Residuals
TAC = 0.2
SD = 0.018
TAC = 0.08
SD = 0.031
Time
ACF
Lag

Resilience of non-intact tropical forests?

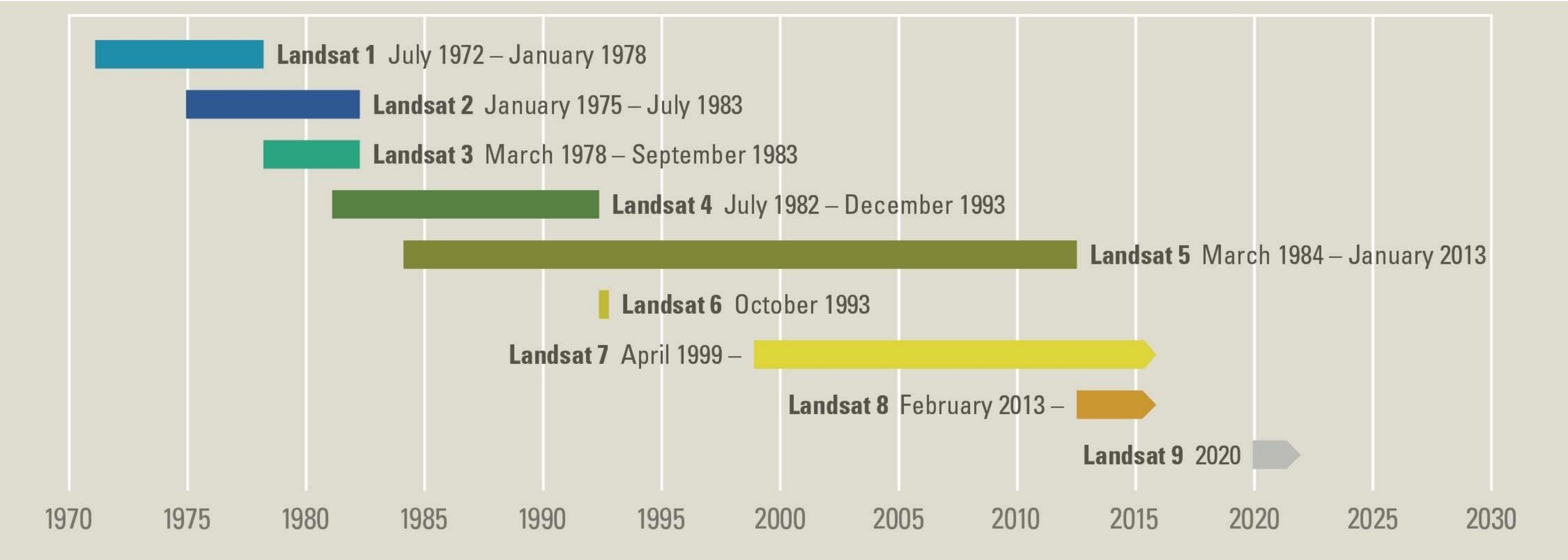
- Effect of small-scale disturbances
  - deforestation and forest degradation
  - shifting cultivation, fires, etc.

- Difficult to study with
  - AVHRR, MODIS, or e.g. TRMM
  - Non-stationary time series



de Jong, R, Verbesselt, J., et al. (2013), RS.

Landsat

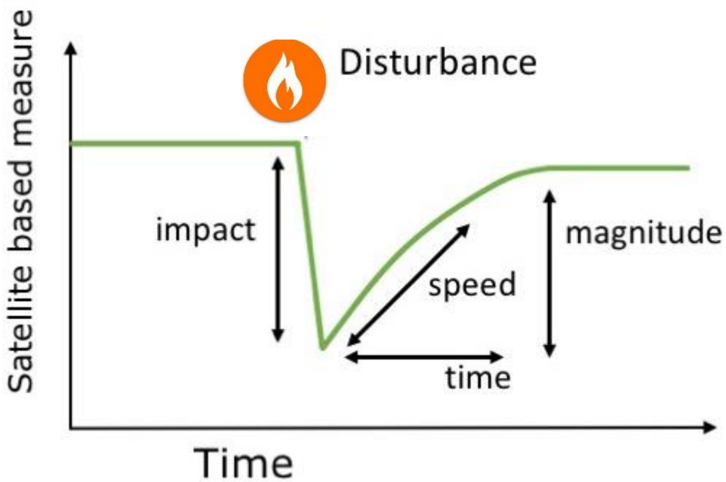


Landsat optical data

- Medium resolution sensor: **30m** spatial resolution
- Revisit time: 16 days
- **Long time span (since 70s)**
- Data **free** of charge
- Sensitive to clouds and atmospheric constituents

New resilience measures?

RRI = recovery magnitude / impact



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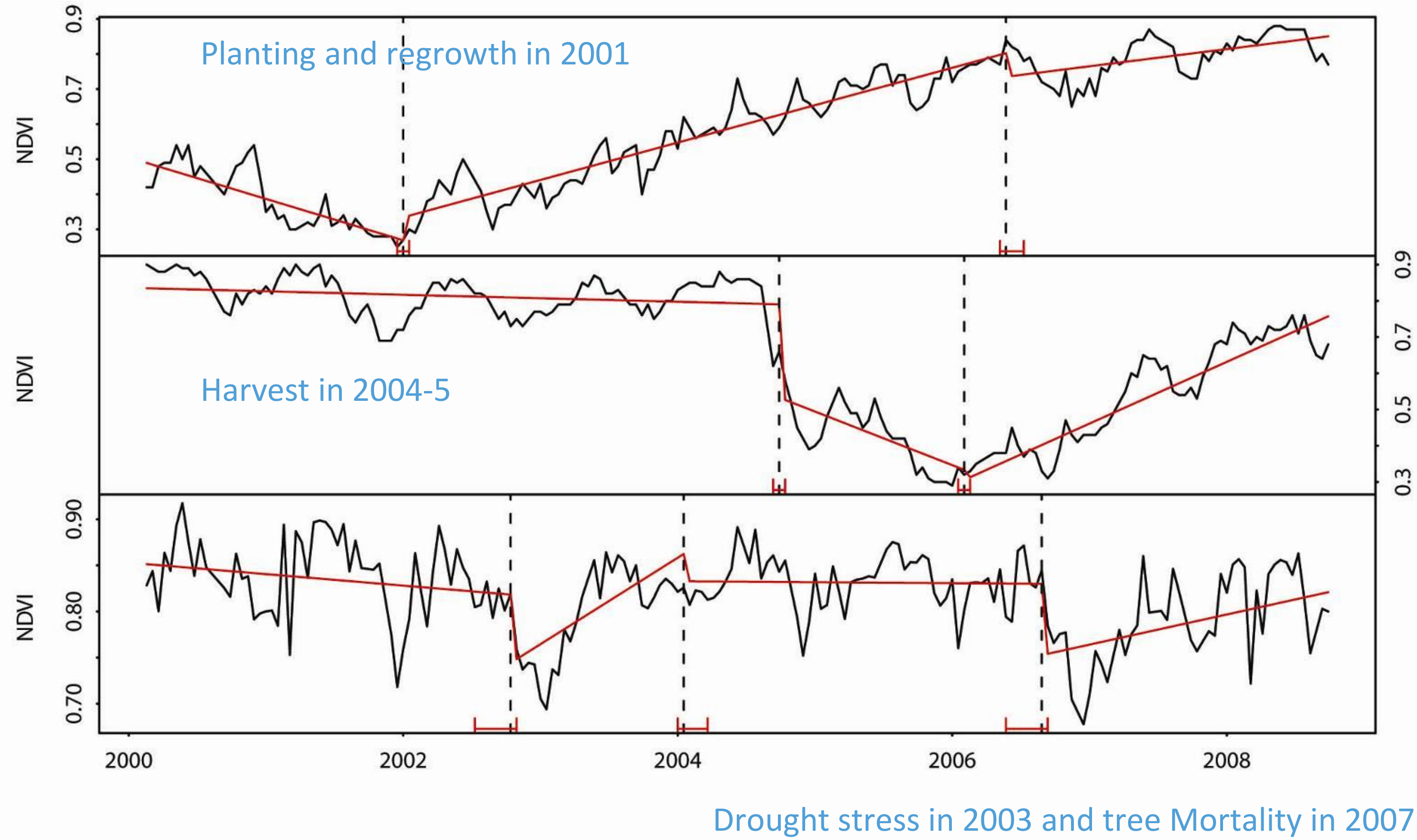
Abrupt change and post-disturbance slopes



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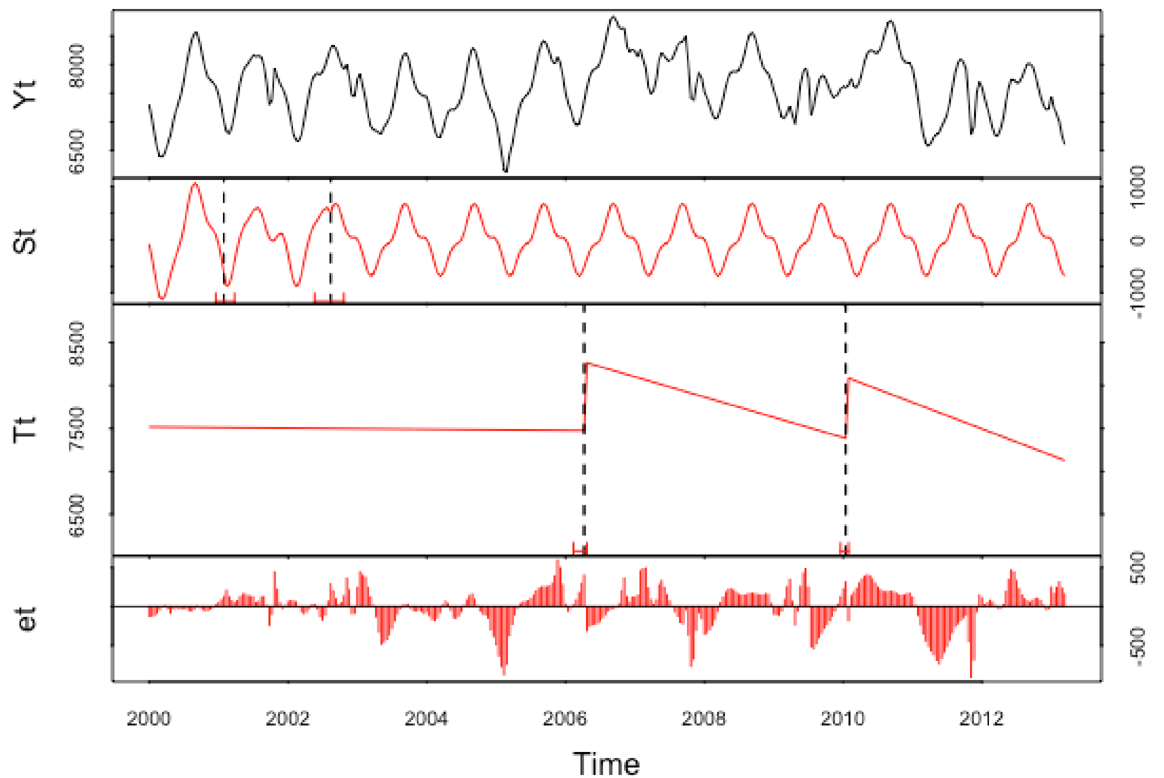
BFAST, Verbesselt, J., et al. (2010). Detecting trend and seasonal changes in satellite image time series. RSE.

Detecting abrupt change

- Breaks For Additive Season and Trend (BFAST) family:
  - BFAST (*bfast()*)
    - All breaks in the time series, with decomposition
    - Cannot handle (many) NAs, order of magnitude slower than BFAST0N
  - BFAST Monitor *(bfastmonitor()/bfastSpatial)*
    - 1 break at the end of the time series
  - BFAST0N *(bfast0n()/breakpoints())*
    - All breaks in the time series, without decomposition
    - Can handle many NAs, order of magnitude slower than Monitor
  - BFAST01 *(bfast01()/bfast01classify())*
    - One break in the time series, change classes

BFAST



BFAST

- Decomposes time series into piecewise linear trend, seasonal and remainder
- General model:
- $Y_t = T_t + S_t + e_t$, t = 1,…, n,
  - Y_t is the observed data at time t,
  - T_t is the trend component,
  - S_t is the seasonal component
  - e_t is the remainder component
- Separate season and deseasonalised trend breaks
- Iterative algorithm
- Latest version available on github: https://github.com/bfast2/bfast

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Components

- S_t is the seasonal component with seasonal break points given by $t_1^{\#},\ldots, t_p^{\#}$, and define $t_0^{\#} = 0$. Then for $t_{j-1}^{\#} < t \le t_j^{\#}$, we assume that:

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

  where s is the period of seasonality and $\gamma_{i,j}$ denotes the effect of season i.

- T_t is piecewise linear with break points $t_1*,\ldots, t_m*$ and define $t_0* = 0$. For $t_{j-1}* < t \le t_j*$ and where $j = 1,\ldots, m$:

  $T_t = a_j + \beta_j t$

Iterative procedure

- Estimate $\hat{S}_t$ by using the STL method (mean of all seasonal sub-series)
- Iterate following steps until the number and position of the breakpoints are unchanged
  - **Step 1** : OLS-MOSUM test for breakpoints in trend component. If breakpoints are present, estimate the number and position of the break points in $Y_t - \hat{S}_t$
  - **Step 2**: Compute trend coefficients using robust regression based on M-estimation.
  - **Step 3**: OLS-MOSUM test for breakpoints in seasonal component. If breakpoints are present, estimate the number and position of the break points in in $Y_t - \hat{T}_t$.
  - **Step 4**: Compute seasonal coefficients using robust regression based on M-estimation.

OLS-MOSUM test for breakpoints

- Consider the standard linear regression model:
  - $Y_i = x_i^{\top} \beta_i + u_i$ $(i = 1, \ldots, n)$,

  where at time i:
    - Y_i is observation of the dependent variable
    - $x_i = (1, x_{i2}, \ldots, x_{ik})^{\top}$ is a $k\times1$vector of observations of the independent variables, with the first component equal to unity,
    - u_i are iid $(0,\sigma^2)$, and
    - β_i is the $k\times1$ vector of regression coefficients.
- The **null hypothesis** of "no structural change":

  H0: $\beta_i=\beta_0$ $(i = 1, \ldots, n)$

  against the alternative that the coefficient vector varies over time

OLS-MOSUM test for breakpoints

- **Generalized fluctuation test**
  - fit a model to the given data and derive an empirical process
  - **Empirical processes capture the fluctuation either in residuals or in estimates**.
  - Limiting processes are known, so that **boundaries** can be computed, whose **crossing probability** under the null hypothesis is α.
  - If the empirical process path crosses these boundaries, the fluctuation is improbably large and hence the null hypothesis should be rejected (at significance level α)

OLS-MOSUM test for breakpoints

- Regression coefficients
  - $\widehat{\beta}(i,j)$ is the OLS estimate of the regression coefficients based on the observations i+1, ... , i+j
  - $\widehat{\beta}(i) = \widehat{\beta}(0,i)$ is the OLS estimate based on all observations up to i.
- X(i) is the regressor matrix based on all observations up to i.
- OLS residuals:

$$\hat{u}(i,j) = y_i - x_i^T \beta(n)$$

with the variance estimate $\widehat{\sigma^2} = \frac{1}{n-k} \sum_{i=1}^{n} \hat{u}_i^2$

OLS-MOSUM test for breakpoints

- OLS-MOSUM
  - Moving sums of residuals
  - Bandwidth parameter h ∈ (0,1)
  - OLS-based MOSUM process is defined by:

$$
\begin{aligned}
M_n^0(t|h) &= \frac{1}{\hat{\sigma}\sqrt{n}}\left(\sum_{i=\lfloor N_n t\rfloor+1}^{\lfloor N_n t\rfloor+\lfloor nh\rfloor} \hat{u}_i\right) \qquad (0 \le t \le 1-h) \\
&= W_n^0\left(\frac{\lfloor N_n t\rfloor + \lfloor nh\rfloor}{n}\right) - W_n^0\left(\frac{\lfloor N_n t\rfloor}{n}\right),
\end{aligned}
$$

Where $N_n = (n - \lfloor nh \rfloor)/(1-h)$

- Boundary b(t) = λ
- Significance test for crossing the boundary

Breakdates

- Given an m-partition $i_1,\dots,i_m$ the least-squares estimates for the β_j can easily be obtained. The resulting minimal residual sum of squares is given by

$$RSS(i_1,\dots,i_m) = \sum_{j=1}^{m+1} rss(i_{j-1}+1, i_j),$$

Where $rss(i_{j-1}+1; i_j)$ is the usual minimal residual sum of squares in the j^{th} segment.

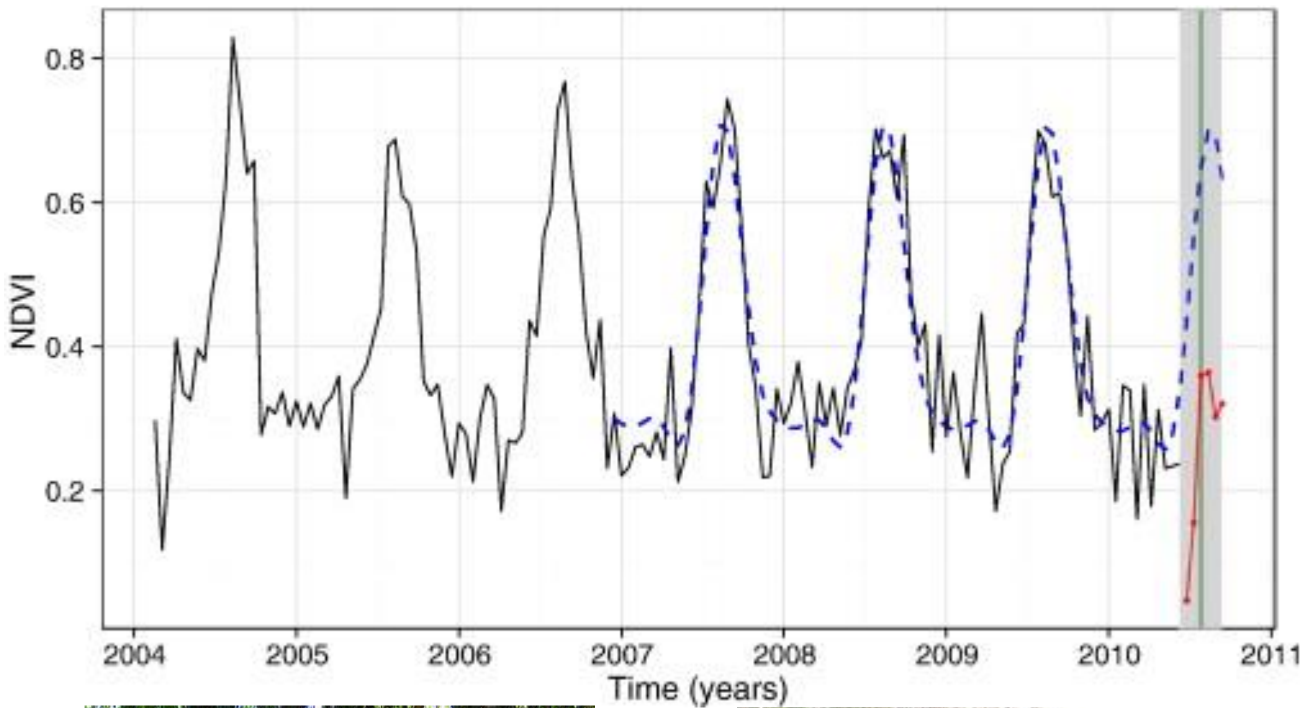
- The problem of dating structural changes is to find the breakpoints $\widehat{i_1},\dots,\widehat{i_m}$ that minimize the objective function

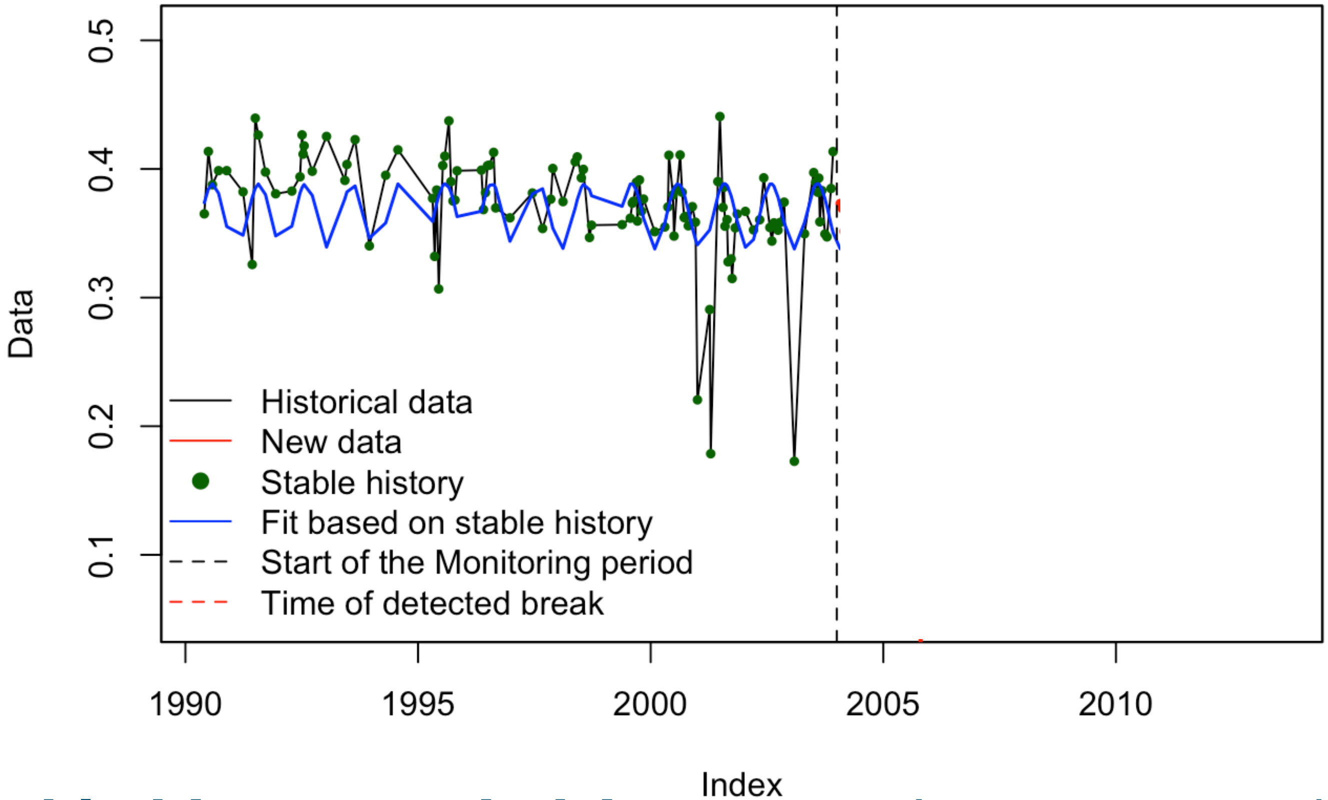
$$(\hat{\imath}_1,\dots,\hat{\imath}_m) = \underset{(i_1,\dots,i_m)}{\operatorname{argmin}} RSS(i_1,\dots,i_m)$$

- For each number of breakpoints the BIC, AIC and RSS are computed

BFASTmonitor

- Detection of abrupt changes at the end of the time series

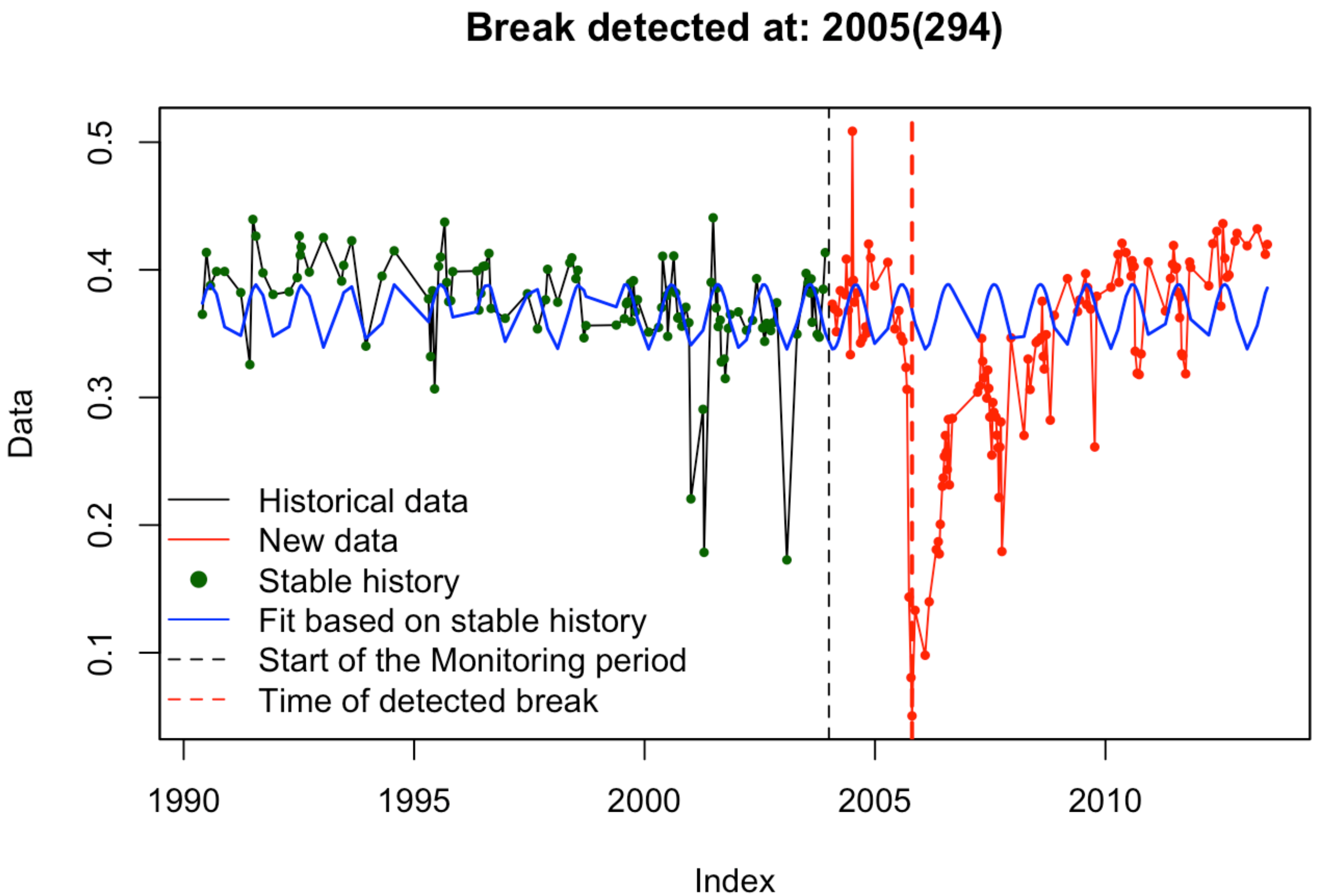




- **Stable history period (t = 1, …, n)**: season-trend model

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

  - Linear trend (intercept a_1 and slope a_2)
  - Harmonic season (amplitudes $\gamma_1, \ldots, \gamma_k$, phases $\delta_1, \ldots, \delta_k$, and frequency f)

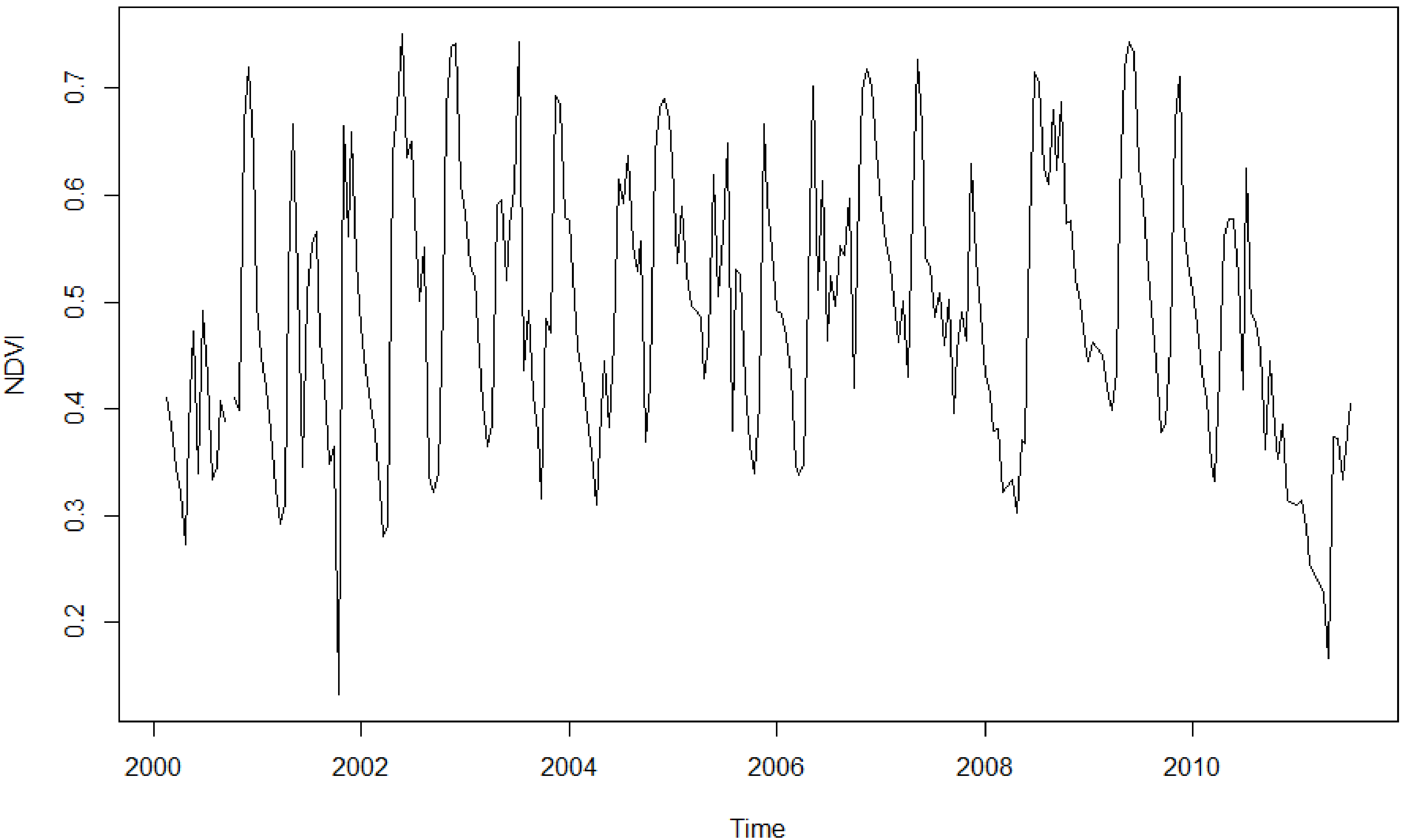


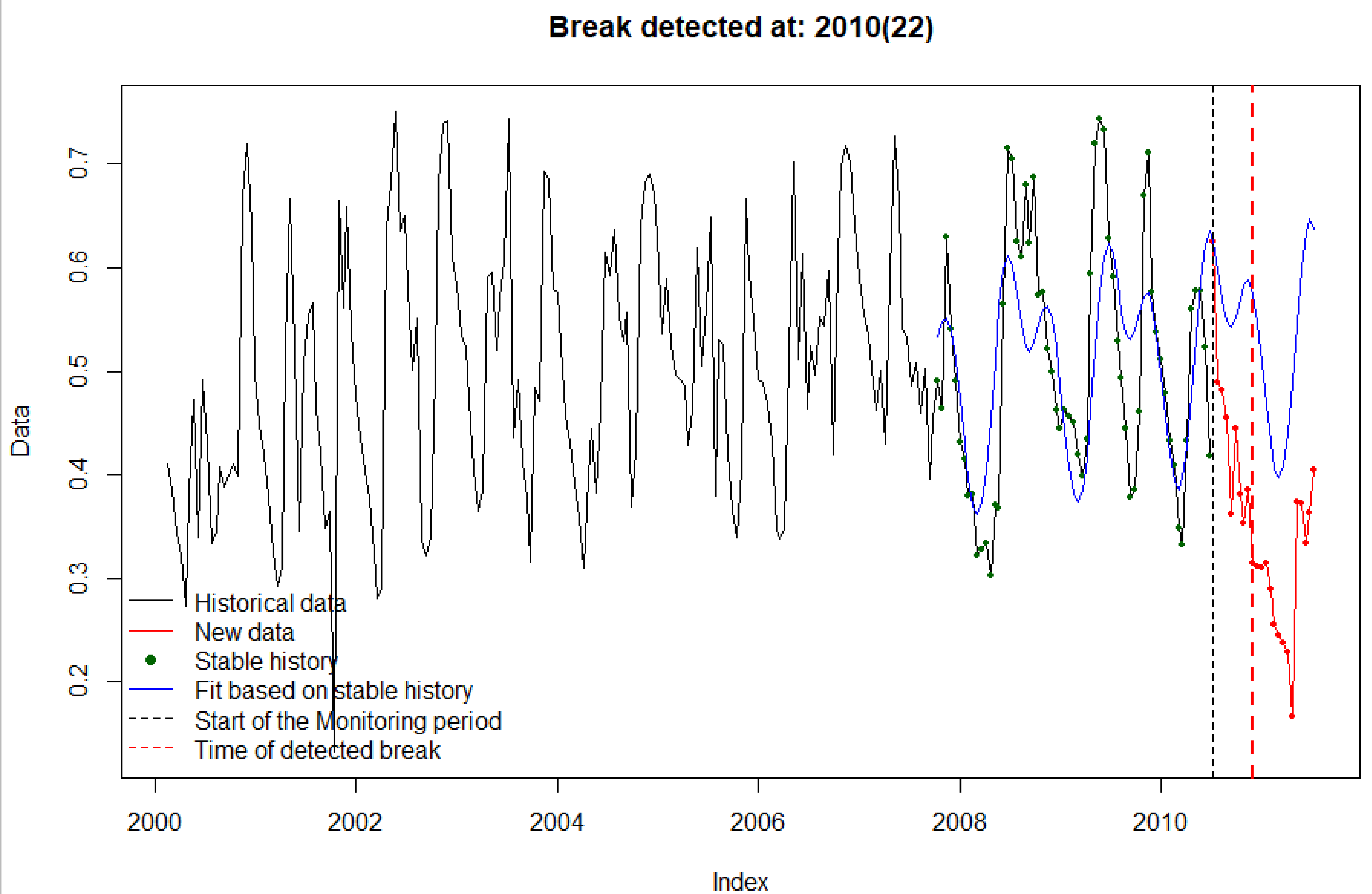
- **Monitoring period (*t* > *n*)**
  - Check whether model still fits the new data
  - Moving sums (MOSUMs) of the residuals in monitoring period

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

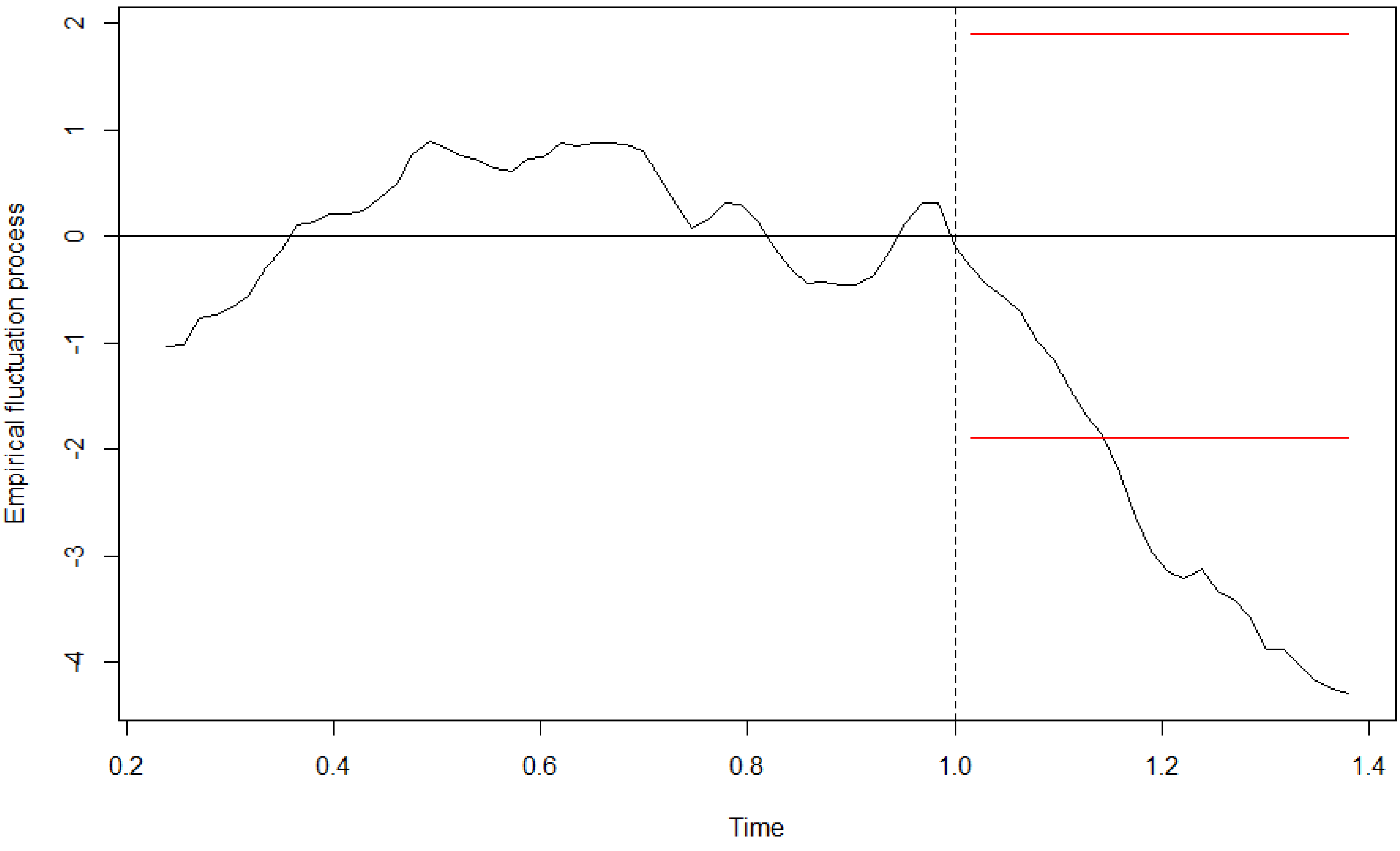
Select stable history

- Not all historical observations can be adequately captured by a single season-trend model
  - use only the last $l, \ldots, n$ observations with $l \geq 1$ so that a stable season-trend model can be fitted.
- Automated selection of a stable history is necessary for monitoring purposes
  - Moving backward in time for $t = n, n-1, n-2, \ldots$ and evaluate a cumulative prediction error until the season-trend model breaks down.


NDVI
0.2
0.3
0.4
0.5
0.6
0.7
2000
2002
2004
2006
2008
2010
Time


Break detected at: 2010(22)
Data
0.2
0.3
0.4
0.5
0.6
0.7
2000
2002
2004
2006
2008
2010
Index
Historical data
New data
Stable history
Fit based on stable history
Start of the Monitoring period
Time of detected break

Monitoring with OLS-based MOSUM test



Further information

- R packages:
  - Latest developments BFAST package: https://github.com/bfast2
  - R (CRAN) release of BFAST package: https://cran.r-project.org/web/packages/bfast/index.html
  - R (CRAN) strucchange package (breakpoint detection): https://cran.r-project.org/web/packages/strucchange/index.html

- Literature:

- Zeileis A., Shah A., Patnaik I. (2010), Testing, Monitoring, and Dating Structural Changes in Ex-change Rate Regimes, Computational Statistics and Data Analysis,54(6), 1696–1706. doi:10.1016/j.csda.2009.12.005.
- Zeileis A., Kleiber C., Krämer W., Hornik K. (2003), Testing and Dating of Structural Changes inPractice,Computational Statistics and Data Analysis,44, 109-123. doi:10.1016/S0167-9473(03)00030-6
- Verbesselt J, Zeileis A, Herold M (2012). Near real-time disturbance detection using satellite image time series. *Remote Sensing Of Environment*, **123**, 98--108. http://dx.doi.org/10.1016/j.rse.2012.02.022
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- Verbesselt J, Hyndman R, Zeileis A, Culvenor D (2010). Phenological Change Detection while Accounting for Abrupt and Gradual Trends in Satellite Image Series. *Remote Sensing of Environment*, **114**(12), 2970--2980. http://dx.doi.org/10.1016/j.rse.2010.08.003

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