DETECTING CHANGE FROM DENSE TIME-SERIES

BFAST

(Breaks For Additive Season and Trend)

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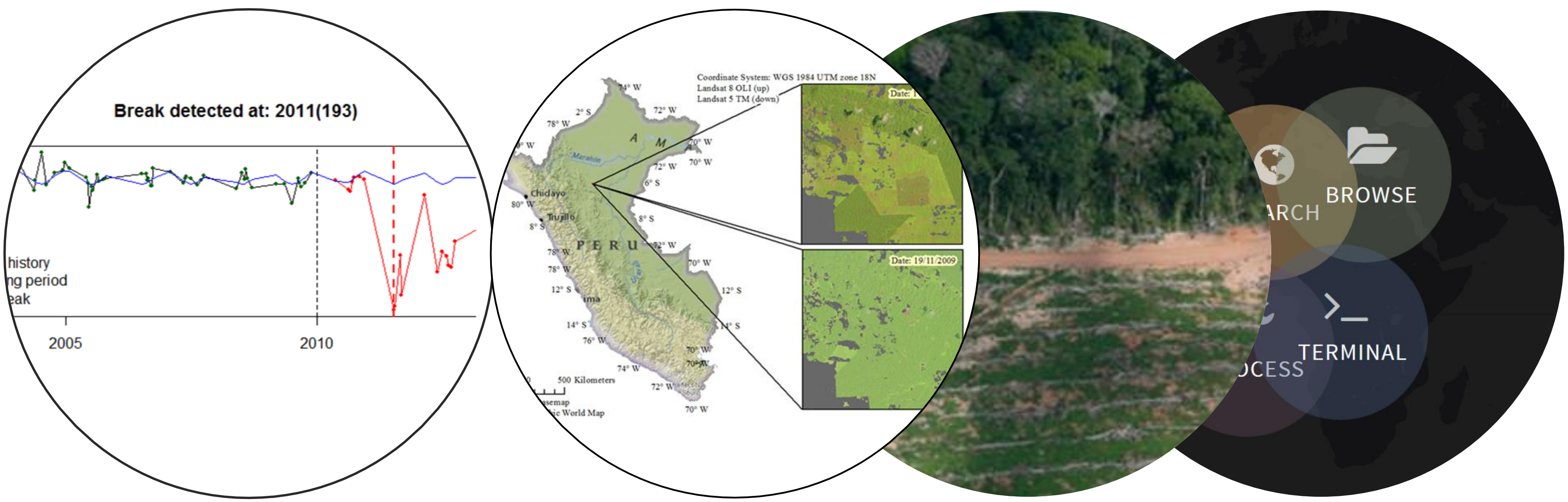

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Introduction

"We are the first generation to feel the effect of climate change and the last generation who can do something about it."
President Obama

Forests play a central role in combating climate change

→ Improve monitoring and quantification of forest loss and forest gain

Why are we interested in time series/time series analysis?

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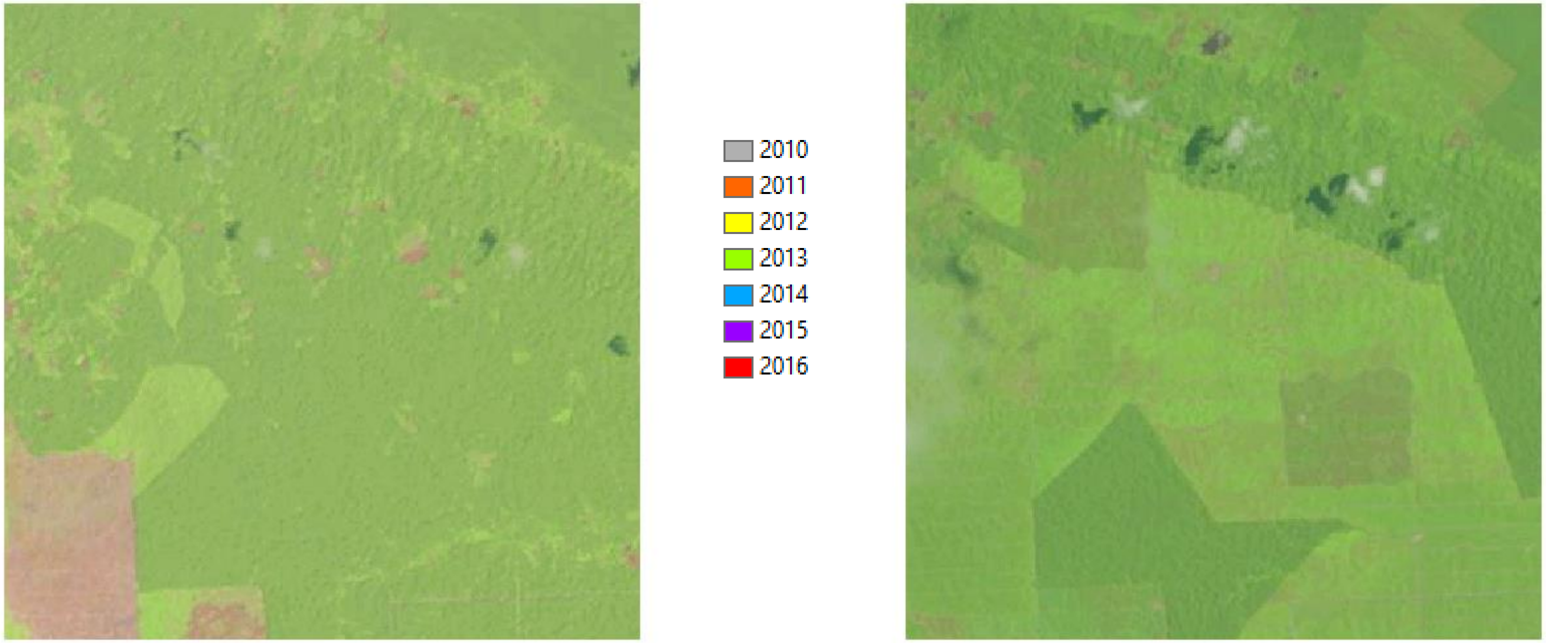
What is BFAST?



Why is Bfast with SEPAL of interest for FAO?

- Bfast is an open source tool
- Countries can use it themselves, adapting it to their needs

Workshop summary

Goal: Understand how BFAST works and how to properly apply it

PART I Understanding the theory (~1hour)

1. Explaining the algorithm: What are BFAST Monitor and bfastSpatial?
2. Analysis overview: from Landsat scenes to forest change monitoring
3. Discuss and understand the parameters of the bfastSpatial function

Break

PART II Practical (~1 hour)

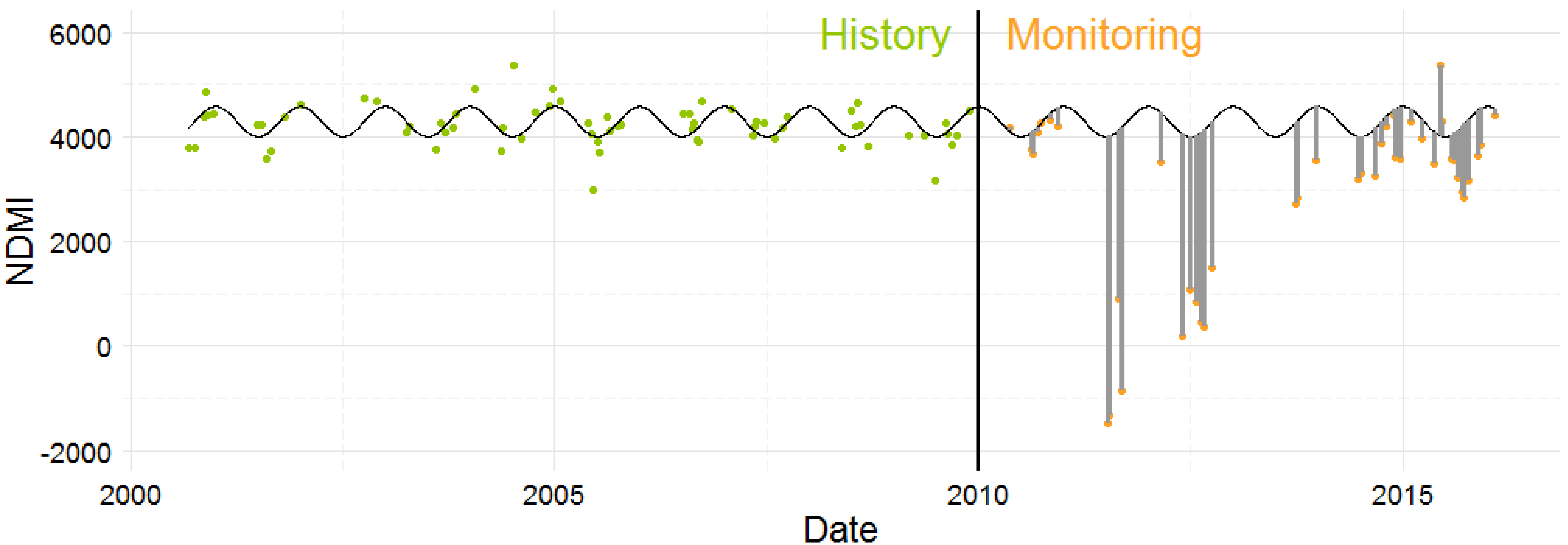
4. Test bfastSpatial function with different parameters on a prepared dataset
5. Post-processing and exploring results
6. Discuss results and the process of applying the algorithm
7. Discuss the future of BFAST: a faster algorithm for larger AOIs (SciDB)

For this, the MOSUM test is applied

Testing the stability of the model = to check if the „new data” still „fits” the model
If the data still fits => no change is detected
else => a break is marked

BFAST Monitor

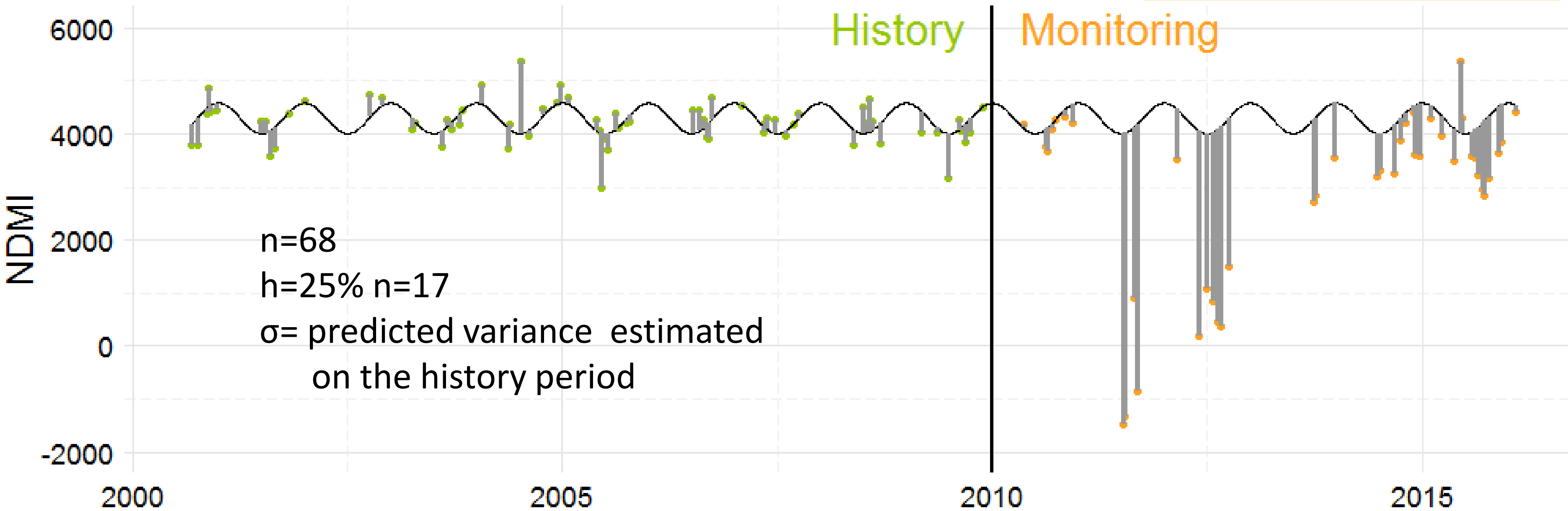
- The method consists in fitting a model to the data by Ordinary Least Squares (OLS) fitting, on a period defined as stable history, and ***testing*** for stability of ***the*** same ***model***, during a period defined as monitoring period.

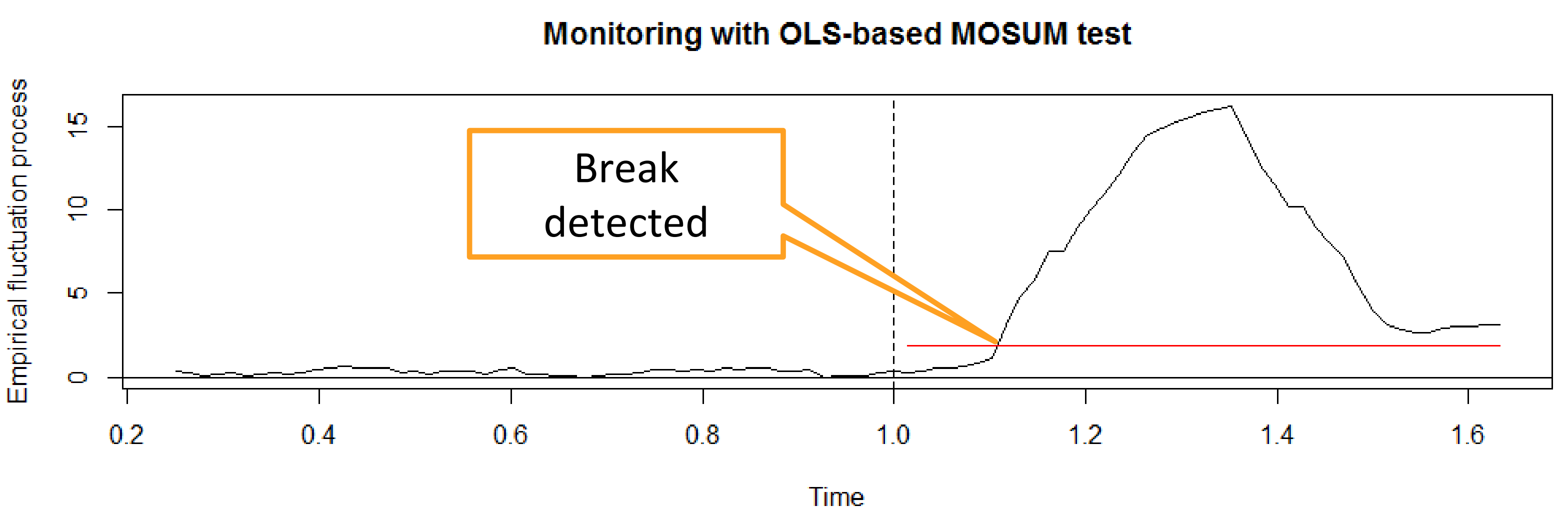


Applying MOSUM

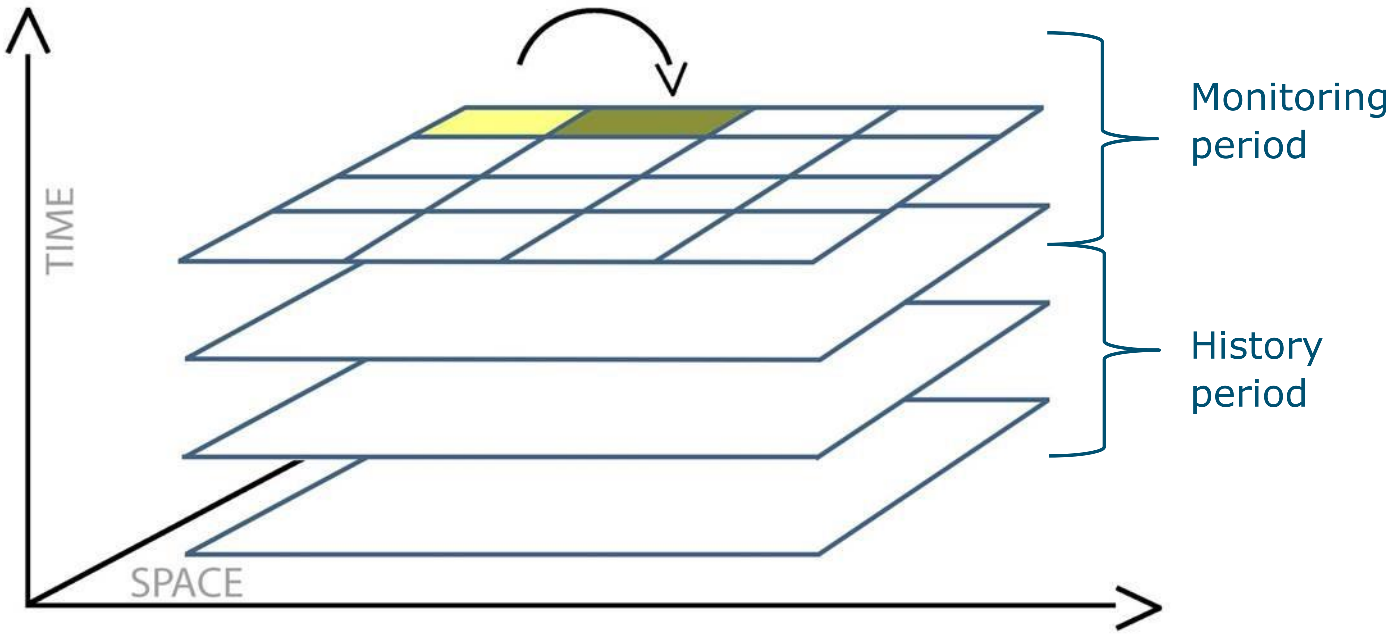
$$MO_t = \frac{1}{\hat{\sigma}\sqrt{n}} \sum_{s=t-h+1}^{t} (y_s - \hat{y}_s)$$

MOSUM detects a break when the MO passes the 95% significance boundary





BFAST Spatial



- all individual time series (one pixel) WILL have the same monitoring period
- all individual time series (one pixel) CAN have the same history period
- each individual time series (one pixel) WILL have the same regression model (ex:harmonic order 1), but different parameters

→ Change detection is unique for each pixel

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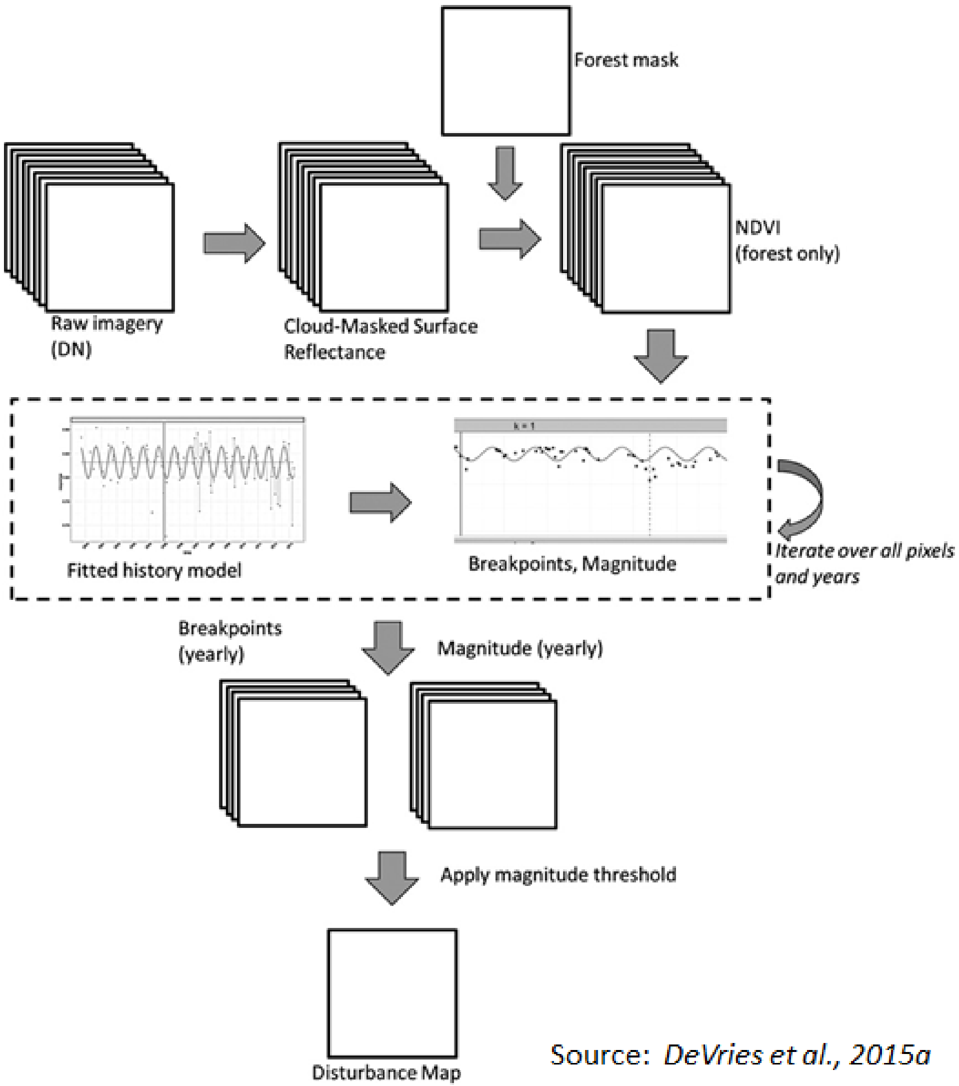
Analysis overview: from Landsat scenes to deforestation detection



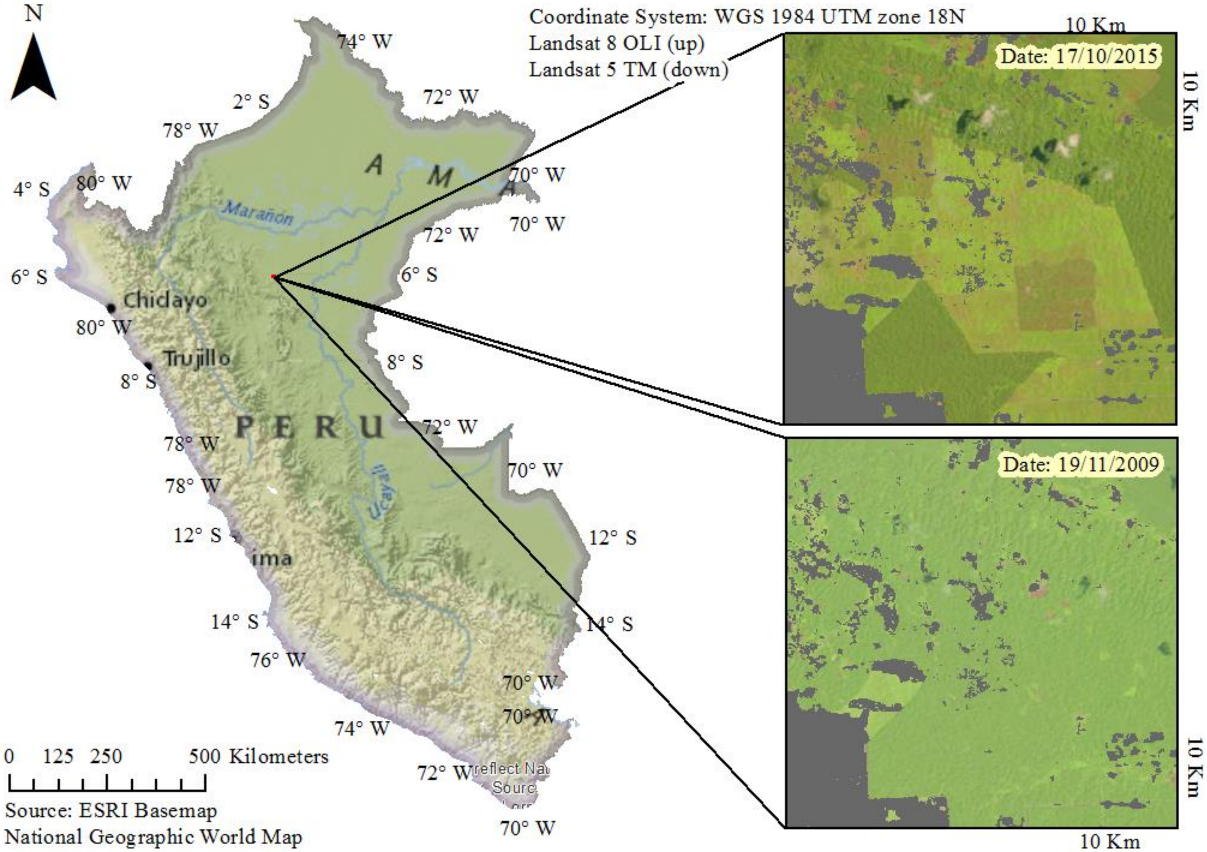
Source: *DeVries et al., 2015a*

=> ***Pre-processing***
(choose the input data and prepare the time-stack)

=> ***Processing***
(applying bfastSpatial function to detect change)

=> ***Post-processing***
(define how change translates to deforestation)

Case study: Peru



Source: *Climate change Knowledge Portal*[1]

Forest Characteristics

- Evergreen forest with seasonality: „selva alta"
- Loreto is the largest region in Peru and has had more hectares deforested than any other (Peruana, 2015 "Revealing the hidden")
- Deforestation in large „blocks resulting from agricultural investments (mainly palm oil)

Source: *Barranquita Resiste*[2]

[1] *http://sdwebx.worldbank.org/climateportal/*

[2] *https://cordilleraescalera.wordpress.com/bbarranquita−resistsb−2/*

Data acquisition and Pre-processing

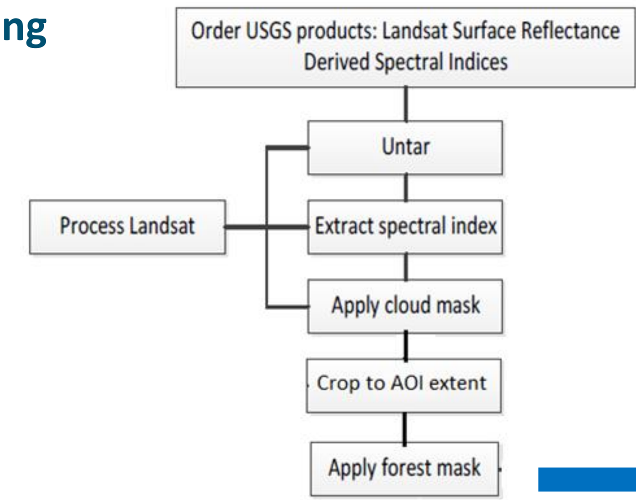
Products acquired:

- NDVI and NDMI derived from Surface Reflectance products
- Cloud Mask
- Forest Mask (for 2010)

proccessed and provided by the USGS

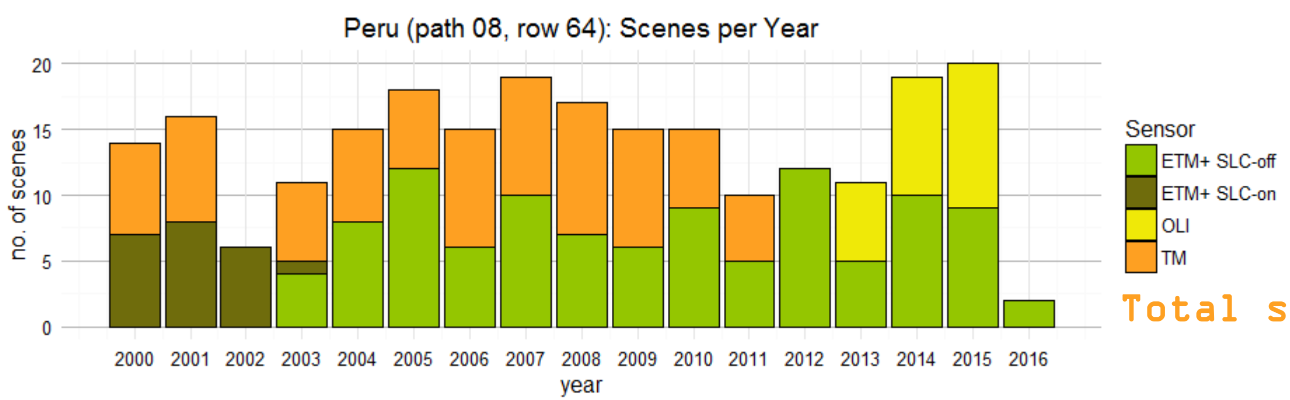
– computed using unsupervised classification: k-means

Pre-proccessing



Online tutorial
http://www.loicdutrieux.net/bfastSpatial/

Create time stack



Total scenes: 235

Discuss and understand the parameters of the bfastSpatial function

```
bfmSpatial(x, dates = NULL, pptype = "irregular", start, monend = NULL,
  formula = response ~ trend + harmon, order = 3, lag = NULL,
  slag = NULL, history = c("ROC", "BP", "all"), type = "OLS-MOSUM",
  h = 0.25, end = 10, level = 0.05, mc.cores = 1,
  returnLayers = c("breakpoint", "magnitude", "error"), sensor = NULL, ...)
```

Guide: https://github.com/rosca002/Testing_BFAST_settings/blob/master/Bfast_Spatial_Guide.md

1. Input data: What vegetation index to use?

Convenient: NDMI or NDVI

Recommended: NDMI

2. History Period

(i) How long should the history period be?

- depends on the regression model
- frequently clouded areas: min 55-60 scenes in the history period
- enough observations per pixel for the algorithm to fit a model (a min of 20 observations per pixel, and a mean of 40-50 observations per pixel)
- the more cloudy the scenes are, the bigger the number of scenes needed.

(ii) How to have a disturbance free history period?

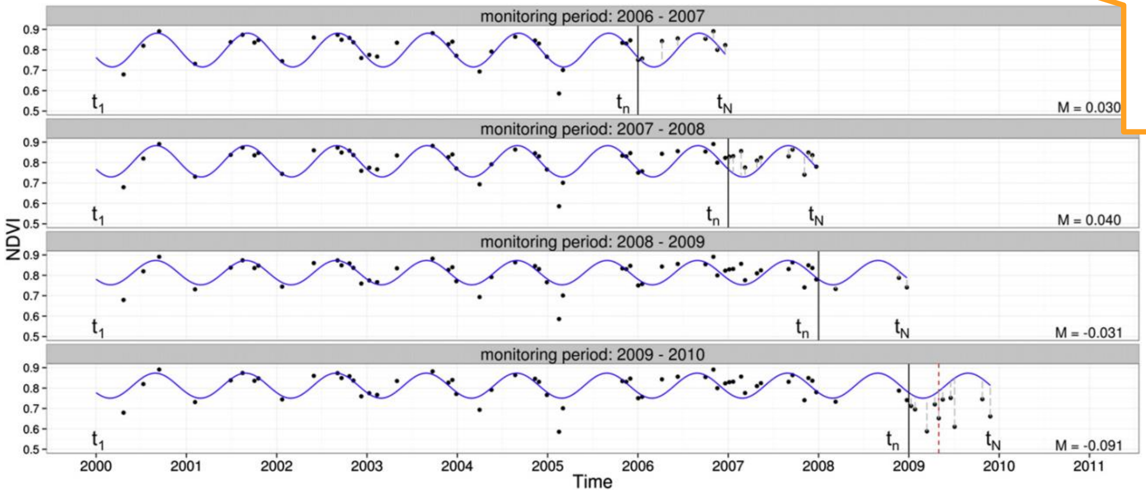
- options: all, ROC
- a moment that delineates a stable period in the history period can be provided by expert knowledge
- or can be calculated automatically using the reverse-order-cumulative sum (ROC or CUSUM) of residuals
- extremely low number of scenes available (due to cloud coverage, e.g. Gabon) it is recommended to use all scenes available in the history period, with the condition to visually assess the study area for disturbances in this period

3. Monitoring period

(i) Full monitoring period approach

```
bfmSpatial(ndmiStack, start = c(2010, 1), formula = response~harmon,
           order = 1, history = c(2000, 1), filename = out))
```

(ii) Sequential monitoring approach



Limits the monitoring period to one year

- the history period is enlarged with every iteration
- this approach can make a big difference in the cases with very few observations available

```
parLapply(ndmiStack,start:end,
          function(year){
            outfl <- paste0(outdir, "/bfm_NDMI_", year, ".grd")
            bfm_year <- bfmSpatial(ndmiStack, start = c(year, 1), monend = c(year + 1, 1), formula = response~harmon,
                                   order = 1, history = "all", filename = outfl)
           })
```

4. Regression model

(i) the phenology of the forest

- choose the harmonic order of the model to follow as closely as possible the seasonal patterns

- decide if trend is, or not, to be included in the model

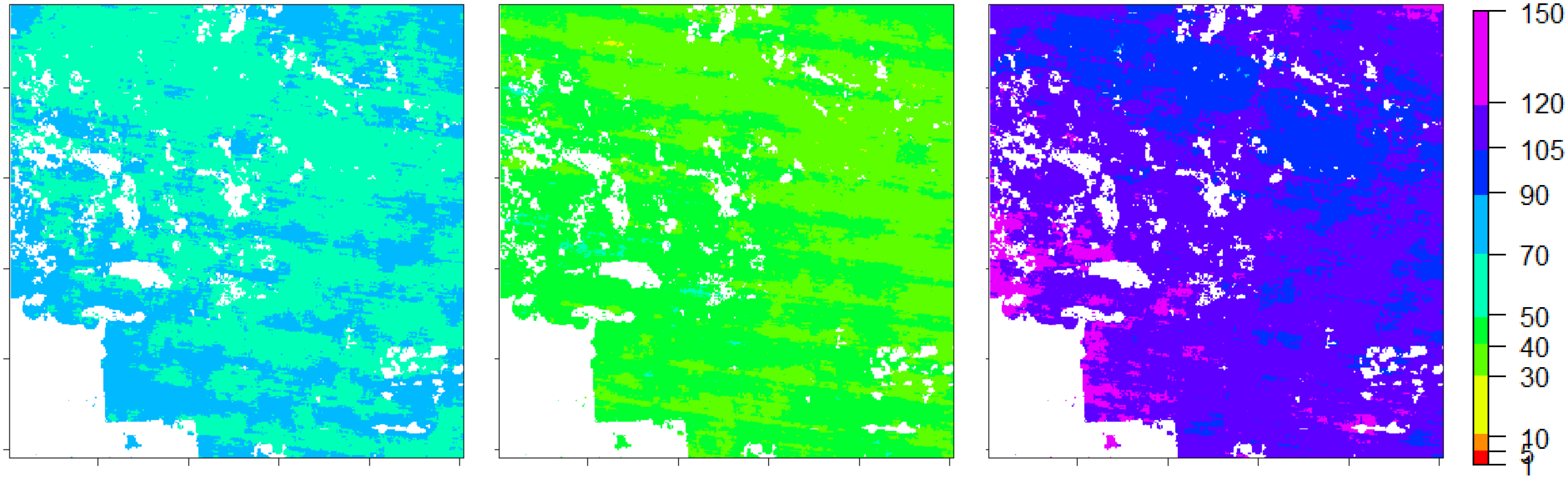
(ii) the number and frequency of the cloud-free available imagery.

- the more complex the regression, more observations are needed in the history period

- even though present, complex seasonal patterns might not be detectable with Landsat data alone, if the AOI is frequently cloud covered

No. Observations per pixel

History period (2000-2010) | Monitoring period (2010-2015) | All observations (2000-2015)

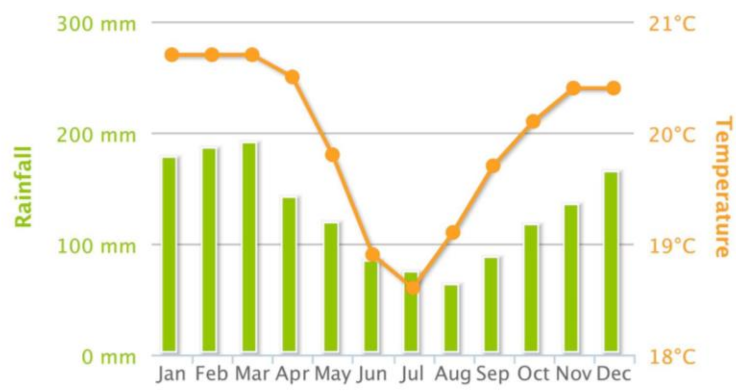


Min: 52
Max: 87

Min: 29
Max: 55

Min: 88
Max: 135

Total scenes: 235



Source: *Climate change Knowledge Portal*[1]

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Next:

Break

PART II

Practical