Detection of trend change-point in passive microwave and optical time series using Bayesian inference over the Dry Chaco Forest

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Argentina Native Forest

Argentina Native Forest is going through a new phase of agricultural expansion (Paruelo et al., 2011).

Argentina Law No. 26,331 promote the territorial planning and regulate the conservation and management of native forest

There is a critical need for methods that enable analysis of satellite image time series to detect forest disturbances, especially in developing countries (e.g. Argentina).

Only visual inspection analysis has been made over Argentina Native Forest (National Forest Service) to detect deforestation

Time series models

- Remote sensing time series provide data for describing landscape dynamics
- Satellite sensors provide consistent and repeatable measurements that enable the capturing of effects of many processes that cause change, including natural (e.g. fires, insect attacks) and anthropogenic (e.g. deforestation, urbanization, farming) disturbances.
- Available open-source software for trend analysis and change detection: BFAST package for R

$$Y_t = T_t + S_t + e_t$$

Objective

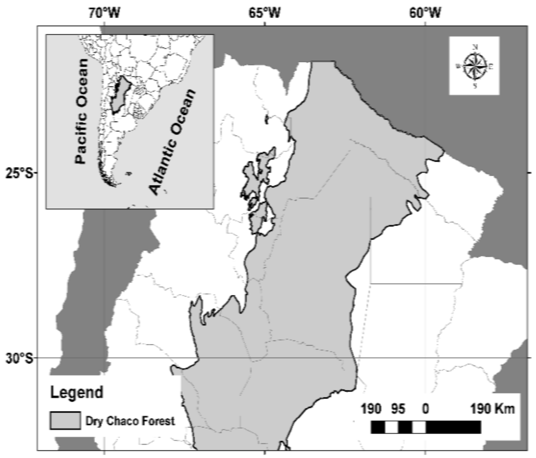
- Evaluate the ability of the Bayesian models to detect the timing of abrupt phenological changes in the vegetation Optical Depth (VOD) and Enhanced Vegetation Index (EVI) time series over the DCF, Argentina.

The main hypothesis is that microwave and optical indices are able to generate complementary information about vegetation condition

The advantages of the Bayesian model (compare to BFAST) are:

(i) it gives the possibility to use prior information about the retrieved variables,
(ii) it can handle uncertainties on the ancillary parameters.

Study Area : Dry Chaco forest (DCF)



- This region presents large homogeneous sites covered by deciduous forest with moderate biomass (70–110 Tn ha-1) and relatively low wood volume (~114 m3 ha-1 per 100 Tn ha-1).

- The Chaco region has the highest absolute deforestation rates of the country. Most of the recently deforested plots in the study area are used for soybean cultivation

Pictures (Gasparri (2015))

Vegetation indices

Optical Indices

$$\mathbf{NDVI} = \frac{\rho\mathbf{2} - \rho\mathbf{1}}{\rho\mathbf{2} + \rho\mathbf{1}}$$

Índice de vegetación normalizado

$$\mathbf{EVI} = \frac{\mathbf{2.5} * (\rho\mathbf{2}(\rho\mathbf{1})}{(\rho\mathbf{2} + \mathbf{6} * \rho\mathbf{1} + \mathbf{6.5} * \rho\mathbf{3} + \mathbf{1})}$$

Índice de Vegetación mejorado

- ✓ Sensitive to chorophyll concentration and LAI
- ✓ Independent of the land cover

Microwave indices

$$\mathrm{VOD} = \cos u + \sqrt{a + 1 + (ad)^2}$$

- ✓ Product
- ✓ Depend on parameters

Sensitive to Woody biomass and vegetation water content

Offline Bayesian change detection

- Change point detection is the identification of abrupt changes in the generative parameters of sequential data.

P(model/data)

Likelihood

Prior probability

$$p\left(\tau_j, m / \tau_j - 1, y_{1:n}\right) = \frac{p\left(\tau_j - 1, y_{1:n} / \tau_j, m\right) * p\left(\tau_j - 1, y_{1:n}\right)}{\iint p\left(\tau_j - 1, y_{1:n} / \tau_j, m\right) * p\left(\tau_j - 1, y_{1:n}\right) dm\, d\tau_j}$$

Posterior

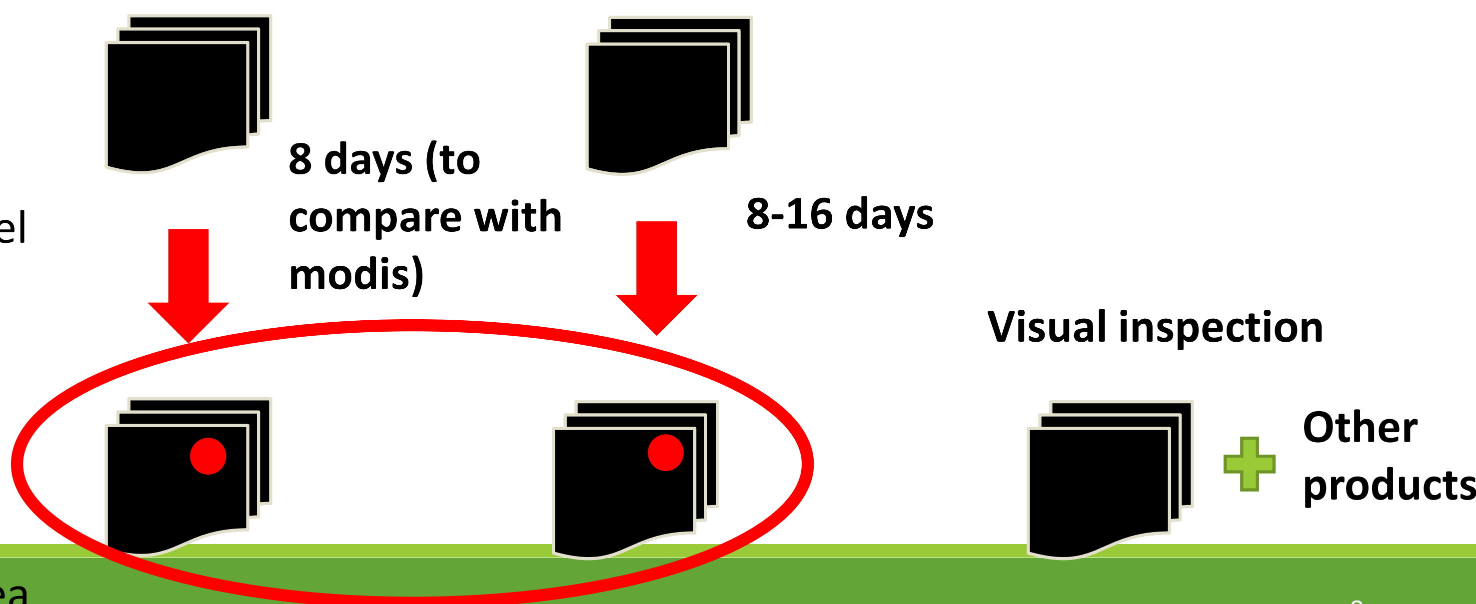
Evidence

- Where there are n observations y1:n=(y1,…,yn). Given m segments, defined by the ordered change points τ0,τ1,…,τm, with τ0=0 and τm=n.

- We assume independent priors for the parameters associated with each segment and also assume that the change points occur at discrete time points, and consider two priors for the change point:
  1- The first prior is based on a prior for the number of change points,
  2- The second conditional prior on their positions.

Dataset

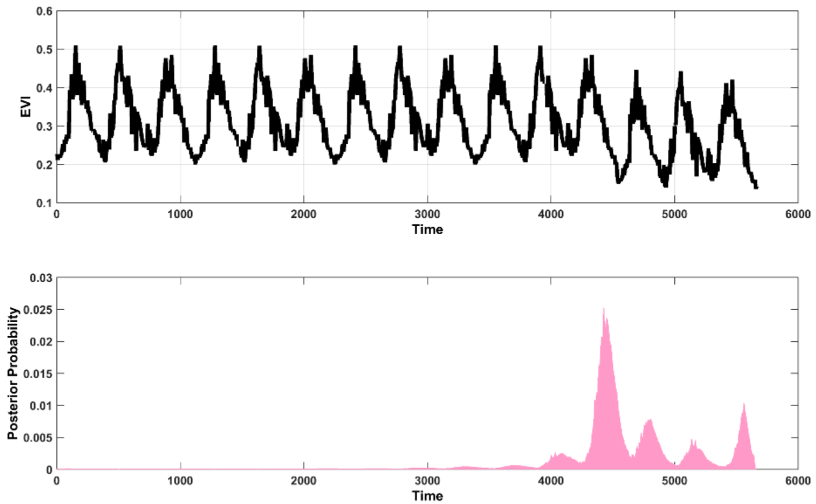
Indices	**VOD**	**EVI**	**EVI**
SENSOR	**TMI/ AMSR-E**	**MODIS**	**Landsat**
Spatial Resolution	**25 Km**	**500-250 m**	**30 m**
Temporal Resolution	**1-3 days**	**8-16 days**	**16 days**



Validation

Simulations

- The objective was to discuss the sensitivity of the model to different characteristic of the time series.



Example of Simulated 8-days EVI time series with change magnitude=0.2 and posterior probability.

Real Dataset

- Real time series, contains more information than the ones presented in the simulation.

- We evaluated this algorithm using real time series (VOD and EVI) from multiple platform (microwave: AMSR-E and TMI/TRMM and optical. EVI MODIS at 500 and 250 m).

  We analyzed the year of the maximum value of posterior probability (PDF) over a subarea in the DCF using optical and microwave time series, and compare the result with the Redaf dataset (Vallejos et al., 2014).

Result

Simulations

Three properties of the method were analyzed (magnitude, noise and amplitude). The accuracy of the model was evaluated using the posterior probability (PDF).

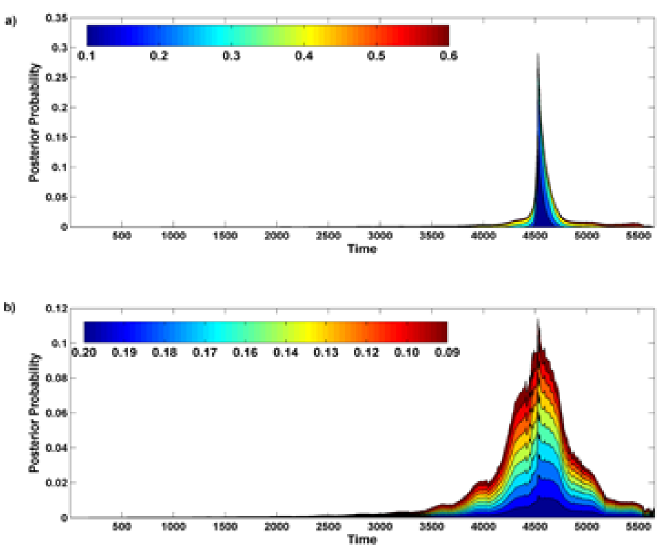


Figure 1. Posterior probability as a function of time and change magnitude (noise=0.08 and amplitude=0.1)(a) and with different amplitude (magnitude=0.2 and noise=0.08) (b) for simulated 8-days EVI.

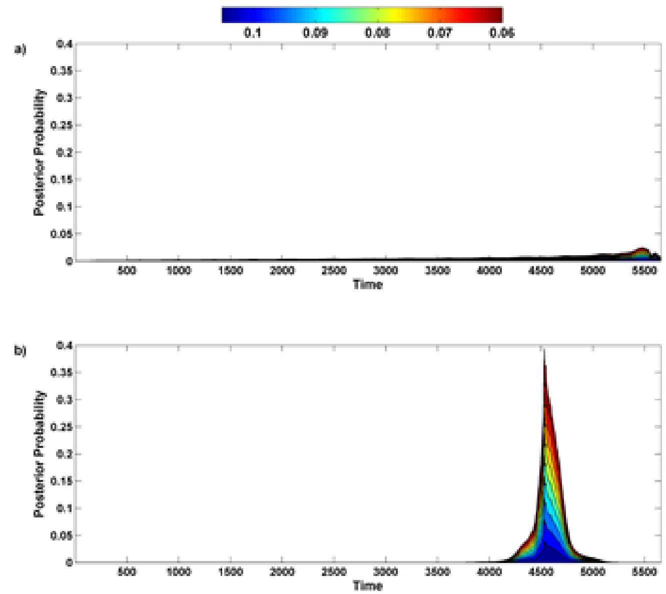


Figure 2. Posterior probability as a function of time and noise level: with magnitude=0 (a) and with magnitude=0.3 (b) for simulated 8-days EVI.

- The results shows (Figure 1a) that the probability of detect a change point increase with the magnitude of that change.
- When no change were simulated (magnitude=0), changes in amplitude did not influence the detection of breackpoint.
- Results of VOD were similar to the ones founded by EVI simulations (result not shown).

Result

VOD AMSR-E y TMI/TRMM

AMSR-E
TMI-TRMM
25 Km
8 days

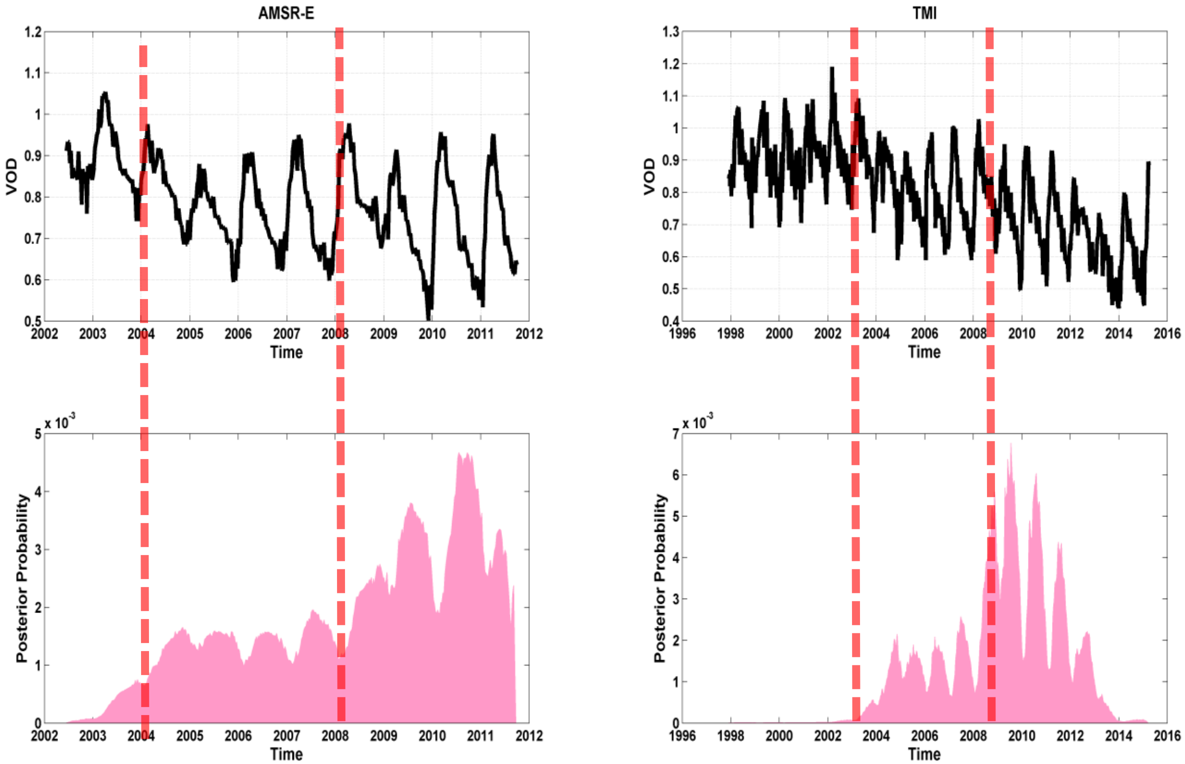
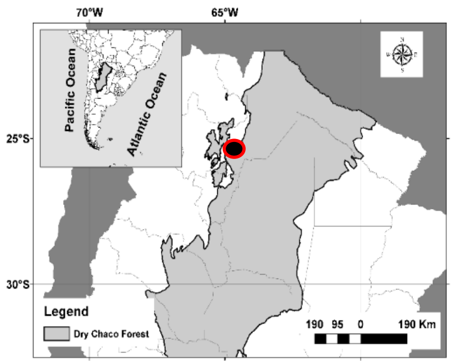


Figure 3a 8-days VOD time series from AMSR-E (left column) and TMI/TRMM (right column) and the posterior probability for each series derived from the Offline Bayesian change detection model.



- **An example of changes detected by the offline Bayesian model in a forest area affected by deforestation was analyzed.**
- **The results shows that a disturbs could be detected by both time series; however using the longer time series it was possible to identify a non-disturbed period**

Result

MODIS 500 m-8 days

MODIS 250 m-16 days

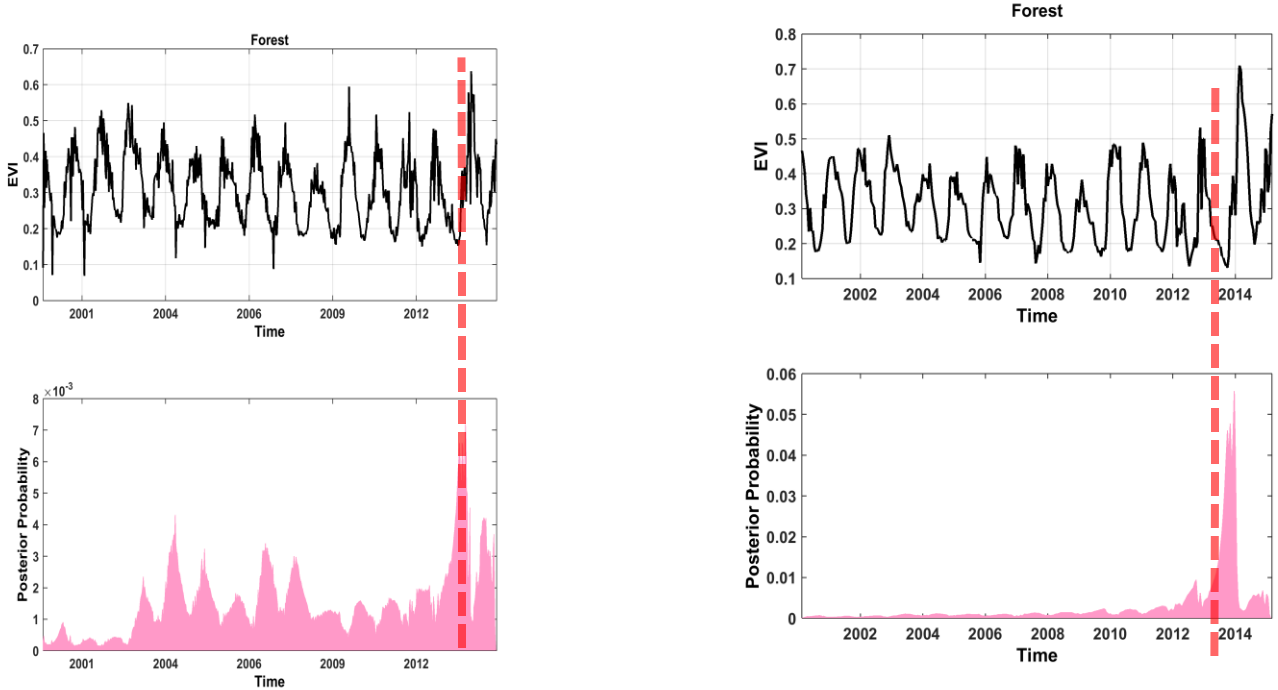
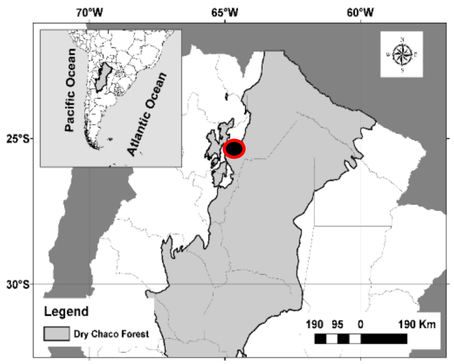


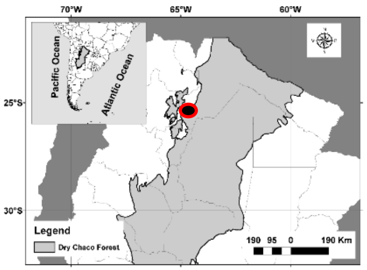
Figure 3b Example of MODIS products and the posterior probability for each series.



- **Figure 3 shows the model results examples of 16-days MODIS EVI at 250 m and 8-days MODIS EVI at 500 m for a forest area inside the selected site. Both results were similar, with the maximum peak at similar times.**

MODIS 250 m – 16 days

- **A full analysis of this area was using 16-days MODIS EVI at 250 m showing that the transformed area presented a posterior probability higher than 0.1**



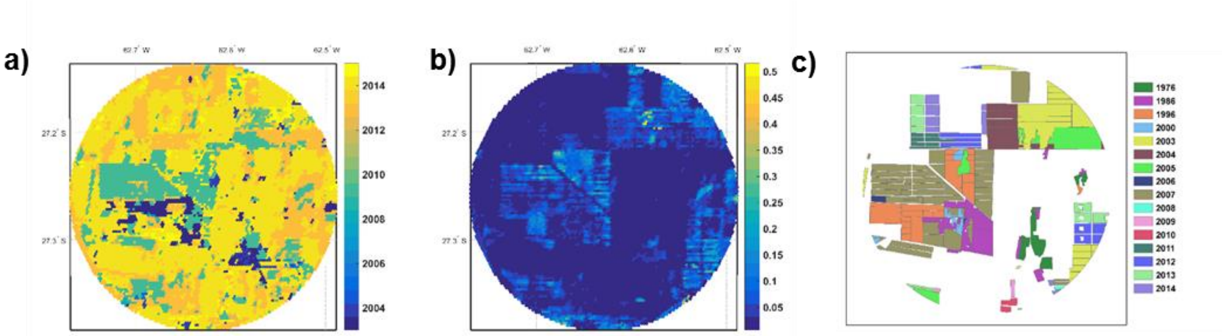


Figure 4. Offline Bayesian change detection results using 8-days MODIS EVI time series over a subarea in the Dry Chaco Forest. (a) The year of the maximum value of posterior probability (PDF) , (b) the PDF and (c) the year of the transformed forest area from Redaf dataset **[12].**

- **There was an agreement in the spatial distribution of the transformed area showed by Redaf results (Vallejos et al., 2014) and Figure 4.**

- **However, if we compared the year of the maximum posterior probably with Redaf results, we found that there were disagreement between them. Since this is a time series analysis, it was evident that more information was presented using the time series model rather than the visual analysis proposed by**

Conclusions

- We show that the offline Bayesian model for changepoint detection is applicable to optical and microwave time series.

- The results shows the advantages of using an automatic model to detect a changepoint (faster, describe the changes processes, etc) than using only visual inspections.

- Furthermore, we analyzed the possibility to combine this model using two types of data series. Simulating time series with varying amounts of seasonality and noise, and by adding abrupt changes at different times and magnitudes, revealed that this model is robust against noise, and is not influenced by changes in amplitude of the seasonal component.

- The result obtained in this manuscript are relevant for the DCF region, since provide a fast and alternative model to the traditional visual analysis made by the forest service.