Mapping burned area at the global scale using remotely sensed data under the fire_cci project: the SPOT-VGT algorithm

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Abstract. We introduce an algorithm for daily, global burned area map, at 1km spatial resolution, using imagery from the Système Probatoire d'Observation de la Terre – VEGETATION (SPOT-VGT) European satellite, developed under the framework of the European Space Agency (ESA) Climate Change Initiative, within the *fire_cci* project. The algorithm relies on time series analysis of near-infrared (NIR) reflectance at the single pixel level. The time series of are preprocessed to extract the minima values of each BRDF-induced oscillation, and then despiked using a robust filtering procedure. Potential burning dates are identified with the recently developed Pruned Exact Linear Time (PELT) change point detection approach. Multiple change points detected at each pixel are scored relatively to their likelihood of corresponding to a burning event. The dates of potential burn detection are also taken into account via the development of local fire climatologies described by fitting von Mises circular statistical distributions to MODIS active fire count data, and scored relatively to their timing of occurrence on the typical local fire season. The change point score and the date score are combined to yield a joint score and joint score maps are revised with a Markov Random field approach, to yield the final burned area maps. Accuracy of the SPOT-VGT burned area maps will be assessed against high spatial resolution imagery, prior to release to the public.

1. Introduction

A key commitment in the United Nations Framework Convention on Climate Change (UNFCCC) is the systematic observation and development of data archives related to the climate system. The Global Climate Observing System (GCOS) is the recognized mechanism for implementing this commitment. GCOS established a list of Essential Climate Variables (ECV) that are highly important for UNFCCC requirements. To respond to this need the European Space Agency (ESA) has initiated the ESA Climate Change Initiative (Plummer, 2009). The Fire Disturbance ECV, as defined by GCOS, includes burned area as its primary variable (active fires and fire radiative power are the secondary variables) requiring climate-standard continuity. Burned area can be combined with information on combustion completeness and available fuel load, to estimate pyrogenic emissions of trace gases and aerosol. Measurements of burnt area can also be used as a direct input (driver) to climate and carbon cycle models or, conditional on the availability of long time series of data, to parameterize climate-driven models for burnt area (Csiszar et al., 2009) .

The goal of the fire_cci project is to develop methodologies for producing long-term global burned area atlases, using coarse spatial resolution European sensors, including the ERS/Envisat (Advanced) Along Track Scanning Radiometer (A)ATSR, the SPOT4-5 VEGETATION, and the Envisat MERIS (ESA CCI, 2010). Our focus in this study is to introduce the algorithm developed under the scope of fire_cci for global burned area mapping using SPOT4-5 VEGETATION imagery (Pereira et al., 2012).

2. Methods

2.1. Algorithm overview

The algorithm for mapping burned areas using SPOT-VEGETATION imagery relies on spectral, temporal, and spatial data. More precisely, it searches for spatial and temporal patterns in spectral data that provide evidence of vegetation burning. We analyze single channel (near infrared, NIR) time series of surface reflectance data, previously screened for clouds, smoke and haze. Permanent and temporary water bodies were also masked out of the dataset (Bachmann et al. 2011). Algorithm development relied on data from various years, coming from 10 500km*500km sites, located in Canada, Russia, Kazakhstan, Portugal, Colombia, Brazil, Angola, South Africa, Borneo, and northern Australia.

The algorithm is designed to answer a series of questions:

a) Did a statistically significant spectral change occur, at any date in the time series? (change point detection)

b) Is the spectral change suggestive of burning? (scoring change points)

c) Did the change occur at a time of the year when burning is plausible, at that location? (seasonal weighting)

d) Is there evidence of burning in the pixel neighborhood, during the change point day and during previous days? (Markov Random Field segmentation)

The first three questions are addressed analysing time series of data at the level of a single pixel, while answering the last question requires taking into account the information contained in areas defined by a variable number of pixels. Question a), estimating the point in time at which the statistical properties of a series of NIR surface reflectance data have changed, is addressed with a Change Point Detection (CPD) technique. Once potentially multiple change points (CP) have been identified, question b) is answered by scoring each CP based on spectral characteristics related to the NIR reflectance change associated with it. Question c) aims at down weighting CP that occur outside of a locally defined typical fire season, and thus are unlikely to represent vegetation burning. This step attempts to reduce potential commission errors. Finally, d) revises the initial (a-c) burned area detection and mapping, in the light of evidence of burning in the spatial neighborhood of a given pixel, during the day it was detected and also during a short preceding period, yielding the final burned area map. Figure 1 illustrates the proposed algorithm.

Prior to performing change point detection on the daily NIR reflectance data at each pixel, the time series are filtered to remove noise observations. Initially, time series turning points are identified, and only the minima values at each BRDF-induced oscillation are kept for further analysis. Next, remaining spurious observations, mostly cloud shadows, are eliminated with the robust filtering approach of Fried et al. (2004).

2.2 Change point detection

Changepoint detection within time series consists of two steps: i) choice of criteria to optimize and ii) algorithm for optimization. The Pruned Exact Linear Time (PELT) algorithm (Killick et al., 2012) produces exact optimization of change point segmentations in linear computational time. This is achieved using dynamic programming to reduce the computational time to $O(n^2)$ and pruning to further reduce the computational time to $O(n)$. PELT can be implemented with many optimization criteria. In this work we seek to identify

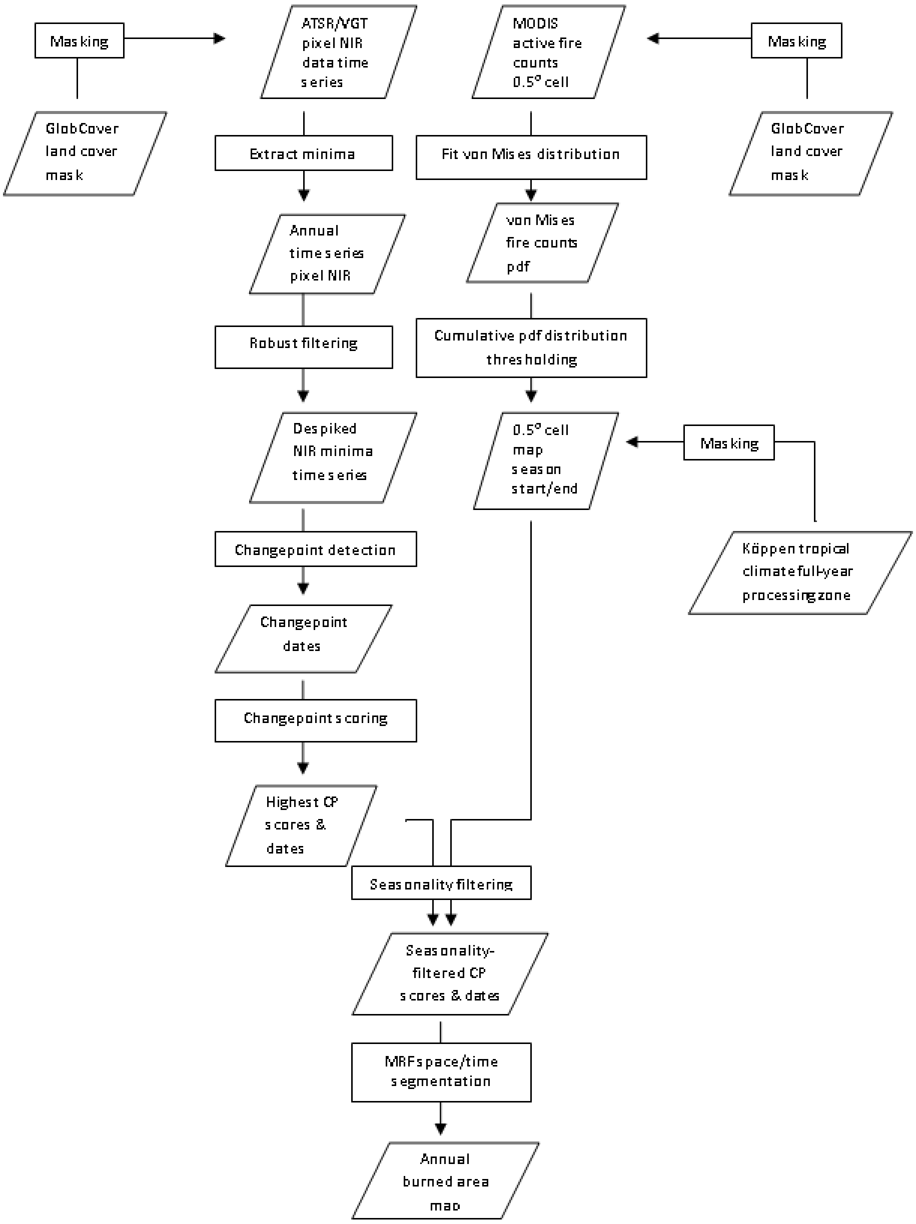

Figure 1: SPOT-VGT burned area classification and mapping algorithm.

changes in mean within NIR reflectan ce data. We assume that the NIR reflectance follows a Normal distribution with a constant variance and changing mean. Although not strictly true, the algorithm is robust vis-à-vis the moderate deviations from normality observed in our data. The Schwarz Information Criterion (SIC) is incorporated into the PELT parameterization, to penalize against identifying too many change points.

2.3 Change point scoring

The PELT/SIC approach to change point detection may yield several change points per pixel / time series, and per season, since the mean value of NIR reflectance data varies not only in response to burning but also as a function of cyclic weather patterns, atmospheric conditions, vegetation phenology and anthropogenic land cover changes. Therefore, it is necessary to determine which change point is the most likely to correspond to the identification of a burning event. Each change point is scored according to Equation 1:

$$1-\frac{\overline{S}_{i+1}-0.8*(\min\{y_i\}_{i=1:n},0.2)}{\overline{S}_i-0.8*(\min\{y_i\}_{i=1:n},0.2)} \qquad (1)$$

where

$\overline{S}_{i+1}$ mean ρNIR of the post-CP time segment

$\overline{S}_i$ mean ρNIR of the pre-CP time segment

$\min\{y_i\}$ minimum ρNIR value of the time series

This step yields two variables, the change point detection date, and the change point score, both of which are used in the subsequent algorithm steps.

2.4 Seasonality weighting

Global vegetation fire displays temporal patterns determined by a combination of climatic and anthropogenic factors (Giglio et al. 2006; Le Page et al., 2010) and typically occurs during the local dry season, which varies greatly in duration and timing. For global burned area mapping it is helpful assign higher weights to change points at dates close to the middle of the fire season, and lower weights to change points occurring either very early or very late in the season, to minimize the risk of false alarms caused by atmospheric effects and land use changes unrelated to vegetation burning. The fire season was defined on a 1° grid cell and 10-day composites, using MODIS global monthly active fire location product (MCD14ML, collection 5) for the period 2001-2009. The data were previously screened using the approach of Mota et al. (2006) and Oom and Pereira (2012). The total number of active fires detected in each grid cell and time composite over the study period were plotted as a circular histogram and fitted with a mixture of *n* von Mises probability distributions (Fisher, 1995). The number of von Mises distributions used varied from 1 to 2 corresponding, to uni and bimodal distributions, respectively. The 1º map of von Mises distributions was smoothed with a weighted mean filter, to avoid excessive influence of relatively local events, in regions with a long fire return interval. Values of the von Mises probability distribution for change points at each grid cell and time step were combined with change point scores using a look-up table approach.

2.5 Markov random field image segmentation

The previous steps of the algorithm lead to a characterization of each pixel of the image through two variables: change point score and detection date / von Mises distribution score. The rationale behind this last processing step is to establish a global classification of the pixels of the image taking into account the spatial relations between pixels and the time relations between dates of detection. The algorithm is a standard image processing algorithm that solves the maximum a posteriori – Markov random field (MAP-MRF) problem, which arises in image segmentation or image restoration. When there are only two classes, the MAP-MRF problem can be converted into finding a minimum cut in a certain graph and can be solved in polynomial time using the Ford-Fulkerson algorithm, or some of its variants Greig et al., 1989). In our case there are only two classes (burned and unburned) and therefore fast algorithms are available. The solution of the problem is the minimum source/sink-cut in the graph, where the source is the vertex “unburned” and the sink is the vertex “burned”. The minimum cut defines a 2-partition of the pixels in the graph: the first element of the partition are the pixels connected to the vertex “unburned” and the second element of the partition are the pixels connected to the vertex “burned”. This partitioning yields the segmentation of the image into unburned and burned pixels.

3. Results

Preprocessing of the data, with the selection of time series minima and data despiking at each pixel yielded a time series much less prone to the detection of spurious change points than the original dataset. Figure 2 shows results of these procedures.

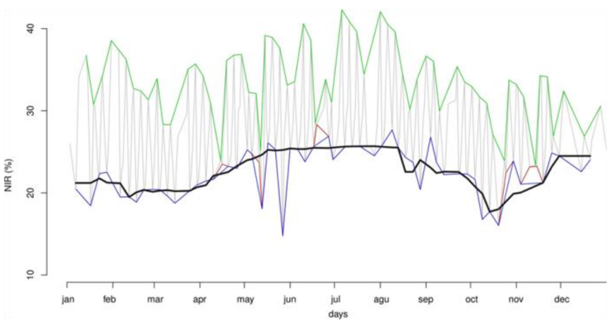

Figure 2: SPOT-VEGETATION time series (grey) for a single pixel over one full year. Turning points are shown in green (maxima) and red (minima). Blue line shows time series of minima without high values produced by spurious oscillations. Black line shows time series of minima with spikes removed by robust filtering.

Figure 3 illustrates the result of change point detection using PELT. In spite of the SIC penalization, multiple change points are still detected. Change point scoring identifies the date considered more likely to correspond to a fire event. Change points associated with an increase in NIR reflectance, not expected to be associated with land surface burning are assigned a negative score.

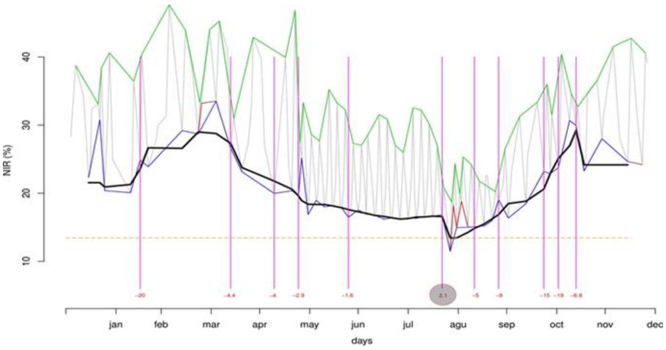

Figure 3: Change points (vertical purple bars) detected on the time series of filtered minima (black line), using PELT/SIC with corresponding scores. Maximum score (gray circle) shows change point most likely to represent a burning event, in late July.

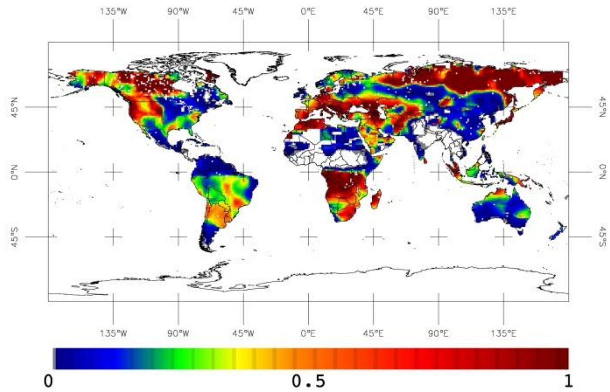

Figure 4. Fire seasonality weights for the period August 1 – 10.

An illustrative example of the graph generated by the MRF algorithm for a 10*10 pixel area is shown in Figure 5. The green links show pixels connected to a certainly unburned pixel and the red links show pixels connected to a certainly burned pixel.

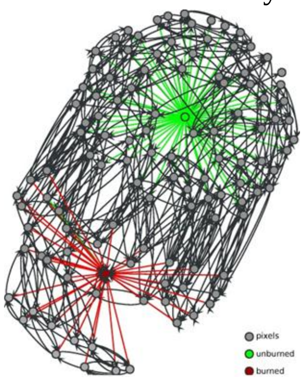

Figure 5: Topology of the graph of the MAP-MRF problem for a 10 x 10 pixel area. The pairs of connected pixels are spatial first-order neighbors and have detection dates at most 20 days apart. The solution of the MAP-MRF problem is partition of the pixels in an "unburned" and a "burned" component defined by the minimum cut in this graph.

An example of intermediate and final image classification maps is provided in figure 6, below, for the northern Australia study site, in 2005. The upper left map shows the change point scores, where red indicates locations more likely to have burned. The upper right side map show the detection dates of the change points. Burned areas appear as spatially coherent patches of similar detection dates. The map on the lower left shows the combination of change point scores and detection date scores and, finally, the lower right map displays the burned area classification, after spatio-temporal revision of the combined scores, performed with the MRF algorithm.

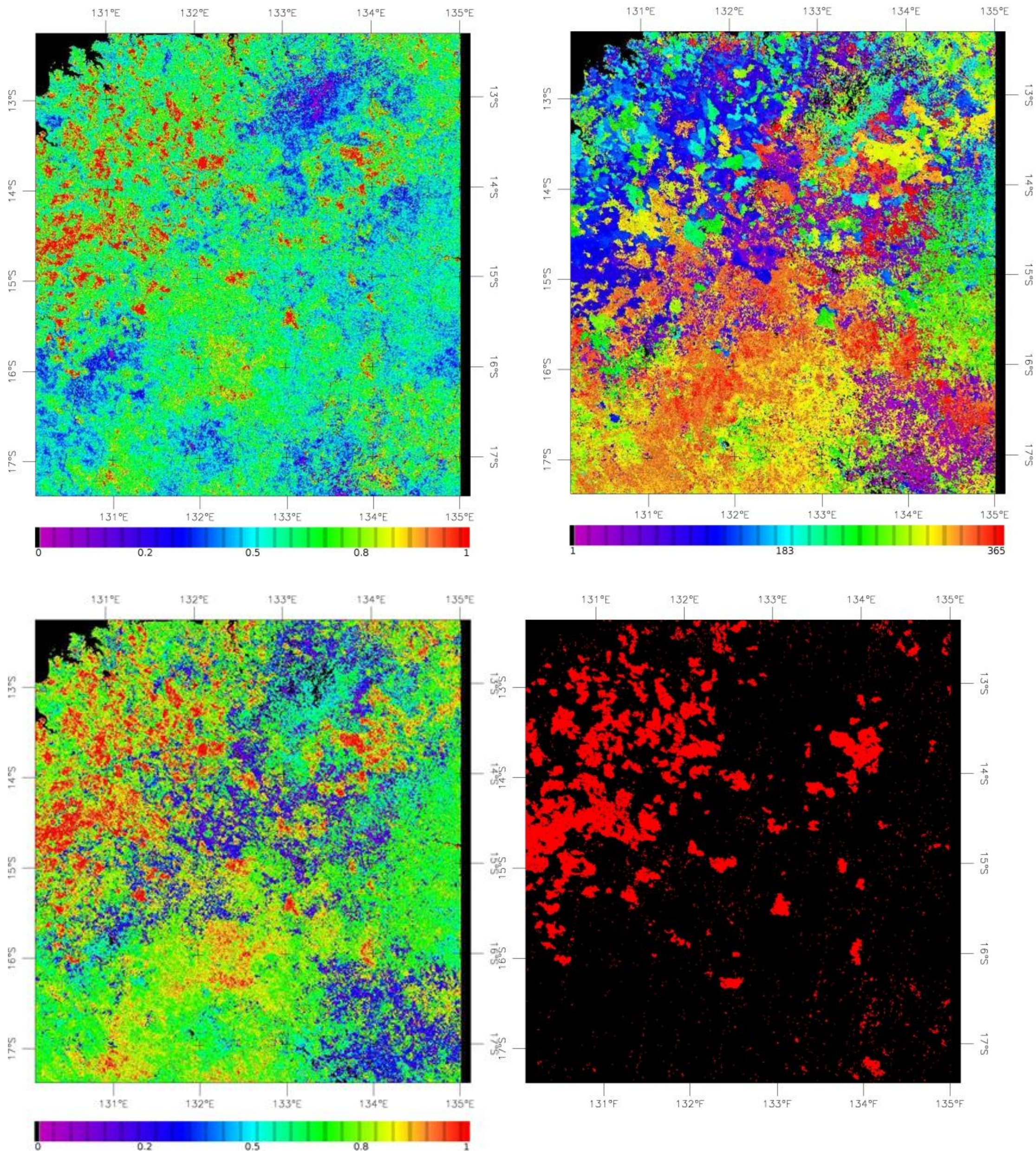

Figure 5. Northern Australia study site, 2005. UL – change point scoring; UR – change point date; LL – combined change point and detection date scores; LR – burned area classification.

4. Conclusions

The proposed algorithm for developing daily global burned area maps at 1 km spatial resolution, using SPOT-VGT satellite imagery produces good results, as illustrated with an example from the northern Australian study site for the year 2005. The algorithm has been applied to the other nine study sites, with comparably good results. The algorithm is currently undergoing minor refinements. The accuracy of final results will be assessed against a large set of high resolution (Landsat-based) burned area maps, prior to release of the dataset for public use.

5. References

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