MODIS 250M Burnt Area Detection Algorithm: A Case Study Applied, Optimized and Evaluated over Continental Portugal.

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<table>
<thead>
<tr>
<th>I – Background</th>
</tr>
</thead>
<tbody>
<tr>
<td>II – Overview</td>
</tr>
<tr>
<td>III – Data</td>
</tr>
<tr>
<td>IV – Algorithm</td>
</tr>
<tr>
<td>V – Optimization</td>
</tr>
<tr>
<td>VI – Results</td>
</tr>
<tr>
<td>VII – Discussion</td>
</tr>
</tbody>
</table>
Background

• **Burned area (BA)** analysis is based on detecting the char/ash/scar signals, if preceded by vegetation, the change highlights a fire event.

• Compared with the **VISIBLE** (0.4-0.7 µm) and the **SWIR** (2.0-2.5 µm) the **NIR** is, unquestionably, the best spectral region to **discriminate** between burned areas and other surfaces, such as vegetation and not-too-dark soils. NIR reflectance can only decrease.
MODIS sensor spectral bands (1-19)

<table>
<thead>
<tr>
<th>Band</th>
<th>Wavelength (nm)</th>
<th>Resolution (m)</th>
<th>Primary Use</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>620–670</td>
<td>250</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>841–876</td>
<td>250</td>
<td>Land/Cloud/Aerosols Properties</td>
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<tr>
<td>3</td>
<td>459–479</td>
<td>500</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>545–565</td>
<td>500</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>1230–1250</td>
<td>500</td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>1628–1652</td>
<td>500</td>
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</tr>
<tr>
<td>7</td>
<td>2105–2155</td>
<td>500</td>
<td></td>
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<tr>
<td>8</td>
<td>405–420</td>
<td>1000</td>
<td></td>
</tr>
<tr>
<td>9</td>
<td>438–448</td>
<td>1000</td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>483–493</td>
<td>1000</td>
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<tr>
<td>11</td>
<td>526–536</td>
<td>1000</td>
<td></td>
</tr>
<tr>
<td>12</td>
<td>546–556</td>
<td>1000</td>
<td></td>
</tr>
<tr>
<td>13</td>
<td>662–672</td>
<td>1000</td>
<td></td>
</tr>
<tr>
<td>14</td>
<td>673–683</td>
<td>1000</td>
<td>Ocean Color/ Phytoplankton/ Biogeochemistry</td>
</tr>
<tr>
<td>15</td>
<td>743–753</td>
<td>1000</td>
<td></td>
</tr>
<tr>
<td>16</td>
<td>862–877</td>
<td>1000</td>
<td></td>
</tr>
<tr>
<td>17</td>
<td>890–920</td>
<td>1000</td>
<td>Atmospheric Water Vapor</td>
</tr>
<tr>
<td>18</td>
<td>931–941</td>
<td>1000</td>
<td></td>
</tr>
<tr>
<td>19</td>
<td>915–965</td>
<td>1000</td>
<td></td>
</tr>
</tbody>
</table>

Band 2 used for BA detection

- The algorithm presented is a spin-off of one of classification algorithms developed for VGT and AATSR under the FIRE-CCI project.
- The algorithm was already applied to the South American tropical forest (EGU 2013 poster)
Aim

Develop a **BA detection** algorithm for NIR imagery captured by satellites with **high frequency** of observation.

**Objective**

**Adjust and optimize** the BA algorithm to MODIS 250 m² imagery for continental **Portugal** for the period (2001-2013).
I – Background

II – Overview

III – Data

IV – Algorithm

V – Optimization

VI – Results

VII – Discussion
Overview

1. Did a significant and persistent drop in reflectance occur at a given pixel?
   - Spectral analysis: Score changes when and how.
     - Change detection algorithm

2. Did it occur in the right time of the year?
   - Temporal revision: Compare with known fire seasonality to separate other from source of change.
     - Prob. LUT of Scores vs. Fire seasonality

3. Is it coherent with its surroundings?
   - Spatial revision: Look for evidence for similar changes in the nearby pixels.
     - MRF segmentation dates & probabilities
I – Background

II – Overview

III – Data

IV – Algorithm

V – Optimization

VI – Results

VII – Discussion
Data

• MODIS 250 m² (MOD09DQ) daily NIR band (2) images for tiles covering continental Portugal (h17v04 and h17v05) for the period 2001-2013 – input to the algorithm

• MOD09DA cloud mask layer information available from the 500 m² reflectance daily images (2001-2013) – cloud screening.

• Fire Activity Distribution (0.5°) based on adjustments made with von Mises distributions to active fire counts (Benali et al. 2012) – penalize off-season events.

• Landsat derived BA binary maps at 30 m² (2001-2009) – parameter optimization and accuracy assessment.
I – Background
II – Overview
III – Data
IV – Algorithm
V – Optimization
VI – Results
VII – Discussion
Time-series analysis

Time-series of the NIR reflectance for a pixel located in the centre of Portugal over forest for year 2005.
**Time-series analysis - Construct a series of ρNIR minima**

Determine the upper and lower envelopes of time series. Oscillation **maxima** are "noisier", affected by residual atmospheric contamination.
• **Robust filtering** of minima time series, to remove cloud shadow spikes in \( \rho_{\text{NIR}} \).

• Determine the absolute **minimum** reflectance of the time-series.

\[
\min\{y_i\}_{i=1:n}
\]
Time-series analysis – Change detection

**Change points** are those points in time which divide a data set into distinct homogeneous segments.

**Pruned Exact Linear Time (PELT):** changes in mean $\rho$NIR, assuming it follows Normal distribution with constant variance and changing mean (Killick *et al.*, 2012).
**Time-series analysis – Change point scoring**

CP scores represent the “likelihood” of corresponding to a perturbation event. The score magnitude at a given CP is determined by the ratio between $\bar{\rho}_{\text{NIR}}$ drop and its potential drop.

$$\frac{\bar{S}_i - \bar{S}_{i+1}}{\bar{S}_i - K}$$

where

- $\bar{S}_{i+1}$ is the mean $\rho_{\text{NIR}}$ of the post-CP time segment
- $\bar{S}_i$ is the mean $\rho_{\text{NIR}}$ of the pre-CP time segment
- $M$ is $\min\{y_i\}_{i=1:n}$
- $K$ is $0.8*M \Rightarrow M < 0.2$

$0.8*0.2 = 0.16 \Rightarrow M \geq 0.2$

- Factor to allow better discrimination post-change
- $\rho_{\text{NIR}} = \text{minimum } \rho \text{ value.}$

- Increases the spectral difference between post-change reflectance and the time series minimum
Form all change points that are associated with a decrease select the one with the highest score. It represents the biggest disturbance leading to lower reflectance.
NIR perturbations due to vegetation removal may also result from other causes: harvesting, grazing, windthrow, or defoliation by plant pests and diseases.

CP score and associated date will serve as inputs to the temporal revision.
The conversion of perturbations into “probabilities” takes into account the date of the year and the magnitude of the scores. LUT probability surface is defined assuming 2 types of score vs. Seasonality relations: Off fire-season (A) and during fire-season (B) and is generated from 3 parameters (P1, P2, P3). Rate of change is defined by a logit function (P4, P5).
Spatial revision

• The last processing step is to **classify the pixels** taking into account the **spatial** and **temporal** relations between them.

• The solution is one that solves the maximum a posteriori – Markov random field (MAP-MRF) problem by determining the **max. flow/min. source-sink cut** in a graph, where the source is the vertex “unburned” and the sink is the vertex “burned”.

• This partition gives the segmentation of the image into unburned and burned pixels.
Spatial revision

Vertex are the pixels that have edges:

1. connecting to “unburned” or “burned” with length defined by the burnt probability. Decision to which made by a threshold (Tr).

2. connecting surrounding pixels with length defined by the day difference over a maximum allowed (Dmax).
MODIS 250M burnt area detection algorithm

Optimization Scheme

**Input Variables**

1. **Bootstrap Resampling**
   - Calibration Data Set (70%)
   - Validation Data Set (30%)

**Optimization**
Search for the Parameters set that Maximize Coen’s Kappa

**Evaluation**

Optimization Scheme

N = 50
II – Overview
III – Data
IV – Algorithm
V – Optimization
VI – Results
VII – Discussion
Algorithm Performance

<table>
<thead>
<tr>
<th>Calibration</th>
<th>Validation</th>
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<tbody>
<tr>
<td>Comission</td>
<td>Comission</td>
</tr>
<tr>
<td>Omission</td>
<td>Omission</td>
</tr>
<tr>
<td>Kappa</td>
<td>Kappa</td>
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</tbody>
</table>

- Initial Empirical Parameters
- Optimized Parameters
- Optimized Parameters with Spatial Revision
I – Background
II – Overview
III – Data
IV – Algorithm
V – Optimization
VI – Results
VII – Conclusions
Conclusions

• The flexibility of the algorithm to bad data and atmospheric contamination.

• Easily adapted to other regions limited only by the availability and consistency of a time series of observations.
Future work

• Explore the use of Object based classifications to the resulted date of the year maps

• Improve the optimization procedure and evaluate the cost function of the spatial revision

• Adjust parameters and apply to Mediterranean regions (not only in Europe but also in US, Australia, South America and Australia)
References

Benali A., Mota B., Pereira J.M.C., Oom D., Carvalhais N. "Global patterns of vegetation fire seasonality" In proceeding of European Geophysical Union General Assembly (2013)


Mota B., Pereira J.M.C., Campagnolo M., Killick R. "MODIS 250m burned area mapping based on an algorithm using change" (2013) In proceeding of European Geophysical Union General Assembly (2013)

Thank you