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Short contribution – Decision Support Systems and Tools

Global generation of long-term burned area with AVHRR-LTDR data

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1. Introduction

Burned Area (BA) information is critical to assess the impacts of biomass burning, both in atmospheric emission models and dynamic vegetation studies (Hantson et al. 2016). Therefore, the fire variable is inside of Essential Climate Variables (ECV) for the Global Climate Observing System (GCOS) program. This work is part of the Fire Disturbance project, part of the Climate Change Initiative (CCI) Programme of the European Space Agency (ESA).

Current global burned area products expand from 1995 to 2017, being consistent as of 2001 (Mouillot et al. 2014). Longer time series would be desirable to analyze the impacts of climate cycles. This paper presents the development of a global BA algorithm adapted to Land Long-Term Data Record (LTDR, version 5, Pedelty et al. 2007), a time series based on NOAA-AVHRR (Advanced Very High Resolution Radiometer) data that covers the period from 1982 to 2017.

2. Methods

2.1. LTDR and composites

The LTDR is based on images acquired by the AVHRR sensor on board the NOAA satellites from 1981 until the present. This dataset includes atmospheric and geometric corrections of AVHRR data and provides daily thermal and reflectance values at 0.05° (≈ 5 km) of spatial resolution (Pedelty et al. 2007). As LTDR daily images present noise, radiometric instability and distortion, monthly composites were created by selecting the most adequate observation for burned area discrimination. The criterion to create the composites was based on selecting the maximum temperature of the period. This method improves the burn pixel separability and avoids clouds and shadows. (Chuvieco et al. 2005).

In addition, the unburnable areas were masked out with information derived from the CCI Land Cover product (Version 1.6.1., Kirches et al. 2013).

2.2. MCD64

The MCD64A1 dataset (Collection 6, Giglio et al. 2009) is generated through MODIS images from it is available (2001-present). The dataset is used to train the model as reference BA.

2.3. Synthetic index

A synthetic index was created from the different spectral bands (RED, NIR, Temperature channel 5), derived indices (GEMI, BAI) and temporal differences. The input bands were selected based on their spectral discriminability between burned and unburned areas. The final formula is:

$$LTDR \quad BA \quad index = \frac{T5 - mean\ T5}{std\ T5} - \frac{T5\_diff - mean\ T5\_diff}{std\ T5\_diff} - \frac{Red - mean\ Red}{std\ Red} +$$

$$\frac{Red\_diff - mean\ Red\_diff}{std\ Red\_diff} - \frac{NIR - mean\ NIR}{std\ NIR} + \frac{NIR\_diff - mean\ NIR\_diff}{std\ NIR\_diff} + \frac{GEMI - mean\ GEMI}{std\ GEMI} +$$

$$\frac{BAI - mean\ BAI}{std\ BAI} + \frac{BAI\_t+1 - mean\ BAI\_t+1}{std\ BAI\_t+1}$$

where

T5 = TOA brightness temperature of Channel 5 (~11.5 – 12.5 μm)

T5_diff = $T5_{t-1} - T5_t$, where t = monthly composite being analyzed, and t-1 = composite of the previous month.

Red = Surface reflectance of Channel 1 (0.5 – 0.7 μm)

Red_diff = $Red_{t-1} - Red_t$

NIR = Surface reflectance of Channel 2 (0.7 – 1.0 μm)

NIR_diff = $NIR_{t-1} - NIR_t$

GEMI (Global Environmental Monitoring Index, Pinty and Verstraete 1992) as:

$$GEMI = \eta * (1 - 0,25\eta) - \frac{\rho_R - 0,125}{1 - \rho_R} \qquad \eta = \frac{2*(\rho_{IR}^2 - \rho_R^2) + (1,5*\rho_{IR}) + (0,5*\rho_R)}{\rho_{IR} + \rho_R + 0,5}$$

Being ρ_R and ρ_{IR} the reflectivity in the red and infra-red bands, respectively.

BAI, the Burned Area Index (Martín and Chuvieco 1998):

$$BAI = 1 / ((\rho_{IR} - \rho_{cIR})^2 + (\rho_R - \rho_{cR})^2)$$

where ρ_{cIR} and ρ_{cR} are the convergence values for burned vegetation (defined for AVHRR as 0.06 and 0.1, respectively).

BAI_{t+1} is the BAI of the posterior monthly composite.

Seasonal variation of this index was also taken into account for training. So, the phenology variability is represented in the different months.

2.4. Random Forest

Random Forest (RF, Breiman 2001) is a machine-learning classifier based on a random combination of decision trees. RF classified each pixel by the number of times that pixel is assigned to a particular category. In our case, 600 trees were created for each monthly model (from January to December). RF models were created combining monthly composites of LTDR data from several years (both with high and low fire occurrence). Then, they were applied to the full-time series, a different model for each month of the year.

The output of RF was a probability per month and year.

2.5. Sensitivity analysis and percentage

Since the burned pixels are much more unlikely than the unburned, we performed a sensitivity analysis to obtain the appropriate cut-off threshold to improve overall accuracy and balance between omission and commission errors. Uncertainty information was estimated from the probability of RF.

A temporal analysis of the pixels that are burned in the MCD64 every month and its percentage was made. A value was assigned to each pixel per month and applied to the result of the sensitivity analysis.

2.6. Validation

The final classification was compared with the most recent NASA BA product (MCD64A C6) for common years (2001 - 2016). The confusion matrix of each model was calculated, in addition to commission and omission error and Dice coefficient.

$$Dice\ Coefficient = \frac{2 \cdot True\ Positives}{2 \cdot True\ Positives + False\ Positives + False\ Negatives}$$

3. Results

The algorithm has been applied for whole time series (1981 - 2017). The product generated is the first to consistently offer such long time series, doubling the current time series. The study of sensitivity and percentage improve significantly the results.

The months with high fire occurrence obtained better results than months with low fire occurrence. Omission and commission errors were found quite balanced in the time series. Specifically, commission and omission error for the month of January is 0.53 and 0.47 and July is 0.49 and 0.57, respectively. Average Dice coefficients were 0.50 for January and 0.46 for July. The best month was December (Figure 1) with 0.41 in commission error, 0.43 as omission error and a Dice coefficients of 0.58.
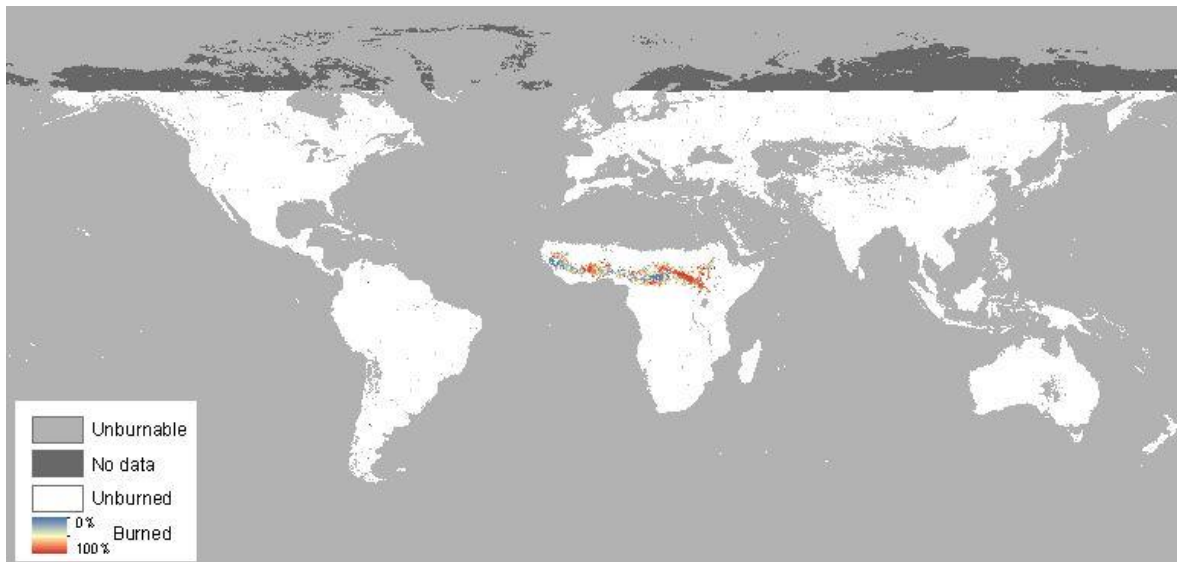

Figure 1 - Percentage BA of LTDR data for December 2008

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