



## Review Article

# Burned area estimations derived from Landsat ETM+ and OLI data: Comparing Genetic Programming with Maximum Likelihood and Classification and Regression Trees

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## ABSTRACT

Every year, large areas of savannas and woodlands burn due to natural conditions and land management practices. Given the relevant level of greenhouse gas emissions produced by biomass burning in tropical regions, it is becoming even more important to clearly define historic fire regimes so that prospective emission reduction management strategies can be well informed, and their results Measured, Reported, and Verified (MRV). Thus, developing tools for accurately, and periodically mapping burned areas, based on cost advantageous, expedite, and repeatable rigorous approaches, is important. The main objective of this study is to investigate the potential of novel Genetic Programming (GP) methodologies for classifying burned areas in satellite imagery over savannas and tropical woodlands and to assess if they can improve over the popular and currently applied methods of Maximum Likelihood classification and Classification and Regression Tree analysis. The tests are performed using three Landsat images from Brazil (South America), Guinea-Bissau (West Africa) and the Democratic Republic of Congo (Central Africa). Burned areas were digitized on-screen to produce mapped information serving as surrogate ground-truth. Validation results show that all methods provide an overestimation of burned area, but GP achieves higher accuracy values in two of the three cases. GP is the most versatile machine learning method available today, but still largely underused in remote sensing. This study shows that standard GP can produce better results than two classical methods, and illustrates its versatility and potential in becoming a mainstream method for more difficult tasks involving the large amounts of newly available data.

## 1. Introduction

In tropical regions, large areas of savanna and woodlands burn every year. Occurring mainly during the dry season when herbaceous vegetation has dried out, fires are one of the main drivers of ecosystem transformation or maintenance (Bucini and Lambin, 2002), also releasing gases and particles into the atmosphere (Smith et al., 2007). In fact, estimates show that burning of savannas and woodlands in Sub-Saharan Africa accounts for more than 50% of the total global emissions from biomass burning during any typical year (Williams et al., 2012).

Land management practices induced by human activities are at the base of the majority of fire occurrences in the tropics. Shifting cultivation, agricultural expansion, deforestation and harvesting are some of the practices involving fires that may contribute to partial or complete

destruction of vegetation cover, depending on fire intensity and combustion efficiency (Bucini and Lambin, 2002; Daldegan et al., 2014). Significant intensification of fire frequency or avoidance of fire occurrence can negatively affect existing ecosystems and have impacts on vegetation composition, landscape patterns, habitat types, and soil erosion processes, which in turn affect hydrological processes and the carbon cycle. Therefore, accurate and multi-temporal burned area maps are important tools that can help fire and land managers understand and assess the impacts of specific interventions, while informing landscape management strategies.

Multi-temporal data records of fire distribution, extent, and timing, correspond to historical activity data, which together with vegetation emission factors, support the quantification of emissions. The establishment of emission baselines against which the results of subsequent

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vegetation and fire management actions can be compared is essential for the Measuring, Reporting and Verification (MRV) activities necessary in carbon accounting procedures. Thus, accurately and frequently mapping burned areas over large extents, using cost advantageous, periodic, and expedite approaches is very desirable.

In the last decade, several methodologies based on remote sensing techniques have been developed and applied to recurrently map burned areas in tropical ecosystems. Some were based on coarse spatial resolution satellite data such as Moderate Resolution Imaging Spectroradiometer (MODIS), Along Track Scanning Radiometer (ATSR)/Advanced ATSR (AATSR), Satellite pour l'Observation de la Terre (SPOT) Vegetation (VGT) and National Oceanic and Atmospheric Administration (NOAA)/Advanced Very High Resolution Radiometer (AVHRR) (Brivio and Maggi, 2003; Giglio et al., 2009; Silva et al., 2005; Grégoire et al., 2003; Zhang et al., 2015). These are adequate for global and regional scale studies but are insufficient for local applications where higher detail is needed and medium to high resolution sensors are preferable for accurately mapping burned areas (Stroppiana et al., 2012).

The higher resolution sensors Landsat TM (Thematic Mapper), ETM+ (Enhanced Thematic Mapper) and OLI (Operational Land Imager) are a valuable source of information and have been widely used in the development of automated methods to detect burned areas (Bastarrika et al., 2011; Chen et al., 2016; Daldegan et al., 2014; Hudak et al., 2004; Júnior et al., 2014; Korontzi et al., 2003; Hawbaker et al., 2017; Meddens et al., 2016; Laris, 2005; Liu et al., 2018; Melchiori et al., 2014; Matricardi et al., 2013; Oumar, 2015; Smith et al., 2007; Stroppiana et al., 2012; Trisakti et al., 2016). Even though classification of burned areas using Landsat images provide satisfactory results with classical approaches (Morton et al., 2011), the spectral similarities between burnt surfaces and other land cover categories, such as, water bodies, shadows, and mixed water-vegetation, still introduce spectral confusion and overlap with other classes. Therefore, it is important to explore new methods capable of increasing the discrimination between burns and other landscape features, minimizing the uncertainties (Giglio et al., 2010; Jain, 2007).

This study aims at investigating if there are comparative advantages in using Genetic Programming (GP) – one of the most powerful and underused flavors of machine learning – for identifying and mapping burned areas in Landsat ETM+/OLI imagery when compared to Maximum Likelihood classification (MLK) and Classification and Regression Tree analysis (CART) – two classical classification methods. Our research is conducted over three study areas located in Brazil, Guinea-Bissau, and the Democratic Republic of Congo. The respective tropical territories are subject to frequent and extensive fires, mainly due to human activity.

The merit of each approach is assessed by calculating the overall accuracy, *Dice* and *kappa* coefficients, and omission and commission errors over a representative sample grid of points extracted from the images. According to Padilla et al. (2014), measures such as the *Dice* coefficient that are focused on a single category (i.e. burned), are the most appropriate in the validation of Burned area products. Additionally, the agreement of the classifications with surrogate ground-truth burned area maps is calculated based on precision and recall measures (Powers, 2007). Surrogate ground-truth is obtained from visual interpretation and on-screen digitizing of burned area perimeters over the entire images. In order to assess the similitude of the overall landscape structure obtained from the on-screen digitizing with that obtained from the classifications, a set of landscape metrics are also derived and compared.

Several authors applied MLK and CART to map burned areas (Chen et al., 2016; Henry, 2008; Meddens et al., 2016; Sá et al., 2003; Sertel and Alganci, 2016; Silva et al., 2003; Thariqa et al., 2016; Verlinden and Laamanen, 2006), however, very few studies exist for GP (Silva et al., 2010). Djerriri and Mimoun (2015) successfully applied a new approach combining unsupervised classification and GP to

automatically extract burned areas from Landsat 8 imagery. Also, Brumby et al. (2001) obtained encouraging results when applying GP to extract wildfire scars from Landsat 7 imagery, but found some confusion with dark cloud shadows and bare ground/rock outcrops. More recently, a different type of GP, called Geometric Semantic Genetic Programming (GSGP) (Vanneschi, 2017), was used by Castelli et al. (2015) for identification of burned areas. Although GSGP is a very powerful method, it does not provide readable models. Even though very few applications of GP for classification/data extraction of remote sensing images can be found in the literature, GP has been successfully used in several other areas, e.g., modeling and regression, image and signal processing, time series prediction, control, medicine, biology and bioinformatics, and even arts and entertainment (Poli et al., 2008). GP often yields results that are not merely academically interesting, but competitive with the work developed by humans (Koza, 2010). It is the master algorithm of evolutionary computation, and the only one with the potential to emulate all the other machine learning approaches (GP can evolve decision trees, neural networks, Bayesian networks, and almost anything else one can think of) (Domingos, 2015).

New sensors, such as those on board of the European Union (EU) Sentinel satellites<sup>1</sup> provide free full global coverage and high frequency optical and radar imagery. The EU Copernicus program, which also aims at providing environmental monitoring services for South America and Africa,<sup>2</sup> can become a driver for the systematic and high periodicity production of high resolution burned area maps over tropical regions. Therefore, methodological developments that contribute to improve operational processes while improving output accuracy may increase the usefulness of products and facilitate their respective diffusion. Recent studies have shown the feasibility of using distributed GP in long running systems dealing with big data (Hodjat et al., 2014).

## 2. Study areas and data

### 2.1. Study areas

One study area located in Brazil and two in Africa were chosen to test the performance of the burned area mapping methods: the south-eastern Amazonian region of Brazil, the Coastal western region of Guinea-Bissau, and the central eastern region of Congo; each corresponding to one complete Landsat image as shown in Fig. 1.

The first area, located in eastern Amazonia, in southeastern Pará, Brazil (BRZ site) lies to the south of the Amazon River which is drier than the central and western parts of the Amazon, with annual rainfall between 1500 mm and 2000 mm and average temperatures ranging from 23 °C to 30 °C. Forests types range from lowland Amazon forest (tall trees to 40 m in height) in the north through submontane dense and open forests in the south (Olson et al., 2001). The Landsat image covers one of the most degraded regions in Amazonia, in the frontier with a drier and more populated zone where intense forest degradation driven by agriculture and cattle raising is occurring, mainly along the roads.

The second area is located in Guinea-Bissau (GB site), which is characterized by a marshy coastal plain with dry to moist (North to South) tropical climate. There are two marked seasons, a dry season between November and May, and a wet season between June and October. Total annual rain values vary from 2400 to 2600 mm in the Southwest region, and from 1200 to 1400 mm in the Northeast region (Marinho, 1946). The monthly average temperature ranges from 25.9 and 27.1 °C (Catarino, 2004). The vegetation consists of mangroves on the coast, and gradually becomes composed of mainly dry forest and savanna inland. The extent of natural vegetation patches has been decreasing in the last decade mainly due to the intensification of

<sup>1</sup> [http://www.esa.int/Our\\_Activities/Observing\\_the\\_Earth/Copernicus/Overview4](http://www.esa.int/Our_Activities/Observing_the_Earth/Copernicus/Overview4).

<sup>2</sup> <http://www.copernicus.eu/>.

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