Proposing an improved routine for quantifying and forecasting fire incidence in Amazonia using remote sensing information

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Abstract. Tropical forest fires are one of the most pressing environmental problems of the 21st century. In Amazonia, fire frequency has increased during the last decade as a consequence of climate variability and prolonged dry seasons (1998, 2005 and 2010 droughts) and human activities. To contribute with the monitoring and mitigation of these fire events, the objective of this paper is to propose a new routine for predicting fire probabilities in Amazonia using information derived from satellite products and field data. Our method is based on weights-of-evidence statistics, which allows the calculation of fire probabilities based on the explanatory power of the driving variables. It takes advantage of the wide range of freely available spatially-explicit products, on deforestation, degradation, land cover, fire incidence, rainfall and sea surface temperature. The modelling routine is divided in 4 stages: (1) Spatial Planning, (2) Anticipated Temporal Action, (3) Immediate Temporal Action, and (4) Monitoring. In this paper we present the model concept and some examples of the input datasets. Our method is based on the state of our knowledge on the drivers of fire occurrence, to produce a method that is scientifically relevant for analysing and predicting fire patterns, but also relevant for policy applications for preventing and mitigating fire problems in Amazonia. By combining historical and short-term drivers of the temporal and spatial variation of fire incidence in a unique model, we expect to significantly improve prediction power of fire occurrence.

Keywords: MODIS, TRMM, fire, spatial planning, fogo, monitoramento.

1. Introduction

Tropical forest fires are one of the most important environmental issues of the 21st century. In the world's largest tropical forest, Amazonia, fire frequency has increased during the last decade as a consequence of climate variability and prolonged dry seasons (1998, 2005 and 2010 droughts) and human activities (Aragão and Shimabukuro, 2010). These fires that can leak into surrounding undisturbed forests are likely to have a relevant contribution to global carbon emissions from land use change. The estimated global flux of CO_2 to the atmosphere from land use change was 1.3 ± 0.7 Pg C yr^{-1} (Pan et al., 2011). This corresponds to 15% of the total fossil fuel emissions (8.7 ± 0.5 Pg C yr^{-1}) in 2008 (Le Quere et al., 2009).

Mitigation of fire in the Amazon region is therefore a critical step for efficient reduction in carbon emissions from land use change. One way forward is to improve our understanding of fire regime and how it may change according to shifts in land use and climate to allow the prediction of fire incidence at an scale that permit operational actions for avoiding fire occurrence and consequent impacts on carbon emissions, ecosystem services and human health.

Pioneering studies have attempted to develop models of fire risk for Amazonia. Cardoso et al. (2003) analysed climatic and biophysical variables to model fire occurrence on a 2.5^o by 2.5^{o}grid cell resolution for the dry seasons of 1995 and 1997. Nepstad et al. (2004) developed RisQue, a model that estimates plant available water (PAW) as an indicator of forest fire risk for the entire Amazon, and Alencar et al. (2004) quantified the relationship between landscape parameters and forest fire occurrence in the eastern Amazon. Finally, Sismanoglu and Setzer (2005) developed a model to calculate the risk of fire at a spatial resolution of 0.25^{o} by 0.25^{o} for the entire Brazilian territory, taking into account climatic and vegetation variables processed at daily time steps. Silvestrine et al. (2011) developed a model to estimate the probability of fire occurrence by integrating climatic conditions (as described by vapour pressure deficit [VPD] data) with a series of biophysical and land-use variables, such as elevation, distance to roads and towns, and legal restrictions (i.e., protected vs. non-protected areas). Recent research from Chen et al. (2011) demonstrated that increased fire intensity is strongly correlated to changes in sea surface temperatures (SSTs) in the Pacific and Atlantic Oceans in Amazonia using 5^{o} by 5^{o}grid cell resolution.

All of these studies have produced significant advances in fire modelling methods and understanding of spatial and temporal dynamics of fires. We aim to build upon this knowledge, taking advantage of the immense amount of freely available satellite-derived information, and propose a novel integration approach for analysing fire risk in Amazonia. To contribute with the monitoring and mitigation of fire events in the region, the objective of this paper is to propose a new routine for predicting fire probabilities in Amazonia using information derived from satellite products and field data. Our method is based on weights-of-evidence statistics, which allows the calculation of fire probabilities based on the explanatory power of the driving variables. The paper is organized in four sections. Section 1 gives a brief introduction to the problem; section 2 focuses on the methodology, mainly describing the dataset to be used as inputs to the model; section 3 presents a discussion on the logic and steps for the development of the conceptual model and section 4 presents the conclusions. In section 3, we also expose examples of key metrics derived from the analysis of temporal and spatial remote sensing information that can be used in the model.

2. Methodology

2.1. Dataset – inputs and outputs

The modelling routine is designed to assimilate historical fire probability maps generated through the integration of a multi-year, decadal scale active fire product derived from MODIS (2000-2011). The system takes into account yearly and monthly deforestation rates derived from the National Institute for Space Research (INPE) PRODES and DETER projects, respectively. These metrics are complemented by historic trends in deforestation and fires that are calculated following the methodology proposed by Aragão and Shimabukuro (2010). Land use management maps are obtained from the Global Land Cover 2000 (GLC2000) dataset (Eva et al., 2004), updated using deforestation information from INPE's PRODES project. Landscape metrics are derived from INPE's TERRACLASS and PRODES data. TERRACLASS is used to derive the area of secondary forests, while PRODES is used to extract the landscape metrics. The metrics that feed the system are: number of fragments, forest edge extent and mean fragment area/perimeter ratio. Fuel loads map for Amazonia are derived from the integration of field-based information on fuel loads in different land cover types, burned scar maps and biomass stocks maps derived from Saatchi et al. (2011). Moreover, the system assimilates spatially explicit information on the pixel based correlations between sea surface temperature (SST) and active fires and rainfall. SST anomalies are produced by the National Oceanic and Atmospheric Administration (NOAA) and include the Atlantic Multidecadal Oscillation (AMO) index and the El Niño index. Fire data is derived from the Moderate Resolution Imaging Spectroradiometer (MODIS) active fire dataset (MOD14) and precipitation from the Tropical Rainfall Measuring Mission (TRMM) 3B43 V7 product. Finally, following the methodology proposed by Aragão et al. (2007), data on the climatological water deficit derived from the TRMM dataset is calculate for inclusion in the system.

3. Development of the Conceptual Model

In this section, we discuss the logic for integrating the above dataset into a fire prediction system. The modelling routine is divided in 4 stages: (1) Spatial Planning, (2) Anticipated Temporal Action, (3) Immediate Temporal Action, and (4) Monitoring. Below we provide an overview of the logical steps for the development of the routine. Stage 3 of our system consists in monitoring the current available information on active fires and burned area and will not be discussed in this article.

2.2.1. Stage 1 - Spatial planning

Historically, a moderate to high occurrence of fires (60-100% probability) is observed during the driest months (July to September) in South America (Carmona-Moreno et al. 2005). With the increased risk of droughts and prolonged dry seasons in tropical zones due to climate change (Marengo et al., 2011), which facilitates the leakage of agricultural fires into surrounding forests (Alencar et al., 2006, Aragão et al., 2007), quantifying the probability of fire occurrence in a given location is the first step for curtailing fire problem. Monthly and annual fire probabilities (fire risk) at regional and local scales and at seasonal and annual basis are modelled in terms of probability. This metrics is defined as the probability of fire occurring in a particular month for any given area. This can be described as the probability for a grid-cell at latitude *i*, longitude *j* to burn in a given unit of time (Carmona-Moreno et al. 2005):

$$\mathrm{P}_{F_{n(i,j)}} = \frac{\sum_{m} F_{n(i,j)}}{\sum_{1}^{12}\sum_{m} F_{n(i,j)}}$$

where $\mathrm{P}_{F_{n(i,j)}}$ is the probability of a cell (latitude *i* and longitude *j*) to burn in a month n of the year; $\sum_{m} F_{n(i,j)}$ is the number of burned pixels detected in the cell (*i*, *j*) for the month n of the year (n = 1 to 12 months); where m is the number of pixels in the cell and $\sum_{1}^{12}\sum_{m} F_{n(i,j)}$ is the total number of burned pixels detected in the cell (*i*, *j*) along the whole time period considered in the analysis. An analogous approach will be carried out at the annual basis.

Information on historical fire probability is not enough for accurately determine the most vulnerable areas to fire at operational level (local scale). It is imperative to also consider the spatial configuration of land use in these areas due to dynamic changes in the deforestation frontier. As we know that deforestation is strongly correlated with fire occurrence, the first step to resolve this problem is to consider long-term trends in fire and deforestation rates. Figure 1 shows an example of long-term fire trend (1998-2007) calculated for the state of Acre.

Including this variable is likely to narrow down the potential areas with high risk of fire incidence. These trends are calculated using INPE’s data (Aragão and Shimabukuro, 2010).

Another key variable to be accounted for in our system is land use type. Recent research have quantified the influence of managed and unmanaged agriculture in Amazonia based on land cover data from the European Commission Join Research Centre and concluded that increasing managing levels can drastically reduce fire incidence (Aragão and Shimabukuro, 2010). Therefore, using this type of information for the spatial planning stage will increase the reliability of mapping vulnerable areas. Figure 2 shows an example of the changes in fire patterns as the percentage of area dominated by managed and unmanaged agriculture increases.

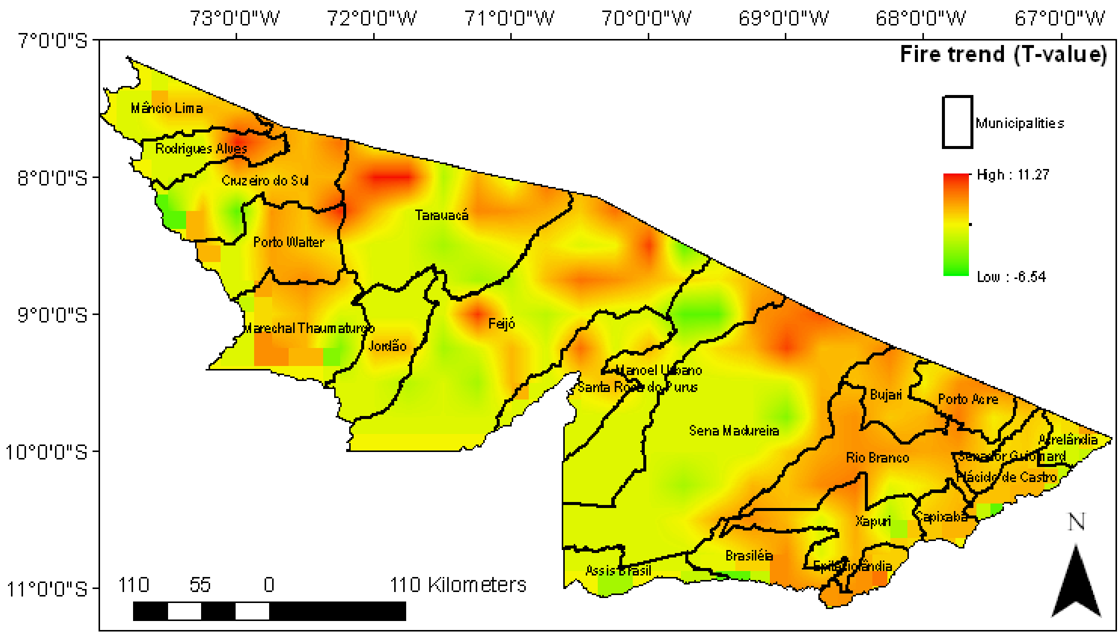

Figure 1. Fire trends in Acre State (1998-2007). Red indicates increasing trend and green decreasing. Values correspond to the T-statistic applied to the slopes of the relationship between fire counts derived from AVHRR/NOAA-12 satellite and years.

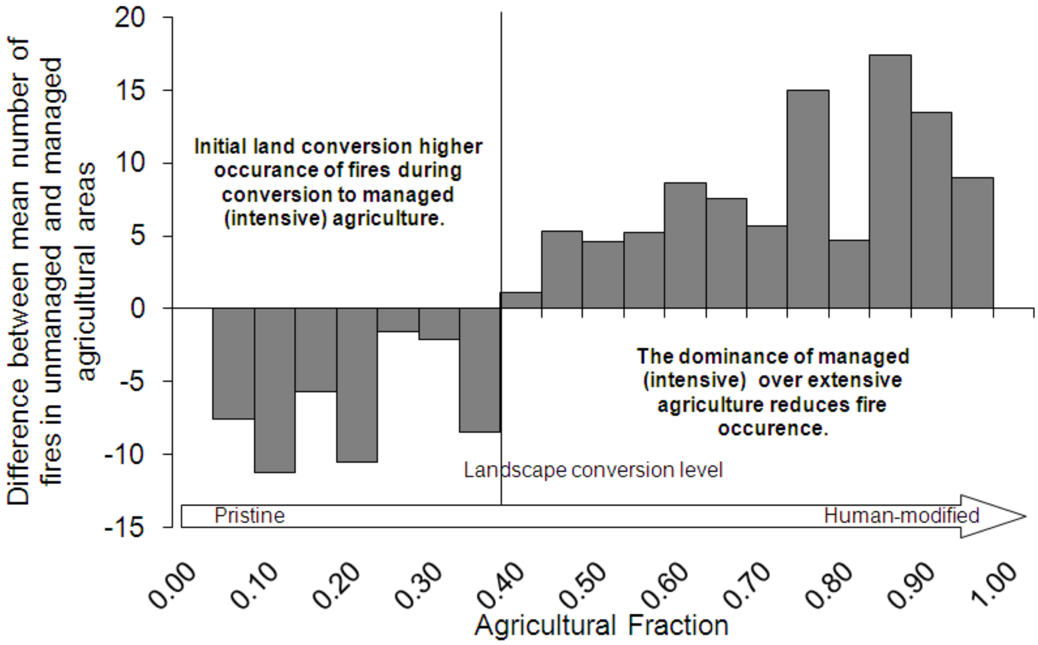

Figure 2. Grey bars are the differences between the mean number of fires in unmanaged and managed agricultural land cover types (mean fires in unmanaged minus mean fire in managed land cover) as a function of the fraction of agricultural area within a 0.25^{o} x 0.25^{o} grid-cell. Land cover data is derived from the GLC 2000 dataset and fires from AVHRR/NOAA12 satellite for the year 2000.

Finally, fire incidence also depends on the distribution of landscape fuel loads and landscape configuration (extent of forest edges, number of fragments and secondary forest area), which can exacerbate fire incidence (Cochrane 2003). For this system, this information is calculated from deforestation and degradation data produced by INPE.

2.2.2. Stage 2- Anticipated Temporal Action

This stage is the key to plan mitigation actions for the forthcoming fire seasons. The information generated here is integrated to the information from previous section (Spatial planning) using weights of evidence technique to identify critical areas to fire occurrence with few months of anticipation.

The model relies on three short-term predictive variables: Sea surface temperature, rainfall and deforestation rates. Anomalies in the sea surface temperatures (SSTs) of the tropical Pacific Ocean related to El Niño Southern Oscillation (ENSO) events has long been recognized as a main cause of Amazonian droughts. El Niño-related droughts have occurred in 1982/1983, 1986/1987 and 1997/1998 (Marengo 1992; Marengo 2004). Recent droughts, however, have been associated to the tropical north Atlantic SST anomalies, in turn partly driven by the Atlantic Multidecadal Oscillation (AMO) (Li et al. 2006; Marengo et al. 2008). The AMO has been implicated as a causal factor of the severe 2005 drought that affected Amazonia (Aragão et al., 2007; Marengo et al. 2008) and is also one of the principal drivers of the 2010 drought (Marengo, 2011). The AMO anomaly is influential in suppressing rainfall in southern and western Amazonia, while ENSO anomaly normally reduces rainfall in the north and eastern Amazonia (Marengo et al., 2008). Here, we demonstrate that the AMO is strongly correlated to increased fire intensity in Acre (Figure 3).

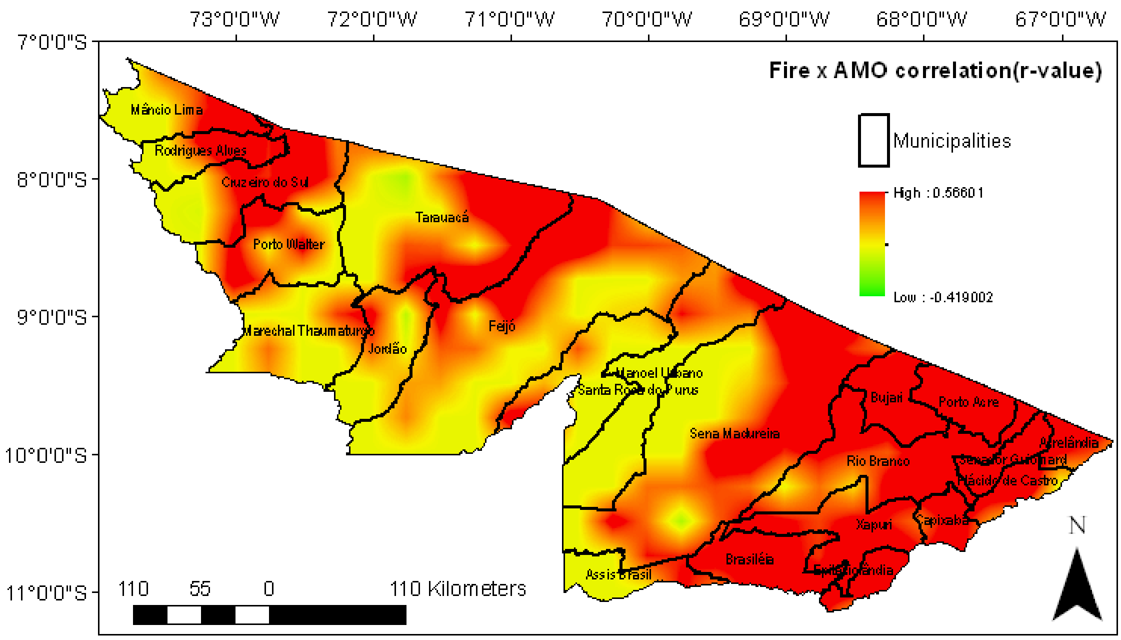

Figure 3. Correlation coefficients (r) for the relationship between active fires from MODIS (MOD14) and the Atlantic Multidecadal Oscillation index (AMO) from NOAA. Red indicates positive correlations and green negative correlations.

Increases in SSTs induce a reduction in rainfall in some parts of the Amazon and monitoring this variable together with derived metrics such as CWD is essential to determine the timing of fire occurrence.

Finally, in this stage it is crucial to explore the spatial relationships between deforestation rates and fire, as there is a clear link between the two variables.

2.2.3. Stage 4- Monitoring

Monitoring carbon stocks in fire affected forests is a crucial step for understanding how fuel load availability, and consequently forest flammability, changes with time since fire and number of repeated fires in the same site. Fuel loads in a system at non-equilibrium conditions (e.g.

disturbed by fire) are not static over time. Initial fires in relatively intact rainforests are low intensity, burning little besides fallen leaf litter. However, these fires are capable of killing 23-44% of the trees > 10cm diameter at the breast height (Cochrane, 2003), and also eradicate small trees and saplings. Recurrent fires are more severe, owing to greater fuel loads due to greater tree mortality in following events (Cochrane, 2003). Moreover, even in once burned forests, fire can induce increased mortality for as long as three years after fire (Barlow et al., 2003). Assessing fuel loads changes over time in burned sites therefore are critical for the refinement of the inputs for the spatial planning stage.

2.3. Integration Routine

The integration of the diverse source of spatial data is based on a weights-of-evidence methodology (Bonham-Carter, 1994). This method will be used to map within a geographical information system (GIS) the probability that a fire event will occur based on its association with the predictive variables (Figure 4). The weights-of-evidence that relies on the Bayes' Rule of Probability is then used to determine the association between training points derived from the data created and compiled at stage 1 and the fire data. This routine, stated in a form of log-linear model allow the addition of the multiple probabilistic evidential layers to produce the response layer, in our case fire probability. This process in a GIS environment follows four main steps:

1. Creation of the spatial database
2. Extraction of predictive evidence for a fire event on an exploration model
3. Calculation of the weights for each predictive variable
4. Combination of evidential probabilities to produce the response layer

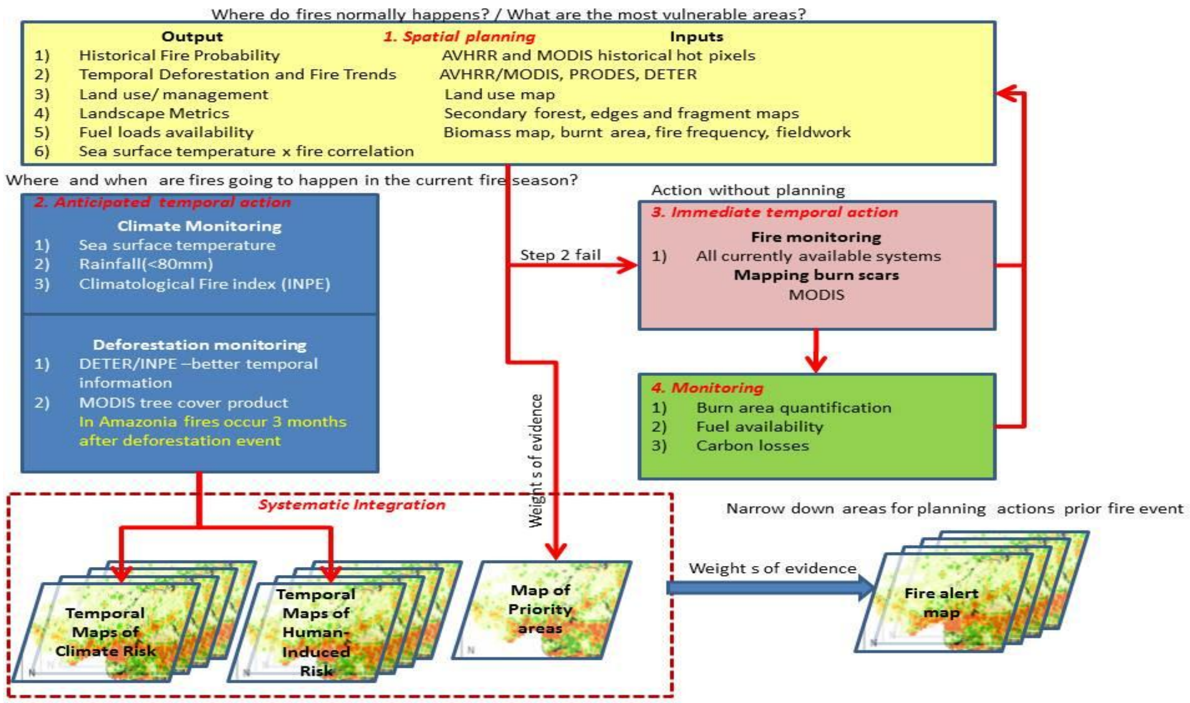

Figure 4. Detailed work flow of the integration routine to predict fire in Amazonia. The flowchart identifies the input variables, the feedbacks within the system and the outputs of the integration.

4. Conclusions

Differently from previous approaches, our proposed routine to predict fire occurrence is based on new developments on the relationships between fires and their drivers. By combining historical and current drivers of fire probabilities we are able to map areas that are historically vulnerable to fire. The inclusion of different climatic metrics including SSTs and CWD with human activity related variables such as deforestation and degradation metrics and land use metrics allow the quantification of short-term fire responses to changes in climate and land-use. Because historical and short-term variables are relate to temporal and spatial patterns of fire incidence in Amazonia, by combining them in a unique model, we expect to significantly improve prediction power of fire occurrence. The model is proposed to run at a 0.25^{o} by 0.25^{o} grid-cell resolution or lower for the entire Amazon. This approximately 25 km grid is a more reasonable resolution for using by decision-makers. Future analysis could be done in higher resolution (~1km) depending on the purpose of the analysis. This will be possible as some of our input data have less than 1 km spatial resolution. One of the key advantages of our system is that it is flexible enough to allow the analysis with available datasets for each region, and can be adapted according to data availability.

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