UNIVERSIDADE TÉCNICA DE LISBOA
INSTITUTO SUPERIOR DE AGRONOMIA

ANTHROPOGENIC AND CLIMATIC CONTROL UPON VEGETATION FIRES: NEW INSIGHTS FROM SATELLITE OBSERVATIONS TO ASSESS CURRENT AND FUTURE IMPACTS.

Yannick Lucien Bernard Le Page

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Doutoramento em Engenharia Florestal
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"Tese apresentada nest Instituto para obtenção do grau de Doutor"

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À praia do Abano...

Resumo

O fogo em vegetação tem papeis importantes na dinâmica dos ecossistemas e na composição da atmosfera. A sua ocorrência e os seus impactos – o "regime do fogo" - são determinados pelo clima, pela vegetação, e pelas actividades humanas, que definem o "triângulo do fogo". Limitações na compreensão deste triângulo dificulta a consideração do fogo na gestão dos ecossistemas, na modelação da vegetação, ou na projecção de alterações climáticas. Este trabalho utilisa observações de satélites para avaliar a influência antropogénica e climática nos regimes do fogo à escala global. Confirma que a variabilidade inter-anual é dominada por padrões climáticos de larga escala, o El Niño-Southern Oscillation sendo o mais influente. A frequência e sasonalidade dos fogos é mais complexa, envolvendo os três factores do triângulo do fogo. A avaliação de um modelo de vegetação-fogo sugere que o factor antropogénico esta insuficientemente representado, originando fortes discrepâncias com a realidade. Este factor é explorado através dum estudo analisando a sua influência na sasonalidade do fogo. Na base destes estudos é desenvolvido um modelo que avalia o potencial do fogo como ferramenta de desflorestação tropical. Revela que o clima actual pode desacelerar o avanço da desflorestação, mas alterações ambientais futuras ameaçam remover essas condicionantes.

Palavras-chave: fogos de vegetação, actividades antropogénicas, clima, modelação do fogo, alteraçãoes ambientais.

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Anthropogenic and climatic control upon vegetation fires: new insights from satellite observations to assess current and future impacts.

Abstract

Vegetation fires actively participate in ecosystem dynamics and atmospheric composition. Their contemporaneous occurrence and impacts – described under the concept of "fire regimes" – is driven by climate, vegetation, and human activities – the components of the "fire triangle". The gaps in our understanding of those drivers hamper the proper consideration of fires in various domains, including ecosystems management, vegetation modeling, and climate change investigation. This thesis capitalizes on satellite observations to depict the anthropogenic and climatic influence on fire regimes. Fire inter-annual variability is shown to be dominated by large scale climatic patterns, of which the El Niño-Southern Oscillation has the most widespread and long term footprint. Fire frequency and seasonality are more complex, being determined by the interaction of all three factors of the fire triangle. The evaluation of a vegetation-fire model thus reveals significant discrepancies. It suggests a great margin of progress on representing of the anthropogenic factor, supported by the wide range of fire practices identified from fire season dynamics. A model specific to tropical deforestation fires is developed, as a regional application of this thesis contributions. Climate is a forceful safeguard against forest conversion progress, but ongoing environmental changes could revert the situation.

Keywords : vegetation fires, anthropogenic activities, climate, fire modeling, environmental changes.

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Table of Contents

INTRODUCTION

The introduction provides the basics of the scientific knowledge about fire ecology, as a context to situate the objectives of this work. Most of this knowledge is detailed in the following key publications:

1. Pyne SJ. Fire: A brief history. 2001.
2. Levine JS. *Global biomass burning*.; 1991:569.
3. Whelan RJ. *The Ecology of Fire*. Cambridge University Press; 1995.
4. Chandler C, Cheney P, Thomas P, Trabaud L, Williams D. *Fire in Forestry. Volume 1. Forest Fire Behavior and Effects*. New York; 1983:450.
5. Glantz, M.H., Katz, R.W. & Nicholls, N. Teleconnections linking worldwide climate anomalies. (1991).

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I. Fires in the earth system

I.1. Fires as a natural process in earth history

The earth has probably been naturally affected by fires since terrestrial vegetation appeared in the Devonian geologic period, about 350-400M years ago[1]. During the ensuing Carboniferous (360-300M years ago), the colonization of the terrestrial biosphere, the evolution of tree species, and the increasing atmospheric oxygen concentration led to widespread and regular fires, evidence of which is found in fossil charcoal deposits and in the presence of black carbon (soot) in marine sediments[2]. Since then, the three elements necessary for the occurrence of fires, referred to as the "combustion triangle[*]", have been present: Oxygen, Fuel (vegetation), and Heat (ignition source, e.g. lightnings, volcanoes and falling rocks).

Fire has an important role in the functioning of ecosystems. As a disturbance agent, it promotes their regeneration, recycles the nutrients, and maintains biodiversity. Many ecosystems would not be sustainable without the occurrence of fires. Boreal forests would evolve towards mono-species stands of low productivity, encouraging other disturbances such as widespread diseases. Savannas are dependent on the frequent occurrence of fires to avoid their evolution into forests. Regarding individual species, fires contribute to plant evolution. Many plants have adapted to survive or thrive on fire disturbances, with some actually requiring fires to ensure their reproduction[1]. The thick bark of cork trees, or the release of Giant Sequoia seeds by the heat of fires favoring full sunlight and competition-free conditions for growth[3] are examples of fire adaptation and dependence.

Beyond their direct impact on vegetation distribution and composition, fires feature many interactions with other components of the biosphere. The combustion process and heat pulse modify various properties of soils, such as porosity, and temporarily reduce the soil fauna. The amount and availability of nutrients generally increases after a fire due to the abrupt release of the elements stored in the vegetation, and supports the regeneration of ecosystems. With the removal of the vegetation cover and the blackening of the surface by charcoal, soils receive and intercept more sunlight radiations, which increases their temperature on longer time scales, affecting biogeochemical processes as permafrost thawing in boreal regions[4].

Fires release various gases and particulate matters in the atmosphere, with important implications[6]. Vegetation is primarily composed of carbon, hydrogen and oxygen that recombine during combustion. The gases emitted depend on the type of vegetation burned, its moisture content, the supply of oxygen on the combustion zone and the type of fire (e.g. flaming, smoldering). Water and carbon dioxide (CO_2) are emitted in large quantities during the flaming phase. Other

* The "combustion triangle" is also referred to as the "fire triangle". In fire ecology however, and in this thesis, "fire triangle" refers to a different concept which is detailed in Section II. of the Introduction.

greenhouse gases like carbon monoxide (CO), methane (CH_4) and nitrous oxide (NO) are mostly produced in the oxygen-deficient smoldering phase. Particulate matters are also emitted and form the visible smoke. Gases and particulate matters (referred to as aerosols) rise in the lowest portion of the atmosphere (troposphere) and may be transported at cross-continental scale[7]. Vertical convection forces of the Inter Tropical Convergence Zone (ITCZ), of storms, or generated by intense wildfires (pyro-convection) distribute aerosols up to the lower stratosphere. They have major impacts in the atmospheric chemistry and physics, either directly or indirectly through a very complex system of chain reactions and feedbacks[8].

I.2. A global overview of contemporaneous fires

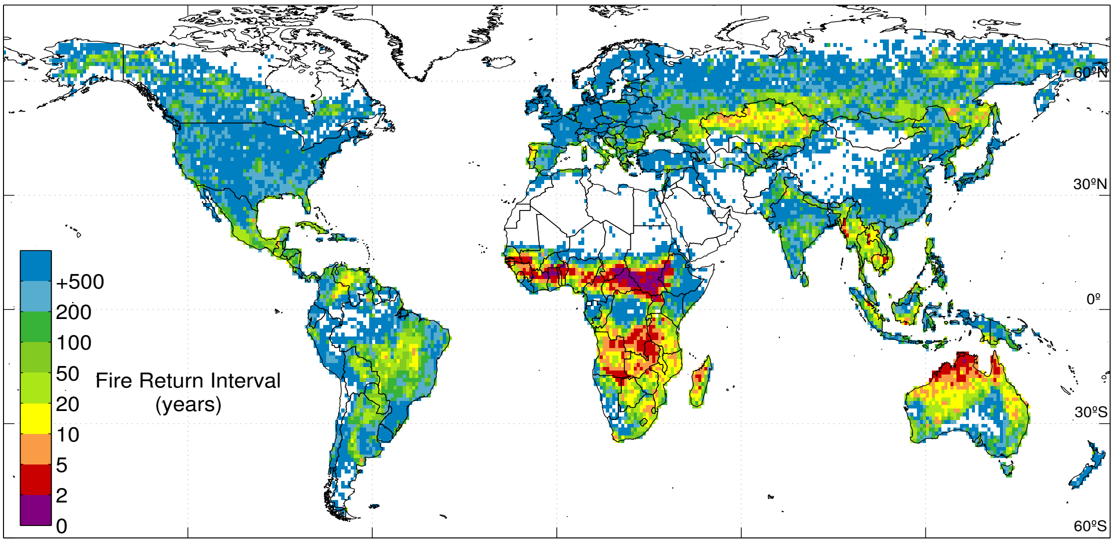
Before the 1990's, field experiments and laboratory analysis had uncovered most of the processes detailed in the previous section. Over the last two decades however, satellites have enabled us to observe fires at global scale. Indeed the heat pulse and local change of optical properties (fire scar) caused by fires are detectable from satellite observations. The first maps of fires in the world revealed the magnitude of the phenomenon[9]: on average, fires burn an area equivalent to the size of India every year. Of this area, Africa has the largest share, mostly in sub-Saharan savannas and Miombo woodlands, and is sometimes referred to as “the burning continent” (Inset 1). In the most affected regions, up to 80% of the surface burns every year. A similar fire incidence is found in savannas and woodlands of northern Australia. In other regions, fire return intervals are longer, from 10-50 years in savannas of South America (“Cerrado”) and in pastures of Kazakhstan, up to 200-500+ years in tropical and boreal forests, and in urbanized regions.

Satellite observations also gave new insights about the atmospheric impacts of fires. Emissions stemming from the combustion process can be estimated based on the area burnt, the characteristics of the vegetation, and on the emission factors specific to the compound considered. Current estimates clearly place fires as a major source of greenhouse gases (Inset 1). Contrarily to fossil fuel emissions, fire emissions are compensated for by the regeneration of the ecosystem on annual (grass) to multi-decadal (forests) timescales, provided that the re-growing vegetation has the same characteristics than the one it replaces. On shorter timescales however, they significantly contribute to the inter-annual variability in the growth rate of various atmospheric species[10], including CO_2. Moreover, in some cases as for example the burning of forests for agriculture expansion, emissions are a net source to the atmosphere (Sect. II.5.3.).

The characterization and quantification of fires in the Earth system introduced in this section is one of the two branches of fire ecology. The second considers upstream processes, i.e. how environmental factors determine fire regimes, and how they may lead to the occurrence of anomalous fire events. The research developed in this thesis focuses on this second aspect, which is introduced in the next section

- Fire Return Interval -

The Fire Return Interval (FRI) represents the average time between two burns at a given location. Source: burned areas from the Global Fire Emission Database version 2 (GFEDv2), based on satellite observations from 1997 to 2006. These data feature high uncertainties (around 50%). In addition, because the FRI is based on just 10 years of observation, the computation in regions rarely affected by fires is not representative of the long term FRI. This is the case in boreal regions for example.



- Fire Emissions -

The amount of a variety of compounds emitted by fires is roughly estimated based on the following equation: $E_c = Ba \times F \times CC \times Ef_c$ where *Ba* is the burned area, *F* the fuel load, *CC* the combustion completeness and *Ef* the emission factor (specific to each compound). The uncertainty about the global estimates is typically in the order of 50%. The following table is a quantitative comparison of vegetation fires and anthropogenic emissions for a selection of compounds.

Compounds	**Fire emissions (Mt/year)[a,b]**	**Anthropogenic emissions (Mt/year)[c]**
CO_2	**8 770**	**18 860**
CO	**427**	**477**
CH_4	**21**	**297**
NO_x	**12**	**82**
N_2O	**1,14**	**2,6**

[a] Van der Werf et al., 2006 (reference #9). Emissions averaged over 1997-2006.
[b] In most cases, emissions from fires are compensated on the long term by vegetation re-growth (see text).
[c] Olivier et al., 1999 (reference #10). Emissions estimated for the year 1990. Anthropogenic emissions include the burning of biomass used as biofuel only.

Inset 1: Global patterns of contemporaneous fires: Fire Return Interval and fire emissions.

II. Fire regimes and the fire triangle

The concept of fire regime integrates the main characteristics associated with the occurrence of fires. In a given ecosystem it describes the types of fuel consumed (soil, ground, crown fires), the size of fires, their intensity (the energy released), severity (the ecological disturbance), frequency (or incidence) and seasonality[11].

In the absence of humans, fire regimes are regulated by climate conditions and the type and structure of the vegetation. In the presence of humans, the anthropogenic variable enters the system of fire determinants. The fire triangle is a schematic representation of the major influence of those three environmental factors on fire regimes (Inset 2).

II.1. Vegetation

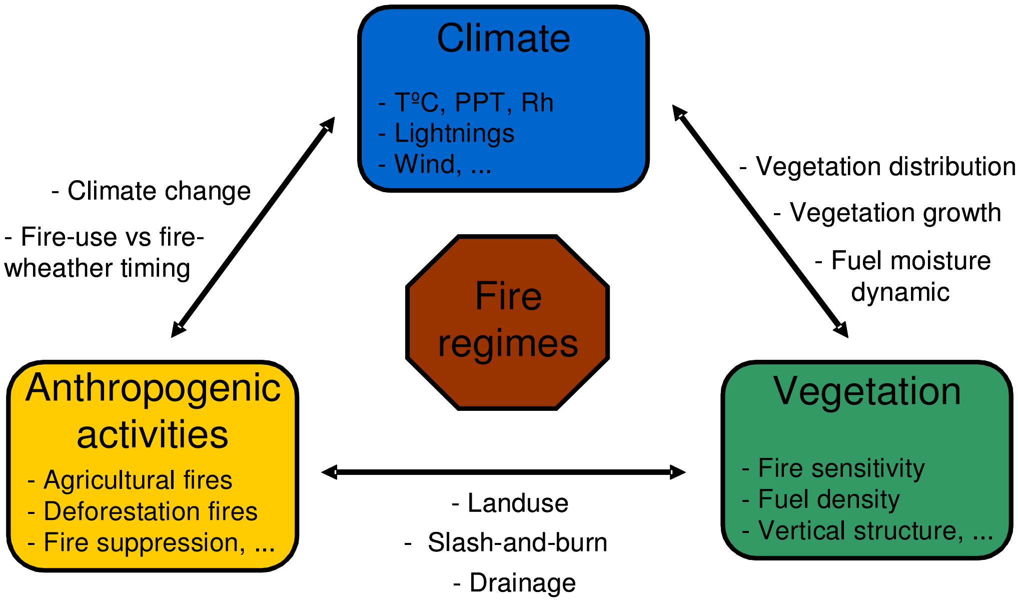
Vegetation is the fuel of fires. It includes live vegetation individuals (e.g. grass, shrubs, trees), aboveground vegetation residues (e.g. leaf litter, fallen branches), and below ground partially decayed biomass (e.g. peats). The type and spread of fires partially depend on the horizontal and vertical structure of the ecosystem: in a forest for example, a continuous understorey cover favors fire spread, and the smaller the fuel gap with the tree canopy, the higher the probability of intense and severe crown fires. Fire severity also depends on the specific fire sensitivity of vegetation species. At larger scales, fire regimes are influenced by landscape heterogeneity, terrain inclination, and by discontinuities as potential fire breaks (e.g. rivers, bare areas).

II.2. Climate

Different aspects of the climatic influence on fires are observed from local to global scale. Locally, weather conditions (e.g. precipitation, temperature and solar incoming radiation) are major determinants of sub-daily to monthly fluctuations in vegetation moisture, therefore of fire susceptibility. Lightning and wind conditions are also important parameters given their respective impacts on the number of fires and their spread/severity. At regional scale, the seasonal dynamics of climate conditions and its impacts on phenology and dead vegetation moisture induces the alternation of fire-prone and fire-antagonist conditions. Generally, one fire season is observed per year, but its timing, duration and intensity vary greatly along regional climates. At both continental and global scales, the ocean-atmosphere interaction generates large scale patterns in climate conditions, which have an extended footprint on fire sensitivity. The El Niño-Southern Oscillation (ENSO) is the best known of these patterns, oscillating between El Niño, neutral and La Niña episodes. Because it is generated in the southern Pacific region, fire regimes in southeastern Asia, Australia and South America clearly bear the signature of this phenomenon, but ENSO-related fire variability has also been observed as far as East Africa, Mexico and Alaska (Chapter I).

- The Fire Triangle -

The fire triangle represents the interactive role of climate, vegetation and anthropogenic activities in determining fire regimes. For each of those three factors and their interaction, 2-3 examples illustrate the variables and mechanisms involved.



Inset 2: The fire triangle.

II.3. Anthropogenic Activities

Globally, a large majority of vegetation fires are ignited by humans. They are widely used around the world for soil fertilization or for the burning of post-harvest residues in agriculture, to regenerate pastures, to support deforestation, as a tool to manage the composition and structure of landscapes, or again for criminal purposes. These fire practices considerably alter natural fire regimes. For example, tropical forest fires are generally rare because of high moisture levels, but are much more frequent at intense deforestation sites in South America, Africa and equatorial Asia (Sect. II.5.3.). Conversely, fire suppression (fire fighting and landscape management) decreases fire frequency around densely populated areas, but the resulting accumulation of vegetation fuel may promote the occurrence of higher intensity fires (Sect. II.5.4.). Fire seasonality is also modified by the specific calendar associated to the considered fire practices, especially in the case of agricultural and land management fires (Chapter III).

II.4. Interactions

The three factors have their specific influence, but their interaction, which acts upon both the physical properties and processes of the fire triangle, is the final determinant of fire regimes. On the long term, climate patterns shape the global distribution of the vegetation. The anthropogenic factor also plays a major role in this interaction through the conversion/management of natural ecosystems associated to agricultural expansion and other activities, and through human-induced climate change. On inter-annual timescales, climate variability also modifies local to regional vegetation characteristics. For example, arid and semi-arid ecosystems are usually insensitive to fires because of the scarcity of the vegetation. The occurrence of anomalously wet conditions over a sufficient period (typically 1-2 successive wet seasons) stimulates vegetation growth, hence a continuous fuel cover that can easily sustain fires during the dry season[12]. Down to the seasonal scale, the fuel moisture cycle is the result of the interaction between climate and the vegetation. In a forest, moisture dynamic is rather slow due to the buffering effect of the canopy and to the presence of coarse fuel, delaying the outbreak of fires. In grasslands, and under a similar climate, fires are likely to burn much earlier, since direct solar radiation, higher air recycling and the dominance of fine fuel all contribute to rapid desiccation[13].

Numerous fire regimes are found along the wide range of possible configurations of the fire triangle. The next section briefly describes the main broad types of fire regimes.

II.5. The main types of fire regimes in the world

II.5.1. Tropical savannas and grasslands fire regimes

Tropical savannas and grasslands of Africa, Northern Australia and South America are the most fire-affected ecosystems in terms of fire frequency (Inset 1), due to a propitious climate and widely applied fire practices (Chapter III). The wet season promotes the growth and accumulation of the vegetation, which subsequently reaches high levels of fire susceptibility during the prolonged dry season. Lightning is a potential source of ignition, but most importantly, fires are voluntarily ignited for various purposes that include landscape management, nutrients recycling for grazing, or pest control. Fire return intervals in the order of 2-10 years are typically observed. In the absence of humans, lower fire frequencies would probably result in the closing of savannas to woodlands or forests. Carbon emissions from these fires are significant at global scale, but are rapidly balanced out by carbon uptake during vegetation re-growth.

II.5.2. Agricultural fire regimes

Agricultural fire practices include pre-seeding burns for soil fertilization, post-harvest burns of crop residues, and regenerative burns in the case of pastures[14,15]. Pre-harvest burns are also applied in specific cases (e.g. to reduce the risk of snakebites during the harvest of bananas). The anthropogenic control of these fires weakens the influence of climate: fire regimes depend primarily on the species cultivated, the cropping system (crop rotation), and on the countries specific regulations on agricultural burns.

II.5.3. Tropical forests fire regimes

Climatic conditions in tropical forests combine high rates of precipitation (1500-3500mm/year) with reduced seasonality, thereby maintaining high levels of vegetation moisture year-round. The thick canopy and deep rooting system further enables the forest to endure transient droughts with limited fire susceptibility. Only large-scale climatic anomalies have the potential to induce droughts of sufficient magnitude to achieve fire-prone conditions: major fire outbreaks have been observed during prolonged droughts related to extreme El Niño phases (1982-83 and 1997-98) [16,17].

Humans have colonized tropical forests of Africa, South America and South East Asia, with a predilection for the accessible outermost areas that have a milder climate (i.e. no too humid). Traditionally, local populations have adopted shifting cultivation as their primary agricultural system. A small area of the forest is cut and burned ("slash-and-burn") to increase soil nutrients content, and cultivated for a few years until soil fertility decreases, and the sequence is then repeated at a nearby location[18]. However, over the last decades large-scale deforestation practices intensified, aiming toward the permanent conversion to croplands and pastures. The conversion process also involves fires as an efficient tool for biomass removal. Contrarily to shifting cultivation, the surface must be totally cleared to permit tractor use, which is achieved through successive piling and burning[19]. Consequently, tropical forests under intense deforestation pressure exhibit some of the highest fire frequency worldwide, in complete contradiction to their natural fire regimes. Besides, enhanced evapo-transpiration rates due to forest fragmentation and canopy openings (logging) result in a lower resilience to droughts. With the combination of increased fire susceptibility and ignition sources probability, tropical forests around colonized areas feature the frequent occurrence of uncontrolled understorey fires. The large amount of carbon emitted is not compensated for by the re-growth of low biomass croplands and pastures, and contribute significantly to the changes observed in atmospheric composition[20].

II.5.4. Fire regimes in highly anthropogenized landscapes

Highly anthropogenized landscapes here refers to densely populated regions where specific activities such as ecosystems management (fire lines, forest understorey cleaning) and fire-fighting efforts aim at limiting the occurrence of damaging fires. These fire suppression efforts are particularly operational in developed countries, which also feature fragmented landscapes between urban, rural and protected areas. Depending on the regional climate and land cover, a wide variety of fire regimes are observed, but fire frequency is generally reduced. In some cases however, the progressive build-up of fuels in over-protected ecosystems may result in the outbreak of devastating fires[21], which initiated the "let-it-burn" policy, whereby fires are allowed to burn in designated areas.

II.5.5. Boreal forests fire regimes

Extended regions of the boreal forests of northern America, northern Europe and Russia are no or very little anthropogenized. As such, their fire regimes mostly depend on the climatic and vegetation factors of the fire triangle[22,23]. The proportion of lightning ignition is higher than in other biomes, and fires may spread for days under fire-prone conditions given their remote location and the scarcity of fire-fighting infrastructures. These fires often burn intensively as stand replacement fires, spreading on the ground, through the aerial vegetation (crown fires), and burning large quantities of organic matter stored in the upper soil layer. They are the major disturbance agent in boreal forests, acting as an essential catalysts of ecosystem regeneration and bio-geochemical cycling[24]. Atmospheric emissions are elevated, and compensated for on the long term with the regeneration of both the vegetation and organic soil layer.

III. Objectives and strategy

III.1. General objectives

The first section of the Introduction illustrated fires as a disturbance agent, capable of burning within just a few minutes the vegetation accumulated over decades. Part of the nutrients stored in the vegetation are returned to the soil as charcoal, ashes, and decomposing unburned fuels, and promote ecosystem regeneration and biodiversity through ecological succession. The matter not recycled locally is emitted to the atmosphere under the form of various gases, such as CO_2, CO and CH4, and as particulate matter, contributing significantly to atmospheric composition and chemistry. Our understanding of these impacts and their magnitude has undergone rapid advances recently, supported by the improving quality of fire observations from satellites. These a-posteriori estimates of fire impacts are relevant to understand the role of fires in the Earth system, and provide the elemental information to explore another major issue in fire ecology:

> → What are the determinants of fire regimes ? Beyond curiosity, the main incentive of this question is our ability to predict the fire-related consequences of potential changes in environmental conditions. If the ensuing impacts on ecosystems functioning and atmospheric emissions can be inferred, and when evaluated as detrimental, appropriate action can be taken. This is a very broad objective of fire ecology, considering either local variability on the short term (e.g. droughts), or global alterations on the longer term (e.g. anthropogenic expansion, climate change). Naturally, it cannot be addressed as a whole, but through progressive advances to which this thesis aims to contribute.

As described in the Sect. II of the Introduction, the conceptual knowledge about the fire triangle enables the delineation of general principles on fire regimes determinants. However, the key to answer the above-mentioned question lies in the exhaustive and quantitative exploration of the variables and processes involved. At the time this thesis was undertaken, the state of the art attempts to compile the current understanding into modeling approaches highlighted the need for further research on the fire triangle. The work presented here was initiated within this context, and was directed towards the following objectives:

- To improve the understanding of the fire triangle, with a special focus on the role of large-scale climate variability and anthropogenic activities, both having a major influence on fire regimes.

- To evaluate and improve the representation of the fire triangle within modeling approaches, such that fire ecology is properly accounted for in Earth system models.

- To predict the consequences of foreseen changes in environmental conditions.

III.2. Structure

This thesis is organized around 4 publications (accepted or submitted). Chronologically, they reflect the progressive orientation of the objectives in light of the findings and new hypotheses achieved throughout the investigation.

The first study is a global scale characterization of the inter-annual variability in fire activity, and investigates the role of the El Niño-Southern Oscillation (ENSO) in the patterns identified. This work was motivated by recent developments concerning that issue: 1/ The major fire outbreaks of 1997-1998 in several regions of the world, due to a strong El Niño episode, which had significant ecological and atmospheric impacts. 2/ Findings suggesting an important contribution of fire emissions to the atmospheric CO_2 growth rate and its variability. 3/ The continuous satellite observation of fires from 1997, at global scale, providing an adequate time span (9 years) to explore inter-annual variability. The main conclusion is the leading role of climate in driving regional to global scale inter-annual fire variability. The ENSO and other large-scale climatic phenomena are able to induce prolonged climatic anomalies, synchronized in time, and over an extended spatial footprint. The associated fire variability has great consequences on the carbon cycle that must be taken into account when considering the Dynamic Global Vegetation Models and their coupling to atmospheric models.

The second study was therefore initiated to evaluate the representation of fires in a Dynamic Global Vegetation Model (DGVMs). The coupling of fires into DGVMs has been undertaken only recently, with little validation of the results. As such, this work considers not only fire inter-annual variability, but also fire frequency, seasonality and carbon emissions, which are essential variables for the modeling of global scale fire ecology. Furthermore, the chosen model is innovative in that it explicitly includes the anthropogenic factor, and can thus be evaluated with contemporaneous fire observations, while previous modeling approaches focused on the role of climate and vegetation only. This study reveals that while the model performs reasonably well on reproducing the influence of climate and vegetation, it fails to capture the profound integration of the anthropogenic factor in the fire triangle. Especially, the anthropogenic scheme does not include sufficient details on the diversity of fire practices and their timing to properly account for the resulting alterations. While climate was highlighted as a dominant driver of global year-to-year fire variability, this study suggests that human activities greatly influence fire frequency and fire seasonality at local to regional scale.

As a direct follow-up, the third study considers the human footprint on fire seasonality (little investigated compared to the human footprint on fire frequency). The objectives are to quantify the spatial magnitude of the alterations, to assess their ecological impacts, and to draw the foundations to improve fire seasonality in DGVM-Fire models. A selection of 10 case studies of the main or most surprising fire regimes are analyzed from specific locations to unravel the mechanisms involved. Overall, the anthropogenic signature on fire seasonality is clearly found in all ecosystems, except in remote boreal regions. The results highlight a large variety of fire practices associated with land management, deforestation and agricultural activities. A direct impact on fire seasonality is achieved through the control of fire ignition, spread and extinction. In parallel, humans also have the ability to accelerate fuel moisture dynamic as an indirect way to enable the use of fire when climate is too humid, as in tropical forest. For modelers, the challenge is to achieve the description of those practices within a modeling framework, for which the coupling of agro-system and deforestation modules is identified as a pre-requisite.

The last work builds upon the above-mentioned studies to explore a specific issue: the threat of fire-driven deforestation in the Amazon forest. Fire is used as a low-cost clearing tool for large-scale agricultural expansion in the region. Meanwhile, climate maintains a great influence on the process, firstly because the average dry season is rather short, limiting fire susceptibility. Secondly, because deforestation is advancing towards wetter conditions, where the current practices may not be efficient anymore (the vegetation is cut to accelerate desiccation, and burned repeatedly to achieve complete clearing). Thirdly, because fire susceptibility varies significantly at inter-annual timescales, especially due to El Niño-induced droughts that are associated with intensified fire practices. In this context, the balance between the anthropogenic and climatic forces is critical for the conservation of the Amazon. The study explores this interaction with observation data, as a support to develop a model assessing the climatic potential for fire-driven deforestation. It suggests that average climate conditions could be constraining enough to prevent a substantial amount of the deforestation projected in the coming decades. However, even in some of the most humid areas, prolonged droughts provide good opportunities to complete the whole conversion process, and climate change could worsen the picture. These results are discussed within the functioning of the whole fire triangle, highlighting the co-importance of other factors, but clearly suggesting the potential of human-induced disturbances to initiate positive feedback loops highly detrimental to the equilibrium of the ecosystem.

CHAPTER I: GLOBAL FIRE ACTIVITY PATTERNS (1996-2006) AND CLIMATIC INFLUENCE: AN ANALYSIS USING THE WORLD FIRE ATLAS.

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ABSTRACT

Vegetation fires have been acknowledged as an environmental process of global scale, which affects the chemical composition of the troposphere, and has profound ecological and climatic impacts. However, considerable uncertainty remains, especially concerning intra and inter-annual variability of fire incidence. The main goals of our global-scale study were to characterize spatial-temporal patterns of fire activity, to identify broad geographical areas with similar vegetation fire dynamics, and to analyse the relationship between fire activity and the El Niño-Southern Oscillation. This study relies on 10 years (mid 1996 – mid 2006) of screened European Space Agency World Fire Atlas (WFA) data, obtained from Along Track Scanning Radiometer (ATSR) and Advanced ATSR (AATSR) imagery. Empirical Orthogonal Function analysis was used to reduce the dimensionality of the dataset. Regions of homogeneous fire dynamics were identified with cluster analysis, and interpreted based on their eco-climatic characteristics. The impact of 1997-98 El Niño is clearly dominant over the study period, causing increased fire activity in a variety of regions and ecosystems, with variable timing. Overall, this study provides the first global decadal assessment of spatial-temporal fire variability and confirms the usefulness of the screened WFA for global fire eco-climatology research.

Keywords: Fire inter-annual variability, El Niño-Southern Oscillation, Empirical Orthogonal Functions, Clustering.

I. Introduction

Vegetation fires are an ecological process strongly responsive to climatic drivers, which have substantial impacts on biogeochemical cycles, at scales ranging from local to global. As an indicator of the relevance of this phenomenon, reports from various sources estimate fires to affect on average 3.5 million km^2 of vegetation in recent years, the size of India, with ensuing carbon emissions almost equivalent to fossil fuel combustion, and further characterized by important year to year variability (Tansey *et al.*, 2004a,b ; Ito and Penner, 2004 ; van der Werf *et al.*, 2006). Bond *et al.* (2005) simulating a world without fires, obtained a virtual land cover where closed forests had doubled their area relatively to actual contemporary extent. Other impacts include for example changes in the Earth's planetary albedo and radiative budget (Govaerts *et al.*, 2002; Schafer *et al.*, 2002 ; Kaufman and Koren, 2006), damages to endangered species (Loboda, 2004), or coral reef asphyxiation (Abram *et al.*, 2003).

The Global Climate Observing System (GCOS, 2006) considered fire disturbance an "Essential Climate Variable" and highlighted the need for long data time series to quantify the links between climate and fire. Originally local phenomena, it becomes globally relevant due to the integrating role of the atmosphere in two distinct ways. Combustion products are entrained and transported at wide range of distances, depending on the nature of the chemical species, atmospheric stability, and fire intensity (Damoah *et al.*, 2004). The second globalizing effect of the atmosphere occurs through the synchronisation of fire weather conditions at distant locations, via teleconnection mechanisms induced by climatic modes. The El Niño – Southern Oscillation (ENSO) is the best known of these mechanisms, but similar roles have been assigned to the Arctic Oscillation (AO) (Balzter *et al.*, 2005; Patra *et al.*, 2005), Pacific Decadal Oscillation (PDO) and Atlantic Multidecadal Oscillation (AMO) (Kitzberger *et al.*, 2007), the Indian Ocean Dipole and the North Atlantic Oscillation (Patra *et al.*, 2005).

This study relies on an improved version of the European Space Agency (ESA) active fire product from 1996 to 2006, the World Fire Atlas (Mota *et al.*, 2006), to address this issue of global fire variability and its climatic control. We emphasize the role of ENSO, because of its global-scale climatic impact, its known relevance for fire activity as described in the next section, and relatively high frequency, including the occurrence of one strong and two weaker El Niño phases over the study period.

II. ENSO-FIRE RELATIONSHIPS

The El Niño-Southern Oscillation is a natural, coupled atmospheric-oceanic cycle in the tropical Pacific Ocean (Trenberth 1997; Diaz *et al.*, 2001). Normal conditions are characterized by warm surface waters in the western Pacific, while cool water wells up in the eastern Pacific, a pattern that is sustained by westward winds. El Niño, the warm phase of ENSO, is set when the trade winds weaken or reverse, due to changes in air pressure gradient over east and west Pacific. Warm waters and the convection zone they induce are therefore driven eastward. El Niño episodes, which occur every 3 to 7 years and last from 12 to 18 months, are characterized by an increase in ocean surface temperature of about 3 to 6ºC, ranging from the coastal zone of Peru and Ecuador to the centre of the equatorial Pacific Ocean. This warming causes long-term meteorological disturbances over the tropical land surface, including a reversal of normal rainfall patterns, and also has substantial impacts on extensive extra-tropical regions. The reverse situation, i.e. a greater sea surface temperature gradient, defines ENSO cold phase, or La Niña episodes, which often follow El Niño events (Diaz *et al.*, 2001).

The above-described meteorological anomalies associated to ENSO are usually referred to as teleconnection patterns, which are characterized by recurring and persistent, large-scale patterns of atmospheric flow that encompass vast geographical areas and possess characteristic long time-scales of variability. Teleconnections are associated to statistically significant links between weather changes occurring in separated regions which, in the case of ENSO, appear to be stronger throughout the tropics and in parts of North America and Oceania (Glantz, 2001). They are also present, but weaker, in Europe and extra-tropical Asia. The direct effects of ENSO and its teleconnections are reflected in precipitation and temperature anomalies (Allan *et al.*, 1996) on a scale dependent basis, major peaks in the spatial extent of drought and excessively wet conditions being generally associated with extreme phases of ENSO (Lyon and Barnston, 2005).

The sequence of events that may lead to changes in fire activity varies with the type of ecosystem considered. In most tropical regions, where net primary productivity is high, El Niño induces droughts, leading to vegetation dryness, tree mortality and fire outbreaks. In semi-arid and arid ecosystems, where precipitation is a limiting factor, increased rainfall under El Niño conditions first results in a pulse of productivity and fuel accumulation followed, when conditions are back to normal or under La Niña phase, by fuel drying and high flammability (Holmgren *et al.*, 2006).

As pointed out in previous teleconnection studies, climate variability in SE Asia is highly determined by the ENSO signal. In particular, under El Niño conditions, rainfall is limited and long periods of droughts may be experienced, while La Niña generally implies wetter than average conditions. Fire – ENSO relations are thus expected to be particularly strong in this region, and numerous studies have focused on the large fires that were observed during the two strongest recent El Niño events, namely in 1982–1983 and in 1997–1998 (Siegert *et al.*, 2001; Schimel and Baker, 2002; Doherty *et al.*, 2006). Fuller and Murphy (2006) reported a strong correlation between fires and ENSO indices, such as the Southern Oscillation Index (SOI) and the Niño 3.4 index, for forested areas located between the latitudes 5.5º S and 5.5º N.

Fire – ENSO teleconnections have been extensively addressed in North America. Simard *et al.* (1985) analyzed 53 years of USA fire statistics and found decreased fire activity during El Niño in the South. Swetnam and Betancourt (1990) used pyro-dendrochronology and fire statistics data from Arizona and New Mexico for the period 1700-1983. They concluded that small areas typically burn after wet spring seasons, associated with El Niño, while larger burned areas tend to burn after dry springs, associated with the La Niña phase of ENSO. Veblen *et al.* (2000) determined that years of extensive burning in Colorado had a tendency to occur during La Niña years, often preceded by two to four years of wetter than average Springs, generally related to El Niño phases, increasing fine fuel production. An alternation of wet and dry periods in two to five year cycles favours widespread fires and displays strong links with ENSO. El Niño also tends to produce unusually warm and dry conditions in interior Alaska (Hess *et al.*, 2001). In this region, during the years 1940 to 1998, 15 out of the 17 biggest fire years occurred under moderate to strong El Niño and were, responsible for 63% of the area burned over the whole period. Other fire – ENSO teleconnections in the USA were also reported for the Rocky Mountains (Schoennagel *et al.*, 2005) and Florida (Beckage *et al.*, 2003).

In the Mexican state of Chiapas, Roman-Cuesta *et al.* (2003) found a clear influence of El Niño on the types of ecosystems affected by fire. In non-El Niño years, burning primarily affects very flammable pine-oak vegetation, while in El Niño years, normally less flammable rainforests burn extensively, due to anomalous drought conditions.

Kitzberger *et al.* (2001) detected inter-hemispheric synchrony between fire seasons in the South West USA and northern Patagonia, Argentina. Major fire years typically occur after a switch from El Niño to La Niña conditions, due to the already mentioned pattern of enhanced fine fuel production during the ENSO warm phase, and prevailing dry conditions during the cold phase.

ENSO also influences Australian fire regimes. Verdon *et al.* (2004) analysed multi-decadal variability of fire weather conditions in eastern Australia. The proportion of days with forest fire danger index values of high or more severe, increase markedly during El Niño periods. Similar conclusions were reported by Lindesay (2003).

Other regions are teleconnected to the ENSO phenomenon, and regional fire regimes are likely to be affected. For example, the East African climate is under the influence of the Indian Ocean

Dipole, which is itself altered by ENSO (Black, 2005). In other cases, the exceptionally intense 1997-98 El Niño episode is believed to be responsible for important fire events in regions previously not reported to be sensitive, such as Far East Siberia (National Climatic Data Centre (NCDC), 1998 Annual Review, 1999).

III. Data and method

III.1. The World Fire Atlas

Several fire datasets have been developed in recent years, and each product is bound to present some advantages and limitations. We evaluated these datasets specific purposes, especially taking into account the available time series and their consistency.

The longest time series were produced using Pathfinder AVHRR Land (PAL) 8km resolution data (Carmona-Moreno *et al.*, 2005; Riaño *et al.*, 2007) spanning 17-20 years, with monthly resolution. The accuracy of these burned area products is, however, limited by the radiometric and orbital inconsistencies in the original dataset in the first case, and by the global application of a burned area mapping supervised classifier trained exclusively with data from Africa, in both cases.

Justice *et al.* (2002) and Giglio *et al.* (2003) developed a multi-year daily active fire product from the Moderate Resolution Imaging Spectroradiometer (MODIS). This product has a good detection rate, due to its 4 daily overpasses, but is only available since early 2000.

The World Fire Atlas (WFA, Arino *et al.*, 2005) is a global active fire product, developed with data acquired by the Along-Track Scanning Radiometer (ATSR-2) and the Advanced Along-Track Scanning Radiometer (AATSR), on-board the second European Remote Sensing Satellite (ERS-2) and the Environment Satellite (ENVISAT), respectively. The full dataset covers the period from November 1995 to the present, with a gap between January and June 1996. The spatial resolution of ATSR-2 and AATSR is 1km at nadir and the 512 km swath width allows for an equatorial revisiting period of 3 days. Data for the WFA are acquired at night (around 10 p.m. local time).

We selected the WFA for its consistency, and the period of data available, which includes 2 minor El Niño events, and the large El Niño event of 1997–1998 followed by an equally important La Niña episode. This product inherently screens out small, short duration fire events, mostly land use management and savannah fires, which show a strong diurnal cycle and do often not burn overnight. Those fires are thus likely to be under-represented. However it was not considered very limiting since by considering anomalies, we reduced the dependency of our results to the absolute fire activity. Larger fires are also more likely to be under strong climatic control.

Two fire databases are available within the WFA, based on two thresholds of the 3.7 μm channel. Algorithm 1 relies on a 312K threshold, while for algorithm 2 a 308K threshold is used. Detection sensitivity ranges from a burning area of 10 m^2 at 600K to 1 m^2 at 800K. The final WFA product consists of date, time, latitude and longitude of all pixels with temperature values exceeding the thresholds.

We chose algorithm 2 data, to reduce the overall underestimation of fire activity (Arino and Plummer, 2001), a known limitation of the WFA. The data were then thoroughly screened to remove observations not corresponding to vegetation fires (Mota el al., 2006). For the study period, about 29% of observations were thus screened out of the WFA.

III.2. WFA exploratory analysis

The spatial and monthly temporal fire variability contained in the WFA was analysed using a simple statistic representation. The screened WFA data were first aggregated by months, at a spatial resolution of 2.5º latitude by 2.5º longitude. As we are interested in anomalous fire events, the time series at each grid-cell were deseasonalized, i.e. seasonal cycles were removed by subtracting to each monthly value the grand mean of the corresponding month for the considered 10-year period (Eq. (1)):

$$F_{ds}(m, y) = F(m, y) - \frac{\sum_{y} F(m)}{10} \qquad \text{Eq. (1)}$$

where F and F_{ds} are respectively the fire activity and deseasonalized fire activity, at month m of year y in a given grid-cell. Time series were subsequently standardized, i.e. each monthly value of the deseasonalized time series is further divided by the standard deviation of the corresponding month computed over the 10-year period (Eq. 2.). Standardisation was performed with the aim of enhancing those fire-sensitive ecosystems that although being rarely affected by fires possess less ability to rebound compared to other fire-dependent ecosystems (The Nature Conservancy, 2006). A weighting factor given by the percentage of continental surface of each grid-cell containing ocean or inland water bodies was finally applied to each standardized value (Eq. (2)):

$$F_a(m, y) = \frac{F_{ds}(m, y)}{\sigma(F_{ds})} \times Lp \qquad \text{Eq. (2)}$$

where F_a is the anomaly, at month m of year y at the considered grid-cell, σ is the standard deviation of F_{ds} of the considered month over the 10-year period and Lp is the land proportion in the grid-cell.

Fire anomaly data were then aggregated by latitudinal bands in a time-latitudinal Hovmöller diagram (Figure 1a). Figure 1b shows the WFA representation of the mean annual fire activity gradient by latitude. Total anomalies over the 10 years, i.e. the deseasonalized sum of raw data, is also shown (Figure 1c).

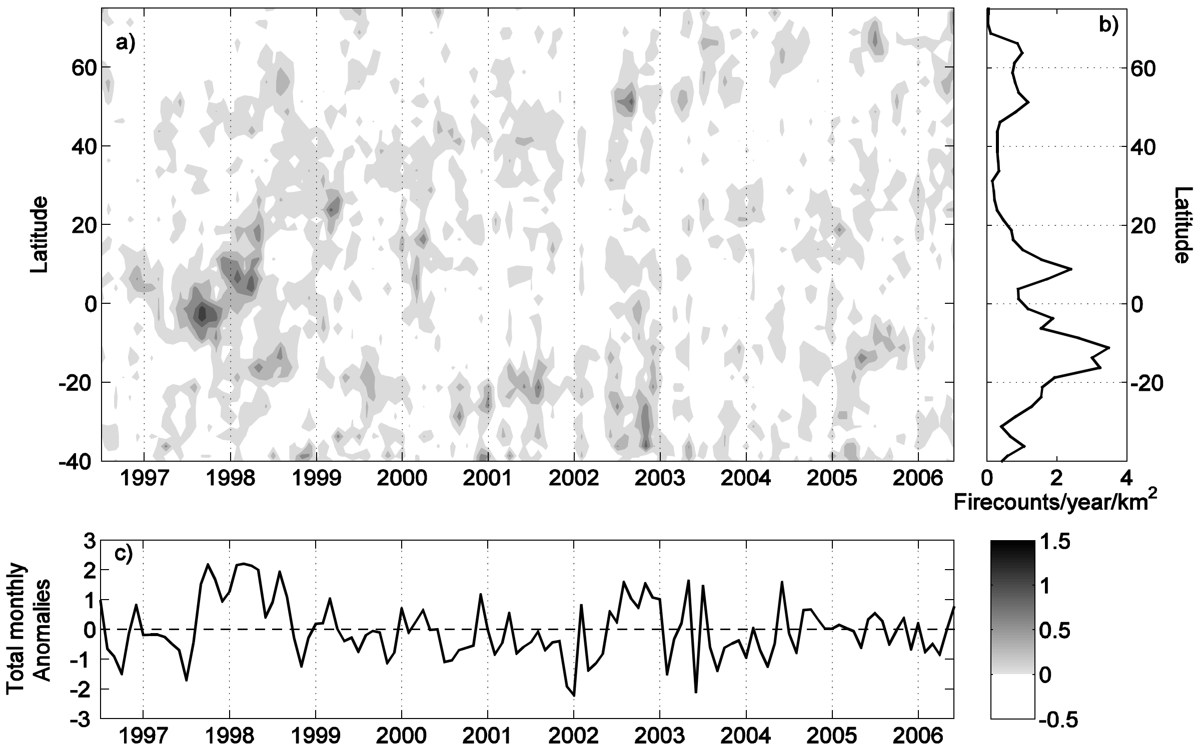


Figure 1: (a) Time-latitude Hovmöller diagram of monthly deseasonalized fire anomalies (positive anomalies only, scale indicated by the colorbar). (b) Fire counts by latitude (detection/year/km2), corrected by continental surface for each latitudinal band. (c) Monthly anomalies of the total deseasonalized fire counts over the 10 years.

The most striking feature in the Hovmöller graph is the highly positive anomaly spanning from mid-1997 to the beginning of 1999 and extend along time to almost the whole range of latitudinal bands. This feature has been linked, at least for the majority of fire events, to the contemporaneous 1997-98 El Niño through its impacts on regional temperature and precipitation (Sect. II.). It reveals very clearly the global scope of this specific event, further pointed out by the total deseasonalized anomaly profile, with a broad peak of high positive values. The intense anomaly first appears around the equator, and then spreads gradually to the higher latitudes, reaching 60ºN by mid-1998.

Other conspicuous fire events include early 2000 in the northern tropics, and a succession of anomalies in southern extra-tropical regions from mid-2000 to early 2003. The last one is contemporaneous with fires in northern mid-latitudes, which greatly increased fire activity on a global scale during the year 2002. 2004 is the less perturbed year in terms of spatial anomalies, but global fire counts where anomalously high in June, due to boreal fires. In 2005, the high northern latitudes and the southern tropics exhibited above normal fire activity.

Although biased by the detection rate variability of the sensor (Sect. III.1.), a broad depression in fire activity centred around 30ºN is identified in Figure 1c, corresponding to the global desert belt. There is another depression in the data over the equator, in spite on the strong 1997-1998 ENSO. Fires in most of those regions are sporadic, only occurring under strong droughts leading to low levels of moisture allowing for fire spread. Conversely, over tropical regions, extensive savannah burning occurs regularly on an annual basis due to the succession of wet and dry season and to agricultural activities.

As pointed out in this section, complex patterns of occurrence of anomalous fire events are detected worldwide, revealing high rates of variability that appear to be driven by both global and regional processes. Time lags between ENSO and climatic anomalies at extra-tropical latitudes further complicate the extraction of clear and meaningful information from simple basic statistics, raising the need for more advanced analyses to unravel the temporal and spatial structuring of global fire activity for the 10-year long fire time series. In particular, the leading role of ENSO, clearly suggested here, is also further explored.

III.3. Principal Component Analysis and clustering procedure

Principal Component Analysis (PCA) is a multivariate statistical technique whose aim is to extract spatio-temporal information when dealing with datasets formed by a large number of variables that are not statistically independent. This technique allows computing an optimal new system of uncorrelated variables, referred to as Principal Components (PCs). Each PC is expressed as a linear combination of the original variables, the coefficients of the linear combination being referred to as the Empirical Orthogonal Function (EOF) of the corresponding PC. Since PCs are uncorrelated, the total variance of the original dataset may be expressed as the sum of the variances of each PC. PCs are usually ranked in terms of decreasing explained variance and the dimensionality of the dataset may be often reduced by retaining a relatively low number of PCs that explain a sufficiently high part of the total variance. Additional information on PCA applied to geosciences may be found in standard books, e.g. Wilks (2005) and von Storch and Zwiers (2002).

PCA is a purely statistical procedure, in the sense that it is entirely based on computing the eigenvectors and eigenvalues of the covariance (or correlation) matrix of the data. However the first EOF/PC pairs often reflect physically meaningful patterns, which are associated to physical mechanisms whose signatures in the dataset are captured by PCA. When such is the case, besides reducing data dimensionality, PCA leads to a better characterization and understanding of the original dataset.

As a first step, WFA data were seasonally aggregated (DJF-MAM-JJA-SON), in order to reduce the matrix dimensionality without loosing too much temporal resolution. The same pre-processing as described in the previous section was also applied to seasonal time series, i.e. data were deseasonalized and then standardized., the applied weights accounting as before for the continental fraction of each grid-cell. Given the usage of a latitude-longitude grid, and because each grid-cell is considered on an individually basis (i.e. no latitudinal aggregation), dependence of size on latitude was also taken into account. The final data matrix contains 2200 pixels (spatial dimension) and covers 40 consecutive seasons (temporal dimension), from June–August 1996 to March–May 2006.

Since there is no optimal criterion to decide on the number of PC/EOF pairs that ought to be retained (Wilks, 2005), and taking into account that the aim of our study is to retain the most outstanding events, (and therefore not to maximise the variance explained), we adopted the approach based on the so-called Log-Eigenvalue (LEV) diagram (Craddock and Flood, 1969). The concept behind LEV is that the more dominant events represent a large proportion of variability, whereas the others explain an exponentially decreasing proportion of variance that appears as a decreasing near straight line towards the tail of the LEV diagram.

In order to further highlight the main modes of variability and better characterize their spatial organization, we performed a cluster analysis on the space of retained EOFs (spatial patterns). For this purpose, we used a hierarchical clustering procedure, i.e. points were incrementally merged into clusters, from singletons (i.e. cluster with one grid-cell) up to one single cluster at the last step. The chosen merging procedure is based on the Ward's linkage method, that uses the increase in the total within-cluster sum of squares as a result of joining two clusters (Ward, 1963; Milligan, 1980). The resulting cluster tree allows identifying the loss of information from step to step, and in particular those merging steps that lead to high increases of the linkage distance. The cluster tree is accordingly used as a support to decide on the final number of clusters to be retained. Our discussion of spatial and temporal patterns of global fire activity, as well as on their relationship to climate and land cover, is ultimately structured around the resulting cluster map.

III.4. The Multivariate ENSO Index and its climatic context

Several ENSO indices have been proposed, built with different meteorological variables and defined over various regions. Hanley *et al.* (2003) published an evaluation of those indices and assessed their sensitivity to El Niño/La Niña events. We used the Multivariate ENSO Index

(MEI), which is calculated as the first unrotated principal component of six observed variables over the tropical Pacific Ocean: sea level pressure, zonal and meridional components of surface wind, sea surface temperature, surface air temperature and total cloudiness fraction of the sky. MEI is expressed by means of standardized departures from zero and is positive (negative) under El Niño (La Niña) conditions. The observed maximum for the strongest recent El Niño events is in the 3.0 range. Most events fall between 1 and 2. MEI correlates well with the Southern Oscillation Index (SOI) and with ENSO indices based on sea surface temperature.

Hanley *et al.* (2003) concluded that the MEI is very sensitive to ENSO and identifies events not detected by other indices. However, they considered it robust, and suitable for global studies, while other indices may be more appropriate for regional-scale research. Time series of MEI are available from 1948 to present, from the National Oceanic and Atmospheric Administration (NOAA: http://www.cdc.noaa.gov/people/klaus.wolter/MEI/). Figure 2 illustrates the recent evolution of the MEI index for the 1996-2006 period and the El Niño (La Niña) events as identified by NOAA.

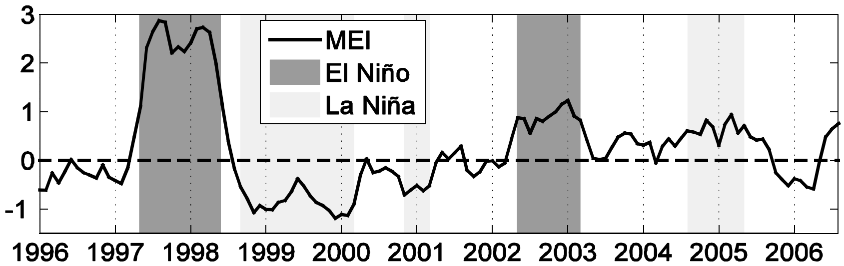


Figure 2: MEI index time series. Darkgray/lightgray patches represent El Niño/La Niña as identified by the NOAA.

Figure 2 shows that one very strong and two mild El Niño, and one strong La Niña events were observed during the considered 10-year period. In 1997-98, the strongest El Niño on record triggered widespread climate perturbations, especially an extended drought in south-east Asia and South America. This was followed by a cold phase from late 1998 through 2000, which is associated with the opposite influence in south-east Asia. 2002-2003 and 2004-2005 warm phases, albeit weaker, also affected large scale atmospheric circulation.

IV. Results

IV.1. Deseasonalized EOF fire count analysis

Visual analysis of the LEV diagram obtained from the EOF outputs (Figure 3) led to the decision of keeping the first nine EOFs, representing 40% of the total variance. The relatively low value of retained variance from 9 EOFs indicates fire anomalies are very scattered in time and space, being less condensible into a few dimension than for example temperature, which classically has larger scale patterns and exhibits higher proportions of variance explained by the first EOFs. The complexity of those patterns is enhanced by our use of 3-monthly data, allowing a high temporal resolution of the observed patterns that would not be observed with annual anomalies. Standardisation also contributes to low values of explained variance, since it tends to give equal importance to all grid-cells. However, as mentioned before this choice is justified so that fire sensitive ecosystems are not ignored. Performing the analysis with non-standardised data would result in focusing almost exclusively on regions of very high fire incidence (e.g. tropical savannas and woodlands, primarily those located in Africa), which was considered undesirable. Figure 4 illustrates the PCs time series of the nine components retained, and Figure 5 displays the spatial patterns extracted associated to EOF-1 and EOF-2.

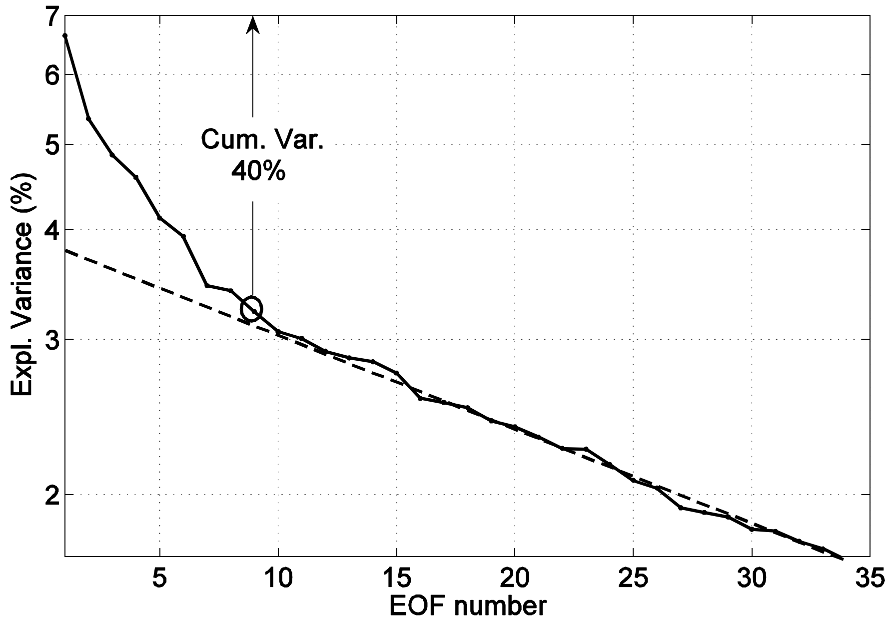


Figure 3 : LEV diagram, based on a log-representation. The threshold is defined as the elbow point of the line (set to 9, for 40% of explained variance).

EOF-1 accounts for 6.6% of the total variance. High positive loadings are concentrated in equatorial Asia and northern South America. The main events identified coincide with El Niño periods (1997-98 and, to a much lesser extent, 2002-03 and 2004-05). The 1997-98 event is remarkable for its length (one year) and the magnitude of the anomaly.

EOF-2 accounts for 5.3% of the total variance. Coherent spatial patterns, with positive loadings are most evident in central East-Africa, Eastern Siberia, Eastern Brazil, Central America and Central/ Western Canada. Those regions also experienced extensive burning in 1998, but the ENSO-related fire activity occurred later than in regions highlighted in EOF-1. This is likely due to the ENSO propagation process and the timing of the fire season, and will be discussed later.

The various regional fire variability patterns represented by later EOFs, also merged through the PCA because of their spatial or temporal coherency, do not have such global driving mechanisms as EOF1 and EOF2. The featured patterns, rearranged through the clustering procedure, are however supported by former publications as will be shown in discussion.

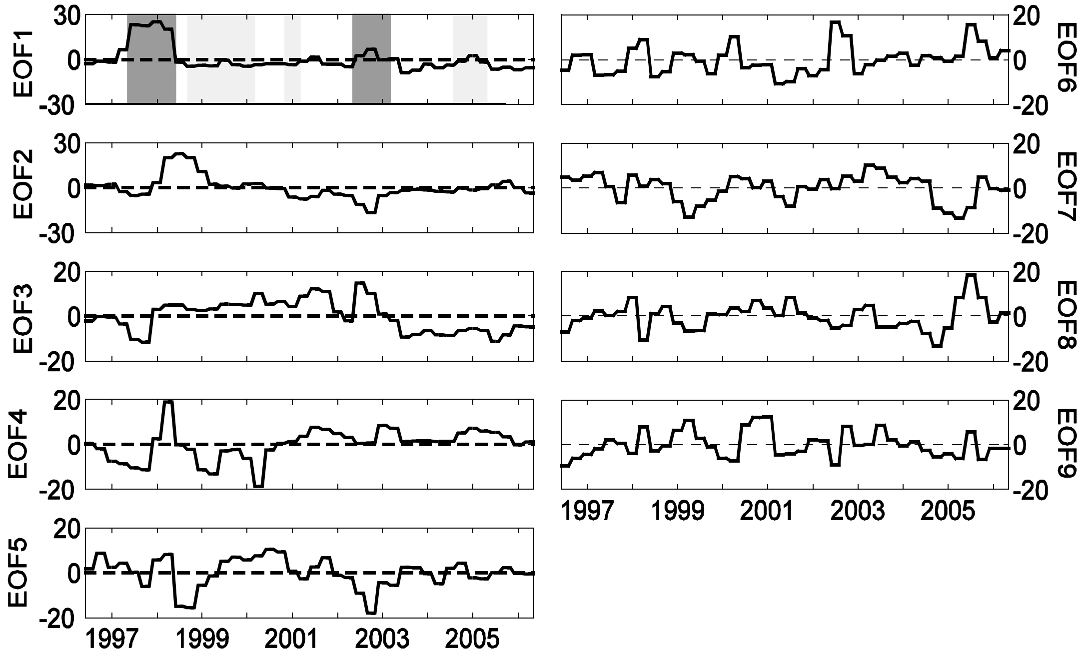


Figure 4: Top nine PCs time series. Dark/Clear patches represent El Niño/La Niña phases.

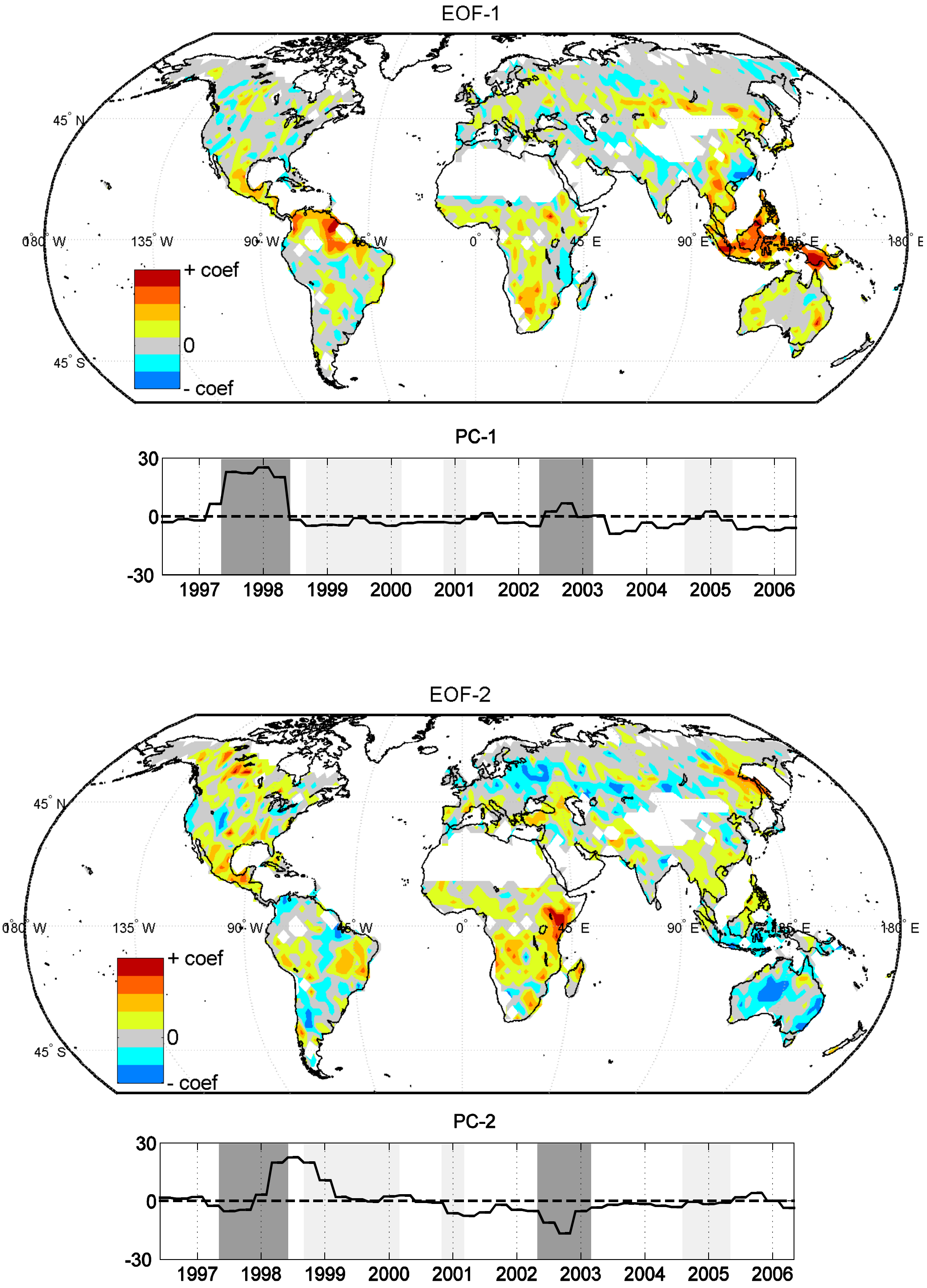


Figure 5: EOF-1 and EOF-2 and corresponding PCs. Colorbar scale is relative.

IV.2. Cluster Analysis

Clustering of areas with similar temporal fire behaviour over the events identified by the nine EOFs was accomplished using hierarchical clustering. Various techniques are available for determining the number of clusters (Wilks, 2005), however the linkage distance dendrogram greatly limits the uncertainty to either 8 or 9 clusters (Figure 6). After visual inspection of the two possibilities, the 8 cluster map was retained, providing clearer and interpretable results. Their centroid absolute coordinates on each of the 9 EOF dimensions is given in Figure 7, suggesting that each cluster is defined by no more than 1 to 4 EOFs. Cluster 8 has very low coordinate values on all dimensions, meaning it does not represent significant spatio-temporal patterns. Figure 8 shows the resulting clusters map. Figure 9 illustrates the corresponding fire variability patterns depicted, computed for each cluster as an average of its grid-cells deseasonalized anomalies, both over the ten years (time series) and for the seasonal cycle. Time series of precipitation data anomalies from the CMAP Precipitation data, provided by the NOAA/OAR/ESRL PSD, Boulder, Colorado, USA, (http://www.cdc.noaa.gov/) are also shown for each cluster, to illustrate the role of precipitation as a fire determinant.

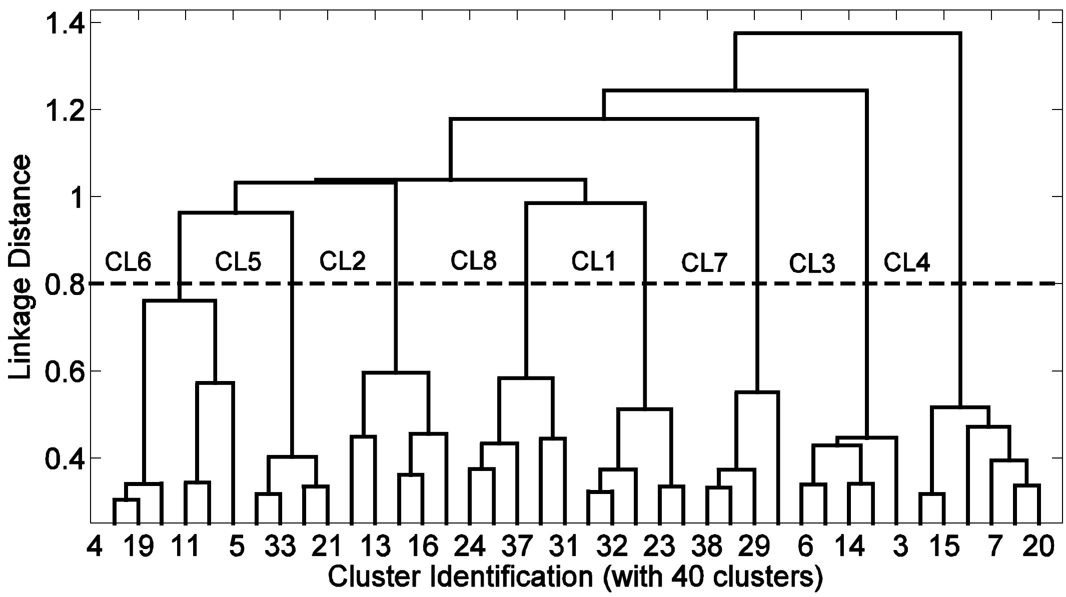


Figure 6: Linkage distance tree. Retained clusters are indicated as CL#.

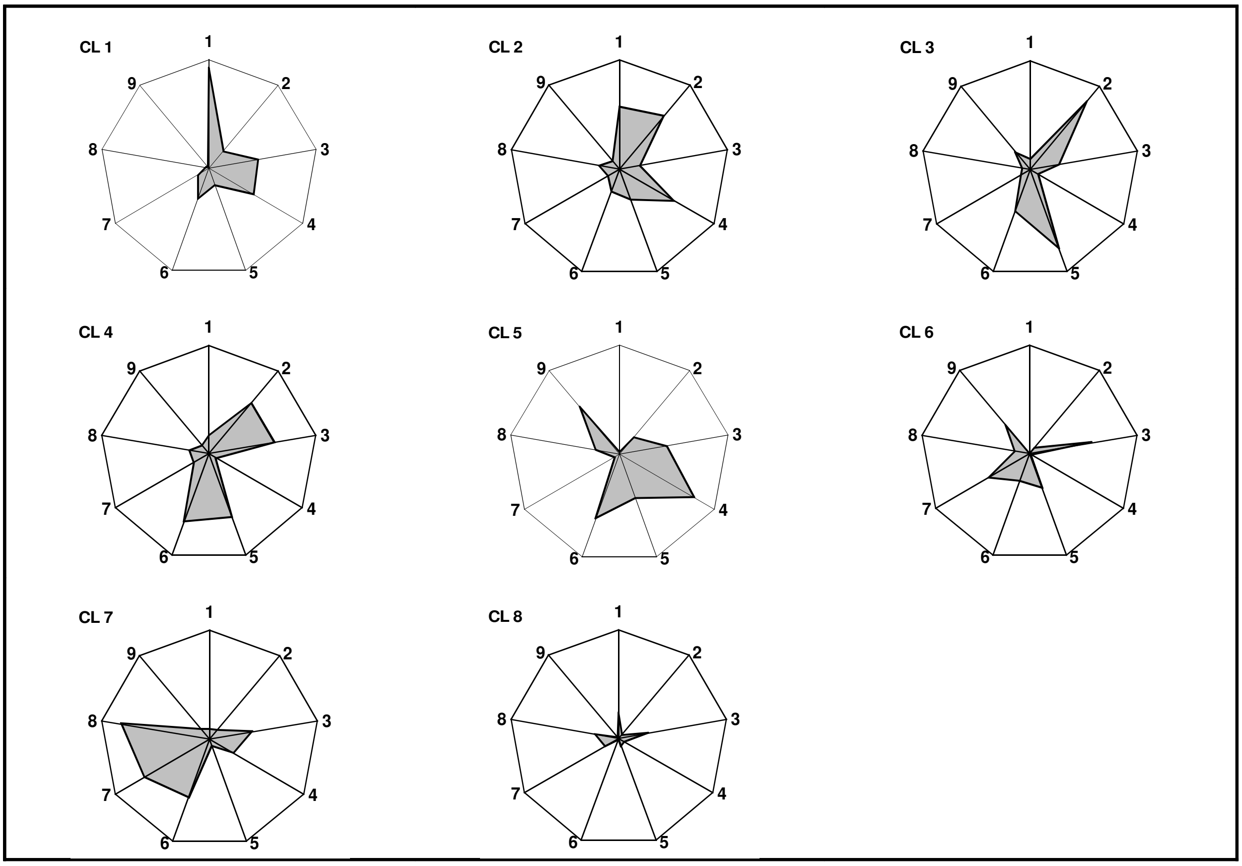


Figure 7: Centroids coordinates of the 8 clusters along the 9 retained EOFs, in absolute value. Star diagram axis length equals 0.04 EOF units.

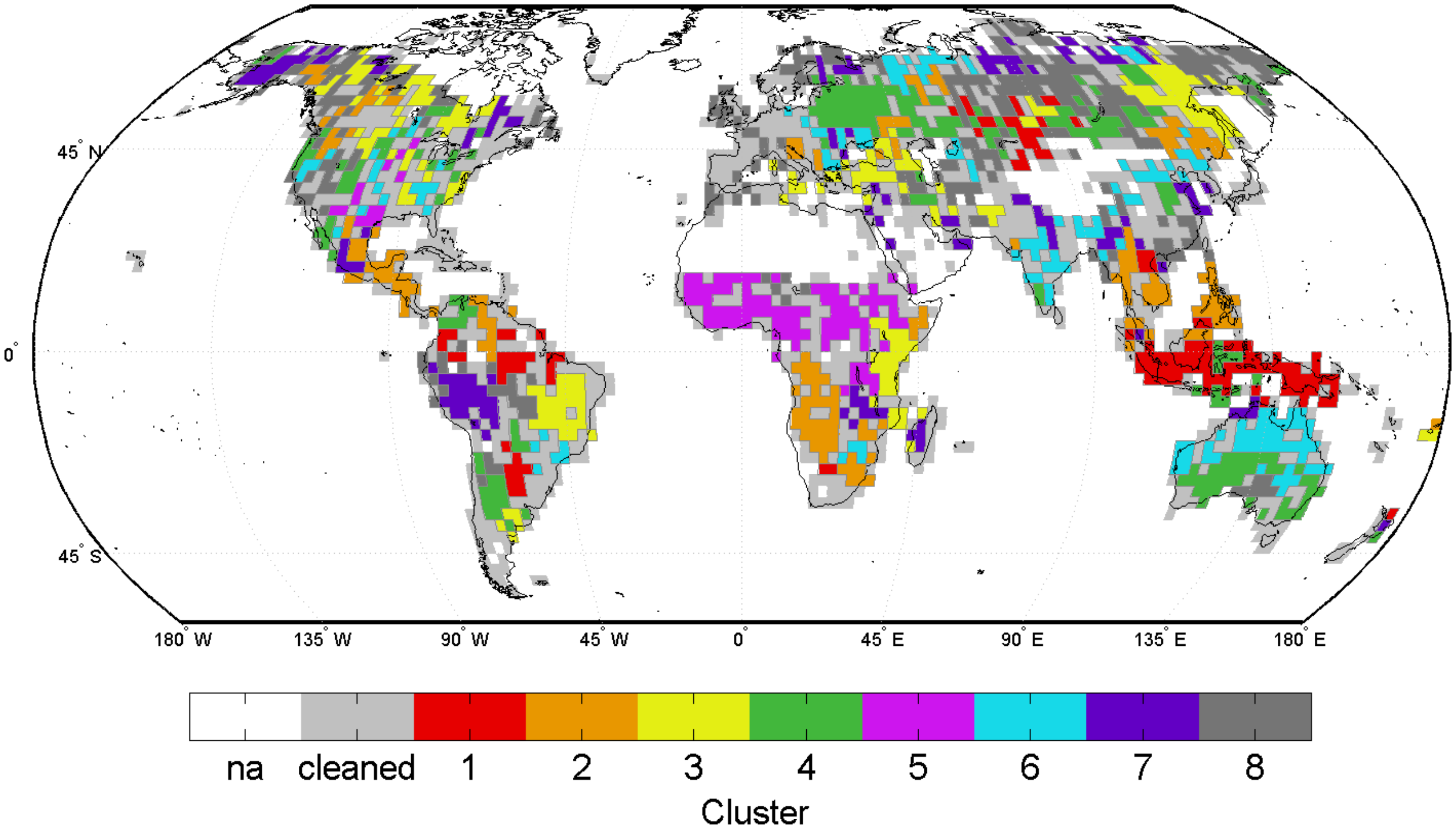


Figure 8: Spatial clusters of fire counts variability from 07/1996 to 06/2006. Isolated pixels were removed for clarity.

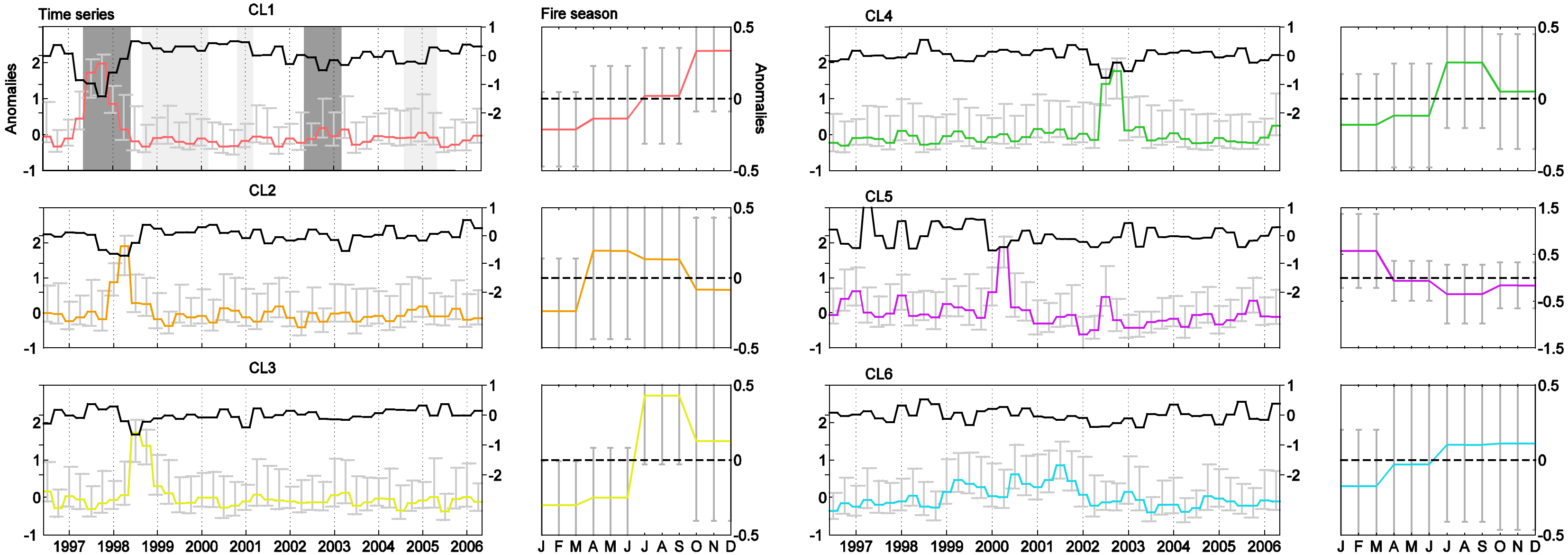
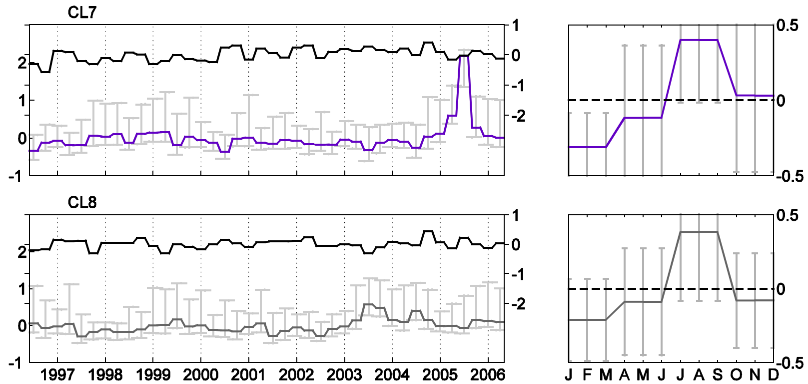


Figure 9: (left) temporal profiles of fires (colored) and precipitation anomalies (CMAP data) and (right) averaged fire season., for each of the 8 clusters.



Using the 1km land cover product from University of Maryland (available online at http://glcf.umiacs.umd.edu/data/), a quantitative assessment of fire-affected ecosystems is given for each year (Table 1), and each cluster (Table 2and Figure 10) to assess the variability in affected ecosystems. We followed the method used by Tansey *et al.* (2004a, b) with the GBA2000 dataset, i.e. land covers are aggregated into 4 broad vegetation types (Needleleaved and Mixed forests (N&MF), Broadleaved forests (BF), Woodlands and Shrublands (W&S), Grasslands and Croplands (G&C)). The quantitative comparison to GBA2000 (Table 1) confirms previous findings that the detection rate of the ATSR sensor varies with land cover. Consequently, fire count distribution by land cover must be considered relatively (between clusters or through time) and not as an absolute quantification.

Table 1. Fire counts proportion (%) by year. GBA2000 indicates proportion of burned areas derived from this product (Tansey *et al.*, 2004).

	NL&M Forest	BL Forest	Woodland & Shrublands	Grasslands & Croplands
1997	2.5	**26.4**	56.8	12.7
1998	**9.7**	19.6	57.3	11.7
1999	4.6	17.0	65.2	11.6
2000	**5.6**	**11.2**	**68.9**	**13.1**
(GBA2000)	(1.5)	(1.2)	(80.7)	(16.6)
2001	3.1	1.2	67.0	16.0
2002	7.8	17.2	60.7	13.3
2003	**14.7**	16.0	55.3	12.4
2004	4.5	**21.5**	62.4	10.6
2005	3.6	**20.9**	60.3	13.5
Total	6.6	17.5	61.5	12-09-09

Table 2. Clusters global characteristics. Rectified surface is the proportion of total grid-cells surface (rectified with latitude) with active fires in the cluster. Fire density is the ratio between the cluster percentage of total active fires and the corresponding rectified surface.

Cluster	Rectified Surface (%)	Fire Proportion (%)	Fire Density
1	4.9	8.1	1.6
2	8.3	9.3	1.1
3	8.4	11.2	1.3
4	10.1	10.3	1.0
5	6.4	10.3	1.6
6	7.9	9.0	1.1
7	6.3	6.9	1.1
8	12.2	9.3	0.8
Total	**64.5**	73.6	

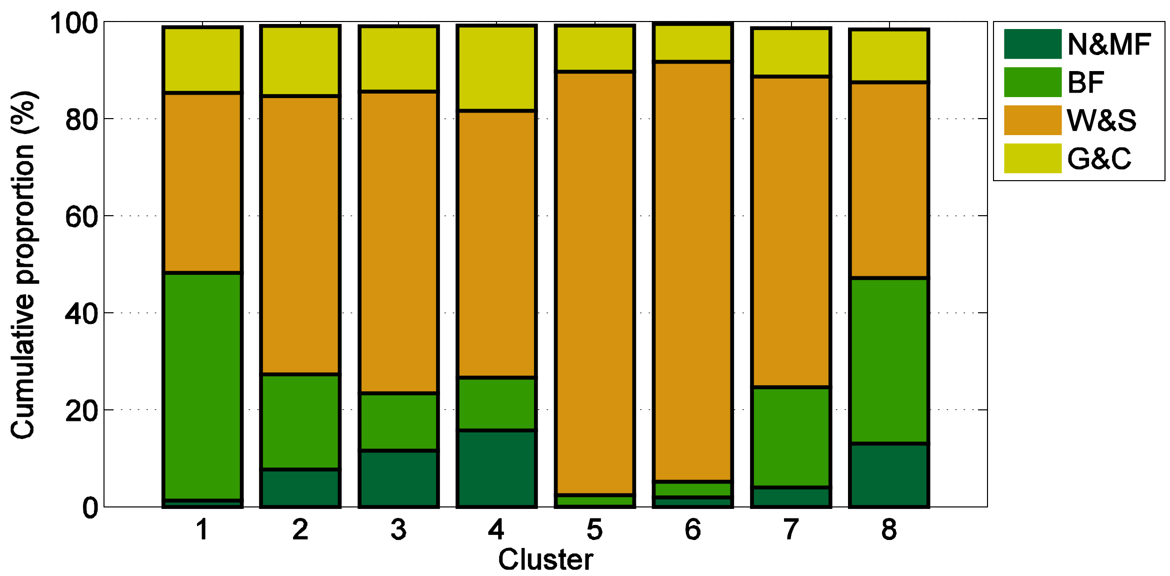


Figure 10: Active fires incidence by landcover (UMD Landcover), for each cluster. N&MF: Needleleaved and Mixed Forests ; BF: Broadleaved Forests ; W&S: Woodlands and Shrublands ; G&C: Grasslands and Croplands.

V. Discussion

V.1. WFA screened data detection characteristics

Results from an analysis based on active fires are expected to differ from those based on burned area, since the correlation between these two types of fire signal has been reported to be relatively weak for some regions or ecosystems (Kasischke *et al.*, 2003; Arino and Plummer, 2001). The relatively low temporal resolution of the WFA (3-4 days) and the night-time overpass (10:00 pm) lead to under-detection of low duration and intensity fires. As a consequence, forest fires represent a higher proportion of our data than in GBA2000 (~17% vs ~3% in 2000). Comparison with MODIS active fires (Justice *et al.*, 2002) and derived burned area data (Giglio *et al.*, 2006) also shows underestimation of fire activity in agricultural areas and, more generally, in Africa (unpublished results), where a large number of fires only burn at daytime. This means that our dataset does not take into account an unknown proportion of small fire events, thus focusing on the larger, longer lasting events, which are more likely to show a strong relationship with climate pattern. It should be stressed that these large vegetation fire events can also be considered to represent the most important fires in terms of biomass burnt and atmospheric emissions. Therefore, we strongly believe that our other results, especially their temporal dynamic, are little affected by this bias since we worked with anomaly data. Finally, findings from Kasischke *et al.* (2003) suggest that remotely sensed fire data have variable inter-annual detection rates. Especially, high fire years exhibit increased fire intensity and decreased cloud cover, enhancing the detection rate. This may magnify the scale of positive anomalies identified in our study.

V.2. Global variability patterns over 1996-2006

The main space-time patterns of fire activity observed during the study period were classified into 8 clusters, illustrated in Figure 8 and Figure 9.

Cluster 1 is mainly driven by EOF1 (Fig. 7). It has the earliest and longest response to El Niño, and includes areas located in south-east Asia, South America and central Asia. The temporal pattern illustrates the large fire episode spanning Jun-Aug 1997 to Dec-Feb 1998, which responded to a severe precipitation deficit. In Indonesia and Papua/New Guinea, monsoon rains were very low due to El Niño, and the ensuing drought led to widespread burning. The evergreen rainforest and peatlands were hugely affected by those fires (Page *et al.*, 2002; Siegert and Hoffmann, 2000). Murdiyarso and Adiningsih (2006) estimated the area affected at about 116000 km^2, resulting in the release of 1.45 GtC, equivalent to half the annual atmospheric CO_2 growth rate.

In South America, cluster 1 includes large parts of the Amazon forest (in the Brazilian states of Amazonas, Roraima and Pará, northern Brazil), as well as in Paraguay, north-east Argentina and southern Colombia. The Amazon basin experienced one of the most severe droughts on record, leading to both tree mortality and intense burning (Williamson et. al, 2000 ; Cochrane *et al.*, 1999). In Roraima, which burned intensively in early 1998, the affected area represented an estimated 7% of the original forest ecosystem and more than doubled its previously deforested area (Barbosa *et al.*, 2003).

In Kazakhstan, 1997 was a very dry year, and large fires affected timber plantations (Arkhipov *et al.*, 2000). However, these have not been connected to El Niño and may result from other factors at the regional scale.

The precipitation profile clearly illustrates the dramatic deficit experienced by those regions, which rapidly led to fire outbreaks. This suggests the exceptional nature of fires in tropical ecosystems, which do not have a regular fire activity, but become highly flammable during occasional severe moisture deficits. This is particularly true in disturbed ecosystems, either subject to selective logging or peatland drainage. Although those regions were generally not much affected by fires over the rest of the period, this cluster has the highest fire density, and almost 50% of the fire activity is detected in tropical forests, further indicating the scale of the 1997-98 El Niño episode (Table 2 and Figure 10). Interestingly, although the 1997-98 event clearly leads the cluster, a slight increase is observed in 2002-03, corresponding to a weaker El Niño phase, mainly affecting insular south-east Asia.

Cluster 2 is driven by EOF1, 2 and 4 (Fig. 7). It is mostly representative of sub-tropical regions affected by El Niño in 1998, including south-east Asia, southern Africa and Central America. The corresponding enhanced fire activity peaks in March-April 1998, i.e. close but clearly afterwards the peak depicted by cluster 1 (Fig. 9). Dry conditions in Central America were provoked by a sub-tropical high pressure area settling over the region in the spring season, due to late El Niño impact (NCDC, 1998 Annual Review, 1999). Agricultural fires escalating out of control were responsible for large areas of destroyed tropical forests. In tropical Mexico alone, Cairns *et al.* (1999) estimated a total of 4820 km^2 affected area, while only 2230 km^2 had been burned in the previous 17 years of satellite data availability, and the region has been reported to be sensitive to ENSO (Román-Cuesta *et al.*, 2003).

In south western Africa, the anomaly was actually due to an early start of the fire season, although fire activity appears not to have been exceptionally high.

South-east Asia, Thailand, Cambodia, Vietnam, Malaysia and the Philippines were highly affected by ENSO-induced dry conditions. In Thailand, extensive crown fires in pine forest and ground fires in peat-swamp forests contributed to a total burned area of more than 10000 km^2, largely above the annual average (Akaakara, 2002). The land cover profile is diversified, but shows a significant percentage of affected tropical forests. The average fire season for this cluster is bimodal, with one peak occurring in the first half of the year in south-east Asia and Mexico, and the other later in the year, in southern Africa. Overall, cluster 2 has a low fire density (1.1), which is not surprising since vegetation fires are very sporadic throughout most of its component regions, perhaps with the exception of Thailand.

Regions in northern China and Canada are also included. They represent the start of two other important fire events connected to El Niño, which further spread during the following months, as identified in cluster 3.

Cluster 3 is mostly driven by EOF2 and EOF5 (Fig. 7). It groups regions in the Siberian Far East, central/western Canada, eastern Brazil and eastern Africa, all having a their fire season cycle in phase, i.e with maxima occurring at approximately the same time of the year. It is characterized by enhanced fire activity in June-August and September-November of 1998, mainly originating from a delayed impact of El Niño. The Siberian Far East was hit by a severe drought for several months, after a high pressure centre persisted from May to September (NCDC, 1998 Annual Review, 1999), leaving the region without adequate rainfall. 72000 km^2 of forests were affected, with roughly 10000 km^2 correspond to high intensity crown fire burns (Shvidenko, 2001). Over North America, very warm temperatures were observed, and fires burned 47000 km^2 (Johnston, 1999). These episodes, although mostly concentrated in the regions highlighted in this cluster, affected the whole boreal ecosystem (forest, steppe and peatland). The total burned area has been estimated at 179000 km^2 (Kasischke and Bruhwiler, 2002).

In eastern Brazil, mature El Niño climatic conditions are partially to blame for enhanced fire activity in Mato Grosso and southern Pará (Alencar *et al.*, 2006). Fires were originally set by farmers and loggers for clearing land, and easily spread through the very dry vegetation.

Finally, the eastern Africa component of cluster 3 is located in Kenya and Tanzania, which were first affected by above average rainfall in 1997, resulting in accumulation of biomass (Anyamba *et al.*, 2001). The reversed situation in 1998, with moderate to strong drought (Kijazi and Reason, 2005), facilitated the outbreak of large fire events.

Clusters 1 to 3 are all related to the El Niño event, illustrating its global scope. They are individualised by the different timing of the fire outbreak, which results from a complex interlocking of several factors. First is the propagation of the ENSO induced changes in precipitation, starting in early-1997, mid-1997 and early-1998 respectively (Figure 10). This time sequence is due to the latitudinal or longitudinal distance to the original ENSO location, involving complex atmospheric circulation patterns. In the case of the eastern Africa regions, affected by fires in mid-1998, the teleconnection may have involved a coupling of ENSO with the Indian Ocean Dipole (Black, 2005). Second, the vegetation state and moisture level at the onset of a drought period is a determinant factor of the delay before fire-prone conditions are actually achieved. Generally, fires are mainly observed during the normal climatologic fire season, but in the case of strong and prolonged droughts, fires may occur at unusual time of the year (south-east Africa in cluster 2), and in rarely affected ecosystems (tropical forests). The sensitivity of those regions to El Niño was tested by repeating the same analyses over 1999-2006 only, thus removing the extreme event of 1997-1998. The results (not shown), indicate that cluster 1 is merged with cluster 4 (see below), which also showed positive anomalies during the 2002 El Niño. This suggests a recurrent impact of ENSO on fires in Indonesia and South America, as was also indicated by EOF1 (Fig. 5). Clusters 2 and 3 do not show this sensitivity to weaker El Niño events.

Cluster 4, driven by EOFs 2, 3, 5 and 6 (Fig. 7), is dominated by a strip covering central Asia, south Australia and western Argentina (Fig. 8). The temporal pattern shows a clear spike in fire activity in the second half of 2002. During this episode, Russia was hit by a widespread heat wave, unprecedented in the previous 30 years (NCDC 2002 Annual Review, 2003), which favoured the occurrence of late season major fire outbreaks, affecting an estimated 120000 km^2 (Giglio *et al.*, 2006). In Australia, Victoria and the Capital Territory experienced intense fire activity, during one of the driest years on record (NCDC 2002 Annual Review, 2003).

Cluster 5 has unique patterns. Although driven by several EOFs (Fig. 7), it is almost exclusively located in sub-Saharan northern hemisphere Africa. Woodlands and shrublands strongly dominate its affected land cover profile, and it is the only cluster with a fire season peak during the boreal winter. The main positive anomaly indicates enhanced biomass burning in early 2000. This was probably favoured by the positive rainfall anomaly during the previous year, as suggested by the precipitation profile. Enhanced fire activity was reported in Africa at this time, particularly in Ethiopia, where large fires led to a multi-national fire fighting campaign through February to the outcome of heavy rainfall in late March (Goldammer and Habte, 2000). This episode was unusual, since mostly forest was burned, in a cluster where woodlands, shrublands and agricultural fires are highly predominant. The fire-density is estimated at 1.6, but this is very likely to be an underestimation, as the ATSR WFA has a relatively low detection rate in agricultural fires, which mainly burn at daytime.

Cluster 6 involves diverse, globally scattered regions, including northern Australia, south-east Asia and the United States (Fig. 8). The time series associated indicates a broad positive anomaly spreading from 1999 to 2001. In the US, 2000 was the second worst fire year since 1960, with more than 30000 km^2 burned (Wildland Fire Statistics, 2007). Central Australia was affected by large bushfires, and the state of Queensland was hit by one of its worst fire seasons in memory (Bureau of Meteorology, Annual Report 2001-2002, 2002). The large standard deviation indicates that the timing of the patterns is variable from one region to another.

Cluster 7 is characterized by a sharp event in the 2005 boreal summer, featured by EOFs 6, 7 and 8 (Fig. 7), affecting Alaska, Peru and the western Brazilian Amazon, mainly (Fig. 8). In Alaska, around 45000 km^2, mostly boreal forest, burned, severely affecting an ecosystem recovering from the previous fire season, which had been the worst of the last 50 years. The 2004 fires do not appear in our analysis since they were not contemporaneous with other regional fire events and thus did not represent sufficient global variability to be retained.

South America was hit by a severe drought, especially along the Brazilian/Peru border region, where it was the most severe of the previous 60 years. Fires especially affected the eastern Brazilian states of Acre and Rondônia (Aragão *et al.*, 2007), which are both included in this cluster.

Cluster 8 includes mainly boreal regions, and, as suggested by the centroid coordinates, does not highlight any significant event. It includes scattered regions, and has the lowest fire density of all clusters.

The main driver of the cluster distribution is, by construction, the variability that was represented by the set of nine selected EOFs. But most of the clusters also exhibit a strong coherence in terms of fire seasonality, suggesting that in most parts of the world the parameters driving fire season have a sufficient strength to contain fires within a certain annual extent. The only exception concerns regions where the usual climatic drivers normally show little intra-annual variability, namely equatorial regions.

Conclusion

Analysis of major space-time patterns of global fire incidence over an entire decade using a screened version of the WFA, reveals important spatial and temporal structuring and a clear major role played by ENSO. The ten years of fire data can be arranged into a small number of clusters, which are interpretable in both ecological and climatic terms, and correspond to regional anomalies described in the literature. The results are valuable to identify the regions mostly affected by each event, and to support ecological studies and atmospheric impact assessments.

The outstanding El Niño event of 1997-1998, controlling the three leading EOFs, is shown to have had global and long term footprints on fire activity, in critical regions, especially tropical forests. This high sensitivity of global fire activity to a global climate phenomenon suggests its mechanisms and implication have to be better understood for both near-future and climate change forecast purposes. Tropical forests have a fundamental role, in many ways. They host the highest biodiversity in the world, and current deforestation rates and enhanced fire activity are exposing those ecosystems to further and more rapid degradation by positive feedbacks mechanisms, as described by Nepstad *et al.*, (1999), Laurance *et al.*, (2001) and Cochrane and Schulze (1999). Forecasts of 21st century tropical timber trade stress the urgency of addressing this issue (Soares-Filho *et al.*, 2006).

Boreal regions have also experienced very destructive fires over the study period, both in Eurasia and North America, some under El Niño conditions (Cluster 3), and others during regional precipitation and temperature anomalies (Clusters 4 and 7). Evidence of an ENSO influence, and of the impact of extreme conditions potentially due to climate change on fire incidence in the Siberian Far East is particularly worrying. This region, which contains important biodiversity resources, is under serious threat (Mollicone *et al.*, 2006), since the capacity for fire fighting and for preventing illegal logging have declined in recent years.

Increasing availability of data is enabling a better understanding of biomass burning, especially through improved satellite sensors and their availability over longer periods. In this perspective, expectations from the MODIS burned area product are high. The AVHRR data, although its resolution and consistency over the whole period are not ideal, should also prove very useful for atmospheric emissions and vegetation disturbance studies. Fire driver investigations, which until now mainly relies on ground studies, could greatly benefit from the availability of such longer data time series. With the support of climatic, vegetation and human dataset and climate models, this would open the possibility of assessing climate change impacts on fire activity.

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CHAPTER II: GLOBAL FIRE PATTERNS AND DRIVERS: A COMPARISON OF A DGVM-FIRE MODEL WITH SATELLITE DERIVED OBSERVATIONS.

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CHAPTER II: GLOBAL FIRE PATTERNS AND DRIVERS: A COMPARISON OF A DGVM-FIRE MODEL WITH SATELLITE DERIVED OBSERVATIONS.

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Abstract

Biomass burning is an important environmental process with a strong influence on vegetation and on the atmospheric composition. It competes with microbes and herbivores to convert biomass to CO_2, and is a major contributor of reduced gases and aerosols to the atmosphere. To better understand and predict global fire occurrence, fire models have been developed and coupled to Dynamic Global Vegetation Models (DGVMs) and Earth System Models (ESMs). These models, however, have not been properly evaluated at global scale, resulting in unknown uncertainties in current assessments and future projections of global fire activity.

We present the first quantitative, global, multi-year comparison between the output of a DGVM-fire module coupling and fire observation data. Burned areas and emissions from the SEVER model are compared to the Global Fire Emission Database version 2 (GFED), derived from satellite observations. We focus both on the model output accuracy and on its assumptions regarding fire drivers, and perform:

1- An evaluation of the predicted spatial and temporal patterns, focusing on fire frequency, seasonality and inter-annual variability.

2- Analyses to evaluate the assumptions concerning the etiology, or causation, of fire, including climatic and anthropogenic drivers, as well as the type and amount of vegetation.

SEVER reproduces the main features of climate driven inter-annual fire variability at a regional scale, such as the large fires associated with the 1997-98 El Niño event in Indonesia, Central and South America, which had critical ecological and atmospheric impacts. Spatial and seasonal patterns of fire frequency reveal substantial model inaccuracies, and we discuss the implications of assumed proxies of human fire practices, the distribution of vegetation types inferred by the DGVM. We further suggest possible development directions, to enable such models to better project future fire activity.

Keywords: DGVM-Fire modelling, Model evaluation, Fire frequency, Fire seasonality, Fire variability.

REVIEW

This paper was submitted for publication in Global Change Biology in October 2008, and was rejected with encouragements to re-submit the manuscript after revision. The major issue raised by the editor and referees concerned the use of consistent climate data throughout the study.

Indeed, although the DGVM-Fire model is run with NCEP precipitation data, the evaluation analyses were performed with CMAP precipitation data. Large discrepancies have been reported between these two datasets, especially in the tropics. However, because CMAP precipitation are clearly more realistic, they were chosen to analyze fire drivers with observed fire data. To keep a consistent model-observation comparison, we also used the CMAP data to analyze the fire driving assumptions in the model. However, in regions where NCEP precipitation is largely erroneous, we cannot determine whether discrepancies in the model are due to its parameterization or to inaccurate input data.

The methodology has been modified to address this issue. The model will be run with CMAP precipitation data. Because the model requires a period longer than the CMAP time series to reach equilibrium, the spin-up will be performed with a repeated CMAP time series. The disadvantages of such a repetition should be largely outmatched by the use of recent and consistent precipitation data.

I. Introduction

The biosphere is affected by fires through physical and chemical pathways, involving interactions between the terrestrial and atmospheric components of carbon, water and nutrients cycles. As a natural phenomenon, fires are an integral part of a majority of ecosystems, influencing soil fertility, stand regeneration, vegetation composition, and succession (Levine et al., 1999). Contemporaneous fire regimes are however largely influenced by the anthropogenic use of fires for agriculture activities, land management practices, and as a clearing tool for ecosystem conversion (e.g. deforestation). It is estimated that, on average, an area equivalent to that of India burns every year, predominantly in savannas and grasslands (Tansey et al., 2004). Burned areas in tropical and boreal forests are smaller, but their high productivity and carbon storage capacity results in significant emissions of numerous greenhouse gases (e.g. CO2, CH4, Andreae & Merlet, 2001; Pereira *et al.*, 1999). Globally, total fire emissions are equivalent to approximately one third of fossil fuel burning emissions (Schultz et al., 2008). Net emissions stemming from deforestation or increased fire activity are smaller, but their quantification is little constrained (van der Werf *et al.*, 2006).

The strong integration of fires with the biosphere system is also emphasized by their dependence on a complex system of interactive drivers dominated by climate, vegetation and human activities, designated as the fire triangle. Climate partly controls the amount of fuel available to burn, its moisture content, and fire behaviour in case of ignition (Crevoisier *et al.*, 2007; Turner *et al.*, 2008). Fire frequency, fire severity, and ensuing emissions are also dependent on the vegetation types, structure and productivity of the ecosystem (Hammill & Bradstock, 2006; Andreae & Merlet, 2001). Finally, anthropogenic activities, as mentioned above, greatly bias the natural occurrence of fires, increased in many regions as a land management tool, or decreased through fire suppression strategies (fire fighting, preventive fires, Veblen *et al.*, 2000). Other factors are involved (topography, natural landscape breaks, grazing), but most important is the interaction between those drivers, which needs to be considered to yield relevant information about fire regimes (Dwyer *et al.*, 2000a).

Dynamic Global Vegetation Models (DGVMs) and Earth System Models (ESMs) simulate vegetation dynamics, but fire is included as an explicit process in only a few of these models (Thonicke *et al.*, 2001; Arora & Boer, 2005; Bachelet *et al.*, 2001). The development of fire modules is essential given the importance of fires, and of great interest to evaluate the coupling with other simulated processes and feedback assumptions. To the best of our knowledge, none of these models has undergone global and extensive assessment against observation data, although a fire model inter-comparison (Bachelet et al., 2003), and a few local to regional validations (Arora & Boer, 2005; Thonicke *et al.*, 2001; Venevsky *et al.*, 2002), have been published.

SEVER-DGVM is a DGVM with daily time step computation (Venevsky & Maksyutov, 2007). A coupled fire module, SEVER-FIRE, estimates fire frequency and emissions based on SEVER-derived vegetation, climate, demographic and socio-economic data. The resulting vegetation disturbance feeds back to the DGVM, ensuring a fully coupled system (see Sect.. for model description).

We compare SEVER outputs with fire data derived from satellite sources, the Global Fire Emission Database version 2 (GFED) (van der Werf *et al.*, 2006), with two objectives. First, a global evaluation of a DGVM-fire model, focusing on fundamental features, namely fire frequency, seasonality, inter-annual variability, and emissions. Second, by identifying the reasons for large inconsistencies we suggest some new directions to improve the representation of fires in SEVER. Current fire modules feature conceptual differences (see model review in Arora & Boer, 2005), but are generally based on similar assumptions. Thus, this study may provide relevant information for other current DGVM fire modules.

II. Data and Methods

II.1. SEVER Model

SEVER-DGVM is a coupled vegetation-fire mechanistic model (Venevsky & Maksyutov, 2007) designed from the LPJ-DGVM (Sitch *et al.*, 2003) to run at a range of temporal (daily to monthly) and spatial (10km to 2.5º) resolution. The fire module SEVER-FIRE is a development of the Reg-FIRM model (Venevsky et al, 2002) for global scale applications (Reg-FIRM was applied to the Iberian Peninsula only). The aim of this recent model is to provide a fully mechanistic description of major characteristics registered in standard fires statistics and/or satellite observations around the world, namely number of fires, area burnt and carbon emissions. Hereinafter, "SEVER" indicates the whole SEVER-DGVM/SEVER-FIRE coupled system.

The most important variables provided by SEVER-DGVM to SEVER-FIRE include the global distribution of 10 Plant Functional Types (PFTs, see), described as a fraction of each grid-cell, net primary productivity (NPP), fuel loading, and soil moisture in the upper 10cm layer. Direct input data are also provided to the fire module to account for the role of climate and anthropogenic activities (described later). SEVER separates human-induced and lightning fires, and feeds back to the DGVM, through the area freed after a fire for competitive occupation by PFTs. Thus, SEVER-DGVM and SEVER-FIRE work in interactive mode, incorporating a representation of fire-vegetation feedbacks.

The SEVER-FIRE module consists of five related components:

- Estimation of the fire weather danger index and fire probability,
- Simulation of human and lightning ignition events,
- Simulation of fire spread after ignition,
- Simulation of fire extinction,
- Estimation of fire effects.

The fire weather danger index, measured from 0 ("no fire danger"), to 1 ("extreme fire danger") is estimated based on the Reg-FIRM fire index (Venevsky et al., 2002). It is calculated as the product of fire probability with the normalized Nesterov Index (Nesterov, 1949). Fire probability is a function of soil moisture in the upper 10 cm layer (Thonicke *et al.*, 2001) and of a PFT-dependent moisture of fire extinction (Table 1), adapted from experimental study of (Albini, 1976). The Nesterov Index is based on the accumulated difference of daily minimum and maximum temperature, re-initialized to zero when daily precipitation exceeds a threshold of 3mm.

Both human and lightning ignitions are considered in SEVER. The number of potential lightning ignitions in a grid-cell is calculated from the number of cloud-to-ground flashes, estimated from convective precipitation as a linear regression function (Allen & Pickering 2002; Cardoso *et al.*, 2008). The number of potential human ignitions is calculated as a polynomial function from population density (Russian Forest Service, personal communication), as in the Reg-FIRM model (Venevsky et al., 2002), and also depends on the socio-economic characteristics of the population. These include the ratio of urban to rural population, provided by the United Nations Population Information Network (POPIN), timing of human pyrogenic activity, wealth status (Svirejeva-Hopkins et al., 2001), and distance from a megacity (urban population density above 400 persons/km^2, as defined by the United Nations Human Settlements (UN-HABITAT)). The timing of human pyrogenic activity is defined separately for the northern and southern hemisphere as a step function, and is mostly based on agricultural and vacation calendars. For example, for the entire northern hemisphere it was set to be maximum in July and August (Summer vacations), from March to May (Spring agricultural activities) and from September to November (Autumn agricultural activities). The distance from a megacity serves as a proxy to estimate the potential density of human ignitions and fire extinction efforts.

Table 1: 5 of the 35 parameters defined for each of the 10 SEVER PFTs.

PFTs	Moisture of extinction[1]	Fire resistance index[2]	Minimum coldest monthly mean T°C[3]	Maximum coldest monthly mean temperature[3]	Bulk density of fuel kg/m2
Tropical Broadleaved evergreen tree	0.3	0.12	15.5	Ø	3
Tropical Broadleaved rain green tree	0.3	0.5	15.5	Ø	2
Temperate Needleleaved evergreen tree	0.3	0.12	-2	22	10
Temperate Broadleaved evergreen tree	0.3	0.12	3	18.8	10
Temperate Broadleaved summer green tree	0.3	0.12	-17	15.5	10
Boreal Needleleaved evergreen tree	0.3	0.12	-32.5	-2	16
Boreal Needleleaved summer green tree	0.3	0.12	Ø	-2	16
Boreal Broadleaved summer green tree	0.3	0.12	Ø	-2	16
C3 perennial grass	0.2	1	Ø	15.5	2
C4 perennial grass	0.2	1	15.5	Ø	2

[1] *Involved in the computation of fire probability*
[2] *Involved in the computation of vegetation disturbance after a fire*
[3] *Ø indicates no limitation from the considered parameter*

The actual number of ignitions is computed as the product of potential ignitions and fire weather danger index. Fire spread after ignition is simulated using a simplified version of the Rothermel thermodynamic equation (Venevsky *et al.*, 2002), which depends on wind speed, fuel bulk density and soil moisture content in the upper 10cm layer as a proxy of fuel moisture. Fuel bulk density (Table 1) is estimated from PFTs bulk densities (Venevsky *et al.*, 2002; Albini, 1976), weighted by PFTs fraction values provided by the vegetation model. As in Reg-FIRM, a fire can not take place below a litter fuel loading threshold of 100g/m^2. The rate of spread is converted to burned area using an elliptic fire spread model (Van Wagner, 1969) similarly to the Reg-FIRM approach.

Fire extinction occurs with the onset of a significant rainfall event (more than 3mm), causing weather danger to drop to zero. Close to cities, fire extinction occurs after a delay dependent on the distance to the city, as a proxy for human fire suppression. A fire can burn from one hour to a maximum of three days.

Daily burned area estimates are aggregated annually to estimate fire effects. The percentage of individual plants killed depends on the resistance of each PFT to fire (Table 1), taken from the Glob-FIRM model (Thonicke *et al.*, 2001). These percentages are then converted to emissions, based on vegetation carbon content (dead PFT individuals are considered to be entirely burned), and daily redistributed following the fire probability profile.

The description of human ignitions is very simplistic and does not have intention to describe complex practices. Because SEVER does not include a description of land use and/or its influence on land cover, the related fire practices are left out or over-simplified.. SEVER aims to describe relatively human-less global vegetation distribution which gets additional drivers as human caused fires. This limitation implies certain constraints on our results in both vegetation distribution and areas burnt, but it also gives an opportunity to identify and locate the areas where the interaction between climate, land use and fire practices should be described explicitly and accurately.

For this study, data from the National Centres for Environmental Prediction (NCEP, http://www.cpc.ncep.noaa.gov/), i.e. minimum/maximum temperature, precipitation and convective precipitation, short-wave radiation and wind speed were interpolated to 0.5 degree longitude/latitude spatial resolution for the period 1957 to 2006 (52 years). Daily wind speed is not well estimated in reanalysis approach (Kalnay *et al.*, 1996), and was thus averaged over the entire period and applied in simulation runs without inter-annual variability. The input soil texture data and CO2 atmospheric concentration over the same period coincides with those of the LPJ-DGVM (Sitch et al., 2003). The model is run globally from bare soil state 15 times with the climate data for 52 years and the CO_2 atmospheric concentration fixed for the year 1957 (spin-up period), in order to achieve equilibrium of soil carbon pools. From this equilibrium state, SEVER is forced by climate and atmospheric CO_2 for the period 1957- 2006 (transient period).

II.2. Burned area and carbon emission validation data

The Global Fire Emission Database (GFED) is a global 1° resolution burned area database (van der Werf *et al.*, 2006), which relies on three different active fire products calibrated to Moderate Resolution Imaging Spectrometer (MODIS) 500 meter burned area, for a temporal coverage spanning 1997-2006 (Giglio et al., 2006). Fire activity data from the Tropical Rainfall Measuring Mission (TRMM) – Visible and Infrared Scanner (VIRS, (Giglio et al., 2003)) and European Remote Sensing Satellites (ERS) Along Track Scanning Radiometer (ATSR, (Arino & Plummer, 2001)) sensors are used for the 1997-2001 period. Over 2001-2006, the calibration is based on active fires from MODIS (Giglio et al., 2006). Carbon emissions are estimated based on burned area estimates, with fuel loads calculated by the Carnegie-Ames-Stanford Approach (CASA) model (van der Werf *et al.*, 2006).

The active fire to burned area calibration step and the use of three different sensors to build this dataset generate significant uncertainties on burned area estimates, which are considered to be about 50% at regional scales, although not quantified in the current version of GFED (G. van der Werf, personal communication). Emission uncertainties are consequently higher, taking into account their further dependence on the CASA model and on fuel loads and emission factor values.

II.3. Fire frequency, fire variability and carbon emission evaluation

We chose to focus primarily on burned area to evaluate the model, as this is a prerequisite to estimate carbon emission. However, carbon emission being an essential aspect of biomass burning, its representation is briefly evaluated. Fire frequency, seasonality, and inter-annual variability from SEVER are compared to GFED data over the 1997-2006 period. As a DGVM, SEVER considers grid-cells to be 100% land or water. This required a few adjustment on both datasets (not detailed), causing minor changes in the original GFED statistics.

Fire frequency is mostly dependent on three factors: fuel availability, readiness of fuel to burn, and ignition sources. SEVER spatial patterns of fire frequency are first compared to GFED with the Burned Fraction metric (BF). BF drivers are then explored with a selection of relevant environmental variables, based on the fire triangle concept::

- Annual amount of precipitation, from the CPC merged Analyses of Precipitation (CMAP, (Xie & Arkin, 1997)), provided by the NOAA/OAR/ESRL PSD, Boulder, Colorado, USA, (http://www.cdc.noaa.gov/).

- An indicator of dry season severity (DSS), which was constructed from precipitation (CMAP) and temperature data (NCEP/NCAR re-analysis project, (Kalnay *et al.*, 1996)).

The indicator (Breckle, 2002), representing a rainfall deficit, is computed as indicated by Figure 1.

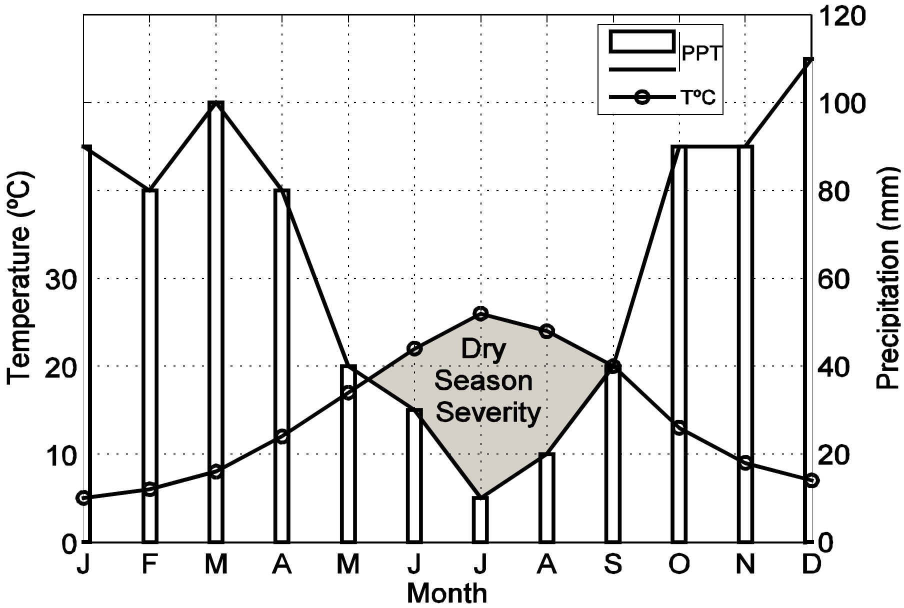

Figure 1. Definition of the dry season indicator on a climatic diagram as the yellow patch area. On the y-scales, 1°C is equivalent to 2mm/year of precipitation, and Dry Season Severity (DSS) is computed as the area of the region where the temperature profile is above the precipitation profile.

- Net Primary Productivity (NPP). Its influence on fires is estimated with NPP estimates from (Imhoff *et al.*, 2004) and from SEVER.

- Land cover spatial distribution. SEVER-DGVM vegetation distribution and its impacts on BF patterns are evaluated with the Global Land Cover for the year 2000 (GLC2000, (Bartholome & Belward, 2005)).

- Human rural and urban population density from the Global Demographic Data Collection (Vorosmarty *et al.*, 2000), provided by the University of New Hampshire, EOS-WEBSTER Earth Science Information Partner (ESIP). An indicator of the rural predominance of the population was defined (Eq. (1)):

$$Rurality = \frac{rpop - upop}{rpop + upop} \qquad \text{Eq. (1)}$$

rpop and *upop* being respectively the rural and urban population of the considered grid cell. *Rurality* varies between 1, fully rural, to -1, fully urban populations.

- Gross Domestic Product (GDP) gridded data (Van Vuuren *et al.*, 2007), provided by the Netherlands Environmental Assessment Agency.

The relationship of these variables with fire frequency is not linear, and involves multi-variable interactions. A more in-depth analysis of fire drivers would thus benefit from the use of multivariate statistics. We chose to avoid this level of complexity, since the most important conclusions are likely to be drawn from straightforward analysis, as a first evaluation of a global fire model. We thus analyze fire frequency through simple bi-dimensional plots.

Seasonality is evaluated via the fire season peak, i.e. the month with maximum fire activity for each grid-cell. Inter-annual variability is compared to GFED both globally and regionally, to identify how the model performs on specific fire events and for different ecosystems. Again, in a similar way to fire frequency, fire inter-annual variability has been shown to depend on climatic and vegetation conditions. (Meyn et al., 2007) highlight three types of fire ecosystems, depending on their annual fire limitation by fuel amount, fuel readiness to burn, or both, considering that the availability of ignition sources is relatively constant in time. Here, we evaluate the ability of the model to reproduce the inter-annual fire variability aggregated in a set of 13 regions. Additionally, we analyse the influence of both fire season precipitation and fire season maximum temperature for fire inter-annual variability, along three ecosystem types (boreal, tropical humid, and dry/semi-dry), to evaluate the hypotheses on the role of climate on the readiness of fuel to burn. To extract these variables, the extent of the fire season in a grid-cell was defined as the months with more than $1/12^{th}$ of the mean annual BF. Fuel availability, the second factor highlighted by (Meyn et al., 2007), is also discussed.

III. Results

III.1. Fire frequency and emissions

Figure 2 shows the spatial distribution of the averaged annual BF for GFED and SEVER. GFED clearly depicts the most extensively burned continents, i.e. Africa and Australia. It also indicates high fire activity at the edges of the tropical forest, due to land clearing and pasture management, in Central and South America and South East Asia (Morton *et al.*, 2006; Langner *et al.*, 2007). Fire frequency is much lower in most temperate and boreal ecosystems, except for the north-western Iberian Peninsula and Kazakhstan. A few other regions display high BF values, for example eastern Siberia and Alaska. Note, however, that for ecosystems with a long fire return interval, as is the case in boreal regions, the statistics computed over 10 years are very sensitive to the occurrence of important fire events during that period, and can not be considered representative of the long term regional fire regime. Eastern Siberia, for example, was highly affected by fires in 1998, boosting the 10 years average (Kajii *et al.*, 2002; Le Page *et al.*, 2008)

SEVER accurately reproduces some of the main spatial patterns of fire frequency, i.e. high BF values over Africa and Australia, very limited fire activity in the tropical evergreen forest and in most temperate and boreal regions. For a better emphasis of the discrepancies, Figure 3 illustrates the mismatch between GFED and SEVER through a normalised difference burned fraction index (NDBF) computed as:

$$NDBF = \frac{BF_{SEVER} - BF_{GFED}}{BF_{SEVER} + BF_{GFED}} \qquad \text{Eq. (2)}$$

Where BF_{SEVER} and BF_{GFED} are the annual fire frequency averaged over 1997-2006 from the model and the observations, respectively. NDBF is constrained between -1 (large model under-estimation) and 1 (large model over-estimation). Finally, Figure 4 shows the gradient of three broad PFTs classes (Bare soil, Grass and Trees), as modelled by SEVER, and areas of large over/under estimation of the actual tree cover percentage inferred from GLC2000. Those results and further comparison with GLC2000 clearly reveal the following patterns:

- Regions with low observed fire frequency and the presence of grass in the model display fire over-estimation, regardless of the GLC2000 land cover, and the more grass, the higher the over-estimation. This is the case for example in North America, India, South America and Papua New Guinea.

- Regions with dominant tree cover, or with a large over-estimation of trees in the model, display under-estimation of fire frequency. This is the case in a large strip covering Kazakhstan and eastern Europe, and in most of South East Asia, for example.

- The model under-estimates the very high fire frequency observed in sub-Saharan Africa.

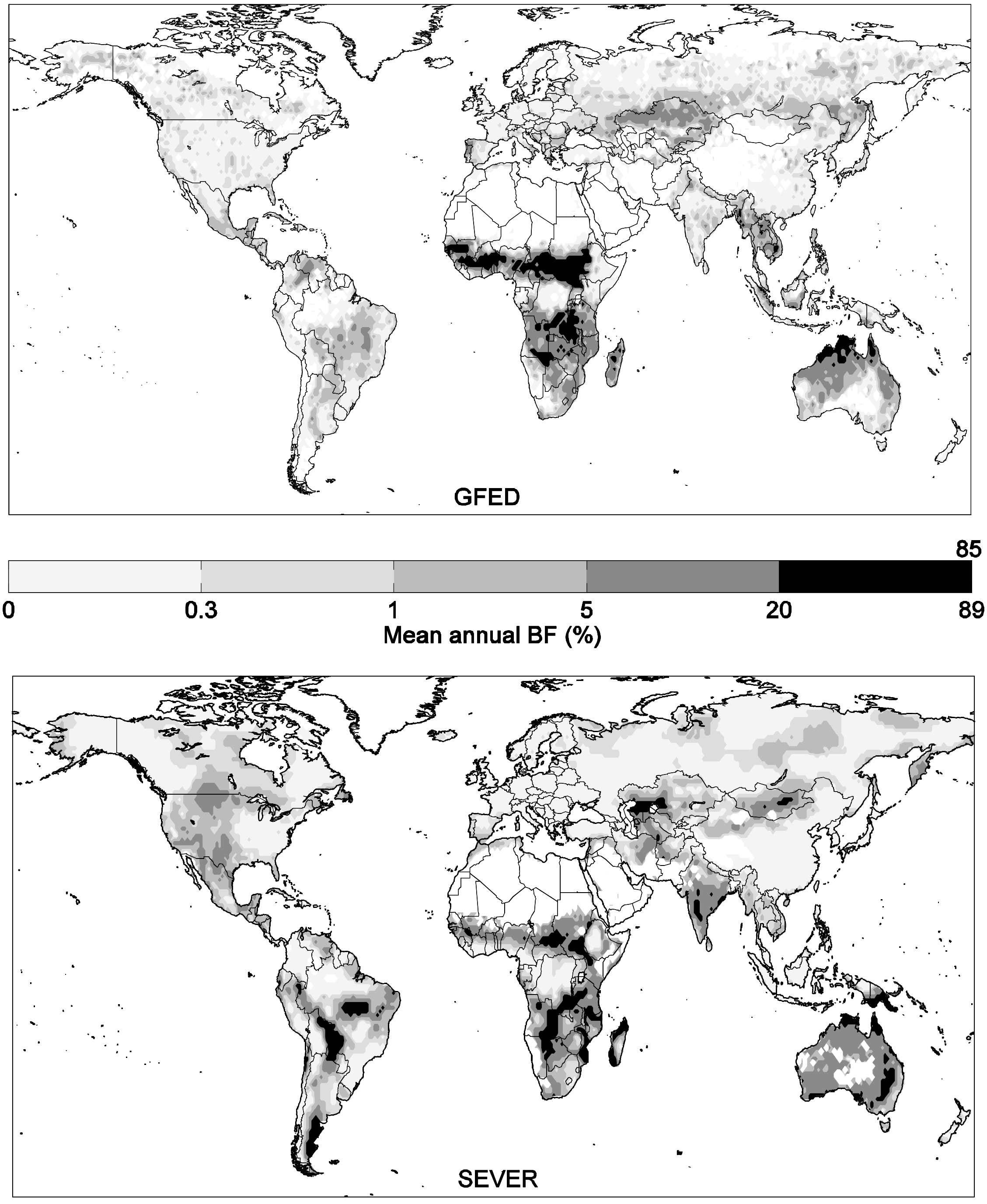

Figure 2. Mean Annual Burned Fraction (percentage) over 1997-2006. Top: GFED ; Bottom, SEVER.

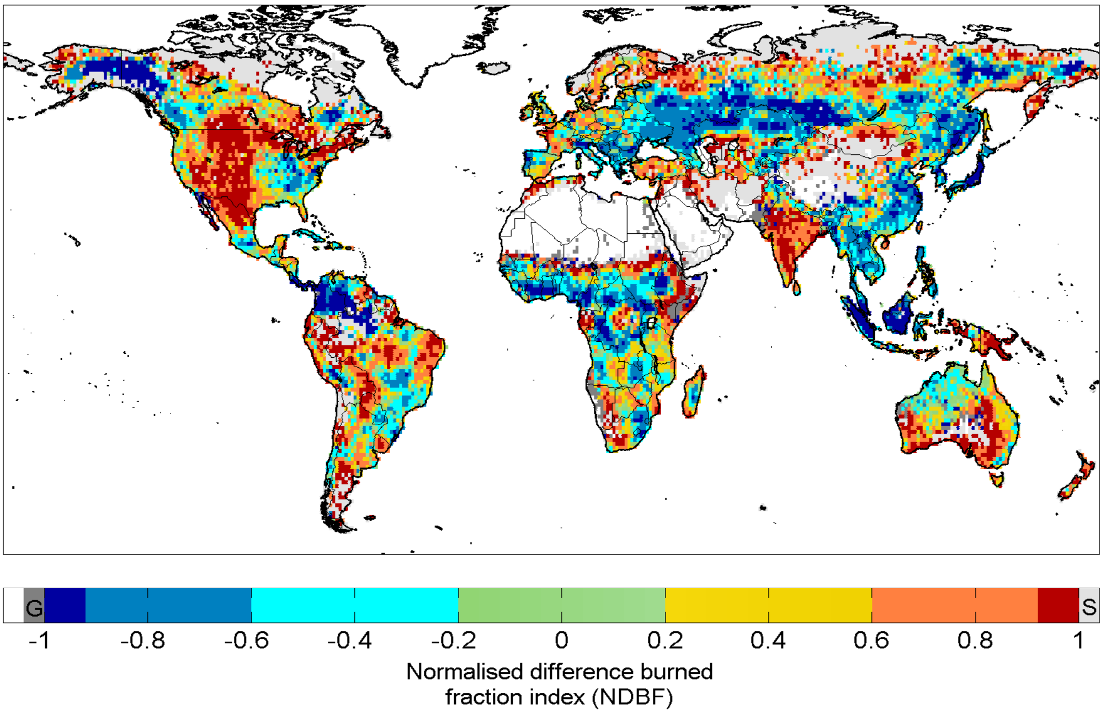

Figure 3. Discrepancies in the model outputs relative to GFED observation derived data, as represented by the normalised difference burned fraction index (see text). Black/grey colours represent grid-cells where fires only occur in GFED/SEVER.

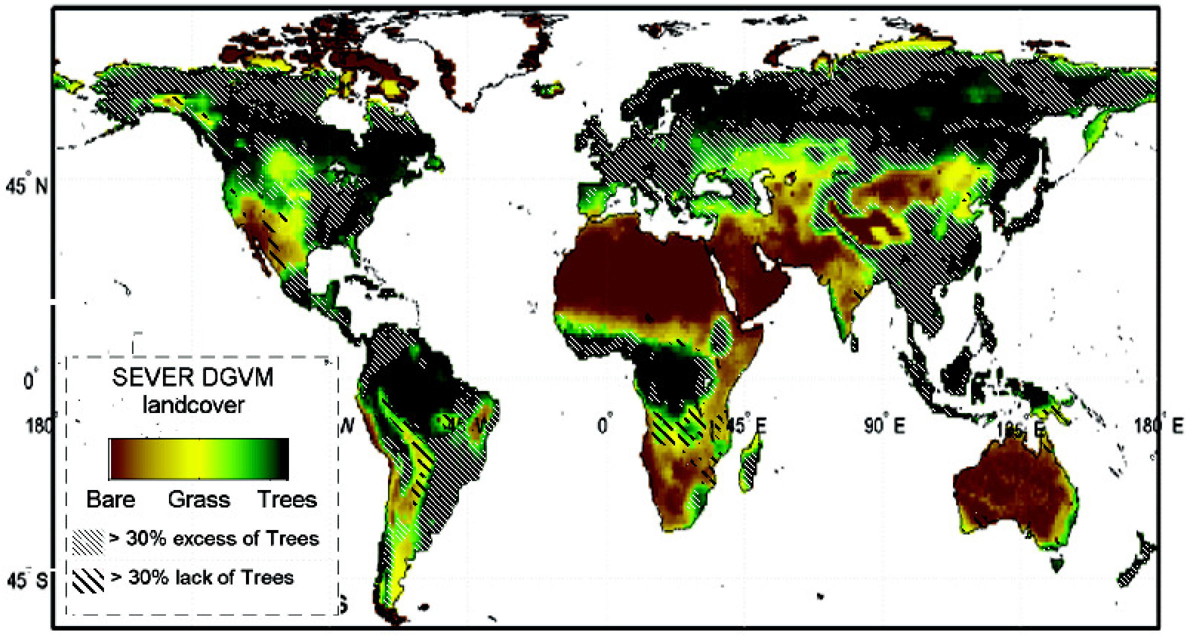

Figure 4. SEVER DGVM Land Cover type gradient: Bare soil, Grass (C3 and C4) and Trees (all Tree PFTs, cf Table 1. Thin/thick line texture correspond to large over/under-estimation of tree cover based on the GLC2000 product.

Considering the drivers of BF spatial distribution, Figure 5 illustrates the interactive influence of paired combinations of the previously described variables. In GFED, the most affected regions are clearly constrained by annual precipitation between 500 and 1500 mm/year and a dry season severity ranging from 150 to 500mm of rainfall deficit (Figure 5a). SEVER is less restrictive regarding this climatic limitation, but the general dependence patterns are similar to the observations. Concerning vegetation characteristics (Figure 5b), fires affect ecosystems of all levels of NPP, although fire frequency is low at the extreme ends of the spectrum. Similar values of NPP and annual precipitation can be found in very different ecosystems, as in boreal and sub-tropical regions for example, with great differences in fire frequency, hence the low predictability of GFED BF by NPP and precipitation. SEVER also shows little constraint of the mean BF by the combination of these two variables. Finally, high fire frequency is biased towards rural regions with very low economic income (<600 US$/capita/year), as shown in Figure 5c, with the exception of Australia, the only wealthy country highly affected by fires. SEVER also shows this rural bias, but also predicts high fire frequency in several wealthy regions, including North America.

Finally, Figure 6 displays the mean annual carbon emissions for GFED and SEVER. Emissions are mainly dependent on fire frequency, the type and moisture content of the affected vegetation, and fire severity. In SEVER, dead PFTs individuals are entirely emitted to the atmosphere, while GFED takes into consideration combustion completeness. Consequently, the absolute level of emissions cannot be compared, being much higher in SEVER, as expected. However, the spatial patterns reveal the importance of tropical savannas and forests in the global partitioning of carbon emissions in both GFED and SEVER, as well as a significant contribution from boreal regions.

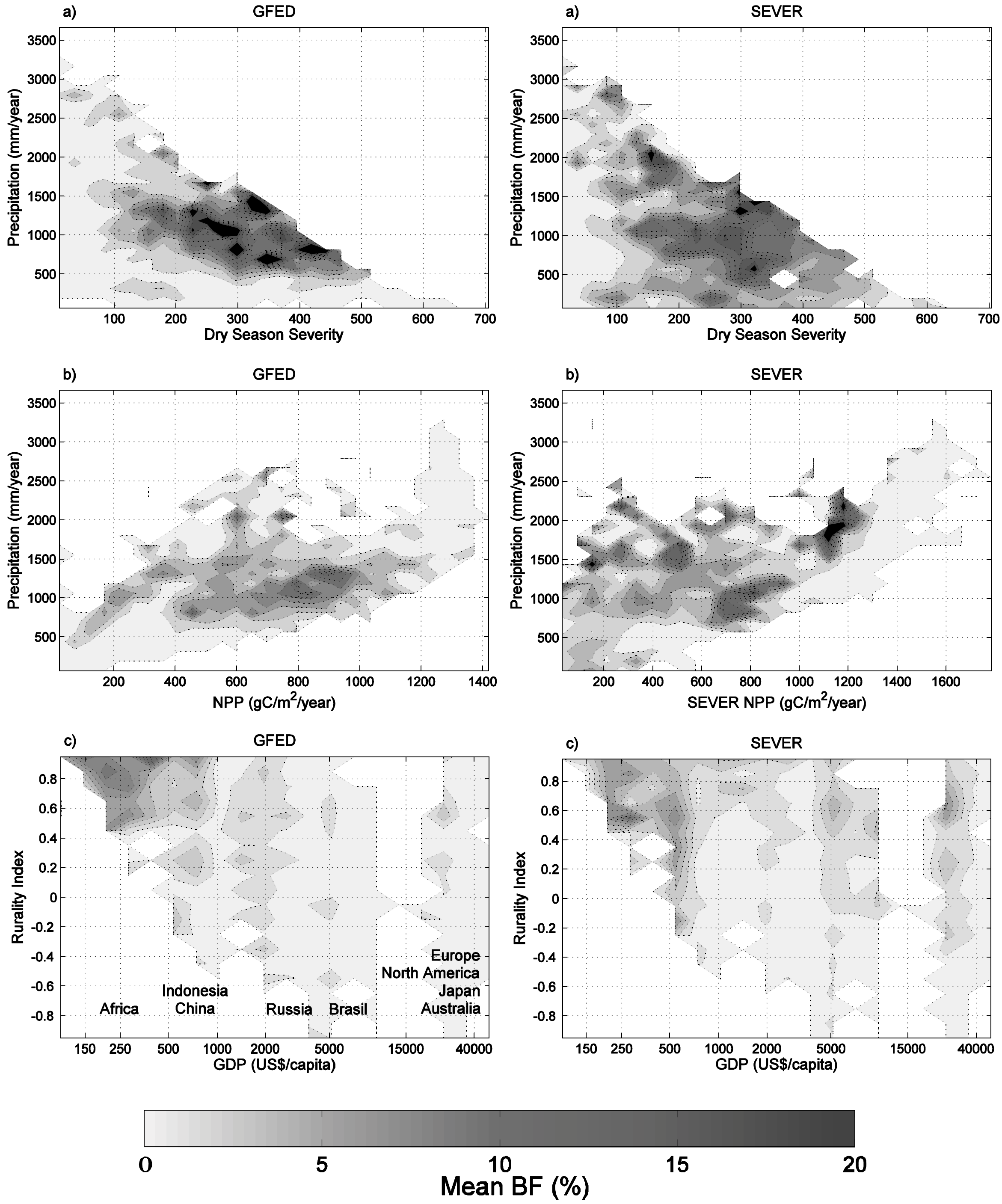

Figure 5. Mean Annual Burned Fraction over 1997-2006 (left: GFED ; right: SEVER) as a function of paired parameters. Top: Annual Precipitation and Dry season severity ; Middle: Precipitation and NPP ; Bottom: Rurality indicator and GDP.

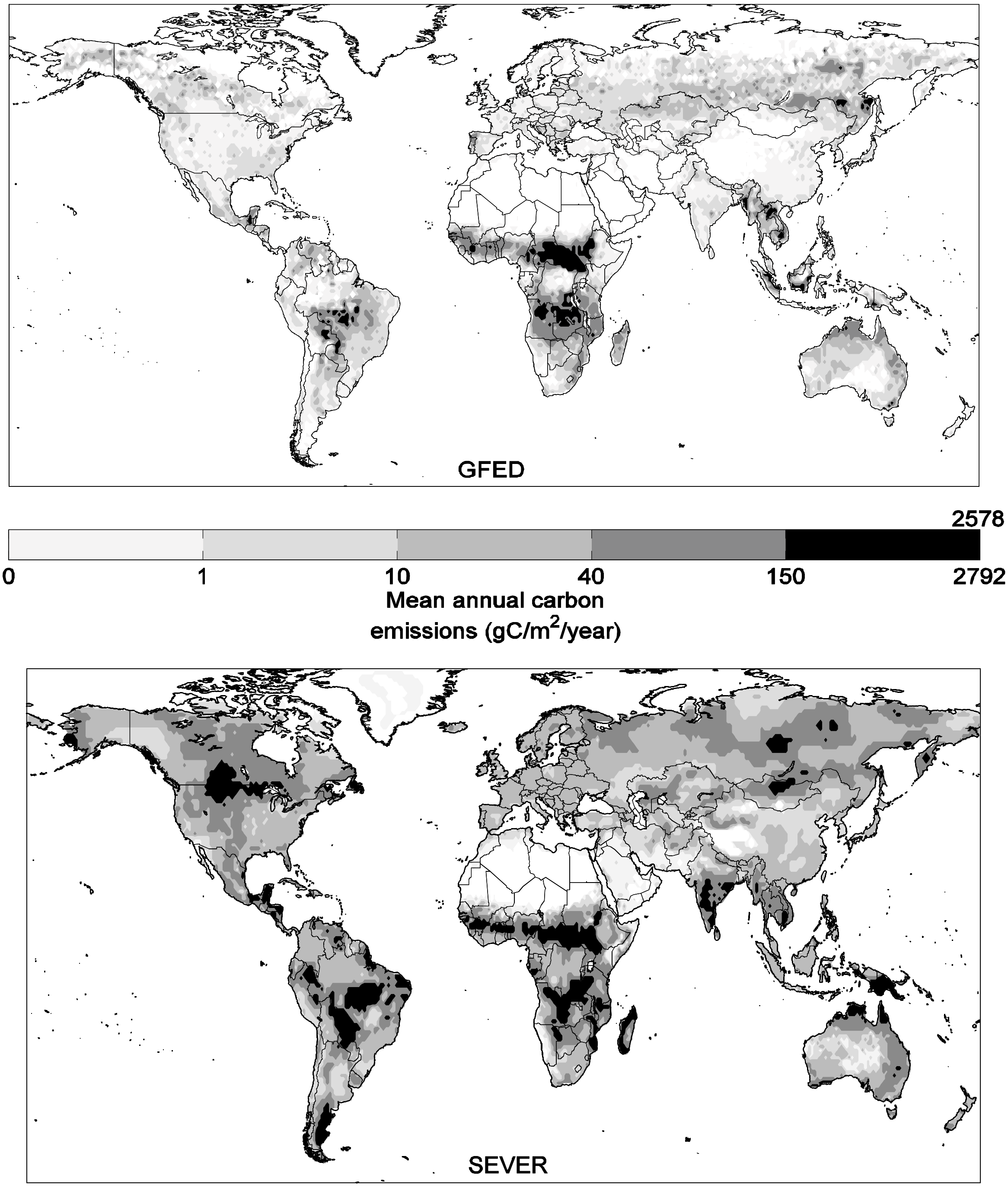

Figure 6. Mean Annual emissions (gC/m^2/year) over 1997-2006. Top: GFED ; Bottom, SEVER.

III.2. Seasonality

Figure 7 (next page) shows the spatial distribution of the month with maximum fire activity, and the mismatch between GFED and SEVER. SEVER roughly reproduces the observed spatial patterns, with 73% of the grid-cells with a mismatch lower than or equal to 2 months. Significant discrepancies occur in Sub-Saharan Africa, which peaks over March to June in the model, while GFED, along with other observation sources, indicate October to February (Dwyer *et al.*, 2000b; Clerici *et al.*, 2004; Barbosa *et al.*, 1999).

The fire seasonal cycle is partially driven by climate, but can also be strongly influenced by human activities. Figure 8 illustrates the averaged profile of the fire season and the dry season over Sub-Saharan Africa, for those grid-cells with a SEVER fire peak discrepancy larger than or equal to 4 months. For each of these cells, we centred the fire season peak month on the x-axis, and derived the corresponding monthly DSS profile. Once averaged over all grid-cells, the fire and DSS profiles show the temporal connection between both variables. Figure 8 clearly indicates that in the grid-cells considered, the fire season is shifted towards the early dry season in GFED, and towards the late dry season in SEVER. In regions with low human pyrogenic footprint, as in boreal forests, the model performs much better and, along with the observations, tends to place the peak month in the middle or late dry season (not shown).

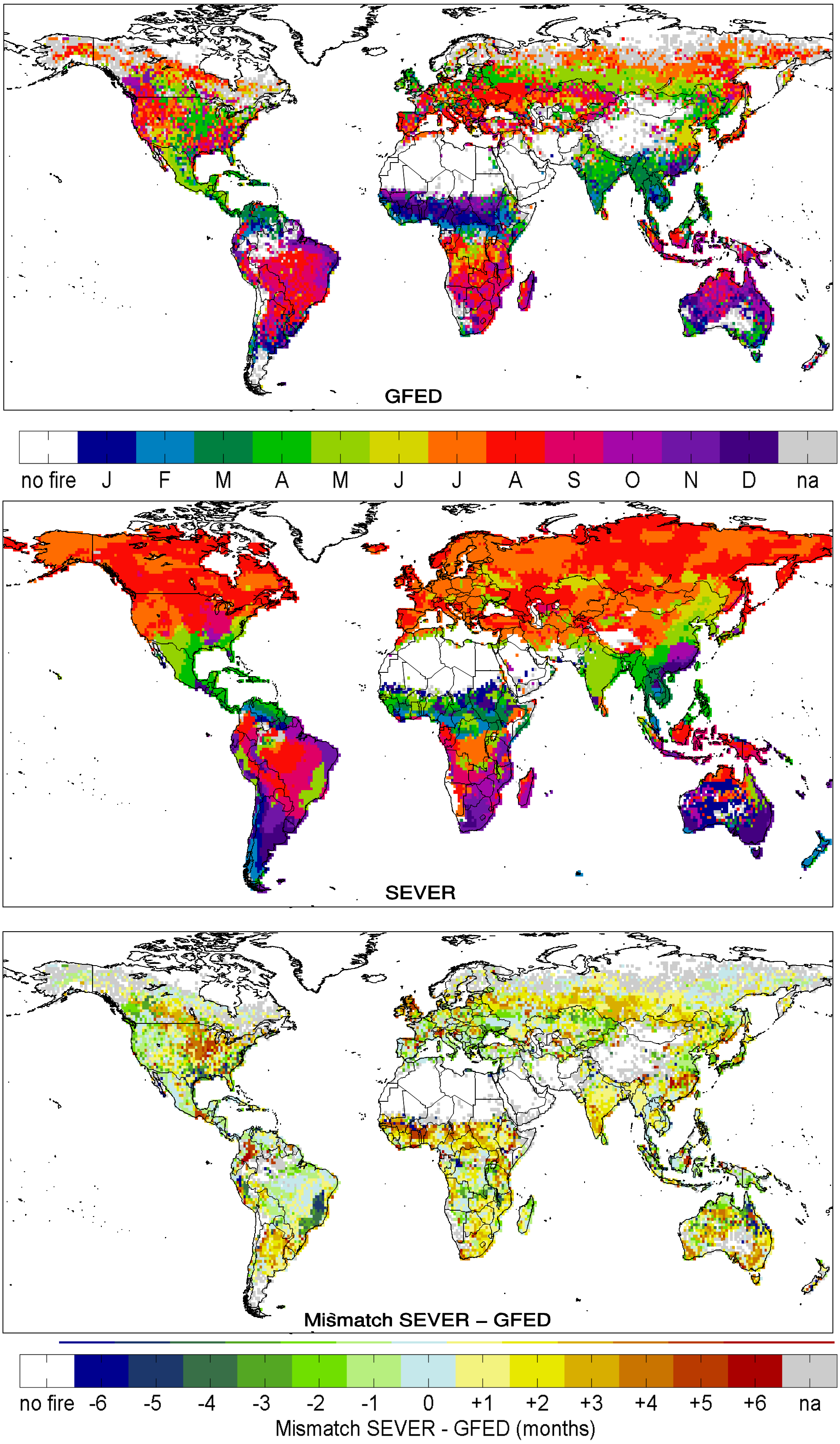

Figure 7. Top: Peak of the fire season. Bottom: relative mismatch between SEVER and GFED peaking month of the fire season.

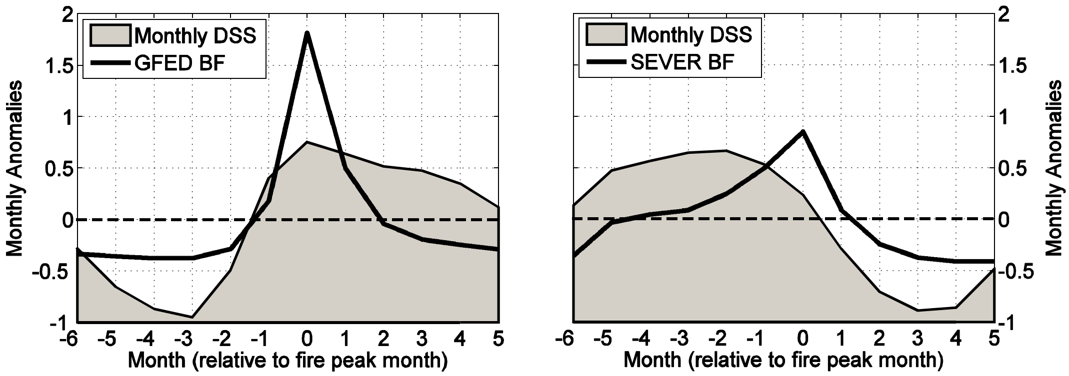

Figure 8. Averaged correspondence of fire season with dry season anomalies over regions of sub-Saharan Africa with a delay in peak month superior or equal to 4.

III.3. Inter-annual variability

Figure 9 shows the grid-cells correlation between annual BF time series from GFED and SEVER. Equatorial Asia, Mexico and a majority of boreal regions are in good agreement, along with part of South America. As discussed later, those regions are characterized by their sensitivity to climate variability, especially to the El Niño of 1997/98 (Le Page et al., 2008). Poorest agreement is found in Africa, India, China, western Russia, south of the USA Great Lakes, and in parts of South America.

The 13 regions used to evaluate large scale inter-annual fire variability are delineated in Figure 10. Globally, and for each of those regions, Figure 11. shows the BF inter-annual anomalies from GFED and SEVER, along with the monthly distribution of fire activity as a further indicator of the timing of specific fire events, and of fire seasonality. The very poor agreement in the global plot was to be expected, given the spatial discrepancies in fire frequency (Figure 2) result in different regional contributions to the total fire anomalies. This is clearly revealed by the monthly plot, showing that total fire activity in December-February, peaking in GFED with the large contribution of sub-Saharan Africa, is very low in SEVER. Consequently, a given fire anomaly in Africa has a much bigger global impact in GFED than in SEVER.

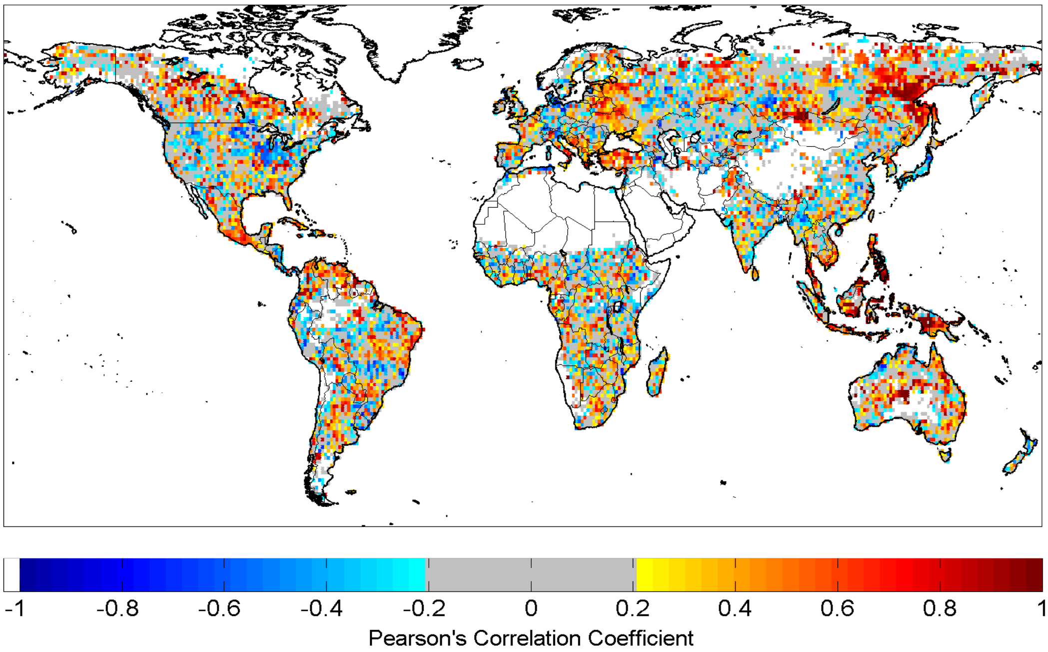

Figure 9. Correlation of annual BF from GFED and SEVER, over 1997-2006.

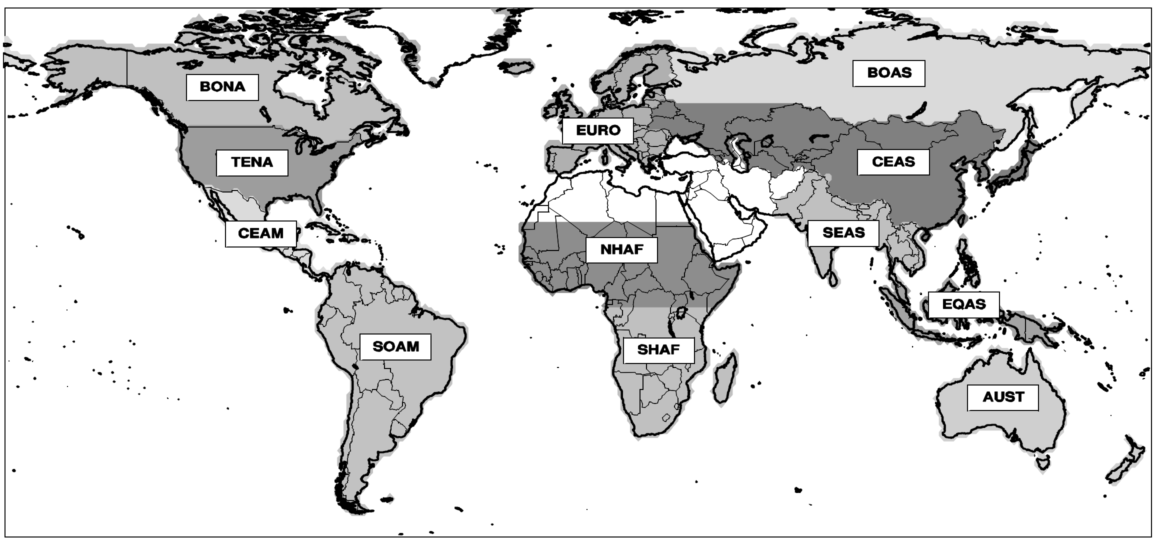

Figure 10. Regions used for inter-annual variability analysis. BONA: Boreal North America ; TENA: Temperate North America ; CEAM: Central America ; SOAM: South America ; EURO: Europe ; NHAF: Northern Hemisphere Africa ; SHAF: Southern Hemisphere Africa ; BOAS: Boreal Asia ; CEAS: Central Asia ; SEAS: South East Asia ; EQAS: Equatorial Asia ; AUST: Australia.

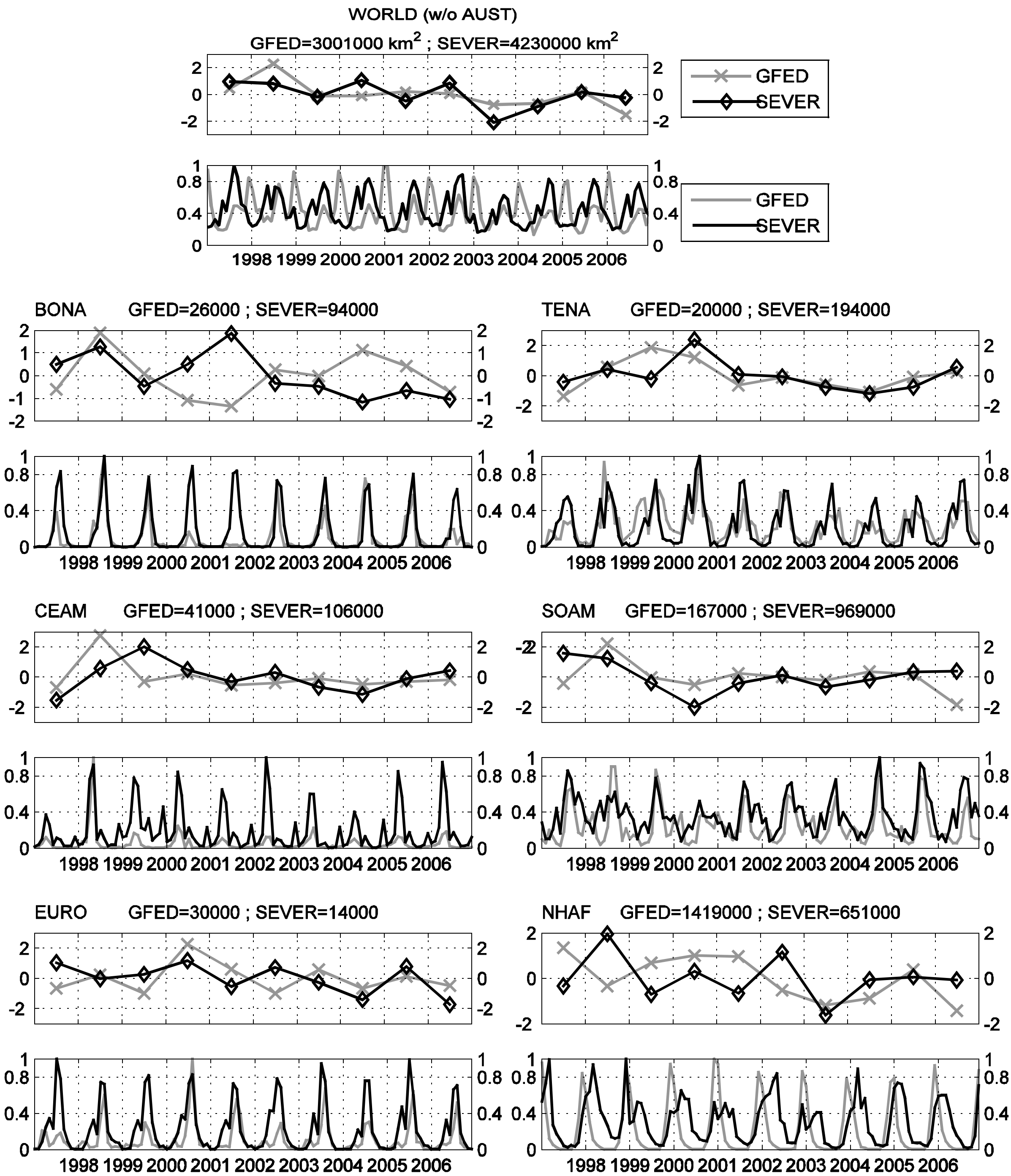

Figure 11. Regional comparison of fire variability over 1997-2006. For each region plots: Top: annual Anomalies ; Bottom: monthly time series constrained to [0 1]. The region name and averaged total annual burned area (km^2) are indicated on top of each plot. The world plots (top) do not include data from Australia as there was a problem with the SEVER output (see AUST plot next page).

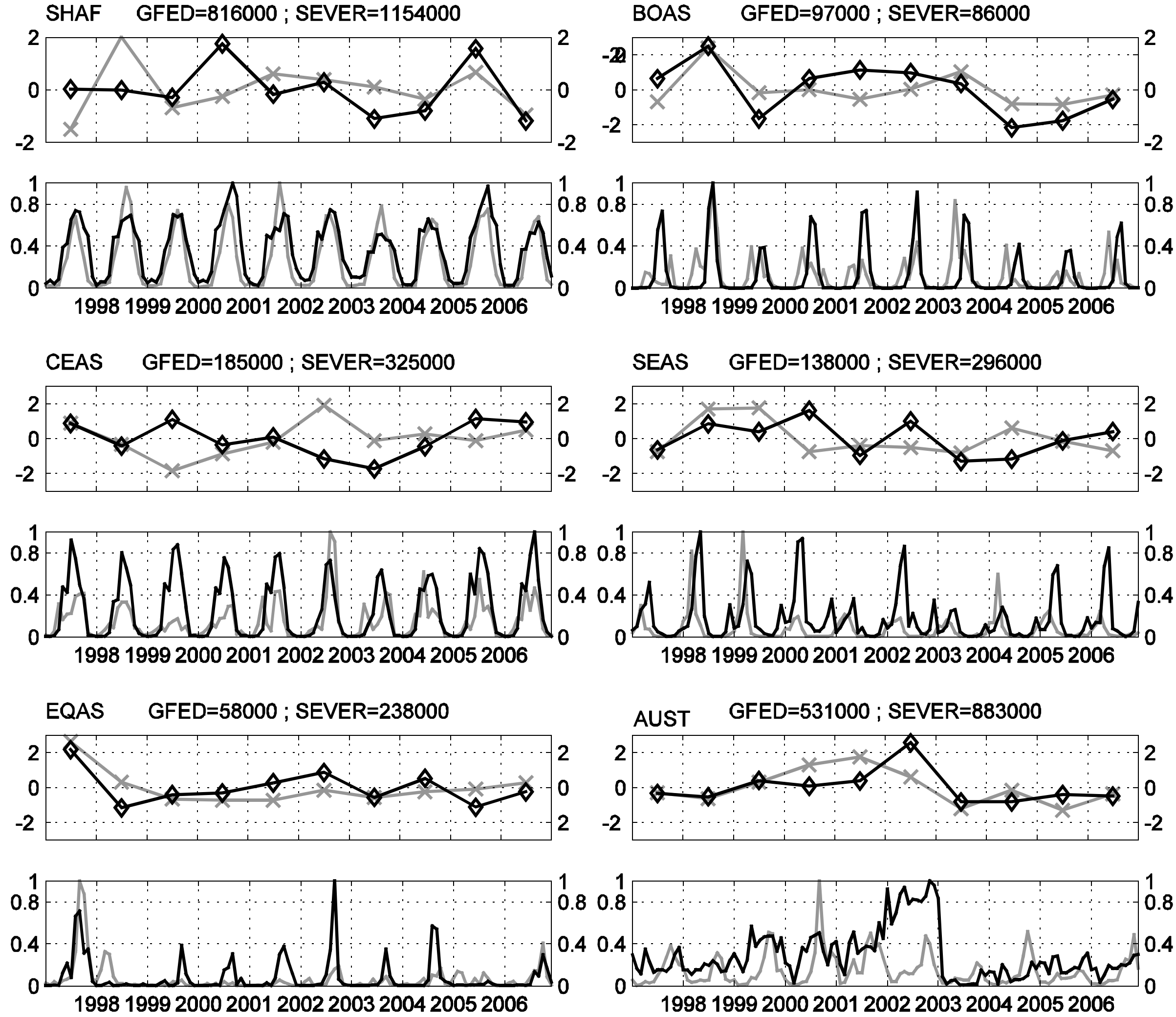

Figure 11. Continue

The Regional partitioning allows to identify and compare specific fire events more easily, especially the ones driven by large scale climatic variability. The El Niño episode of 1997-1998 appears clearly in the BONA, SOAM, CEAM, BOAS and EQAS regions in the observations, and is generally captured by the model with precise timing. Annually, the importance of those events is also reproduced for EQAS and BOAS, with respectively 1997 and 1998 being the peaking year in both GFED and SEVER. Generally, fire patterns in other regions are not properly represented. The monthly resolution plots also give further insights into the problems for the model to reproduce fire seasonality in NHAF, AUST and CEAM.

Figure 12 displays the dependence of fire anomalies on precipitation and temperature anomalies over the fire season due to their effect on soil and vegetation moisture status. The relationship is first pictured globally (Figure 12), showing that both precipitation and temperature anomalies are strong drivers, restricting positive fire anomalies almost exclusively to precipitation deficits, and towards positive temperature anomalies. This relationship is then analysed in GFED for three types of ecosystems:

- Boreal ecosystems, a spatial aggregation of the BONA and BOAS regions. Boreal fires are shown to be strongly dependent on temperature, at a level comparable to precipitation.

- Tropical humid regions, selected within South America, Africa and Equatorial Asia, as the pixels with annual precipitation above 1500mm. Their fire anomalies are also strongly related to precipitation, while temperature is a weak driver.

- Semi-dry and dry African and Australian regions (annual precipitation below 500mm). For these regions, both fire season precipitation and temperature anomalies are poor predictors of fire anomalies. Contrastingly, wet season precipitation is more influential, as illustrated in Australia (Figure 13).

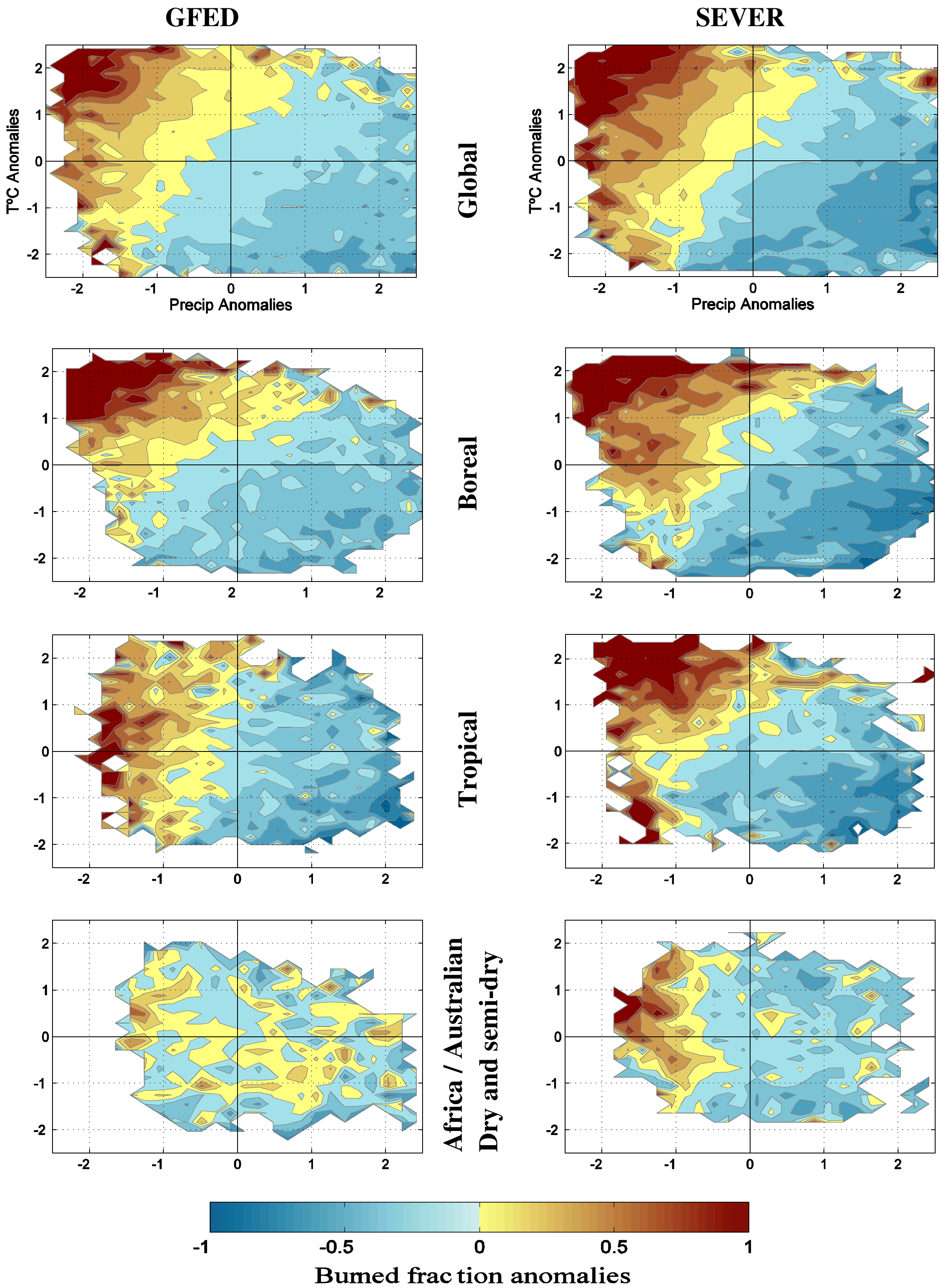

Figure 12. Dependence of fire anomalies to temperature and precipitation for three types of ecosystem.s

Those patterns are well reproduced on a global scale (Figure 12). In boreal/tropical humid ecosystems, SEVER shows the same trends towards more/less dependence on temperature, although not as neatly as in GFED. In the case of semi-dry and dry African and Australian regions, the model also shows a weaker dependence on precipitation and temperature, but stronger than in the observations. In Australia, the vegetation scheme did not perform well, and the role of wet season precipitation is not properly represented (not shown).

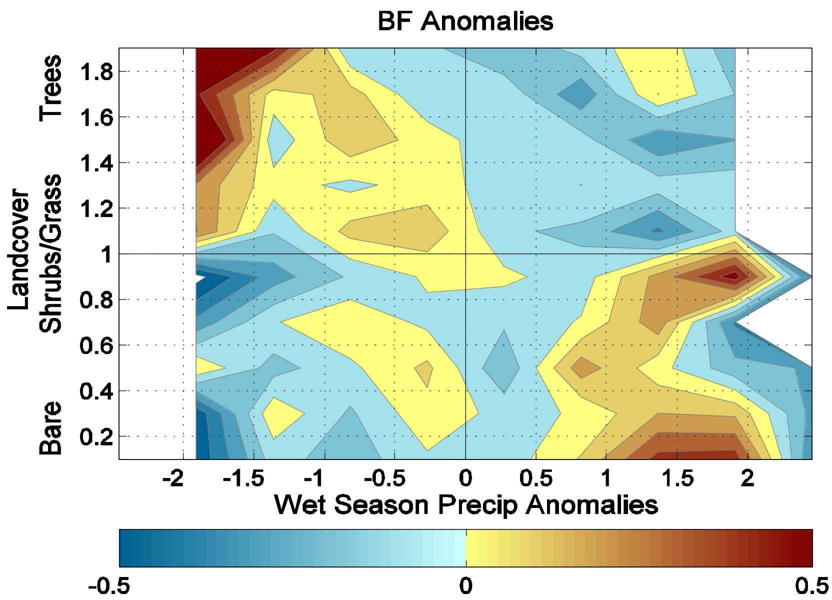

Figure 13. Dependence of fire anomalies to wet season precipitation and land cover type gradient in Australia.

IV. Discussion

Perhaps one of the most important achievements of SEVER is the realistic modelling of large scale climate driven fire anomalies, such as the biomass burning events resulting from El Niño-induced droughts in various regions of the world. This climate induced variability is known to be considerable and has important consequences for atmospheric composition, the terrestrial carbon cycle, and biodiversity, as discussed in the Introduction. As such its accurate representation in DGVMs and ESMs is essential.

The in-depth analysis of this climatic influence highlights the variability of the dependence of fire patterns on precipitation and temperature. Boreal regions are characterized by great annual amplitudes of precipitation and temperature. As such, both play an important role in the dynamics of soil and vegetation moisture status through rainfall and evaporation, thus the strong dependence of fires on both variables. In tropical humid regions, temperature variability is much lower, and only a major and prolonged precipitation deficit will result in fire prone conditions (van der Werf *et al.*, 2008).

Finally, semi-dry and dry regions of Africa and Australia are characterized by a low dependence on both parameters. Those regions are under specific climatic conditions, characterized by a rather short and irregular wet season for vegetation growth, followed by a long dry season (Peel et al., 2007). Under these conditions, fuel availability, rather than its readiness to burn, limits the occurrence of fires (Meyn et al., 2007; van der Werf *et al.*, 2008; Holmgren *et al.*, 2006). Under low wet season precipitation, vegetation build-up may be too low to sustain a fire. Under high wet season precipitation, vegetation growth leads to less patchy vegetation, which desiccates over the following dry season, thereby turning highly susceptible to fires. This scheme is very specific of these hot dry and semi-dry regions dominated by annual herbaceous vegetation. In the case of middle to high productivity ecosystems with the presence of woody vegetation, the relationship is generally reversed: enhanced wet season precipitation leads to higher soil and vegetation moisture status, delaying desiccation over the dry season, thus reducing fire susceptibility.

At global scale, SEVER is shown to be fairly realistic regarding this temperature/precipitation dependence, which was to be expected since both variables are involved in the fire weather danger and fire spread calculations. However, the variability of the relationship along ecosystem types (boreal, tropical humid, semi-dry/dry), resulting from complex interactions between fire drivers, is not as straightforward to capture. The achievement of realistic results for such an interactive system suggests that the feedback mechanisms as defined in the SEVER-DGVM/SEVER-Fire coupled scheme do reach a reasonable level of complexity and accuracy, especially in the case of boreal and tropical ecosystems, and despite the large discrepancies in fire frequency.

The mean burned fraction is a more challenging feature for the model to replicate. Key associations represented in the fire triangle (Schoennagel et al., 2004) are, however reproduced, i.e. the fire limitation by moisture in very humid ecosystems, or by low fuel amount in arid regions. Unfortunately, SEVER models potential - not actual - vegetation cover, hampering an in-depth diagnostic of the fire frequency estimates. However, grass/trees appear to be over/under sensitive to fires, with the exception of highest fire frequency regions (Africa, northern Australia), where SEVER underestimates fire activity, independent from the vegetation cover. The main PFT parameters controlling fire frequency are bulk density (fire ignition and spread), and flammability (fire danger index computation). Flammability takes the same value for all tree PFTs, and a distinct value for both C3 and C4 grasses together. As such, it may be a relevant factor to correct the over/ under estimation observed in grass/trees. Of critical importance for fires are also three vegetation types not yet included in SEVER-DGVM: croplands and pastures (land management fires, Pyne, 2001), savannas, and peatlands (modest land extent, but major carbon hotspot, Page *et al.*, 2002; Turquety *et al.*, 2007).

It is also essential to improve our understanding of anthropogenic impacts on fire frequency. The initial assumptions of the model, with population and wealth status as the most important human proxies, are to be re-assessed carefully, given the implication of other factors. Especially, the most evident cases of human induced increased or decreased fire activity are related to land use and climate, more than to economic and social status. In Africa for example, the combination of a strong seasonal wet-dry climate with regular human ignitions favours high fire frequency. Relating those ignitions to low wealth status, as done in SEVER, is certainly functional after a few adjustments, but seems less robust to other regions. As an illustration, wealth status is not adapted to account for high fire frequency in northern Australia (Russell-Smith et al., 2007) or in tropical deforestation hotspots (Aragao *et al.*, 2008; Morton *et al.*, 2008). Alternative/additional proxies could include deforestation activities (Zhan et al., 2002), land use and land cover data (Thenkabail et al., 2006).

Advantages of including land use in SEVER would also extend to a better representation of fire seasonality. In northern hemisphere sub-Saharan Africa for example, the fire season (October-February) is shifted towards early months of the dry season, which mainly results from the use of fires for agricultural and land management practices (Clerici et al., 2004). For the whole northern hemisphere, human pyrogenic activity in SEVER is set to reach a maximum from March to May and September to November, which is not realistic in the case of sub-Saharan Africa. Africa, referred to as the burning continent, is highly affected by fires (Tansey *et al.*, 2004; Dwyer *et al.*, 2000c), therefore the inability of SEVER to reproduce fire seasonality is one of its major limitations. Investigating how land use and climate drive fire seasonality would bring valuable information for fire modelers.

Conclusions

This paper analyzes results from a DGVM which includes an interactive, dynamically-linked fire module. It reveals that the most important climate driven fire features are reproduced by the model, while the dependence on vegetation characteristics and human activities prevents the development of realistic estimates of fire frequency and fire seasonality.

Integrating fires in DGVMs is an important step that has received much attention in recent years, and has been undertaken for an increasing number of models (Thonicke *et al.*, 2001; Bachelet *et al.*, 2001; Arora & Boer, 2005). Because of the peculiar driving mechanisms of fires, it has to be done from both perspectives, i.e. integrating fires in DGVMs and adapting DGVMs for fire modelling. PFTs, human population, socio-economic features and human interaction with ecosystems are especially important and, in general, not sufficiently detailed in the current versions of DGVMs.

Recent efforts towards specifying more plant functional types and especially the ones related to human activities (Bondeau et al., 2007) are an essential step forward.

Our understanding of global fire activity is improving with the availability of more accurate and longer time series of observations. Most of the fire models are based on general assumptions formulated from field-derived statistics, using a much smaller amount of the information as is now available. While they achieve a fair global representation of fires as shown here, the definition of a new generation of fire models constrained by information of fire activity derived from satellite data could significantly improve their performance. Especially, empirical statistical models, easily dealing with large amounts of data and interactions between co-variates, may provide useful information to help structure and parametrize process-based models.

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CHAPTER III: SEASONALITY OF VEGETATION FIRES AS MODIFIED BY HUMAN ACTION: OBSERVING THE DEVIATION FROM ECO-CLIMATIC FIRE REGIMES.

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CHAPTER III: SEASONALITY OF VEGETATION FIRES AS MODIFIED BY HUMAN ACTION: OBSERVING THE DEVIATION FROM ECO-CLIMATIC FIRE REGIMES.

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Abstract

Aim In any region affected, fires exhibit a strong seasonal cycle, driven by the dynamic of fuel moisture and ignition sources along the year. In this paper we investigate the global patterns of fire seasonality, which we relate to climatic, anthropogenic, land cover and land use variables.

Location Global, with detailed analyses from single 1°x1° grid-cells.

Methods We use a fire risk index, the Chandler Burning Index (CBI), as an indicator of the "natural", eco-climatic fire seasonality, across all types of ecosystems. A simple metric, the middle of the fire season, is computed from both gridded CBI data and satellite-derived fire detections. We then interpret the difference between the eco-climatic and observed metrics as an indicator of the human footprint on fire seasonality.

Results Deforestation, shifting cultivation, cropland production or tropical savanna fires are associated with specific timings due to land use practices, sometimes largely decoupled of the CBI dynamic. Detailed time series from relevant locations provide comprehensive information about those practices and how they are adapted to eco-climatic conditions.

Main conclusions We find a great influence of anthropogenic activities on global patterns of fire seasonality. The specificity of the main fire practices and their easy identification from global observation is a potential tool to support land use monitoring efforts. Our results should also prove valuable to develop a methodological approach for improving the representation of anthropogenic fire practices in dynamic global vegetation models.

Keywords: Fire season, Chandler Burning Index, Dry season, Anticipated/Delayed fire season, Fire drivers, Anthropogenic fires.

I. Introduction

The occurrence of vegetation fires is characterized by a strong annual cycle. The fundamental aspect of this cycle is the alternation of a fire-free season and a fire occurrence season, which is mostly controlled by climate (Dwyer *et al.*, 2000; Giglio *et al.*, 2006). Broadly, most of the temperate and boreal northern hemisphere regions are affected by fires from May to September, when dry conditions are predominant. In the tropics, the movement of the Inter-Tropical Convergence Zone with its associated rains induces a fire season from November to March north of the equator, and from June to October in the southern hemisphere tropical savannas and forests. Further south in the temperate and Mediterranean-like regions of Australia, Africa and South America, fires mostly burn from October to March.

On intra-seasonal timescales, the distribution of fire activity depends on the evolution of the factors controlling fire ignition, fire spread and fire extinction. The interaction between climate and ecosystems governs the dynamic of fuel moisture (Cheney & Sullivan, 2009; Nelson, 2001). Fine vegetation or dead fuels desiccate rapidly after the dry season starts, and are thus predisposed to early season fires, as is the case in grasslands and savannas. Live and wooded vegetation have a slower moisture dynamic, and fire sensitivity may be reached only late in the dry season, as in tropical forests. Early, middle and late season fires have different ecological impacts. Because the vegetation gets drier over the course of the dry season, a late season fire will spread fast and with high intensity, and may be difficult to control and suppress until it reaches a landscape fire break. On the contrary, early fires tend to be easily controlled since the vegetation is greener, and because night temperatures may reach dew point, disrupting dead fuel desiccation dynamic. Consequently, early fires are used as a tool to fragment the landscape and limit the spread of late season fires in Australian and African savannas (Williams *et al.*, 1998; Laris, 2002; Russell-Smith & Edwards, 2006). This difference from early to late season fires is also to be taken into account when quantifying atmospheric impacts. Carbon monoxide, methane and nitrous oxides are mostly produced during the oxygen-deficient smoldering phase (incomplete combustion), which is favored during early season fires due to high moisture content. Conversely, carbon dioxide is mostly emitted during the flaming phase (oxidation combustion), which prevails during late season fires (Hoffa *et al.*, 1999; Russell-Smith *et al.*, 2009).

Besides the eco-climatic tendency towards early or late season fires, human pyrogenic behavior also influences fire seasonality. Fires are used for many purposes related to land use practices, with preferential timings. Agricultural burnings are applied worldwide for soil fertilization (pre-seeding fires), to prepare fields for harvest work (e.g. sugar cane pre-harvest fires) and to dispose of crop residues (post-harvest fires) (Yevich & Logan, 2003; Korontzi *et al.*, 2006). At large scale tropical forest conversion sites (Morton *et al.*, 2008) and in shifting cultivation systems (Thrupp *et al.*, 1997), the area to be deforested is cut at the end of the wet season, and fires are set late in the dry season to maximize fuel consumption. Eco-climatic fire regimes are thus altered, and depicting this signal is a potential tool to identify fire practices associated with specific land use types. In this paper, the terms "anticipated" and "delayed" refer to changes in the fire season resulting from these practices, in parallel with "early" and "late", which refer to the dynamic of fuel moisture.

Fire seasonality is also an essential feature to consider when integrating fires into dynamic global vegetation models. Fire modules were initially developed with a strong emphasis on the fire relationship with vegetation and climate to estimate natural fire return intervals, fire seasonality and vegetation disturbances (Thonicke *et al.*, 2001; Arora & Boer, 2005). In these models, the anthropogenic component is either absent or simply accounted for by constant fire ignition probabilities. Explicit modeling of human ignition potential has been explored in the Iberian Peninsula using population density as its determinant (Venevsky *et al.*, 2002), but leaving unconsidered fire practices and their specific agenda. However, a proper representation of large scale ecological (Bond *et al.*, 2005; Haberl *et al.*, 2007; Morton *et al.*, 2008) and atmospheric (van der Werf *et al.*, 2006; van der Werf *et al.*, 2008) impacts of fires requires a realistic assessment of their timing and incidence. This will be especially important for the models evolving toward an "anthropogenized" framework (Bondeau *et al.*, 2007).

The first objective of this study is to quantify the anthropogenic influence on fire seasonality. We base our investigation on the use of a simple parameter: the timing of the middle of the fire season. Our approach consists in assessing the eco-climatic seasonality with a fire danger metric, the Chandler Burning Index (CBI), which accounts for vegetation moisture dynamic (Chandler *et al.*, 1983). The difference between the middle of the CBI and fire seasons is interpreted as being largely of anthropogenic origin. Our second objective is to uncover the reasons of such disparities. At global scale, spatial patterns of the anthropogenic influence are explored with information on human pyrogenic behavior and land use. Locally, we further discuss a selection of eleven case studies representative of relevant fire regimes, with detailed fire, CBI and other climate variables time series, and with additional support from the literature.

II. Data and Method

Our analyses compare the seasonality of the CBI, based on temperature and relative humidity, to the seasonality of observed fires. Precipitation and lightning data are also used as a support to interpret the results, but are not involved in the seasonal computations. All the datasets were interpolated or aggregated for a final resolution of 1°x1° spatially, and 8 days temporally. The time series span from July 2002 to June 2007.

II.1. Fires

We used fire data from the MODIS-derived 8-day Climate Modeling Grid (CMG) collection 5 product (Giglio, 2007). This dataset contains active fire detections on a global scale, with a spatial resolution of 0.5°x0.5°, from both the TERRA and AQUA satellites (Justice *et al.*, 2002). To keep consistent time series, we limited our study to the overlap between both satellites, and with complete 12-month periods only, from July 2002 to June 2007.

Active fires and burned area products provide different representations of fire regimes (Roy *et al.*, 2008). In our case, active fires have the advantage to account for major practices that are not well detected with burned area algorithms. In the case of large scale deforestation for example, a substantial amount of biomass is piled prior to be ignited, resulting in a spectral signature too small to be detected in burned area products (Roy *et al.*, 2008). On the other hand, active fires are not a measure of the size of fires, but have been shown to be a useful estimator, albeit imprecise, for coarse resolution applications in most ecosystems (Giglio *et al.*, 2006; van der Werf *et al.*, 2006). Large fires are detected several times by active fire observation, when the flaming fronts span an area larger than the sensor resolution (in our case, 1 km), and when a fire burns longer than the overpass interval (with TERRA and AQUA combined, any location is observed at least four times a day).

II.2. Eco-climatic fire susceptibility

Although climate is the major determinant of the seasonal cycle of fire susceptibility, the structure and composition of the vegetation also have a significant influence. Soil water retention capacity, rooting depth, canopy density and fuel size determine the capacity of an ecosystem to maintain humidity when climate gets drier (Nelson, 2001; Cheney & Sullivan, 2009). As the most illustrative comparison, tropical grasslands dry out rapidly after the end of the wet season, while rainforests under similar climate conditions may sustain a fire only late in the dry season (Uhl & Kauffman, 1990). This dynamic has to be considered to evaluate the eco-climatic seasonality.

The Chandler Burning Index (CBI) is an index of fire susceptibility based on temperature and relative humidity, originally designed for application at a monthly time scale (Chandler *et al.*, 1983). Although primarily climatic, the CBI integrates a basic representation of the above-mentioned role of the vegetation. Indeed, the moisture buffering capacity of an ecosystem interacts with relative humidity through water exchanges between the soil-fuel-vegetation layer and the atmosphere (Nelson, 2001; Cheney & Sullivan, 2009). Relative humidity is the main variable of most soil moisture indices (Sharples *et al.*, 2009).

The CBI has been applied to study fire weather in the U.S. (McCutchan and Main, 1989; Lin and Fujioka, 1995), and globally (Roads *et al.*, 2008). It is computed as:

$$CBI = \frac{((110 - 1.373 \times RH) - 0.54 \times (10.20 - T)) \times 124 \times 10^{(-0.0142*RH)}}{60} \qquad \text{Eq 1}$$

where RH is the relative humidity and T the temperature. Both variables were obtained at sub-daily time step from the NCEP Reanalysis dataset (NOAA/OAR/ESRL PSD, http://www.cdc.noaa.gov), at a native resolution of 2.5x2.5º. RH and T are classified as B variables, of intermediate reliability, since both the model and available observations influence their computation during data assimilation (Kalnay *et al.*, 1996; Kistler *et al.*, 2001).

Preliminary assessments of the CBI revealed an inconsistent behavior over boreal regions during winter, when low RH induces increased CBI values, while T is negative and the ground covered by snow. The index was thus modified to be minimum when T is negative, by forcing the RH to 100%.

II.3. Precipitation

We used the 1ºx1º daily precipitation dataset (GPCP-1DD) from the Global Precipitation Climatology Project (GPCP) (Huffman *et al.*, 2001), which merges satellite and gauge data to produce daily estimates from October 1996 to present. Validation work revealed important errors in the daily estimates, which rapidly decrease with temporal and/or spatial aggregation (Huffman *et al.*, 2001).

II.4. Lightning flashes

For natural sources of fire ignition, we used lightning flash detections produced by the NASA LIS/OTD Science Team, available from the Global Hydrology Resource Center (Boccippio *et al.*, 2000; Christian *et al.*, 2003; Mach *et al.*, 2007). This dataset contains both inter-cloud and cloud-to-ground flashes, as detected over April 1995 to March 2000 by the Optical Transient Detector (OTD), and over January 1998 to December 2005 by the Lightning Imaging Sensor (LIS). Since global coverage over our study period was not available as time series, we used the 0.5 degree High Resolution Annual Climatology product (HRAC). Note that HRAC only represents the average likelihood of lightning ignitions over a typical year, while inter-annual variability is known to be important (Chronis *et al.*, 2008).

II.5. The TIMESAT program

TIMESAT was initially developed to extract seasonal parameters from Normalized Difference Vegetation Index (NDVI) time series (Jonsson & Eklundh, 2004; Heumann *et al.*, 2007). It processes data of any temporal resolution in three steps. The pre-filtering step aims at removing outliers within a single time series and at eliminating time series with unclear seasonality. The adaptation step consists of generating smooth time series of the pre-filtered data, based on the use of an adaptive filter of the *Savitzky-Golay* type (Savitzky & Golay, 1964) or on the fitting of either a Gaussian or a double logistic function. Finally, a set of seasonal parameters are extracted (Fig. 1).

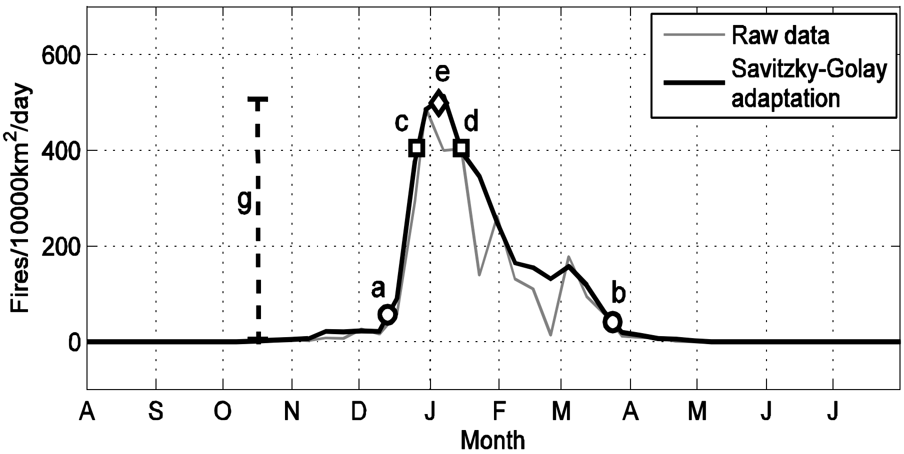

Figure 1. Illustration of fire season parameter extraction with the TIMESAT software, over a grid-cell in Africa. (a,b): start and end of the fire season, positioned where the fitted function reaches 10% of the amplitude (g) ; (c, d): positions at which the fitted function reaches 80% of the amplitude ; (e): middle of the fire season, centered between (c) and (d).

We adapted TIMESAT to process non-continuous time series, as is the case with fire data (many consecutive 8-day periods with no fire detection). Further, we carefully selected the user-adjustable processing parameters. The pre-filtering options did not prove adjustable enough to the diversity of fire regimes, and we developed our own post-filtering rules, instead. These rules, applied as a last step, test for adequate fire activity and seasonality. Most importantly, fire seasons with a peak fire activity below 10 detections over an 8-day period were discarded, along with a few cases of unrealistic time series or computations (e.g. a fire season spanning more than 10 months). Regarding the adaptation step, we used the *Savitzky-Golay* three steps filtering, which clearly out-performed the two fitting alternatives. The seasonal parameters were then extracted, imposing a single fire season per year. The procedure for the CBI variables was very similar but for the post-processing step, which we made less restrictive given the clearer seasonality and generally trouble-free processing in TIMESAT.

II.6. Averaged seasonality and case studies

Over the five years time series, we obtain a maximum of four values (or dates) per grid-cell for the middle of the fire season (MFseas) and middle of the CBI season (MCBIseas) metrics (one year is always left unprocessed by the program and additional years may be filtered out during the post-processing step). For each grid-cell, the seasons with one of the two metrics undefined (i.e. not computed or filtered out) are discarded. This ensures we do not compare the fires and CBI from different seasons, which could be misleading in regions of significant inter-annual variability in fire seasonality. The mean MFseas or MCBIseas is then computed as the date minimizing its cumulated distance (in days) to the set of one to four middle season dates, as direct averaging of dates is meaningless (day 1 in January and 365 in December would average to early July). A global view of the relationship between the fire and CBI seasons is then simply achieved by mapping the time gap between their respective middle dates (MFseas minus CBIseas). Note however that the results inferred in ecosystems with irregular fire seasons are specific to the 5 years considered and do not assess the long term seasonality. This is especially the case of boreal forests (stochastic ignitions by lightning), and of ecosystems under the strong influence of low frequency climate modes (e.g. El Niño-Southern Oscillation in tropical forests of South America and South East Asia).

To further depict the role of the CBI, precipitation, lightning and anthropogenic activities, we also extract time series and seasonal parameters of eleven grid-cells selected as representative of the most relevant fire regimes.

III. Results

The global distribution of the MCBIseas reveals large scale latitudinal patterns (Fig. 2). Temperate and boreal regions of the northern hemisphere have a CBI dry season over May to September, the period of maximum incoming solar radiation. The opposite is observed in the southern hemisphere temperate regions, with a dry season spanning from October to March. In the tropics and sub-tropics, which receive a rather constant amount of solar radiation year-round, the timing of the dry season is driven by the position of the tropical rain belt, associated with the Inter-Tropical Convergence Zone. Two opposite fire timings are observed, roughly separated by the equator, with a dry season from November to March in the northern hemisphere tropics, and from June to September in the southern hemisphere tropics.

The global distribution of the MFseas (Fig. 3) is very similar to that obtained by Dwyer *et al.* (2000) over 1992-93, with a different dataset. As expected, the MFseas patterns are partially related to the MCBIseas, with a clear latitudinal gradient. However, the relative time gap between the MFseas and the MCBIseas (Fig. 4(a)) reveals significant dissimilarities. Regions of anticipated and delayed fire season (Fig. 4(b)) appear to be spatially related to the distribution of broad land cover and land use types (Fig. 5) and to climate classes (Peel *et al.*, 2007). Major agricultural regions generally display little synchrony in CBI and fire seasonality, with both anticipated (North America, around the Corn Belt) and delayed (eastern China, southern Australia) fire seasons. The transition from arid to tropical ecosystems is clearly apparent, especially in Africa where grass and savannas ecosystems are associated with anticipated fires, while a slightly delayed fire season is found in the most equatorial regions covered by evergreen rainforests. Unexpected patterns are also identified, in south western Canada forests for example with a delayed MFseas around October to December, at the beginning of winter. Finally, the whole range of fire seasonality is found in boreal forests, with a spatial variability that does not seem to be related to eco-climatic or anthropogenic factors, suggesting a natural variability in fire seasonality.

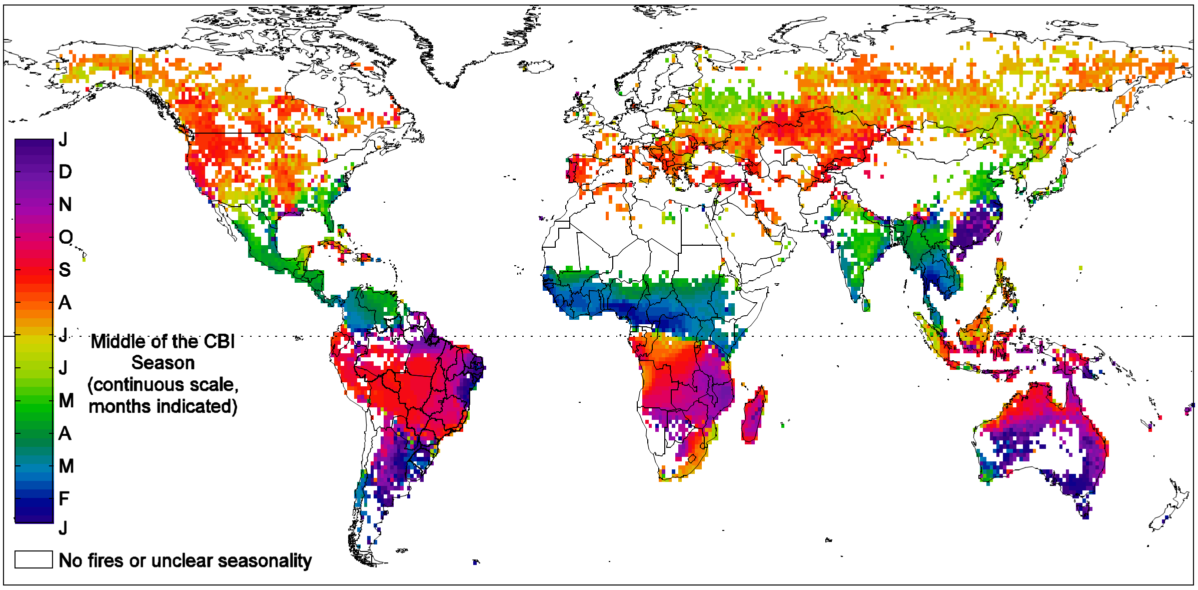

Figure 2. Middle of the Chandler Burning Index dry season (MCBIseas).

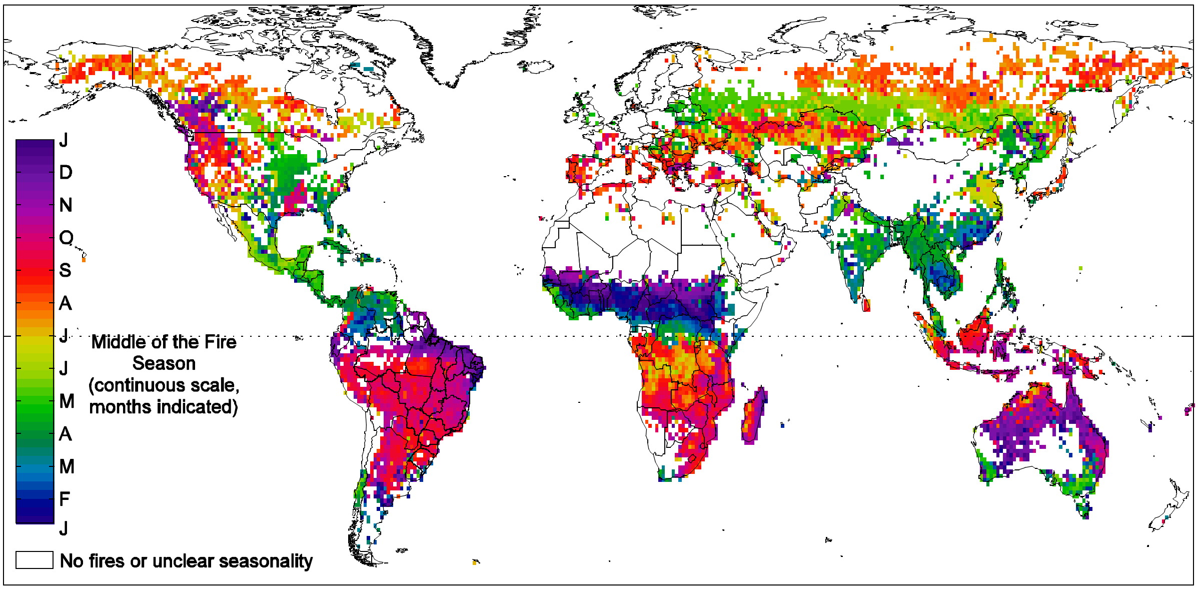

Figure 3. Middle of the fire season (MFseas).

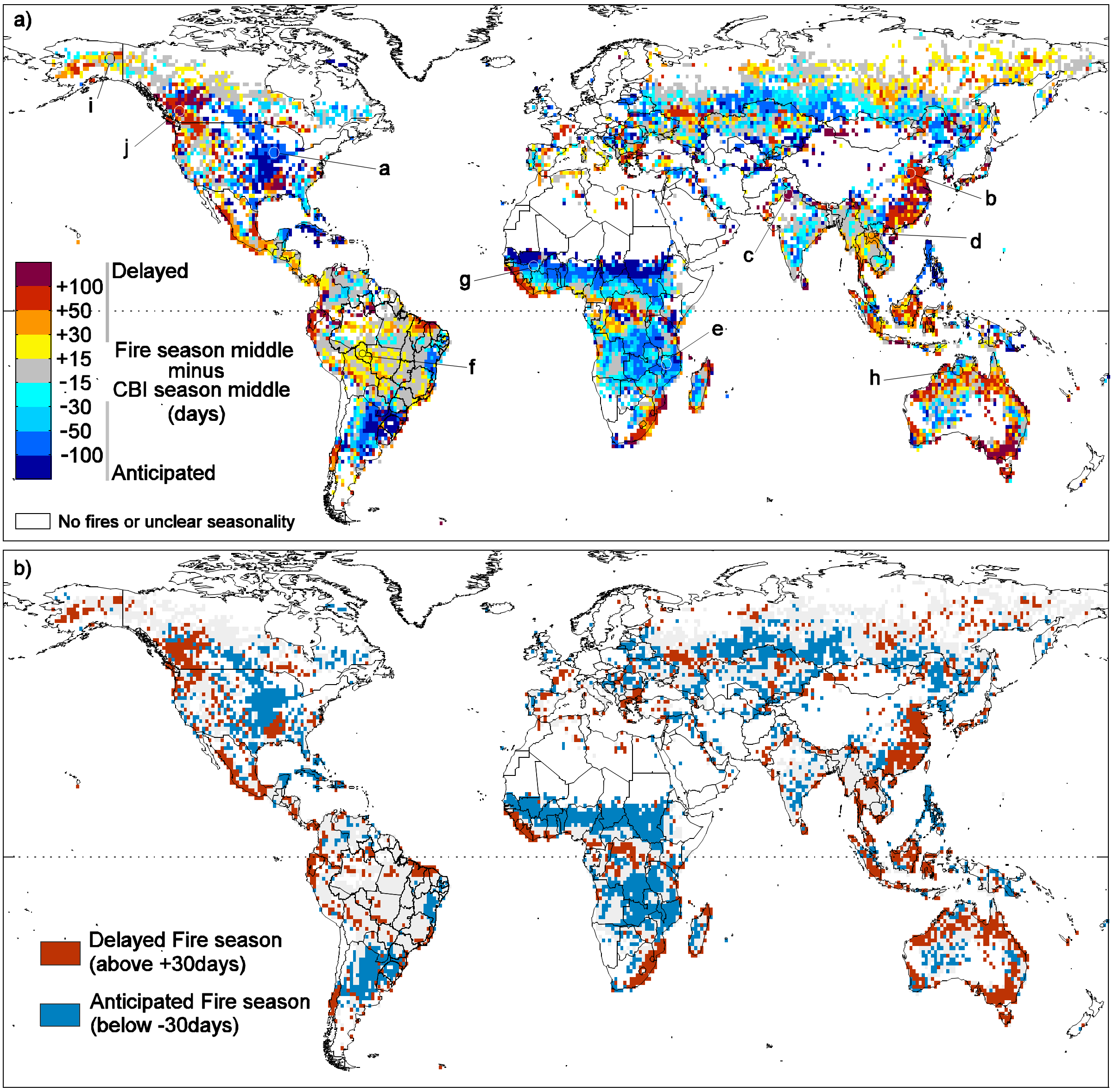

Figure 4. a) Difference between the Middle of the Chandler Burning Index dry season (MCBIseas) and the Middle of the fire season (MFseas), and location of the case study grid-cells, from a to k, b) map of early and late fire seasons (threshold at +/-30 days of difference between the MFseas and MCBIseas).

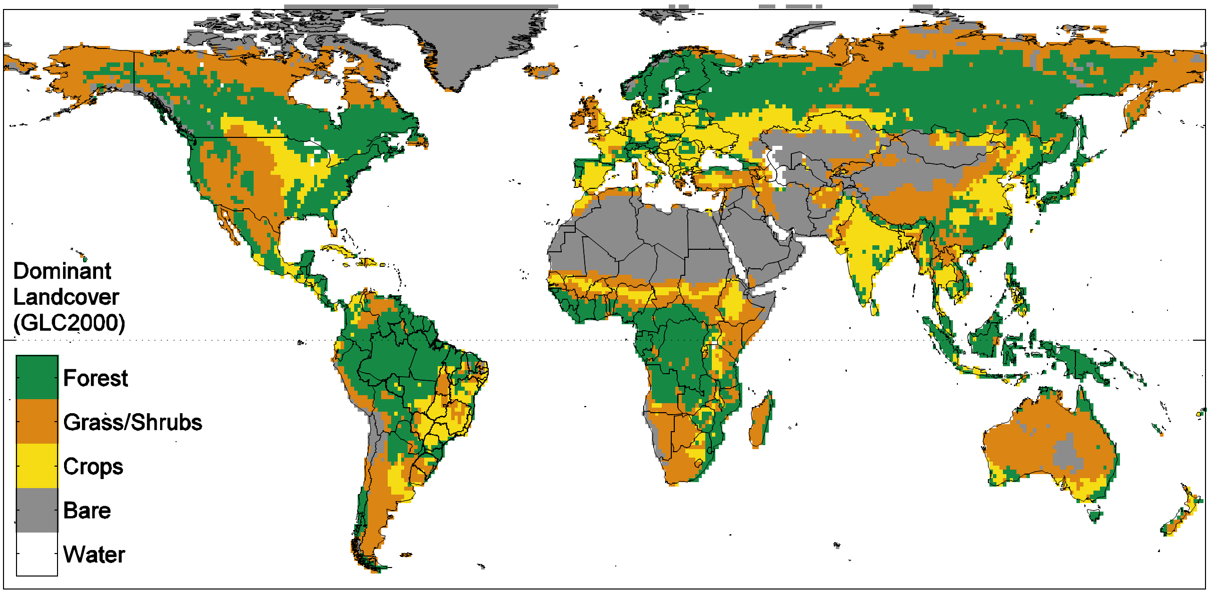

Figure 5. Dominant land cover from the Global Land Cover for the year 2000 (GLC2000, Bartholome and Belward, 2005).

The wide range of interactions between climate, vegetation and anthropogenic activities suggested by these results are explored with the eleven case studies, which location is indicated in Fig. 4(a). Their respective time series of active fires, CBI and precipitation (Fig. 6(a) to (k)) are detailed and analyzed in the Discussion section. The annual cycle in lightning activity is also illustrated, but provides little support since significant natural ignitions are generally observed during extreme lightning events only, which are not depicted in the averaged climatology.

IV. Discussion

IV.1. Permanent agriculture fires

Most regions dominated by permanent agriculture display an important positive or negative time gap between the MFseas and MCBIseas, according to the role fire plays in the crop management cycle. Lightning ignitions are likely to be marginal.

In northern America, the large agricultural region extending from Alberta (Canada) to Missouri and Oklahoma (United States of America, USA), has a MFseas around late March to early June, some 50 to 150 days before the MCBIseas. A variety of crops are found along this whole region, including corn, spring wheat, sunflower, soybean and canola (US 2002 Census Publications from the United States Department of Agriculture (USDA); Canada 2006 Census of Agriculture from Statistics Canada). These burnings are related to field clearing practices and to the harvest of winter, spring and durum wheat (J. McCarty, personal communication). In the Corn Belt, dominated by a corn-soybean rotation system, a short crop (October to April) of winter wheat is commonly grown every third to fifth year, to increase nutrients in the soil. These crops are harvested and burned early (April-May) before the next planting of corn or soybean (J. McCarty, personal communication). Note the gradual change of the MFseas, from early April in the south to late May in the northernmost grid-cells, suggesting a slightly delayed crop calendar in the north due to a longer winter. The case study reveals a very short fire season, when the CBI just starts increasing in early spring (Fig. 6(a)). Fire activity is rather low, as is generally in the whole region, compared to the south-eastern USA (McCarty *et al.*, 2005), and rather irregular, with years of very little activity.

Ukraine, Russia and Kazakhstan are among the main world agricultural regions (Leff *et al.*, 2004), where the use of fire is very common and significant at a global scale (Tansey *et al.*, 2004; Korontzi *et al.*, 2006). Contrasting MFseas are found in the region, one around March and the second around August (Fig. 4). Inspection of the time series from various grid-cells (not shown) indicates a bimodal fire season, the dominant peak being retained by TIMESAT given the constraint of a single fire season per year. In between those two peaks, fire activity is almost nonexistent. The first fire peak occurs in March, related to crop preparation before the planting of summer crops (barley, sunflower, sugar beets, oat, mainly). The second peak occurs immediately after winter crops are harvested, suggesting the burning of crop residues.

In China, most of the wheat and rice crops are concentrated in the eastern part of the country (Leff *et al.*, 2004). Although residues have been reported to be mostly used as biofuels (Yevich & Logan, 2003), recent studies pointed to significant burning in the field (Yan *et al.*, 2006; Cao *et al.*, 2008). The MFseas occurs around early June, some 50 to more than 100 days after the MCBIseas (Fig. 4(a)), and the fire season is very short, from late May to early June, while the rest of the year is fire-free. Although the CBI seasonality is not very obvious, the precipitation time series clearly establishes a late fire season, just before heavy rainfalls set the beginning of the wet season. These findings precisely match the local crop calendar and burning practices reported by Xiao *et al.* (2002): "*By late May, wheat crops ripened and were ready for harvest. Following the harvest of winter wheat, stubble was typically burned and then, within 1–2 weeks, fields were ploughed and flooded*".

In India, the world's second largest producer of rice and wheat, most of the agricultural regions exhibit an anticipated fire season, with a MFseas from February to April. Clearly standing out is the north western Punjab state, with a short fire season around October, and a very high number of fire detections (Fig. 6(c)). The CBI and precipitation profiles attest to an anticipated fire season concentrated just after the end of the wet season, contrarily to Fig. 4(a) which indicates a delayed fire season (this miscalculation is due to the MFseas of season *n* being closer to the MCBIseas of season *n-1* than to the MCBIseas of season *n*). Wheat-rice double crop is the dominant crop system in Punjab, and these fires correspond to the burning of residues from the rice harvest, which is a

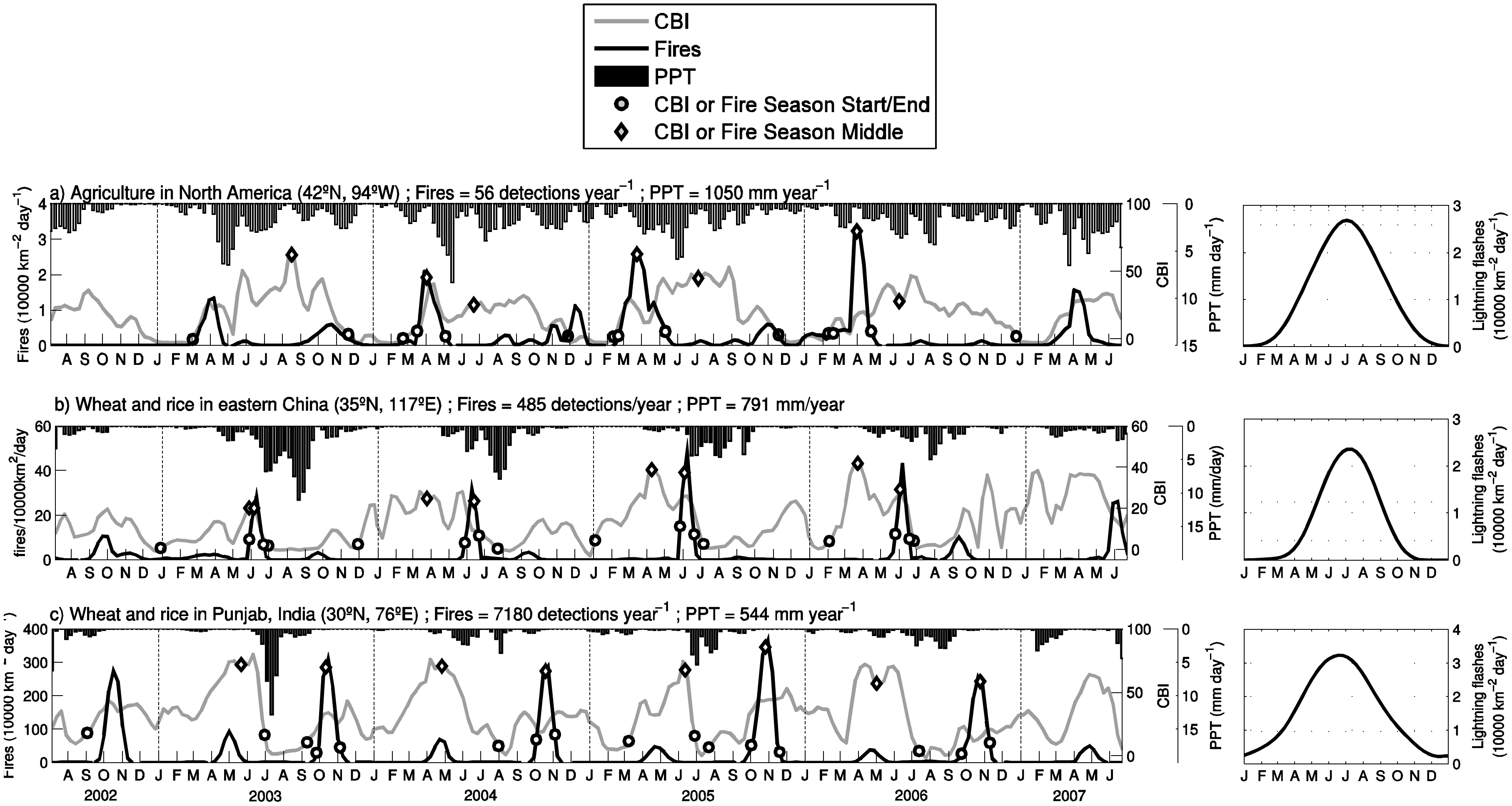

Figure 6. Filtered Chandler Burning Index (CBI) and fire time series, and unfiltered precipitation time series from the eleven case studies (a to k), along with their lightning climatology. Averaged annual fire detections and precipitation are also indicated.

very common practice (Badarinath *et al.*, 2006; Punia *et al.*, 2008). The second peak of lower amplitude in April-May is due to the burning of wheat stubble. Wheat residues are largely used for animal feed, while rice residues are generally not valued and burned in the field (Badarinath *et al.*, 2006), hence the clear dominance of the October fires, which were again observed in 2008 (http://earthobservatory.nasa.gov/NaturalHazards/view.php?id=35765).

IV.2. Shifting cultivation fires

Shifting cultivation is the most complex form of agriculture in the world and is practiced by a majority of small-scale farmers in tropical regions of Africa, Central and South America and Southeast Asia. It is found in diverse ecosystems, ranging from tropical moist forests to dry forests and savannas, grasslands, and even seasonal floodplains (Thrupp *et al.*, 1997). Shifting cultivation is defined as an agricultural system that involves an alternation between cropping for a few years on selected and cleared plots and a fallow period, during which the soil fertility is restored (Ruthenberg, 1976). In the most common systems, vegetation is cut, allowed to dry for some time and then burnt, rising the level of nutrients just before the preparation of the soil for planting.

Two shifting cultivation case studies were selected. The first one is located in northern Laos, dominated by deciduous monsoon rain forest, where shifting agriculture is generalized (Seidenberg *et al.*, 2003). The burning occurs in March and April mostly, with a slight delay compared to the CBI, but clearly at the very end of the precipitation-derived dry season (Fig. 6(d)). This timing maximizes vegetation flammability and avoids the establishment of weeds prior to plantation (Thrupp *et al.*, 1997). It is also observed in other shifting agriculture systems of tropical Africa and South America. Contrarily, in south eastern Africa, namely in the south of the Democratic Republic of the Congo, in Zambia, Tanzania and Mozambique, shifting cultivation is associated to an anticipated fire season. These regions correspond to the distribution of Miombo woodlands, tropical woodlands and dry forest formations growing under a strongly seasonal climate (Frost, 1996). As shown from the province of Niassa in Mozambique, the dry season is longer than in tropical forests (Fig. 6(e)). Late season fires would be damaging because the biomass gets very dry, and burns are thus applied earlier to prevent damaging fires (Chidumayo et al., 1996). However, the MFseas is still located in the second part of the dry season (anticipated late fire season).

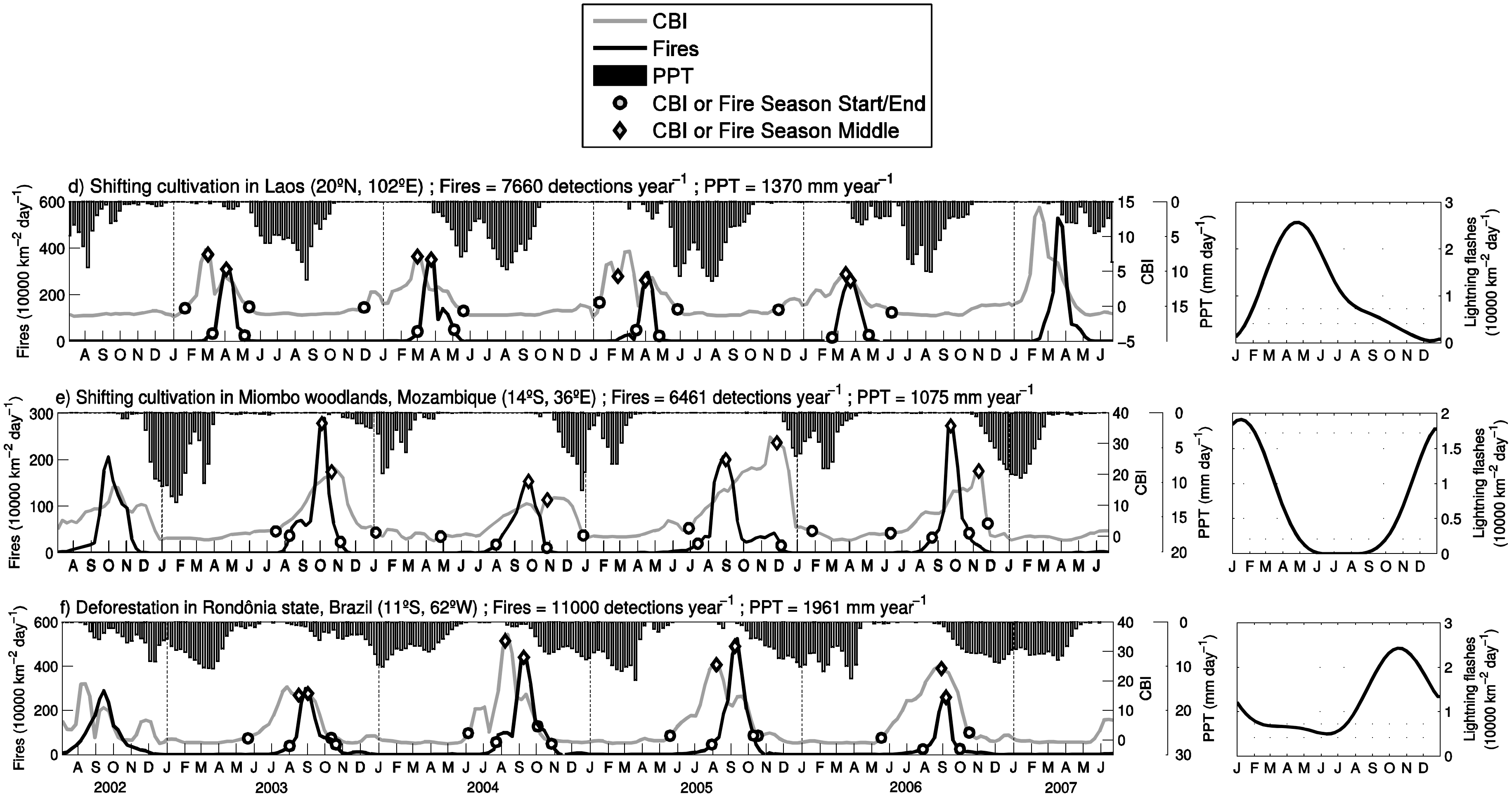

Figure 6. Continued

IV.3. Tropical forest conversion fires

Unlike shifting cultivation, forest conversion, usually applied at large scale, is intended to completely clear portions of the forest for the establishment of permanent croplands and pastures. Large areas of tropical forests have been converted to farming and cattle raising activities over the past decades (Mayaux *et al.*, 2004), and current observations still point at high deforestation rates (Hansen *et al.*, 2008). The classic sequence of forest conversion is similar to tropical shifting cultivation, i.e. the vegetation is cut after the wet season and burned at the end of the dry season. For the most active deforestation sites, the transition of large patches of mature forest to bare ground ready to be cultivated is achieved within a few months through heavy mechanization (Morton *et al.*, 2006). The vegetation is repeatedly piled and burned, causing a fire activity among the highest worldwide (Morton *et al.*, 2008).

In agreement with those practices, the MFseas over the main tropical forests of South America, Africa and South East Asia is found to be either similar to the CBIseas or delayed up to 100 days (Fig. 4). Smaller tropical forest patches are also depicted, e.g. in Madagascar with a clear transition from an anticipated fire season in the western grasslands and shrublands, to a delayed fire season in the eastern tropical forest (Kull, 2008). The case study was selected in the Brazilian state of Rondônia, under active deforestation. Its fire season peaks in August/September, the last months of a dry season that normally starts in May (Fig. 6(g)).

In the case of both shifting cultivation and conversion fires in tropical forests, a delayed fire season may be rather the sign of the forcing of a fire season. Indeed, the MCBIseas has little meaning for fire seasonality as eco-climatic conditions rarely allow the natural occurrence of fires. The observed delays could thus indicate that the CBI has a faster dynamic than the desiccation of recently cut coarse vegetation.

IV.4. Fires in highly seasonal wet-dry climates of Africa and Australia

Large regions of Africa (Barbosa *et al.*, 1999) and Australia (Russell-Smith *et al.*, 2007) are highly affected by fires, due to the combination of a very seasonal climate, ideal for successive vegetation growth and curing, with high ignition probability from widespread and diversified fire practices (Levine *et al.*, 1999; Bradstock *et al.*, 2002).

The sub-Saharan region of northern hemisphere Africa is affected by fires during the boreal winter (October to March), with a MFseas ahead of the MCBIseas by 30 days in the south to up to 180 days (6 months) in the regions closest to the desert. The case study located in southern Mali (Fig. 6(g)) illustrates the three burning phases reported by Laris (2002) based on interviews with the local population and field observations. Very early in the dry season (November), fires are lit in the short annual grass growing on gravel soils, which is unpalatable and dries out very rapidly due to little soil water retention capacity. Those fires are set preventively to avoid damaging fires later in the season and are easily controlled, since other types of adjacent vegetation (perennial grass, savannas) are too moist to burn, thus acting as fire barriers (P. Laris, personal communication). In a second phase, fires are mostly set in fallow lands in late December, after the harvest, to avoid damages to crops. Again, fire spread is usually limited by earlier burns and other landscape discontinuities. These two phases are very well reproduced by the data, with a peak in November and another in late December almost every year (not always apparent in the filtered time series). Finally, late season fire activity is associated with crop preparation and with the occurrence of few but large uncontrolled fires which spread to the wooded savannas, especially in areas not sufficiently fragmented with earlier burns.

The second Malian case study is located only 200 km north of location (g), but with a different fire seasonality (Fig. 6(h)). The wet season is shorter, from June to September, and fires do occur at the beginning of the dry season only, the MFseas being some 150 days ahead of the MCBIseas. This disparity in two neighboring locations has also been reported in the adjacent Senegal, at the same latitudes, and linked to changes in land cover and human activities (Mbow *et al.*, 2000). The landscape in northern regions, which receives less precipitation, is largely dominated by annual grasslands, with little or no woody biomass. Fires are set by herders in low lying areas covered by perennial grass, which do gain nutritive value for livestocks when re-sprouting after an early fire. Delayed fires are ignited late in the dry season to remove dry grasses and stimulate the growth of new vegetation (Mbow *et al.*, 2000), but are not apparent in MODIS data for unknown reasons.

In northern Australia, fire is used as a tool to manage pasture and savanna landscapes (Dyer *et al.*, 2001). Traditional burning by Aboriginal people is also associated with various practices, from land clearing and grass re-growth stimulation to spiritual obligations. The case study (Fig. 6(i)) is located south of Darwin in the Northern Territory, dominated by eucalypt woodlands with a grass ground layer where as much as 50 to 70% of the landscape may burn annually (Dyer *et al.*, 2001). It indicates an extended dry season, from April to October, with a changeable regime of early and/or late season fires. This variability suggests the reduction of fire management practices, attributed in Nothern Australia to the loss of man power and to the abandonment of traditional fire use in Aboriginal lands (Dyer *et al.*, 2001). In the Kakadu National Park, around 200 km northeast of location i), anticipated preventive burns are applied to limit the occurrence of late dry season intense wildfires. Consequently, fire seasons are more regular, and clearly display the signature of an anthropogenic anticipation (Fig. 4 and Russell-Smith *et al.*, 1997).

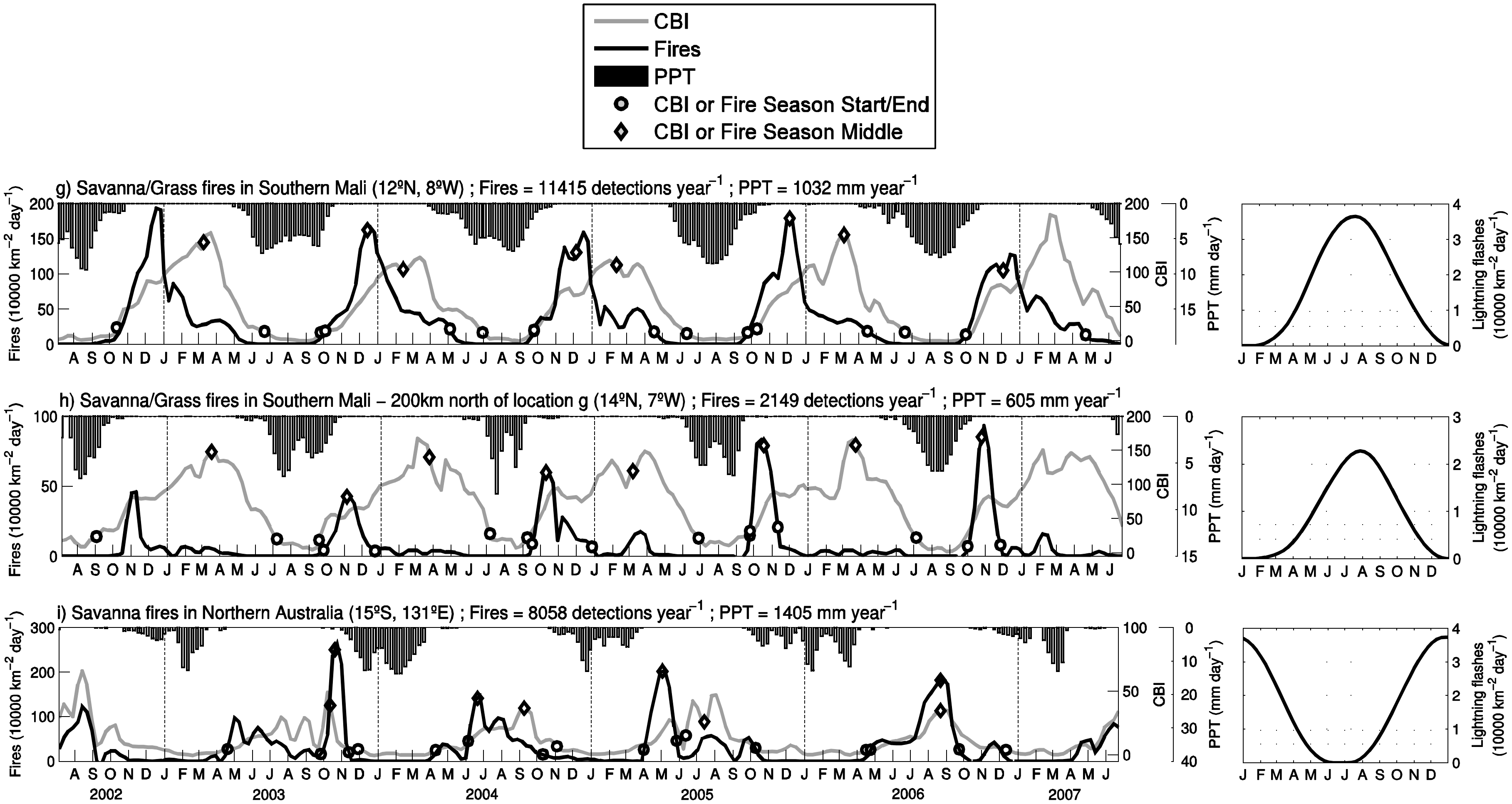

Figure 6. Continued

IV.5. Boreal forest fires

Boreal forests contain a significant part of the world biomass and very large stocks of both above and below-ground carbon (Kasischke, 2000). Fire plays a crucial role in shaping the vegetation (Bond-Lamberty *et al.*, 2007) and in driving the carbon balance of these forests (Harden *et al.*, 2000). Very large areas of forest can be burned during a single fire event, spreading freely over several days or weeks in low human footprint regions, with no or little fire fighting facilities. Those remote boreal fires are probably the most representative of the "wildfire" concept, since beyond little human intervention to stop their spread, ignition is often caused by lightning strikes (Gromtsev, 2000; DeWilde & Chapin, 2006; Ivanova & Ivanov, 2005).

In the eastern Alaska case study, the CBI is minimum from November to April, and rapidly increases with temperature turning positive and snow melt (Fig. 6(j)). The driest conditions are observed from June to August, a period when the occurrence of thunderstorms is a potential source of lightning ignitions. Over the 5 years of the time series, significant fire activity only occurred in 2004, suggesting natural fire regimes with sporadic ignitions. 2004 is the worst fire year on record in Alaska (Annual report on the Climate of 2004, National Climatic Data Center). Over a few days in mid-June, around 15000 lightning strikes ignited numerous fires, which burned through July and August (http://visibleearth.nasa.gov/view_rec.php?id=7009).

A surprising pattern is observed over the managed forests of south western Canada, with a MFseas estimated from October to December (Fig. 3), long after the most favorable eco-climatic conditions (Fig. 4). Winter is establishing at this time of the year, with the first snowfalls, hence a low risk of fire. However the case study (Fig. 6(k)) indicates that this delayed fire activity does happen every year, and is limited to October and November mostly, discarding the hypotheses of gas flares or other types of false detections. Two sources related to fire exploration activities have been identified for these fires (B. Hawkes, personal communication): 1/ dry forest restoration burnings, mostly prescribed in the spring but also in fall, until October to November, before the first snowfalls ; and 2/ pile burning after logging, usually after the first snowfalls.

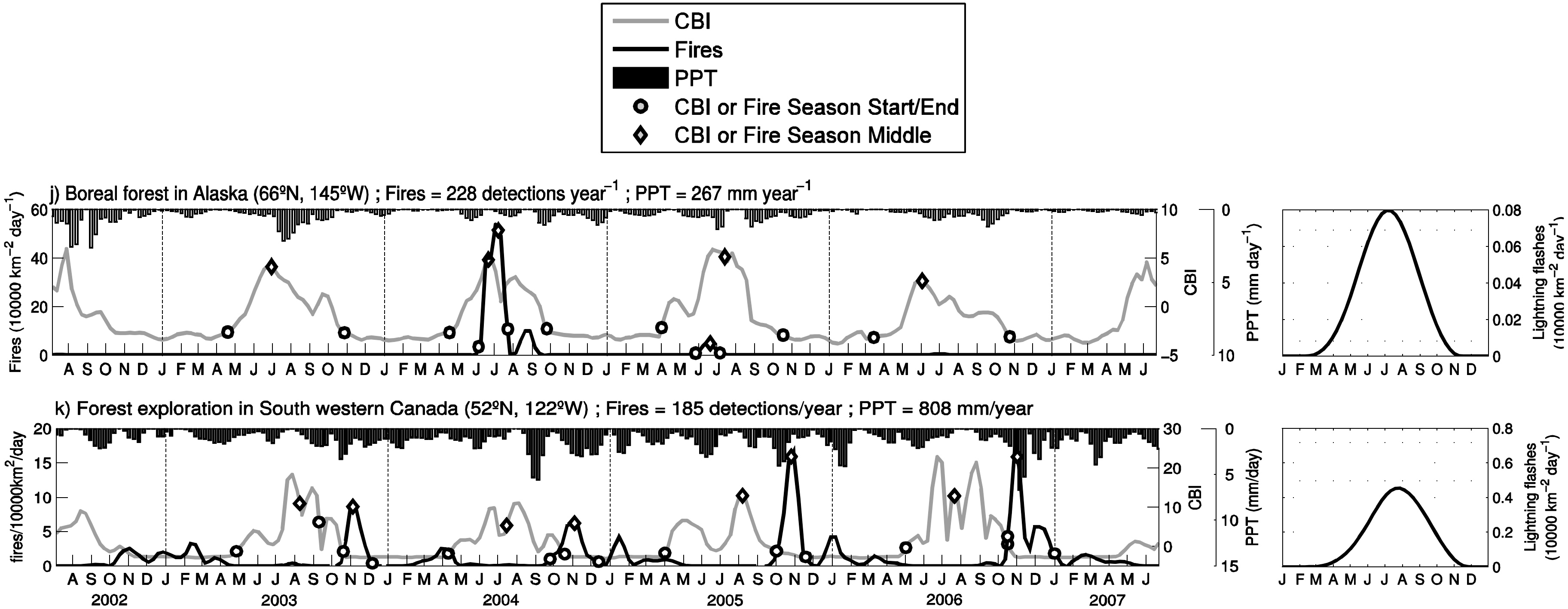

Figure 6. Continued

IV.6. Limitations

The main limitation of this study arises from the spatial aggregation of active fires. Land cover and land use can be very heterogeneous in a single 1ºx1º grid-cell, in which case the fire time series may hide important information or point to misleading conclusions. For example, the aggregation of anticipated season agricultural fires with adjacent delayed forest fires in the same grid-cell may lead to a time series that does not depict any of the two fire regimes. At the time of writing this paper, raw active fire data from MODIS are being made available to the scientific community. Overlapped with a land cover map and other sources of land use data, this type of analyses may provide comprehensive information about the seasonality of single fire types (i.e. agricultural fires, deforestation fires, etc).

This study also bears the generalization of one particular methodology at global scale. We use the CBI as a global estimator of fire sensitivity, which is dependent on a complex system of interactions (Bachelet *et al.*, 2001; Meyn *et al.*, 2007). Relative humidity and temperature have a constant weight in the CBI equation (Eq. 1), which may hide ecosystem-specific response or the involvement of other variables, for example the accumulation of ground litter throughout the dry season (Dyer *et al.*, 2001). In addition, the native resolution of NCEP data (2.5ºx2.5º) implies that relevant spatial patterns are not accounted for at 1ºx1º, including the CBI variability due to regional changes (2.5º~300 km at the equator) in the interaction between climate and vegetation (see Data and Method Section).

Conclusion

This study reveals a great diversity of fire season regimes, each consistently associated with the regional climate, vegetation, land use and anthropogenic environment. We demonstrate a prevalent anthropogenic influence, while the climatic control is loosened. In agricultural regions, climate only acts as a constraint to set the beginning and ending date of the fire potential window and the fire season clearly bears the signature of human practices. A deeper exploration has the potential to uncover specific associations of fire and land use, to identify dominant crop productions or to infer information about the location and progress of shifting cultivation and permanent deforestation practices.

The coupling of a fire module to a dynamic global vegetation model entails extensive work if the impacts of anthropogenic fires are to be properly modeled. We suggest that timing fire ignitions on eco-climatic conditions only, as done in most models, is not appropriate. We propose that three broad types of anthropogenic fires should be considered as the most relevant to model, not only to improve fire seasonality but also to account for changes in fire frequency and the ensuing emissions. 1/ Agricultural fires, for which a model has to include major crop types along with their productivity and management to assess the timing of fires and the amount of biomass burnt. Regarding crop management, the harvest and planting dates, and the crop specific fire use (pre-seeding, pre-harvesting or post-harvesting) are the key practices to be considered. Several models have already been implemented with agro-ecosystem modules (de Noblet-Ducoudre *et al.*, 2003; Bondeau *et al.*, 2007; Stehfest *et al.*, 2007), and should provide good support to evaluate strategies to integrate fire use. 2/ Tropical deforestation fires, given their widespread use and considerable impact on the vegetation (Cochrane and Schulze, 1999) and carbon balance (Nepstad *et al.*, 1999) of an ecosystem rarely affected under natural conditions. 3/ Fire practices in tropical savannas of Africa and Australia, where fire regimes are greatly altered by human activities, resulting in the highest fire frequency worldwide which climate driven fire models can not reproduce (Thonicke *et al.*, 2001), and in a strongly biased seasonality. Accounting for these major fire practices should in turn benefit the vegetation scheme itself by analogy to the natural feedbacks of fires on ecosystem dynamics (Bond *et al.*, 2005), and improve the computation of atmospheric emissions.

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CHAPTER IV: MODELING FIRE-DRIVEN DEFORESTATION POTENTIAL IN AMAZONIA UNDER CURRENT AND PROJECTED CLIMATE CONDITIONS.

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ABSTRACT

Fire is a widely used tool to prepare deforested areas for agricultural use in Amazonia. Deforestation is currently concentrated in seasonal forest types along the 'arc of deforestation', where dry-season conditions facilitate burning of clear-felled vegetation. Interior Amazon forests, however, are less suitable for fire-driven deforestation due to more humid climate conditions. These forests will ultimately come under more intense pressure as the deforestation frontier advances. Whether these regions continue to be protected by humid conditions partly determines land use changes in interior Amazon forests. Here, we present a study of the climate constraint on deforestation fires in Amazonia under present-day and projected climate conditions. We used precipitation data and satellite-based active fire detections to model fire-driven deforestation potential. Our model results suggest that 58% of the Amazon forest is too wet to permit fire-driven deforestation under current average climate conditions. Under the IPCC B1 scenario, the model indicates increased fire potential by 2050 in eastern Amazonia, while dry-season precipitation may provide limitations on projected deforestation by 2050 in central and western Amazonia. However, the entire region is very sensitive to a possible drying with climate change; a reduction in dry-season precipitation of 200 mm/year would reduce the climate constraint on deforestation fires from 58% to only 24% of the forest. Our results suggest that dry-season climate conditions will continue to shape land use decisions in Amazonia through mid-century, and should therefore be included in deforestation projections for the region.

Keywords: Amazon forest, Fire-driven deforestation, Climate, Fire potential model, Climate change.

I. Introduction

Global demands for food crops, animal ration, and agricultural biofuels have intensified efforts to expand worldwide agricultural production (Naylor *et al.*, 2005). The search for new crop and pasture lands contributes to tropical deforestation (Morton *et al.*, 2006), as large areas of tropical forest are suitable for agriculture use (Balmford *et al.*, 2005; Nepstad *et al.*, 2008). The Brazilian Amazon accounted for nearly half of all tropical deforestation during 2000-2005 (Hansen *et al.*, 2008), where cumulative forest losses for agricultural expansion over the last 20 years cover an area equivalent to the size of Spain (INPE, 2008).

Fire is the dominant method to remove forest biomass during the deforestation process. In Amazonia, the clearing sequence begins with clear-felling trees during the wet season, and deforested areas are then allowed to cure before burning occurs during dry-season months (Carvalho *et al.*, 2001). Along the existing 'arc of deforestation', three to five months with little rainfall may permit multiple fires in the same dry-season. After the first fire, unburned trunks, branches and roots can be mechanically piled and burned repeatedly (Morton *et al.*, 2008). From a climate change perspective, repeated burning results in rapid loss of the majority of carbon in aboveground biomass to the atmosphere, with little compensation by regrowing vegetation in crops or pastures (Morton *et al.*, 2008; van der Werf *et al.*, 2008a). Current forest conversion pressure is highest in regions where the dry-season is long enough to permit fire-driven deforestation. However, the deforestation frontier is advancing into less seasonal forest types, where more humid conditions limit fire efficiency (van der Werf *et al.*, 2008b). Currently, there is no cost-effective alternative to fire for clearing large areas of tropical forests.

Future degradation of the Amazon forest will thus partly depend on the climatic conditions that govern fire deforestation potential (FDP), and on a confluence of other factors: 1. The definition and application of conservation policies, i.e. protected areas (Nepstad *et al.*, 2006), or preservation incentives (Ebeling and Yasue, 2008; Hall, 2008) ; 2. The dynamics of agricultural expansion and logging pressure (Morton *et al.*, 2006; Soares-Filho *et al.*, 2006) ; 3. The eco-climatic requirements for agricultural use (soils, precipitation seasonality (Jasinski *et al.*, 2005; Nepstad *et al.*, 2008)) ; 4. The development of new transport infrastructure (roads, electricity Nepstad *et al.*, 2001; Soares-Filho *et al.*, 2006) ; 5. The resilience of the forest to changes in climate conditions (Mayle *et al.*, 2007; Mayle and Power, 2008) and to anthropogenic disturbances such as fire (Cochrane and Laurance, 2008).

Recent modeling efforts to predict deforestation dynamics in the coming decades integrate many of these key factors (Michalski *et al.*, 2008; Soares-Filho *et al.*, 2006). Deforestation projections provide insights into the suitability of forested land for agricultural use on the basis of infrastructure availability, conservation policies, and socio-economic factors. However, they do not consider whether climate conditions will permit fire-driven deforestation. On the other hand, fire modeling aproaches account for the role of climate (Arora and Boer, 2005; Cardoso *et al.*, 2003; Golding and Betts, 2008; Thonicke *et al.*, 2001), but deforestation practices which alter fire susceptibility and fire incidence are not represented (i.e. clear-fells, vegetation piling, multiple ignitions). These models thus give little information about the spatial feasability of large-scale tropical forest conversion. Two recent studies identified the dependence of deforestation on fire efficiency - and thus on climate - based on monthly or seasonal drought indices (Aragao *et al.*, 2008; van der Werf *et al.*, 2008b).

In this study, we build on these works and developed a model of fire-driven deforestation potential (FDP) based on precipitation data and satellite-based deforestation fire detections to define the current climatic envelope for large-scale deforestation in the Amazon. We propose a methodology addressing the issue at a 10-day time scale consistent with vegetation and soil moisture dynamics and the anthropogenic readiness to take advantage of short dry windows to ignite fires (Uhl and Kauffman, 1990). We then ran the model using current (1980-2000) precipitation data and projections of 2050 climate to 1. study how climate change may impact the area of Amazon forest in which fire-driven deforestation is possible, and 2. evaluate the fraction of projected forest loss by 2050 that falls within regions with high FDP. Finaly, we considered how annual or seasonal changes in precipitation alter FDP to characterize a "tipping point" for human-dominated landscapes in Amazonia - the point at which dry-season precipitation no longer limits fire-driven deforestation.

II. Data and Methods

II.1. Data

II.1.1. Deforestation fires

The deforestation fire dataset from (Morton *et al.*, 2008) is based on a subset of the MODIS collection 4 fire detections product (Justice *et al.*, 2002) taking only the high-confidence fire detections into account to eliminate the false alarms detected frequently at the forest-agriculture interface (Schroeder *et al.*, 2008). The methodology to separate deforestation fires from other types of fires is based on the practice of repeated fires at the same location in preparation for agricultural use; detections of two or more fires during the same fire year within a 1 km radius are tagged as deforestation fires. A fire year is defined as July-June north of the equator, January-December in the southern hemisphere. We selected data from both Terra and Aqua satellites to maximize the sampling of the daily fire cycle, resulting in four complete fire years (mid-2002 to 2006). Daily 1 km deforestation fire detections were aggregated to 1°x1° spatial resolution for three ~10-day intervals each month, calculated as two 10-day periods from the 1st to 20th, and one 8- to 11-day period from the 21st to the end of the month.

II.1.2. Climate observations

Daily precipitation rates at 1ºx1º resolution over 2002-2006 were obtained from the Global Precipitation Climatology Project (GPCP) version 2, which combines various data sources (Huffman *et al.*, 2001). Over 1979-1999, we used the pentad (5-day) precipitation dataset at 2.5ºx2.5º resolution from the CPC merged Analyses of Precipitation (CMAP, (Xie and Arkin, 1997), provided by the NOAA/OAR/ESRL PSD, Boulder, Colorado, USA, (http://www.cdc.noaa.gov/). Both datasets were aggregated to 10-day periods and the CMAP data was regridded to 1ºx1º to match the resolution of the deforestation fire data.

II.2. Model development

Deforestation fires are the culmination of numerous factors that drive land use decisions in Amazonia (Figure 1). Here, we focused on the climate-mediated potential for fire-driven deforestation. Figure 2 shows 10-day time series of deforestation fires and precipitation over 2003-2006 for three grid-cells. Precipitation patterns define the seasonal timing of fire activity; fires only occur during the dry-season, mostly as late season fires (Schroeder *et al.*, 2005). At an intra-seasonal time scale, wet 10-day periods within the dry-season result in a drop of deforestation fire activity (e.g. last 10-day of August 2004 in Mato Grosso). These examples suggest that climate can dissuade human ignitions and/or influence whether these fires will be successful through direct impacts on vegetation and soil moisture (Figure 1, arrows *a*, *b*, *d*, *f* and *h*). Finally, fire activity also varies significantly at inter-annual time scale: figure 2a illustrates how drought conditions in Rondônia in 2005 increased deforestation fire potential (845 deforestation fires versus 354 in 2004).

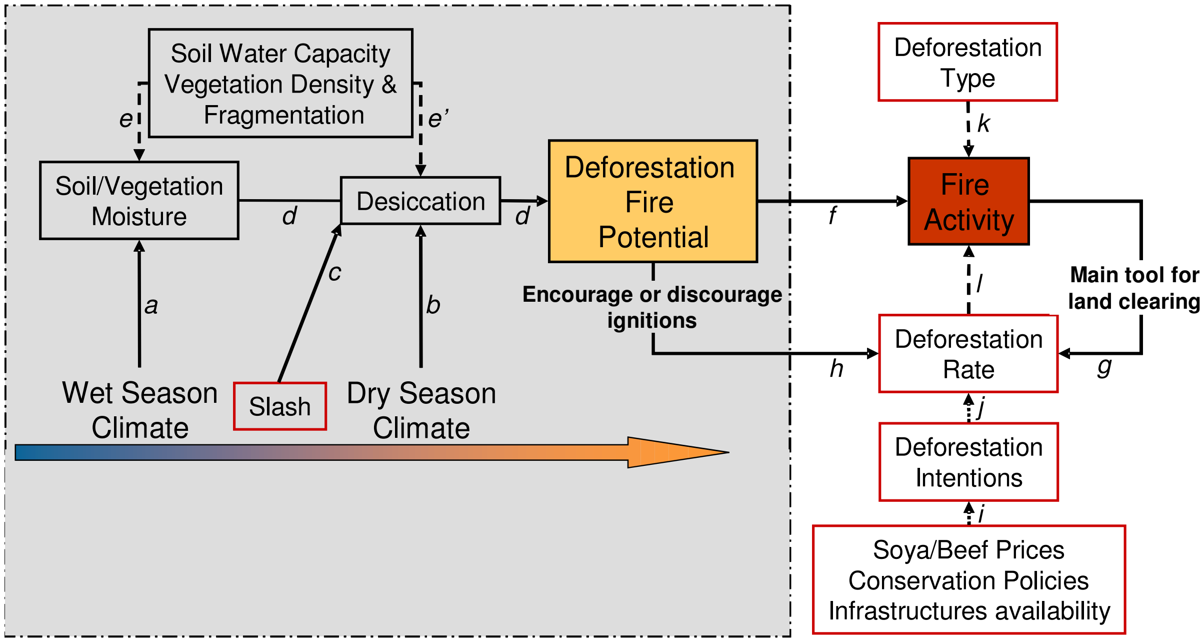


Figure 1. Interactions among climate, vegetation and anthropogenic factors in the context of fire-driven deforestation. Climatic conditions govern fuel moisture following deforestation, described as the deforestation fire potential, whereas land-use decisions on the amount and type of agricultural expansion in Amazon regions ultimately determine the fire activity within periods with suitable climate for fire-driven deforestation. Feedbacks from deforestation on local climate or moisture dynamics due to fragmentation were excluded.

Since we aim to model the *potential* use of fires, independent of any deforestation projections, climate is the factor to isolate. However, factors of anthropogenic origin are also involved, and need to be taken into account to quantify the variability driven by climate. First, vegetation curing dynamics itself is intentionally accelerated by cutting trees, preventing them from accessing ground water (Figure 1, arrow *c*). Further, for a given fire potential, humans decide whether they use the climatic window. In Rondônia for example, increased fire activity in 2005 compared to 2004 may have various explanations. Economic incentives for deforestation may have been stronger in 2005 (arrows *i* and *j*), possibly aided by new infrastructure facilitating deforestation (arrows *i* and *j*). Alternatively, 2004 had a rather moist dry-season which may have limited the use of fires (through arrows *a* and *b*, and see Figure 2a). The predominant type of deforestation could also be involved (arrow *k*); in the state of Mato Grosso conversion to cropland involves nearly three times as many fires as conversion to cattle ranching (Morton *et al.*, 2008). Unfortunately, information about these anthropogenic factors is not always available at the spatio-temporal resolution required to perform satisfying statistical analyses at the scale of the Amazon. One could argue that gridded information on deforestation rates (Achard *et al.*, 2007; Hansen *et al.*, 2008) provide a single proxy accounting for the combined influence of these factors, and could be used to remove the fire variability due to changes in deforestation pressure rather than climate variability. A drawback of this approach is that deforestation and fires are both a cause and a consequence of each other: a lower deforestation rate may be either the cause of decreased fire activity (arrow l, unwanted variability) or its consequence if climate was too humid (arrows *f*, *g* and *h*, variability under study).

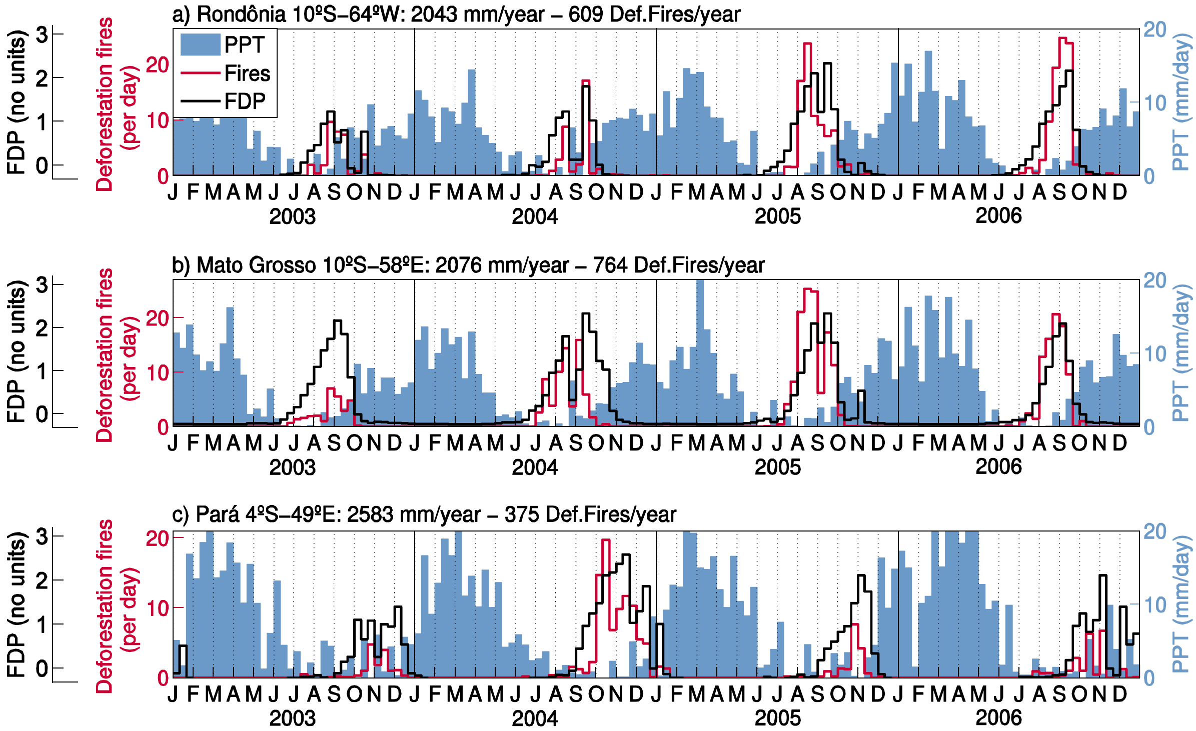


Figure 2. 10-day time series of precipitation rates (blue bars), deforestation fire detections (red stairs), and Fire Deforestation Potential (FDP, black stairs), during 2003-2006 for three 1x1 degree cells in southern Amazonia.

Consequently, building a fire potential model required transforming the fire observation data to make it independent on the extent and type of deforestation. This was partially achieved by computing intra-annual fire anomalies for each grid-cell and each year, based on two assumptions:

1- The anthropogenic will to deforest is rather constant within a year, i.e. conversion plans are decided early and do not change much over the course of the dry-season (other than for climatic reasons), and economic or political factors impacting deforestation are stable at an annual time scale.

2- The distribution of deforestation fires within a year is mostly driven by climate, other potential drivers being considered insignificant. (Morton *et al.*, 2008), for example, showed that the intra-annual timing of fires changes slightly with conversion type.

Fire intra-annual anomalies were computed as follows (Eq(1)):

$$Fa_{y,d} = \frac{F_{y,d} - mean(F_{y,d=1:36})}{std(F_{y,d=1:36})} \quad \text{Eq. (1)}$$

Where $F_{y,d}$ is the fire activity during the 10-day period *d* of year *y* (36 10-day periods per year), and $Fa_{y,d}$ the corresponding fire anomaly. To avoid unrealistic anomalies, we discarded 1ºx1º degree grid-cells with a peak fire activity of less than 10 fires in a 10-day period, or with less than four 10-day periods with observed fires.

To study the relationship between fire anomalies and climate, we defined two indicators of moisture conditions based on Figure 1, detailed observations of the data (as in Figure 2), and reported deforestation practices:

1- The long term precipitation (LTppt) variable represents the vegetation sensitivity to fires due to climate conditions on monthly timescales. This indicator captures desiccation dynamics of the slashed trees (fuels) during the dry-season, as fire efficiency increases with curing time following clear-felling of vegetation (Carvalho *et al.*, 2001). LTppt is calculated as follows:

$$LTppt_d = \frac{\sum_{\mathrm{i=d-m}}^{\mathrm{d-1}} \mathrm{PPT_i} \times (b + i - d - m)}{(\mathrm{b}+1) \times m} \qquad \text{Eq. (2)}$$

Where *d* is the current 10-day period, *m* the number of previous 10-day periods to be considered (the "memory" of the indicator), PPT_i the precipitation at 10-day period *i*, and *b* a constant value controlling the decrease of the weight of 10-day periods with time (conditions during the most recent 10-day periods have a greater impact on LTppt). Various studies point at a delay of two to five months after the wet season to reach significant fire sensitivity (Carvalho *et al.*, 2001; Field and Shen, 2008; Schroeder *et al.*, 2005; van der Werf *et al.*, 2008b). Accordingly, we apply a memory (*m*) of 15 10-day periods, equivalent to 5 months. *b* was assigned a value of 6, which means that precipitation during the most recent 10-day period is three times as important as the oldest (15^{th}) 10-day period in computing LTppt. Note also that LTppt does not depend on precipitation during the 10-day period under consideration, which is captured with the short term precipitation paramater (see below).

2- The short term precipitation (STppt) variable, which represents the vegetation sensitivity to fires due to climate conditions over recent days. The STppt metric captures the rapid dynamics of superficial moisture due to daily weather (Holdsworth and Uhl, 1997; Ray *et al.*, 2005; Uhl and Kauffman, 1990). This indicator is taken as the weighted mean of the precipitation over the considered (weighting 75%) and previous (weighting 25%) 10-day period.

For each grid cell and for each 10-day period we computed fire anomalies, LTppt and STpp. LTppt and STppt were binned into 25 equal intervals, and each fire anomaly was attributed to the observed LTppt and STppt. To strengthen the independence of the results to other sources of variability that may limit fire use even under favorable climate conditions (Sect. II.2), the fire deforestation potential (FDP) under each LTppt/STppt pair was then computed as the upper quartile (at 0.75) of the corresponding fire anomalies (Figure 3a). These results were finally smoothed to avoid unrealistic behavior of the final model (using a classic moving window average filter and forcing a decreasing FDP along increasing LTppt and STppt), as presented in Figure 3b. A second metric, the annual fire deforestation potential (anFDP), is defined as the sum of all positive 10-day FDP values in a given year (negative values of FDP always result in no or insignificant fire activity). Fire anomalies as used here represent the fire climate potential, i.e. under what climatic conditions do the fires actually burn in a given year. Although raw anomalies are not quantitative, the removal of unrealistic anomalies, the use of the upper quartile, and the annual aggregation make of the anFDP metric a relevant indicator of the maximum fire activity possible during a given dry season (see Results section).

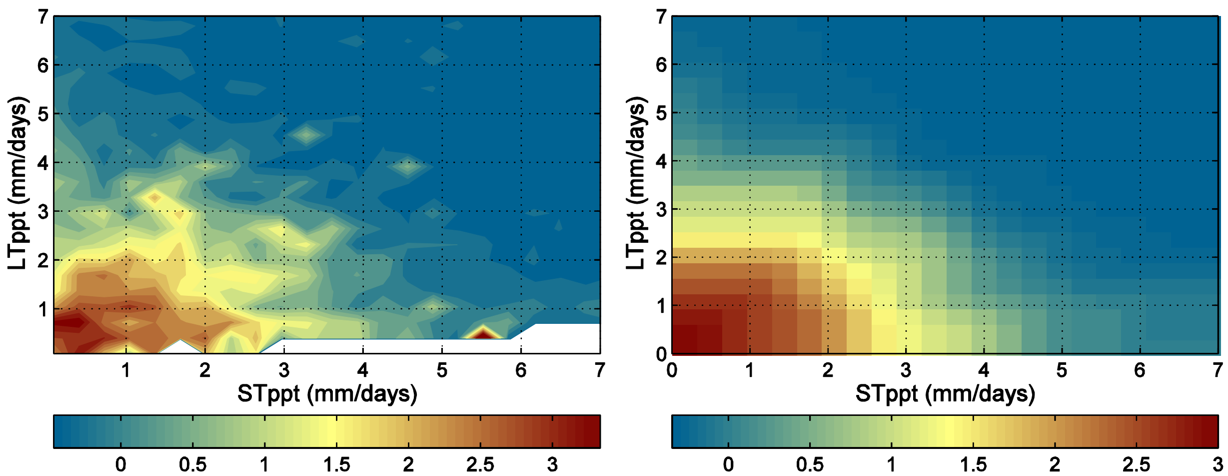


Figure 3. Contour plot of the upper-quartile FDP based on climate and fire detections during 2002-2006 (left) and final model configuration after smoothing (right). FDP is unitless (standardised anomalies).

We excluded several factors in our model that influence moisture dynamics (Figure 1, arrows *e* and *e'*), including forest fragmentation (Broadbent *et al.*, 2008; Laurance and Williamson, 2001), vegetation type and density (Saatchi *et al.*, 2007) and soil water retention capacity (Nepstad *et al.*, 2004). Further, our model represents moisture conditions with two indicators based on precipitation, while temperature also modulates evapotranspiration rates. We chose not to include temperature in the model as it shows little seasonality in most tropical forests, indicating that moisture anomalies are largely a function of precipitation. However, we acknowledge that projected changes of 3-8°C (IPCC, 2007) and model-based estimates of warmer temperatures over deforested areas (Pongratz *et al.*, 2006) could affect FDP.

II.3. Climate and deforestation scenarios

II.3.1. Deforestation scenarios

To estimate how climatic conditions may impact deforestation in the coming decades, we used deforestation projections developed by (Soares-Filho *et al.*, 2006). Their model runs at 1km resolution with annual time steps, based on recent deforestation trends, infrastructure availability (proximity to roads, towns and rivers), biophysical features (e.g. soils, slope) and protected areas, with distinct simulation parameters for each of the 47 socio-economic subregions defined in the Amazon basin.

II.3.2. IPCC climate scenarios

Precipitation projections were computed from the IPCC AR4 General Circulation Model (GCM) runs (IPCC, 2007), provided by the World Climate Research Programme's (WCRP's) Coupled Model Intercomparison Project phase 3 (CMIP3) multi-model dataset. We selected the A2 and B1 greenhouse gases emission scenarios to provide high and low estimates of projected climate changes, respectively. A2 represents a differentiated world, with slow transfers of new technologies, and the highest population trajectory. B1 represents a convergent world, with the development of clean and efficient technologies and a lower population trajectory.

Precipitation projections have been made available by the IPCC, using the Climate Research Unit (CRU) Global Climate Dataset (Mitchell and Jones, 2005) as the climatological baseline to which is applied the projected change of a given scenario compared to the reference scenario (called 20C3M, forced with greenhouse gas concentration changes observed through the 20th century). A preliminary assessment of the CRU precipitation data over the Amazon revealed important discrepancies, up to 1500mm/year in some regions. Given the sensitivity of fires to small changes in climate conditions, this bias was not acceptable for our study. We thus retained the CMAP data, with a much better agreement, as our climatological baseline over 1979-1999.

We computed projections from all IPCC models for which both the A2 and B1 scenarios were available (17 models), over the 2049-2069 period. Due to limitations in computing capacities we used monthly rather than daily model outputs to compute the precipitation change ratio. The same ratio was thus applied to each monthly group of three 10-day periods of the climatological baseline, which downsamples the eventual annual cycle in climatic anomalies, but not the variability at the 10-day time time scale which is conserved from the baseline data. There was little agreement within the 17 IPCC models used, with some models projecting much drier conditions over a large area of the Amazon, and others suggesting little change or increased precipitation. Averaged over all models, precipitation did not change much over most grid-cells. We therefore show the lower (0.25) and upper (0.75) quartile of the projected FDP to represent the inter-model variability.

II.3.3. Statistical climate scenarios

As an alternative to climate model projections, we estimated the precipitation reductions necessary to reach three thresholds of annual deforestation fire potential (low, high, and unlimited, as defined in the Results section). We gradually altered the CMAP 1979-1999 precipitation data towards drier conditions and ran the FDP model at each step, following two different methodologies. In the first case, the annual decrease in precipitation was evenly distributed over all 10-day periods with non-zero precipitation to simulate a "uniform" climate change scenario. In the second case, decreases in preciptation were attributed to the 10-day period with least (but non-zero) precipitation, thus concentrating the change over the dry-season, as a simulation of enhanced "seasonal" climate change.

III. Results

III.1. Fire potential under current conditions

Figure 2 illustrates the modeled FDP time series for three grid-cells. We plotted observed fires and FDP together to provide a qualitative comparison of actual and potential fire activity, yet active fires and FDP are not directly comparable in either scale or in time as FDP is only dependent on climate. However, at the seasonal scale, FDP and active fires define a similar fire season length, supporting the robustness of our methodology. On a 10-day scale, FDP and fire variability are closely related when climate turns less favorable to fires: low FDP results in low fire activity. When fire potential is increasing or high, fire activity is generally elevated, but variable. This variability in fire use during suitable climate periods suggests that drivers other than climate influence landowner decisions for deforestation, and motivated our use of the upper quartile to represent fire potential (Sect. II.2).

Figure 4 explores how and to what extent the FDP relates to the use of fire, as a validation of our main hypothesis. Grid-cells were grouped according to their mean annual FDP metric, anFDP. Within each group, we computed for each grid-cell the correlation between the time series of anFDP and annual deforestation fire activity (4 fire-years for each grid-cell over mid-2002 to 2006). The correlation coefficients of each group give an indication whether inter-annual fire variability is related to anFDP variability. We further show the upper decile (0.9) of observed annual deforestation fire activity as a function of anFDP. In the most humid regions of the Amazon affected by fires (low mean anFDP), we depict high correlations between anFDP and fire activity (with small inter-quartile range and deviation). For these grid-cells, inter-annual variability in fire activity is thus strongly driven by climate. For regions with intermediate or high values of mean anFDP, the correlation is lower on average and highly variable (large inter-quartile range and deviation). In these regions fire activity is thus less constrained by climate: although drier years allow for more fires, the main source of variability here is more likely of anthropogenic origin as discussed before. Based on these results, we defined three anFDP thresholds. Above HiFDP (anFDP=10), precipitation patterns have less influence on fire potential (high variability of the fire-climate correlation), and significant levels of fire activity are observed. Below HiFDP, precipitation becomes increasingly constraining, and below LoFDP (anFDP=3), we estimate that the use of fire for deforestation is virtually impossible. This lower limit for fire activity, however, is difficult to quantify, as the most humid regions of the Amazon basin had little deforestation within our study period. Finally we set the UlmFD (anFDP=17) as a threshold of clearly unlimited fire use. It corresponds to regions with a long dry-season, where intense deforestation fire activity with numerous repeated burns were observed.

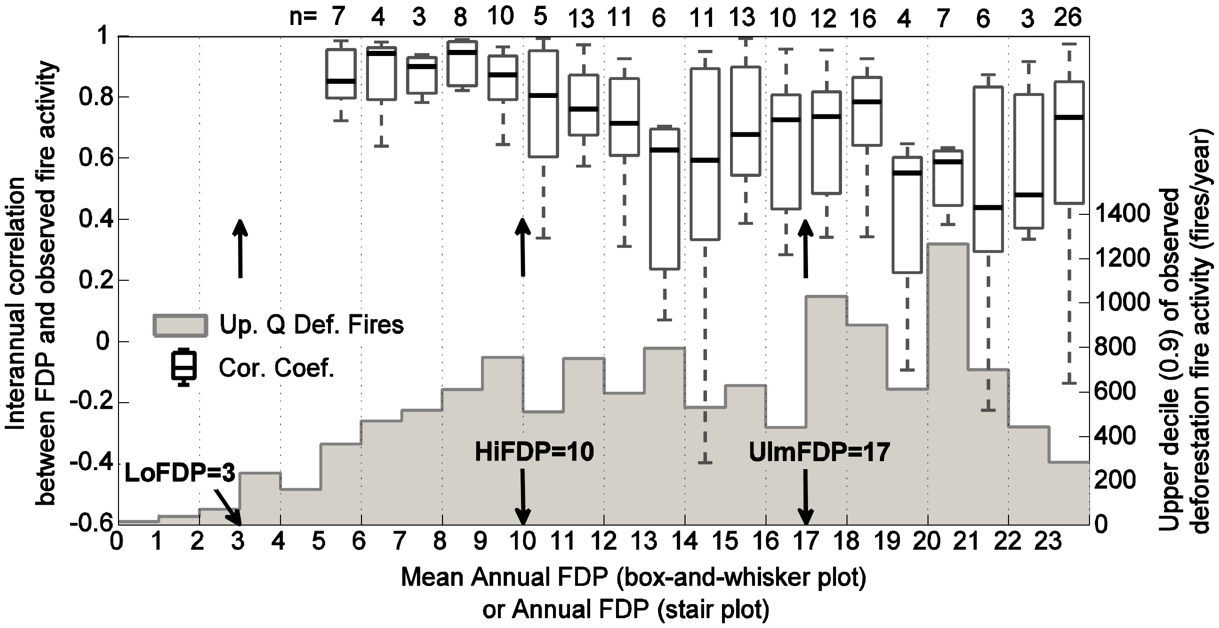


Figure 4. Climate constraint on deforestation fires in the Amazon over 2002-2006. Box-and-whisker plots : for each grid-cell within the corresponding mean anFDP interval ([0 1],]1 2], etc), the correlation between the timeseries of anFDP and observed deforestation fires (4 years) is computed. The box represents the median, upper and lower-quartile values of the correlation coefficients. The whiskers represent the most extreme values within 1.5 times the inter-quartile range from the end of the box (standard). The number of grid-cells to build each box-and-whisker is indicated on top. The stair plot represents the 0.9 upper-decile of the observed deforestation fire activity as a function of anFDP. anFDP=3 (LoFDP), anFDP=10 (HiFDP) and anFDP=17 (UlmFDP) are the low, high and unlimited anFDP thresholds defined on the base of these results (see text).

The spatio-temporal patterns in contemporaneous anFDP and observed deforestation activity are shown in Figure 5. Figure 5a shows the distribution of the mean anFDP over 1980-1999. It reveals a strong north-south gradient in anFDP, from high values from the in southern Amazonia and Roraima State in northern Brazil to low values in Amazonas State, southern Colombia and eastern Perú. 42% of the remaining forest (as of 2001 in the data of Soares-Filho *et al.*, 2006) was suitable for fire-driven deforestation (above HiFDP) under average climatic years, but deforestation activity (Figure 5c) already reached regions where climate reduces fire practices efficiency (below HiFDP).

However, the maximum anFDP reached over these 20 years (Figure 5b) indicates that a large part of the forest under low mean anFDP experienced significant fire potential during drier years: 76% of the forest exceeded the HiFDP threshold at least one year over the 1980-1999 periods. Basin-wide drought events are generally contemporaneous to positive anomalies in the El Niño-Southern Oscillation (ENSO) especially to the 1982-83 El Niño event (Figure 5d).

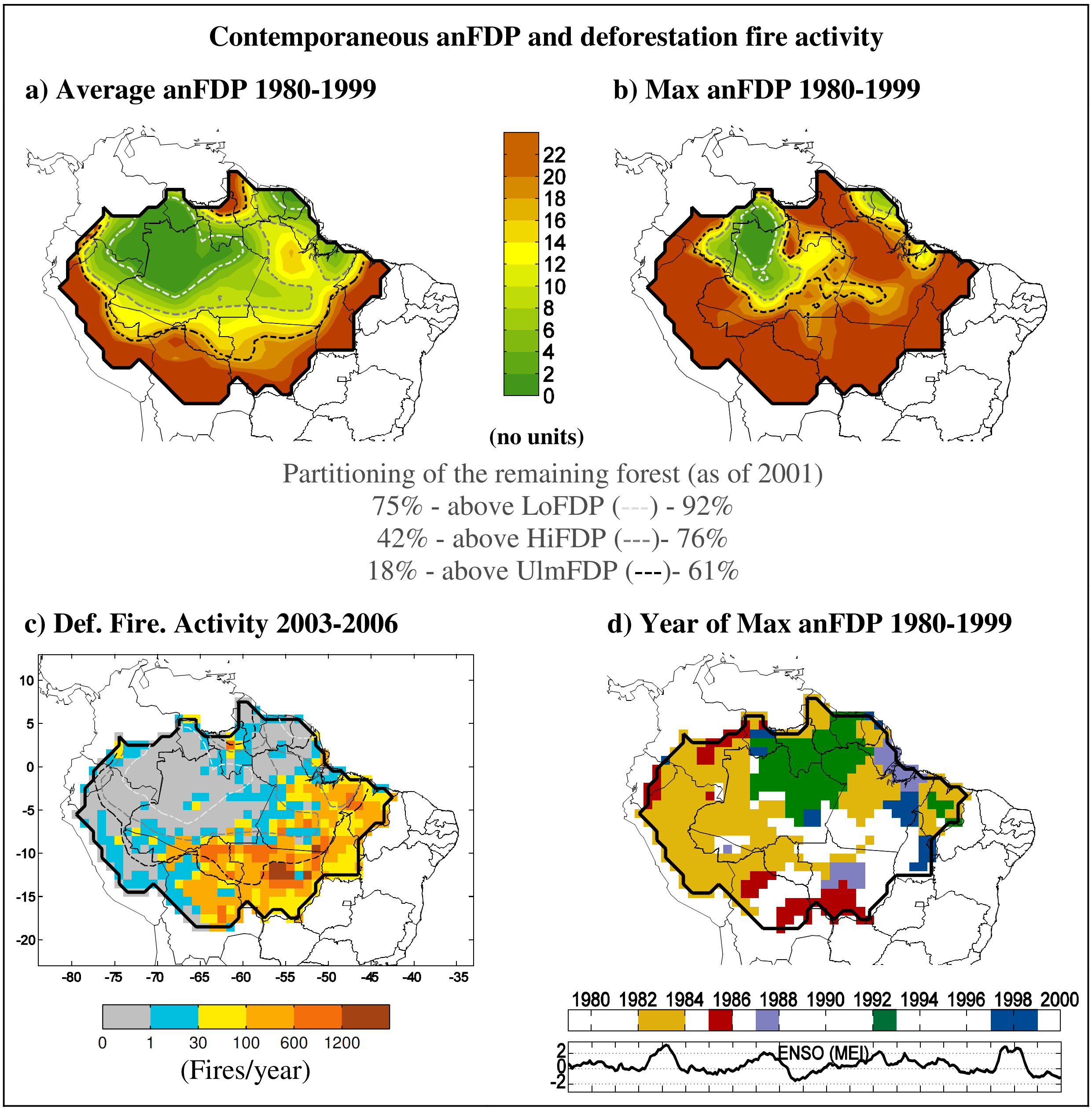


Figure 5. a) Average and b) Maximum anFDP under 1980-1999 CMAP precipitation conditions. White/Grey/Black dotted lines indicate the location of the LoFDP, HiFDP and UlmFDP thresholds, respectively. c) Annual averaged deforestation fire activity over mid2002-2006. d) year of maximum anFDP, along with timeseries of the MEI ENSO index (from the National Oceanic and Atmospheric Administration (NOAA: http://www.cdc.noaa.gov/people/klaus.wolter/MEI/).

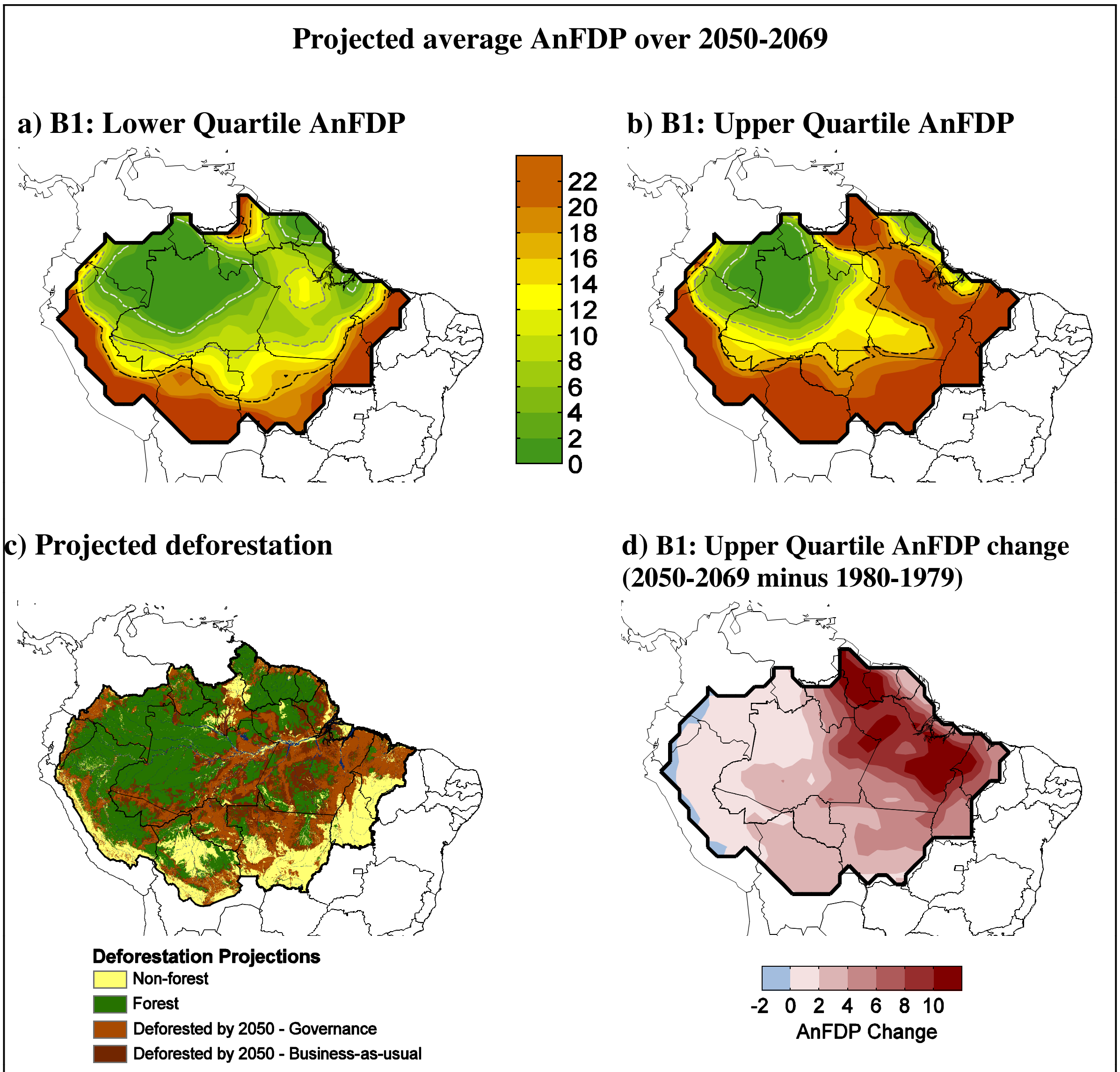
III.2. Fire potential under a changing climate

III.2.1. IPCC projections

The projected average fire potential over 2050-2069 in the Amazon under the B1 scenarios highlights the range of climate model projections (Figure 6a,b). We here discuss the results from the B1 scenario only since the B1 and A2 scenarios yielded very similar results (Figure 6e). In the B1 lower quartile case, the forest area in each anFDP category in 2050 is slightly lower than under current climate conditions (Figure 6e). In the upper quartile case, the HiFDP boundary expands to 63% of remaining forest areas versus 42% under current climate conditions. Changes in AnFDP by 2050 were concentrated in eastern Amazonia, while interior Amazon forests retained low AnFDP values in 2050 even in the upper quartile of B1 projections (Figure 6d). As a result, a substantial portion of projected deforestation by 2050 could be limited by precipitation constraints on fire-driven forest clearing (Figure 6c,e). Based on average anFDP years, climate conditions could limit 1/3-1/2 of projected deforestation by 2050 under current climate conditions or the B1 lower quartile case. Results for the upper quartile of B1 projections suggest that only 11-12% of projected deforestation would face climate limitations to fire-driven deforestation.

III.2.2. How much change in precipitation will make the region vulnerable to fire?

Model runs with the iterative precipitation change (Sect. 2.3.3) reveal a great sensitivity of anFDP to seasonal changes in precipitation, and indicates that a substantial portion of the remaining forest is close to a climatic tipping point for fire-driven deforestation (Figure 7). With a loss of 200mm of precipitation over the dry-season, the percentage of the forest above HiFDP would increase from 42% to 64% and 76% in the uniform and seasonal change case, respectively. Considering the UlmFDP threshold, at which intense deforestation fire activity is currently observed and climate constraints are minimal, the 200mm change results in an increase from 18% to 34% (uniform) and 61% (seasonal). For the seasonal change case, the climatic distance to go from LoFDP to HiFDP amounts to ~200mm, and to 100-150mm from HiFDP to UlmFDP.



e)

		Percentage of the forest above			% Def . by 2050 within HiFDP	
		LoFDP	HiFDP	UlmFDP	Business-as-Usual	Governance
Current Climate		75	42	18	62	68
B1 *(A2)* scenario	Lower Quartile	71 *(78)*	33 *(38)*	15 *(16)*	51 *(57)*	60 *(63)*
	Upper Quartile	84 *(81)*	63 *(61)*	38 *(39)*	88 *(86)*	89 *(89)*

Figure 6. a) Lower and b) Upper quartile of the projected average AnFDP over 2050-2069 under the B1 scenario. c) Projected deforestation by 2050 (Soares-Filho *et al.*, 2006). d) Change in AnFDP for the B1 upper quartile run, to highlight regional changes. e) Partitioning of the Amazon forest (as of 2001) along the three anFDP thresholds, and percentage of the projected deforestation assessed to be feasible with fire by the model.

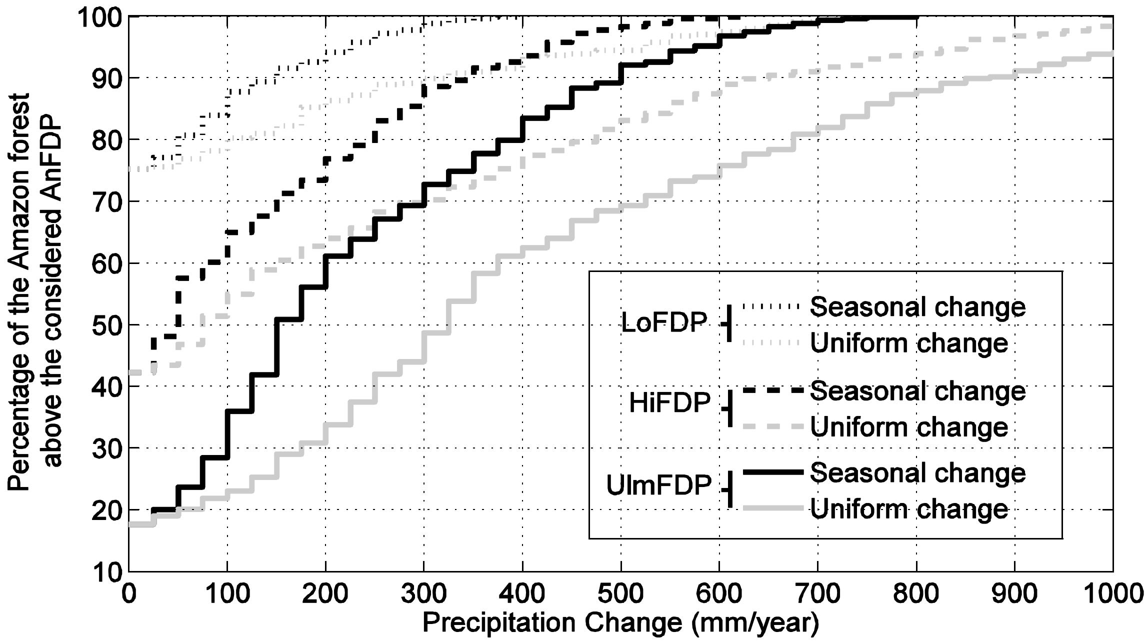


Figure 7. Proportion of the Amazon above the three anFDP thresholds considered (LoFDP, HiFDP and UlmFDP) as a function of 2 types of precipitation change. Seasonal change is distributed over the driest 10-day periods, while the uniform change scenario distributes reductions in precipitation evenly throughout the year (see text).

IV. Discussion

IV.1. Strong limitation for deforestation progression under current climate

We estimate that more than half (58%) of the remaining forest of the Amazon is currently protected by climate against fire-driven deforestation. In these areas, the dry-season is not long nor dry enough to reach high fire potential. The location of the existing deforestation frontier now abuts these regions with reduced suitability for fire-driven deforestation, suggesting that deforestation rates may decrease during years with average climate conditions. However, anFDP increases dramatically during drought episodes, rendering fire-driven deforestation possible across much of Amazonia; from 1980 to 1999, only 24% of the forest never reached HiFDP fire prone conditions. Intense droughts provide an opportunity to intensify fire practices, as illustrated in 2005 with a 43% increase in the number of fires per deforested unit (Aragao *et al.*, 2008), linked to a warming of sea surface temperature in the tropical North Atlantic circulation (Marengo *et al.*, 2008).

IV.2. The eastern Amazon at risk of a retreat of the climatic constraint

The IPCC models projecting significant climate change over the Amazon basin tend to reduce rainfall in eastern regions (IPCC, 2007; Malhi *et al.*, 2008), namely in the Brazilian states of Parà, Mato Grosso, Rondônia and eastern Amazonas. The gradient of anFDP in these regions is very gradual, such that small changes in precipitation result in a large increase in forest areas with HiFDP. In the upper quartile B1 run, 63% of the forest was susceptible to fire-driven deforestation, compared to 42% under current climate conditions. These regions also contain the most suitable soils for mechanized agriculture (Jasinski *et al.*, 2005; Nepstad *et al.*, 2008), and are likely to be under strong deforestation pressure in the coming decades (Soares-Filho *et al.*, 2006).

The iterative scenarios also point at the potential of a drying climate to enable fire practices in the eastern Amazon, this region being largely responsible for the expansions of the HiFDP and UlmFDP boundaries along the first iterations (not shown). Further, these expansions happen twice as fast in the case of a seasonal change compared to a uniform change. This suggests that the occasional rain during the dry-season strongly limits ignitions over the considered 10-day period via STppt, and has an impact on following 10-day periods via LTppt. If these dry-season rainfall events disappear, fuel curing proceeds uninterrupted and fire prone conditions are reached earlier, potentially increasing the efficiency and number of repeated burns over a single dry-season. The seasonal precipitation change scenarios are consistent with rain-free periods during El Niño and other droughts.

IV.3. Implications for forest conservation in Amazonia

Deforestation and fires are expected to dominate forest changes relative to direct climate impact (Barlow and Peres, 2008; Golding and Betts, 2008). Because fire is indispensable for large-scale forest conversion, the fate of the Amazon will greatly depend on the evolution of fire susceptibility and agricultural expansion.

The fire threat stems from deforestation practices as studied here, as well as from understorey fires. Understorey fires induce significant tree mortality, and consecutive fire events lead to the invasion of pioneer species replacing primary forest trees, similar to forest secundarization (Barlow and Peres, 2008). They are more common in years of longer or stronger dry-seasons, and in areas of degraded or fragmented forest with dead fuel and increased evapo-transpiration rates (Alencar *et al.*, 2006). Usually, they result from escaped fires (leakage fires) associated with deforestation and susbsequent agricultural activities. As such, droughts synchonize two essential factors for escaped fires (frequent ignitions and a dry understorey), such that our anFDP metric provides insights on the co-evolution of deforestation feasability, and understorey fire risk.

Changes in deforestation potential also suggest probable changes in agricultural potential. Cultivated species raise sustaining yields within a certain range around optimal climatic and soil conditions (Nepstad *et al.*, 2008), spatially referred to as agricultural zoning. An increase in dry season severity as scenarised in this study would tend to shift these zonings towards the remaining forest. Areas currently too wet or aseasonal for a given species would have longer dry seasons and could turn suitable cultivation lands. Meanwhile, areas on the drier margins of the current zoning would turn too dry unless new adapted cultivars are developped, and the resulting loss in production would further increase the pressure for expansion on new lands. A study from the Brazilian Agricultural Research Corporation (EMBRAPA) and University of Campinas (UNICAMP) shows that temperature is also an essential variable regarding this issue, and foresees a decreased area for the cultivation of most species in the Amazon with the prospect of rising temperature (Assad *et al.*, 2008). The spatial intersection of the HiFDP boundary with agricultural zonings will thus have a major influence on the evolution towards the expansion of agriculture in forested areas, or its intensification on degraded pastures along with the generalization of crop rotation to maintain land fertility.

Beyond the direct impact on the ecosystem, the damages inflicted to the forest through deforestation and fires may initiate positive feedback loops with long-lasting footprints (Cochrane, 2003). For example, enhanced evapo-transpiration rates following degradation weakens the resilience of forests to droughts and increases fire susceptibility (Broadbent *et al.*, 2008; Laurance and Williamson, 2001), and the removal of a significant portion of the forest could tip the whole basin towards a new equilibrium state of savannas and semi-desertic ecosystems (Nepstad *et al.*, 2008; Oyama and Nobre, 2003). Also, fire smoke aerosols have been reported to delay or suppress precipitation through their action on cloud droplet size (Kaufman *et al.*, 2002; Rosenfeld, 1999), although their overall consequence is uncertain given their complex influence on the hydrological cycle (Lohmann and Feichter, 2005; Ramanathan *et al.*, 2001).

Conclusions

In this study, we evaluated the climatic constraints on fire-driven deforestation in Amazonia using satellite-based fire detections and precipitation data. The model captures substantial intra and inter-annual deforestation dynamics, especially in low to intermediate fire potential regions where the climate-fire-deforestation link is stronger. Under average contemporary precipitation regimes, 1/3-1/2 of the projected advance of the deforestation frontier by 2050 would be limited by wet conditions in interior Amazon regions. However, climate change under the B1 emissions scenario may increase the potential for fire-driven deforestation across a wide range of Amazon forest types, although climate projections differ substantially. A simulation of seasonal changes in precipitation indicated that a moderate reduction in precipitation (<200 mm) during dry-season months could facilitate fire-driven deforestation in 70% of remaining forest areas.

We thus suggest that the climatic influence on fire susceptibility defines a "tipping point" that is essential to consider for projections of future forest loss and agricultural expansion in Amazonia. Current deforestation models generally focus on socio-economic and drought stress direct impacts (Ashton *et al.*, 2008; Soares-Filho *et al.*, 2006). Our findings provide complementary information to these projections, and most importantly should support the extension of these models to include the interaction between deforestation, fire and climate. By extension, exploring the Amazon forest response to current changes in its structure and environmental conditions should associate within a common framework all 6 essential factors defined in the Introduction.

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GENERAL CONCLUSIONS AND PERSPECTIVES

GENERAL CONCLUSIONS AND PERSPECTIVES

The determinants of fire regimes emerge as the central topic of all four chapters. This thesis sought to contribute to unravel the functioning of the fire triangle, to reproduce it through modeling, and to apply this knowledge to evaluate the potential alterations of fire regimes and their consequences.

UNDERSTANDING OF THE FIRE TRIANGLE

Contribution

Several aspects regarding the role of climate and humans have been explored. Chapter I emphasized climate as a source of synchronization of global fire activity. The three leading principal components of inter-annual fire anomalies are driven by the ENSO, accounting for approximately 17% of the total variance over 1997-2006. Changes in climate conditions induced by the 1997-98 El Niño phase progressively spread from the southern Pacific regions to all continents causing major fire outbreaks in all types of ecosystems. These alterations not only prevailed on global fire variability over a period of nearly two years, but also increased the share of burning in tropical and boreal forests and peat lands. The other retained components, of decreasing magnitude, were all related to climatic determinants. Although there was no sign of an anthropogenic influence on these spatio-temporal scales, it was probably concealed within some of the inferred patterns. Indeed, humans can analyze the configuration of the fire triangle and adapt their practices, at times magnifying the influence of climate. In regions where the average moisture conditions are limiting, droughts are the occasion to intensify fire practices. This is the case with fire-driven tropical forest conversion, as shown in Chapter IV. During a prolonged drought, the magnitude of fire outbreaks in tropical forests results from the synchronization of both climate-induced fire susceptibility and extra anthropogenic ignitions.

Conversely, the seasonal dynamics of climate and fire practices are often largely asynchronous. This divergence is explored in Chapter III, which was the first attempt to discriminate the anthropogenic driving of fire seasonality on a global scale, and elucidate related practices. This study revealed four types of human-climate-vegetation interactions. In areas of intensive agriculture, fire regimes are almost entirely driven by crop calendars, with very little influence left for climate, except in the case of escaped fires. In regions where eco-climatic conditions represent a threat, inducing high fire susceptibility and hence favoring the occurrence of devastating fires, practices tend to anticipate the natural occurrence of fires to achieve controlled burns. In regions where eco-climatic conditions limit fire-related human activities (e.g. deforestation), practices tend to accelerate fuel desiccation and multiply ignitions to induce a fire season. Finally, in regions of low anthropogenic pressure, as in pristine boreal and tropical forests, fire regimes are largely driven by the natural dynamics of fuel moisture and fire weather, and by stochastic ignitions. For each of these broad classes, specific examples have been selected and the determinants of fire seasonality inferred.

Perspectives

The role of climate on fire regimes is relatively well understood. Field experiments uncovered the fundamental principles, before satellite observations provided the globalization necessary to study fire-climate interactions in a wide range of ecosystems and from sub-daily to multi-annual timescales. However, their quantification is problematic because other factors entering the fire triangle are not so well depicted, thus limiting the potential of multivariate analyses. Specifically and somewhat ironically, the role of humans is rather obscure. As with climate, localized information on fire practices has been reported, but little is known as to their global distribution and prevalence. The alterations of fire frequency, seasonality and emissions by these practices are highly significant. This should stimulate more research regarding their characterization in the same manner that Chapter III demonstrated the valuable support provided by satellite observations in this respect.

Representation the fire triangle within a DGVM

Contribution

Up to the end of the 1990's, most Dynamic Global Vegetation Models accounted solely for the interaction of climate and vegetation, casting aside major factors such as land use or fires. In Chapter II, the representation of fire regimes in a DGVM was evaluated with satellite-derived fire data. The analyses were initially designed to diagnose the fire module itself. Instead, they pointed to key pre-requisites necessary to ensure a proper representation of the three factors of the fire triangle prior to the actual exploration of fire driving in greater detail. SEVER-Fire, as any global scale model, requires the simplification or omission of several aspects of vegetation dynamics, but some are too limiting for fire modeling. Especially, plant functional types of major relevance are absent, as savannas for example, and the lack of a land use scheme causes large discrepancies in vegetation distribution. Also, the innovative modeling of human pyrogenic behavior should be further developed to capture the wide range of practices and their timing. Finally, the climatic factor was not properly represented either, due to discrepancies in the input data. The substitution of NCEP by CMAP precipitation should improve both the vegetation and climatic factors, easing the exploration of the driving assumptions.

With these limitations, SEVER-Fire was bound to simulate patterns of fire incidence and fire seasonality largely different to the ones observed. Yet it did capture fire inter-annual variability to a satisfactory degree given that this is less sensitive to misrepresentations in vegetation distribution and anthropogenic activities. In particular, most of the fires anomalies associated to the El Niño 1997-98 (Chapter I) were depicted.

Perspectives

Models are catching up on the integration of fire as an essential driver of vegetation dynamics and atmospheric composition. However, large gaps in our understanding of the fire triangle must be addressed in order to achieve realistic simulations. Up until now, satellite observations have been surprisingly disregarded in modeling approaches, despite having the potential to support fire driving investigations (Chapters I to IV) and to improve model parameterization (Chapter II and IV).

The modeling of anthropogenic activities is the most restrictive component of DGVM-fire models. The coupling of a land use scheme and the explicit description of fire practices are an indispensable step forward. Land use modeling was beyond the scope of this thesis, but is being undertaken[25] and will favour the maturation of the approach to model fire practices. The timing of fires (Chapter III) would then depend on the land use scheme in agricultural areas. In other types of land covers, human pyrogenic behavior is largely an adaptation to eco-climatic conditions, to which it could be statistically related (see the Contribution of the previous section). Likewise, fire frequency could benefit of a switch from socio-economic to eco-climatic determinants. Indeed, decreased fire frequency in many developed countries is largely the result of landscape fragmentation and landuse, while high fire frequency in tropical savannas results from their elevated susceptibility to fires, independent of the wealth status of the regional population (e.g. Australia).

The mission of the Intergovernmental Panel on Climate Change is to regularly assess the knowledge on human induced climate change. Coupled vegetation-atmospheric models have a leading role in these assessments, but none of them includes landuse nor fires, which are extremely relevant disturbances in evaluating the likelihood of two potential scenarios: the attenuation of anthropogenic perturbations (e.g. increased carbon uptake, adaptation of vegetation species), or the existence of positive feedback loops and tipping thresholds accelerating the induced changes. Such over-simplified hypotheses are probably a necessary step in the evolution of these models, but should be remedied as soon as possible. Meanwhile, future projections are specific to an environment different from the one we live in, and have little if no predictive value.

Predicting the consequences of changes in fire-related environmental conditions

Contribution

Chapter IV was designed from the former conclusions to build a realistic model of the fire triangle in the case of fire-driven deforestation in the Amazon. As recommended in Chapter II, the methodology takes advantage of the remote sensing detectability of deforestation fires to infer the role of climate and humans in the dynamics of tropical forests fire susceptibility. Their combined impact on fire regimes is accounted for by a simple parameterization, which defines the climatic envelope for fire to be an efficient clearing tool. The model describes specific patterns previously depicted, relative to fire frequency (Chapter II), seasonality (Chapter III), and inter-annual variability (Chapter I).

On the positive side, Chapter IV revealed that deforestation has now reached the spatial margins of this climatic envelope, so that its progression will probably slow down, because combustion should be restricted solely to drought years. More than 30% of the projected deforestation by 2050 would face limited fuel flammability if climate was to remain the same. However, moderate changes toward increased droughts frequency and/or drier averaged conditions would greatly expand the area of potential deforestation.

Perspectives

As detailed in the discussion of Chapter IV, fires in the Amazon forest act as an immediate destructive tool, and as a vector of perturbation threatening the equilibrium of ecosystem on a larger scale. The future of tropical ecosystems will depend on these impacts and on a wide range of other factors, including environmental policies, agricultural zoning, or again economic incentives, and equally important, their interaction. The research around these topics in the Amazon is maturing rapidly. It expands the scope for the construction of an exhaustive enough framework to evaluate the mechanisms involved, and to point to realistic solutions for forest conservation. In particular, merging fire potential with agricultural suitability and protected areas would serve to clarify the risk represented by deforestation.

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