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Characterising fire spatial pattern interactions with climate and vegetation in Colombia

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ABSTRACT

Vegetation burning in tropical countries is a threat to the environment, causing not only local ecological, economic and social impacts, but also large-scale implications for global change. The burning is usually a result of interacting factors, such as climate, land-use and vegetation type. Satellite-derived monthly time series datasets of rainfall, burned area and active fire detections between December 2000 and 2009 were used in this study. A map of vegetation types was also used to determine these factors' spatial and temporal variability and interactions with the total amount of burned area and active fires detected in Colombia. Grasslands represented the vegetation most affected by fires every year in terms of burned area (standardised by their total area), followed by secondary vegetation, pasture and forests. Grasslands were also most affected by active fires, but followed closely by pasture, agricultural areas, secondary vegetation and forests. The results indicated strong climate and fire seasonality and marked regional difference, partly explained by climatic differences amongst regions and vegetation types, especially in the Orinoco and Caribbean regions. The incidence of fire in the Amazon and Andes was less influenced by climate in terms of burned area impacted, but the strength of the ENSO phenomenon affected the Orinoco and the Andes more in terms of burned area. Many of the active fires detected occurred in areas of transition between the submontane and lowland Andes and the Amazon, where extensive conversion to pasture is occurring. The possible high impact of small fires on the tropical rainforest present in this transition area and the Amazonian rainforest deserves more attention in Colombia due to its previous lack of attention to its contribution to global change.

1. Introduction

Fire has always been a natural and anthropogenic disturbance influencing ecosystem patterns and processes, as well as maintaining diversity, productivity and nutrient cycling ecosystems throughout the world (Wan et al., 2001; Cochrane, 2003; Bowman et al., 2009). Fire is also used as a management tool for forest and land clearance for grazing improvement (Bond and Keeley, 2005; van der Werf et al., 2008; Bowman et al., 2009). Despite its known importance, there is a great lack of knowledge about fire's role in Earth system processes and its full range of environmental change to our planet (Bowman et al., 2009). Fires occurring in tropical regions have recently become a major issue, given their great impact on tropical ecosystem structure and function (Cochrane and Laurance, 2008). In part, this is due to the availability of new burned area datasets from satellite observations, which indicate up to 4 million km^2 burned between 2000 and 2006 (Chang and Song, 2009). A great deal of this area was burned in tropical and subtropical regions, leading to an estimated 0.65 Pg C year^{-1} contribution from fire-induced anthropogenic CO_2 emissions caused by tropical deforestation (Bowman et al., 2009). Furthermore, between 5% and 9% of the total global burned area occurs in South-America (Chang and Song, 2009).

Fire distribution and fire incidence studies focusing on tropical ecosystems have generally had global scale approaches (Dwyer et al., 1999; Giglio et al., 2006). Some studies have had a regional focus (Chuvieco et al., 2008; Di Bella et al., 2006; Siegart et al., 2001; Barbosa et al., 1999; Eva and Lambin, 1998) and several of them have been made specifically in Latin-American countries

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(Kitzberger et al., 1997; Román-Cuesta et al., 2003; Román-Cuesta and Martínez-Vilalta, 2006; Di Bella et al., 2006; Armenteras et al., 2009). This fire research in South America is mainly focused on modelling emissions from biomass burning from deforestation (Nepstad et al., 1999; Alencar et al., 2006), linking fire, land use and climate change (Aragao et al., 2008; Cochrane and Laurance, 2008) or analysing the effectiveness of reserves (both protected areas and indigenous lands) as protection against forest fires (Nepstad et al., 2006; Adeney et al., 2009).

Interactions between climate, vegetation and fire are complex, although it is widely believed that climate is one of the natural factors influencing both vegetation distribution and vegetation fire regime characteristics (van der Werf et al., 2008). Few of these studies have included the effect of climate on fire incidence dynamics and frequency (Nepstad et al., 2006; Aragao et al., 2008; van der Werf et al., 2008), although fire is a seasonal phenomenon having dry season-associated peaks (Aragao et al., 2008). Some studies focusing on Latin America have looked at fires' climate-related inter-annual variability (Román-Cuesta et al., 2003; Alencar et al., 2006). Fires mainly occur in northern South America during a dry season lasting from December to early April, specifically in Colombia and Venezuela (Dwyer et al., 1999; Romero-Ruiz et al., 2009). Climate changes have indeed resulted in increased occurrence of extreme drought seasons, leading to increasing areas burned, fire frequency, intensity and longer fire seasons (van der Werf et al., 2008).

Colombia is a megadiverse country that is extremely rich in species and ecosystems (Mittermeier et al., 1997). Given its particular geographic conditions, it is the only South American country to border both the Pacific Ocean and the Caribbean Sea. Colombia represents an excellent pilot case for studying fire regimes and their relationship to vegetation and climate change. Moreover, Colombia hosts the northern tip of the Andean mountain range and almost 50% of its territory extends into both the Orinoco and Amazon basins. Colombian territory includes dry forests, savannah and rainforests, as well as Andean mountain forests, all being affected by fire to different extents (Armenteras et al., 2009). In addition, this country has strong environmental and climatic variability and is suffering great social and political changes, making it a challenge to study fire regimes given such high spatial heterogeneity. This paper was aimed at evaluating to what extent the spatial and temporal patterns of vegetation burning in Colombia could be explained by regional and climatic variation. This will therefore provide a comprehensive review of regional fire patterns and help to improve measurement of inter-annual biomass burning variability and support natural resource management in Colombia.

2. Methodology

2.1. Study area

Colombia stretches across the northwestern tip of South-America (located 12°26′46 North, 4°13′30 South, 66°50′54 East and 79°02′33 West) and is the only South American country to have coasts on both the Pacific (1350 km long) and the Caribbean (over 1600 km). Colombiais the fourth largest country in South America (after Brazil, Argentina and Peru, in size) and covers 1,141,748 km^2. It is bordered by the Caribbean Sea in the north, Venezuela (2219 km of border) and Brazil (1645 km) in the east, Peru (1629 km) in the South, Ecuador in the southwest (568 km) and the Pacific Ocean and Panama (266 km) in the northwest (IDEAM et al., 2007).

Colombia is a geographically variable country. The western part is mostly mountainous (45% of the territory). However, a major part of the country consists of plains lying below 500 m. The territory can be divided into six large natural regions due to its topographic variety determined by the presence of mountain systems, the diversity of climates and the great number of soil classes. These regions are the Andean region (including the three Andes ranges and Inter-Andean valleys), the Caribbean (Atlantic) littoral, the Pacific region, the Orinoquian region (embracing the plains of the Orinoco River Basin, a huge open savannah lying in the basin of the Orinoco river), the Amazonian region (embracing the Amazonian forests) and an Insular region which has not been covered in this study. Following Olson's classification of the world's major ecosystems (Olson et al., 1983), Colombia is mainly dominated by tropical rainforest (52.2%), followed by savannahs (13.9%), crops, grasslands and shrublands (9%).

2.2. Datasets

2.2.1. Burned area and active fire data

The NASA Moderate Resolution Imaging Spectroradiometer (MODIS) on the Terra and Aqua satellites provides a suite of global MODIS land products, including the MODIS Burned Area Product (MOD45A1) at 500 m resolution (Roy et al., 2005, 2008), which was used in this study. Available monthly datasets were downloaded from December 2000 to February 2009. This product, amongst other metadata, has information regarding quality assessment of the burned area for each pixel (BA pixel QA) with information on detection confidence (1 – most confident to 4 – least confident). Only pixels having a confidence of 1 were used for this study (i.e., those most confidently detected as burned areas) (Boschetti et al., 2009). The images for Colombia were downloaded in HDF-EOS format, which was then converted to GeoTIFF using the conversion tool to stitch, re-project and subset tiles (USGS, 2004). Overlapping areas for each image of the previous month were eliminated so as not to overestimate burned area per month (i.e., if a pixel was detected as a burned area 1-month and the following again, it was only considered as a burned area during the first month). The monthly data were used to build up the dry season dataset, defined as being the 3-month period including December, January and February (DJF, see below).

Another MODIS product used was the fire hotspots series processed in the Collection 5 temporal thermal analysis active fire dataset (FIRMS, 2007; Davies et al., 2009). The daily set ranging from December 2000 to March 2009 was downloaded from FIRMS (Fire Information for Resource Management System: Archiving and Distributing MODIS Active Fire Data, Collection 4; Davies et al., 2009). Active fire detection is based on detecting the thermal signature of fires and uses a contextual algorithm (Giglio et al., 2003). Actively burning fires are thus typically much smaller in area than the spatial resolution of remote sensing images (smaller than the 500 m pixel of the burned area product), but it has been suggested that their intense thermal emission (in the mid-infrared-MIR channel) was able to detect fire covering only 0.1% or even 0.01% of a pixel (Roberts and Wooster, 2008; Csiszar, 2009).

2.2.2. Natural regions and vegetation cover types

Information regarding both the natural regions (Andes, Pacific, Caribbean, Amazonia and Orinoco; Fig. 1) and types of vegetation cover was used. The five natural regions were derived from the 90 m digital elevation model (DEM, SRTM, 2000) using the 500 m asl (meters above sea level) altitude limit. In the case of both Amazonia and the Orinoquia, the limit between the savannah and the forest as frontier were drawn amongst regions using the official ecosystem map of Colombia (IDEAM et al., 2007). Some of the isolated mountainous formations, such as the Sierra Nevada of Santa Marta or the Macarena Serrania were included in their neighbouring natural region. The resulting five regions exhibited different natural history, flora and fauna and have also been subjected to different

Table 1
General vegetation, population and climate characteristics of each natural region and the main factors associated with fire.

Region	Main vegetation type	Population	Climatic pattern	Fire pattern	Main factors associated to fires	Influence of ENSO on fires
Amazonia	Tropical rainforest	Low density, but active colonisation front	Wet most of the region has annual precipitation between 3000 and 4500 mm	Temporal pattern associated to climate and spatial pattern associated to colonisation front	Deforestation and expansion of agricultural frontier, Illegal crops	Not strong
Andes	Montane forests Agriculture Pastures	High	Highly diverse, with low precipitation (up to 2000 mm) in the Eastern range, and some interandean valleys, and areas with maximum precipitation (3000–5000 mm) in the Mid-Magdalena and Cauca watershed	Associated to agriculture and pastures, most of it on colonisation frontiers towards lowland areas	Agriculture Invasive species	High
Caribbean	Pastures grasslands secondary vegetation	Medium	Average annual precipitation between 500 and 2000 mm	Temporal pattern associated to climate. Spatial pattern associated to pastures	Agriculture	High
Orinoquia	Herbaceous (grasslands and savannahs)	Low density	Diverse, ranges from 2000 to 3000 mm in the central and eastern part of the region, with areas near the Andes up to 6000 mm. In the northern part, rainfall below 1500 mm	Temporal pattern associated to climate. Spatial pattern associated to pastures	Cattle ranching agricultural frontier rainfall vegetation type	High
Pacific	Tropical rainforest	Low density	Extremely wet, annual precipitation ranges from 3000 to 12,000 mm	Colonisation front	Deforestation	None

uses (IDEAM et al., 2007). They have some important climatic differences, as the drier regions were the Orinoco and the Caribbean (dry season rainfall <50 mm per month). The Amazon and Andes were geographically distributed in wetter areas (dry seasons having more than 50 mm monthly rainfall but below 150 mm in the Amazon and 100 mm in the Andes) and the Pacific was located in an extremely wet area in the western part of the country (monthly rainfall during the dry season being above 100 mm on average).

Information concerning vegetation cover was derived from the official cartography of Colombia's continental, coastal and marine ecosystems, which originally used Landsat 2000–2002 images (IDEAM et al., 2007) available on a 1:500,000 scale. One of the limitations of the study was that we only could use information that matched the start of the period of study, but the only information available for this period covered the whole country. The 23 classes of vegetation cover described in this dataset were summarised and integrated into seven classes that have traditionally been subjected to different fire regimes in Colombia: humid forests, dry forests, secondary vegetation, agricultural areas, pastures, grasslands and other. The latter category was not included in the analysis. Pasture was separated from grasslands since the latter category covered larger areas of land dominated by grass-like vegetation in the Orinoco, while pastures were smaller and had more farming activity. Combining the different vegetation cover categories in the five natural regions gave 26 classes for the whole country (Appendix A). Classes having less than 1000 ha were eliminated for the purpose of this study. Table 1 indicates some general characteristics of each one of the regions analysed in regards to main vegetation type present, general climatic patterns, alleged influence of ENSO (El Niño-Southern Oscillation), main factors causing fire and fire pattern characteristics and population density descriptions.

2.2.3. *Rainfall data and rainfall standardised anomalies*

Rainfall data was derived from tropical rainfall measuring mission data (TRMM) from January 1998 to February 2009 at 0.25° (=25 km) spatial resolution. A monthly cumulative rainfall dataset derived from the original daily dataset and also the TRMM V6 dataset (Kummerow et al., 1998; NASA, 2009). Most of Colombia has an annual cycle with rainfall peaks during April–May and October–November, as well as dry periods, mainly in December–February, and periods of less rain from June to August (Poveda et al., 2006). Cumulative rainfall per the 3-month periods was calculated by summing the values for December, January and February (DJF) as the dry season (considered as being the three consecutive months having the lowest rainfall and at least one of the months having less than 100 mm rainfall). This was done for each spatial pixel separately. A similar approach was undertaken by Aragao et al. (2007), who considered the length of the dry season to be the sum of all months having less than 100 mm rainfall. Three-month rainfall standardised anomalies (DJF rainfall anomaly) were also quantified per pixel as the departure from the 1998 to 2009

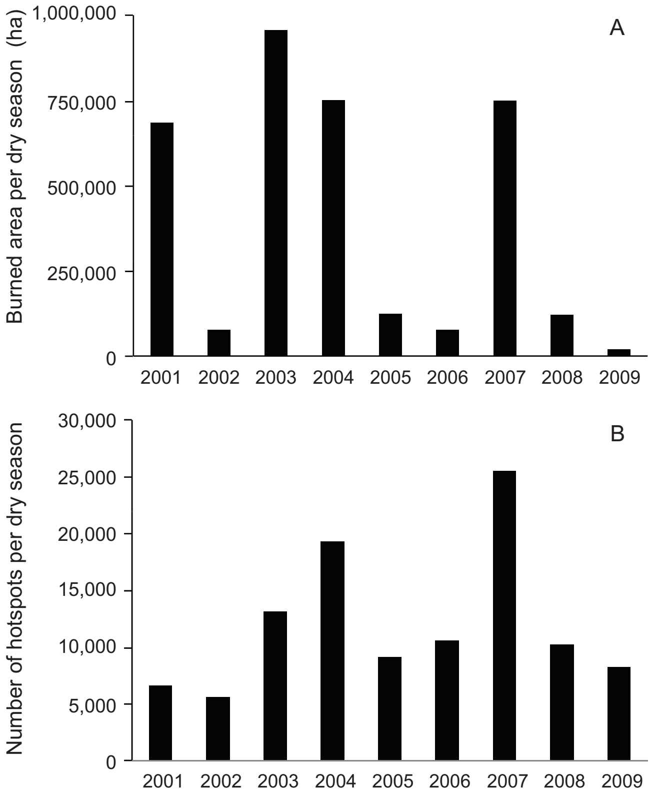

Fig. 1. (a) Total burned area (ha) and (b) number of fire hotspots detected during the dry season. The dry season of year t extends from December of year t^{-1} to February of year t.

mean for a year i (Eq. (1)):

$$\text{DJF rainfall anomaly in year } i = \text{mean rainfall for all DJF periods from 1998 to 2009} - \frac{\text{DJF rainfall in year } i}{\text{standard deviation of all DJF from 1998 to 2009}} \quad (1)$$

where positive values indicate DJF periods drier than the average rainfall for the 1998–2009 DJF and negative values indicate wetter DJF than average. Notice that the mean and standard deviations in Eq. (1) were calculated for each pixel separately. The DJF rainfall anomaly time series were subsequently averaged spatially.

2.2.4. *Multivariate ENSO Index data*

We selected the Multivariate ENSO Index (MEI) to capture ENSO variability (El Niño-Southern Oscillation) (Wolter and Timlin, 1993), available on-line from the NOAA Earth System Research Laboratory (http://www.cdc.noaa.gov/people/klaus.wolter/MEI/). This index was calculated as the first unrotated principal component of six observed variables over the tropical Pacific and has been used to identify the presence and intensity of El Niño/La Niña episodes. We selected two periods to estimate the influence of the Pacific warming: (i) Dec–Jan–Feb of the fire season year (e.g., Dec2000–Jan2001–Feb2001), because these were supposed to be the months were El Niño was stronger, and (ii) Sep–Oct–Nov months since these corresponded to the months previous to the fire season in Colombia. We calculated the mean MEI values for both periods and correlated their annual means to the total burned area of the different natural regions.

2.3. *Data analysis*

The monthly burned area, hotspots and rainfall patterns (either cumulative or anomaly) were explored to identify possible seasonality in the datasets. Prior to the analysis, a linear trend was removed from the time series. The datasets were also tapered with a cosine window applied to 10% of the data at the beginning and end of the time series. These time series were then compared by means of spectral analysis (Priestley, 1981; Bloomfield, 2000; Aragao et al., 2008). Individual power spectra, plus pair wise squared coherence (labelled as “Power” in the figures below) and phase spectra, were computed. All calculated spectra were smoothed with a modified Daniell kernel of length 5 and equivalent bandwidth ∼0.01 cycles per year (Bloomfield, 2000, page 191). Values in the squared coherence spectrum lied between 0 and 1, with 0 indicating no dependence and 1 showing complete linear dependence at the corresponding frequency. Values in the phase spectrum lied between $-\pi$ and π radians, and specified whether one signal led to the other, and by how much, in a cycle at the corresponding frequency. Squared coherence was defined as the square of the correlation coefficient of the components of the signal at each frequency. The sign of that correlation could be derived from the phase information: a strong coherence between two signals at a given frequency will be positive if their phase difference is larger than zero and less than π, and negative otherwise. See also Appendix B.

The spatial variation in vegetation burning was also studied to determine whether or not different vegetation types showed differences in the five natural regions. We determined whether the relationship between climate (rainfall and rainfall standardised anomaly during the dry season, when most fires occurred) and observed monthly and inter-annual variability in fire activity throughout the country was significant by means of Spearman's Rho correlation analysis (given the lack of normality of fire and climatic data) using $N = 9$ dry season periods. Given the relatively low N, significant ($p < 0.10$) values were accepted throughout the manuscript. Correlations were made using either the dry season data for the whole country or for each region considered separately, and standardised values for hectares or the number of hotspots according to the unit of analysis (e.g., the standardised values for burned area per vegetation type were obtained by dividing the area burned in ha by the total area of each vegetation type).

3. Results

3.1. *Temporal variability of burned area, hotspots and rainfall*

Burned areas in Colombia presented a strong variability between years. The average burned area during the dry season in Colombia over the 9-year period analysed was 395,644 ± 377,000 ha (mean ± standard deviation). However, there were large differences in burned area by year (Fig. 1a). The year having the highest burned area was 2003 (December 2002–February 2003), with almost a million hectares (955,750 ha) burned, and 2009 was the year having the lowest burned area (20,459 ha). There were some differences in the number of fire hotspots detected (Fig. 1b), with 2007 having the highest number of active fires (over 25,514 hotspots) and 2002 at the other extreme (5590 hotspots). Furthermore, there was a positive significant relationship between burned area and number of hotspots ($r^2 = 0.35$, $p = 0.09$, $N = 9$).

The presence of autocorrelation in the dry season burnt area dataset was explored by computing a 1-year lag Pearson correlation between two subsets of the time series. The simple bootstrap percentile confidence limits gave a p-value of 0.54, which did not allow us to reject the null hypothesis that there was no autocorrelation in the dataset.

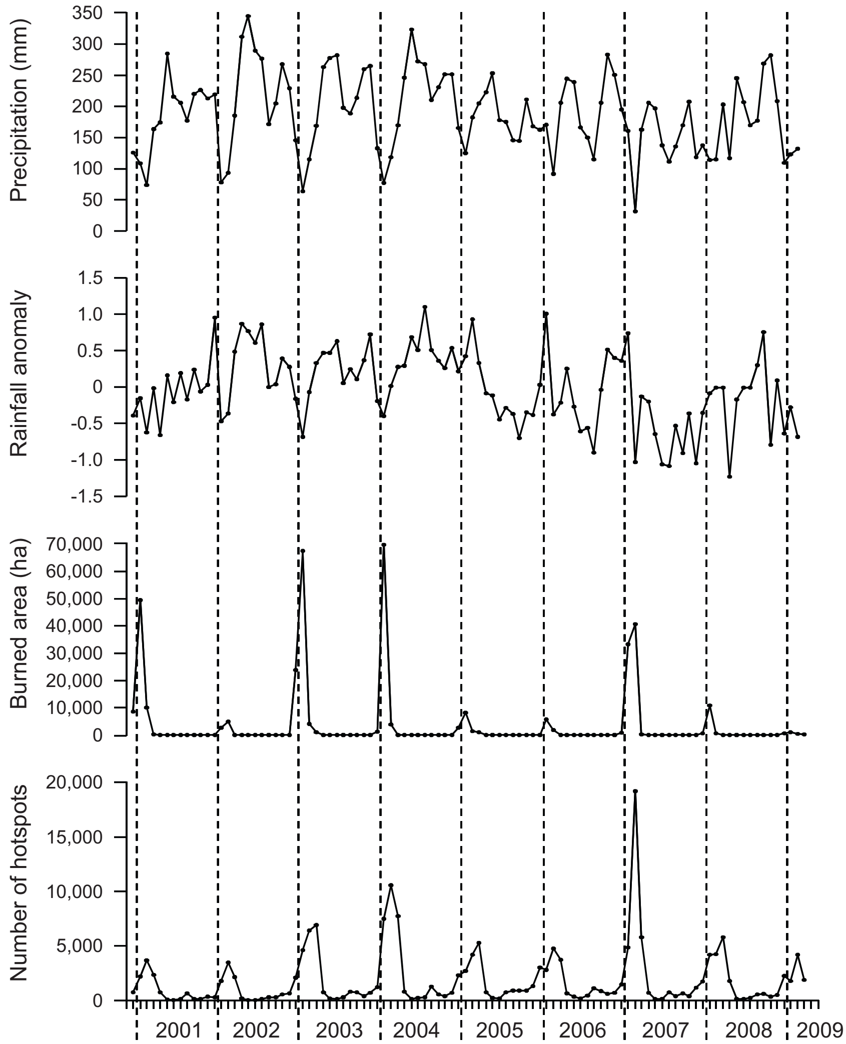

Fig. 2. Monthly time series of (a) burned area (ha), (b) number of hotspots detected, (c) dry season total rainfall (mm) and (d) dry season precipitation anomalies in Colombia.

Our correlation analyses showed that there was a negative relationship between the burned area per dry season with the 3-month cumulative rainfall accumulated for each dry season (Rho = −0.483, p = 0.094; Table 2). There was also a positive relationship between dry season rainfall standardised anomalies and the number of hectares that were burned over that dry season (Rho = 0.643, p = 0.043; Table 2). No significant relationship was found between the climatic conditions of the months before the dry season and the burned areas. The number of hotspots was not related to the two climatic variables considered ($p > 0.4$ in both cases). The strength of the ENSO phenomenon was positively related to the burned area in the Andes (Rho = 0.62, p = 0.08) and Orinoco (Rho = 0.65, p = 0.06) (N = 9), but only for the months before the fire season (SON).

Table 2
Spearman's correlation between dry season (DJF) values of burned area (ha) and number of hotspots, mean cumulative precipitation (mm) and rainfall standardised anomalies. N = 9 in all cases.

	Test	Dry season mean cumulative precipitation (mm)	Dry season precipitation anomaly
Dry season burned area (ha)	Spearman's rho p	−**0.483**[*]	**0.643**[**]
		0.094	**0.043**
Dry season hotspots (number)	Spearman's rho p	−0.050	0.019
		0.449	0.480

[**] In bold, significant values are $p < 0.05$.
[*] In bold, significant values are $p < 0.10$.

The seasonality of burning, active fire detection, monthly rainfall and rainfall standardised anomalies in Colombia showed marked annual periodicity (Fig. 2). The major peaks in the burned areas and hotspots time series occurred in the months of the dry season (December, January and February), often after years with higher-than-average rainfall. Spectral analysis (row labelled Power in Fig. 3) of the monthly data for monthly rainfall and rainfall standardised anomalies showed a clear seasonal pattern, having a peak at frequencies of 1 and 2 cycles per year (Fig. 3). In the case of the rainfall results, the 2 cycle per year signal was much stronger than the one at 1 cycle. This agreed well with the rainfall results in Fig. 2, which showed that every 12 months there was one strong minimum in January-February and then another, less conspicuous, minimum in July–August which separated two periods with abundant rainfall. It was that strong minimum that matched the fire signals. In addition, the number of hotspots and total burned area also showed a marked peak at one cycle per year (December to March) and a series of spurious sidelobes at frequencies that were multiples of 1 cycle per year (see Appendix B). The rainfall anomaly time series also revealed an intriguing feature: a slow-varying, sinusoidal-like signal whose period was approximately that of the whole time series (∼8 years). This signal could hardly be

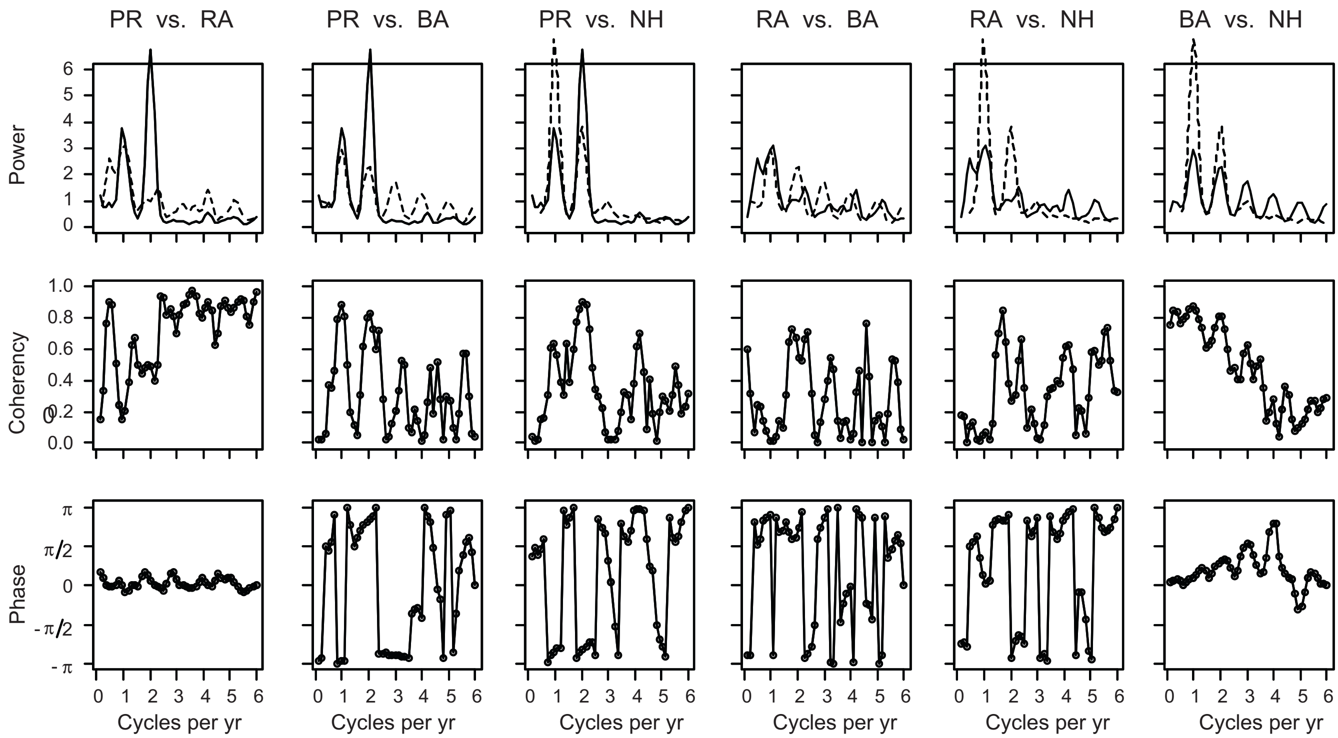

Fig. 3. Spectral analysis of the monthly time series showing (a–e) power spectra, (f–j) squared coherence and (i–m) phase (indicating the lag between the two series) between pairs of time series of fire (either burned area or number of hotspots) and climate (total rainfall and rainfall anomaly) during the dry season. In each power graphic, the first variable is drawn with a solid line and the second variable with a dotted line. PR, precipitation; RA, rainfall anomaly; BA, burned area; NH, number of hotspots.

seen in the rainfall time series. We decided to leave this feature out of the present study and postpone its analysis until more rainfall data (i.e., before 2001) are available to us.

The coherence spectrum between burned area and hotspots was high (Fig. 3) at 1 cycle per year, whereas their phase difference was close to 0, which agreed with a visual inspection of Fig. 2. Coherence ranged from 0.6 to 0.8 between monthly rainfall and the two fire variables at 1 cycle per year. In these cases, the phase spectrum showed a phase shift of $-\pi$, or 6 months, which is consistent with fires being driven by severe drought. Moreover, the coherence spectra between rainfall standardised anomalies and the two fire variables were close to 0 at 1 cycle per year, indicating low correlation between these series. Note that, finally, the low coherence (<0.2) between rainfall and rainfall anomaly time series, especially at 1 cycle per year. This fact indicated that, locally, years of very low/high rainfall correlated poorly with total amount of rainfall in the whole area of study. At 2 cycles per year (i.e., the 6-month component), the coherence between these two time series improved from below 0.2 up to approximately 0.5.

3.2. *Spatial variability of fires across natural regions and vegetation types*

Fig. 4 illustrates the distribution of burned areas and hotspots throughout the whole of Colombia during the nine years studied. These maps show areas of high annual recurrence of fires, such as in the east and northeast of the study area, while other areas in the south and the west showed much lower fire recurrence. Overall, the standardised mean values for the area burned per dry season in the different regions showed that Orinoquia was the region having the highest values, followed quite far behind by Amazonia and the Caribbean (Fig. 5a). Slightly different results appeared when analysing the standardised values for the number of hotspots per region, as Amazonia then had the highest number of hotspots detected per dry season, closely followed by Orinoquia, while the Caribbean and Andean regions had few hotspots and the Pacific almost none (Fig. 5b).

Comparing burned areas per vegetation type showed that, nationally, grassland vegetation was the most burned type, followed by secondary vegetation, pastures and forests, dry forests and agricultural areas (Fig. 6a). The pattern for the number of hotspots was quite different; grassland vegetation again showed the highest value, closely followed by pastures, agricultural areas, secondary vegetation and forests (Fig. 6b).

The temporal pattern between fire and climate over the 9-year period in the different natural regions followed a similar pattern to that found at the Colombian level. There was thus a significant negative correlation between burned area and dry season cumulative rainfall in all four regions tested, with the exception of the Andes. There was a significant positive correlation between burned area and rainfall anomaly for the Caribbean and Orinoquia regions, but neither for the Andes nor Amazonia (Table 3). No significant correlation was found between the number of hotspots and the two climate variables in any of the regions considered (Table 3).

Table 4 summarises the differences per vegetation type of burning and active fires within the regions. When looking at the relative impact per vegetation type area (Table 4), the Orinoco grasslands presented the highest burned area (mean standardised value ± SE of 3.11 ± 0.98), three times higher than the relative burned area of grasslands in Amazonia (1.04 ± 0.57), followed by Orinoco pastures (0.88 ± 0.29), secondary vegetation (0.80 ± 0.16) and forests (0.65 ± 0.25). Forests in the Caribbean had the second highest forest burned area value (0.025 ± 0.01), followed by Amazonian forests (0.005 ± 0.002). Pastures in the Caribbean and Amazon appeared highly affected by fires (0.08 ± 0.01 and 0.05 ± 0.02, respectively). Considering the active fires or hotspots data per vegetation type in each region (Table 4), grasslands in Amazonia were the most influenced by hotspots (0.06 ± 0.01), followed by the Orinoco grasslands (0.052 ± 0.006) and the agricultural areas of Amazonia (0.04 ± 0.01).

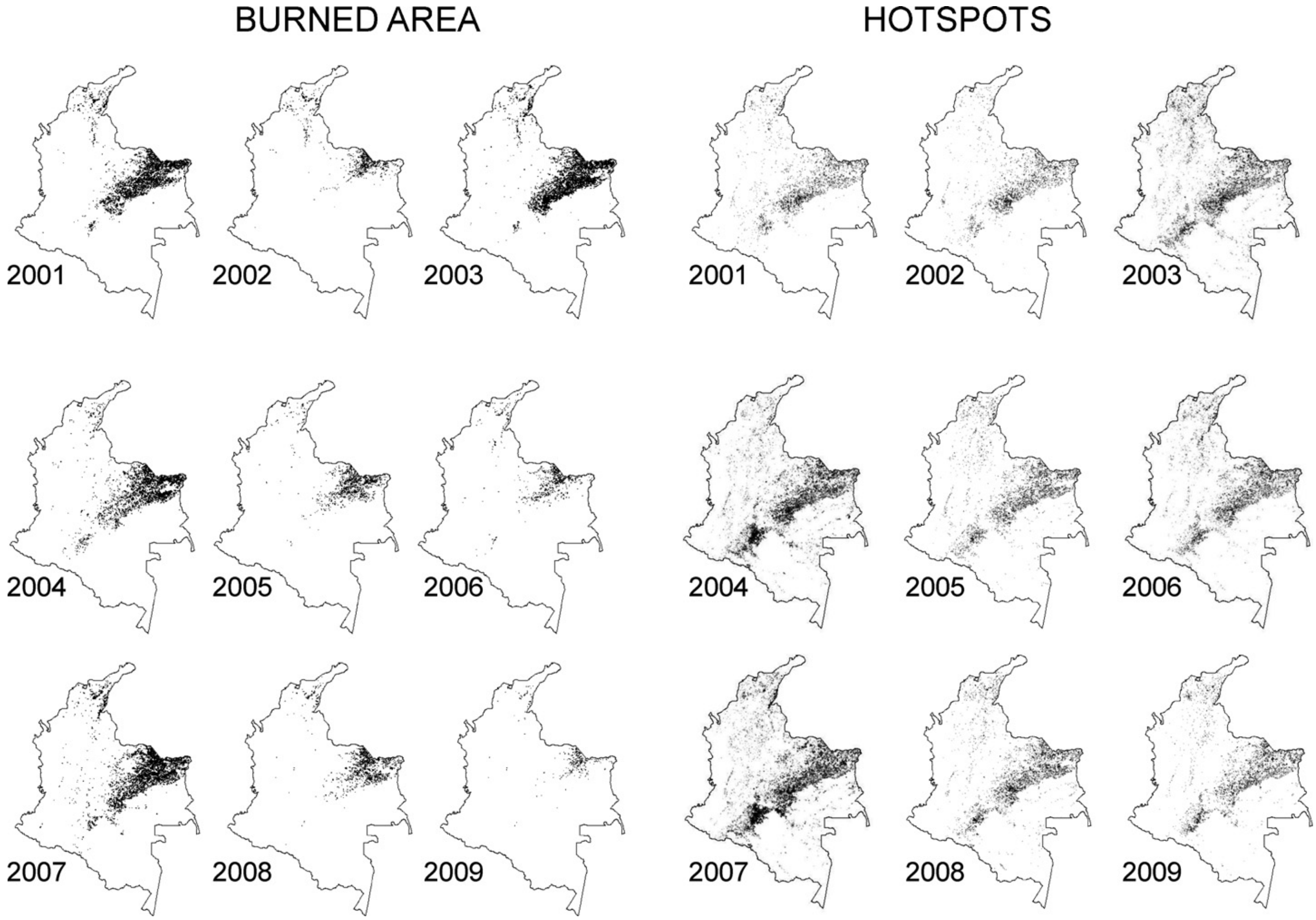

Fig. 4. Maps of Colombia showing the spatial distribution of (a) burned area and (b) number of hotspots for the dry season of nine consecutive years (2001–2009). Burned areas and hotspots are shown in black.

4. Discussion

Global and regional vegetation fire studies showed that most burning was started by humans in areas having low water deficit (Di Bella et al., 2006), and that climate was the leading driver for large fires (Bowman et al., 2009). Satellite data regarding monthly rainfall, burned areas, active fires and vegetation were used to study the climatic effect on burning activity in Colombia. The results supported the idea that spatial patterns and inter-annual variability of fires were related to climatic factors. Indeed, fire activity increased during the drier months, which usually corresponded to December, January and February in Colombia. There was also a short

Table 3
Spearman's Rho correlation values (r) and significance (p) between dry season (December, January and February) values of burned area (ha), number of hotspots (number), mean cumulative precipitation (mm) and rainfall standardised anomalies in the different regions. The Pacific region has not been included because burning area and hotspots were minimal in this region. $N = 9$ in all cases.

Region	Variable DJF values	Correlation analysis	DJF precipitation (mm)	DJF rainfall anomaly
Amazonia	Burned area (ha)	r	−**0.533**[*]	0.476
		p	**0.070**	0.116
	Number of hotspots	r	−0.150	−0.022
		p	0.350	0.480
Andes	Burned area (ha)	r	−0.400	0.074
		p	0.143	0.431
	Number of hotspots	r	−0.283	−0.031
		p	0.230	0.471
Caribbean	Burned area (ha)	r	−**0.667**[**]	**0.518**[*]
		p	**0.035**	**0.094**
	Number of hotspots	r	−0.100	0.056
		p	0.399	0.447
Orinoquia	Burned area (ha)	r	−**0.633**[**]	**0.667**[**]
		p	**0.034**	**0.035**
	Number of hotspots	r	−0.150	0.350
		p	0.350	0.198

[**] In bold, significant values are $p < 0.05$.
[*] In bold, significant values are $p < 0.10$.

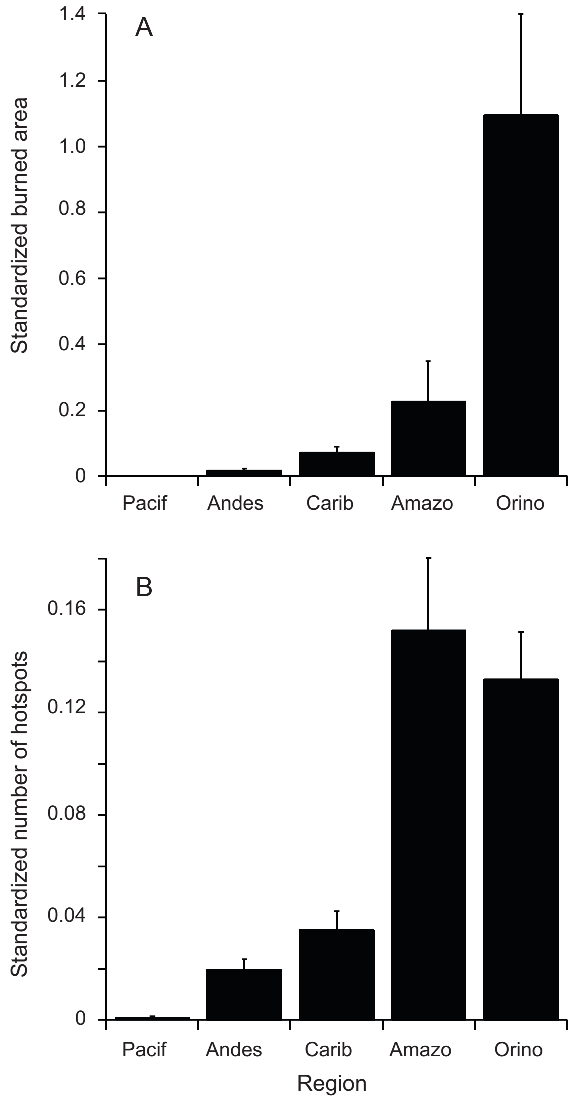

Fig. 5. Mean (+SE) of (a) dry season burned area (standardised values) and (b) hotspots per region. $N = 9$ dry seasons. Pacif, Pacific; Carib, Caribbean; Amano, Amazonia; Orino, Orinoquia.

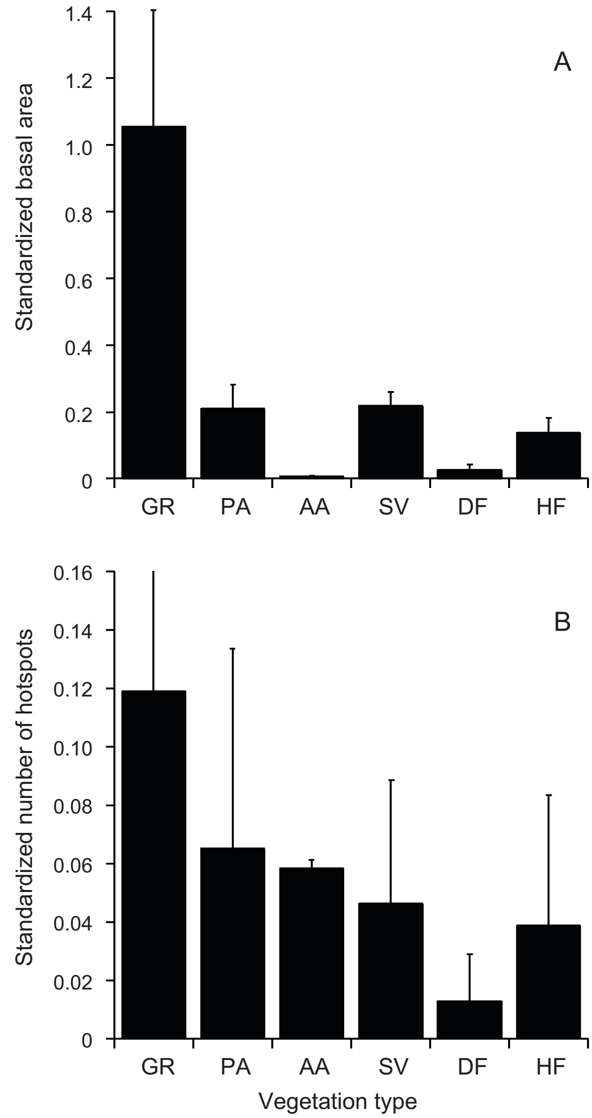

Fig. 6. Mean (+SE) of (a) dry season burned area (standardised values) and (b) hotspots per vegetation type. $N = 9$ dry seasons. GR, grasslands; PA, pastures; AA, agricultural areas; SV, secondary vegetation; DF, dry forests; HF, humid forests.

period (usually a month) of low rainfall during the middle of the 12-month period for some years (around July or August). There was also evidence that burning was closely linked to dry season intensity, considered in terms of mm cumulative rainfall during the December-January-February period of each year.

The results also confirmed the fact that inter-annual variability (both in dry season cumulative rainfall and rainfall anomaly) had a marked impact on fire activity from year to year in Colombia. For example, the maximum in the number of hotspots (fires) occurred 1 month after the minimum in rainfall in the period 2001–2005, whereas they coincided (i.e., 0 lag) afterwards (Figs. 2 and 3). These results agreed well with the results presented by Aragao et al. (2008) for the Brazilian Amazon, who reported 0 lag between the two signals in 1998, 1999, 2000, 2001 and 2004, and a 1-month offset in 2002, 2003, 2005 and 2006. These small differences might have arisen from the intrinsic stochasticity of fire events or from the way monthly signals were derived. This link was very clear in the three years associated with the El Niño-Southern Oscillation phenomenon (2002–2003, 2004 and 2006–2007 (dry season 2007)) as has been reported in many other tropical countries (Román-Cuesta et al., 2003; van der Werf et al., 2004; Bowman et al., 2009). The ENSO phenomenon showed a stronger link with the regions of the Andes and the Orinoquía, which had an influence on the dynamics of the country, since the Orinoquía leads Colombia's fire responses. The fact that extensive burning also occurred in 2001 (not considered to be an El Niño year, but which had a dry seasons with very low rainfall) also reaffirmed the influence of rainfall as a factor for the incidence of burning throughout the whole country, as has been observed in other Latin American regions (Nepstad et al., 2006; Aragao et al., 2008; van der Werf et al., 2008).

Spatial variability within the country could be observed in terms of burning. The results indicated that burned areas were not uniform throughout the country. The Orinoco region of Colombia had the most area burned every dry season, followed by Amazonia, the Caribbean and the Andes. Interestingly, almost no fires were detected in the Pacific region.

The Orinoco is a scarcely populated, relatively flat region dominated by herbaceous vegetation (grasslands and pastures cover more than 75% of the area, Appendix A), having little small-scale agriculture, but considerable gallery forests associated with its extensive river network. These environmental conditions, associated with the strong dry season that Orinoco experiences every year, make it more susceptible to widespread fires, thereby mak-

Table 4
Mean values (+SE) of (A) burned area and (B) number of hotspots (in the two cases, standardised values were obtained by dividing the original values by the total area of each vegetation type per region) per vegetation type in each region. $N = 9$ dry seasons. AA, agricultural areas; HF, humid forests; DF, dry forest; G, grasslands; SV, secondary vegetation; PA, pastures (– refers to non-existing unit).

Vegetation type/region	Amazonia	Andes	Caribbean	Orinoco	Pacific
(A)					
AA					
Mean	0	0.004	0.005	0.021	0
Std. error	0	0.001	0.002	0.010	0.002
DF					
Mean	–	0.000	0.052	–	–
Std. error	–	0.000	0.031	–	–
HF					
Mean	0.005	0.002	0.025	0.656	0
Std. error	0.002	0.001	0.010	0.213	0
GR					
Mean	1.046	0.036	0.023	3.111	–
Std. error	0.579	0.014	0.004	0.980	–
PA					
Mean	0.057	0.032	0.080	0.885	0
Std. error	0.023	0.011	0.017	0.298	0
SV					
Mean	0.021	0.025	0.238	0.804	0
Std. error	0.011	0.008	0.058	0.160	0
(B)					
AA					
Mean	0.044	0.003	0.002	0.006	0.000
Std. error	0.017	0.000	0.000	0.001	0.000
DF					
Mean	–	0.002	0.010	–	–
Std. error	–	0.002	0.003	–	–
F					
Mean	0.004	0.002	0.004	0.027	0.000
Std. error	0.001	0.000	0.000	0.003	0.000
G					
Mean	0.061	0.004	0.001	0.052	–
Std. error	0.010	0.001	0.000	0.006	–
P					
Mean	0.027	0.003	0.006	0.027	0.000
Std. error	0.009	0.000	0.001	0.003	0.000
SV					
Mean	0.014	0.003	0.009	0.018	0.000
Std. error	0.004	0.000	0.001	0.002	0.000

ing the landscape more prone to fire due to herbaceous fuel drying out (van der Werf et al., 2008). However, climatic variability in this type of ecosystem seems to be due to other factors (van der Werf et al., 2008). It has been said that fires in Orinoco are mainly induced as a traditional cultural practice (Bilbao et al., 2009) to improve grass quality for cattle ranching and to expand the agricultural frontier (Armenteras et al., 2005; Romero-Ruiz et al., 2009; Barbosa and Fearnside, 2005). Some authors have even suggested that the association of fire-prone plant species with fire regimes and the alteration of these regimes by year was the origin of grassland type vegetation, thus influencing the risk of fire (Bowman et al., 2009; Bond et al., 2003; Silva et al., 2001). This might even convert fire into an important agent in maintaining a balance between forest advance and retreat on the savannahs (Hoffmann et al., 2003). Moreover, in relation to total area burned, the results found in this study did not exactly match those reported by Romero-Ruiz et al. (2009), but showed the same tendency indicated by Chuvieco et al. (2008). These differences could lie in the remote sensing data protocol, the non-removal of monthly detection of the same burned areas and/or in the algorithms used for estimating burned area. Given these large differences and the possible implications in greenhouse counting emissions, a standardised scheme for monitoring fires in Colombia and similar regions in Latin America with remote sensing data must thus be established.

It should be recognised that despite some recent attention having been given to burning in savannahs (Romero-Ruiz et al., 2009), the Amazonia and Caribbean regions have been largely ignored. Despite the lack of attention, fires have a great impact on fragile ecosystems, such as tropical rainforests and the highly threatened dry forests of South America (van der Werf et al., 2008). The Caribbean region is traditionally the driest region in the country and it has been highly transformed (21% secondary vegetation), having few remnants of natural vegetation and only a few patches of dry forest (1.1%). This region has a much higher extension of pastures (51%) where many fires are ignited by human activity, as fire is used as a management practice to a lesser extent here than in the Orinoco. Moreover, interactions between grazing, agriculture and climate are complex. Land is burned by people living on the Caribbean littoral to get rid of agricultural waste or weeds and to enrich soils. Some other regional practices include ignition of seasonal small fires near wetlands where some turtle species are hunted. However, to what degree landowners and small farmers modify their management practices in this type of vegetation regarding the use of fire in response to dry periods remains unknown (van der Werf et al., 2008) and deserves further study in Latin America.

Amazonia has the highest number of hotspots, probably due to the fact that it is one of the most active colonisation fronts in the country (Rodríguez et al., submitted). Almost 92% of the Amazonia is still rainforest and, although most fires occur in the western part close to the Andes (starting in the piedmont), the expansion of the agricultural frontier via the river network is evident. The Amazonia is Colombia's second wettest region. Dry season rainfall standardised anomalies here are not significantly correlated to vegetation burning, but rainfall cumulative values are. Nevertheless, temporal patterns associated to El Niño years could be appreciated in this region, especially when analysing the number of active fires. van der Werf et al. (2004) indicated an unclear and uniform interdependence of fire with climate in American rainforests, and the present study's results showed a similar trend. Active fires were not strongly correlated to climate but the high number of hotspots per area detected might indicate fire-driven deforestation, land-use change and colonisation occurring in this part of the Amazon basin, with small fires having a lower incidence, but high incidence in land use, fragmentation and biodiversity loss.

Aragao et al. (2007) have shown several critical areas in Brazilian Amazonia where climate (severe drought) and human-originated fire have caused extensive deforestation and highlighted the increasing role of droughts in fire expansion over directly deforested areas. Aragao et al. (2008) also showed the marked seasonality of rainfall and fires, and that human-related forces determine the seasonality and annual patters of fires in the Amazon. Burning in the Amazonian region is of extreme importance given the fact that the contribution of forest fires to greenhouse gas emission is much higher than other vegetation types, such as savannahs, because there is much more biomass to burn (van der Werf et al., 2008). Feedback mechanisms regarding climatic circulation patterns and deforestation (e.g., reduced evaporation-transpiration) have not been considered, although some authors have suggested that land surface-atmosphere interactions constitute significant drivers of climate variability in Amazonia (Poveda et al., 2006).

The Andes (Colombia's most densely populated region) has been highly transformed and the dry season burning was found to be correlated with monthly rainfall. This mountainous region's characteristics (high intensity solar radiation and the presence of invasive species, some prone to fire, such as the common gorse (*Ulex europaeus* L.)) increase the risk of fire when fuel dries out herbaceous vegetation, such as the paramos. However, fire is also used for some agricultural practices, but, being an intensively colonised region, propagating fires and the subsequent extension of burned areas (mostly small) is more easily controlled by humans than in other regions. This could explain why burned areas were smaller in the Andes. Some Andean burned areas and hotspots occurred in the colonisation frontier located in the transition area between lower montane forests and lowland Amazonia and the Pacific or towards the Caribbean. An increase in lower montane colonist population, small farms, grazing and livestock production, as well as some illicit crop production, have been associated with 0.71% annual deforestation rates (Armenteras et al., submitted). Some burning and hotspots detected in the Cauca River Valley may be associated with extensive sugarcane production, which uses fire as a common harvesting practice.

5. Conclusions

This study's results analysed climate, regional variability and vegetation types, but did not look deeply into factors such as land tenure and distribution of lots, which might have further explained the differences observed between regions. The different types of land use and management practices which people applied in each region were not studied either. Such studies should consider different productivity levels of vegetation types and also land managers' decision-making regarding whether to use fire for agricultural cycles or for stimulating aboveground biomass growth as forage for livestock.

Besides the climate differences observed, there were also differences in socio-economic factors. Previous studies in the Amazon have thus far suggested that most fire-driven deforestation/land-use change has not been fully limited by the extent of the dry season, but was influenced much more by socio-economic factors (van der Werf et al., 2008). This phenomenon might be driving the fire dynamics detected in the Colombian part of Amazonia in this study and might explain the weaker link between fires and climate in this region. Land-use changes in the Andes (a mountainous region wetter than the Orinoco and Caribbean regions) were also strongly influenced by socio-economic factors (Armenteras et al., submitted). Some drivers of land-use change in the Pacific region (the wettest region in Colombia, partly explaining the reduced hotspot and burned area observed there), such as mining and timber extraction, do not include fire as a management option. More research is needed, however, to quantify the relative importance of socio-economic factors and the use of fire as a management technique.

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Appendix A.

Area in hectares of vegetation types per natural region.

Vegetation type per region	Area (ha)	Percentage of the region (%)
Agricultural areas/Amazonia	8,595	0.0
Agricultural areas/Andes	2,967,117	10.6
Agricultural areas/Caribbean	867,299	6.2
Agricultural areas/Orinoco	419,955	2.5
Agricultural areas/Pacific	131,431	1.9
Dry forests/Andes	8,544	0.1
Dry forests/Caribbean	159,075	1.1
Grasslands/Amazonia	1,244,090	2.7
Grasslands/Andes	1,182,671	4.2
Grasslands/Caribbean	728,147	5.2
Grasslands/Orinoco	9,155,744	55.1
Humid forests/Amazonia	41,638,103	91.7
Humid forests/Andes	9,437,692	33.8
Humid forests/Caribbean	2,191,600	15.5
Humid forests/Orinoco	3,310,841	20.0
Humid forests/Pacific	4,478,473	65.4
Pastures/Amazonia	1,959,341	4.3
Pastures/Andes	9,160,971	32.8
Pastures/Caribbean	7,203,366	51.0
Pastures/Orinoco	3,346,081	20.2
Pastures/Pacific	739,629	10.8
Secondary vegetation/Amazonia	551,817	1.2
Secondary vegetation/Andes	5,149,423	18.5
Secondary vegetation/Caribbean	2,975,129	21.1
Secondary vegetation/Orinoco	366,337	2.2
Secondary vegetation/Pacific	1,503,679	21.9

Appendix B.

When periodic spike-like signals were present in a time series, as our BA and NH datasets in Fig. 4a and b show, the Fourier power spectrum must be interpreted with care. An infinitely narrow periodic temporal signal, also known as an impulse train or Dirac comb, consists of a series of shifted impulses spaced at intervals T:

$$\psi_T(t) = \sum_{n=-\infty}^{\infty} \delta(t - nT)$$

where δ is the Dirac delta function. The Fourier transform (FT) of this Dirac comb is another Dirac comb (see e.g., James, 2002):

$$\psi_T(t) = \sum_{n=-\infty}^{\infty} \delta(t - nT) \stackrel{FT}{\longleftrightarrow} \Psi_T(f) = \frac{1}{T} \sum_{k=-\infty}^{\infty} \delta\left(f - \frac{k}{T}\right)$$

The delta functions in Fourier space are now located at frequencies which are multiples of $1/T$.

Datasets BA and NH could be looked at as if they were approximate Dirac combs convolved with a given time-limited function (e.g., a Gaussian or a triangle function). In the frequency domain this convolution was equal to the multiplication of the Fourier transform of the Dirac comb with the Fourier transform of the time-limited function. The result was a series of spike signals at frequencies $1/T$, $2/T$, $3/T$... of decreasing amplitude, as is seen in the power spectra in Fig. 5, and which did not indicate the presence of periodic components other than the one at $1/T$. Therefore, in the case of the BA and NH time series, we will only consider the results at frequency $1/T$ (i.e., 1 cycle per year).

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