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Human and biophysical drivers of fires in Semiarid Chaco mountains of Central Argentina

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HIGHLIGHTS

- We determined the drivers of fires in Semiarid Chaco mountains of Central Argentina.
- We identified the drivers' ranges at which fire activity was higher.
- Climate was the most important driver, followed by human and biological predictors.
- Fires were more frequent at intermediate levels of rainfall and productivity.
- Fires were more frequent where temperature and productivity were more variable.

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ABSTRACT

Fires are a recurrent disturbance in Semiarid Chaco mountains of central Argentina. The interaction of multiple factors generates variable patterns of fire occurrence in space and time. Understanding the dominant fire drivers at different spatial scales is a fundamental goal to minimize the negative impacts of fires. Our aim was to identify the biophysical and human drivers of fires in the Semiarid Chaco mountains of Central Argentina and their individual effects on fire activity, in order to determine the thresholds and/or ranges of the drivers at which fire occurrence is favored or disfavored. We used fire frequency as the response variable and a set of 28 potential predictor variables, which included climatic, human, topographic, biological and hydrological factors. Data were analyzed using Boosted Regression Trees, using data from near 10,500 sampling points. Our model identified the fire drivers accurately (75.6% of deviance explained). Although humans are responsible for most ignitions, climatic variables, such as annual precipitation, annual potential evapotranspiration and temperature seasonality were the most important determiners of fire frequency, followed by human (population density and distance to waste disposals) and biological (NDVI) predictors. In general, fire activity was higher at intermediate levels of precipitation and primary productivity and in the proximity of urban solid waste disposals. Fires were also more prone to occur in areas with greater variability in temperature and productivity. Boosted Regression Trees proved to be a useful and accurate tool to determine fire controls and the ranges at which drivers favor fire activity. Our approach provides a valuable insight into the ecology of fires in our study area and in other landscapes with similar characteristics, and the results will be helpful to develop management policies and predict changes in fire activity in response to different climate changes and development scenarios.

1. Introduction

Fire is a natural disturbance agent in many ecosystems around the world. Many species depend on fires that create or maintain suitable habitats for them and, in some cases, fires also favor reproduction (Bond et al., 2005). However, human interventions on fire regimes, triggered by both increased ignitions and fire suppression (including firefighting and reduction of fuel loads and connectivity), have altered the frequency, intensity, severity and distribution of fires (Archibald et al., 2012; Hantson et al., 2015; Keeley et al., 1999; Syphard et al., 2007). These changes have increased the vulnerability of ecosystems to fires (Chuvieco et al., 2014) by reducing the diversity and extent of forests (FAO, 2010; Hansen et al., 2013), affecting biogeochemical and hydrological cycles, releasing greenhouse gasses, accelerating erosive processes (Bowman et al., 2009; Whelan, 1995) and implying higher

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risk to humans and their infrastructure, especially in areas of wildland–urban interface, because of the proximity of houses to fuels (Radeloff et al., 2005).

Patterns of fire occurrence are variable in space and time (Parisien et al., 2011), as a consequence of the interaction of the multiple factors that are heterogeneous at both dimensions. The ignition and spread of a fire depend on the type, load, arrangement and moisture content of fuels, wind speed, slope gradient and aspect of the hillside (Whelan, 1995). Climate and weather will determine the availability and moisture content of fuels; however, the type of land use can also modify fuel loads and connectivity. Additionally, in mountain landscapes, fire activity can be strongly controlled by topography that influences winds, water balance and heat transfer (Agee, 1993; Rollins et al., 2002; Sharples, 2009). Fuel moisture content is a key factor for the ignition of fires and along with the amount and connectivity of fuels will determine the extent of the burned area and fire intensity (Rollins et al., 2002).

A fundamental approach to determine the occurrence of fires involves understanding how fire drivers interact in space and how their dominance changes under different conditions. This information is essential to help decision making about fire management and to predict fire risk, which becomes a challenging task in a context of global change induced by population dynamics, biological invasions, land use and climate changes (Dukes and Mooney, 1999; Flannigan et al., 2000; Grimm et al., 2008).

The study of the environmental factors controlling fire activity has considered different approaches. For instance, fire determinants may be identified using generalized linear regression models (e.g. Cardille et al., 2001; Hawbaker et al., 2013), but only the direction of their (linear) effect on fire activity (i.e. positive or negative) can be determined using this approach. Additionally, in an analysis of potential nonlinear effects of predictor variables on fire activity, Syphard et al. (2007) identified thresholds at which fires were more prone to occur. Being aware of those nonlinear relationships, Aldersley et al. (2011), Archibald et al. (2009) and Wu et al. (2014) analyzed fire drivers using decision trees, a non-parametric supervised learning method used for classification and regression. As a result, they identified the combination of variables and thresholds determining the amount of burned area.

Advantages of regression trees include the ability to handle different types of predictor variables, are unaffected by differing scales of measurement among predictors and automatically model interactions between predictors (Elith et al., 2008). However, regression trees can be sensitive to small changes in training data and sometimes are less accurate than other methods and fail to detect important interactions when predictor variables are correlated (De'ath, 2007; Olden et al., 2008). To overcome some of these limitations, regression trees can be combined with boosting, a method to improve model accuracy that combines and averages several less precise rules to achieve more accurate predictions (De'ath, 2007; Olden et al., 2008). Besides accuracy improvements, Boosted Regression Trees (BRTs) analyze the functional effects of each predictor variable in the final BRT (Friedman, 2001), allowing the identification of the ranges and/or thresholds along the entire range of values assumed by predictors at which the effect on the response variable is favored or neglected, reaches its maximum, etc. This possibility makes BRTs a valuable tool to further understand the relationships between predictor and dependent variables.

To the best of our knowledge, BRTs have been barely used to study fire drivers. For instance, Parisien and Moritz (2009) reported some thresholds for predictor variables at which fires were more prone to occur, but failed to state the functional effect of predictor variables beyond those thresholds. Moreover, the dependent variable used by those authors assumed only burned/unburned values, which might neglect combinations of variables and thresholds associated with higher fire frequencies and fire risk. Similarly, Parisien et al. (2011) studied the environmental controls of fires at different spatial scales, employing circular areas from 100 to 100,000 km^2 as sample units and reporting partial dependent plots where to analyze thresholds and ranges.

Studies addressing environmental drivers of fires worldwide have been conducted in fire prone ecosystems of North America (e.g. Hawbaker et al., 2013; Parisien et al., 2011; Rollins et al., 2002; Syphard et al., 2009), Europe (e.g. Pausas and Fernández-Muñoz, 2012; Viedma et al., 2009), South Africa (e.g. Archibald et al., 2009), Russia (e.g. Dubinin et al., 2011) and Australia (e.g. Bradstock, 2010). In South America, fire drivers were studied mainly in Amazonia (Armenteras and Retana, 2012), Cerrado (Hoffmann et al., 2012), Mediterranean vegetation of Chile (Carmona et al., 2012) and other tropical rainforests and savannas (Armenteras-Pascual et al., 2011). However, very few studies have focused on the drivers of fire in the Gran Chaco (e.g. Bravo et al., 2010; Fischer et al., 2012), the most geographically extensive seasonally dry forest in South America (Moglia and Giménez, 1998), where fires are a recurrent disturbance (Kunst and Bravo, 2003).

Here, we modeled the relationship between fire frequency and a series of potential explanatory variables using BRTs with the aim of identifying key environmental drivers of fires in Semiarid Chaco mountains of central Argentina. Particularly, we focused on the mountain range known as Sierras Chicas, because it is the area most affected by fires, with nearly 254,000 ha burned between 1999 and 2011 (i.e. 31% of the study area) and higher fire frequencies and number of large fires than the surrounding mountain ranges (Argañaraz et al., 2015). Additionally, population size in Sierras Chicas has grown rapidly in the last decades, driven by people moving from big cities to nearby wildland areas (Gavier and Bucher, 2004), as occurred in many other areas worldwide. Such development is of low density, with houses inserted in a matrix of wildland vegetation with high risk of fire (Hawbaker et al., 2013; Radeloff et al., 2005; Syphard et al., 2007). In addition, Sierras Chicas is the second most important touristic area of Argentina, and tourism sometimes produces wildfires as a result of improper management of outdoor activities in wild areas. As a consequence of human intervention in fire regimes, fires produce several negative impacts in the region, including reduction and degradation of native vegetation (Giorgis et al., 2013; Renison et al., 2002; Zak et al., 2004) and avifauna (Albanesi et al., 2014), pollution of water reservoirs providing water to more than 1.3 million people (Bonansea and Fernandez, 2013), household destruction and livestock death.

Previous regional studies have addressed the effects of fires on soil, water and biota, showing their importance in our study area. However, developing fire management strategies aiming to minimize the negative impacts of fires requires information about fire regimes and fire drivers. To our knowledge, in our study area, the work of Miglietta (1994) is the only one describing the seasonality of fires and its relationship with climatic conditions; however, that work did not use spatially explicit data. More recently, Argañaraz et al. (2015) studied the recent fire history of the mountains of central Argentina, analyzing the spatial and temporal patterns of fire activity. Hence, in order to generate essential information to improve our understanding of the fire ecology in Semiarid Chaco mountains we analyzed the relationship between the number and area of fires and a set of environmental fire drivers. Our main objectives were i) to determine the biophysical and human drivers of fires in the Sierras Chicas of Córdoba, Central Argentina, ii) to understand the individual effect of these drivers across their range of values, in order to identify the thresholds and/or ranges at which fire occurrence is favored or disfavored, and iii) to analyze the effects of interactions among fire drivers. The generated information will contribute to the development of adequate management policies aiming to reduce the negative impacts of fires. In addition, the BRT approach will provide novel information on fire ecology that may be extrapolated to other arid and semiarid landscapes worldwide.

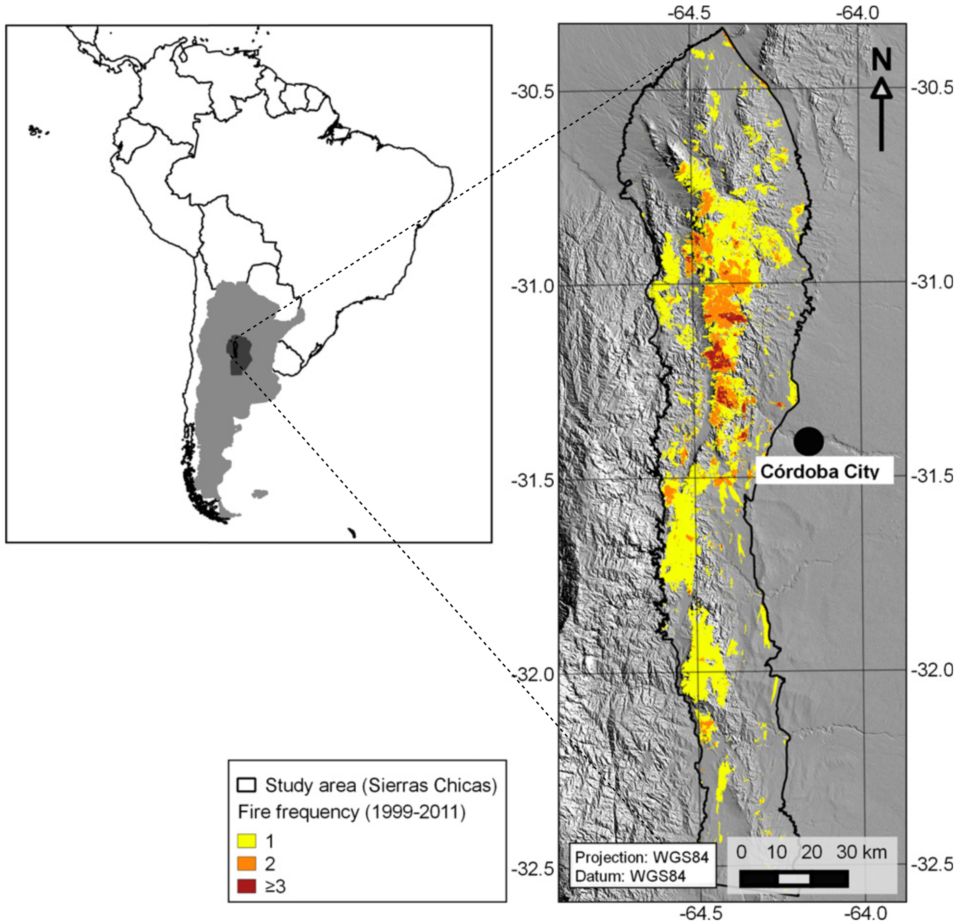

Fig. 1. Location and fire frequency (1999–2011) in Sierras Chicas, Córdoba Province, Argentina.

2. Methods

2.1. Study area

The Sierras Chicas of Córdoba stretch in a north–south direction, with an altitudinal range between 500 and 1947 ma.s.l (Fig. 1). Our study area occupies nearly 8100 km^2 and excludes the southern tail of this mountain range. Sierras Chicas encompasses the southern portion of Semiarid Chaco forests. Vegetation consists of a mosaic of lowland forests (<750 ma.s.l., dominated by *Aspidosperma quebracho-blanco*, *Prosopis* spp. and *Acacia* spp. forests), Serrano forests (between 700 and 1200 ma.s.l. dominated by *Lithraea molleoides* and *Zanthoxylum coco* forests), shrublands (between 1000 and 1100 ma.s.l., dominated by *Heterothalamus alienus*), and grasslands (usually >1000 ma.s.l., dominated by *Festuca hieronymi*, *Stipa* spp., and *Poa* spp.) (Gavier and Bucher, 2004; Zak and Cabido, 2002).

Natural vegetation communities have been substantially altered by land use history. In lowland areas, most forests have been replaced by crops, whereas mountain vegetation is under pressure from grazing, selective logging, exotic invasive plants and fire. In particular, forests are of most concern because they are being lost at high rates (2.8% of remaining forest cover per year), increasing forest fragmentation (Gavier and Bucher, 2004) and resulting in a lower water catchment capacity of basins (Cingolani et al., 2008). Regionally, fires are used by ranchers to reduce senescent biomass and promote forage re-growth during the dry season (Fischer et al., 2012; Kunst and Bravo, 2003).

Climate is temperate semiarid, with a monsoonal rain regime, average annual rainfall of 960 mm and mean annual temperature of 16.8 °C.[1] Most precipitations occur between October and March (spring and summer). Winter is dry and mild, with relatively high temperatures occurring in August and September, inducing seasonal fires in winter (Miglietta, 1994; Argañaraz et al., 2015). Large fires (>1000 ha) account for 74% of burned area, although they only represent 3.5% of fire events and fires larger than 15,000 ha burned every 1 to 3 years between 1999 and 2011 (Argañaraz et al., 2015). According to the Fire Management Plan of Córdoba province, almost 95% of ignitions are caused by humans, with fire season spanning from June to December.

2.2. Modeling strategy

We analyzed the environmental drivers of fires modeling the relationship between the frequency of fires as the response variable and a set of potential predictor variables that included human, climatic, biological, topographic and hydrological variables. To model that relationship and to determine the most important drivers and their interactions, we used Boosted Regression Trees.

2.2.1. Response variable

A fire frequency map for the period 1999–2011 was used to obtain the response variable (Table 1). Burned scars from Sierras Chicas were

[1] Mario Navarro, Observatorio Meteorológico Salsipuedes, Salsipuedes, Córdoba. Precipitation data from the period 1988–2012 and temperature data from the period 2002–2011.

Table 1
Summary and description of input variables for BRT models. Variables in bold indicate remaining predictor variables after collinearity analysis.

Variables	Acronym and units	Original resolution	Source and attributes
Fire data			
Fire Frequency	Fire.freq (#)	30 m	Derived from Landsat TM/ETM+ data
Human			
1) **Distance to urban areas**	Urban.dist (km)	30 m	Polygons of urban areas were mapped by visual interpretation of Google Earth images
2) **Distance to roads**	Road.dist (km)		Road vector layer from Instituto Geográfico Nacional of Argentina, improved by visual interpretation of Quickbird images from Google Earth and supporting information from Dirección Provincial de Vialidad (Roads Administration of Córdoba Province)
3) **Distance to waste disposals**	Waste.dist (km)		Waste disposals were mapped by visual interpretations of Google Earth images, supporting information (e.g. Nirich (2000))
4) **Population density**	Ln.DensPop (inhabitants/km^2)	Radius level	Population Census of Córdoba Province 2008. Census radius is the smallest level at which data is publicly available (mean size ≈ 34 km^2)
5) Housing density	Ln.DensHous (houses/km^2)		
Climatic			
6) **Annual precipitation**	PP.annual (mm)	30 arc sec (≈1 km at equator)	WorldClim. BIO12
7) **PP of the driest quarter**	PP.dry (mm)		WorldClim. BIO17
8) PP of the wettest quarter	PP.wet (mm)		WorldClim. BIO16
9) PP of the fire season	PP.fs (mm)		Derived from monthly data from WorldClim
10) **PP seasonality**	PP.seas (%)		WorldClim. BIO15. Coefficient of variation
11) Mean annual Temperature	T.mean (10 × °C)		WorldClim. BIO1
12) **Temp. seasonality**	T.seas (100 × °C)		WorldClim. BIO4. Standard deviation x 100
13) Temp. of the driest quarter	T.dry (10 × °C)		WorldClim. BIO9
14) Mean temp. of the fire season	T.mean.fs (10 × °C)		Derived from monthly data from WorldClim
15) Max. mean temp. of the fire season	T.max.mean.fs (10 × °C)		Derived from monthly data from WorldClim
16) **Annual potential evapotranspiration**	PET.annual (mm)		CGIAR-CSI Global-Aridity and Global-PET Geospatial Database
17) Aridity index	AI.annual (unitless)		CGIAR-CSI Global-Aridity and Global-PET Geospatial Database. AI = PP.annual/PET.annual
18) Effective precipitation	Eff.PP (mm)		Derived using data from WorldClim and CGIAR-CSI. Eff.PP = PP.annual - PET.annual
Biological			
19) **Land cover class**	Land.cover	30 m	Modified from Zak (2008). Classes: Forests, Grasslands, Shrublands, Cultivated lands, Other, Unclassified.
20) **NDVI mean**	NDVI.mean (unitless)	250 m	Derived from MOD13Q1 product and TIMESAT software (Jönsson and Eklundh, 2004)
21) **NDVI standard deviation**	NDVI.SD (unitless)		
22) NDVI coefficient of Variation	NDVI.CV (unitless)		
23) **NDVI max. mean**	NDVI.max (unitless)		
Topographic			
24) Altitude	Altidude (m.a.s.l)	30 m	DEM from GLS2005 (Gutman et al., 2008)
25) **Slope**	Slope (degrees)		Derived from DEM. Aspect includes 8 classes: N, NE, E, SE, S, SW, W, NW.
26) **Aspect**	Aspect		
27) **Solar radiation**	Solar.rad (WH/m^2)		
Hydrological			
28) **Distance to water bodies**	Water.dist (m)	30 m	Water bodies vector layer (updated at April 2013) was provided by Secretaría de Recursos Hídricos y Coordinación of Córdoba Province (Secretary for Water Resources)

mapped from Landsat TM and ETM+ imagery (30-m spatial resolution, Path/Rows: 229/81 and 229/82, between 1999 and 2011) using ABAMS (Automatic Burned Area Mapping Software), based on the two phase algorithm proposed by Bastarrika et al. (2011). During the first phase, pixels with high chances of being burnt are identified (seeds) and then they serve as the starting point during the second phase, when a region growing algorithm is applied to finish delimitation of the burned patch and its unburned interior islands. The minimum mapping unit of the fire database is 5 ha, because smaller areas have higher confusion rates and they account for a small proportion of the total burned area. Producer's accuracies of the fire database ranged from 88% to 97% (i.e. 3–12% omission errors) and user's accuracies from 71% to 96% (i.e. 4–29% commission errors) (Argañaraz et al., 2012; Argañaraz et al., 2015).

2.2.2. Explanatory variables

2.2.2.1. Human activities. Anthropogenic influences on fire regimes are associated with human presence and activities. The proxies considered were Euclidean distances to roads, urban areas and urban solid waste disposals (Table 1). The latter was included because there are many open sky waste disposals in Sierras Chicas and fires are sometimes used to reduce trash volume and pests (Nirich, 2000). Fires frequently remain lit and spread to neighboring areas during hot and windy days. We also included population and housing density, which were ln + 1-transformed. Although transformations are not necessary for BRTs, we pursued the reduction of the range of these variables to facilitate result interpretation.

2.2.2.2. Climatic variables. We included seven bioclimatic variables (climatic averages) obtained from the WorldClim Global Climate Data (Hijmans et al., 2005) (Table 1). We also used monthly data to calculate the averages of precipitation, maximum temperature and mean temperature for the fire season (June–December). Additionally, we included the annual potential evapotranspiration and the aridity index datasets available at (http://www.cgiar-csi.org) (Zomer et al., 2007, 2008) and calculated effective precipitation (Table 1). The latter were included as indicators of water availability that will determine biomass production and moisture status of fuels. Seasonality variables indicate annual ranges in temperature and precipitation (Table 1) and were included assuming that highly variable areas in terms of precipitation and temperature might allow fuel accumulation under favorable conditions, and that fuel will burn later during dry and warm periods.

2.2.2.3. Biological variables. Considering that fire occurrence differs among vegetation types in Sierras Chicas (Argañaraz et al., 2015), we included a land cover map derived from Landsat imagery (Zak, 2008) (Table 1). Considering that physiognomy types alone might fail to reflect fuel loads (for instance, grazed vs. ungrazed grasslands) and vegetation state, we also included the Normalized Difference Vegetation Index (NDVI) as an indicator of primary productivity and fuel availability (Paruelo et al., 2004).

Because this index has intra- and inter-annual variability, we analyzed the time series of NDVI MODIS product (MOD13Q1) provided every 16 days at 250 m spatial resolution for the period 2001 to 2011. NDVI time series were analyzed with TIMESAT (Jönsson and Eklundh, 2004). During this process, a function is fitted for each pixel to describe NDVI variation over time and the beginning and end of the growing seasons (GS) of the period (10 growing seasons). Then, two seasonal parameters were extracted for each GS: the small seasonal integral and the maximum value for the fitted function during the season (peak of productivity); see Eklundh and Jönsson (2012) for further details. This integral is a proxy of the net primary production in each GS (Ruimy et al., 1994). Using these two parameters we derived four predictor variables (Table 1). Dispersion measures of NDVI were included under the assumption that highly variable sites were more prone to fire, because of the sequence of more productive periods in which fuels accumulate and lower productive periods (presumably drier) in which fires find suitable environmental conditions for burning.

2.2.2.4. Topographic and hydrological variables. Topographic variables included altitude, slope, aspect and annual solar radiation (Table 1). We considered radiation as a topographic variable because, at a given latitude and without considering clouds, solar radiation depends on topography. We also included the Euclidean distance to water bodies because they can act as physical barriers to fire spread by creating humid conditions and by the presence of water itself (Table 1). Slope was calculated using ENVI 4.8 and Solar radiation using ArcGis 9.1.

2.3. Statistical analyses

2.3.1. Data preparation and sampling scheme

The subset of predictor variables was filtered by dropping those with Spearman's correlation $|r| > 0.7$, prioritizing variables with a clearer functional meaning for fires (e.g. PET.annual over Altitude) and general and more frequently available data (e.g. PP.annual over PP.fs). As a result, 17 out of 28 potential predictor variables were included in our analysis (Table 1). This filtering was necessary to avoid overfitting of BRTs and a distorted effect of individual variables (Olden et al., 2008; Parisien et al., 2011).

Sampling recommendations of classical statistics are hard to fulfill in remote sensing studies (Chuvieco, 2002). A completely proportional to area sampling strategy was not possible because the higher fire frequency areas were too small compared to the lower frequency areas. We had to use a larger proportion of points in the higher fire frequency areas to be able to model them correctly. We randomly selected 7000 points in unburned areas (fire frequency = 0); 1400, 1060 and 780 for fire frequencies = 1, 2 and 3, respectively. We performed a systematic random sampling for fire frequencies 4 and 5, resulting in 253 and 18 points; respectively. The sampled proportion was around 0.1% for the fire frequencies of 0 and 1, and between 0.4 and 10% for higher fire frequencies. The total sample size was 10,511 points. In all cases, the minimum distance between samples was 90 m, and the average shortest distance between points and standard deviation were 433 m and 250 m, respectively.

2.3.2. Boosted Regression Trees

Boosted Regression Trees (BRTs) are a nonparametric machine learning technique that combines two algorithms: regression trees and boosting. In boosting, a collection of regression trees are fitted iteratively, but successive trees are fitted on the residuals of the previously existing trees, with emphasis on poorly modeled observations. The process is stagewise and the final BRT is a polynomial of hundreds to thousands of terms, where each term is a regression tree (Elith et al., 2008). The relative importance of predictors is quantified by considering the number of times the variable is selected as a tree node, weighted by the squared improvements to the model resulting from each split, and then averaged over the collection of all trees (De'ath, 2007). In general, the most relevant predictors are identified with a 5% limit of relative importance (Johnstone et al., 2010; Parisien et al., 2011). To quantify the magnitude of the interaction between a pair of variables, predictions for all possible combination of values of these predictors are calculated while setting values for all other variables to their respective means. Then, the residual variance of the linear model that relates these predictions to the two marginal predictors indicates the relative strength of the interaction (Elith et al., 2008).

There are two key parameters to fit BRTs: the learning rate (*lr*) and tree complexity (*tc*). The former shrinks the contribution of each subsequent tree in the final model, whereas the latter controls the interactions allowed in each tree. The number of trees (*nt*) for optimal predictions depends on these parameters and lower *lr* values need to be compensated by more iterations (i.e. higher *nt*) (De'ath, 2007; Elith et al., 2008).

BRTs have several advantages as a result of the combination of both algorithms. BRTs are able to handle a large number of predictors of different types (numerical, categorical, binary, etc.); they automatically model interactions among predictors and are sensitive to nonmonotonic relationships between the independent and dependent variables (Archibald et al., 2009; De'ath, 2007; Elith et al., 2008; Olden et al., 2008).

We ran BRTs with R 3.1.0 (R Core Team, 2014) using the “gbm” package (Ridgeway, 2013) and followed recommendations and R script of Elith et al. (2008). The optimal number of trees was determined using 10-fold cross-validation using 50% of data each time (bag fraction = 0.5). The first BRT included all uncorrelated predictor variables (see next section) and we then simplified the dataset by dropping the least important variables.

2.3.3. Spatial autocorrelation

The presence of Spatial Autocorrelation (SAC) in model residuals can lead to the selection of unimportant explanatory variables and poorly estimated parameters (Dormann, 2007), resulting in poor understanding of the system and predictions (Crase et al., 2012). Spatial autocorrelation was analyzed by calculating the Moran's Index on our model residuals, considering a spatial lag of 100 m. Moran's Index typically ranges from −1 (strong negative SAC) to 1 (strong positive SAC), with 0 indicating no SAC and values between ±0.3 indicating weak SAC (O'Sullivan and Unwin, 2010). Moran's Index was calculated with R 3.1.0 (R Core Team, 2014) using the “ncf” package (Bjornstad, 2013).

3. Results

The final BRT model included 14 out of the 17 predictor variables, after dropping Solar radiation, Aspect and Precipitation seasonality. The explained deviance of the model was 75.6%, indicating a good performance to adequately determine the environmental drivers of fires in Sierras Chicas. Moran's Index values were always lower than 0.3 (Fig. 2), indicating a weak SAC.

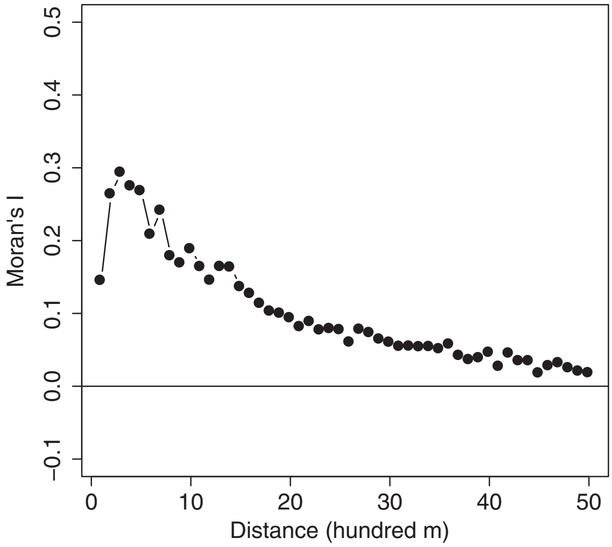

Fig. 2. Moran's index for final BRT model residuals. All values are significant ($P < 0.05$).

Considering the 5% limit of relative importance used by other authors (Elith et al., 2008; Parisien et al., 2011) that in our model would be 3.8% of explained variability, all the groups of variables, except for the hydrological one, were included among the most important predictors determining fire frequency, with a clear dominance of climate. Particularly, annual precipitations explained 14.7% of the observed variability, followed by slope (10.7%), potential evapotranspiration (8.6%), temperature seasonality (6.6%), population density (6%), distance to waste disposals (5.4%), and maximum NDVI (4.1%) (Fig. 3). Distance to urban areas and water bodies were near the 3.8% limit (3.6% each). The least important variables, explaining less than 3%, included precipitation of the driest quarter, mean and standard deviation of NDVI, distance to roads and land cover class (Fig. 4). In total, climatic variables accounted for 32.2% of observed variability, followed by human (15.0%), biological (11.6%), topographic (10.7%) and hydrological (3.6%) predictors.

3.1. Effect of explanatory variables on fire activity

3.1.1. Climate

Fire frequency was higher in areas with annual rainfall ranging between 650 and 700 mm, and decreased monotonically as precipitation increased above 700 mm and steeply when precipitation decreased below 650 mm (Fig. 3). Fire frequencies decreased monotonically as PET.annual increased above 1350 mm and showed an inverse behavior with higher precipitations of the driest quarter, meaning that fires were more prone to occur with increasing PP.dry. Fire frequency also increased with increasing annual range of temperature (i.e. Temperature seasonality) up to 46 °C (4600 in the partial dependent plot of Fig. 3), rapidly decreasing above that threshold.

3.1.2. Human variables

The most important human variables explaining fire frequency were population density and distance to waste disposals. Fire activity increased slightly with higher population densities up to a value of the ln-transformed variable of ≈ 2 (≈ 6.5 inhabitants/km^2), and then showed an irregular pattern. Fire frequency remained relatively stable within the first 8 km distance from waste disposals and then decreased at longer distances (Fig. 3). Conversely, fire activity was minimal at the edge of urban areas and roads, but increased rapidly at very short distances. Fire frequency was higher at a distance between 1 and 5 km from urban areas, decreasing slowly at longer distances (Fig. 4).

3.1.3. Biological variables

Primary productivity proxies were the most important variables controlling fire frequency. Fires were less prone to occur with increasing NDVI.max and decreasing inter-annual variability (NDVI.SD). Conversely, the effect of NDVI.mean was convex, with maximum fire frequency at intermediate productivity values. Furthermore, fires were more frequent in forests, grasslands and shrublands than in any other land cover classes, but without showing important differences among these three land covers (Figs. 3 and 4).

3.1.4. Topographic and hydrological variables

In general, fire frequency increased with slope, with increases being slower between 0% and 6% and faster between 6% and 15% (Fig. 3). Moreover, fire activity was lower at shortest distances to water bodies, but it rapidly increased within the first 500 m distance and then it monotonically increased up to 5 km (Fig. 4).

3.2. Interactions between fire drivers

The three predictor variables most frequently appearing in the strongest pairwise interactions were PP.annual, T.seas and Water.dist (Table 2). We observed that near the water bodies, the dominance of this fire driver increases and weakens the marginal effect exerted by PP.annual and NDVI.max on fire frequency (Fig. 5a). The control of T.seas on fire activity becomes considerably important in areas where precipitations of the driest quarter were higher than 35 mm. Moreover, even though precipitations between 675 and 700 mm were associated with higher fire frequencies, lower precipitations between 650 and 670 mm produced similar or higher fire activity when combined with annual temperature ranges between 44 and 46 °C (Fig. 5b). Finally, the marginal effect of distance to urban edges on fire frequency was exacerbated at low population densities. The interactions ranked ≥ 6 (Table 2) did not show a different pattern than the one expected for each individual predictor.

4. Discussion

4.1. Effect of predictor variables on fire activity and their importance

Our results indicate that climatic variables were the most important predictors of fire frequency. In general, previous studies have found that human variables are more closely associated with fire ignitions, but the amount of burned area depends greatly on climatic conditions that determine fuel availability and suitable conditions for fires (e.g. Aldersley et al., 2011; Archibald et al., 2009; Hawbaker et al., 2013; Mundo et al., 2013; Parisien et al., 2011; Syphard et al., 2007; Wu et al., 2014).

The highest fire frequencies occurring between 650 and 700 mm of annual precipitation suggest a balance between the amount of fuel production and dry conditions allowing fires to ignite and spread at this range (Pausas and Ribeiro, 2013). The limiting factor with low rainfall as well as with higher potential evapotranspiration should be fuel availability and with high rainfall, fuel moisture content. The increasing fire frequencies with increasing precipitation of the driest quarter support the idea that fuels are a limiting factor in our study area, as in other semiarid landscapes worldwide (Bradstock, 2010; Rollins et al., 2002; van der Werf et al., 2008). Our results agree with those of Bravo et al. (2010), who reported greater fire activity in Chaco savannas in years with precipitations ranging between 600 and 750 mm and lower fire occurrence with rainfall lower than 600 mm. Likewise, in Mediterranean areas of Catalonia, Spain, severe fires occur with annual rainfall between 550 and 700 mm (Díaz-Delgado et al., 2004). However, fire activity can reach a maximum at different ranges of mean annual precipitation, such as 700–900 mm in northwestern ranges of Argentina (Grau, 2001) and 1000–1600 mm in Africa (van der Werf et al., 2008).

Even though this moisture–fire relationship is nonlinear (Bradstock, 2010), different thresholds of higher fire activity are imposed in

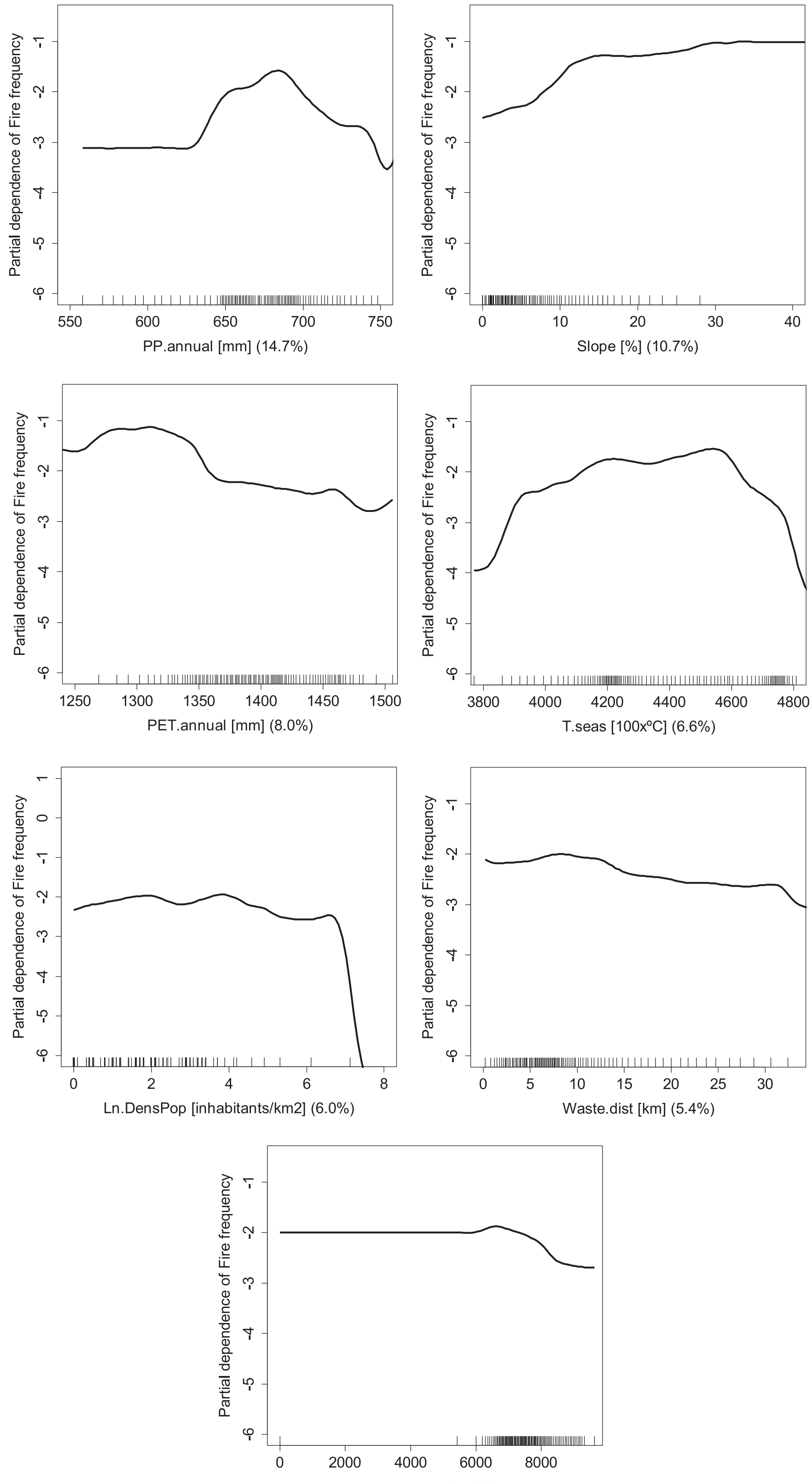

Fig. 3. Partial dependence plots of fire frequency on the seven most important explanatory variables (>3.8%). The y axis shows the marginal effect of the predictor variable on the logit(p) of the response variable, with all other variables being held constant. Rug plots on the x-axis represent the distribution of the respective data space in percentiles. Percentages on the x label represent the percentage of explained variability.

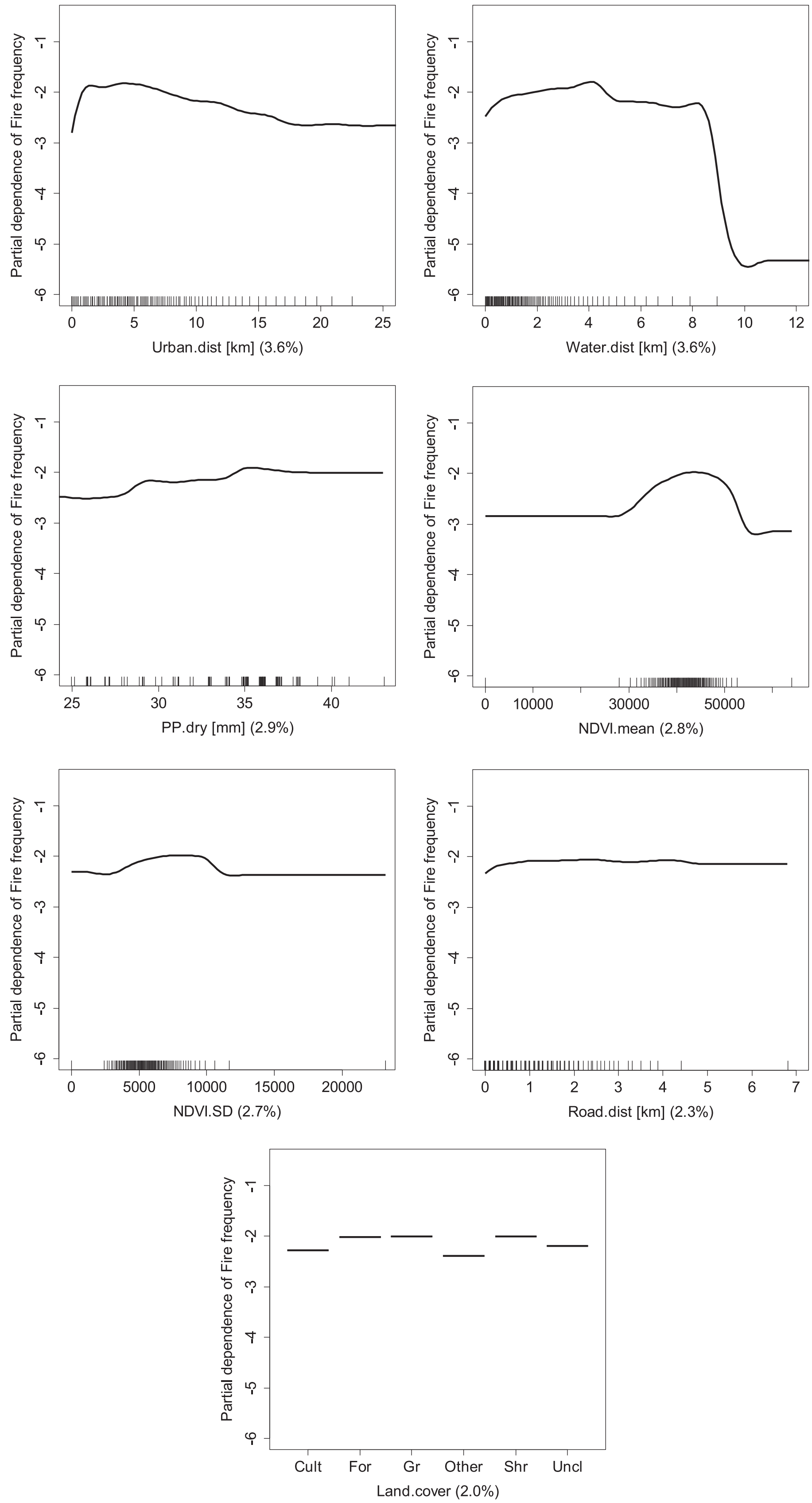

Fig. 4. Partial dependence plots of fire frequency on explanatory variables with relative importance <3.8%. The y axis shows the marginal effect of the predictor variable on the logit(p) of the response variable, with all other variables being held constant. Rug plots on the x-axis represent the distribution of the respective data space in percentiles. Percentages on the x label represent the percentage of explained deviance rescaled to the total deviance explained by the model.

Table 2
Ranking of the eight strongest interactions between predictor variables for a BRT model predicting fire frequency in the Semiarid Chaco mountains of central Argentina.

Ranking	Predictor 1	Predictor 2	Interaction strength
1	Water.dist	PP.annual	341.7
2	Ln.DensPop	Urban.dist	207.4
3	Water.dist	NDVI_max	205.6
4	T.seas	PP.dry	139.1
5	T.seas	PP.annual	102.5
6	PET.annual	PP.annual	80.0
7	PP.annual	Slope	69.1
8	NDVI.mean	T.seas	61.8

different ecosystems, depending on the length of the fire season in wetter ecosystems and on fuel availability in drier ecosystems (van der Werf et al., 2008), which can also be conditioned by rainfall seasonality and vegetation characteristics. For instance, in the Chaco ecoregion, hardwood forests can still stand at precipitation gradients of 300–500 mm (Arid Chaco) and 450–900 mm (Serrano Chaco) (Naumann, 2006), whereas in other ecosystems, woody cover would be considerably lower (Sankaran et al., 2005), allowing more grasses to grow and thus increasing the loads of fine fuels that burn more easily.

The increasing fire occurrence with the increasing temperature seasonality was expected under the assumption that occasional conditions favoring biomass burning occur with increasing temperatures. However, in areas with very high temperature seasonality, fire activity was very low. Most of these areas are agricultural lands which have bare soils at some point during the year, that might reach higher temperatures (Lagouarde et al., 1995) increasing T.seas. The observed low fire activity in cultivated lands is expected due to the spatial and temporal variability of fuel loads.

The increasing fire frequency associated with steeper slopes, is due to the expected faster rate of spread of fires, associated to improved efficiency in heat transfer upslope, which pre-dries fuels located above (Whelan, 1995), stronger fire induced winds behind the fire front (Pimont et al., 2012) and other complex interactions between wind and terrain (Sharples, 2009). Other studies found similar tendencies (Hawbaker et al., 2013; Syphard et al., 2008), with increasing burned area at sites with slopes >10% or steeper (Díaz-Delgado et al., 2004); however, in our study area there are few slopes above 15%.

Our results indicate that aspect and solar radiation are not determinants of fire activity in Sierras Chicas. Similar results were reported in areas with gentle slopes (Wu et al., 2014), where solar radiation differs little among facets (Heyerdahl et al., 2001). However, southern slopes are less suitable for fires in Sierras Chicas, because fuel moisture is higher, whereas northern slopes are more prone to fires (Fabián Freccia, Personal communication). In fact, the partial dependence plot for this variable, previous to model simplification, showed that north-eastern slopes were slightly more prone to fires. This negligible effect of aspect and solar radiation might be related to the scale of our analysis and data resolution. While different aspects might burn differently (e.g. low burn severity on southern slopes), such information was not available in our fire database. Moreover, nearly 74% of the total burned area is affected by large fire events (>1000 ha) (Argañaraz et al., 2015) that usually occur under extreme conditions and probably burn independently of aspects as of many other variables (Hawbaker et al., 2013).

Fire activity was slightly higher with small increases in population density, probably associated to increased ignitions, as is reported in previous studies (Aldersley et al., 2011; Syphard et al., 2007, 2009). Nevertheless, the slenderness of this relationship indicates that very few people might provide enough ignition opportunities to burn large areas (Archibald et al., 2009). The higher fire frequency at short distances from waste disposals supports the idea that they may be sources of fires in Sierras Chicas. This is the result of the burning of waste disposals to reduce trash volumes and pests (Nirich, 2000), and spotting during hot and windy days, which commonly occur during late winter and early spring. The reduced fire activity found over the edge of urban areas agrees with previous studies indicating lower availability and continuity of fuels as the level of development increases (Syphard et al., 2007). However, higher fire frequencies occurred in the surroundings of urban areas indicating a balance between more frequent human ignitions and fuel available for burning. This result might also be related to the short distances usually separating urban solid waste disposals from associated urban areas (3.5 km on average).

The low fire activity at very short distances from roads indicates that roads mainly act as fire breaks in Sierras Chicas, and this is probably due to the lower fuel loads on the shoulders, higher visibility allowing early detections and easier access for suppression activities. In general, increasing human accessibility and activity tend to be positively associated with both fire occurrence and number of ignitions (Penman et al., 2013). However, large wildfires seem to burn where human presence is low (Cardille et al., 2001), because vegetation is typically continuous (Syphard et al., 2008).

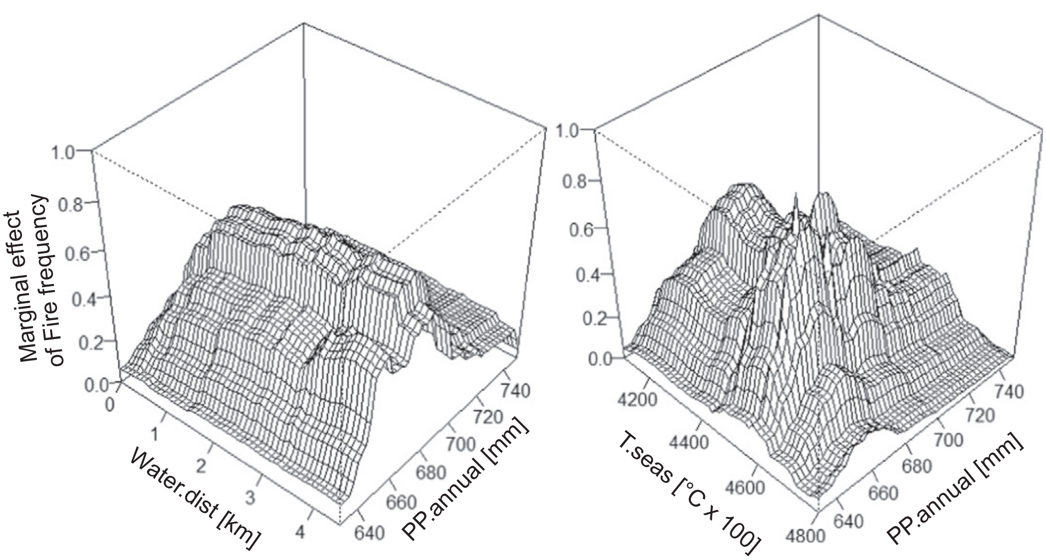

Fig. 5. Three-dimensional partial dependence plots for interactions between annual precipitations and distance to water bodies (left) and temperature seasonality (right).

Similar to precipitations, fires would be limited by fuel availability at lower productivities and by fuel moisture at higher productivities (NDVI.mean and NDVI.max). Our results are consistent with findings reported for dry ecosystems worldwide (e.g. Pausas and Ribeiro, 2013; van der Werf et al., 2008) and support the intermediate fire-productivity hypothesis (Pausas and Bradstock, 2007). Higher fire frequencies in areas where productivity is more variable is in accordance with our assumptions of alternating periods of biomass accumulation during "good years", which are available to burn during "bad years".

Finally, the fact that land cover class was the least important predictor variable is surprising because previous studies indicated that grasslands burned more frequently than other land cover classes (Argañaraz et al., 2015). However, this could be related to other variables included in the present work eroding the explanatory power of land cover classes as reported by Wu et al. (2014). In general, grasslands are located at high altitudes where potential evapotranspiration is lower, and we found high fire frequencies at low values of this variable. Additionally, the land cover class is not always a good indicator of fuel loads (e.g. grazed vs. ungrazed grasslands). Herbivory affects NDVI (Blanco et al., 2008) and these variables were in fact better predictors of fire occurrence than land cover classes. Similarly, other studies observed that vegetation classes had lower predictive power when productivity and climatic variables were included in the analysis (Hawbaker et al., 2013). Conversely, in the absence of such kind of predictors, vegetation classes significantly contributed to explaining fire activity (Syphard et al., 2007).

Fires are less prone to burn at very short distances to water bodies, probably due to more humid conditions near water bodies, creating unsuitable environment for fires; thus, water bodies become natural firebreaks (Cardille et al., 2001). The weakened effect of mean annual precipitation and maximum NDVI in the area adjacent to water bodies suggests that available humidity exerts a dominant control and limits fire occurrence. In addition, some water bodies are in the middle of ravines, where fires have serious difficulties to advance downslope on such steep terrains (Whelan, 1995).

4.2. Model accuracy

Our results indicate that Boosted Regression Trees were a useful and precise tool to determine the drivers with greatest influence on fire occurrence patterns in Sierras Chicas. Our final BRT model showed a good performance, capturing near 76% of the variability of fire frequency. Parisien et al. (2011) obtained similar deviance values (about 80%) using sampling areas of 10^4 km^2, and lower values with smaller sample areas (e.g. near 25% for sampling areas of 100 km^2). Parisien and Moritz (2009) assessed their BRT model using AUC (area under the operating curve) and obtained values between 0.83 and 0.92, which is considered as good/very good.

Moran's index values were always between 0 and 0.3, indicating weak spatial autocorrelation. Under such circumstances, SAC is usually neglected in model fitting (e.g. Jung et al., 2006; O'Sullivan and Unwin, 2010; Reino et al., 2013). Additionally, spatial dependence of our data is expected to be even lower, since 50% of data was used at each iteration of BRT (i.e. bag fraction = 0.5, see Section 2.3.1). It is also possible that BRTs accounted for some SAC (Crase et al., 2012).

5. Conclusions and management implications

Our results contribute to a better understanding of the ecology of fires in Semiarid Chaco mountains. Boosted Regression Trees proved to be a useful and accurate tool to determine both biophysical and human drivers of fires. This approach allowed us to get a deep insight into the effects of each driver on fire activity, modeling their interactions and identifying the thresholds and/or ranges increasing fire activity. Our findings might be extrapolated to other similar arid and semiarid landscapes, especially in mountain regions, where topography plays a key role in fire behavior, and areas where the wildland–urban interface is expanding and human ignitions find enough fuels to burn.

Fire activity in Sierras Chicas is mainly controlled by climate (determining fuel availability and fuel moisture content) and humans (probably involved in the number of fire ignitions).

These results imply major management challenges in terms of future urban development, climate change and their interactions. Fire management policies are usually aimed at reducing fire risk, which is a function of both the probability of occurrence and the amount of damage that can be caused. As expected, human values are prioritized and management actions tend to concentrate near urban or WUI areas, therefore demanding higher management resources. Considering the current tendencies of urban development, it is probable that WUI communities will continue to grow in Sierras Chicas, increasing the number of people and buildings at risk. Hence, land-use policies should allow novel urban developments only in areas unsuitable for fires, such as areas with gentle slopes in drier or humid zones where fuel loads or moisture content limit fires, respectively. Additionally, urban solid waste should be managed properly, avoiding open sky disposals and applying sanitary measures in the already existing ones.

Our findings about the climatic conditions favoring fire occurrence are of great value to estimate future fire activity under different scenarios of climate change. Such estimations will help support proper decision making as to fire management prevention in space and time. However, climate change itself is full of uncertainties as to the amount and directions of change, as well as variability and interactions with other processes (Bradstock, 2010). For instance, in areas of Sierras Chicas undergoing increases of annual rainfall (reaching between 650 and 700 mm), fire frequency is expected to increase as well; however, if the rainy season begins earlier, its effect on fire activity will not be as expected. Therefore, future fire activity estimations driven by climate change should be considered with caution.

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