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Is chlorophyll-a the best surrogate for organic matter enrichment in submicron primary marine aerosol? / Rinaldi, Matteo; Fuzzi, S; Decesari, Stefano; Marullo, Salvatore; Santoleri, Rosalia; Provenzale, Antonello; von Hardenberg, Jost; Ceburnis, Darius; Vaishya, Aditya; O'Dowd, Colin D.; Facchini, Maria Cristina. - In: JOURNAL OF GEOPHYSICAL RESEARCH. ATMOSPHERES. - ISSN 2169-897X. - 118:10(2013), pp. 4964-4973.

Availability:

This version is available at: 11583/2814818 since: 2020-04-22T12:11:28Z

Publisher:

AMER GEOPHYSICAL UNION

Published

DOI:10.1002/jgrd.50417

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Impact of climate variability on summer fires in a Mediterranean environment (northeastern Iberian Peninsula)

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Received: 19 January 2012 / Accepted: 20 May 2012 / Published online: 7 June 2012
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Abstract We analyse the impact of climate interannual variability on summer forest fires in Catalonia (northeastern Iberian Peninsula). The study period covers 25 years, from 1983 to 2007. During this period more than 16000 fire events were recorded and the total burned area was more than 240 kha, i.e. around 7.5% of Catalonia. We show that the interannual variability of summer fires is significantly correlated with summer precipitation and summer maximum temperature. In addition, fires are significantly related to antecedent climate conditions, showing positive correlation with lagged precipitation and negative correlation with lagged temperatures, both with a time lag of two years, and negative correlation with the minimum temperature in the spring of the same year. The interaction between antecedent climate conditions and fire variability highlights the importance of climate not only in regulating fuel flammability, but also fuel structure. On the basis of these results, we discuss a simple regression model that explains up to 76% of the variance of the Burned Area and up to 91% of the variance of the number of fires. This simple regression model produces reliable out-of-sample predictions of the impact of climate variability on summer forest fires and it could be used to estimate fire response to different climate change scenarios, assuming that climate-vegetation-humans-fire interactions will not change significantly.

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1 Introduction

Forest fires are a complex process associated with factors of different origin, such as climate and weather, human activities and vegetation conditions (Bowman et al. 2009), whose relative importance at different scales can be difficult to quantify (Bonan 2008). At local scale, the occurrence of fire needs oxygen, fuel and ignition temperature. At landscape scale the main drivers are fuel, weather, and topography (Pyne et al. 1996; Díaz-Delgado et al. 2004; Oliveras et al. 2009). At regional or global scale, fires are determined by climate variability, human activities and vegetation distribution, and in turn they feed back on vegetation distribution and structure, the carbon cycle, and climate (Venevsky et al. 2002; Pausas and Keeley 2009; Bowman et al. 2009).

The role of human actions on fires is essential. Human activities have had an increasing influence on fire regimes (Dube 2009; Harrison et al. 2010): Anthropogenic ignition is dominant in most Mediterranean regions (Macias Fauria et al. 2011) and, on the other hand, humans also invest a lot in fire-fighting. The change of land use is another crucial anthropogenic factor affecting fires (Pausas and Fernández-Muñoz 2011; O'Connor et al. 2011).

Anthropogenic effects usually have a limited interannual variability on the scales of decades. Among the potential drivers of fires at regional scale, only climatic factors have a large interannual variability, analogous to that of fire itself. The hypothesis that climate is a primary driver of the interannual variability of fire is supported by several studies (see, e.g. Dwyer et al. 2000; Westerling et al. 2006; Archibald et al. 2009; Krawchuk et al. 2009), some of which consider a Mediterranean ecosystem which is very close to that of the area studied here (Viegas and Viegas 1994; Piñol et al. 1998; Pausas 2004; Pereira et al. 2005; Trigo et al. 2006; Pausas and Paula 2012).

Meyn et al. (2007) proposed a conceptual model suggesting that, at first approximation, climatic processes act as top-down controls on the regional pattern of fire, controlling both fuel moisture, i.e. fuel flammability, and nature and availability of fuel (fuel structure). This model identified three ecosystem types depending on the importance of fuel moisture and fuel structure as limiting factors for fires: (1) abundant fuels but rarely dry ecosystems, where fires are mainly limited by fuel moisture; (2) fuel-limited ecosystems, that can have frequent potential ignitions but where fire spread is limited by the fuel amount; (3) "intermediate" cases ecosystems, where both fuel moisture and fuel structure can have some role in shaping fire regimes. The area of interest in this work, Catalonia, can be classified as a type 3 ecosystem, as indicated by other studies which considered neighbouring regions (Viegas and Viegas 1994; Pausas 2004; Pausas and Paula 2012). In this ecosystem, climate acts in two main ways: antecedent climate regulates the fuel amount and its continuity, whilst current climate, e.g. by means of drought and warming, promotes the fuel load (i.e. the amount of (dry) biomass available to burn in a wildfire).

Adopting the view that climate is the main controlling factor of the interannual variability of fire, in this work we analyse the links between climate and fire variability using the *Spain02* (Herrera et al. 2010) climate data and the historical fire data in Catalonia. In particular, we want to explore whether short-term climatic oscillations determine the fuel structure and fuel moisture that, in turn, influence the fire regimes. To this end, we investigated 25 years of Catalonia fire history together with temperature and precipitation data to determine whether and how interannual fire variability is determined by climatic factors. We also present a simple regression

model that links the variability of summer fires in Catalonia to climatic variables. We show that this simple model can be used to produce reliable out-of-sample predictions.

The rest of this paper is organized as follows. Section 2 describes the observational fire and climate data used and their characteristics; Section 3 evaluates the relationship between climate and fire and introduces the regression model. Finally, Section 4 discusses and synthesizes the main results of our study.

2 Climate and fire data

2.1 Characteristics of the study area

The study area of this work is Catalonia, a Spanish region of 32000 km² in the North-East of Iberian Peninsula (Mediterranean coast, Fig. 1). About 60% of Catalonia is covered with shrubland and forest. The high percentage of forest surface is due to a crisis of rural areas leading to abandonment of cultivations during the last century (Hill et al. 2008). Consequently, a considerable portion of the forest area is recent, i.e. without massive presence of mature woodland ecosystems (Terradas 1996).

Most of Catalonia displays a Mediterranean climate with dry and hot summers and mild winters. The rainiest season is autumn, with a secondary maximum in spring. The spatial variability of rainfall and temperature is very high (Martín Vide 1992): annual precipitation values range from 300 mm in the south to 1200 mm in the Pyrenees and annual average temperatures vary between 17°C in the south coast

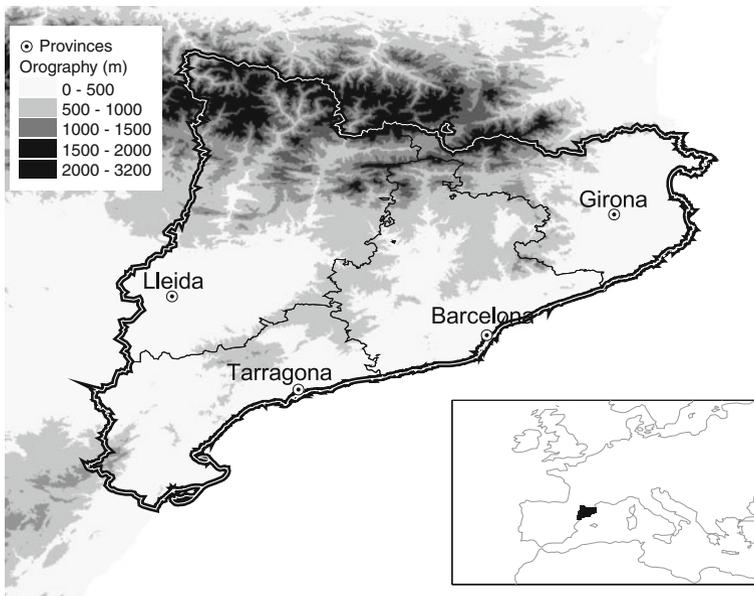


Fig. 1 Schematic map of Catalonia showing its orography and provinces. The inset shows a geographical map at larger scale

and about 0°C at the Pyrenean peaks. Note that our hypothesis that the Catalonia ecosystem can be classified as type 3 according to Meyn et al. (2007), could be wrong in the areas of the Catalonian peaks. However, due to the limited areal extension and the small number of fires at the highest elevations, the results of this study should not be affected by this heterogeneity. Notwithstanding the significant elevation range, interannual climate variability in Catalonia is generally coherent over the entire area, that is, dry (wet) years are usually dry (wet) over the whole region.

2.2 *Spain02* dataset

The daily precipitation and temperature data used in this study are provided by the high-resolution ($0.2^\circ \times 0.2^\circ$, approximately 20×20 km) gridded dataset, called *Spain02*. This dataset was produced using data from quality-controlled stations with long records (525 rain-gauges and 237 thermometers with at least 40 years of data) from the Spanish Meteorological Agency (AEMET), covering Spain over the period 1950–2008. Readers are referred to Herrera et al. (2010) for the development and analysis of the *Spain02* dataset.

For each of the 112 points of the dataset within Catalonia, monthly averages are computed from the daily time series of minimum and maximum temperature and monthly rainfall cumulates are computed from the daily precipitation data. We also average the climate data over the whole area to obtain a mean regional climatic record. Since temperature and precipitation series display a dependence on elevation, we standardized the individual series in order to reduce the presence of possible biases in the regional average. The standardized series are dimensionless quantities obtained by (a) defining an anomaly by subtracting the long-term mean from the original series and (b) dividing the anomaly by its long-term standard deviation.

2.3 Fire data

Accurate data for fire occurrence and burned area were obtained from the Forest Fire Prevention Service of the "Generalitat de Catalunya" (SPIF). The data consist in the characteristics of 16753 fire events which occurred in Catalonia during the period 1983–2007. Although there are fire records also in previous years, the database can be considered homogeneous only after 1983 since prior to this date there are no records for the province of Lleida (Fig. 1).

Another aspect that may affect the homogeneity of the data is the minimum burned area for which a fire is recorded. Indeed this minimum area is not constant over time: for example, the first part of the database has no records with area smaller than 0.01 ha. To obtain a homogeneous series it is thus necessary to retain only those fires whose area is above a fixed threshold (Malamud et al. 2005). In the following, we have restricted the analysis to fires with burned area of at least 0.5 ha.

Fires in Catalonia display a marked seasonality. Although fires in this region occur throughout the year, about 60% of the fires occur in summer (here defined as JJAS, i.e. June–September). Summer fires also burn a larger area, which amounts to about 86% of the annual burned area. For this reason, we have concentrated our analysis on the burned area (hereafter, BA) and on the number of fires (NF) over the summer months.

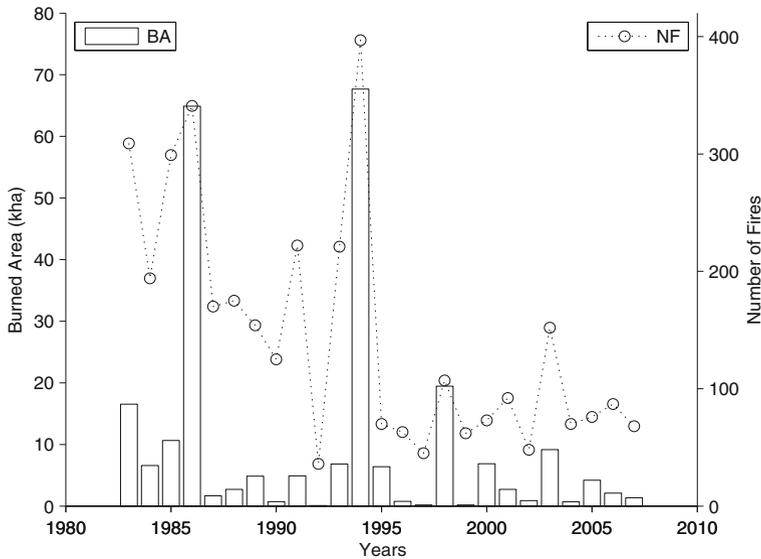


Fig. 2 Total summer burned area (BA) and number of fires (NF) with area larger than 0.5 ha

Both BA and NF display a high interannual variability, with two peaks in 1986 and 1994, when about 70,000 ha burnt (Fig. 2). Besides, NF in Catalonia is decreasing. The Mann-Kendall test confirms a significant downward trend of around 9 fires/year ($pvalue = 0.003$). By contrast, BA does not show any significant trend. A decreasing fire number at European level was recently reported by Camia et al. (2011).

After the big fires of 1986 and 1994, prevention measures have been improved. In particular, after the exceptional summer 1994 (Llasat 1997), a specific plan of civil protection for preventing and limiting forest fires (INFOCAT, see <http://www.gencat.cat/>) has been launched. The increasing effort to fire management (including both fire prevention and fire suppression) could explain at least a part of the decrease in NF (Llasat and Corominas 2010).

Both BA and NF are positively skewed (skewness 2.7 and 1.1 respectively). Since most statistical analyses in the following are based on the hypothesis of normality, we opted for the standard gaussianization of the data based on logarithmic transformation (Crimmins and Comrie 2004; Camia and Amatulli 2009).

3 Fire response to climate variability

3.1 Identification of key variables

As discussed above, we assume that Catalonia ecosystem is of type 3 according to the conceptual model proposed by Meyn et al. (2007). In this type of ecosystem, climate is a primary driver for interannual fire variability which acts on two main processes: control of fuel moisture (direct effect) and fuel structure (indirect effect). Our working hypothesis is that (a) current (i.e. same summer) temperature and

precipitation are good proxies for fuel moisture, and (b) antecedent temperature and precipitation are good proxies for fuel structure. In the following, we use an empirical approach and systematically explore same-year and lagged cross-correlations (r) between climate variables and fires. To this aim, climatic monthly data are aggregated in multi-month values called $P_{(n-m)(\tau)}$ and $T_{(n-m)(\tau)}$, where n and m indicate the first and last months of the aggregation period considered, and τ the time lag (in years, not specified if it is equal to 0).

The presence of long-term trends in the time series can bias the correlation analysis (Lobell and Field 2007). For this reason, all time series with a significant trend ($pvalue \leq 0.05$) were detrended (removing a linear trend) prior to the analysis.

The properties of the key variables (e.g. the duration and time lag, i.e. the values of n , m and τ) are estimated by maximizing the correlation between climate variables and fires (log-transformed NF and BA). The results of the cross-correlations between climatic data and fires are reported in Table 1. For sake of conciseness, only the two highest correlations for each variable with similar features (with a confidence level of at least 95%) are shown.

As expected, precipitation (with high correlation for the summer months and for the period ranging from winter to summer) is negatively correlated with BA and NF, while maximum temperature in summer has a positive correlation with the fire

Table 1 Cross-correlations (r) between climate variables (precipitation, $P_{(n-m)(\tau)}$, maximum temperature, $Tx_{(n-m)(\tau)}$, and minimum temperature, $Tn_{(n-m)(\tau)}$, during the months from n to m at the time lag τ , in years) and the fire variables (log-transformed BA and NF in JJAS)

Variable	Months	τ (years)	r ($\log(BA)$)	r ($\log(NF)$)
$P_{(6-7)}$	Jun–Jul	0	−0.72	
$P_{(12-8)}$	Dec–Aug	0	−0.70	
$Tx_{(6-6)}$	Jun–Jun	0	0.56	
$Tx_{(6-7)}$	Jun–Jul	0	0.51	
$Tn_{(11-4)}$	Nov–Apr	0	−0.42	
$Tn_{(3-4)}$	Mar–Apr	0	−0.40	
$P_{(2-3)(2)}$	Feb–Apr	2	0.47	
$P_{(1-3)(2)}$	Jan–Apr	2	0.46	
$Tx_{(2-3)(2)}$	Feb–Apr	2	−0.61	
$Tx_{(2-2)(2)}$	Feb–Feb	2	−0.57	
$Tn_{(2-10)(2)}$	Feb–Oct	2	−0.59	
$Tn_{(1-10)(2)}$	Jan–Oct	2	−0.58	
$P_{(5-8)}$	May–Aug	0		−0.82
$P_{(6-8)}$	Jun–Aug	0		−0.81
$Tx_{(6-8)}$	Jun–Aug	0		0.68
$Tx_{(6-9)}$	Jun–Sep	0		0.68
$Tn_{(4-5)}$	Apr–May	0		−0.41
$Tn_{(1-5)}$	Jan–May	0		−0.39
$P_{(3-3)(2)}$	Mar–Mar	2		0.48
$P_{(1-3)(2)}$	Jan–Mar	2		0.47
$Tx_{(2-2)(2)}$	Feb–Feb	2		−0.53
$Tx_{(1-3)(2)}$	Jan–Mar	2		−0.51
$Tn_{(2-2)(2)}$	Feb–Feb	2		−0.63
$Tn_{(2-6)(2)}$	Feb–Jun	2		−0.54

variables. Not surprisingly, there are more summer wildfires and their burned area is larger in dry and hot summers.

More interesting are the cross-correlation results between antecedent climatic variables. Minimum temperature in winter/spring is negatively correlated with BA and NF. This result suggests that low temperature or frost, especially late ones, may play a role in increasing the amount of fuel in the following summer. There is a significant positive correlation between BA and NF and winter precipitation with a time lag of two years. Maximum temperatures in winter and minimum temperatures in winter/spring are negatively correlated with BA and NF, again with a time lag of two years. Correlations with a time lag of one year are not significant, and even the combination of climatic variables cumulated during the previous two years does not produce any significant correlation with NF or BA. Furthermore, neither the climatic variables, nor the fire data, exhibit any significant autocorrelation. In particular, we can disregard another potential lag effect, where a year with low fire activity is followed by a year with above-average fire activity. These results suggest that there is a specific relationship between fires and climate variability with a time delay of two years: High rainfall and cool temperatures (proxies for the amount of water in the soil) in winter of two years before presumably allow for the fine-fuel to grow and ensure fuel continuity.

The values reported in the table were obtained by statistical analysis. On the other hand, the purely empirical emergence of the climate variables which are significantly correlated with fires is consistent with the presence of specific physical processes. In particular, the results reported in the table are in keeping with our initial hypothesis, i.e., that climate variability influences fires in Catalonia by affecting fuel moisture and fuel structure. The similarity between the results found for BA and NF supports this interpretation.

Finally, note that there is the possibility of collinearity between some of the key variables that could lead to over-fitting in the regression model and thus affect the interpretation of the results. Among the key variables of Table 1, some significant ($p\text{value} \leq 0.05$) correlations between precipitation and temperature parameters have been found. Specifically, wet summers are usually cool ($r = -0.52$) and a similar relationship holds for winter ($r = -0.53$). We take into account this collinearity in developing the regression model, as discussed in the next Section.

3.2 Construction of empirical models of fire response

Multiple linear regressions were performed separately for BA and NF:

$$Y_i = \exp \left(\beta_0 + \sum_{j=1}^p \beta_j X_{i,j} + \epsilon_i \right) \quad (1)$$

where, for the i th year, Y_i is the response variable (BA or NF), $X_{i,1}, \dots, X_{i,p}$ are p predictors, and ϵ_i is the residual (noise) term expected to be Gaussian and temporally uncorrelated (Tong 1993). The values of the coefficients β_0, \dots, β_p are determined by least-squares fits to the data.

As for the correlation analysis, time series with a significant trend ($p\text{value} \leq 0.05$) were detrended prior to the analysis to minimize the influence of slowly changing

factors. For the model for NF, we take into account its negative trend in NF following two different approaches. First, we have included the time t (in years) as a separate regressor in the model for the (non-detrended) NF as a function of the (detrended) climate variables. Second, we have detrended the values of both NF and the climate variables and we have fitted the model as in Eq. 1.

The variables displaying the largest correlations (see Section 3.1) were considered as potential predictors. However, there are some correlations between climate variables (e.g. wet winter are usually cool) that can hamper the model development. Indeed, including dependent predictors there is the danger of over-fitting, or conversely, excluding some predictors could increase the risk of omitting some important effects of climate on fire. For instance, while the case with correlation 1.0 between two predictors is obvious, what happens when the correlation is lower (e.g., 0.5 as in our case) is less clear. This requires a careful predictor choice. Our approach consists in systematically testing for the importance of all possible combinations of the potential predictors, and sorting the resulting models based on their Akaike Information Criterion score (*AIC*; Akaike 1974). The *AIC* measures the goodness of a statistical model based on a trade-off between its accuracy (that is, the explained variance, R^2) and its complexity (that is, the number of free parameters). By this criterion, the model with the lowest *AIC* should be preferred. The number of the possible models with Np potential predictors is $2^{Np} - 1$, which for $Np = 12$ (see Table 1; the *AIC* corrected for finite sample size provides qualitatively similar results) is 4095. We have fitted all these models and we have calculated their performance, and in the end the 5 models with lowest *AIC* are retained for further analysis (Table 2). These regression models are the simplest empirical models with the largest explanatory power.

Table 2 Performance of the best 5 models for log(BA) and log(NF). Each rows reports the predictors used in the model, the Akaike Information Criterion *AIC* and the explained variance, R^2

log(BA) models	Predictors ^a					<i>AIC</i> ^b	R^2
BA.1	$P_{(12-8)}$	$Tx_{(6-6)}$	$Tx_{(6-7)}$	$Tn_{(3-4)}$	$Tx_{(2-3)(2)}$	-28.04	0.80
BA.2	$P_{(12-8)}$	$Tx_{(6-6)}$	$Tn_{(3-4)}$	$Tx_{(2-3)(2)}$		-25.72	0.76
BA.3	$P_{(12-8)}$	$Tx_{(6-6)}$	$Tx_{(6-7)}$	$Tx_{(2-3)(2)}$		-24.52	0.75
BA.4	$P_{(6-7)}$	$P_{(12-8)}$	$Tx_{(6-6)}$	$Tx_{(6-7)}$		-24.44	0.75
BA.5	$P_{(12-8)}$	$Tx_{(6-6)}$	$Tx_{(6-7)}$	$Tn_{(3-4)}$		-24.28	0.75
log(NF) models	Predictors ^c					<i>AIC</i>	R^2
NF.1	$P_{(6-8)}$	$Tx_{(6-8)}$	$Tn_{(1-5)}$	$P_{(3-3)(2)}$	$Tn_{(2-2)(2)}$	-47.26	0.91
NF.2	$P_{(6-8)}$	$Tx_{(6-8)}$	$Tn_{(1-5)}$	$Tn_{(2-6)(2)}$		-46.99	0.91
NF.3	$P_{(6-8)}$	$Tx_{(6-8)}$	$Tn_{(1-5)}$	$Tn_{(2-2)(2)}$		-46.60	0.90
NF.4	$P_{(5-8)}$	$Tx_{(6-8)}$	$Tn_{(1-5)}$	$Tn_{(2-2)(2)}$		-45.83	0.90
NF.5	$P_{(5-8)}$	$P_{(6-8)}$	$Tx_{(6-8)}$	$Tn_{(1-5)}$		-45.50	0.90

^aFor the notation see also Table 1; As an example for the reader’s convenience, $Tx_{(2-3)(2)}$ refers to the Maximum Temperature aggregate between February (2) and March (3) with a time-lag of two years

^bWe consider the *AIC* normalized by the variance of the response variable (BA or NF). Note that using the ratio of the variances, the value of *AIC* does not depend on the units of the data

^cNote that for NF we include the time t (in years) as a separate predictor

All these models perform well in reproducing $\log(\text{BA})$ and $\log(\text{NF})$ and, considering only the ranking of Table 2, one should choose the models $\text{BA}.1$ and $\text{NF}.1$. However, we consider the models $\text{BA}.2$ and $\text{NF}.2$ as more robust since, even having similar performance, they are more parsimonious and therefore less susceptible to the danger of over-fitting. The model residuals were also tested, with the result that the assumption of residual Gaussianity and zero temporal autocorrelation cannot be rejected.

Finally, the model for BA is:

$$\text{BA} = \exp(17.22 - 0.75P_{(12-8)} + 0.95Tx_{(6-6)} - 0.69Tn_{(3-4)} - 0.58Tx_{(3-4)(2)} + \epsilon) \quad (2)$$

Whilst for NF is:

$$\text{NF} = \exp(139 - 0.07t - 0.24P_{(6-8)} + 0.33Tx_{(6-8)} - 0.28Tn_{(1-5)} - 0.22Tn_{(2-6)(2)} + \epsilon) \quad (3)$$

For both model (Eqs. 2 and 3), the individual parameter significance (*pvalue*) is always lower than 0.05, except for $Tn_{(3-4)}$, that is equal to 0.058. While in the "best" model for BA, there are no correlated predictors (Eq. 2), in the NF model (Eq. 3), the concurrent climate variables are correlated ($r = -0.52$). Note that all the models for NF with lower AIC include precipitation and summer temperatures (Table 2). Moreover, the coefficients of the model are statistically significant ($pvalue \leq 0.05$). This means that precipitation and summer temperatures are very important for NF, and omitting one of these two variables, may lead to attributing too much importance to the included one. Ultimately, these variables could presumably be considered as proxies for the climatic factors that affect fuel dryness.

Since the climatic variables used in the empirical model are regional averages of standardized (dimensionless) series, the quantitative values given in Eqs. 2 and 3 provide estimates of the relative importance of the different predictors. In the data set considered here, for NF the antecedent and concurrent climate variables have similar weights, while a reasonable expectation is that concurrent climate conditions are more important. This result should thus be checked on other, possibly longer, data sets than that considered here.

Finally, the explained variance for the $\log(\text{BA})$ model is 0.76, indicating that this parsimonious model shows skill in reproducing the observed BA. The model for the number of fires (including the time t , in years, as a separate regressor) shows even better performance, with R^2 equal to 0.91. Also when considering the detrended NF, the chosen model (now with no time dependence) displays high skill ($R^2 = 0.83$), confirming that a simple linear regression model is able to explain at least some of the main processes determining the effects of climate variability on the number of fires in Catalonia.

3.3 Out-of-sample prediction of summer fires

An important test of the models described in the previous section is to verify their ability to perform out-of-sample prediction, i.e. to forecast BA or NF fluctuations

from the knowledge of climatic data outside the period used to train the model. Out-of-sample prediction involves determining the model parameters on one subset of the data (training set), and validating the prediction on the other subset (testing set). Here a cross-validation method is applied (von Storch and Zwiers 1999), in which a moving window of five consecutive years, without overlapping periods, is used as the validation data and the remaining observations as the training data. For example, the first test period lasts from 1983 to 1987 and the empirical model is calibrated in the period 1988–2007; the second test period goes from 1988 to 1992 and the model is trained on the remaining 20 years of data, and so on. Consequently, a total of five test periods is available.

Obviously, a good out-of-sample prediction is more difficult to obtain than pure hindcast (reproduction), especially when the calibration period is not very long. To estimate the uncertainty of the prediction we followed the methodology proposed by Calmanti et al. (2007). The practical implementation of this method is summarized in the following steps:

1. The variance of the residuals in the calibration period is estimated;
2. Then, an ensemble of 1000 Gaussian, temporally uncorrelated stochastic residual time series are generated, with variance equal to that estimated from the calibration period;
3. Finally, the stochastic residuals are added to the predicted model values, generating an ensemble of 1000 predictions which include the residual stochasticity.

Figure 3a and b show the BA and NF data together with the median of the ensemble of 1000 realizations and the uncertainty bands, defined by the 2.5th and the 97.5th percentiles of the ensemble of the 1000 out-of-sample predictions.

The correlations of the out-of-sample predictions with the data, $r = 0.73$ for BA and $r = 0.83$ for NF, indicate good model skill also in prediction mode. However, Fig. 3a reveals a large uncertainty of model results during the summers which had a large burned area. The performance of the model is much better for the number

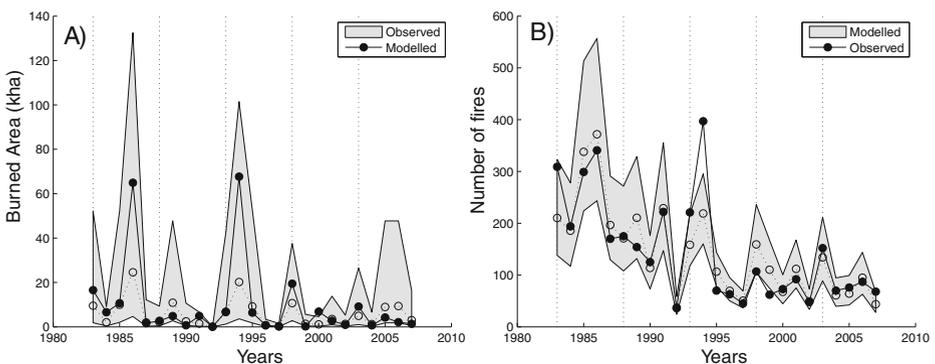


Fig. 3 Out-sample prediction for (a) BA and for (b) NF. The *continuous line with solid circles* represents the observed data. The *dotted line with empty circles* is the median of 1000 different out-of-sample predictions; the *dashed band* include 95% of the members of the ensemble of out-of-sample predictions. *Vertical dotted lines* show the edges of the 5 test periods considered

of fires, Fig. 3b. For NF, only the exceptional summer of 1994 is far outside the uncertainty bars. These results confirm that these simple regression models have predictive ability for summer fires in Catalonia. Besides, the results of our out-of-sample test suggest that climate-vegetation-fire relationships have been substantially stable over the last 25 years. For instance, we can disregard substantial changes in fuel and fire dynamics by invasive species. Indeed, Pino et al. (2005) indicates that the mean percentage of alien plant invasion in Catalonia is less than 7%, less than the average in Spain (around 13%) and in other areas of Europe (e.g. 47% in U.K.).

4 Discussion and Conclusions

The goal of this study was to analyse the relationships between the interannual variability of climate and summer fires in a typical Mediterranean region. To this end, we focused on Catalonia, a northwestern Mediterranean region, and we used the fire data and the Catalonia subset of the *Spain02* data for precipitation and temperature in the period 1983–2007. The results of this study indicate that the interannual variability of fires in Catalonia is significantly correlated with the concurrent climatic conditions during the summer and with antecedent climatic conditions. In detail, the Number of Fires and the Burned Area are significantly correlated with summer maximum temperature and precipitation for the same year (proxies for the climatic factors that affect the dryness of the fuel) and with temperature and precipitation with a time delay of two years (proxies for the climatic factors that influence the fuel structure). Besides, also the minimum temperature of winter / spring before the fire season seems to play a role in increasing the fuel amount. Note that a positive correlation between precipitation and fires with a time delay of two years was also found by Pausas (2004), who analyzed the changes in fires and climate in the eastern Iberian Peninsula, immediately south of Catalonia.

These results suggest the importance of climate not only in regulating fuel flammability, but also fuel structure. Specifically, some period of drought is presumably needed to have a sufficient amount of biomass available for burning (fuel load) in a wildfire. The so called "Mediterranean scrub", characterized by relatively high abundance of fine fuels, needs short periods to dry sufficiently. Indeed fine fuels respond quickly, while coarse fuels may take weeks or months of arid conditions to dry. Besides, fine fuels generally have a rather high proportion of annual vs. perennial vegetation, i.e. high amount of dead fuel, that dry rapidly. Regarding this point, our results suggest that low temperature or frost, especially late ones, may play a role in increasing the amount of fuel in the following summer. In addition to these direct effects, climate may influence the abundance, continuity, and type (fine vs. coarse) of fuels. As for fuel drying, the importance of antecedent climate could depend on climate and vegetation of the region. The lag time of two years detected in this study suggests that the increased production is probably linked to the fine leaves and stems of the existing vegetation. This fine live material is very important for rapid fire growth, especially when its water content is low (many tons/m of fine vegetation with low water content). In addition, the Mediterranean ecosystem is dry enough to have patchy fuels. In these regions, antecedent climate favours fuel gaps to be filled within the landscape with the results of an increase of abundance and continuity of fuel load.

In this study we also built a data-driven, empirical linear model that links the fire activity to the climatic variables. A simple regression model, based on these variables, explains 76% of the variance of $\log(\text{BA})$ and 91% of the variance of $\log(\text{NF})$. We show that a parsimonious model can be used to produce out-of-sample predictions of BA and NF. Note, also, that the interpretation and application of this model are made easier by the use of simple variables. Although it is possible and appropriate to nest the fire model developed here into regional climate scenarios, the simplicity of the model and the complex relationships linking climate, human activities, vegetation and fires presumably hamper its applicability to conditions that are much different from the current ones. As an extreme example, this model cannot be applied in case of desertification.

The fact that NF is related to climate seems counter-intuitive since in this area most fires were ignited by people. But while people influence the probability of potential ignition, climate controls the conditions which can be conducive to the ease of ignition and to fire spreading. In particular, ignition depends on the fine fuel moisture and (live and death) fuel load. Likewise the initial spread depends on the presence of dead fuel or of very fine living material in unfavourable conditions, as well as on rain conditions. Thus, even for the same number of potential ignitions, unfavourable fire years lead to a lower number of successful ignitions. The opposite could happen during favourable years. This may also be related to the fact that the NF model explains more variance than the BA model. Indeed, as a result of the skewed distribution of BA, most of the burned area is due to a few large fires, which dynamics could be influenced by several factors. Possibly, for extreme seasons, there are nonlinear mechanisms by which, above a certain level of favourable conditions, fires can propagate out of proportion.

Understanding the main drivers of the interannual variability of fire, at regional scale, is important not only to better understand fires and predict their change, but also to provide new insights for the management implications. Indeed the hypothesis that in Catalonia both moisture and fuel can have some role in shaping fire regimes (i.e. type 3 ecosystems; Meyn et al. 2007), suggests that fire suppression might increase the chance of large fires since the extinction of all reported fires can lead to higher fuel loads, and only one more prerequisite is then necessary, i.e. low fuel moisture. Despite the long cohabitation of humans and fires (Pausas and Keeley 2009), our fire management capacities remain limited and may be more complex in the future (Bowman et al. 2009; Flannigan et al. 2000) owing to climate, vegetation and fire regime changes.

In the future, it is expected that a warmer and drier climate can affect wildfire activity not only by leading to more favourable conditions for burning, but also modifying the structure of the fuel (availability and continuity) to be burned. In addition, other drivers and feedbacks could become relevant. Unfortunately, to realistically simulate the complex interactions existing between climate, vegetation, humans and fire regime changes remains a challenge (Mouillot et al. 2002; Bowman et al. 2009; Macias Fauria et al. 2011; Hessler 2011).

Acknowledgements This work was supported by esTcena project (Exp. 200800050084078), a strategic action from Plan Nacional de I+D+i 2008-2011 funded by Spanish Ministry of Medio Ambiente y Medio Rural y Marino. The authors thank AEMET and UC for the data provided for this work (*Spain02* gridded precipitation data set) and the Forest Fire Prevention Service of

“Generalitat de Catalunya” (SPIF) for the fire data. Special thanks to Xavier Castro, Antoni Tudela and Esteve Canyameras from SPIF for the helpful discussions on the matter.

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