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How a new fire-suppression policy can abruptly reshape the fire-weather relationship

J. Ruffault[1,2,3,†] and F. Mouillot[1]

[1]CEFE UMR 5175, CNRS-Université de Montpellier–Université Paul-Valéry Montpellier–EPHE-IRD, F-34293, Montpellier cedex 5, France
[2]CEREGE UMR 7330, CNRS/Aix-Marseille Université, Europole de l'Arbois, BP 8013545, Aix-en-Provence cedex 4, France
[3]Irstea, UR EMAX Ecosystémes méditerranéens et risques, 3275 route Cézanne, CS 40061, 13182 Aix-en-Provence cedex 5, France

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Abstract. Understanding how the interactions between anthropogenic and biophysical factors control fire regimes is increasingly becoming a major concern in a context of climate, economic and social changes. On a short time scale, fire activity is mainly driven by the variations in weather conditions. But while the assessment of this fire-weather relationship is an essential step towards fire hazard estimations, reconstructions or projections, still little is known about the impact of human practices on this relationship. In this study, we examined the recent fire history in southern France where a new fire policy, introduced during the 1980s, suddenly brought new fire suppression and prevention practices. We aimed at assessing the impact of these changes on fire activity and on the relationships between fire and weather, usually assumed to be constant over time. To do so, we used a statistical framework based on spatially explicit daily fire occurrence data, the corresponding weather variables and the associated fuel moisture derived from a process-based model. Our results showed that the introduction of the new fire policy resulted in a sharp decrease in fire activity but also impacted the daily fire-weather relationship in two main ways. On the one hand, fewer wildfires ignited for similar weather conditions. On the other hand, the probability of a fire to spread over significant surfaces shifted from a fuel-dryness driven system to a system driven by the concomitance of fuel dryness and strong winds. These observations suggest that mid-term (decadal) social factors can affect the short-term (seasonal to daily) relationship between weather conditions and fire activity. Thus, the interactions between human and climate factors should be taken into account when reconstructing or projecting fire activity and including the impact of fire policies on the fire-weather relationships in fire models would be an important step towards more realistic fire regimes simulations.

Key words: abrupt changes; fire regime changes; fire-suppression policy; fire weather; global changes; large fires; Mediterranean ecosystems.

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† **E-mail:** julien.ruff@gmail.com

Introduction

Wildfire is a widespread and critical process in the earth system, shaping ecosystems structure and functioning (Bond and Keeley 2005, Pausas and Keeley 2009), influencing biogeochemical cycles (Körner 2003, Van der Werf et al. 2010) and threatening human lives and structures (Chuvieco et al. 2014). Understanding how the interactions between anthropogenic and biophysical factors influence fire regimes appears as a major concern in a context of ongoing human and climate changes (Bowman et al. 2011, Pausas and Keeley 2014).

The occurrence of fires at the landscape scale is controlled by three requirements: (1) an ignition, (2) biomass resources available for burning and (3) atmospheric conditions conducive to combustion (Pyne et al. 1996, Moritz et al. 2005). But beyond this relatively simple physical process, the probability of fire occurrence and the final size of a fire patch are the result of numerous biotic and abiotic factors operating at different scales (Moritz et al. 2005). Thus, once an ignition has occurred, fire start (i.e., when an ignition turn into a wildfire) is mainly driven by the biophysical factors affecting fuel flammability. Then fire spread (i.e., fire that becomes greater in size) is mostly determined by wind conditions, available fuel and its water status. Climate therefore dictates the distribution and quantity of flammable vegetation to burn but also fire activity through its control on the variations in weather conditions and fuel moisture (Swetnam and Betancourt 1990, Krawchuk and Moritz 2011). Within this framework, humans affect both the probability of fire start and spread by three main ways: by starting and preventing ignitions, by actively fighting fire spread and on a long-term basis by modifying fuel structure/load spatial patterns.

In several biomes worldwide, daily to annual variations in fire activity are mainly dependent on weather conditions and their time lag effect on fuel moisture conditions. Several semi-physical or empirical models (Pausas 2004, Flannigan et al. 2005, Pereira et al. 2005, Balshi et al. 2009, Thonicke et al. 2010) have therefore been developed to identify the "fire weather", defined as the weather conditions that influence fire ignition, behavior and suppression (sensu Moreira et al. 2011). But using such relations for fire hazard prevention, historical reconstructions and future projections implies that the relationship between the meteorological variables and fire risk is constant over time and space. Yet, several studies showed that vegetation (Littell et al. 2009, Pausas and Paula 2012, Lehman et al. 2014, Wang et al. 2014), or human practices (Archibald et al. 2010, Parks et al. 2012) have an impact on the spatial characteristics of the fire-weather relationship. But few studies investigated how the fire-weather relationships might change over time (Bowman et al. 2011, Moreira et al. 2011).

Among human practices acknowledged to alter fire regimes, fire-suppression has been suggested as one of the most influential factor explaining the reduction of total burned area along the 20th century (Mouillot and Field 2005, Marlon et al. 2008, Pechony and Shindell 2010). Although their efficiency has been debated (Keeley et al. 1999, Piñol et al. 2005), there are some evidences that the introduction of enhanced fire-suppression policies (early intervention, fire lighting prevention and fuel management) reduced the number, severity and size of fires in regions where large and infrequent fires dominate (Cumming 2005, Mouillot and Field 2005, DeWilde and Chapin 2007). Several studies suggested that fire-suppression practices acted by reducing the probability that a fire spread over significant surfaces (Cumming 2005, Podur and Martell 2007, Podur and Wotton 2011). Following this assertion, Wang et al. (2014) showed that some bottom-up factors (vegetation composition and cover, ignition patterns, human suppression) could modify the ratio between realized spread days (i.e., day with observed large fires) and potential fire spreads day (i.e., days which corresponds to hot, dry, and windy conditions and which are more likely to result in non-negligible fire spread). These findings, as well as the regional to national spatial heterogeneity in the drivers of fire regimes in different areas worldwide suggest that changes in fire-suppression practices may also have an impact on which and how biophysical factors control fire activity. But so far, few studies, if any, investigated the impact of changes in fire management and suppression policies on the relative importance of biophysical factors controlling fire occurrence and spread. We might point here the lack of case studies where fire suppression has been thoroughly and efficiently applied and the lack of long-term daily fire statistics, or to the fact that fire-suppression changes generally occur concomitantly with land cover and/or climate changes that prevent from disentangling each effect independently.

Southern France, where a rigorous fire prevention and suppression program was launched in 1987 (Alexandrian 2008, Fox et al. 2015), provides a relevant study case to test the impact of changes in fire-suppression practices on the fire-weather relationships. Unlike its neighboring southern European countries where fire activity has increased in the last half of the 20th century due to land abandonment and/or climate change (Pausas 2004, Koutsias et al. 2012, Pausas and Fernández-Muñoz 2012), fire activity largely decreased in southern France in the recent decades (Alexandrian 2008). We developed a statistical framework to analyze the response of fire occurrence probabilities to different keystone climatic variables (air temperature, air humidity, wind speed) and fuel moisture of litter and vegetation derived from a process-based water budget model. Then, we used national fire statistics covering the 1973–2006 period (almost 15 years before and after 1987) to test for any abrupt shift in the fire activity and the daily fire-weather relationship and to investigate the concomitance of these changes with the introduction of the new fire-suppression policy.

Materials and Methods

Study area

The study area covers 4 French administrative districts (called "départements;" 21,637 km^2) located in Southern France and delimited by the Pyrenees Mountains in the South, the Massif Central foothills in the North and the Mediterranean coastline (Fig. 1A, B). In this area, climate is Mediterranean; winters are cool and wet while a high evaporative demand along with low rainfall amounts are responsible for a prolonged water deficit in summer (58 days $\pm$ 29 days; Ruffault et al. 2013). Over the region, a rainfall gradient is closely related to topography and ranges from 600 mm on the coast (elevation = 0 m) up to 1630 mm in the Massif Central foothills (elevation = 1450 m). Forest type known as "garrigues" cover 65% of the region and is dominated by Mediterranean evergreen tree species (*Quercus ilex*, *Pinus halepensis*) and shrublands (*Cistus monspeliensis*, *Quercus coccifera*). Agricultural areas (mainly vineyards) cover 28% of the landscape and are mostly distributed in the major floodplains. Urban areas cover the remaining 7% and mostly distributed on the coast (French national geographic database; BDTOPO 2006).

Frequent but relatively small fires characterize the current fire regime (more than 80% of fires are smaller than 5 ha). Only a handful (1%) of large fires (larger than 100 ha) are responsible for more than 60% of burnt area (Alexandrian 2008). Fire duration is very short in the mediterranean eurozone; over the period 2007–2009, more than 80% of fires lasted less than 3 hours and 100% of forest fires did not last more than a day (DaCamara et al. 2014). As in the other southern European countries (see Moreira et al. 2011), humans are responsible for most of fire ignitions (97% during the 1973–2006 period; www.promethee.com).

Over the last 40 years, fire-practices in Southern France can be split into two distinct periods as a result of the introduction of a new fire policy in 1987. This new fire policy was set up in response to a couple of years of extensive fire events at the national level (Viret and Queyla 2004). This new fire prevention and suppression strategy was based on the anticipation and massive attack of incipient fires in order to "intervene in less than 10 minutes" with faster call-to-site reactivity and better communication tools during surveillance and fire fighting. The Conservatory of Mediterranean Forests (CFM) was created as the operative structure gathering fire prevention and suppression management actions in southern France. Fox et al. (2015) thoroughly discussed the adopted official strategy and the associated technical and strategic measures that occurred in southeastern France. At the regional level, an annual budget of 15M€ was used for several fire suppression and prevention efforts, including prescribed fires, fuel management, increased human resources with better equipments and the design of a network of forest paths for better accessibility. This date also initiated the start of anticipated procedures based on daily meteorological thresholds in order to early deploy and warn fire-fighting forces (Alexandrian and Esnault 1999). These main decisions were followed by interdictions of public access to forests during periods of high fire risk.

Forest fire dataset

Fire data were extracted from the PROMETHEE fire database (available on line at www.promethee.com). This database covers southern France and has been managed by the French forest services since 1973. The PROMETHEE fire database is based on the information observed by firefighters in the field. It distinguishes forest fires from urban and crop fires and provides for

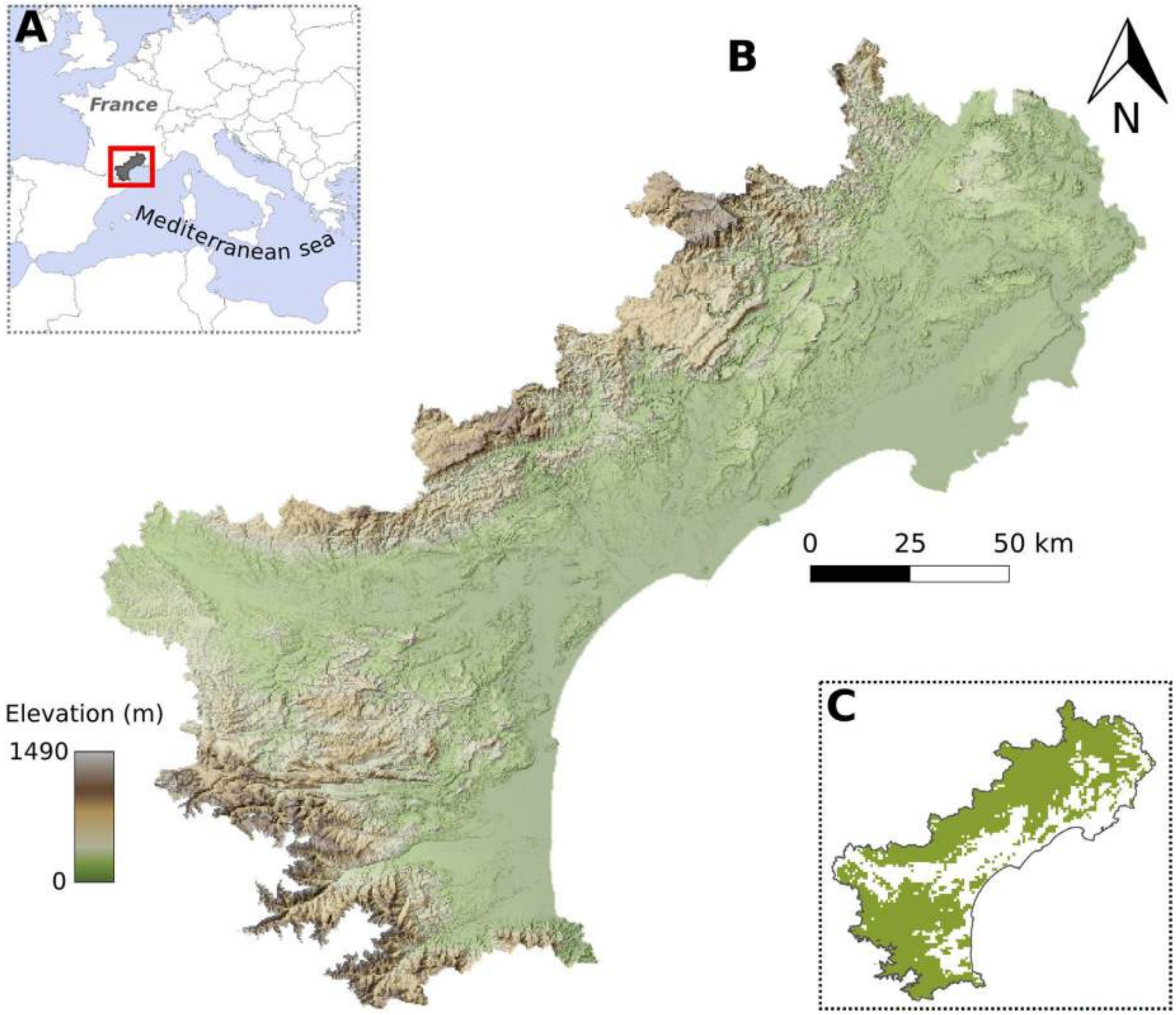

Fig. 1. Location (A) and digital elevation model (B) of the Mediterranean studied region. The small panel on the bottom right (C) indicates the areas whose natural vegetation cover is higher than 50% and selected for this study.

each registered fire, its date, surface and location of ignition on a 2 × 2 km administrative grid system (DFCI reference grid). To avoid any biases arising from the potential growing consideration of smaller fires in fire number estimates during recent time, we carefully checked for the minimum fire size reported by fire authorities over the study period (see Appendix: Fig A1). A breakpoint was detected in 1992, the date before which fires under 0.1 ha were not reported. All statistical analyses were therefore performed on a filtered datasets in which all fires under 0.1 ha were removed. The final dataset consisted of 10,830 fires for the period 1973–2006. Each fire was classified into one or more of seven classes of resulting burned area: >0 ha, >1 ha, > 6 ha, >10 ha, >15 ha, > 30 ha and > 50 ha. We will note here that a fire spreading over an area larger than 50 ha therefore belongs to the last class (>50 ha) but also to the 7 previous ones. The presence or absence of fire in each voxel (i.e., for each day in each DFCI grid cell) was then described as a binary response variable.

Recent studies brought up suspicion and doubts on national fire statistics by pointing out some inaccuracies in reported burnt areas and/or fire counts as well as inconstancies along time and space (Goforth and Minnich 2007, Turco et al. 2013) that could affect the results of our analyses. It should be noted here that it has been the main purpose of the PROMETHEE structure to provide temporal and spatial homogeneous fire data since its creation in 1973. Besides, Husson (1985) evaluated the French national PROMETHEE fire dataset by comparing LANDSAT images with reported burned area over the 1973–1980 period. Despite an overall good agreement, he identified three main type of errors in the PROMETHEE database: (1) small fires were often rounded in 5 ha steps, (2) an overestimation of the area of the largest fires up to two times, (3) some small fires were not reported. We used fire size classes rather than raw burnt area reports to reduce the uncertainty related to these errors.

Modelling framework for assessing the daily fire-weather relationship

To examine the daily fire-weather relationship, we used a spatio-temporal framework based on the statistical association between historical fire events, the daily variations in weather conditions (weather variables) and the time-lag effect of weather on fuel moisture content (through the use of functional drought indices). The region was divided into three-dimensional space–time samples, called voxels. Spatial partitioning followed the administrative grid system of 4 km^2 (DFCI grid; see previous section) devised by the French fire and forest management agency over the French territory. Each DFCI grid cell in the study region was considered as the spatial sampling unit. In order to avoid any effect resulting from the lack of fuel load and connectivity on fire spread possibilities in heterogeneous landscapes, grid cells with less than 50% of natural vegetation cover were discarded from our study. The resulting spatial extent of our study consisted of 3540 grid cells (Fig. 1C). Our study was carried out on the 1973–2006 period. Daily meteorological data, fuel moisture indices and fire data were collected for each grid cell for this period and summarized for each day thereby providing the daily temporal dimension of the voxel.

Fire weather was estimated through the use of a few selected factors acknowledged to control fire start and spread probabilities in forested ecosystems (Chandler et al. 1983): temperature (T_{emp}), wind speed (W_S), air relative humidity (H_R) and fuel moisture content (FMC). To represent the differential effect of different fuel compartments on fire behavior, we used two different indices to estimate the moisture of dead vegetation and litter fuel on the one hand (Superficial drought; D_S) and to the moisture of living fuel on the other (Vegetation drought; D_V). These two indices take into account the non-linear response of vegetation to weather in water-limited ecosystems by accounting for an integrated view of precipitation, potential evapotranspiration and the capacity of plants to extract water in soils (Stephenson, 1990, Ruffault et al. 2013). They were estimated by using a process-based water balance model. Then, to predict the probability of fire occurrence within each voxel, we used a machine-learning algorithm, boosted regression trees (BRT) using weather and fuel variables as explanatory variables and fire occurrence as the response variable. More details about the data, the water balance model and the BRT statistical models are presented in the next sections.

Weather data.—Daily weather variables were derived from the 8×8 km grid SAFRAN climatic database (CNRM France; Habets et al. 2008). The SAFRAN database is derived from the interpolation of daily measured weather ground data and has been validated over France (Quintana-Seguí et al. 2008). Daily precipitation (Ppt), temperature (T_{emp}), global radiation (R_G), wind speed (W_S) and specific air humidity (H_S) were extracted for the 1973–2006 period. Weather conditions exhibit a strong spatial heterogeneity in the study area (Ruffault et al. 2013). Daily weather variables were therefore re-interpolated to match the lower spatial resolution adopted for our analyses (4 km^2; DFCI grid) using the following procedure validated over the region by Ruffault et al. (2014). Given the dependency of Ppt and T_{emp} to elevation in the study area, these two variables were downscaled using a thin plate spline interpolation procedure implemented in the packages "fields" and 'raster' in R (R Core Team, 2012). Daily R_G, W_S and H_S were resampled at 4 km^2 by the inverse distance weighting method. Relative humidity (H_R) was then computed from interpolated values of T_{emp} and H_S. See details in the supplementary materials of Ruffault et al. (2014).

Estimations of fuel moisture content.—Two proxies of fuel moisture content (FMC) were derived from a daily process-based water budget model developed to run at a 1 km^2 spatial resolution and validated in forest stands over southern France by Ruffault et al. (2013). In this model, variations in soil water content (SWC) are simulated on a daily time step using the water balance between precipitations (P) and water outputs

$$\Delta SWC = P - In - D - E - T \tag{1}$$

where the amount of precipitation intercepted by the canopy (In), the soil evaporation (E), the transpiration of vegetation (T) and the drainage (D) are all expressed in mm. Soil is represented by a 3-layer bucket model. For each grid-point, the model inputs consist of species functional parameters, soil features and daily weather variables: precipitation, temperature and global solar radiation. Potential evapotranspiration (PET) is computed using the Priestley–Taylor equation. Then T is expressed as a function of PET modulated by LAI and canopy conductance through daily simulations of soil water potential (Ψ_{soil}). Ψ_{soil} is related to soil water content (SWC) by the power function model for the retention curve (Campbell 1974). Water balance estimations were computed for a single plant functional type (PFT) representative of the woody evergreen deep-rooted species (trees and large shrubs) encountered in our study area (see details in Ruffault et al. 2013). In order to estimate LAI of the vegetation, the water balance model was coupled with a carbon assimilation and allocation model (Mouillot et al. 2001). We then used a spin-up procedure over the 1973–2006 period to compute a theoretical LAI in equilibrium with site-specific water stress according to the ecohydrological equilibrium theory (see details in Ruffault et al. 2013). For all simulations, we used the LAI estimated over the 1973–2006 period; therefore, we did not consider changes in vegetation type and distribution over time. Soil parameters (texture, rock fragment content and soil depth) were extracted from the regional DONESOL database (1/250000; INRA; Gaultier et al. 1993).

Superficial drought (S_D) used as a proxy of the litter and herbaceous layer moisture content was computed from daily simulations of soil water content, and expressed as the ratio between the actual soil water content of the first soil layer (θ, 0–20 cm) and the soil water content of this same layer at field capacity (θ_{fc})

$$D_S = 1 - \max(1, \theta/\theta_{fc}). \tag{2}$$

Vegetation drought (D_V), used as a proxy for plant moisture content was related to the soil water content across the whole root profile and plant water extraction capacity. This index was estimated as the ratio between actual evapotranspiration (AET) and maximum transpiration (ET_{max}; transpiration without water stress) as follows:

$$D_V = 1 - (AET/ET_{max}). \tag{3}$$

These two indices vary between 0 for no drought stress to 1 for absolute dry conditions.

Logistic regression models.—We used a machine-learning algorithm, boosted regression trees (BRT; De'ath 2007, Elith et al. 2008) to predict the probability of fire occurrence within each voxel. BRT uses the iterative partitioning approach of regression trees, but reduces predictive error by "boosting" initial models with additional, sequential trees that model the residuals in randomized subsets of the data (De'ath 2007, Elith et al. 2008). This makes them particularly suitable when the nature of the process is presumed to be complex and when an emphasis is on accurate predictions and a transparent interpretability of output in describing relationships between dependent and independent variables (De'ath 2007, Elith et al. 2008).

BRT models need information about presences and absences of fire to determine the weather and fuel conditions that are more likely to result in a fire. As the natural prevalence of "presence voxels" was very low in the study area, a reduced number of random "absence voxels" were selected for model fitting. For a better comparability between models performed for different fire size and periods, prevalence (the proportion of presence voxels) were equaled among models and set to 0.1. The learning rate or shrinkage parameter (lr), the tree complexity (tc) and the number of trees (nt) are the main parameters of BRT models and were set according the procedure recommended by Elith et al. (2008). For all models, a bag fraction of 0.5 was used meaning that, at each step, 50% of the data were randomly drawn from the training dataset. According to preliminary analyses, we set the ts to 4. As the number of sample could subsequently vary between models, we then determined the lr to a value that resulted in an average test error being minimized between approximately 1000 and 2000 trees (Elith et al. 2008). BRT models, like many other statistical approaches, are vulnerable to model overfitting when input variables are highly correlated (Olden et al. 2008). For each model, any correlation among input variables was evaluated in a cross-correlation matrix (Spearman ρ). As the explanatory variables were not strongly correlated ($\rho < 0.55$), all variables were kept for all models.

We used the area under the receiver operating characteristics (ROC) curve (AUC) to evaluate models suitability. For each model, 70% of the observations were randomly selected from the complete dataset to build the statistical model (training dataset). The remaining observations (30%) were used to evaluate the accuracy of model classification (validation dataset). We also reported the commission error (false positive rate) and omission error (false negative rate) at the probability threshold that maximizes the sum of sensitivity and specificity values. BRT models were computed in R (R Core Team 2012) with the gbm package (Ridgeway 2006) and custom functions created by Elith et al. (2008). All BRT models were computed using a Bernoulli (logistic) error structure. To limit the stochasticity in model outcomes caused by the subsampling and the bagging, we created an ensemble of 25 BRT models and then averaged the results.

We interpreted the BRT models by first looking at the relative contribution of the variables to the predictive models. This contribution of the different predictors was estimated from the sum of squared improvements associated with this variable and averaged across all trees in the boosted models (De'ath 2007, Elith et al. 2008). We also examined the relative influence of each variable by plotting the partial dependencies of responses to individual predictor (De'ath 2007, Elith et al. 2008). The partial dependence represents the estimated marginal effect of an exploratory variable on the fire occurrence prediction when the responses of all other variables are held constant at their mean.

Analyses of historical changes in fire activity and in the fire-weather relationship

Historical changes in fire activity.—We studied the historical fire activity over the 1973–2006 period by focusing on three components of the fire regime: annual burnt area (BA), number of ignitions (NI) and number of large fires (fires >15 ha; NL). Based on preliminary results, this 15 ha threshold was selected as the fire size that can be used to discriminate the weather and fuel conditions favoring fire start from those favoring fire spread (see results and discussion sections). For each of these variables (BA, NI and NL), we tested for any significant shifts and their timing over the 1973–2006 period. As errors in shift detection are more likely to arise when data are relatively short (less than 40 time steps) or when shifts are situated at the extreme of the time series (see Andersen et al. 2009), two statistical tests were used. (1) We computed an *F* statistic for every potential breaking point (sequential *F*-test) and then used the *supF* statistic used to test their significance. (2) We also used the empirical fluctuation processes tested by the cumulative sums of scaled residuals (OLS-based CUSUM test). These methods have been successfully used for time series analysis of fire and ecological data (Andersen et al. 2009, Pausas and Fernández-Muñoz 2011, Loepfe et al. 2012). In this study, we considered shifts to be significant when p-values were lower than 0.05 for both tests and compared the results of these tests to determine the timing of the shift. These two tests were computed with R (R Core Team 2012) with the strucchange package (Zeileis et al. 2003).

Temporal variations in the fire-weather relationship.—A two-step approach was developed to investigate how weather conditions control the spatial and temporal variations in fire start and spread probabilities and to assess how the introduction of the new fire policy might have affected these relationships.

(1) In a first step, we investigated how weather variables and drought indices influence fire occurrence by looking at the relative contribution of the variables to the predictive models as well as the partial dependencies of responses to each individual predictor. As weather conditions controlling fire start might differ from those that control fire spread, this process was performed for the seven classes of final fire size (see *Forest*

fire dataset). Similarly, as we hypothesized that fire-suppression practices could have an impact on the fire-weather relationship, we explore the fire-weather relationship for two distinctive periods: before and after the introduction of the new fire-suppression policy in 1987.

(2) In a second step, we performed a trend analysis to ensure that the changes in the fire-weather relationship we observed (see results and discussion) followed an abrupt breakpoint rather than a smooth trend line and were concomitant with the introduction of the new fire policy. For this purpose, we analyzed the interannual variability of the fire-weather relationship over the 1973–2006 period by processing BRT models on 5-year moving windows progressing along the whole time period on a 1-year time step. We then tested for any significant shifts in the contribution of each explanatory variable during the period covering the introduction of the new fire policy using the two statistical time series analysis tools described above (see previous section). This 5-year temporal window was determined as being the best compromise for considering that climate and land cover did not overly change during this period and sufficient fire data for model performance. Based on the results of the first step, we investigated the fire-weather relationship for all fire occurrences (i.e., fire start conditions) and for fires larger than 15 ha (i.e., fire spread conditions).

Results

Historical changes in fire activity

The statistics on fire activity in the study area showed an important interannual variability as well as significant break points for burnt area (sequential *F*-test and CUSUM; $p < 0.05$; Fig. 2A), number of fires ($p < 0.001$; Fig. 2B), and number of large fires ($p < 0.001$; Fig. 2C), all of them concomitantly occurring in 1986 (see Appendix: Fig. B1). A total of 473 ($\pm$ 152) fires per year were recorded for the earlier period (before 1987) but twice as less (203 $\pm$ 79) over the most recent one (post 1986). Similarly, the number of large fires decreased from 71 ($\pm$ 34) to 18 ($\pm$ 14) fires.year^{-1} and burnt area decreased from 65.2 ($\pm$ 59.9) to 18.1 ($\pm$ 22.4) km^2.year^{-1}.

Fire weather conditions

The overall performance of boosted regression trees (BRT) models predicting fire probability reached AUC values higher than 0.78 (Appendix: Fig. C1) with commission and omission errors respectively lower than 30% and 25% (at the probability threshold that maximizes specificity and sensitivity). We will note that the predictive performance of the BRT models was higher for larger fires and for the most recent period.

The relative contribution of the weather variables and drought indices to the probability of fire occurrence showed a fire-size dependent pattern, but whose features substantially differed between the two studied periods (before and after the introduction of the new fire policy; Fig. 3). The drivers influencing the fire start (fires > 0 ha) were similar for both periods. Fire probability was mainly explained by the three following variables: vegetation drought (D_V; about 20%; Fig. 3A), superficial drought ($D_{S;}$ about 23%; Fig. 3B) and relative air humidity ($H_{R;}$ about 35%; Fig. 3C). But as fire size increased, we observed some differential changes in the relative contribution of weather variables and drought indices to fire probabilities whether we considered one period or the other. When considering the earliest period (before 1987), we observed a decrease in H_R contribution (from 35% for fires > 0 ha to 25% for fires >15 ha; Fig. 3C) when increasing fire size, while the contribution of D_V increased from 20% to 28% (Fig. 3A). By contrast, for the most recent period (post 1987), the relative contribution of W_S increased when increasing fire size, from 10% for fires > 0 ha to 30% for fires >15 ha (Fig. 3D) whereas the relative contribution of H_S decreased by 20% (Fig. 3C). We can note here that beyond this 15 ha threshold, the relative contribution of weather variables and drought indices explaining fire probability remained similar. This 15 ha fire size was then considered as a threshold value beyond which weather conditions are suitable for larger fires to occur.

Fig. 4 represents the partial effect of each explanatory variable in BRT models on fire occurrence and spread probabilities and illustrates the large diversity of response pattern depending on the considered variable. For instance, the responses of fire probabilities to fuel moisture proxies (D_S and D_V) were largely a function of threshold values (0.1 for Dv and 0.2

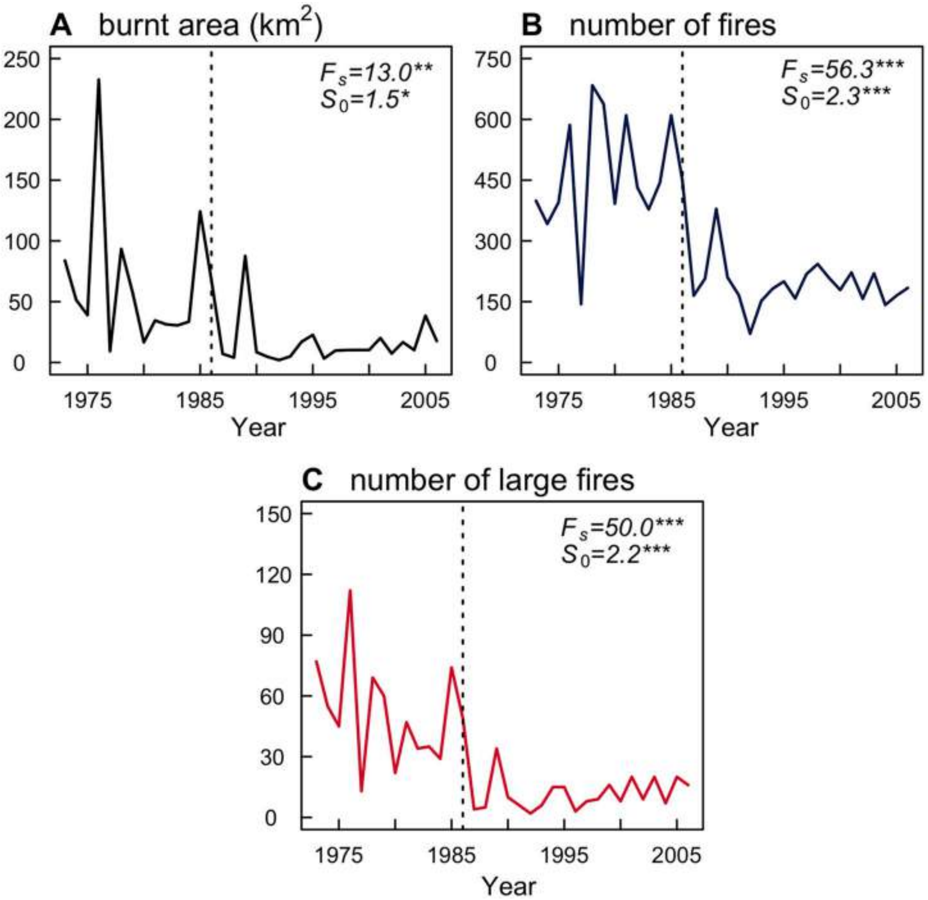

Fig. 2. Temporal variations in annual (A) burnt area, (B) number of fires and (C) number of large fires (>15 ha) in the study area over the 1973–2006 period. The historical changes in fire activity were investigated using two statistical methods: a sequential *F*-test (maximum *F* statistic over the period: F_S) and a OLS-based CUSUM test (statistic: S_0; ns: $P > 00.5$, * $P < 0.05$, ** $P < 0.01$, *** $P < 0.001$). For the three studied variables, both statistical tests indicate that a significant shift in fire activity occurred in 1986 (dotted line, see Appendix: Fig. B1). Two period can therefore be delimited: 1973–1986 and 1987–2006.

for Ds) beyond which fire probabilities were reduced. Above these thresholds, fire probabilities were constant whatever the drought intensity. Decreasing H_R linearly contributed to higher fire risk (Fig. 4C), while the effect of Temp was noteworthy only during the hottest days of the year above a threshold of 25°C (Fig. 4E). All these variables had a quite similar partial effect on fire probability regardless of the fire model under study (fire start or fire spread) and the considered time period. By contrast, the partial effect of W_S on fire probabilities varied over time as we observed a little effect of W_S before 1987 (Fig. 4D, dashed lines) compared to the stronger and quite linear effect on the most recent period (Fig. 4D, full line) until a threshold of 12 m s^{-1}, particularly when considering fire spread probability (Fig. 4D, red lines). The right tails of the relationships may be less reliable, because they are based on a relatively small number of data points.

Temporal shifts in the fire-weather relationship

Based on these previous results that illustrate the contrasting contributions of weather variables to fire probabilities, we computed BRT models on a 5-year average moving window to test whether these changes in the fire-weather

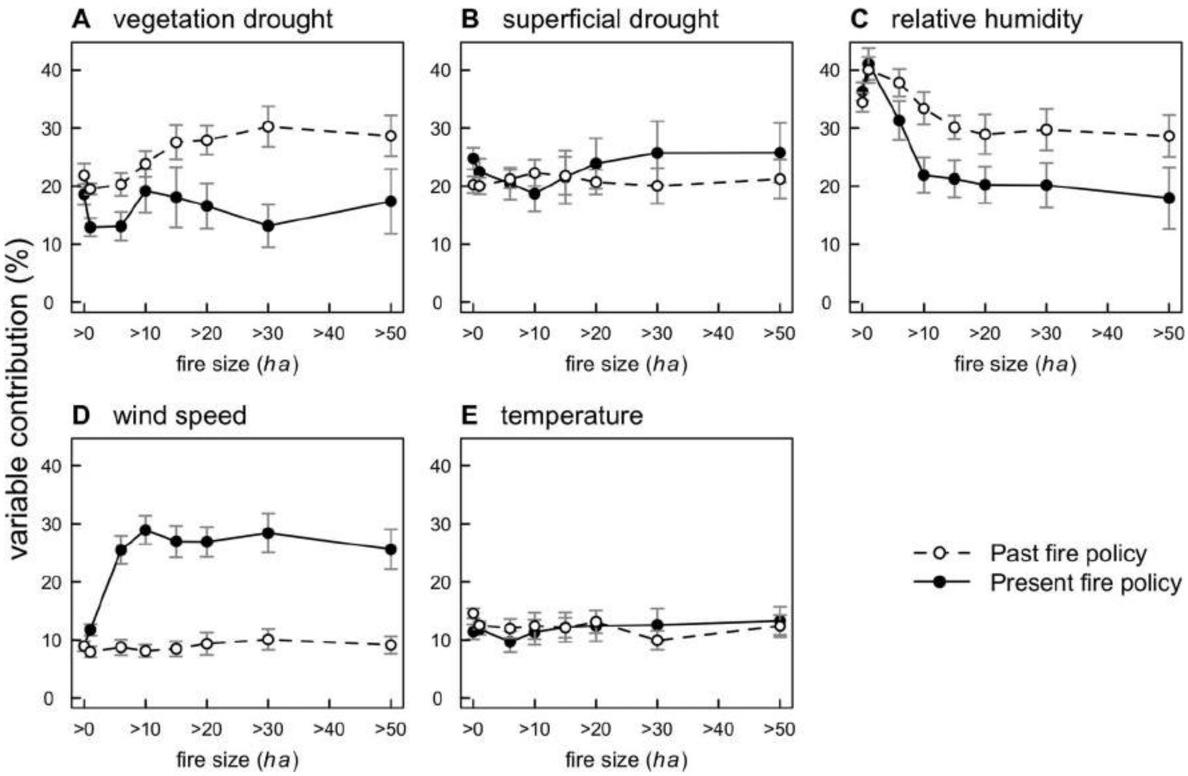

Fig. 3. Relative contribution of explanatory variables in BRT models predicting the probability of fire occurrence for different classes of final fire sizes and for two distinct temporal periods: before and after the introduction of the new fire policy in 1987. Mean and confidence intervals of an ensemble of 25 models are reported. See Appendix: Fig. C1 for results on models performance.

relationship were the results of smooth processes or sharp shifts around 1987. Overall, the performance of the BRT models predicting fire start and spread probabilities over a 5-year average window was good (AUC > 0.79; Appendix: Fig. D1) so no bias was observed on this short time frame compared to the AUC obtained for the whole period. Similarly to previous results (see Appendix: Fig. C1), model performance was higher when predicting fire spread probabilities than fire occurrence (Appendix: Fig. D1, sequential *F*-test and CUSUM; $p < 0.01$ for all fires; $p < 0.001$ for large fires).

The relative contribution of weather variables to the probability of fire start and spread showed a high interannual variability with significant and abrupt changes over the study period, all of them co-occurring during the time frame covering the year 1987 (Fig. 5). Affected variables were different whether fire start or fire spread probabilities were considered. When considering the probability of fire start (fires >0 ha), we observed some break points in the variable contribution of superficial drought (S_D; sequential *F*-test and CUSUM; $p < 0.05$) and temperature (T_{emp}; $p < 0.05$) but only with minor changes in the quantitative contribution of these variables (Fig. 5B, F). When focusing on the factors controlling fire spread (fire >15 ha), we also observed break points in the variable contributions, with an increase for W_S (sequential *F*-test and CUSUM, $p < 0.001$; Fig. 5D), a decrease for R_H ($p < 0.01$; Fig. 5C) and a slight but significant decrease for T_{emp} ($p < 0.05$; Fig. 5E).

Discussion

Changes in fire-suppression practices triggered an abrupt decrease in fire activity

Like most Euro-Mediterranean regions, Southern France has experienced important climatic and socio-economic changes over the last de-

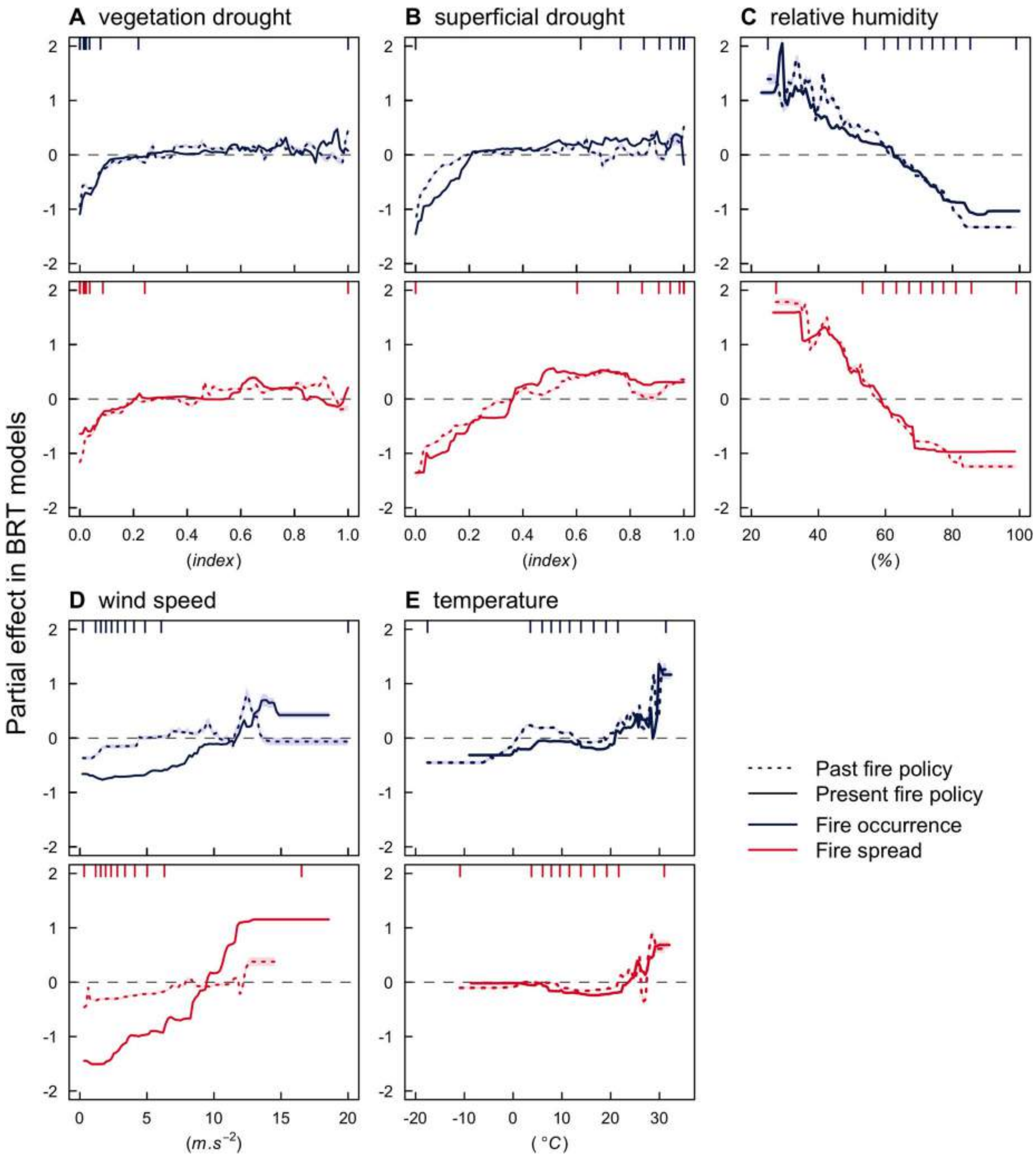

Fig. 4. Comparative estimated partial dependence of explanatory variables in BRT models predicting fire start probabilities (fires > 0 ha) and fire spread probabilities (fires > 15 ha) between two distinct temporal periods: before and after the introduction of the new fire policy in 1987. Partial dependency plots represent the estimated marginal effect of a variable on fire probability when all other variables are held constant. Mean (curve) and confidence intervals (colored areas) of an ensemble of 25 models are reported. Ticks at the inside top of the plots show deciles of distribution across the variable. See Appendix: Fig. C1 for results on models performance

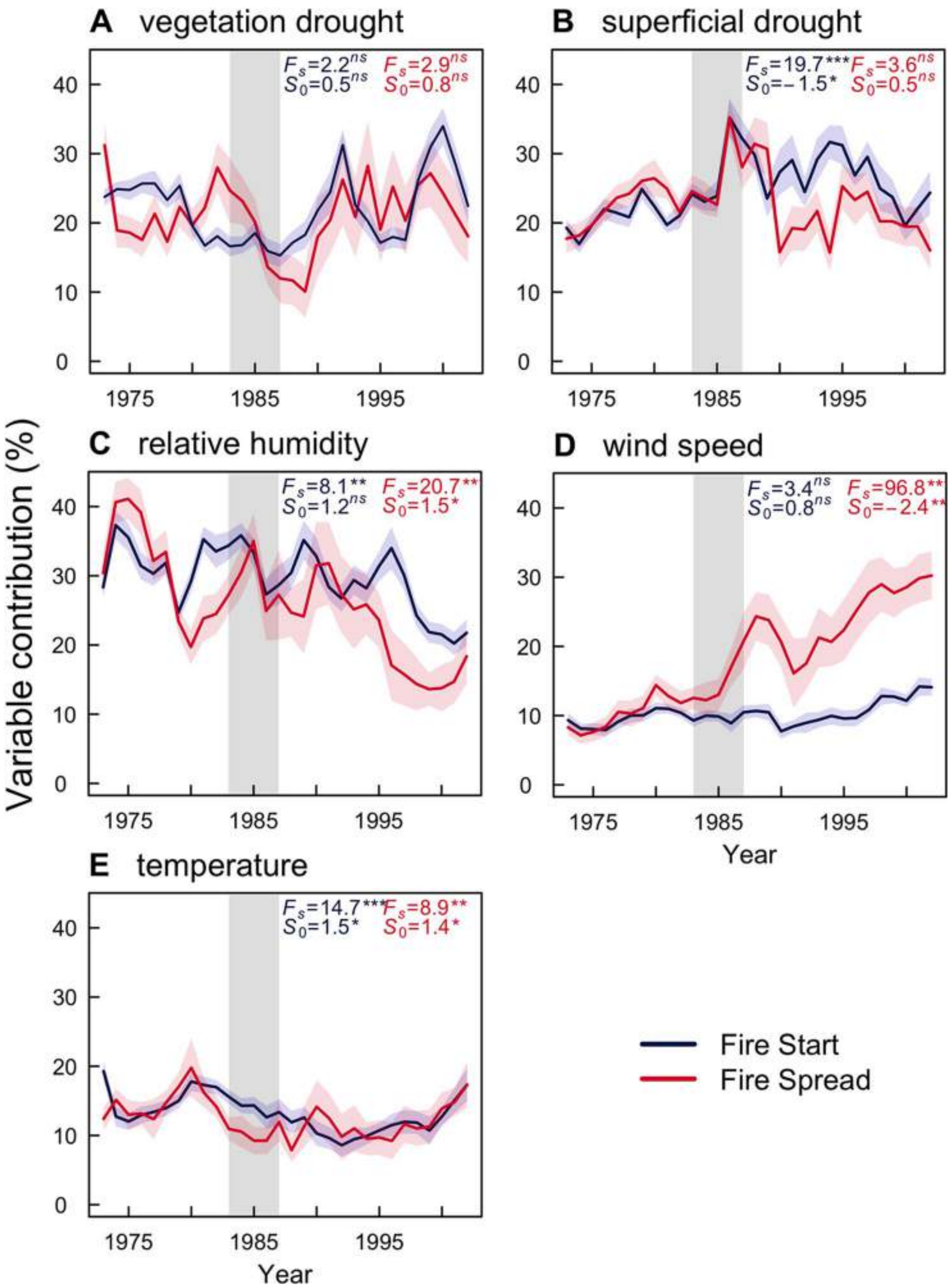

Fig. 5. Temporal variations in the relative contribution of explanatory variables in BRT models predicting fire start probability (fire > 0 ha) and fire spread probabilities (fires > 15 ha). All models were applied on a 5-year moving average window. Mean (curve) and standard deviation (colored area) of an ensemble of 25 models are reported. The grey shaded areas indicate the beginning and the end of the 5-year time period during which the new fire policy was introduced. The historical changes in variable contribution during this period were investigated using two statistical methods: a sequential F-test (maximum F statistic over the period: F_S) and an OLS-based CUSUM test (statistic: S_0; ns: $P > 00.5$, * $P < 0.05$, ** $P < 0.01$, *** $P < 0.001$). See Appendix: Fig. D1 for results on model performance.

cades, with climatic trends towards drier conditions (Ruffault et al. 2013), a smooth and continuous population increase from 1,450 M to 2,650 M inhabitants from 1950 to 2000 (Abrantes et al. 2010) and land cover changes with forest cover replacing vineyards. These human and land cover changes were mostly initiated in the middle of the 20th century (Debussche et al. 1999, Schaab et al. 2000), much earlier than in other most of other Mediterranean countries (Spain, Portugal, Israel and Greece) where most changes occurred in the 1980s (see a review in Moreira et al. 2011). All of these climatic and human changes have been identified as key drivers for increasing fire activity in the Euro-Mediterranean context. Yet, fire activity showed a different pattern in our study area, with a sudden drop around the year 1987 characterized by a reduction in burnt area (BA), the number of fires (NF) and the number of large fires (NL; >15 ha) by a factor of 3.5, 2 and 4 respectively (Fig. 2; Appendix: Fig. B1). The concomitant introduction of the new fire policy (the only identified mechanism potentially leading to decrease fire hazard) is the most plausible factor explaining this shift in fire activity. This hypothesis suggests that the new fire practices (fuel management, prescribed burnings, ignition prevention and firefighting) had a quick and strong efficiency in this region, as already observed in Southeastern France by Fox et al. (2015).

This abrupt shift in fire activity, caused by "a non-climatic factor" (sensu Pausas and Keeley 2014), highlights the importance of fire policies in determining fire regime characteristics on a long-term basis (Marlon et al. 2008, Bowman et al. 2011). In contemporary history, similar scenarios have been observed for regions where fire-suppression practices suddenly changed. In southeastern France, early testimonies indicate a reduction of burnt area by a factor of 2 between 1870 and 1890, consecutive to a new French law for fire prevention (Fisher 1894). In the US, burnt area decreased by a factor of 10 within 2 decades between 1930 and 1950 (Mouillot and Field 2005, Nowacki and Abrams 2008). We will note that in these two examples, the shifts in fire activity were not as sudden as the one we observed in southern France but were obtained with fire fighting tools less efficient than the recent ones. More recently, Salis et al. (2014) reported a similar abrupt decrease in burnt area and number of fires during the 1990s in Italy, which was partly due to the enhancement of suppression capabilities.

Weather conditions controlling fire activity

To predict fire occurrence probability, we used a set of variables describing the instantaneous weather conditions and the mid-term (a few days to weeks) time-lag effect of weather conditions on fuel moisture. These variables performed well for predicting the spatio-temporal variability in fire activity in the Mediterranean forested ecosystems encountered in our study area (Fig. 3; Appendix: Figs. C1, D1). This is coherent with well-documented patterns in fire-conducive weather in Mediterranean ecosystems (Chandler et al. 1983). In addition, the important relative contribution of the vegetation drought and superficial drought indices (D_V and D_S) confirms the premises that litter and dead moisture content (DFMC) facilitate ignition and favor fire spread whereas low moisture content of the living biomass (LFMC) can induce crowning and prevent from an effective and quick suppression (e.g., Viegas et al. 2013).

As recognized by different authors, functional indices are a promising way for a deeper insight in the factors controlling fires as they allow accounting for the complex interactions between weather, soil and vegetation (Thonicke et al. 2001, Mouillot et al. 2002, Pausas and Paula 2012), though further studies should be done to assess the accuracy of such process-based approaches for spatially explicit estimations of fuel moisture content (Pellizzaro et al. 2007). Here, our study area being located at the northern bound of the Mediterranean area and characterized by a uniform "garrigue" type cover, vegetation was considered as a unique non fuel-limited Mediterranean type ecosystem. However, this assumption might blur some species effects on fire occurrence probabilities due to a different functional response to weather and soil conditions but also to a lower priority given to fire fighting in some vegetation type (Bessie and Johnson 1995, Krawchuk et al. 2006, Moreira et al. 2010). In addition and in regions where the effect of fuel limitation is more important, the moist conditions preceding the fire season determine fuel build-up and can have a significant importance in the upcoming fire activity (e.g., Littell et al. 2009, Pausas and Paula 2012). We supposed in this study that fire probability was more drought-limited than fuel-limited in Southern France, which was confirmed by the high modeling performance. Nevertheless, adding this information might improve our modeling performance and would undoubtedly extent our modeling framework to other environments and biomes.

Based on the fire-size dependent pattern of fire occurrence to weather variables (Fig. 3), one of our main hypotheses was to consider a threshold of 15 ha to define large fires. When comparing to other regions and ecosystems (Hantson et al. 2015), this burnt area of 15 ha is rather small to be considered as a 'large fire'. But in the Euro-Mediterranean area where landscapes are highly fragmented, most of the fires are small and only few fires reach extended surfaces (Ricotta et al. 2001). Besides, our analytical results leading to this threshold are consistent with fire services reports which indicate that a size of about 17 ha is the maximum final burnt area if (1) fire fighters are able to intervene in less than 10 minutes after ignition and (2) the fire size before intervention does not exceed 1 ha (Lacomblez et al. 2004). When these initial conditions are not met, fire spread over an average size of 193 ha. We did not observe differences in the relative contribution of the explanatory beyond this 15 ha threshold but as the size of fire increases, the weather control on fire occurrence probability became stronger (Appendix: Fig B1), that could suggest that weather control is more important for the largest fire. Nevertheless, there are also many reasons why a fire might not grow despite favorable weather conditions that we did not explore here such as fuel structure and accumulation or a geographic impediment to spread (Koutsias et al. 2012, Wang et al. 2014).

Historical changes in the fire-weather relationship

The sudden decrease in fire activity observed in our study area implies a concurrent shift in the fire-weather relationship. A close examination reveals two different mechanisms.

Firstly, while the number of fires suddenly decreased around 1987 (Fig. 2A), the relative contribution of the weather factors explaining fire starts remained constant over the 1973–2006 period. Fire suppression can then be considered as a process that quantitatively affects the number of fire starts. Such a reduction in fire start probabilities resulting from the introduction of fire-suppression policies has already been observed (Keeley et al. 1999, Podur and Martell 2007). It could be due to a better prevention policy that contributed to a diminution of human ignitions by informing and warning populations on fire risk and by preventing recreational population fluxes through a strict control in national forest sites during high fire risk periods.

Secondly and concomitantly with the decrease in the number of fires and burnt area (Fig. 2), we observed a sudden and significant shift in the relative contribution of the weather factors that control the spread of fires over a large area (Figs. 3 and 5). Nowadays, under the new fire suppression and prevention policy, large fire occurrence is controlled by a combination of dry fuel moisture conditions and strong wind speed. This pattern is in accordance with the conditions generally identified as major drivers of fire spread in temperate and Mediterranean forested ecosystems because of the inefficiency of suppression during these dry and windy days (e.g., Keeley et al. 1999, Piñol et al. 2005, Moritz et al. 2010, Podur and Wotton 2011). But interestingly, before the introduction of this new fire policy, dry moisture conditions alone control the probability of fires to spread. Fewer studies reported that dry conditions could be sufficient for larger fires to occur when suppression practices are less intense (but see Bradstock et al. 2014). This could be due to the fact that most studies providing some daily assessments of the fire-weather relationship focus on regions and periods for which accurate fire and climatic datasets are available, which generally correspond to regions where efficient fire-suppression policies are applied.

We observed that the daily fire-weather relationship was stronger for the most recent period when human suppression is more important (Appendix: Figs. C1 and D1) whereas it is generally assumed that the control of climate/weather on burnt area is weaker when human intervention is greater (e.g., Balshi et al. 2009, Wang et al. 2014). In our study area, the introduction of enhanced fire fighting and prevention practices lower fire spread probabilities under mild conditions (i.e., weather conditions where vegetation is dry enough to propagate fire but without extreme wind and/or heat). Under these conditions, the probability that a fire ignition spreads over a significant area is very stochastic under a low-controlled fire strategy as it depends on several other miscellaneous variables (fuel continuity, topography, facility of access for fire fighters), which are far from being homogeneous in the Euro Mediterranean area. Under these similar weather conditions but when fire suppression is stronger, fire fighters are able to intervene rapidly and large fire events rarely occur, which therefore increases the performance of statistical model to predict daily fire probabilities.

Implications for fire regime management and predictions

Contrasted national and regional fire policies have been developed and introduced worldwide (Carreiras et al. 2014). These policies are highly dependent on political, economic and societal fast changing factors and major changes in fire-suppression practices and/or in the expenditures dedicated to firefighting could happen in the near future (Chuvieco et al. 2014). We provided evidence that fire-suppression practices can change the relative importance of wind and drought conditions associated with the occurrence of large fires and therefore shape the climatic definition of a "potential fire spread day" (sensu Podur and Wotton 2011). This information is essential for a better understanding of the multi-scale biophysical and anthropogenic factors driving fire regimes (Moritz et al. 2005) since it implies that mid-term (decadal) social factors could affect the short-term (seasonal to daily) relationship between weather conditions and fire activity. Thus, the reduction (or increase) in the number of largest fires following the introduction of a fire policy could be explained by a decrease (or increase) in the number of potential fire spread days.

Numerous changes in fire practices occurred concurrently in southern France and the impact each of those changes is therefore hardly evaluable. Our results suggest than improving fire suppression in southern France would involve a better prediction of when and where dry and windy conditions occur in order to set-up adapted fire prevention and fire fighting strategies. But fire management in this region should also be assessed in the context of its own impacts on the fire-weather relationship and its subsequent consequences for fire regimes. For instance, changes in fire-suppression practices could lead to an offset of the fire seasonality to moments of extreme winds or extreme droughts (Moritz et al. 2010) or to some spatial shifts of fire zones towards the windiest or driest areas (DeWilde and Chapin 2007). We might also question here the benefits of this strong fire suppression without significant fuel load control that might increase biomass and lead to mega fires, although this issue remains controversial in the Euro Mediterranean context (Piñol et al. 2005).

We provided evidence that the empirical fire-weather relationships, generally calibrated for a specific period and ecosystems, could fail to provide robust fire risk and fire activity estimations in a case of changes in fire policies. Several studies have shown that fire suppression strategies should explicitly be taken into account if realistic outputs on fire regime characteristics are sought (Loepfe et al. 2012, Brotons et al. 2013). However, these mechanisms are hardly embedded in models simulating fire activity on large scales. For instance, the general hypothesis concerning humans' impacts on fire regime in Dynamic Global Vegetation Models (DGVMs) is that increasing population increases ignition but also decrease the frequency of large fires through increasing controls on fire spread. But when using this hypothesis temporally with varying population density along the century, models are not able to simulate accurately the abrupt decrease/increase in burnt area observed along the 20th century (Kloster et al. 2010, Thonicke et al. 2010, Pfeiffer et al. 2013, Yue et al. 2014), which suggests that some key constraints are not adequately represented. If human decision-making modeling in DGVMs has just started to be implemented for land use change scenarios (Arneth et al. 2014), the mechanisms driving changes in fire policy are far from being identified. Historical (based on national information) or future scenarios of fire suppression practices could be assembled and used as a time-varying variable to drive the fire weather-relationship and improve model simulations of fire regimes.

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Literature Cited

Abrantes, P., C. Soulard, F. Jarrige, and L. Laurens. 2010. Dynamiques urbaines et mutations des espaces agricoles en Languedoc-Roussillon (France). Cybergeo 485.

Alexandrian, D. 2008. Les statistiques "feux de forêt" de ces trente dernières années. Forêt Méditerraneenne 29:377–384.

Alexandrian, D., and F. Esnault. 1999. Public policies affecting forest fires in the Mediterranean Basin. Forestry Paper. Food and Agriculture Organization, Rome, Italy.

Andersen, T., J. Carstensen, E. Hernandéz-García, and C. M. Duarte. 2009. Ecological thresholds and regime shifts: approaches to identification. Trends in Ecology and Evolution 24:49–57.

Archibald, S., A. Nickless, N. Govender, R. J. Scholes, and V. Lehsten. 2010. Climate and the inter-annual variability of fire in southern Africa: a meta-analysis using long-term field data and satellite-derived burnt area data. Global Ecology and Biogeography 19:794–809.

Arneth, A., C. Brown, and M. D. A. Rounsevell. 2014. Global models of human decision-making for land-based mitigation and adaptation assessment. Nature Climate Change 4:550–557.

Balshi, M. S., A. D. McGuire, P. Duffy, M. Flannigan, J. Walsh, and J. Melillo. 2009. Assessing the response of area burned to changing climate in western boreal North America using a Multivariate Adaptive Regression Splines (MARS) approach. Global Change Biology 15:578–600.

Bessie, W. C., and E. A. Johnson. 1995. The relative importance of fuels and weather on fire behavior in subalpine forests. Ecology 76:747–762.

Bond, W. J., and J. E. Keeley. 2005. Fire as a global "herbivore:" the ecology and evolution of flammable ecosystems. Trends in Ecology and Evolution 20:387–394.

Bowman, D. M. J. S., J. Balch, P. Artaxo, et al. 2011. The human dimension of fire regimes on Earth. Journal of Biogeography 38:2223–2236.

Bradstock, R., T. Penman, M. Boer, O. Price, and H. Clarke. 2014. Divergent responses of fire to recent warming and drying across south-eastern Australia. Global Change Biology 20:1412–1428.

Brotons, L., N. Aquilué, M. de Cáceres, M. J. Fortin, and A. Fall. 2013. How fire history, fire suppression practices and climate change affect wildfire regimes in Mediterranean landscapes. PLoS ONE 8:e62392.

Campbell, G. S. 1974. A simple method for determining unsaturated conductivity from moisture retention data. Soil Science 117:311–314.

Carreiras, M., A. J. Dinis Ferreira, S. Valente, L. Fleskens, Ó. Gonzales-Pelayo, J. L. Rubio, C. R. Stoof, C. O. A. Coelho, C. S. S. Ferreira, and C. J. Ritsema. 2014. Comparative analysis of policies to deal with wildfire risk. Land Degradation and Development 103:92–103.

Chandler, C., et al. 1983. Fire in forestry. Volume 1. Forest fire behavior and effects. John Wiley and Sons, Hoboken, New Jersey, USA.

Chuvieco, E., S. Martínez, M. V. Román, S. Hantson, and M. L. Pettinari. 2014. Integration of ecological and socio-economic factors to assess global vulnerability to wildfire. Global Ecology and Biogeography 23:245–253.

Cumming, S. 2005. Effective fire suppression in boreal forests. Canadian Journal of Forest Research 35:772–786.

DaCamara, C. C., T. J. Calado, S. L. Ermida, I. F. Trigo, M. Amraoui, and K. F. Turkman. 2014. Calibration of the fire weather index over Mediterranean Europe based on fire activity retrieved from MSG satellite imagery. 2014. International Journal of Wildland Fire 23(7):945–958.

De'ath, G. 2007. Boosted trees for ecological modeling and prediction. Ecology 88:243–51.

Debussche, M., J. Lepart, and A. Dervieux. 1999. Mediterranean landscape changes: evidence from old postcards. Global Ecology and Biogeography 8:3–15.

DeWilde, L., and F. S. Chapin. 2007. Human impacts on the fire regime of interior Alaska: interactions among fuels, ignition sources, and fire suppression. Ecosystems 9:1342–1353.

Elith, J., J. R. Leathwick, and T. Hastie. 2008. A working guide to boosted regression trees. Journal of Animal Ecology 77:802–813.

Fisher, W. 1894. New French law for the prevention of forest fires. Nature 49:233–234.

Flannigan, M. D., K. A. Logan, B. D. Amiro, W. R. Skinner, and B. J. Stocks. 2005. Future area burned

in Canada. Climatic Change 72:1–16.
Fox, D. M., N. Martin, P. Carrega, J. Andrieu, C. Adnès, K. Emsellem, O. Ganga, F. Moebius, N. Tortorollo, and E. A. Fox. 2015. Increases in fire risk due to warmer summer temperatures and wildland urban interface changes do not necessarily lead to more fires. Applied Geography 56:1–12.
Gaultier, J. P., J. P. Legros, M. Bornand, D. King, J. C. Favrot, and R. Hardy. 1993. L'organisation et la gestion des donnees pedologiques spatialisees: le projet DONESOL. Revue de geomatique 3:235–253.
Goforth, B. R., and R. A. Minnich. 2007. Evidence, exaggeration, and error in historical accounts of chaparral wildfires in California. Ecological Applications 17:779–90.
Habets, F., A. Boone, J. L. Champeaux, P. Etchevers, L. Franchisteguy, E. Leblois, E. Ledoux, P. Le Moigne, E. Martin, and S. Morel. 2008. The SAFRAN-ISBA-MODCOU hydrometeorological model applied over France. Journal of Geophysical Research 113:D06113.
Hantson, S., S. Pueyo, and E. Chuvieco. 2015. Global fire size distribution is driven by human impact and climate. Global Ecology and Biogeography 24:77–86.
Husson, A. 1985. Télédétection des incendies de forêts en Corse entre 1973 et 1980. Méditerranée 54(1):53–59.
Keeley, J. E., C. J. Fotheringham, and M. Morais. 1999. Reexamining fire suppression impacts on brushland fire regimes. Science 284:1829.
Kloster, S., N. M. Mahowald, J. T. Randerson, P. E. Thornton, F. M. Hoffman, S. Levis, P. J. Lawrence, J. J. Feddema, K. W. Oleson, and D. M. Lawrence. 2010. Fire dynamics during the 20th century simulated by the Community Land Model. Biogeosciences 7:1877–1902.
Körner, C. 2003. Slow in, rapid out: carbon flux studies and Kyoto targets. Science 300:1242–1243.
Koutsias, N., M. Arianoutsou, A. S. Kallimanis, G. Mallinis, J. M. Halley, and P. Dimopoulos. 2012. Where did the fires burn in Peloponnisos, Greece the summer of 2007? Evidence for a synergy of fuel and weather. Agricultural and Forest Meteorology 156:41–53.
Krawchuk, M. A., S. G. Cumming, M. D. Flannigan, and R. W. Wein. 2006. Biotic and abiotic regulation of lightning fire initiation in the mixedwood boreal forest. Ecology 87:458–68.
Krawchuk, M. A., and M. A. Moritz. 2011. Constraints on global fire activity vary across a resource gradient. Ecology 92:121–132.
Lacomblez, C., M. Chavent, and B. Patouille. 2004. Analyse des données statistiques sur les feux de forêt. Prévention sécurité 77:8–11.
Lehmann, C. E. R., et al. 2014. Savanna vegetation-fire-climate relationships differ among continents. Science 343:548–52.
Littell, J. S., D. Mckenzie, D. L. Peterson, and A. L. Westerling. 2009. Climate and wildfire area burned in western U.S. ecoprovinces, 1916-2003. Ecological Applications 19:1003–1021.
Loepfe, L., J. Martinez-Vilalta, and J. Piñol. 2012. Management alternatives to offset climate change effects on Mediterranean fire regimes in NE Spain. Climatic Change 115:693–707.
Marlon, J. R., P. J. Bartlein, C. Carcaillet, D. G. Gavin, S. P. Harrison, P. E. Higuera, F. Joos, M. J. Power, and I. C. Prentice. 2008. Climate and human influences on global biomass burning over the past two millennia. Nature Geoscience 1:697–702.
Moreira, F., F. X. Catry, F. Rego, and F. Bacao. 2010. Size-dependent pattern of wildfire ignitions in Portugal: when do ignitions turn into big fires? Landscape Ecology 25:1405–1417.
Moreira, F., O. Viedma, M. Arianoutsou, T. Curt, N. Koutsias, E. Rigolot, A. Barbati, P. Corona, P. Vaz, G. Xanthopoulos, F. Mouillot, and E. Bilgili. 2011. Landscape–wildfire interactions in southern Europe: implications for landscape management. Journal of Environmental Management 92:2389–402.
Moritz, M. A., T. J. Moody, M. A. Krawchuk, M. Hughes, and A. Hall. 2010. Spatial variation in extreme winds predicts large wildfire locations in chaparral ecosystems. Geophysical Research Letters 37:L04801–L04801.
Moritz, M. A., M. E. Morais, L. A. Summerell, J. M. Carlson, and J. Doyle. 2005. Wildfires, complexity, and highly optimized tolerance. Proceedings of the National Academy of Sciences USA 102:17912.
Mouillot, F., and C. B. Field. 2005. Fire history and the global carbon budget: a 1ox 1o fire history reconstruction for the 20th century. Global Change Biology 11:398–420.
Mouillot, F., S. Rambal, and R. Joffre. 2002. Simulating climate change impacts on fire frequency and vegetation dynamics in a Mediterranean-type ecosystem. Global Change Biology 8:423–437.
Mouillot, F., S. Rambal, and S. Lavorel. 2001. A generic process-based SImulator for meditERRanean landscApes (SIERRA): design and validation exercises. Forest Ecology and Management 147:75–97.
Nowacki, G., and M. Abrams. 2008. The demise of fire and "mesophication" of forests in the eastern United States. BioScience 58 : 123-138.
Olden, J. D., J. J. Lawler, and N. L. Poff. 2008. Machine learning methods without tears: a primer for ecologists. Quarterly Review of Biology 83:171–194.
Parks, S. A., M.-A. Parisien, and C. Miller. 2012. Spatial bottom-up controls on fire likelihood vary across western North America. Ecosphere 3(1):20.
Pausas, J. G. 2004. Changes in fire and climate in the eastern Iberian Peninsula (Mediterranean basin).

Climatic Change 63:337–350.

Pausas, J. G., and S. Fernández-Muñoz. 2012. Fire regime changes in the Western Mediterranean Basin: from fuel-limited to drought-driven fire regime. Climatic Change 10:215–226.

Pausas, J. G., and J. E. Keeley. 2009. A burning story: the role of fire in the history of life. BioScience 59:593–601.

Pausas, J. G., and J. E. Keeley. 2014. Abrupt climate-independent fire regime changes. Ecosystems 17:1109–1120.

Pausas, J. G., and S. Paula. 2012. Fuel shapes the fire-climate relationship: evidence from Mediterranean ecosystems. Global Ecology and Biogeography 21:1074–1082.

Pechony, O., and D. T. Shindell. 2010. Driving forces of global wildfires over the past millennium and the forthcoming century. Proceedings of the National Academy of Sciences USA 107:19167–70.

Pellizzaro, G., C. Cesaraccio, P. Duce, A. Ventura, and P. Zara. 2007. Relationships between seasonal patterns of live fuel moisture and meteorological drought indices for Mediterranean shrubland species. International Journal of Wildland Fire 16:232–241.

Pereira, M. G., R. M. Trigo, C. C. DaCamara, J. Pereira, and S. M. Leite. 2005. Synoptic patterns associated with large summer forest fires in Portugal. Agricultural and Forest Meteorology 129:11–25.

Pfeiffer, M., A. Spessa, and J. O. Kaplan. 2013. A model for global biomass burning in preindustrial time: LPJ-LMfire (v1.0). Geoscientific Model Development 6:643–685.

Piñol, J., K. Beven, and D. X. Viegas. 2005. Modelling the effect of fire-exclusion and prescribed fire on wildfire size in Mediterranean ecosystems. Ecological Modelling 183:397–409.

Podur, J., and B. M. Wotton. 2011. Defining fire spread event days for fire-growth modelling. International Journal of Wildland Fire 20:497.

Podur, J. J., and D. L. Martell. 2007. A simulation model of the growth and suppression of large forest fires in Ontario. International Journal of Wildland Fire 16:285.

Pyne, S. J., P. L. Andrews, and R. D. Laven. 1996. Introduction to wildland fire. John Wiley and Sons, Hoboken, New Jersey, USA.

Quintana-Seguí, P., P. Le Moigne, Y. Durand, E. Martin, F. Habets, M. Baillon, C. Canellas, L. Franchisteguy, and S. Morel. 2008. Analysis of near-surface atmospheric variables: validation of the SAFRAN analysis over France. Journal of Applied Meteorology and Climatology 47:92–107.

R Core Team 2012. R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. http://www.R-project.org/

Ricotta, C., M. Arianoutsou, R. Diaz-Delgado, B. Duguy, F. Lloret, E. Maroudi, S. Mazzoleni, J. M. Moreno, S. Rambal, R. Vallejo, and A. Vázquez. 2001. Self-organized criticality of wildfires ecologically revisited. Ecological Modelling 141:307–311.

Ridgeway, G. 2006. Generalized boosted regression models. Documentation on the R package "gbm," version 1.5 7.

Ruffault, J., N. Martin-StPaul, C. Duffet, F. Goge, and F. Mouillot. 2014. Projecting future drought in Mediterranean forests: bias correction of climate models matters!. Theoretical and Applied Climatology 117:113–122.

Ruffault, J., N. Martin-StPaul, S. Rambal, and F. Mouillot. 2013. Differential regional responses in drought length, intensity and timing to recent climate changes in a Mediterranean forested ecosystem. Climatic Change 117:103–117.

Salis, M., A. A. Ager, M. A. Finney, B. Arca, and D. Spano. 2014. Analyzing spatiotemporal changes in wildfire regime and exposure across a Mediterranean fire-prone area. Natural Hazards 71:1389–1418.

Schaab, G., R. Steinbrecher, B. Lacaze, and R. Lenz. 2000. Assessment of long-term vegetation changes on potential isoprenoid emission for a Mediterranean-type ecosystem in France. Journal of Geophysical Research 105:28863.

Stephenson, N. L. 1990. Climatic control of vegetation distribution: the role of the water balance. American Naturalist 135:649–670.

Swetnam, T., and J. Betancourt. 1990. Fire-Southern Oscillation relations in the southwestern United States. Science 249:1017–120.

Thonicke, K., A. Spessa, I. C. Prentice, S. P. Harrison, L. Dong, and C. Carmona-Moreno. 2010. The influence of vegetation, fire spread and fire behaviour on biomass burning and trace gas emissions: results from a process-based model. Biogeosciences 7:1991–2011.

Thonicke, K., V. Venesky, S. Sitch, and W. Cramer. 2001. The role of fire disturbance for global vegetation dynamics: coupling fire into a Dynamic Global Vegetation Model. Global Ecology and Biogeography 10:661–677.

Turco, M., M. C. Llasat, A. Tudela, X. Castro, and A. Provenzale. 2013. Brief communication: decreasing fires in a Mediterranean region (1970–2010,NE Spain). Natural Hazards and Earth System Science 13:649–652.

Viegas, D., J. Soares, and M. Almeida. 2013. Combustibility of a mixture of live and dead fuel components. International Journal of Wildland Fire 22:992–1002.

Viret, J., and J. L. Queyla. 2004. La prévention des risques incendie de forêt dans le Sud-Méditerranée. Outils juridiques et enjeux de terrain. Revue

Forestière Française 56:187–202.

Wang, X., M.-A. Parisien, M. D. Flannigan, S. A. Parks, K. R. Anderson, J. M. Little, and S. W. Taylor. 2014. The potential and realized spread of wildfires across Canada. Global Change Biology 20:2518–2530.

Van der Werf, G. R., J. T. Randerson, L. Giglio, G. J. Collatz, M. Mu, P. S. Kasibhatla, D. C. Morton, R. S. DeFries, Y. Jin, and T. T. van Leeuwen. 2010. Global fire emissions and the contribution of deforestation, savanna, forest, agricultural, and peat fires (1997–2009). Atmospheric Chemistry and Physics 10:11707–11735.

Yue, C., et al. 2014. Modelling fires in the terrestrial carbon balance by incorporating SPITFIRE into the global vegetation model ORCHIDEE–Part 1: simulating historical global burned area and fire regime. Geoscientific Model Development, 2014 7(6):2747–2767.

Zeileis, A., C. Kleiber, W. Krämer, and K. Hornik. 2003. Testing and dating of structural changes in practice. Computational Statistics and Data Analysis 44:109–123.

Supplemental Material

Ecological Archives

Appendices A–D are available online: http://dx.doi.org/10.1890/ES15-00182.1.sm