# Contribution of human and biophysical factors to the spatial distribution of forest fire ignitions and large wildfires in a French Mediterranean region

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**Running head**: Spatial distribution of forest fires

**Abstract**

Identifying the factors that drive the spatial distribution of fires is one of the most challenging issues facing fire science in a changing world. We investigated the relative influence of humans, land cover and weather on the regional distribution of fires in a Mediterranean region using boosted regression trees and a set of seven explanatory variables. The spatial pattern of fire weather, which is seldom accounted for in regional models, was estimated using a semi-mechanistic approach and expressed as the length of the fire weather season. We found that the drivers of the spatial distribution of fires followed a fire size dependent pattern in which human activities and settlements mainly determined the distribution of all fires whereas the continuity and type of fuels mainly controlled the location of the largest fires. The spatial structure of fire weather was estimated to be responsible for an average of 25% of the spatial patterns of fires, suggesting that climate change may directly affect the spatial patterns of fire hazard in the near future. These results enhance our understanding of long term controls of the spatial distribution of wildfires and predictive maps of fire hazard provide useful information for fire management actions.

**Summary**

We examined the human and biophysical factors driving the regional distribution of wildfires in a Mediterranean area. We found a fire size dependent pattern in which humans control the distribution of all fires whereas land cover and fire weather mainly explained the location of the largest fires. These factors should therefore be taken into consideration when projecting fire hazard.

## Introduction

Wildfire is a widespread ecological disturbance, but one with a heterogeneous spatial distribution (Krawchuck *et al.* 2009; Bowman *et al.* 2011). Identifying the drivers of the distribution of fires is crucial for the design of appropriate fire policies, especially in regions where fire regimes are being altered by global changes as is the case in the Mediterranean area (Moreira *et al.* 2011).

Regional fire distribution is the result of interactions between three environmental conditions: ignitions patterns, fuel availability and atmospheric conditions that favor combustion (Moritz *et al.* 2005; Archibald *et al.* 2009). Biophysical factors, including fuel type and continuity, topography and weather conditions play an important role in determining the spatial patterns of fires (Parks *et al.* 2012; Parisien *et al.* 2014). Humans also affects regional fire distribution through three main mechanisms: by igniting fires, by limiting the spread of fires and by modifying land cover (Bowman *et al.* 2011). Because of the complex interactions between biophysical and human influences, the extent to which they determine the spatial patterns of fires varies geographically, according to ecosystem characteristics (Parisien and Moritz 2009), orographic and synoptic conditions (Heyerdahl *et al*. 2001) or to the level and nature of the human imprint (Parisien *et al*. 2016).

In the Euro-Mediterranean region, evidence is accumulating that the spatial pattern of ignitions is mainly determined by human settlements and activities, while the continuity and type of fuels largely control fire spread probabilities, and therefore the location of the largest fires (Moreira *et al.* 2010; Duane *et al.* 2015; Fernandes *et al.* 2016). However, there is no consensus on the extent to which spatial variations in weather control the spatial patterns of fires at landscape to regional scales (Moreira *et al.* 2011).

Yet, in regions of complex orography like the Mediterranean, we observe steep weather gradients (Lionello *et al.* 2006) that could help define areas where wildfires are most likely to occur (Moritz *et al.* 2010). In the Mediterranean, this knowledge gap is often mentioned as one of the major source of uncertainty when projecting future fire likelihood at the regional level (Piñol *et al.* 1998; Martínez *et al.* 2009; Moreira *et al.* 2011) and part of the problem is the difficulty in identifying and mapping wildfire danger.

First, quantifying the contribution of weather requires unravelling the multiscale temporal relationships between climate and fire activity. Climate affects fire probability both indirectly, through its long term control of vegetation, and directly through what is termed fire weather, i.e. the weather conditions that influence fire ignition, fire behavior and suppression (Bradstock 2010). In turn, fire weather is the result of atmospheric processes at different time scales: fuel production and desiccation in the medium term and instantaneous conducive atmospheric conditions in the short term (Ruffault *et al.* 2016). Hence, linking fire activity to mean climatic conditions helps determine the biophysical niche of fires (e.g. Parisien and Moritz 2009; Whitman *et al.* 2015). These indices nevertheless cannot separate the indirect from the direct effects of climate on the spatial distribution of fires, nor do they represent the co-occurrence of several multiscale weather events associated with fires.

Second, in regions with marked climate seasonality like the Mediterranean, variations in climate over time have a much greater influence than spatial variations, making it difficult to extract the impact of its spatial component on fire activity. Finally, as the fire-weather relationship is shaped by both the vegetation (Pausas and Paula 2012) and human practices (Marlon *et al.* 2008; Ruffault and Mouillot 2015), the weather conditions that drive the fire occurrence and fire spread processes can vary considerably in space and over time (Ruffault and Mouillot 2015; Higuera *et al.* 2015).

In this context, we conducted a comprehensive evaluation of the effects of weather, fuel and human variables on the spatial distribution of fires in a French Mediterranean area (Fig. 1). In this area, the fire regime is dominated by typical Mediterranean crown fires in shrublands and in mixed oak-pine woodlands, which are mostly ignited by humans and usually last less than a day (Fréjaville and Curt 2015). Fire activity is "drought-limited", i.e. fires are most likely to occur when two conditions occur simultaneously: vegetation drought and meteorological fire prone days (Ruffault *et al.* 2016, 2017). We used a set of seven explanatory variables describing the spatial patterns of human, fuel and fire weather factors in the study area. We assessed the relative importance of environmental controls on the spatial distribution of fires for individual variables as well as for the grouped variables humans, land cover and weather. Our objectives were (i) to identify the spatial structure of fire weather, (ii) to quantify the contribution of the human, land cover and weather variables to the spatial distribution of fires, and (iii) to assess whether the relative contribution of these factors varies with increasing fire size.

## Materials and Methods

### *Study area*

The study area covers four French administrative districts (total area 21,637 km$^2$) in southern France (Fig. 1). The climate is Mediterranean with hot dry summers, cool wet winters and high inter-annual variability. The rainfall gradient depends on the topography and ranges from 550 mm at the coast (elevation = 0 m) to 1,630 mm in the central foothills (elevation = 1,450 m). Closed forests dominated by Mediterranean evergreen tree species (*Quercus ilex*, *Pinus halepensis*) and shrublands (*Cistus* *monspeliensis*, *Quercus coccifera*) cover 65% of the study area (French national forest inventory, 2006). Agricultural land use (mainly vineyards) accounts for 28% and urban areas the remaining 7%.

*General method and selection of the variables*

We assessed the drivers of the spatial distribution of fires for a range of final fire size classes by modeling the relationship between fire presence as the response variable and a set of potential human, weather and land cover factors as predictor variables. The spatial partitioning of the study area followed the French fire management agency's 4-$km^2$ grid system for the French territory. We limited our analysis to the most recent period (1990-2006) to avoid biases resulting from the shift in fire activity observed at the end of the 1980s in the study area (Ruffault and Mouillot 2015). For each class of final size of fire, a binary variable was generated to represent its corresponding spatial fire distribution for each grid cell, positive if at least one fire had occurred over the 17-year study period. The decisions to select a variable (or not) were based on both objective analysis (ease of interpretation and a range of final fire size classes) and the results of previous studies conducted in the Euro-Mediterranean region (Martínez *et al.* 2009; Moreira *et al.* 2010; 2011; Oliveira *et al.* 2012; Duane *et al.* 2015; Fernandes *et al.* 2016). Seven variables (Table 1) were selected to build a model by iteratively eliminating correlated and non-informative variables from an original set of 21 variables (Table S1). To this end, the correlation between all explanatory variables was assessed to identity variables correlated above a threshold of $|\rho|=0.7$. Then the fits of spatial fire distributions were assessed against these two correlated variables to decide which variable to retain. Variables with spurious effects were also discarded. Regional maps of fire distribution, weather, human and land cover variables were then collected at the 4-$km^2$ grid scale. For land cover and human factors, all the explanatory variables were mapped to reflect the average conditions over the study period (1990-2006) as closely as possible, but due to the lack of historical data for some variables, the conditions prevailing on a single date had to be chosen as representative of the 17-year period (see details below). However, as no major economic or societal changes occurred during this period, we did not expect this simplification to be a major limitation.

*Fire data*

The location, date and size of fires in the period 1990 to 2006 were extracted from the PROMETHEE fire database (available on line at *www.promethee.com*). This database is managed by the French forestry services and includes the final size, the day and location of ignition for each registered fire on a 4-km$^2$ reference grid. A total of 6,381 fires occurred in the study area between 1990 and 2006. Most were small (median = 1 ha; mean = 6.5 ha), and because only 16 fires spread beyond the area of the reference grid cell (400 ha), we assumed that fires did not spread beyond their ignition grid cell. Each fire was then attributed to one or more of the five classes of final fire size burned area: > 0 ha (all fires); > 1 ha; > 6 ha; > 15 ha; > 30 ha (large fires); representing respectively the 0$^{th}$, 50$^{th}$, 90$^{th}$, 95$^{th}$, 97$^{th}$, 98$^{th}$ percentile of the fire size distribution over the study period. A binary response variable was then selected to describe the presence or absence of fire in each grid cell. Forty-six percent of the grid cells experienced at least one fire over the 1990 to 2006 period, but this percentage decreased sharply with an increase in fire size. For instance, fires covering an area of more than 6 ha and 30 ha were observed in 10% and 3.3% of grid cells, respectively (Fig. 1).

*Fire weather maps*

Spatial variations in fire weather were described by using a single and integrative variable and expressed for each grid cell as the fire weather season length (hereafter FWSL, i.e. the annual number of days suitable for burning). This approach is therefore similar to that successfully used by Jolly *et al*. (2015) on a global scale, but in our case, was based on the prior identification of the fire-weather relationship. In addition, as the conditions controlling the probabilities of fire start differ from those driving fire spread in Mediterranean France (Ruffault and Mouillot 2015; Ruffault *et al.* 2016, 2017), the FWSL was computed for each fire size class. We used the following two-step methodology to map the FWSL:

(i) First, to determine the fire-weather relationship, we assessed the relative importance of several key weather variables in the probability of fire occurrence using the spatio-temporal framework of Ruffault and Mouillot (2015). For each fire, we extracted the associated weather conditions in our basic spatio-temporal unit (or voxel, on 4-km$^2$ grid cells and at a daily time step). Boosted regression tree (BRT, see description below) models were then used to describe the relationship between fire occurrence and the weather by comparing the conditions associated with fire voxels (positive elements) with those associated with a sample of non-fire voxels (absence elements). Five variables were used to capture the weather conditions driving fire occurrence and fire spread probabilities: a proxy of fuel moisture content of litter (Surface drought), a proxy of fuel moisture content of living biomass (Vegetation drought), relative air humidity, temperature and wind speed. The two proxies of fuel moisture content were derived from a daily process based water-budget model, validated in forest stands in southern France by Ruffault *et al.* (2013), and computed here for a single plant functional type (PFT) representative of the deep-rooted evergreen woody species (trees and large shrubs) encountered in our study area. Surface drought is expressed as the relative soil water content of the uppermost soil layer. Vegetation drought is expressed as the ratio of actual evapotranspiration to maximum transpiration (transpiration without water stress).

(ii) In the second step, we used the regional statistical models between weather variables and fire occurrence to determine the daily probabilities of fire occurrence in each grid cell between 1990 and 2006. The FWSL was then determined as the averaged annual number of days when their fire probability was higher than a given probability threshold. To facilitate comparisons among fire size classes, this threshold value was set as equal to the prevalence (percentage of positive fire voxels) observed in the original sampling dataset.

Daily historical observations of precipitation, relative humidity, temperature, and global solar radiation, used as inputs in the process based water budget model and in the BRT analyses, were obtained from the SAFRAN dataset (Vidal 2010). SAFRAN is a reanalysis of daily surface observations on an 8-km resolution grid of France. To match the resolution of our spatial sampling unit (national reference grid, 2x2 km), these daily variables were previously re-interpolated using altitude-dependent methods described and validated over the region by Ruffault *et al.* (2014). Soil data used as inputs for simulations of the water budget were extracted from the regional DONESOL database (1/250000; INRA; Gaultier *et al.* 1993).

*Human variables*

Three variables were selected to represent the pattern of human influence over the study area: road density, housing density, and the percentage of wildland urban interface (WUI). Vectorial information related to roads and human habitats was extracted from the BD-Topo database (IGN 2007). The density of roads is expressed as the total road length per unit land area. The density of houses was calculated as the fraction of unit area covered by urban polygons. The WUI percentage was calculated as the distance to aggregated and open human habitat according to the method proposed by Lampin-Maillet *et al.* (2010) and is expressed as the percentage of WUI in each grid cell. Fig. S1 shows a map of these variables.

*Land cover variables*

Three variables were selected to represent the patterns of land cover in the study area: percentage of shrubland area, percentage of forest area, and the diversity of vegetation types. All these variables were derived from the Corine land cover database 2000 (EEA 1994), which was previously reclassified into four main categories (shrublands, forests, grasslands and other non-fire prone areas: urban area, crops, bare ground) according to the method described in Moreira *et al.* (2010). Shrubland and forest areas were calculated as the percentage area of the grid cell covered by forest and shrubland type vegetation, respectively. The landscape diversity represents the diversity in the fractional distribution of land cover types that make up the landscape and was calculated with the Shannon diversity index with a 10-km wide moving window using FRAGSTATS V3 (McGarigal *et al.* 2002). Fig. S1 shows a map of these variables.

*Fire spatial model*

We used a machine-learning algorithm, boosted regression trees (BRT; De'ath 2007; Elith *et al.* 2008) to predict the spatial pattern of fires. 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). BRT methods have been increasingly recommended for ecological analyses because of their flexibility in modeling complex nonlinear relationships and interactions without the restrictive assumptions of parametric statistics (Olden *et al.* 2008).

BRT models need information about the presence and absence of fires in the grid cells to be able to determine the conditions associated with fire. To be able to compare the models more easily, the prevalence (the percentage of fire presence grid cells in the sample dataset) was fixed at 0.1. The absence data for each fire size class was randomly selected from the pool of absence grid cells. The learning rate (*lr*), the tree size or 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. As the number of samples could subsequently vary between models, we set *tc* to 4 (based on preliminary analyses) and then determined *lr* as a value that resulted in the average test error being minimized between approximately 1,000 and 2,000 trees (Elith *et al.* 2008). The *nt* in each BRT model was selected automatically using 10 fold cross-validation to avoid model overfitting. BRT models were computed in R with the *gbm* package (Ridgeway 2006) and custom functions created by Elith *et al.* (2008) computed using a Bernoulli (logistic) error structure.

We used the area under the receiver operating characteristics (*ROC*) curve (*AUC*) to evaluate the suitability of the models. 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 report the commission error (false positive rate) and omission error (false negative rate) at the probability threshold that maximizes the sum of sensitivity (the fraction of true positives) and specificity (the fraction of false positives) values (Lobo *et al.* 2007). To limit the stochasticity in model outcomes caused by the subsampling and 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. The contribution of the different predictors was estimated from the sum of squared improvements associated with that variable and averaged across all trees in the boosted model (De'ath 2007; Elith *et al.* 2008). The relative importance of environmental factors controlling the spatial distribution of fires was assessed for individual variables as well as for the grouped variables for humans, land cover and weather (Table 1). The contributions of the grouped variables were determined by adding the percentage contributions of their constituent variables. To estimate the degree of similarity among variable contributions among different classes of fire size classes, a rank (Spearman) correlation was performed on the mean contribution of the variables in pair-wise combinations of fire size classes. A lack of significance ($p < 0.05$) in a correlation indicates that the relative importance of environmental controls differs among sizes. We also examined the relationship between the dependent and independent variables by plotting the partial dependencies of responses to individual predictors. Finally, we computed the fire hazard maps, which were derived from statistical models between the spatial distribution of fires and its environmental drivers.

## Results

*Regional patterns of fire weather season length*

Fire activity in southern France was shown to be mainly linked to drought conditions but with an increasing contribution of wind speed with increasing fire size (Fig. S2, see also Ruffault and Mouillot 2015). A significant spatial gradient was observed in the fire weather season length (FWSL), as shown for two contrasted sizes of fires: fires > 0 ha (hereafter all fires) and fires > 30 ha only (hereafter large fires) (Fig. 2). For all fires, the FWSL ranged from 40 to180 days.year$^{-1}$ (Fig. 2a). The lowest values were observed in the western part of the region where rainfall and mean temperature are respectively, higher and lower than the regional means (Ruffault *et al.* 2013). By contrast, a longer FWSL was observed in the drier coastal areas (Ruffault *et al.* 2013). Some marked local variations were also detected according to the variations in soil water holding capacity that influenced the variations in live fuel moisture content, and in turn, the FWSL. For large fires, the regional pattern of fire weather was similar to the one observed for all fires (Fig. 2b) but with a coherently shorter FWSL (ranging from about 10 days.year$^{-1}$ in the western part of the region to 100 days.year$^{-1}$ in the coastal area).

*Relative contribution of climate, land-cover and human variables to the spatial distribution of fires.*

The BRT fire spatial models performed well (AUC$\geq$ 0.72) and similarly in the different fire size classes (Table 2), with commission and omission errors of about 30%. The performance metrics variability was higher for larger fire size classes, most likely due to the exponential reduction in the number of “presence” grid cells with increasing fire size.

The relative contribution of the explanatory variables to the spatial fire distribution models showed a size-dependent pattern (Fig. 3). The distribution of all fires was largely controlled by the percentage of wildland urban interface (*WUI*; 26.0%), the FWSL (18.8%) and road density (16.4%). The relative importance and ranking of the explanatory variables changed significantly with an increase in fire size: a major shift was observed between fires > 1 ha and fires > 6 ha (Table 3, Spearman test, p-value<0.1). When the individual contributions of all fires and large fires were compared, there was a significant increase in shrubland area (from 6% to 24% and from 18.4% to 27%, respectively) (Fig. 2c) and in the FWSL (Fig. 2a) and a significant decrease (from 26% to 9%) in WUI (Fig. 2f). When these contributions were grouped, we observed marked control of human variables over spatial fire patterns, but increasing influence of climate and land cover factors with increasing fire size (summarized in Fig. 3e)

Individual relationships between each explanatory variable and fire hazard showed different patterns (Fig. 4). Fire probabilities were higher under intermediate levels of human pressure (Fig. 4b,d,f) but this pattern tended to disappear with increasing fire size. As one might expect, the FWSL positively and monotonically affected fire probability, regardless of the final fire size (Fig. 4a). Finally, vegetation and land cover variables showed some contrasting patterns. The probability of large fire occurrence increased with an increase in the shrubland area (Fig. 4c) but decreased with increasing forest area. The probabilities of ignition and large fires both increased with higher landscape diversity but the impact of this variable was greater on fire ignitions (Fig. 4e).

*Fire hazard maps*

Despite the variability of fire hazard at local scale, some regional patterns emerged with, on average, less relative probability of fire in the western part than in the southern and eastern parts of the region (Fig. 5a). A very similar pattern was observed for larger fires, but with more contrasted differences (Fig. 5b).

## Discussion

The peculiar Euro-Mediterranean context points to an advanced stage of anthropogenic fire-regime transformation (Moreira *et al.* 2011). Accordingly, in southern France, where the majority of fires are caused by humans (Curt *et al.* 2016), the distribution of fires was mainly driven by variables that reflect the level and nature of human pressure (Fig. 3). This is further evidence for the overwhelming impact of anthropogenic factors on the spatial patterns of fire ignitions in the Euro-Mediterranean area (Martinez *et al.* 2009; Oliveira *et al.* 2012), as also observed in a number of fire prone areas where anthropic pressure is high and can override the effects of biophysical factors (Cardille *et al.* 2001; Syphard *et al.* 2008; Hawbaker *et al.* 2013; Faivre *et al.* 2014; Mann *et al.* 2016). Fire-start hazard was higher under intermediate levels of anthropogenic pressure (Fig. 4), a pattern that has been reported in other anthropogenic fire regimes (Syphard *et al.* 2007; Moreira *et al.* 2010, Parisien *et al.* 2012).

In southern France, the greater influence of human-related variables on the spatial pattern of fires tended to decrease with an increase in fire size, with a concomitant increase in the importance of fuel characteristics and land cover (Fig. 3). This result strengthens the fire size dependence hypothesis that was previously proposed to explain the spatial patterns of fires in Western Europe (Moreira *et al.* 2010). It also suggests that fuel fragmentation is one the most important factors limiting the occurrence of large fires in the Mediterranean. A direct outcome of this phenomenon is that the areas where most wildfires occur did not match those where the largest fires occur (Fig. 5). Most small fires typically occurred in locations where human development and natural vegetation intermingle, in the most complex landscape mosaics and with frequent or long lasting droughts. By contrast, large fires are most likely to occur in landscapes characterized by a dense shrubland cover, low but still significant human pressure to enable frequent ignitions, and by frequent severe fire weather conditions favoring extreme fire behavior and hence ineffective fire suppression operations. The greater probability of large fires in shrublands compared to forested ecosystems is common in the Mediterranean basin (Moreira *et al.* 2011) and was particularly high in Mediterranean France although we were unable to conclude whether it is due to the higher flammability of this type of fuel or less intense fire suppression efforts in shrublands than in forested ecosystems. Finally, we did not observe a higher probability of large fires in continuous and homogeneous landscapes (Fig. 4), in contrast to what is generally observed (Cardille *et al.* 2001; Heyerdahl *et al.* 2001; Viedma *et al.* 2009; Loepfe *et al.* 2010; Fernandes *et al.* 2016) or simulated from landscape fire succession models (Hargrove *et al.* 2000; Cary *et al.* 2006). One possible explanation is the need for a balance between a complex urban/wildland interface and homogeneous landscape pattern for fires to start and spread, but generally leading to a weak effect of landscape diversity on large fire hazard. In addition, our large fire threshold (> 30 ha) is low compared to other regions and ecosystems (Hantson *et al*. 2015) and it is therefore also possible that the relative contribution of weather, human and land-cover factors is quite different when larger fires are considered (Liu *et al.* 2013; Fernandes *et al.* 2016).

One interesting finding of our study is that the spatial variations in weather conditions also largely influenced the location of fires in Mediterranean France. We estimated that the FWSL accounted for between 20% and 30% in the BRT models predicting the spatial distribution of fires. These figures are not surprising given the marked regional and local variability in drought and wind conditions (Ruffault *et al.* 2013), two of the critical variables for the probability of large fires occurring in this region (Ruffault *et al.* 2017). Given the rapid and non-uniform changes towards hotter and drier conditions that are projected in the Mediterranean area in the coming decades (López-Moreno *et al.* 2008), the spatial patterns of fire hazard might be modified through some changes in fire weather. Of particular concern are the western and northern parts of our study area both located at the edge of the Mediterranean bioclimatic area. In these peculiar locations, the FWSL is still short (Fig. 3) but these areas are expected to undergo the most intense changes (Ruffault *et al.* 2014).

A similar hypothesis about the control of weather over the spatial patterns of fires could apply to several parts of the Euro-Mediterranean region. Unfortunately, it is difficult to compare our figures with the results of similar studies, as most spatial models of wildfires did not include the impact of fire weather in a meaningful way (e.g. Martínes *et al.* 2009; Moreira *et al.* 2010; Duane *et al.* 2015). However, the 30% reported here for large fires is in the same order of magnitude as the 29.2% found by Parisien *et al.* (2011a) in a flat boreal region with a relatively low fire suppression. One might have expected the influence of fire weather to be higher in our study area because the topography generally increases the spatial variations in weather. But many other factors can also influence the importance of fire weather in controlling the spatial patterns of fires, and in many different ways. For instance, evaluating the net effect of suppression policies is challenging because they may simultaneously have opposite influences. On the one hand, fire suppression policies are likely to reduce the importance of the spatial structure of weather on wildfire probabilities. On the other hand, fire suppression also distorts the relationship between fires and the weather and can increase the role of specific combinations of synergic weather conditions (or fire weather types, Ruffault *et al.* 2016) for which fire suppression operations are not effective. For instance, it is likely that the implementation of a new fire policy in southern France resulted in an increase in the relative probability of fires in the windiest areas (Ruffault and Mouillot 2015).

Here our aim was to provide a comprehensive understanding of the regional spatial pattern of wildfires and we consequently limited our analyses to a small number of relevant explanatory variables (Table 1). Nevertheless, we obtained AUC values that are in the same range as those observed by other authors predicting the spatial distribution of fires at a regional scale in the Mediterranean (Moreira *et al.* 2010, Duane *et al.* 2015,) and elsewhere in fire prone areas with fragmented landscapes (Syphard *et al.* 2008; Bar-Massada *et al.* 2013; Hawbaker *et al.* 2013; Faivre *et al.* 2014). Three important methodological choices are worth mentioning here. First, a variable that estimated the distance to the nearest fire station (Table S1) had to be discarded from our statistical models despite its relative contribution in BRT models (up to 14% for large fires, not shown). Indeed, we observed that fire hazard was higher in areas located close to the fire stations, surely because they were intentionally located to maximize suppression, as also shown by Robinne *et al.* (2016) in a region in Canada. This is a good example of the complex impact of humans on the spatial patterns of fires, with both direct and indirect impacts that challenge our assessment of their net effect (Brotons *et al.* 2013; Parisien *et al.* 2016). In our study, we separated groups of human and land cover variables, which was helpful from a methodological point of view (Fig. 3, Tables 1 and 2) but this boundary is very blurred in Mediterranean landscapes that are largely shaped by the history of human activities. Our second important methodological choice was not to include topographical variables. There is compelling evidence that topography directly influences fire spread through slope steepness and local atmospheric air movements (Rothermel 1991) and is related to several spatial fire metrics (Parks *et al*. 2012; Duane *et al*. 2015; Liu and Wimberley 2016) but the indirect effects of topography, expressed through contrasting vegetation types, fuel amounts or fuel moisture are often more relevant (Mouillot *et al.* 2003). In fact, the indirect effects of topography on vegetation were partially taken into consideration in our study, through our altitude dependent methods for the interpolation of daily precipitation and temperature data, and the impact of weather on LAI estimations and functional drought indices. Third, we paid particular attention to providing some realistic estimations of the spatial structure of fire weather. To this end, we based our approach on the prior identification of the fire-weather relationship using a few relevant weather variables and drought indices, thereby avoiding generic fire danger indices whose validity may be limited in areas, ecosystems or anthropogenic contexts for which they were not designed. In addition, our drought indices were estimated with a process based water balance model and therefore have the advantage of accounting for weather, local soil conditions and vegetation functioning in a single metric. The use of such functional indices as proxies of fuel dryness is a step forward in our understanding of the fuel-weather interactions (Ruffault and Mouillot 2015; Williams *et al*. 2015; Boer *et al*. 2016).

## Conclusion

Wildfire is a highly scale-dependent process (Moritz *et al.* 2005), as are the relative contributions of the drivers of wildfire distribution (Heyerdahl *et al.* 2001; Parisien and Moritz 2009; Parisien *et al.* 2011b) but the implementation of effective fire policies and landscape management relies on the identification of the drivers of wildfire at landscape to regional scales. Here, we provide evidence that, in the French Mediterranean area, where important funds are dedicated to fire prevention and suppression, the spatial pattern of fire likelihood remains extremely uneven (Fig. 5) due to the spatial interactions between top-down (climate) and bottom-up (fuel, ignition patterns) factors. While the projected extent of WUI and vegetation shifts due to climate change has been identified as one of the critical factors that will determine future shifts in wildfire hazard (Moreira *et al.* 2011; Batllori *et al.* 2013; Liu and Wimberley 2016), our results also suggest that local changes in fire weather should be taken into account when projecting fire hazard in the Mediterranean region.

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Table 1. Selected explanatory variables used as inputs in boosted regression tree (BRT) models for predicting the spatial distribution of fires in Mediterranean France. Maps of the fire weather season length (FWSL) are shown in Fig. 2. Maps of the human and fuel-related variables are shown in Fig. S1. Human and land cover variables were derived from the BD Topo (IGN 2007) and Corine land cover (EEA 1994) databases, respectively.

| **Variable** | **Unit** | **Data source** |
|---|---|---|
| *Humans* | | |
| Road density | $km.km^{-2}$ | BD Topo |
| Housing density | $nb.km^{-2}$ | BD Topo |
| Wildland Urban interface (WUI) | $km^{2}.km^{-2}$ | BD Topo |
| *Fuel/Land cover* | | |
| Shrubland area | *%* | Corine land cover |
| Forest area | *%* | Corine land cover |
| Landscape diversity | - | Corine land cover |
| *Weather* | | |
| Fire weather season length (FWSL) | *days* | |

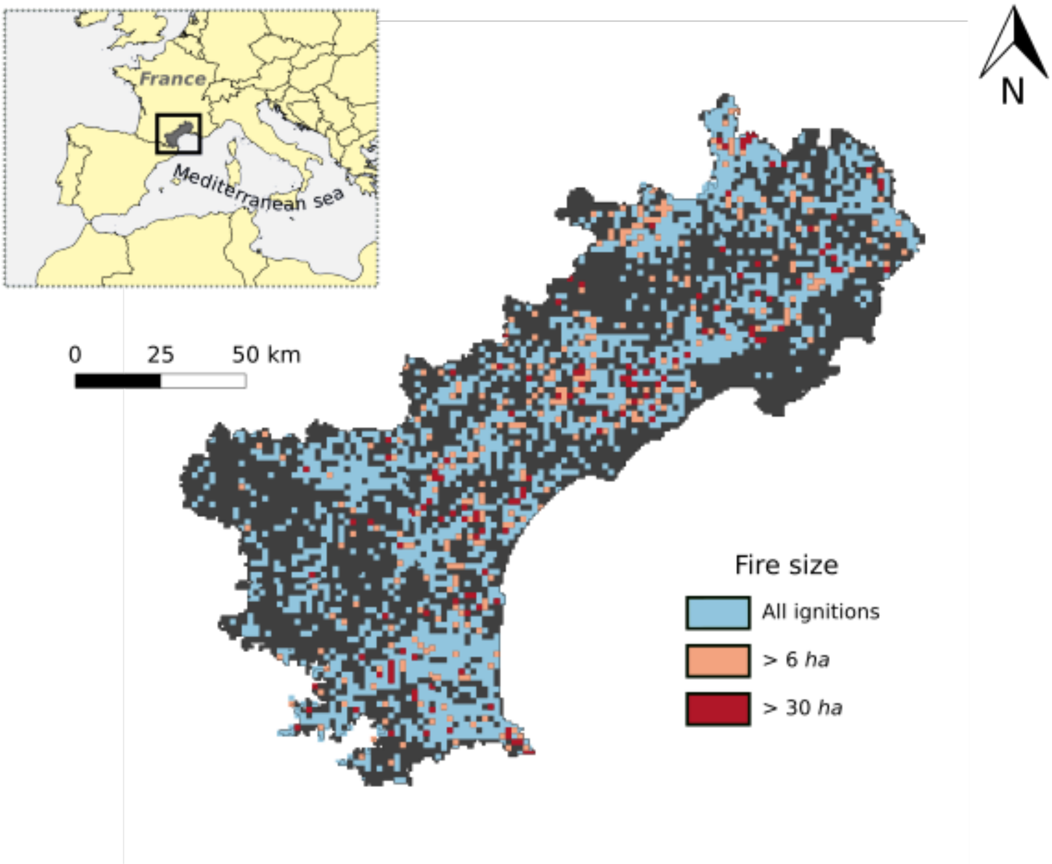
Table 2. Performance of spatial boosted regression tree (*BRT*) models in predicting the spatial distribution of fires in southern France between 1990 and 2006 and for different final fire size classes. For each model, 70% of the grid cells were used to build models and the remaining 30% were used for validation. Means and standard deviations of an ensemble of 25 *BRT* models are given. AUC is the area under the receiving operator curve (ROC) curve. The commission error (false positives) is the percentage of fire events misclassified as absences. The omission error is the percentage of non-fire events misclassified as presences (false negatives). The probability threshold is minimized according to the sum of these two values.

| **Fire size** | **Omission error (%)** | **Commission error (%)** | **AUC** |
|---|---|---|---|
| > 0 ha | 34.0. (3.5) | 31.0 (2.8) | 0.73 (1.2) |
| > 1 ha | 33.8 (3.6) | 32.6 (3.7) | 0.72 (1.6) |
| > 6 ha | 34.7 (3.3) | 31.9 (5.3) | 0.72 (2.7) |
| > 15 ha | 35.0 (5.4) | 32.7 (6.4) | 0.72 (3.6) |
| > 30 ha | 34.7 (8.3) | 32.0 (8.9) | 0.72 (4.3) |

Table 3. Correlation among the mean contributions of each variable to boosted regression tree (BRT) models predicting the spatial distribution of fires for different final fire size classes. Spearman correlation coefficient (ρ) and its associated P-value are reported (*P< 0.1; **P< 0.01).

| **Fire size** | **> 0 ha** | **> 1 ha** | **> 6 ha** | **> 15 ha** | **> 30 ha** |
|---|---|---|---|---|---|
| **> 0 ha** | 1 | | | | |
| **> 1 ha** | 0.92** | 1 | | | |
| **> 6 ha** | 0.17 | 0.50 | 1 | | |
| **> 15 ha** | 0.14 | 0.46 | 0.75 | 1 | |
| **> 30 ha** | 0.32 | 0.59 | 0.89* | 0.89* | 1 |

682 **Figure 1**




683

684 Figure 1: Map of the study area showing the spatial distribution of fires as a function
685 of the maximum fire size observed in each grid cell between 1990 and 2006.

**Figure 2**

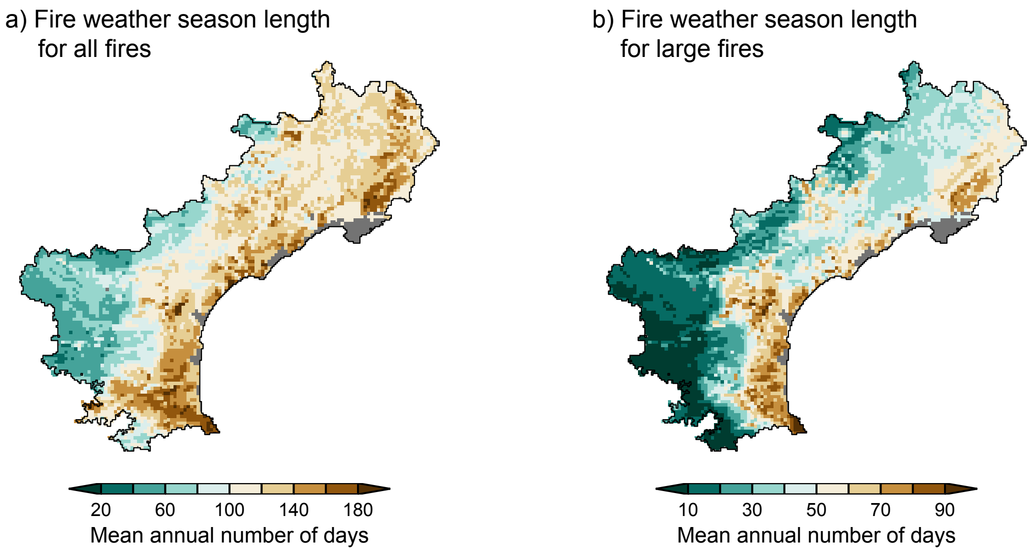



Figure 2**.** Mean annual fire weather season length (FWSL) between 1990 and 2006 for a) all fires and b) large fires (30 ha). Note the different scales between the two panels.

**Figure 3**

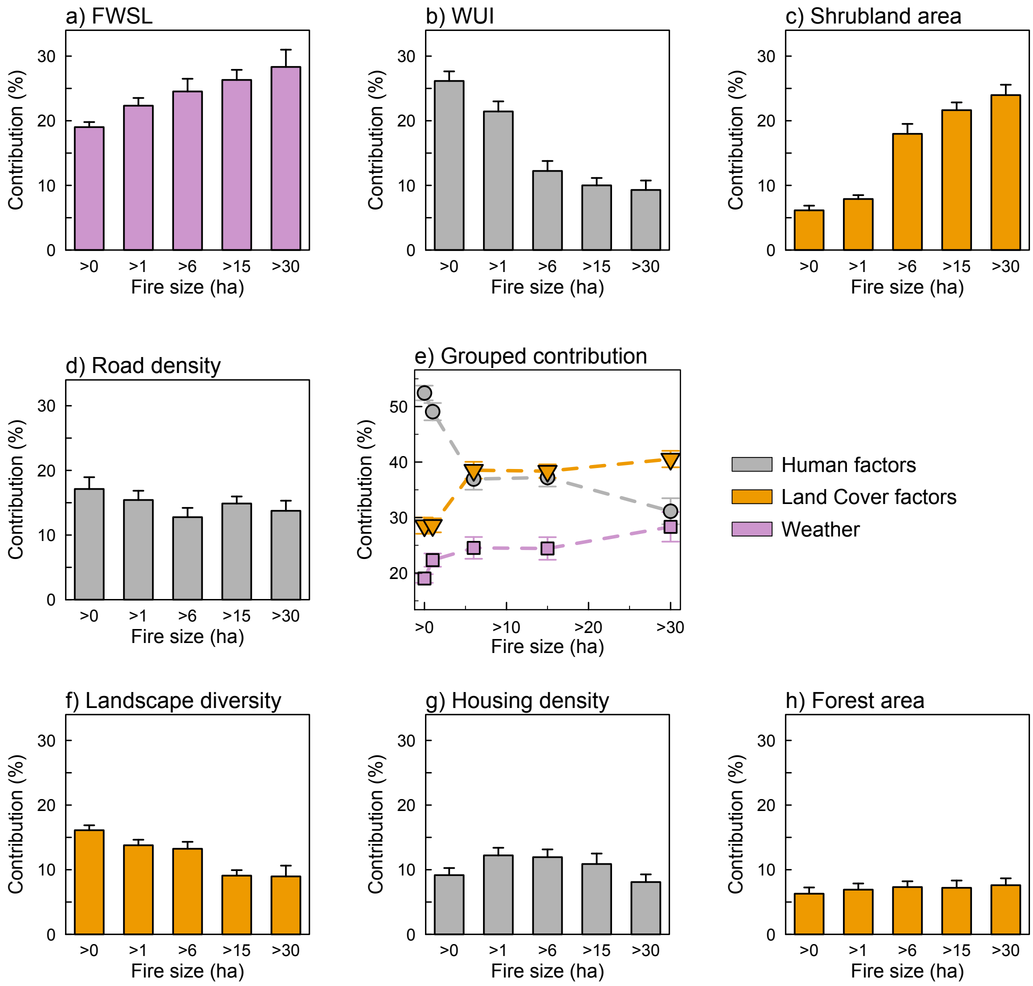



Figure 3. Relative contribution of explanatory variables in the boosted regression tree (BRT) models predicting the spatial distribution of fires for different final fire size classes between 1990 and 2006. The contributions of individual (a-d, f-h) and grouped variables (e) are given. For each fire size, the mean and the standard deviation of an ensemble of 25 models are represented. FWSL is the fire weather season length. WUI is the wildland urban interface.

**Figure 4**

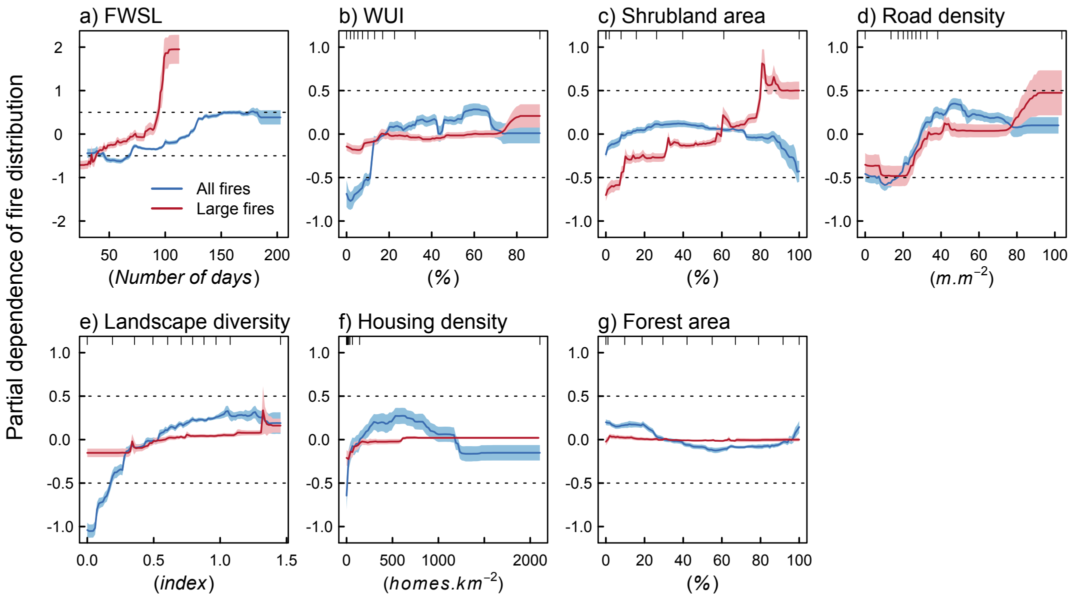



Figure 4. Partial dependence of spatial distribution of all fires and large fires (> 30 ha) on the 7 explanatory variables. Partial dependence expresses the expected response in the spatial distribution of fires for a variable of interest when all other variables are held constant. The mean and the confidence interval of an ensemble of 25 models are given. FWSL is the fire weather season length and WUI is the wildland-urban interface.

**Figure 5**

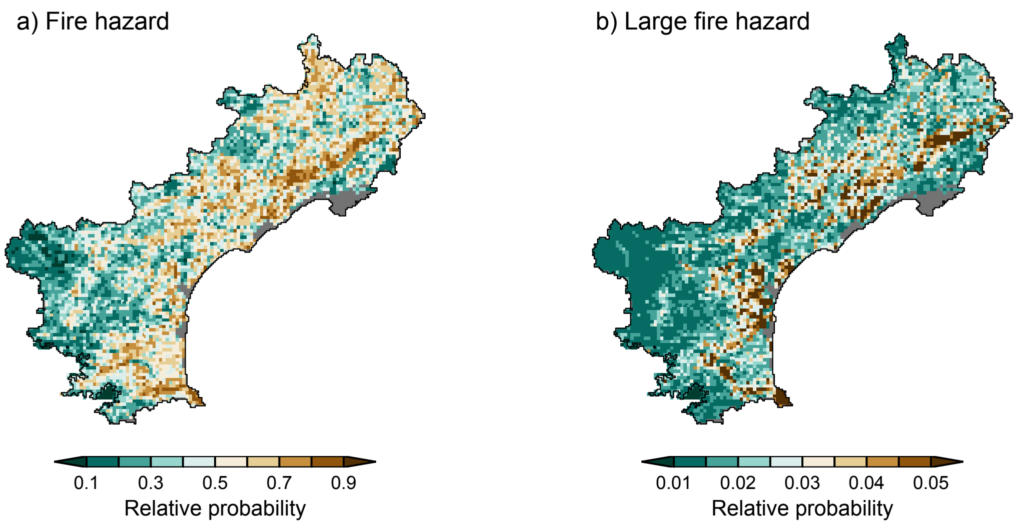



Figure 5. Fire hazard for a) all fires and b) large fires (> 30 ha) determined with boosted regression tree (BRT) models from 7 key explanatory variables related to humans, weather and land cover characteristics of the landscape between 1990 and 2006. Note the different scales between the two panels.