



**HAL**  
open science

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

Julien Ruffault, Florent Mouillot

► **To cite this version:**

Julien Ruffault, Florent Mouillot. Contribution of human and biophysical factors to the spatial distribution of forest fire ignitions and large wildfires in a French Mediterranean region. *International Journal of Wildland Fire*, 2017, 26 (6), pp.498-508. 10.1071/WF16181 . hal-01681548

**HAL Id: hal-01681548**

**<https://hal.science/hal-01681548v1>**

Submitted on 15 May 2018

**HAL** is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

1 **Title: Contribution of human and biophysical factors to the spatial distribution of**  
2 **forest fire ignitions and large wildfires in a French Mediterranean region**

3 *Julien Ruffault<sup>1,2,3,4</sup> and Florent Mouillot<sup>1</sup>*

4 (1) IRD, UMR CEFE (Centre d'écologie fonctionnelle et évolutive), IRD 1919 route de  
5 Mende Montpellier cedex 5, France.

6 (2) Aix-Marseille University, CEREGE UM 34 CNRS, Aix en Provence, France.

7 (3) IRSTEA, UR RECOVER, Aix en Provence, France

8 (4) IMBE, Aix Marseille Université , CNRS, IRD, Avignon Université , Marseille  
9 Cedex 03, France.

10 \* Corresponding author: Julien Ruffault

11 E-mail: [julien.ruff@gmail.com](mailto:julien.ruff@gmail.com)

12 Tel: +33 4 67 61 32 92

13 Fax: +33 4 67 41 21 38

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

**15 Abstract**

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

**31 Summary**

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

## 37 **Introduction**

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

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

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

61 Yet, in regions of complex orography like the Mediterranean, we observe steep weather  
62 gradients (Lionello *et al.* 2006) that could help define areas where wildfires are most  
63 likely to occur (Moritz *et al.* 2010). In the Mediterranean, this knowledge gap is often  
64 mentioned as one of the major source of uncertainty when projecting future fire  
65 likelihood at the regional level (Piñol *et al.* 1998; Martínez *et al.* 2009; Moreira *et al.*  
66 2011) and part of the problem is the difficulty in identifying and mapping wildfire  
67 danger.

68 First, quantifying the contribution of weather requires unravelling the multiscale  
69 temporal relationships between climate and fire activity. Climate affects fire probability  
70 both indirectly, through its long term control of vegetation, and directly through what  
71 is termed fire weather, i.e. the weather conditions that influence fire ignition, fire  
72 behavior and suppression (Bradstock 2010). In turn, fire weather is the result of  
73 atmospheric processes at different time scales: fuel production and desiccation in the  
74 medium term and instantaneous conducive atmospheric conditions in the short term  
75 (Ruffault *et al.* 2016). Hence, linking fire activity to mean climatic conditions helps  
76 determine the biophysical niche of fires (e.g. Parisien and Moritz 2009; Whitman *et al.*  
77 2015). These indices nevertheless cannot separate the indirect from the direct effects of  
78 climate on the spatial distribution of fires, nor do they represent the co-occurrence of  
79 several multiscale weather events associated with fires.

80 Second, in regions with marked climate seasonality like the Mediterranean, variations  
81 in climate over time have a much greater influence than spatial variations, making it  
82 difficult to extract the impact of its spatial component on fire activity. Finally, as the  
83 fire-weather relationship is shaped by both the vegetation (Pausas and Paula 2012) and  
84 human practices (Marlon *et al.* 2008; Ruffault and Mouillot 2015), the weather

85 conditions that drive the fire occurrence and fire spread processes can vary considerably  
86 in space and over time (Ruffault and Mouillot 2015; Higuera *et al.* 2015).

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

## 101 **Materials and Methods**

### 102 *Study area*

103 The study area covers four French administrative districts (total area 21,637 km<sup>2</sup>) in  
104 southern France (Fig. 1). The climate is Mediterranean with hot dry summers, cool wet  
105 winters and high inter-annual variability. The rainfall gradient depends on the  
106 topography and ranges from 550 mm at the coast (elevation = 0 m) to 1,630 mm in the  
107 central foothills (elevation = 1,450 m). Closed forests dominated by Mediterranean  
108 evergreen tree species (*Quercus ilex*, *Pinus halepensis*) and shrublands (*Cistus*

109 *monspeliensis*, *Quercus coccifera*) cover 65% of the study area (French national forest  
110 inventory, 2006). Agricultural land use (mainly vineyards) accounts for 28% and urban  
111 areas the remaining 7%.

#### 112 *General method and selection of the variables*

113 We assessed the drivers of the spatial distribution of fires for a range of final fire size  
114 classes by modeling the relationship between fire presence as the response variable and  
115 a set of potential human, weather and land cover factors as predictor variables. The  
116 spatial partitioning of the study area followed the French fire management agency's 4-  
117 km<sup>2</sup> grid system for the French territory. We limited our analysis to the most recent  
118 period (1990-2006) to avoid biases resulting from the shift in fire activity observed at  
119 the end of the 1980s in the study area (Ruffault and Mouillot 2015). For each class of  
120 final size of fire, a binary variable was generated to represent its corresponding spatial  
121 fire distribution for each grid cell, positive if at least one fire had occurred over the 17-  
122 year study period. The decisions to select a variable (or not) were based on both  
123 objective analysis (ease of interpretation and a range of final fire size classes) and the  
124 results of previous studies conducted in the Euro-Mediterranean region (Martínez *et al.*  
125 2009; Moreira *et al.* 2010; 2011; Oliveira *et al.* 2012; Duane *et al.* 2015; Fernandes *et*  
126 *al.* 2016). Seven variables (Table 1) were selected to build a model by iteratively  
127 eliminating correlated and non-informative variables from an original set of 21  
128 variables (Table S1). To this end, the correlation between all explanatory variables was  
129 assessed to identify variables correlated above a threshold of  $|\rho|=0.7$ . Then the fits of  
130 spatial fire distributions were assessed against these two correlated variables to decide  
131 which variable to retain. Variables with spurious effects were also discarded. Regional  
132 maps of fire distribution, weather, human and land cover variables were then collected  
133 at the 4-km<sup>2</sup> grid scale. For land cover and human factors, all the explanatory variables

134 were mapped to reflect the average conditions over the study period (1990-2006) as  
135 closely as possible, but due to the lack of historical data for some variables, the  
136 conditions prevailing on a single date had to be chosen as representative of the 17-year  
137 period (see details below). However, as no major economic or societal changes  
138 occurred during this period, we did not expect this simplification to be a major  
139 limitation.

#### 140 *Fire data*

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

156 *Fire weather maps*

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

166 (i) First, to determine the fire-weather relationship, we assessed the relative importance  
167 of several key weather variables in the probability of fire occurrence using the spatio-  
168 temporal framework of Ruffault and Mouillot (2015). For each fire, we extracted the  
169 associated weather conditions in our basic spatio-temporal unit (or voxel, on 4-km<sup>2</sup> grid  
170 cells and at a daily time step). Boosted regression tree (BRT, see description below)  
171 models were then used to describe the relationship between fire occurrence and the  
172 weather by comparing the conditions associated with fire voxels (positive elements)  
173 with those associated with a sample of non-fire voxels (absence elements). Five  
174 variables were used to capture the weather conditions driving fire occurrence and fire  
175 spread probabilities: a proxy of fuel moisture content of litter (Surface drought), a proxy  
176 of fuel moisture content of living biomass (Vegetation drought), relative air humidity,  
177 temperature and wind speed. The two proxies of fuel moisture content were derived  
178 from a daily process based water-budget model, validated in forest stands in southern  
179 France by Ruffault *et al.* (2013), and computed here for a single plant functional type  
180 (PFT) representative of the deep-rooted evergreen woody species (trees and large

181 shrubs) encountered in our study area. Surface drought is expressed as the relative soil  
182 water content of the uppermost soil layer. Vegetation drought is expressed as the ratio  
183 of actual evapotranspiration to maximum transpiration (transpiration without water  
184 stress).

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

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

#### 201 *Human variables*

202 Three variables were selected to represent the pattern of human influence over the study  
203 area: road density, housing density, and the percentage of wildland urban interface  
204 (WUI). Vectorial information related to roads and human habitats was extracted from

205 the BD-Topo database (IGN 2007). The density of roads is expressed as the total road  
206 length per unit land area. The density of houses was calculated as the fraction of unit  
207 area covered by urban polygons. The WUI percentage was calculated as the distance to  
208 aggregated and open human habitat according to the method proposed by Lampin-  
209 Maillet *et al.* (2010) and is expressed as the percentage of WUI in each grid cell. Fig.  
210 S1 shows a map of these variables.

### 211 *Land cover variables*

212 Three variables were selected to represent the patterns of land cover in the study area:  
213 percentage of shrubland area, percentage of forest area, and the diversity of vegetation  
214 types. All these variables were derived from the Corine land cover database 2000 (EEA  
215 1994), which was previously reclassified into four main categories (shrublands, forests,  
216 grasslands and other non-fire prone areas: urban area, crops, bare ground) according to  
217 the method described in Moreira *et al.* (2010). Shrubland and forest areas were  
218 calculated as the percentage area of the grid cell covered by forest and shrubland type  
219 vegetation, respectively. The landscape diversity represents the diversity in the  
220 fractional distribution of land cover types that make up the landscape and was  
221 calculated with the Shannon diversity index with a 10-km wide moving window using  
222 FRAGSTATS V3 (McGarigal *et al.* 2002). Fig. S1 shows a map of these variables.

### 223 *Fire spatial model*

224 We used a machine-learning algorithm, boosted regression trees (BRT; De'ath 2007;  
225 Elith *et al.* 2008) to predict the spatial pattern of fires. BRT uses the iterative  
226 partitioning approach of regression trees, but reduces predictive error by "boosting"  
227 initial models with additional, sequential trees that model the residuals in randomized  
228 subsets of the data (De'ath 2007; Elith *et al.* 2008). BRT methods have been

229 increasingly recommended for ecological analyses because of their flexibility in  
230 modeling complex nonlinear relationships and interactions without the restrictive  
231 assumptions of parametric statistics (Olden *et al.* 2008).

232 BRT models need information about the presence and absence of fires in the grid cells  
233 to be able to determine the conditions associated with fire. To be able to compare the  
234 models more easily, the prevalence (the percentage of fire presence grid cells in the  
235 sample dataset) was fixed at 0.1. The absence data for each fire size class was randomly  
236 selected from the pool of absence grid cells. The learning rate (*lr*), the tree size or tree  
237 complexity (*tc*) and the number of trees (*nt*) are the main parameters of BRT models  
238 and were set according the procedure recommended by Elith *et al.* (2008). For all  
239 models, a bag fraction of 0.5 was used, meaning that, at each step, 50% of the data were  
240 randomly drawn from the training dataset. As the number of samples could  
241 subsequently vary between models, we set *tc* to 4 (based on preliminary analyses) and  
242 then determined *lr* as a value that resulted in the average test error being minimized  
243 between approximately 1,000 and 2,000 trees (Elith *et al.* 2008). The *nt* in each BRT  
244 model was selected automatically using 10 fold cross-validation to avoid model  
245 overfitting. BRT models were computed in R with the *gbm* package (Ridgeway 2006)  
246 and custom functions created by Elith *et al.* (2008) computed using a Bernoulli  
247 (logistic) error structure.

248 We used the area under the receiver operating characteristics (*ROC*) curve (*AUC*) to  
249 evaluate the suitability of the models. For each model, 70% of the observations were  
250 randomly selected from the complete dataset to build the statistical model (training  
251 dataset). The remaining observations (30%) were used to evaluate the accuracy of  
252 model classification (validation dataset). We also report the commission error (false

253 positive rate) and omission error (false negative rate) at the probability threshold that  
254 maximizes the sum of sensitivity (the fraction of true positives) and specificity (the  
255 fraction of false positives) values (Lobo *et al.* 2007). To limit the stochasticity in model  
256 outcomes caused by the subsampling and bagging, we created an ensemble of 25 BRT  
257 models and then averaged the results.

258 We interpreted the BRT models by first looking at the relative contribution of the  
259 variables to the predictive models. The contribution of the different predictors was  
260 estimated from the sum of squared improvements associated with that variable and  
261 averaged across all trees in the boosted model (De'ath 2007; Elith *et al.* 2008). The  
262 relative importance of environmental factors controlling the spatial distribution of fires  
263 was assessed for individual variables as well as for the grouped variables for humans,  
264 land cover and weather (Table 1). The contributions of the grouped variables were  
265 determined by adding the percentage contributions of their constituent variables. To  
266 estimate the degree of similarity among variable contributions among different classes  
267 of fire size classes, a rank (Spearman) correlation was performed on the mean  
268 contribution of the variables in pair-wise combinations of fire size classes. A lack of  
269 significance ( $p < 0.05$ ) in a correlation indicates that the relative importance of  
270 environmental controls differs among sizes. We also examined the relationship between  
271 the dependent and independent variables by plotting the partial dependencies of  
272 responses to individual predictors. Finally, we computed the fire hazard maps, which  
273 were derived from statistical models between the spatial distribution of fires and its  
274 environmental drivers.

## 275 **Results**

### 276 *Regional patterns of fire weather season length*

277 Fire activity in southern France was shown to be mainly linked to drought conditions  
278 but with an increasing contribution of wind speed with increasing fire size (Fig. S2, see  
279 also Ruffault and Mouillot 2015). A significant spatial gradient was observed in the fire  
280 weather season length (FWSL), as shown for two contrasted sizes of fires: fires > 0 ha  
281 (hereafter all fires) and fires > 30 ha only (hereafter large fires) (Fig. 2). For all fires,  
282 the FWSL ranged from 40 to 180 days.year<sup>-1</sup> (Fig. 2a). The lowest values were observed  
283 in the western part of the region where rainfall and mean temperature are respectively,  
284 higher and lower than the regional means (Ruffault *et al.* 2013). By contrast, a longer  
285 FWSL was observed in the drier coastal areas (Ruffault *et al.* 2013). Some marked local  
286 variations were also detected according to the variations in soil water holding capacity  
287 that influenced the variations in live fuel moisture content, and in turn, the FWSL. For  
288 large fires, the regional pattern of fire weather was similar to the one observed for all  
289 fires (Fig. 2b) but with a coherently shorter FWSL (ranging from about 10 days.year<sup>-1</sup>  
290 in the western part of the region to 100 days.year<sup>-1</sup> in the coastal area).

### 291 *Relative contribution of climate, land-cover and human variables to the spatial* 292 *distribution of fires.*

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

298 The relative contribution of the explanatory variables to the spatial fire distribution  
299 models showed a size-dependent pattern (Fig. 3). The distribution of all fires was  
300 largely controlled by the percentage of wildland urban interface (*WUI*; 26.0%), the  
301 FWSL (18.8%) and road density (16.4%). The relative importance and ranking of the  
302 explanatory variables changed significantly with an increase in fire size: a major shift  
303 was observed between fires > 1 ha and fires > 6 ha (Table 3, Spearman test, p-  
304 value<0.1). When the individual contributions of all fires and large fires were  
305 compared, there was a significant increase in shrubland area (from 6% to 24% and from  
306 18.4% to 27%, respectively) (Fig. 2c) and in the FWSL (Fig. 2a) and a significant  
307 decrease (from 26% to 9%) in *WUI* (Fig. 2f). When these contributions were grouped,  
308 we observed marked control of human variables over spatial fire patterns, but increasing  
309 influence of climate and land cover factors with increasing fire size (summarized in  
310 Fig. 3e)

311 Individual relationships between each explanatory variable and fire hazard showed  
312 different patterns (Fig. 4). Fire probabilities were higher under intermediate levels of  
313 human pressure (Fig. 4b,d,f) but this pattern tended to disappear with increasing fire  
314 size. As one might expect, the FWSL positively and monotonically affected fire  
315 probability, regardless of the final fire size (Fig. 4a). Finally, vegetation and land cover  
316 variables showed some contrasting patterns. The probability of large fire occurrence  
317 increased with an increase in the shrubland area (Fig. 4c) but decreased with increasing  
318 forest area. The probabilities of ignition and large fires both increased with higher  
319 landscape diversity but the impact of this variable was greater on fire ignitions (Fig.  
320 4e).

321 *Fire hazard maps*

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

326 **Discussion**

327 The peculiar Euro-Mediterranean context points to an advanced stage of anthropogenic  
328 fire-regime transformation (Moreira *et al.* 2011). Accordingly, in southern France,  
329 where the majority of fires are caused by humans (Curt *et al.* 2016), the distribution of  
330 fires was mainly driven by variables that reflect the level and nature of human pressure  
331 (Fig. 3). This is further evidence for the overwhelming impact of anthropogenic factors  
332 on the spatial patterns of fire ignitions in the Euro-Mediterranean area (Martinez *et al.*  
333 2009; Oliveira *et al.* 2012), as also observed in a number of fire prone areas where  
334 anthropic pressure is high and can override the effects of biophysical factors (Cardille  
335 *et al.* 2001; Syphard *et al.* 2008; Hawbaker *et al.* 2013; Faivre *et al.* 2014; Mann *et al.*  
336 2016). Fire-start hazard was higher under intermediate levels of anthropogenic pressure  
337 (Fig. 4), a pattern that has been reported in other anthropogenic fire regimes (Syphard  
338 *et al.* 2007; Moreira *et al.* 2010, Parisien *et al.* 2012).

339 In southern France, the greater influence of human-related variables on the spatial  
340 pattern of fires tended to decrease with an increase in fire size, with a concomitant  
341 increase in the importance of fuel characteristics and land cover (Fig. 3). This result  
342 strengthens the fire size dependence hypothesis that was previously proposed to explain  
343 the spatial patterns of fires in Western Europe (Moreira *et al.* 2010). It also suggests  
344 that fuel fragmentation is one the most important factors limiting the occurrence of

345 large fires in the Mediterranean. A direct outcome of this phenomenon is that the areas  
346 where most wildfires occur did not match those where the largest fires occur (Fig. 5).  
347 Most small fires typically occurred in locations where human development and natural  
348 vegetation intermingle, in the most complex landscape mosaics and with frequent or  
349 long lasting droughts. By contrast, large fires are most likely to occur in landscapes  
350 characterized by a dense shrubland cover, low but still significant human pressure to  
351 enable frequent ignitions, and by frequent severe fire weather conditions favoring  
352 extreme fire behavior and hence ineffective fire suppression operations. The greater  
353 probability of large fires in shrublands compared to forested ecosystems is common in  
354 the Mediterranean basin (Moreira *et al.* 2011) and was particularly high in  
355 Mediterranean France although we were unable to conclude whether it is due to the  
356 higher flammability of this type of fuel or less intense fire suppression efforts in  
357 shrublands than in forested ecosystems. Finally, we did not observe a higher probability  
358 of large fires in continuous and homogeneous landscapes (Fig. 4), in contrast to what  
359 is generally observed (Cardille *et al.* 2001; Heyerdahl *et al.* 2001; Viedma *et al.* 2009;  
360 Loepfe *et al.* 2010; Fernandes *et al.* 2016) or simulated from landscape fire succession  
361 models (Hargrove *et al.* 2000; Cary *et al.* 2006). One possible explanation is the need  
362 for a balance between a complex urban/wildland interface and homogeneous landscape  
363 pattern for fires to start and spread, but generally leading to a weak effect of landscape  
364 diversity on large fire hazard. In addition, our large fire threshold (> 30 ha) is low  
365 compared to other regions and ecosystems (Hantson *et al.* 2015) and it is therefore also  
366 possible that the relative contribution of weather, human and land-cover factors is quite  
367 different when larger fires are considered (Liu *et al.* 2013; Fernandes *et al.* 2016).

368 One interesting finding of our study is that the spatial variations in weather conditions  
369 also largely influenced the location of fires in Mediterranean France. We estimated that

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

381 A similar hypothesis about the control of weather over the spatial patterns of fires could  
382 apply to several parts of the Euro-Mediterranean region. Unfortunately, it is difficult to  
383 compare our figures with the results of similar studies, as most spatial models of  
384 wildfires did not include the impact of fire weather in a meaningful way (e.g. Martínez  
385 *et al.* 2009; Moreira *et al.* 2010; Duane *et al.* 2015). However, the 30% reported here  
386 for large fires is in the same order of magnitude as the 29.2% found by Parisien *et al.*  
387 (2011a) in a flat boreal region with a relatively low fire suppression. One might have  
388 expected the influence of fire weather to be higher in our study area because the  
389 topography generally increases the spatial variations in weather. But many other factors  
390 can also influence the importance of fire weather in controlling the spatial patterns of  
391 fires, and in many different ways. For instance, evaluating the net effect of suppression  
392 policies is challenging because they may simultaneously have opposite influences. On  
393 the one hand, fire suppression policies are likely to reduce the importance of the spatial  
394 structure of weather on wildfire probabilities. On the other hand, fire suppression also

395 distorts the relationship between fires and the weather and can increase the role of  
396 specific combinations of synergic weather conditions (or fire weather types, Ruffault *et*  
397 *al.* 2016) for which fire suppression operations are not effective. For instance, it is likely  
398 that the implementation of a new fire policy in southern France resulted in an increase  
399 in the relative probability of fires in the windiest areas (Ruffault and Mouillot 2015).

400 Here our aim was to provide a comprehensive understanding of the regional spatial  
401 pattern of wildfires and we consequently limited our analyses to a small number of  
402 relevant explanatory variables (Table 1). Nevertheless, we obtained AUC values that  
403 are in the same range as those observed by other authors predicting the spatial  
404 distribution of fires at a regional scale in the Mediterranean (Moreira *et al.* 2010, Duane  
405 *et al.* 2015,) and elsewhere in fire prone areas with fragmented landscapes (Syphard *et*  
406 *al.* 2008; Bar-Massada *et al.* 2013; Hawbaker *et al.* 2013; Faivre *et al.* 2014). Three  
407 important methodological choices are worth mentioning here. First, a variable that  
408 estimated the distance to the nearest fire station (Table S1) had to be discarded from  
409 our statistical models despite its relative contribution in BRT models (up to 14% for  
410 large fires, not shown). Indeed, we observed that fire hazard was higher in areas located  
411 close to the fire stations, surely because they were intentionally located to maximize  
412 suppression, as also shown by Robinne *et al.* (2016) in a region in Canada. This is a  
413 good example of the complex impact of humans on the spatial patterns of fires, with  
414 both direct and indirect impacts that challenge our assessment of their net effect  
415 (Brotons *et al.* 2013; Parisien *et al.* 2016). In our study, we separated groups of human  
416 and land cover variables, which was helpful from a methodological point of view (Fig.  
417 3, Tables 1 and 2) but this boundary is very blurred in Mediterranean landscapes that  
418 are largely shaped by the history of human activities. Our second important  
419 methodological choice was not to include topographical variables. There is compelling

420 evidence that topography directly influences fire spread through slope steepness and  
421 local atmospheric air movements (Rothermel 1991) and is related to several spatial fire  
422 metrics (Parks *et al.* 2012; Duane *et al.* 2015; Liu and Wimberley 2016) but the indirect  
423 effects of topography, expressed through contrasting vegetation types, fuel amounts or  
424 fuel moisture are often more relevant (Mouillot *et al.* 2003). In fact, the indirect effects  
425 of topography on vegetation were partially taken into consideration in our study,  
426 through our altitude dependent methods for the interpolation of daily precipitation and  
427 temperature data, and the impact of weather on LAI estimations and functional drought  
428 indices. Third, we paid particular attention to providing some realistic estimations of  
429 the spatial structure of fire weather. To this end, we based our approach on the prior  
430 identification of the fire-weather relationship using a few relevant weather variables  
431 and drought indices, thereby avoiding generic fire danger indices whose validity may  
432 be limited in areas, ecosystems or anthropogenic contexts for which they were not  
433 designed. In addition, our drought indices were estimated with a process based water  
434 balance model and therefore have the advantage of accounting for weather, local soil  
435 conditions and vegetation functioning in a single metric. The use of such functional  
436 indices as proxies of fuel dryness is a step forward in our understanding of the fuel-  
437 weather interactions (Ruffault and Mouillot 2015; Williams *et al.* 2015; Boer *et al.*  
438 2016).

## 439 **Conclusion**

440 Wildfire is a highly scale-dependent process (Moritz *et al.* 2005), as are the relative  
441 contributions of the drivers of wildfire distribution (Heyerdahl *et al.* 2001; Parisien and  
442 Moritz 2009; Parisien *et al.* 2011b) but the implementation of effective fire policies and  
443 landscape management relies on the identification of the drivers of wildfire at landscape

444 to regional scales. Here, we provide evidence that, in the French Mediterranean area,  
445 where important funds are dedicated to fire prevention and suppression, the spatial  
446 pattern of fire likelihood remains extremely uneven (Fig. 5) due to the spatial  
447 interactions between top-down (climate) and bottom-up (fuel, ignition patterns) factors.  
448 While the projected extent of WUI and vegetation shifts due to climate change has been  
449 identified as one of the critical factors that will determine future shifts in wildfire hazard  
450 (Moreira *et al.* 2011; Batllori *et al.* 2013; Liu and Wimberley 2016), our results also  
451 suggest that local changes in fire weather should be taken into account when projecting  
452 fire hazard in the Mediterranean region.

### 453 **Acknowledgments**

454 This work is a contribution to the UE 7th FP Env.1.3.1.1 FUME “Forest fires under  
455 climate, social and economic changes in Europe, the Mediterranean and other fire-  
456 affected areas of the world,” Grant agreement no. 243888. A doctoral research Grant  
457 to J. Ruffault was provided by the Languedoc-Roussillon (LR) region and the *Centre*  
458 *National de la Recherche Scientifique* (CNRS). This work is also a contribution to the  
459 Labex OT-Med (ANR-11-LABEX-0061) funded by the “*Investissements d’Avenir*,”  
460 French Government program of the French National Research Agency (ANR) through  
461 the A\*Midex project (ANR-11-IDEX- 0001-02). We thank the associate editor and two  
462 anonymous reviewers for their constructive comments, which helped us improve our  
463 paper.

464 **References**

- 465 Archibald S, Roy DP, Van Wilgen BW, Scholes RJ (2009) What limits fire? An examination of drivers  
466 of burnt area in Southern Africa. *Global Change Biology* **15**, 613–630. doi:10.1111/j.1365-  
467 2486.2008.01754.x.
- 468 Batllori E, Parisien MA, Krawchuk MA, Moritz MA (2013) Climate change-induced shifts in fire for  
469 Mediterranean ecosystems. *Global Ecology and Biogeography* **22**, 1118–1129.  
470 doi:10.1111/geb.12065.
- 471 Bar-Massada A, Syphard AD, Stewart SI, Radeloff VC (2013) Wildfire ignition-distribution modelling:  
472 a comparative study in the Huron–Manistee National Forest, Michigan, USA. *International Journal*  
473 *of Wildland Fire* **22**, 174–183. doi: 10.1071/WF11178
- 474 Boer MM, Bowman DMJS, Murphy BP, Cary GJ, Cochrane MA, Fensham RJ, Krawchuk MA, Price  
475 OF, Resco De Dios V, Williams RJ, Bradstock RA (2016) Future changes in climatic water balance  
476 determine potential for transformational shifts in Australian fire regimes. *Environmental Research*  
477 *Letters* **11**, 65002. doi:10.1088/1748-9326/11/6/065002.
- 478 Bowman DMJS, Balch J, Artaxo P, Bond WJ, Cochrane MA, D'Antonio CM, Defries R, Johnston FH,  
479 Keeley JE, Krawchuk MA, Kull CA, Mack M, Moritz MA, Pyne S, Roos CI, Scott AC, Sodhi NS,  
480 Swetnam TW (2011) The human dimension of fire regimes on Earth. *Journal of Biogeography* **38**,  
481 2223–2236. doi:10.1111/j.1365-2699.2011.02595.x.
- 482 Bradstock RA (2010) A biogeographic model of fire regimes in Australia: Current and future  
483 implications. *Global Ecology and Biogeography* **19**, 145–158. doi:10.1111/j.1466-  
484 8238.2009.00512.x.
- 485 Brotons L, Aquilué N, de Cáceres M, Fortin MJ, Fall A (2013) How Fire History, Fire Suppression  
486 Practices and Climate Change Affect Wildfire Regimes in Mediterranean Landscapes. *PLoS ONE*  
487 **8**, e62392. doi:10.1371/journal.pone.0062392.
- 488 Cardille JA, Ventura SJ (2001) Environmental and Social Factors Influencing Wildfires in the Upper  
489 Midwest, United States. *Ecological Applications* **11**, 111–127. doi:10.1890/1051-  
490 0761(2001)011[0111:EASFIW]2.0.CO;2.
- 491 Cary GJ, Keane RE, Gardner RH, Lavorel S, Flannigan MD, Davies ID, Li C, Lenihan JM, Rupp TS,  
492 Mouillot F (2006) Comparison of the sensitivity of landscape-fire-succession models to variation  
493 in terrain, fuel pattern, climate and weather. *Landscape Ecology* **21**, 121–137. doi:10.1007/s10980-  
494 005-7302-9.
- 495 Curt T, Fréjaville T, Lahaye S (2016) Modelling the spatial patterns of ignition causes and fire regime  
496 features in southern France: Implications for fire prevention policy. *International Journal of*  
497 *Wildland Fire* **25**, 785–796. doi:10.1071/WF15205.
- 498 De'ath G (2007) Boosted trees for ecological modeling and prediction. *Ecology* **88**, 243–251.  
499 doi:10.1890/0012-9658(2007)88[243:BTfEMA]2.0.CO;2.
- 500 Duane A, Piqué M, Castellnou M, Brotons L (2015) Predictive modelling of fire occurrences from  
501 different fire spread patterns in Mediterranean landscapes. *International Journal of Wildland Fire*  
502 **24**, 407–418. doi:10.1071/WF14040.
- 503 EEA (1994) Corine Land Cover report. (European Environmental Agency) Available at  
504 <http://www.eea.europa.eu/publications/COR0-landcover>
- 505 Elith J, Leathwick JR, Hastie TJ (2008) A working guide to boosted regression trees. *Journal of Animal*  
506 *Ecology* **77**, 802–813. doi:10.1111/j.1365-2656.2008.01390.x.
- 507 Faivre N, Jin Y, Goulden ML, Randerson JT (2014) Controls on the spatial pattern of wildfire ignitions  
508 in Southern California. *International Journal of Wildland Fire* **23**, 799–811.  
509 doi:10.1071/WF13136.
- 510 Fernandes PM, Monteiro-Henriques T, Guiomar N, Loureiro C, Barros AMG (2016) Bottom-Up  
511 Variables Govern Large-Fire Size in Portugal. *Ecosystems* **19**, 1362–1375. doi:10.1007/s10021-  
512 016-0010-2.

- 513 Fréjaville T, Curt T (2015) Spatiotemporal patterns of changes in fire regime and climate: defining the  
514 pyroclimates of south-eastern France (Mediterranean Basin). *Climatic Change* **129**, 239–251.  
515 doi:10.1007/s10584-015-1332-3.
- 516 Gaultier JP, Legros JP, Bornand M, King D, Favrot JC, Hardy R (1993) L'organisation et la gestion des  
517 données pédologiques spatialisées: Le projet DONESOL. *Revue de Géomatique* **3**, 235–253.
- 518 Hantson S, Pueyo S, Chuvieco E (2015) Global fire size distribution is driven by human impact and  
519 climate. *Global Ecology and Biogeography* **24**, 77–86. doi:10.1111/geb.12246.
- 520 Hargrove W W, Gardner R H, Turner M G, Romme WH, Despain DG (2000) Simulating fire patterns in  
521 heterogeneous landscapes. *Ecological Modelling* **135**, 243–263. doi:10.1016/S0304-  
522 3800(00)00368-9.
- 523 Hawbaker TJ, Radeloff VC, Stewart SI, Hammer RB, Keuler NS, Clayton MK (2013) Human and  
524 biophysical influences on fire occurrence in the United States. *Ecological Applications* **23**, 565–  
525 582. doi:10.1890/12-1816.1.
- 526 Heyerdahl EK, Brubaker LB, Agee JK (2001) Spatial controls of historical fire regimes: A multiscale  
527 example from the interior west, USA. *Ecology* **82**, 660–678. doi:10.1890/0012-  
528 9658(2001)082[0660:SCOHFR]2.0.CO;2.
- 529 Higuera PE, Abatzoglou JT, Littell JS, Morgan P (2015) The changing strength and nature of fire-climate  
530 relationships in the northern Rocky Mountains, U.S.A., 1902–2008. *PLoS ONE* **10**, e0127563.  
531 doi:10.1371/journal.pone.0127563.
- 532 IGN (2007) BD Topo 2000, Institut Géographique National. Available at  
533 <http://professionnels.ign.fr/bdtopo>
- 534 Jolly WM, Cochrane MA, Freeborn PH, Holden ZA, Brown TJ, Williamson GJ, Bowman DMJS (2015)  
535 Climate-induced variations in global wildfire danger from 1979 to 2013. *Nature Communications*  
536 **6**, 7537. doi:10.1038/ncomms8537.
- 537 Krawchuk MA, Moritz MA, Parisien M-A, Van Dorn J, Hayhoe K (2009) Global pyrogeography: The  
538 current and future distribution of wildfire. *PLoS ONE* **4**, e5102. doi:10.1371/journal.pone.0005102.
- 539 Lampin-Maillet C, Jappiot M, Long M, Bouillon C, Morge D, Ferrier JP (2010) Mapping wildland-urban  
540 interfaces at large scales integrating housing density and vegetation aggregation for fire prevention  
541 in the South of France. *Journal of Environmental Management* **91**, 732–741.  
542 doi:10.1016/j.jenvman.2009.10.001.
- 543 Lionello P, Malanotte-Rizzoli P, Boscolo R, Alpert P, Artale V, Li L, Luterbacher J, May W, Trigo R,  
544 Tsimplis M, Ulbrich U, Xoplaki E (2006) The Mediterranean climate: An overview of the main  
545 characteristics and issues. *Developments in Earth and Environmental Sciences* **4**, 1–26.  
546 doi:10.1016/S1571-9197(06)80003-0.
- 547 Liu Z, Wimberly MC (2016) Direct and indirect effects of climate change on projected future fire regimes  
548 in the western United States. *Science of the Total Environment* **542**, 65–75.  
549 doi:10.1016/j.scitotenv.2015.10.093.
- 550 Liu Z, Yang J, He HS (2013) Identifying the threshold of dominant controls on fire spread in a boreal  
551 forest landscape of Northeast China. *PLoS ONE* **8**, e55618. doi:10.1371/journal.pone.0055618.
- 552 Lobo JM, Jiménez-Valverde A, Real R (2008) AUC: A misleading measure of the performance of  
553 predictive distribution models. *Global Ecology and Biogeography* **17**, 145–151.  
554 doi:10.1111/j.1466-8238.2007.00358.x.
- 555 Loepfe L, Martínez-Vilalta J, Oliveres J, Piñol J, Lloret F (2010) Feedbacks between fuel reduction and  
556 landscape homogenisation determine fire regimes in three Mediterranean areas. *Forest Ecology and*  
557 *Management* **259**, 2366–2374. doi:10.1016/j.foreco.2010.03.009.
- 558 López-Moreno JI, Goyette S, Beniston M (2008) Climate change prediction over complex areas: Spatial  
559 variability of uncertainties and predictions over the Pyrenees from a set of regional climate models.  
560 *International Journal of Climatology* **28**, 1535–1550. doi:10.1002/joc.1645.
- 561 Mann ML, Batllori E, Moritz MA, Waller EK, Berck P, Flint AL, Flint LE, Dolfi E (2016) Incorporating  
562 Anthropogenic Influences into Fire Probability Models: Effects of Human Activity and Climate  
563 Change on Fire Activity in California. *PLoS ONE* **11**, 1–21. doi:10.1371/journal.pone.0153589.

- 564 Marlon JR, Bartlein PJ, Carcaillet C, Gavin DG, Harrison SP, Higuera PE, Joos F, Power MJ, Prentice  
565 IC (2008) Climate and human influences on global biomass burning over the past two millennia.  
566 *Nature Geoscience* **1**, 697–702. doi:10.1038/ngeo468.
- 567 Martínez J, Vega-García C, Chuvieco E (2009) Human-caused wildfire risk rating for prevention  
568 planning in Spain. *Journal of Environmental Management* **90**, 1241–1252.  
569 doi:10.1016/j.jenvman.2008.07.005.
- 570 McGarigal K, Cushman SA, Neel MC, Ene E (2002) FRAGSTATS: Spatial Pattern Analysis Program  
571 for Categorical Maps. *Analysis* **3.3**, The following citation is recommended by the autho. doi:Cited  
572 By (since 1996) 586rExport Date 3 May 2012.
- 573 Moreira F, Catry FX, Rego F, Bacao F (2010) Size-dependent pattern of wildfire ignitions in Portugal:  
574 When do ignitions turn into big fires? *Landscape Ecology* **25**, 1405–1417. doi:10.1007/s10980-  
575 010-9491-0.
- 576 Moreira F, Viedma O, Arianoutsou M, Curt T, Koutsias N, Rigolot E, Barbati A, Corona P, Vaz P,  
577 Xanthopoulos G, Mouillot F, Bilgili E (2011) Landscape--wildfire interactions in southern Europe:  
578 implications for landscape management. *Journal of Environmental Management* **92**, 2389–402.  
579 doi:10.1016/j.jenvman.2011.06.028.
- 580 Moritz MA, Morais ME, Summerell LA, Carlson JM, Doyle J (2005) Wildfires, complexity, and highly  
581 optimized tolerance. *Proceedings of the National Academy of Sciences of the United States of*  
582 *America* **102**, 17912–7. doi:10.1073/pnas.0508985102.
- 583 Moritz MA, Moody TJ, Krawchuk MA, Hughes M, Hall A (2010) Spatial variation in extreme winds  
584 predicts large wildfire locations in chaparral ecosystems. *Geophysical Research Letters* **37**,  
585 L04801–L04801. doi:10.1029/2009GL041735.
- 586 Mouillot F, Ratte JP, Joffre R, Moreno JM, Rambal S (2003) Some determinants of the spatio-temporal  
587 fire cycle in a mediterranean landscape (Corsica, France). *Landscape Ecology* **18**, 665–674.  
588 doi:10.1023/B:LAND.0000004182.22525.a9.
- 589 Olden JD, Lawler JJ, Poff NL (2008) Machine learning methods without tears: a primer for ecologists.  
590 *The Quarterly Review of Biology* **83**, 171–193. doi:10.1086/587826.
- 591 Oliveira S, Oehler F, San-miguel-ayanz J, Camia A, Pereira JMC (2012) Forest Ecology and  
592 Management Modeling spatial patterns of fire occurrence in Mediterranean Europe using Multiple  
593 Regression and Random Forest. *Forest Ecology and Management* **275**, 117–129.  
594 doi:10.1016/j.foreco.2012.03.003.
- 595 Parisien MA, Parks SA, Krawchuk MA, Flannigan MD, Bowman LM, Moritz MA (2011b) Scale-  
596 dependent controls on the area burned in the boreal forest of Canada, 1980–2005. *Ecological*  
597 *Applications* **21**, 789–805. doi:10.1890/10-0326.1.
- 598 Parisien MA, Parks SA, Miller C, Krawchuk MA, Heathcott M, Moritz MA (2011a) Contributions of  
599 Ignitions, Fuels, and Weather to the Spatial Patterns of Burn Probability of a Boreal Landscape.  
600 *Ecosystems* **14**, 1141–1155. doi:10.1007/s10021-011-9474-2.
- 601 Parisien MA, Parks SA, Krawchuk MA, Little JM, Flannigan MD, Gowman LM, Moritz MA (2014) An  
602 analysis of controls on fire activity in boreal Canada: Comparing models built with different  
603 temporal resolutions. *Ecological Applications* **24**, 1341–1356. doi:10.1890/13-1477.1.
- 604 Parisien MA, Moritz MA (2009) Environmental controls on the distribution of wildfire at multiple spatial  
605 scales. *Ecological Monographs* **79**, 127–154. doi:10.1890/07-1289.1.
- 606 Parisien MA, Miller C, Parks SA, DeLancey ER, Robinne F-N, Flannigan MD (2016) The spatially  
607 varying influence of humans on fire probability in North America. *Environmental Research Letters*  
608 **11**, 75005. doi:10.1088/1748-9326/11/7/075005.
- 609 Parisien MA, Snetsinger S, Greenberg JA, Nelson CR, Schoennagel T, Dobrowski SZ, Moritz MA  
610 (2012) Spatial variability in wildfire probability across the western United States. *International*  
611 *Journal of Wildland Fire* **21**, 313–327. doi:10.1071/WF11044.
- 612 Parks SA, Parisien MA, Miller C (2012) Spatial bottom-up controls on fire likelihood vary across western  
613 North America. *Ecosphere* **3(1)**, 20. doi:10.1890/ES11-00298.1.

- 614 Pausas JG, Paula S (2012) Fuel shapes the fire-climate relationship: Evidence from Mediterranean  
615 ecosystems. *Global Ecology and Biogeography* **21**, 1074–1082. doi:10.1111/j.1466-  
616 8238.2012.00769.x.
- 617 Piñol J, Terradas J, Lloret F (1998) Climate warming, wildfire hazard, and wildfire occurrence in coastal  
618 eastern Spain. *International Journal of Wildland Fire* **11**, 95–106. doi:10.1023/A:1005316632105.
- 619 Ridgeway G (2006) Generalized boosted regression models. *Documentation on the R Package 'gbm',*  
620 *version 1*, 7.
- 621 Robinne FN, Parisien M-A, Flannigan M (2016) Anthropogenic influence on wildfire activity in Alberta,  
622 Canada. *International Journal of Wildland Fire* **25**, 1131–1143. doi:10.1071/WF16058.
- 623 Rothermel RC (1991) Predicting behavior and size of crown fires in the northern Rocky Mountains.  
624 *USDA Forest Service, Intermountain Research Station, Research Paper 46*.
- 625 Ruffault J, Moron V, Trigo RM, Curt T (2017) Daily synoptic conditions associated with large fire  
626 occurrence in Mediterranean France: evidence for a wind-driven fire regime. *International Journal*  
627 *of Climatology* **37**, 524–533. doi:10.1002/joc.4680.
- 628 Ruffault J, Moron V, Trigo RM, Curt T (2016) Objective identification of multiple large fire  
629 climatologies: an application to a Mediterranean ecosystem. *Environmental Research Letters* **11**,  
630 75006. doi:10.1088/1748-9326/11/7/075006.
- 631 Ruffault J, Mouillot F (2015) How a new fire-suppression policy can abruptly reshape the fire-weather  
632 relationship. *Ecosphere* **6**, 1–19. doi:10.1890/ES15-00182.1.
- 633 Ruffault J, Martin-StPaul NK, Rambal S, Mouillot F (2013) Differential regional responses in drought  
634 length, intensity and timing to recent climate changes in a Mediterranean forested ecosystem.  
635 *Climatic Change* **117**, 103–117. doi:10.1007/s10584-012-0559-5.
- 636 Ruffault J, Martin-StPaul N, Duffet C, Goge F, Mouillot F (2014) Projecting future drought in  
637 Mediterranean forests: bias correction of climate models matters! *Theoretical and Applied*  
638 *Climatology* **117**, 113–122. doi:10.1007/s00704-013-0992-z.
- 639 Syphard AD, Radeloff VC, Keeley JE, Hawbaker TJ, Clayton MK, Stewart SI, Hammer RB (2007)  
640 Human influence on California fire regimes. *Ecological Applications* **17**, 1388–1402.  
641 doi:10.1890/06-1128.1.
- 642 Syphard AD, Radeloff VC, Keuler NS, Taylor RS, Hawbaker TJ, Stewart SI, Clayton MK (2008)  
643 Predicting spatial patterns of fire on a southern California landscape. *International Journal of*  
644 *Wildland Fire* **17**, 602. doi:10.1071/WF07087.
- 645 Vidal JP, Martin E, Franchistéguy L, Baillon M, Soubeyroux JM (2010) A 50-year high-resolution  
646 atmospheric reanalysis over France with the Safran system. *International Journal of Climatology*  
647 **30**, 1627–1644. doi:10.1002/joc.2003.
- 648 Viedma O, Angeler DG, Moreno JM (2009) Landscape structural features control fire size in a  
649 Mediterranean forested area of central Spain. *International Journal of Wildland Fire* **18**, 575–583.  
650 doi:10.1071/WF08030.
- 651 Whitman E, Batllori E, Parisien MA, Miller C, Coop JD, Krawchuk MA, Chong GW, Haire SL (2015)  
652 The climate space of fire regimes in north-western North America. *Journal of Biogeography* **42**,  
653 1736–1749. doi:10.1111/jbi.12533.
- 654 Williams AP, Seager R, MacAlady AK, Berkelhammer M, Crimmins MA, Swetnam TW, Trugman AT,  
655 Buening N, Noone D, McDowell NG, Hryniw N, Mora CI, Rahn T (2015) Correlations between  
656 components of the water balance and burned area reveal new insights for predicting forest fire area  
657 in the southwest United States. *International Journal of Wildland Fire* **24**, 14–26.  
658 doi:10.1071/WF14023.

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

665

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

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

675

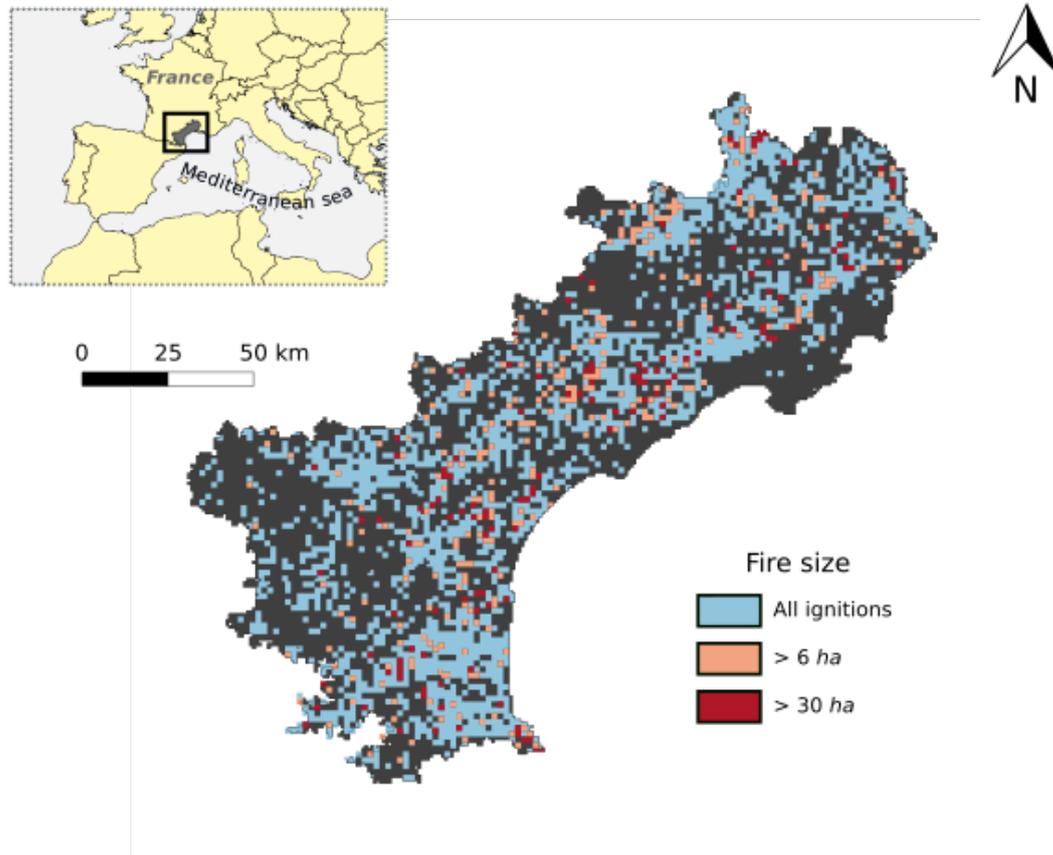
<b>Fire size</b>	<b>Omission error (%)</b>	<b>Commission error (%)</b>	<b>AUC</b>
> 0 ha	34.0 (3.5)	31.0 (2.8)	0.73 (1.2)
> 1 ha	33.8 (3.6)	32.6 (3.7)	0.72 (1.6)
> 6 ha	34.7 (3.3)	31.9 (5.3)	0.72 (2.7)
> 15 ha	35.0 (5.4)	32.7 (6.4)	0.72 (3.6)
> 30 ha	34.7 (8.3)	32.0 (8.9)	0.72 (4.3)

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

680

<b>Fire size</b>	<b>&gt; 0 ha</b>	<b>&gt; 1 ha</b>	<b>&gt; 6 ha</b>	<b>&gt; 15 ha</b>	<b>&gt; 30 ha</b>
<b>&gt; 0 ha</b>	1				
<b>&gt; 1 ha</b>	0.92**	1			
<b>&gt; 6 ha</b>	0.17	0.50	1		
<b>&gt; 15 ha</b>	0.14	0.46	0.75	1	
<b>&gt; 30 ha</b>	0.32	0.59	0.89*	0.89*	1

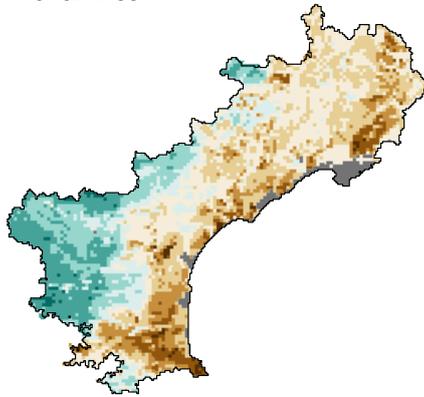
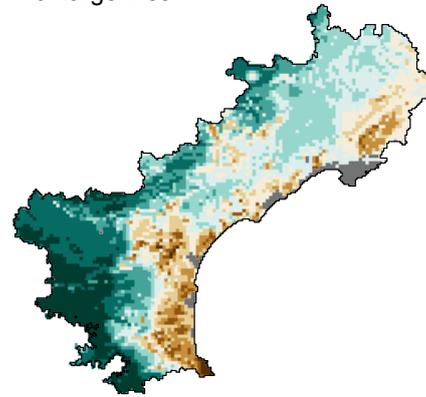
681

682 **Figure 1**

683

684 Figure 1: Map of the study area showing the spatial distribution of fires as a function

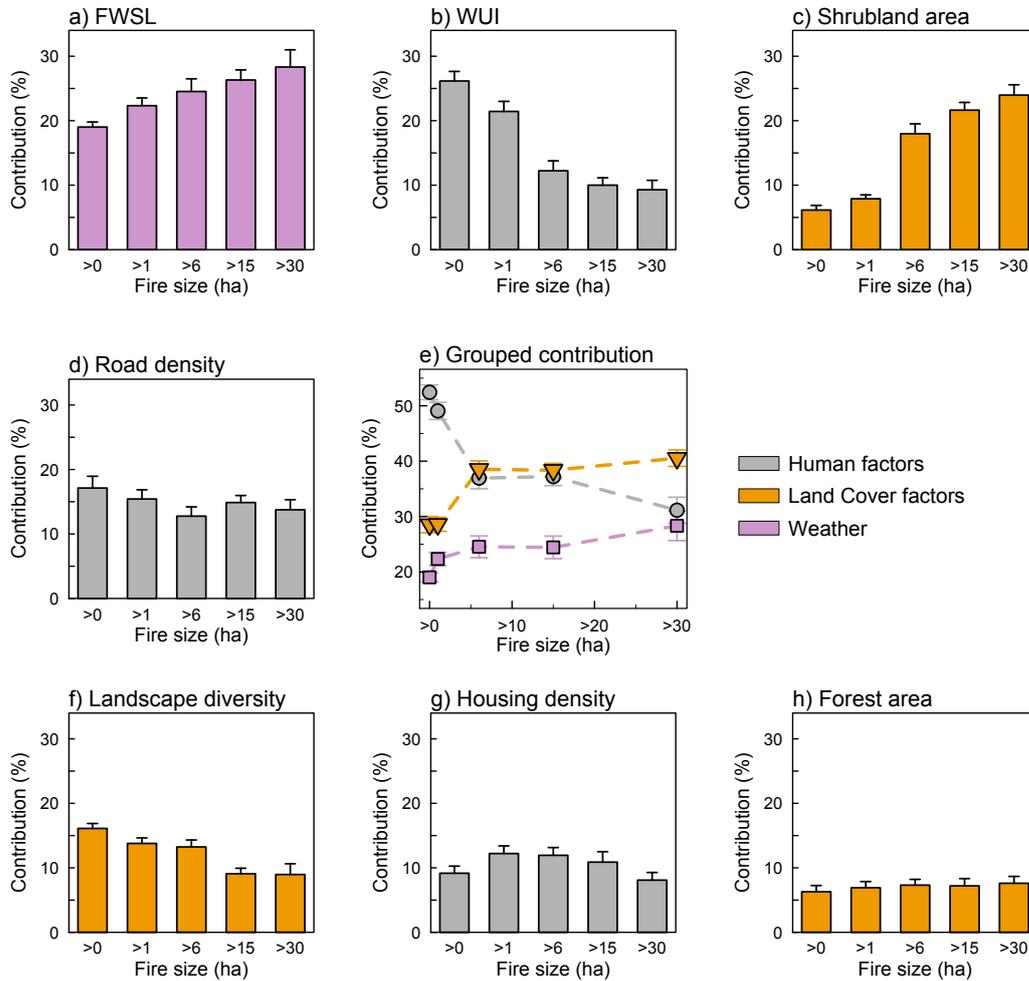
685 of the maximum fire size observed in each grid cell between 1990 and 2006.

686 **Figure 2**a) Fire weather season length  
for all fires20 60 100 140 180  
Mean annual number of daysb) Fire weather season length  
for large fires10 30 50 70 90  
Mean annual number of days

687

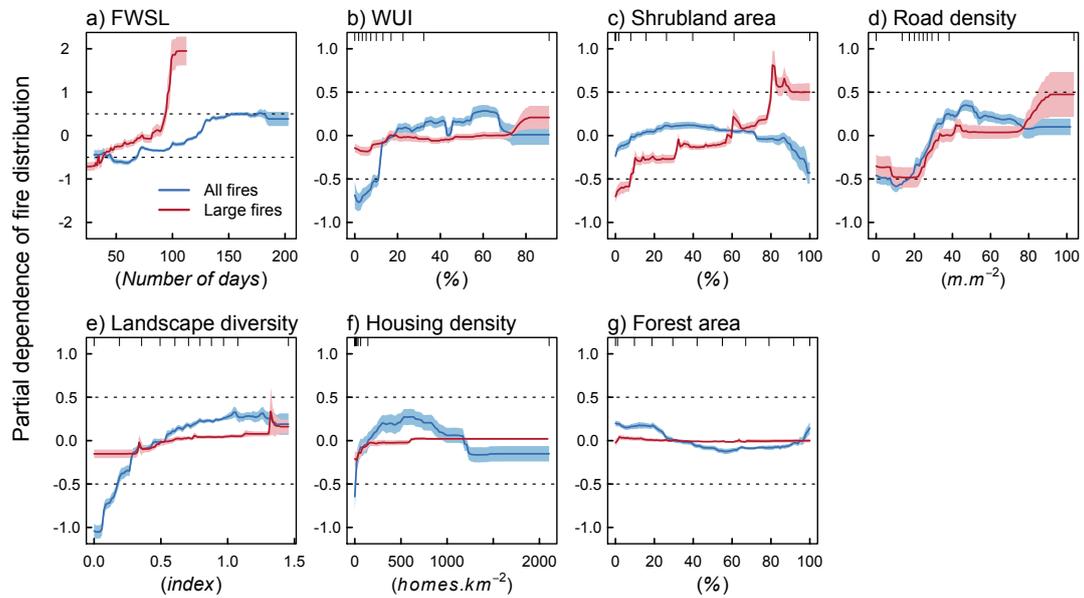
688 Figure 2. Mean annual fire weather season length (FWSL) between 1990 and 2006 for  
689 a) all fires and b) large fires (30 ha). Note the different scales between the two panels.

690 **Figure 3**



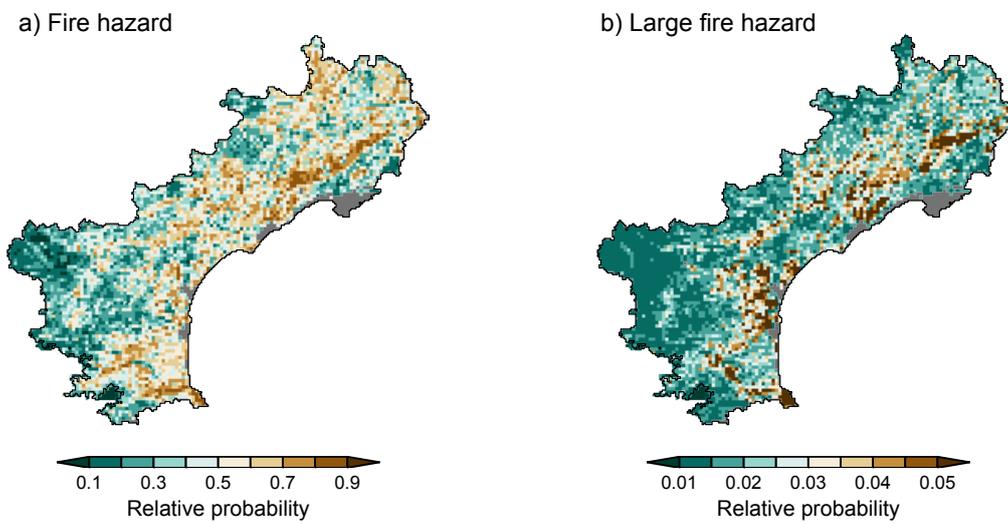
691

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

698 **Figure 4**

699

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

705 **Figure 5**

706

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