

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**

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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 km²) 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 km² 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-km² 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). 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-km² 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 0th, 50th, 90th, 95th, 97th, 98th 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-km² 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⁻¹ (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⁻¹
290 in the western part of the region to 100 days.year⁻¹ 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.

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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

| Variable | Unit | Data source |
|-----------------------------------|----------------|--------------------|
| <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

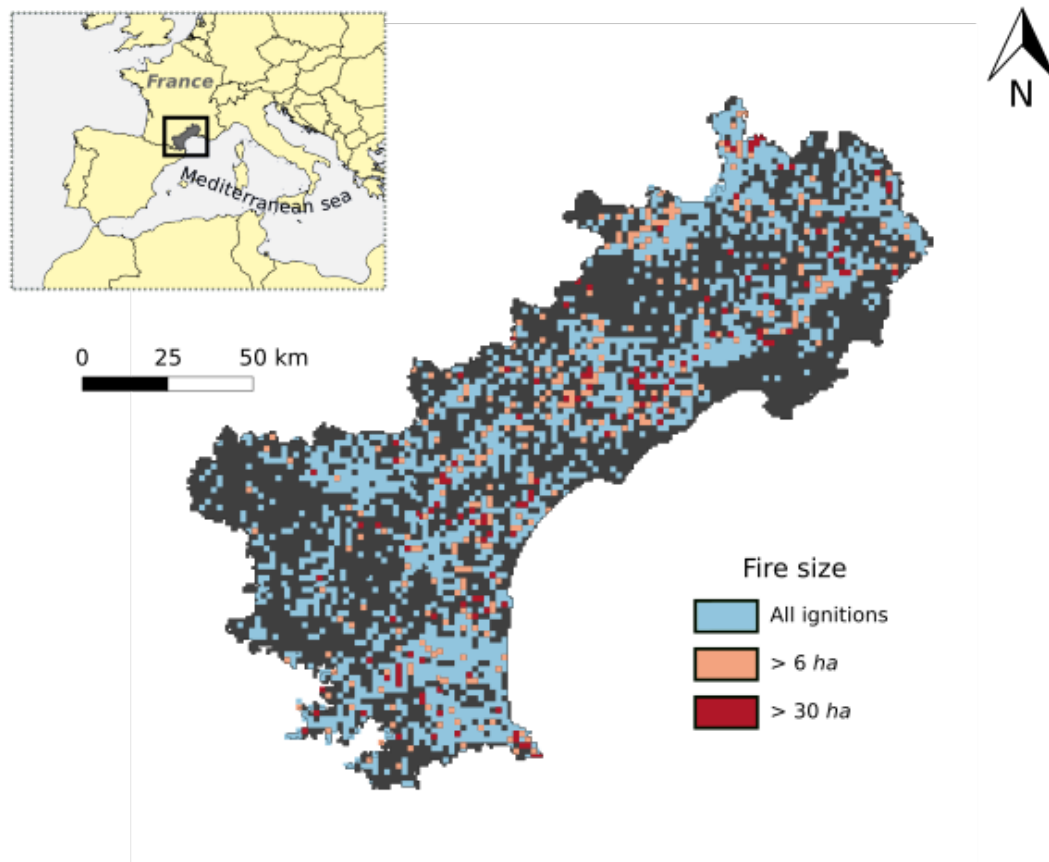
| Fire size | Omission error (%) | Commission error (%) | AUC |
|------------------|---------------------------|-----------------------------|------------|
| > 0 ha | 34.0 (3.5) | 31.0 (2.8) | 0.73 (1.2) |
| > 1 ha | 33.8 (3.6) | 32.6 (3.7) | 0.72 (1.6) |
| > 6 ha | 34.7 (3.3) | 31.9 (5.3) | 0.72 (2.7) |
| > 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) |

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 (ρ) and its associated P-value
 679 are reported (* $P < 0.1$; ** $P < 0.01$).

680

| 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 |

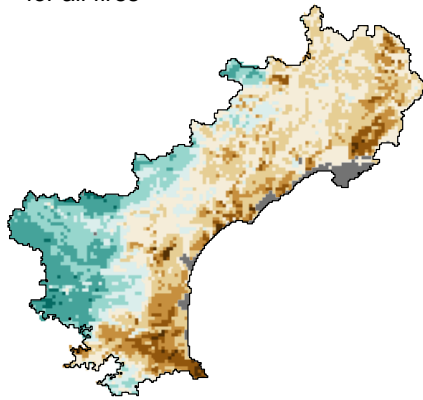
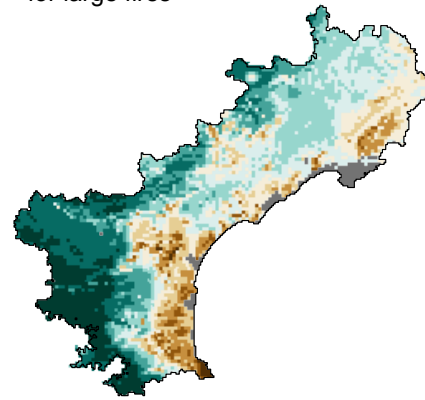
681

682 **Figure 1**

683

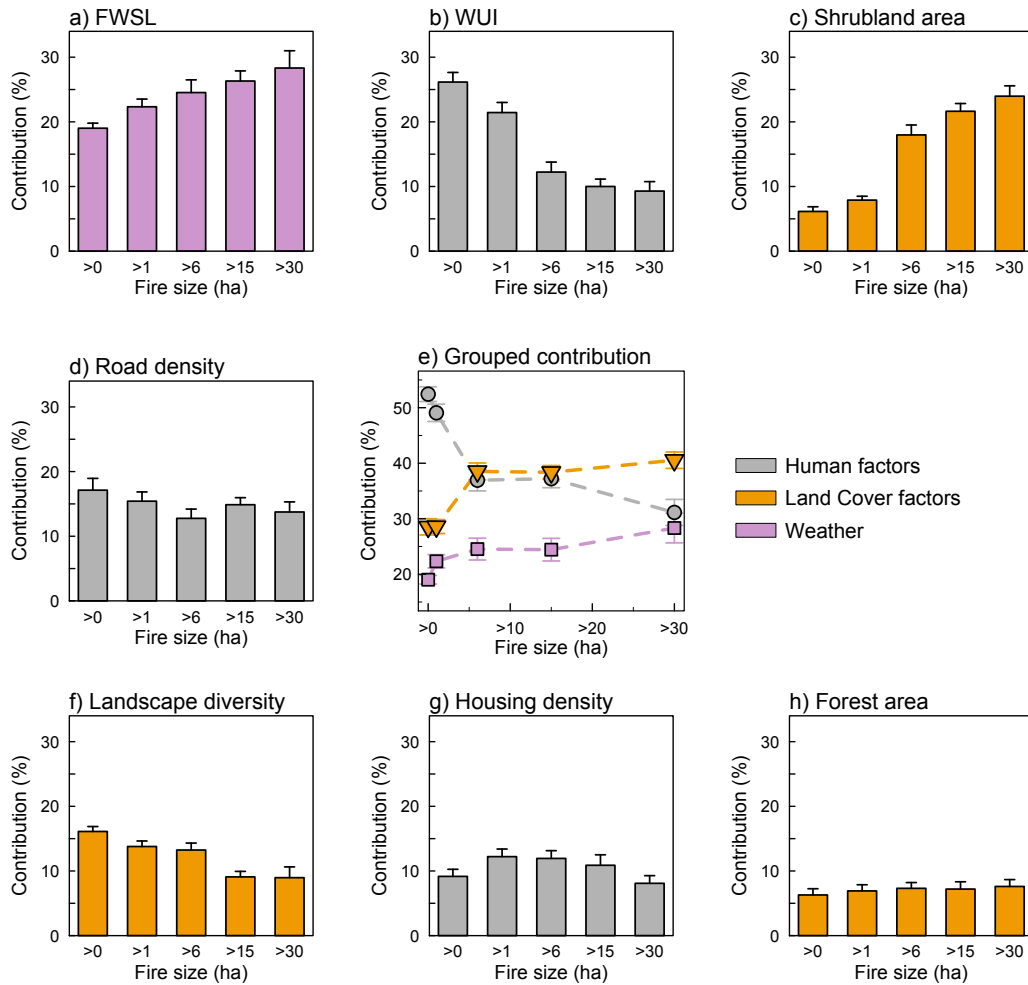
684 Figure 1: Map of the study area showing the spatial distribution of fires as a function

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

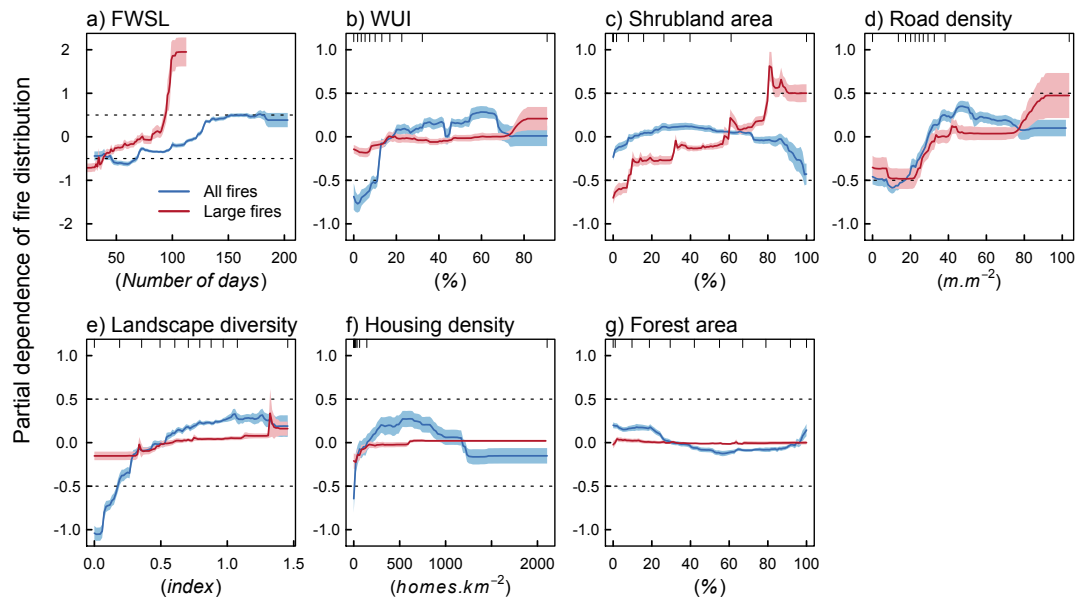
687

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**

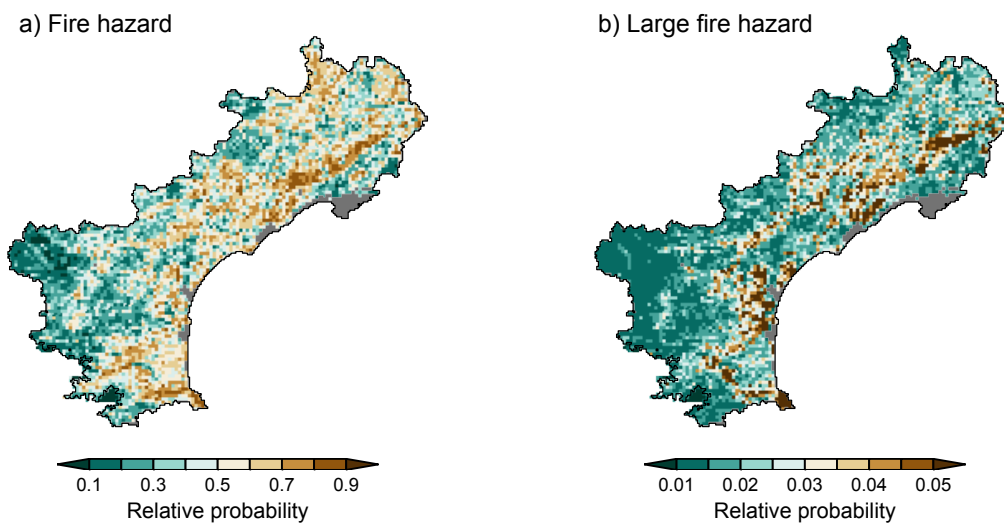
691

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.