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

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[1,2,3,4] and Florent Mouillot[1,]*

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 <u>E-mail</u>: 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^2) 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^2 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 identity 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^2* 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-km^2 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-km^2 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 to180 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. Martínes

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.

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, Martinez-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-Garcia 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) 586\rExport 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 wilfire occurence 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   Buenning 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

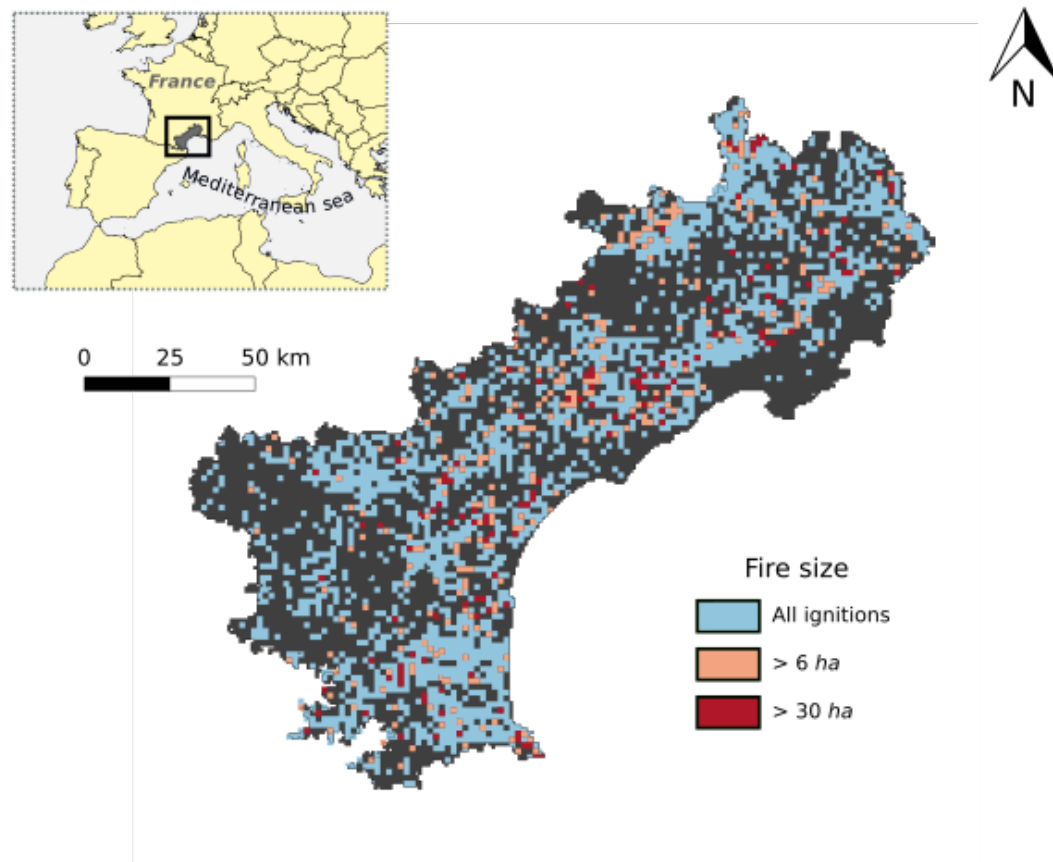663   derived from the BD Topo (IGN 2007) and Corine land cover (EEA 1994) databases,

664   respectively.

665

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

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
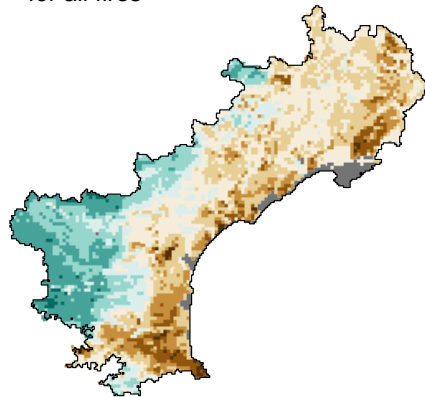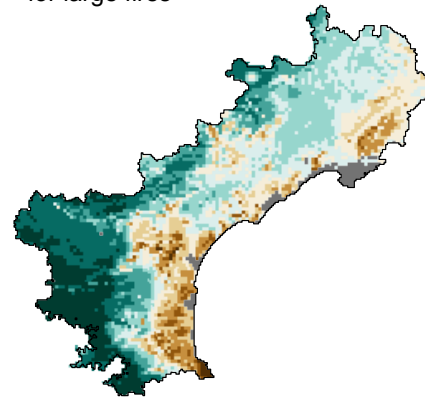
679   are reported (*P< 0.1; **P< 0.01).

680

681

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

682   **Figure 1**

683

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

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

686   **Figure 2**

a) Fire weather season length
   for all fires

b) Fire weather season length
   for large fires

20   60   100   140   180
Mean annual number of days

10   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.
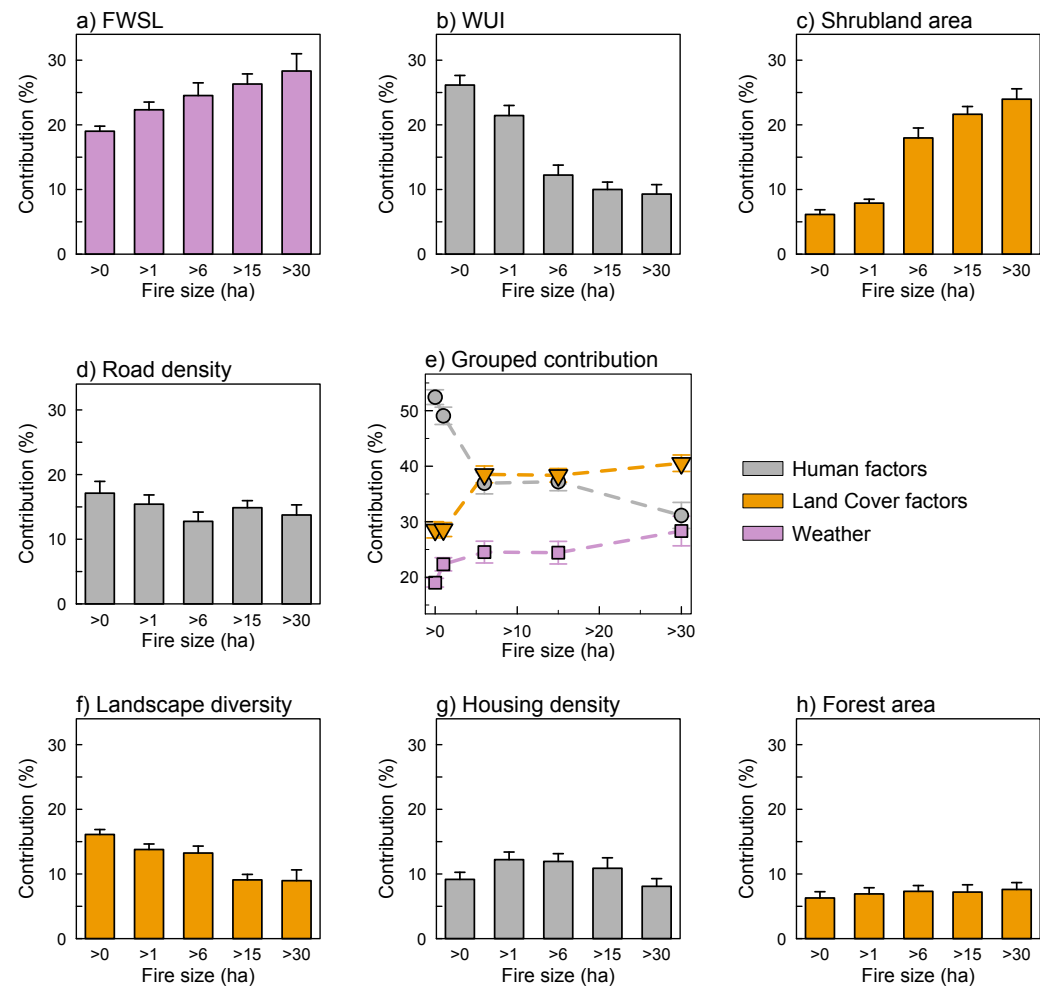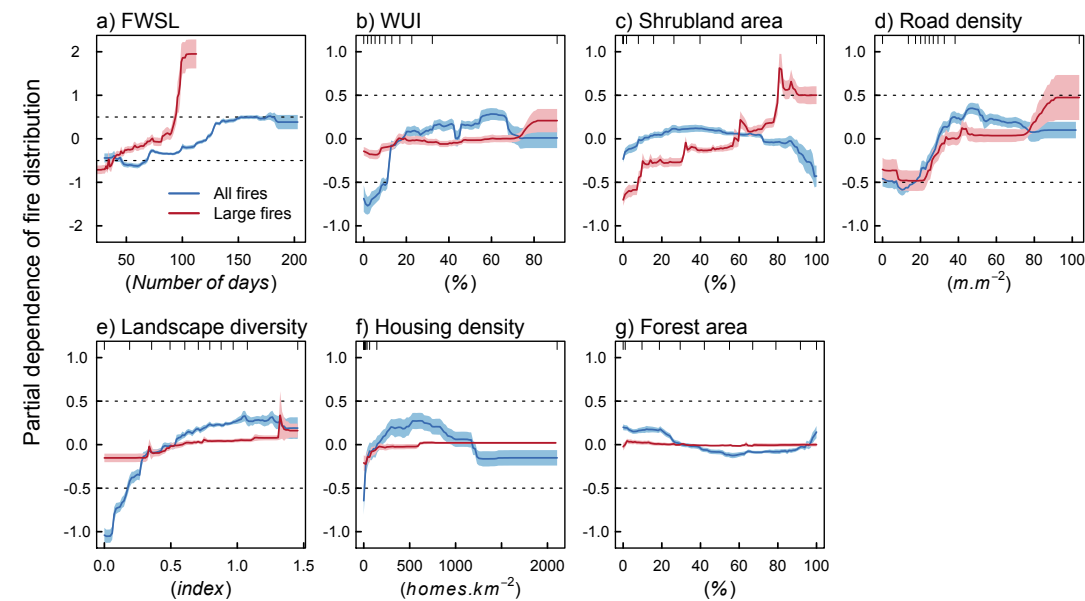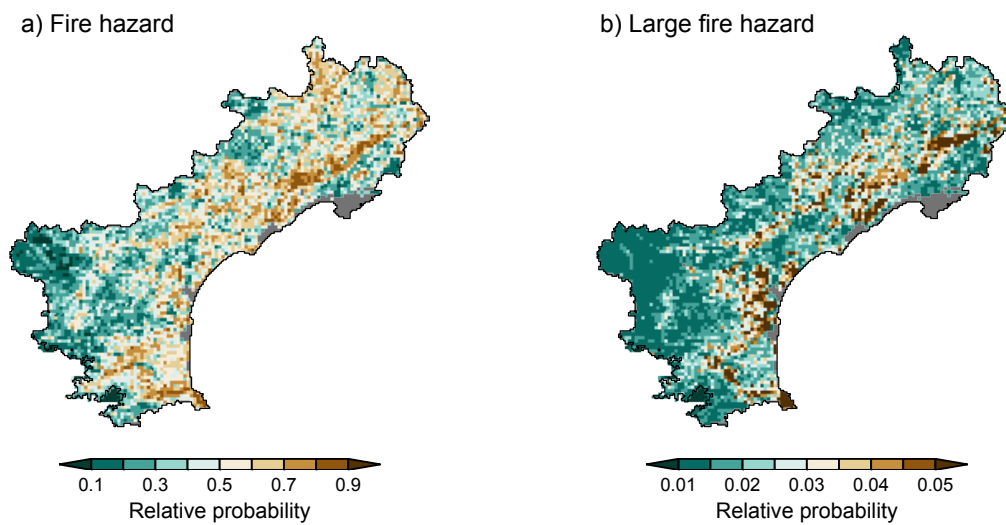
690   **Figure 3**

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**

a) Fire hazard

b) Large fire hazard

Relative probability

Relative probability

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.