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1 Running Head: Probabilistic fire activity modeling

2

3 **Title**

4 Prediction of regional wildfire activity in the probabilistic Bayesian framework of *Firelihood*

5

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18 **Abstract**

19 • Modelling wildfire activity is crucial for informing science-based risk management and
20 understanding the spatio-temporal dynamics of fire-prone ecosystems worldwide. Models help
21 disentangle the relative influences of different factors, understand wildfire predictability and
22 provide insights into specific events.

23 • Here, we develop *Firelihood*, a two-component Bayesian hierarchically-structured
24 probabilistic model of daily fire activity, which is modelled as the outcome of a marked point
25 process: individual fires are the points (occurrence component), and fire sizes are the marks
26 (size component). The space-time Poisson model for occurrence is adjusted to gridded fire
27 counts using the integrated nested Laplace approximation (INLA) combined with the Stochastic
28 Partial Differential Equation (SPDE) approach. The size model is based on piecewise-estimated
29 Pareto and Generalized-Pareto distributions, adjusted with INLA. The Fire Weather Index
30 (FWI) and Forest Area are the main explanatory variables. Temporal and spatial residuals are
31 included to improve the consistency of the relationship between weather and fire occurrence.

32 • The posterior distribution of the Bayesian model provided 1000 replications of fire activity
33 that were compared with observations at various temporal and spatial scales in Mediterranean
34 France. The number of fires larger than 1ha across the region was coarsely reproduced at the
35 daily scale, and was more accurately predicted on a weekly basis or longer. The regional weekly
36 total number of larger fires (10 to 100 ha) was predicted as well, but the accuracy degraded with
37 size, as the model uncertainty increased with event rareness. Local predictions of fire numbers
38 or burnt areas also required a longer aggregation period to maintain model accuracy.

39 • The estimation of fires larger than 1ha was also consistent with observations during the
40 extreme fire season of the 2003 unprecedented heat wave, but the model systematically
41 underrepresented large fires and burnt areas, which suggests that the FWI does not consistently
42 rate the actual danger of large fire occurrence during heat waves.

43 • *Firelihood* enabled a novel analysis of the stochasticity underlying fire hazard, and offers a
44 variety of applications, including fire hazard predictions for management and projections in the
45 context of climate change.

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49 **Keywords:** Bayesian; fire; *Firelihood*; INLA; Mediterranean; spatiotemporal; Fire Weather

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51

52 1. INTRODUCTION

53 Wildfires contribute to shape ecosystems across large parts of the world and threaten human
54 lives and properties. Mapping features of fire regimes such as frequency, size, intensity, severity
55 or pattern of fires across time and space is useful for planning fire and natural resource
56 management, assessing risk and evaluating ecological conditions (Morgan et al. 2001). Indeed,
57 fire regimes vary substantially over time and space at multiple scales, in response to weather,
58 climate, vegetation, orography, as well as local and regional human influences (e.g. Bradstock
59 2010, Bowman et al. 2011, Parks et al. 2012). Understanding fire regimes and their economic,
60 social and ecological consequences is a major challenge for scientists, especially in the context
61 of climate change, which is expected to increase fire activity in many regions of the world (e.g.
62 Flannigan et al. 2009, Barbero et al. 2015a, Turco et al. 2018, Dupuy et al. 2020).

63 Fire regimes are strongly influenced by contemporary fire management, which often aims at
64 reducing fire activity. In some locations (US), burnt areas increased substantially despite large
65 suppression expenditures that led to increased fire hazard through fuel accumulation, which
66 suggests the need to reexamine policies (Stephens and Ruth 2005, Calkin et al. 2015). By
67 contrast, fire suppression policies have likely been effective for reducing burnt areas in many
68 regions of the Mediterranean basin (Turco et al. 2016), but the long-term adequacy of such
69 policies in the context of climate warming and fuel build-up is currently debated (Moreira et al.
70 2020). In this context, the design and application of new policies require reinforced land
71 management and planning, while fire suppression must continue to play a key role in the
72 protection of human lives and assets. For planning purposes, managers and policy makers need
73 to anticipate future scenario-based fire regimes, while for preparedness and response actions,
74 fire managers need to be informed on daily, weekly and seasonal bases of the expected number,
75 size, duration and spread rate of fires (Taylor et al. 2013; Xi et al. 2019).

76 While wildfire regimes depend on multiscale interactions between climate, vegetation and
77 humans (Moritz et al. 2005), weather has long been recognized as the main factor driving
78 regional fire activity from daily to seasonal scale (Abatzoglou and Kolden 2013, Barbero et al.
79 2015b, Turco et al. 2017). Much effort has been dedicated to developing and evaluating
80 weather-based fire danger rating systems, including the widely used Canadian Fire Weather
81 Index (FWI, Van Wagner 1987), the Australian McArthur index (FFDI, Noble et al. 1980) or
82 the American National Fire Danger Ratings System (NFDRS, Deeming et al. 1978). These
83 indices operate at the daily time scale and can be computed in real time from local weather
84 variables to inform managers, or they can be projected under future climatic scenarios to
85 anticipate the effect of climate change (Dupuy et al. 2020). However, the link between fire
86 danger rating systems and observed fire activity is not straightforward. Indeed, fire events are
87 fairly rare at local and daily scales, and hence, highly random in nature. To handle this
88 stochasticity, observations are often aggregated over time and space prior to examining
89 empirical relationships between fire activity and average indices, typically using weekly to
90 monthly bases (e.g. Krawchuck et al. 2009, Barbero et al. 2014, Turco et al. 2018).
91 Unfortunately, these correlative approaches cannot appropriately account for a number of
92 operational and research applications that require daily predictions on fine scales. Indeed,
93 climate, land cover and human variables can vary substantially over short distances in some
94 regions (Fréjaville and Curt 2015). Likewise, weather processes, such as wind or hot
95 temperature events, can influence fire activity on daily or even sub-daily timescales. This is
96 typically the case in the Mediterranean region, where most fires spread during less than a day
97 and the final fire size is less than 1000 ha, contrary to other regions where fires can spread over
98 several weeks, for which daily variations would be less relevant.

99 The rareness and the stochastic nature of individual fire events can be addressed in a formalized
100 probabilistic framework (Brillinger et al. 2003, Preisler et al. 2004, Preisler and Westerling

101 2007, Turner 2009, Vilar et al. 2010, Woolford et al. 2014, Serra et al. 2014a&b). In this
102 approach, observed patterns of fire occurrence are viewed as realizations of a spatio-temporal
103 point process, where points correspond to locations and times of ignition of a fire, and the burnt
104 area is used as a mark for the points. The latent (*i.e.*, unobserved) spatio-temporal intensity
105 function that has generated the observed point pattern is then estimated. In practice, this point
106 process is often approximated by a Bernoulli probability of fire presence in discrete and fairly
107 small space-time cells (called voxels, typically some km² X days) in which at most one fire has
108 generally been observed. The notion of intensity (*i.e.*, expected counts) is crucial since it
109 provides more information than only susceptibility (*i.e.*, presence-absence); in particular,
110 intensities can be additively aggregated within any spatio-temporal unit. Such fire occurrence
111 modelling can be combined with fire size distribution models, typically expressed as the
112 probability for a fire to exceed a given size, to simulate fire hazard (Preisler et al. 2004, 2011).
113 These probabilistic models have most commonly been adjusted within the framework of
114 generalized linear modeling (GLM), or of related extensions such as generalized additive
115 modeling (GAMs, Wood et al. 2006), where the latter have been shown to perform better
116 (Woolford et al. 2011), since they allow replacing linear effects of explanatory variables (such
117 as fire danger and/or human activity metrics) by more flexible shapes in nonlinear effects.
118 Besides accounting for non-linear effects of explanatory variables – as many other techniques–,
119 GAM can include model components to account for spatial residuals (Preisler et al. 2004)),
120 *i.e.*, spatial coordinates are used as explanatory variables with smooth nonlinear effects.
121 More recently, Bayesian methods have also been used as an alternative to these frequentist
122 methods (Serra et al. 2014a&b, Joseph et al. 2019). They allow including and accurately
123 estimating random components in the predictor to capture variation in components of fire
124 activity that cannot be explained by a deterministic influence of other available explanatory
125 variables. Moreover, expert knowledge can guide the choice of prior distributions of predictor

126 components and smoothing parameters (*e.g.*, variances and dependence ranges). In particular,
127 the complexity of sophisticated model components can be controlled by shrinking them towards
128 simpler baselines when no strong signal in the data exists. Therefore, Bayesian analysis
129 provides a convenient and flexible setting for inference in hierarchically structured models. In
130 particular, spatially correlated data can be handled, for example with the Stochastic Partial
131 Differential Equations approach that allows for highly resolved spatial random effects (SPDE,
132 Lindgren et al. 2011). Moreover, posterior distributions of parameters allow for interpretation
133 of uncertainties and provide decision support thanks to credible intervals. Finally, predictive
134 distributions for unavailable observations (*e.g.*, future observations) -not only point predictions-
135 can be naturally generated from the posterior distributions and new explanatory variables.
136 Probabilistic models in general -but mostly in a frequentist setting- have been used for a variety
137 of applications, including forecasts of large fires (Preisler et al. 2008), the projection of future
138 fire activity (Ager et al. 2018), the estimation of suppression costs (Preisler et al. 2011), or the
139 estimation of extreme fire size (Joseph et al. 2019).

140

141 Despite their potential for wildfire predictions, probabilistic approaches still present some
142 challenges and limitations, and some of which have not been fully addressed. First, the
143 evaluation of the underlying model performance in a probabilistic framework is not
144 straightforward. Indeed, it requires checking the goodness-of-fit and model parsimony in the
145 model-building framework through various approaches including information criteria,
146 comparisons of predictions and uncertainty bounds with observations aggregated on various
147 temporal and spatial scales, and external validation using hold-out data (Xi et al. 2019). Second,
148 even if early probabilistic approaches combined models of occurrence and exceedance of fire
149 size above high fixed thresholds, they did not simulate the size of fire events. Notable
150 exceptions are Westerling et al. 2011 and Ager et al. (2014, 2018), who fitted generalized Pareto

151 distributions with parameters depending on explanatory variables to simulate the size of
152 individual fires. Third, probabilistic approaches have seldom been used to evaluate the potential
153 predictability of fire activity (i.e. the degree to which observations can be deterministically
154 predicted) across a range of spatial and temporal scales. Indeed, it is expected that fire activity
155 is less predictable at short temporal and/or fine spatial scales and for rare events (large fires),
156 than more frequent events (small fires) over longer and/or broader scales. Probabilistic
157 approaches provide a suitable framework to quantify this predictability, which should help
158 managers to understand observed activity patterns. Moreover, probabilistic models help
159 understand the extent to which catastrophic events are (un)expected, and can therefore provide
160 useful information regarding their likelihood of occurrence, such as return periods and levels.

161

162 The objective of the present study is to assess the predictability of fire activity at various
163 temporal and spatial scales in the French Mediterranean region, through a Bayesian
164 probabilistic approach. To this aim, we present and use a full framework of fire activity
165 modelling, called *Firelihood*, which simulates potential scenarios of daily fires occurring in
166 small pixels (8 x 8 km). We then assess the overall model performance, the relative importance
167 of selected explanatory variables, and the predictability at scales ranging from the pixel to the
168 region, and from days to periods of multiple years. The assessment of model performance
169 includes a specific focus on the catastrophic 2003 year characterized by a severe synoptic-scale
170 heat wave in summer following a prolonged drought (Trigo et al. 2005). We finally discuss the
171 strength and weaknesses of the current model and its potential applications for wildfire-related
172 research avenues and the improvement of operational fire suppression and management.

173

174 2. METHODS

175 2.1. Data and site description

176 **Study site and fire activity.** The study area consists of 15 NUTS3-level French administrative
177 units located in southeastern France (Fig. 1a, 75,560 km²), which concentrate the vast majority
178 of burnt area during the summer season in France. The climate of this area is mostly
179 Mediterranean, characterized by cool and moist winters and hot and dry summers, but exhibits
180 strong variations with orography, from the high mountains in the Alps to coastal plains. The
181 population is mostly concentrated near the Mediterranean coast and the Rhône river valley.
182 These climatic and socio-economic contrasts strongly shape variations in fire activity over time
183 and space. Fire activity is the highest near the coast and in the Corsican island, where human
184 activities, drought and wind bursts come together (Fig. 1c). Burnt area shows a bimodal
185 seasonal pattern, with a first peak in spring associated with agricultural, pastoral and forestry
186 practices, during which fires are generally not a major threat, and a more important second peak
187 during the summer dry season, during which most large fires occur (Fig. 1b). At the interannual
188 scale, fire activity is highly variable (Fig. 1d) and mostly dictated by annual drought conditions
189 (Ruffault et al. 2016, Barbero et al. 2019). The outstanding burnt area of the 2003 summer was
190 due to several extreme fires that occurred during an unprecedented heatwave (Trigo et al. 2005,
191 Ruffault et al. 2018a). Following these 2003 extreme fires, fire prevention and fighting was
192 enhanced with a modernization of the fire management law in 2004. This might explain the
193 decrease in the number of fires larger than 1 ha and in burnt areas after 2003 (Fig. 1d, Curt et
194 al. 2018). In France, fires larger than 1 ha are of special interest, as limiting fire size to 1 ha is
195 a goal of fire suppression services during the dry season. Fires larger than 1ha will therefore be
196 referred to as “escaped fires” in the remainder of the article.

197 Fire records were extracted from the Prométhée fire database (<http://www.promethee.com/>) for
198 the period from 1995 to 2018. This period was selected so that the dataset was large enough to

199 allow the fitting of robust models. We discarded, however, the pre-1995 period, because of the
200 lack of consistency of the weather data prior to 1995 (monitoring station number had evolved
201 until 1995, Vidal et al. 2010) and of reliability and completeness issues in earlier fire records.
202 Similarly, to limit the uncertainties associated with small fires in fire databases (Turco et al.
203 2013, Ruffault and Mouillot 2015), only fires larger (or equal) than 1 ha (or escaped fires) were
204 retained. One should note, however, that the increasing precision of size records over time has
205 led to a temporal decline of the proportion of fires exactly equal to 1ha among small fires.
206 We focused our analysis on the summer season (weeks 22-44, 25th may to 31th October, Fig.
207 1b), as most burnt areas occur during summer, and because the causes and the factors behind
208 spring fires are quite different and would have blurred the fire-climate relationships we sought
209 to explore.

210 ***Explanatory variables.*** The main explanatory variable was the daily Fire Weather Index (FWI),
211 which represents temporal and spatial variations in meteorological fire danger. FWI was
212 computed onto an 8 km-resolution grid from 12:00 LST meteorological variables (24h-
213 cumulated precipitation, mean wind speed, mean temperature and minimum relative humidity,
214 calculated using specific humidity and maximum temperature) following Bedia et al. (2014),
215 using the ‘cfdrs’ R package (Wang et al. 2017). These variables were extracted from the
216 SAFRAN reanalysis (Vidal et al. 2010).

217 The second explanatory variable was the forest area in each 8-km pixel, which is expected to
218 affect both the number and size of fires. It shows significant spatial variability (Appendix S1:
219 Fig. S1). Forest area was obtained from the CORINE land-cover database (CLC,
220 <https://land.copernicus.eu/pan-european/corine-land-cover>), by merging the patch areas
221 covered by sublevels “Forests” and “Scrub and/or herbaceous vegetation association” in each
222 pixel. This forest area (FA, in ha or in % cover of the pixel) was estimated on a yearly basis by
223 linear interpolation of CLC inventories available in 1990, 2000, 2006, 2012 and 2018.

224

225 **2.2. Probabilistic model of fire activity**

226 **Model overview.** *Firelikelihood* consisted of two hierarchically structured components: one
227 describing the occurrence of escaped fires, and another describing the size of each fire event
228 conditional to its occurrence (Fig. 2). For the occurrence component, the response variable was
229 the daily number of escaped fires (i.e. fires larger than 1 ha), for each pixel of the FWI grid. For
230 the size component, the response was a continuous positive quantity (size of each escaped fire
231 event) modelled with a piecewise distribution, for flexibility.

232 Both the occurrence and size components included FWI and forest area as explanatory
233 variables. The occurrence model also included two temporal factors and a spatial model.
234 Models were fitted in a Bayesian framework, using the integrated nested Laplace approximation
235 (INLA) implemented in R software (www.r-inla.org) and described in (Rue et al. 2009,
236 Lindgren and Rue 2015). INLA can be applied to large datasets using sophisticated hierarchical
237 structure and provides accurate and (relatively) fast inference by means of analytical
238 approximations of the posterior model, in contrast to standard, simulation-based Bayesian
239 approaches (Markov-Chain Monte-Carlo). It allows non-linear responses to explanatory
240 variables to be estimated through flexible Gaussian prior distributions for spline functions in
241 combination with spatial models.

242 Model components were trained with data from 1995-2014 (training sample), the years 2015-
243 2018 being withheld for the evaluation of the predictive performance (validation sample). The
244 dataset for fire occurrence contained fire counts (≥ 1 ha) for approximately 4.44 million pixels-
245 days, whereas the dataset of observed fire sizes contained 7193 fires (≥ 1 ha).

246 In the next two subsections, we describe the “full” model that includes all explanatory variables
247 (Table 1). To verify the added value of the “full” model and to avoid overfitting (*i.e.* the
248 situation where prediction performance on validation data decreases) (Xi et al. 2019),

249 intermediate models for fire occurrence and size with less explanatory variables were also
250 estimated, and their corresponding information criteria were compared with those of the “full”
251 model.

252 Combining both components of the models enable simulation, according to the estimated
253 posterior model, of an unlimited number of replications (here: 1000) of the potential daily fire
254 activity in each pixel, in the form of escaped fire lists whose number and sizes were simulated
255 with each model component. These simulations can then be aggregated at different spatial and
256 temporal scales for corresponding predictions and evaluations against observations.

257

258 ***Fire occurrence component.*** We built the fire occurrence model for escaped fire (≥ 1 ha)
259 counts in 8 km X 8 km daily voxels, as a Poisson random variable (Fig. 2). Following the
260 approach of Brillinger et al. (2003), we incorporated residual spatial and temporal random
261 effects (at the pixel size and weekly, respectively), to account for unknown sources of variations
262 in escaped fire probability. They can be viewed as spatial and temporal scaling factors between
263 FWI and the observed number of escaped fires.

264 The voxel size was considered as a good approximation for the “true” Poisson distribution
265 resulting from grouping intra pixel variations, since pixel-day probabilities remained small
266 (Brillinger et al. 2003). Contrary to large voxels in which multiple fires can occur more often
267 (e.g. Joseph et al. 2019), our Poisson-based method was applied to an almost binary dataset,
268 and spatial correlations were accounted for with a spatial model, so that over-dispersion was
269 less of a concern (Taylor et al. 2013). For the same reasons, the use of a zero-inflated Poisson
270 model was not required. Moreover, this resolution was fine enough to explicitly link the fire
271 occurrence probability to locally observed fire conditions (weather data and forest area), rather
272 than some average value at a coarser scale (Taylor et al. 2013). To identify the range of variation
273 of spatial biases unexplained by the available predictor variables (FWI, FA, season), the pixel

274 size should be much smaller than the distance at which the correlation in the spatial model drops
 275 to near zero. This avoids issues related to within-pixel overdispersion and overestimation of the
 276 smoothness of occurrence intensity maps. Model fit showed that this range was approximately
 277 30 km, which is indeed substantially larger than pixel size. Finally, the pixel size was consistent
 278 with the computational and memory costs of INLA, which strongly increase with the size of the
 279 dataset and the resolution of spatial and temporal random effects.

280 The partial effects of the models were assumed to be multiplicative, based on an additive
 281 decomposition of the log of expected fire counts, which has been shown to be adequate for time
 282 and space in Woolford et al. (2011). The form of the “full” model, including all explanatory
 283 variables (“FWI+2003+FA+WEEK+SPATIAL”, see Table 2) was:

$$284 \quad \log N_i \sim \log (FA) + \beta(YEAR_i > 2003) + f_{FWI}(FWI_i) + f_{FA}(FA_i) + f_{X,Y}(X_i, Y_i) + f_{WEEK} \\ 285 (WEEK_i) \quad (1)$$

286 where $\log(FA)$ was a deterministic offset, β the fixed effect (with a different value before and
 287 after 2003), and the f-terms captured nonlinear influences of the covariates FWI and FA, as
 288 well as spatial and temporal effects.

289 Because escaped fires cannot occur in non-forested area (urban areas, crops, etc.), the area of
 290 each pixel in which fire “points” could happen was not spatially constant. This variability was
 291 incorporated in the Poisson model with an offset equal to forest area (FA). The model allowed
 292 non-linear effects of FWI, but also of FA – in addition to the offset – as a land use factor.
 293 Indeed, it is expected that the probability to get a fire per area of forest decreased for high forest
 294 area, since interface, road and urban densities decreased. Spatial effects were represented using
 295 the Stochastic Partial Differential Equation approach (SPDE, Lindgren et al. 2011), which
 296 estimates the spatial model for residuals, through continuous spatial random effects at high
 297 resolution. Temporal effects were incorporated as a non-linear weekly seasonal factor and a
 298 fixed effect “post 2003”. This “post 2003” effect should not be interpreted as an actual shift in
 299 the relationship that occurred exactly in 2003, but more as a convenient and simple manner to

300 incorporate in the model the temporal evolution of the fire-weather relationship. In this study,
301 we decided to ignore other annual effects in order to develop a model applicable to predictions
302 and projections. Contrary to other studies (e.g. Opitz et al. 2020), we did not seek to model time
303 variation in spatial patterns.

304 The prior distributions of the different predictors were Gaussian processes. The nonlinear f-
305 functions in (1) were modelled with piecewise constant first-order random walks, with 30, 18
306 and 23 segments, for FWI, FA and the seasonal effect, respectively. For each of them, one
307 hyperparameter (called *precision*) governed curve smoothness (i.e., the size of the small steps
308 between consecutive segments), as a Bayesian variant of smoothers used in GAM models (e.g.
309 Preisler et al. 2004). For the spatial component, the SPDE approach consists in implementing a
310 numerically convenient approximation to the Matérn covariance function for the Gaussian
311 random field prior of $f_{X,Y}$ in the 1143 pixels (meshing the study site). Two hyperparameters
312 were estimated for this random field: precision (to control the spatial variability of field values)
313 and range (to control spatial dependence, *i.e.* the smoothness of the spatial surface). For
314 hyperparameters, we specified Penalized Complexity priors (Bakka et al. 2018), which
315 penalized the distance of a model component towards a basic baseline (*i.e.*, absence of effect),
316 and we fixed penalty parameters that ensured fairly smooth estimated posterior effects. In order
317 to limit computational and memory costs, we took advantage of the additivity of the Poisson
318 process to aggregate data in segment classes to reduce dataset size, which initially contained
319 4.44 million voxels. The numerical design described above enabled keeping the number of
320 observed classes below 500,000, which avoids numerical instabilities when running R-INLA,
321 and models are estimated within several minutes to several hours in case of the full model. Such
322 an aggregation is an appealing alternative to approximations often implemented for large
323 datasets (e.g. subsampling of non-fire voxels, in Brillinger et al. 2003), which have shown to
324 decrease model robustness (Woolford et al. 2011).

325

326 ***Fire size component.*** We built a probabilistic model for sizes of escaped fires (conditional on
327 a fire being larger than 1 ha), which corresponded to the marks of the “fire” point-process
328 (Fig. 2). The fire size distribution is usually not well reproduced by any of the commonly used
329 probability distributions over the whole range of observations -in particular for small and large
330 fires- (Cui and Perera 2008). Consequently, we used a piecewise specification of the distribution
331 based on Pareto and Generalized Pareto Distributions (GPD) in the different size segments, as
332 justified by the asymptotic theory of threshold exceedances (Davison and Huser 2015). In each
333 segment, size distributions depended on both FWI and FA of the voxel (8 km X 8 km by daily
334 cell) in which the fire initially spread. In principle, we could have estimated the probability of
335 a given fire to exceed the upper threshold of each segment by using the exceedance probability
336 derived from the fire size distribution within this segment. However, because of the small
337 fraction of fire sizes in the higher parts of each segment (*i.e.*, most fires have size closer to the
338 lower than the upper bound of each segment), we obtained more accurate estimates of
339 exceedance probabilities with specific logistic regressions for each threshold (Bernouilli
340 process, see Fig. 2). In summary, the size model was generative and had hierarchical structure
341 using a piece-wise specification over intervals of burnt area (Fig. 2). First, a logistic-regression-
342 based model determined the segment into which each individual fire should fall (1-10 ha, 10-
343 100 ha, 100-1000 ha or larger than 1000 ha). Then, the exact size was simulated according to
344 the distribution of the corresponding segment.

345 Contrary to other regions of the world where fires can spread over tens of km² during several
346 days (e.g. Joseph et al. 2019), most fires in the study area spread for less than a day and were
347 smaller than 1000 ha (which was much smaller than the pixel area of 6400 ha). Therefore, it is
348 appropriate to stick to the voxel scale for fire size modeling, even if a few fires spread over
349 more than one voxel. The rationale for including FA (in addition to the FWI) was that a small

350 forest area is thought to limit fire spread. Contrary to the fire occurrence model, we did not
 351 include any other spatio-temporal factors in the size model, as the dataset size was too small to
 352 develop robust models. The form of the size component of this “full” model was hence
 353 “FWI+FA” (Table 1), except for the GPD (Table 3).

354

355 The piecewise model of fire size distribution was developed using standard modeling
 356 techniques suggested by extreme-value theory, based on threshold exceedances. We carried out
 357 preliminary analyses of the response of fire size distributions in different FWI classes based on
 358 mean excess plots (Hall and Wellner 1981) of the log-transformed escaped fire sizes. The
 359 number of exceedances over increasingly high thresholds suggested a slow power-law-like tail
 360 decay for most of the thresholds except the highest ones, for which exceedance numbers seem
 361 to decrease much faster as in the power-law setting, similar to the findings in Cui and Perera
 362 (2008). For our data, the behavior of mean excess curves of log fire sizes, and of related curves
 363 (cumulative distributions in log-log scale), tended to change around fire sizes of 10 ha, 100 ha
 364 and 1000 ha. Therefore, we assumed that the distribution of fire sizes could be modelled through
 365 piecewise Pareto distributions between thresholds $u_1 = 1$, $u_2 = 10$, $u_3 = 100$ and u_4
 366 $= 1000$ ha, which depended on both FWI and FA (equivalently, through piecewise exponential
 367 distributions for log fire sizes). More precisely, given a threshold u_k , we estimated exponential
 368 regression models for $\log\left(\frac{S_i}{u_k}\right)$, where S_i corresponds to an observed fire size larger than u_k , for
 369 segments $k=1, 2, 3$; moreover, we censored observations $S_i > u_{k+1}$, so that the model provides
 370 a good fit for $u_k \leq S_i < u_{k+1}$ by construction. The estimation was conducted with INLA using
 371 its survival model framework for handling censoring, and FWI and FA were used as covariates
 372 with potentially nonlinear influence:

$$373 \quad \log\frac{S_i}{u_k} \sim e^{\eta_i}, \eta_i = \beta_0^{exc,u} + f_{FWI}^{exc,u}(FWI_i) + f_{FA}^{exc,u}(FA_i) \quad S_i > u \quad (2)$$

374 where the f-terms captured nonlinear influences of the covariates FWI and FA, with piecewise
 375 constant first-order random walks, with 20 and 10 segments, respectively.

376 Finally, for the category with largest fire sizes (exceeding 1000 ha and containing 33 and 7 fires
 377 for the periods 1995-2014 and 2015-2018, respectively), we selected a generalized Pareto
 378 distribution (GPD), which allows for a finite upper endpoint if its shape parameter is negative,
 379 since an upper bound – even a very large one – must necessarily exist for physical
 380 considerations. The GPD has shown to perform generally well for large fire sizes (Schoenberg
 381 et al. 2003; Westerling et al. 2011). Therefore, we estimated the shape ξ and scale σ parameters
 382 of the GPD, by fitting it to $\log\left(\frac{S_i}{1000}\right)$ for observations $S_i > 1000$. Since this model was not
 383 available within INLA with a negative shape parameter (due to some peculiarities of its density,
 384 *e.g.*, de Haan and Ferreira 2007), we estimated the GPD parameters using frequentist maximum
 385 likelihood, followed by a careful inspection of the estimated model. Owing to the small sample
 386 size, we chose a more parsimonious parametrization of covariate influence using only linear
 387 coefficients:

$$388 \quad \begin{cases} \log\left(\frac{S_i}{1000} \mid S_i > 1000\right) \sim GPD\{\xi(FWI_i, FA_i), \sigma(FWI_i, FA_i)\} \\ \xi(FWI_i, FA_i) = \xi_0 + \xi_1 * FWI_i + \xi_2 * FA_i \\ \log\sigma(FWI_i, FA_i) = \sigma_0 + \sigma_1 * FWI_i + \sigma_2 * FA_i \end{cases} \quad (3)$$

389 However, because the sample size was small, uncertainty on the FA coefficient was high and
 390 confidence intervals and information criteria advised against including FA in this model (see
 391 Appendix S2 for details). We hence selected for the “Full” model a GPD with parameters
 392 function of FWI only.

393 As mentioned above, we cannot expect a good estimation of exceedance probabilities derived
 394 from the three Pareto distribution due to the relatively small sample fraction of fire sizes in the
 395 higher segments. For example, a moderate number of fires were greater than 10 ha (1348 fires

396 among 7193), and only few of them (280, approx. 4 % of fires larger than 1 ha) were also larger
 397 than 100 ha. Between 1995 and 2018, only 40 fires reached more than 1000 ha (0.6% of fires
 398 larger than 1 ha). Therefore, we separately modeled and estimated these exceedance
 399 probabilities p_i^u , for a threshold u and a voxel i , with INLA, based on logistic regressions for
 400 the indicator variables of threshold exceedances (i.e., 1 if fire size exceeds u_k and 0 otherwise),
 401 given FWI and FA:

$$402 \quad \log \frac{p_i^u}{1-p_i^u} = \beta_0^{p,u} + f_{FWI}^{p,u} \quad \text{for } u = 10, 100, 1000 \quad (4)$$

403 where the f-terms captured nonlinear influences of the covariates FWI and FA, with piecewise
 404 constant first-order random walks, with 20 and 10 segments, respectively.

405 These three probabilities and the four estimated fire size distributions were hence combined to
 406 predict the size of each fire larger than 1 ha, given FWI and FA, through a sequential approach
 407 consisting in simulating i) in which segment the size of the fire is, and, conditional to the
 408 segment, ii) the exact size (in this segment).

409

410 ***Variable selection and model evaluation.*** The final “full” model was developed by including
 411 the different explanatory variables and non-linear functions step by step, checking information
 412 criteria of the intermediate probabilistic models. A selection of intermediate models is presented
 413 in Tables 1,2,3, ranging from the simple “FWI-linear” to the “full” model. Information criteria
 414 aimed to assess goodness-of-fit of models while safeguarding against overly complex models
 415 that overfit data (Vehtari et al 2017), and were an appropriate means to check if the structure of
 416 each response to an explanatory variable, as implemented in the “full” model, was significant
 417 and parsimonious. We used the DIC (Deviance Information Criterion) and the WAIC (Widely-
 418 Applicable Information Criterion) for variable selection in submodels, which are
 419 generalizations of the well-known Akaike Information Criterion (AIC) for Bayesian models.

420 The WAIC is known to better reflect posterior uncertainty in the models' prediction than DIC,
421 which can sometimes select over-fitted models (Vehtari et al 2017). For the Generalized Pareto
422 Distribution of largest fires, we simply used the AIC of the model fit. The robustness of the
423 occurrence model was checked in a preliminary development, thanks to a 7-fold cross validation
424 procedure, holding out 3 randomly selected years in each fold, which demonstrated little
425 sensitivity to data sample (Fargeon 2019).

426 We evaluated the performance of the model by two different means. First, we evaluated the
427 subcomponents of the model with Area-under-the-Curve measures (AUC, Fawcett 2006).
428 AUCs rate the model ability to diagnose the realization in voxels of different events, here "at
429 least one escaped fire" and a selection of "size exceedances", by verifying that their occurrence
430 probabilities were better predicted when including more explanatory variables and/or non-
431 linear responses. AUC values range between 0 and 1, with 1 indicating perfect prediction of the
432 binary presence/absence information, whereas 0.5 indicates a random prediction. AUCs were
433 computed for both the 1995-2014 (training) and 2015-2018 (validation) periods. Second, we
434 evaluated model performance by comparing simulations with historical observations
435 aggregated on various temporal and spatial scales (Xi et al. 2019). These evaluations were
436 carried out from 1000 replications of fire occurrence per voxel, which were sampled as a
437 Poisson process according to draws from the posterior predictive distributions of the occurrence
438 intensity. Note that INLA (in contrast to Markov Chain MonteCarlo, MCMC) does not provide
439 simulations of the posterior model's component during the estimation process, but sampling
440 from the fitted model is nevertheless straightforward (e.g. Fuglstad and Beguin 2018). A fire
441 size was then randomly assigned to each simulated escaped fire based on the size submodels
442 (Fig. 2) parametrized with posterior mean parameters. This approach allowed considering the
443 inherent variability of the stochastic processes at stake. This variability was used to draw
444 pointwise envelopes showing the spread between 5th and 95th percentiles of fire activity, and to

445 compute central tendencies for the different spatio-temporal aggregations of simulated fire
446 activity.

447 The overall goodness-of-fit between central tendencies and observations were measured with
448 mean absolute error (MAE, in %). These errors were examined with respect to model
449 uncertainty (MU, in %), which quantified the stochasticity of the corresponding trend,
450 expressed as the variability of simulated quantities over the 1000 simulations. MU was
451 computed as the mean absolute deviation of the simulated activities to rate the model spread,
452 expressed in % of the observed value. The last metric used to evaluate the model was the
453 coverage probability (CP) of the 95% confidence interval, which measured how often
454 observations fall within the estimated confidence interval. The CP of a perfect model is exactly
455 equal to 95 %. A coverage significantly different from 95% means that the model is either
456 biased or exhibits an incorrect variability.

457

458 ***2.3. Model applications***

459 Once the model has been evaluated, it can be used to analyze the stochasticity in fire activity,
460 given that 1000 replicates of the models can provide more insight than the single realization of
461 observations. Two example applications were developed in the present paper.

462 ***Detailed analysis of year 2003.*** For the first application, we provided detailed comparisons of
463 seasonal predictions and observations and fire size distribution in 2003, during which the total
464 burnt area was extremely high for study area.

465 ***Predictability analysis.*** In order to better understand the predictability of fire activity, we
466 compared simulated fire activity for years 2015-2018 to observations (validation sample) within
467 a crossover plan of spatio-temporal aggregations, and for a selection of fire sizes. We used six
468 classes for spatial aggregation (ranging from the single 8-km pixel to the whole studied area)
469 that were crossed with seven classes for time aggregation (ranging from a single day to the four

470 2015-2018 years). MAE and MU, as defined in the previous section, were computed based on
471 the 1000 simulations for the corresponding 42 aggregation classes, for fire numbers ranging
472 between 1 and 500 ha and for total burnt area. The predictability was analyzed by comparing
473 the model uncertainty and prediction errors (i.e., expected minus observed value). When both
474 were of the same order of magnitude, the model correctly represented the stochasticity at play.
475 Hence, low uncertainty and error indicated a high predictability, whereas high uncertainty and
476 error revealed low predictability. Uncertainty lower than error meant that a bias was present in
477 the model predictions, making predictability assessment tricky if the bias was not constant, even
478 if a high model uncertainty likely indicated low predictability. This approach allowed to
479 diagnose the fire sizes and aggregation scales for which simulations were in agreement with
480 observations.
481

482 3. RESULTS

483 3.1. Presentation of the “Full” model

484 *Partial effects of the “Full” model.* The partial effects of both components (occurrence, size)
485 of the “full” fire activity model for the different explanatory variables on escaped fire numbers
486 and on a selection of exceedance probabilities are shown in Fig. 3. The 95th credible intervals
487 were obtained from the posterior predictive distributions. As expected, the FWI had a strong
488 effect on the expected number of escaped fires, which was about 60 times higher for a FWI of
489 60 than one of 5 (Fig. 3a). This effect was however marginal for FWI above 60, with wider
490 credible intervals, due to smaller sample size for the most extreme values. We observed a
491 positive effect of forest area (FA, including both f_{FA} and the offset, see Eq. 1) on the expected
492 number of escaped fires with a maximum around 30%. The slight decrease starting at around
493 40 % reflected a strong decrease in escaped fire density (number of fires per unit of forest area)
494 observed in pixels with the highest FA.

495 The partial effect of the season showed a constant increase between mid-June and the end of
496 August, and then decreased during autumn. Even if the magnitude of this effect was moderate,
497 it indicated that the FWI was not fully consistent to rate escaped fire occurrence over the course
498 of the fire season. For instance, for a same fire danger level, escaped fires were 1.6 times more
499 numerous in late August than in mid-June. The spatial effect was much stronger in magnitude,
500 indicating that very different fire activities were associated with the same FWI level at different
501 locations. The last effect was the “post-2003” effect (Eq. 1), which was equal to 0.46 in
502 posterior mean, meaning that the number of fires was roughly reduced by half after 2003, with
503 a high statistical significance. The transition between the two periods will be further analyzed
504 and discussed below. Among these different effects, the FWI and -in a lesser extent- the spatial
505 model exhibited the strongest magnitudes.

506

507 The effects of FWI and FA on the size of escaped fires showed that the probability to exceed a
508 given size generally increased with both explanatory variables. Moreover, these exceedance
509 probabilities decreased when larger fire size were considered, as expected (Fig. 3b). For
510 example, the probability to exceed 10 ha in a pixel with FA=30 % increased from 0.069 for a
511 FWI of 7.3 to 0.325 for a FWI of 64. Also, the probability to exceed 500 ha could be larger than
512 to exceed 100 ha, depending on the value of FWI, which illustrates that fire size is strongly
513 impacted by this index. It should be noted, however, that the magnitude of these effects was
514 generally much smaller in the size than in the occurrence model.

515 Surprisingly, the exceedance probability decreased for fires larger than 2000 ha at higher FWI,
516 with however little significance because of small sample issues. We further point out (see last
517 subsection of 3.2) that highest FWI values were not equally distributed in space but were most
518 often observed in areas less prone to large fires (e.g. coastal populated areas where suppression
519 is high). The surprising decrease could hence be explained by a confounding spatial effect. The
520 use of a spatial model -as in the occurrence model, see Fig. 9 for details- in the size model could
521 have dampened the impact of missing spatial factors, but the dataset was too small to afford it
522 for the size model. More surprising was the moderate decrease observed for FWI lower than
523 10. In the dataset, a non-negligible number of medium and large fires was recorded for very
524 low FWI (<5), with 60 fires larger than 10 ha occurring with FWI lower than 5. For example,
525 three large fires (936, 2369 and 4378 ha) occurred in 2003 when FWI was lower than 1, 2 and
526 4, respectively. A range of factors might explain this, including the development of burnt area
527 of these fires on the days following ignition (for which the FWI at ignition day is a not relevant
528 fire danger metric for size), by sub-daily scale events (e.g. afternoon thunderstorms following
529 fire events inducing rapid change in FWI during the ignition day), by uncertainties in the
530 weather reanalysis (SAFRAN), or simply, poor rating of actual fire danger conditions by the
531 FWI.

532

533 ***Example simulated scenarios of fire activity with the “Full” fire activity model.*** As an
534 illustration of the model practical utility, fire activity simulations aggregated for the whole zone
535 were compared to historical observations (black dots) at daily (for escaped fires only) or weekly
536 scales (escaped fires, fire number larger than 10, 50 and 100 ha, as well as burnt areas). Results
537 are shown in Fig. 4 for the example year 2001, but similar figures for other years of the study
538 period are available in Appendix S5. As expected, the uncertainty due to stochasticity (MU, in
539 %) was larger for daily than for weekly escaped fires, and tended to increase with the fire size
540 of interest, partly because the numbers to predict were smaller. Although not exactly equal to
541 95%, coverage probabilities (CP) were of the right order of magnitude, even when the width of
542 the confidence intervals was fairly narrow (e.g. weekly escaped fire number, CP=70%). MAE
543 were most often slightly larger than MU, but on the same order, which illustrated model skills,
544 despite high stochasticity in the data.

545 Next, to study in detail the ability of our modeling framework to reproduce observed patterns
546 of fire size distribution, simulated cumulative distributions of fire size were compared to
547 observations for the same example year in Fig. 5. Although observations may deviate from
548 expectations for the largest fires, most exceedance probabilities fell into the simulation-based
549 95th confidence interval. Note that in this example, the simulated trend for 2001 was close to
550 the mean simulation (orange dotted line, for year 1995-2018), but this was not the case in
551 general (e.g. years 1997 or 2002, see Appendix S6 for details).

552

553 ***3.2. Model evaluation and importance of each explanatory variable***

554 ***Variable selection and model fits.*** Model information criteria (DIC, WAIC), and AUCs for
555 years 1995-2014 (training sample) and 2015-2018 (validation sample), are systematically
556 reported in Tables of Appendix S2. A selection of these AUCs is presented in Fig. 6. The

557 performance of the “full” occurrence component was high (>0.8) on both training and
558 validation subsets, and better than the simple FWI-linear model. Regarding the size component
559 model, the predictability of medium fire sizes (50 to 500 ha) was highest, with $AUC > 0.75$.
560 AUCs were in general on the same order for the validation (2015-2018) and the training sample
561 (1995-2014), showing the encouraging performance of the model beyond the training sample.

562 ***Evaluation of central tendencies and spatial patterns.*** In order to more comprehensively
563 evaluate the model, fire activity simulations were compared to the historical observations for
564 spatially aggregated annual and seasonal data as well as temporally aggregated data at the pixel
565 level in Fig. 7 (escaped fire numbers) and Fig. 8 (burnt areas). Orange lines and left maps
566 (“Full” model) compared generally well to observations, contrary to blue lines and right maps,
567 which correspond to different intermediate models, with less explanatory variables. This
568 demonstrates the absence of major bias of the “Full” model (metrics in orange), as well as the
569 limitations of intermediate models (metrics in blue).

570 In particular, annual trends in escaped fire number (Fig. 7a) were poorly predicted without the
571 “Post-2003” effect, with a CP of only 4.2 % and a MAE of 40 %. The systematic overestimation
572 of fire activity after 2003 with this model clearly indicates that the fire-weather relationship
573 changed over time. The “Full” model performed much better than the intermediate one but
574 remained still slightly biased and did not fully accounted for the evolution of the fire-climate
575 relationship over years, or underestimated confidence intervals (CP of 58%, lower than 95%).

576 In particular, we note that the “Full” model underestimated escaped fire numbers in years 2004-
577 2007, suggesting that the transition was probably less abrupt in observations than assumed with
578 a single fixed “Post-2003” effect. Several factors could explain this strong evolution near 2003.
579 This includes the evolutions in fire management after 2003 (modernization of the fire
580 management law, increase in airborne armed-guard funding), as well as the increase in the
581 precision of fire size recordings that has decreased the proportion of fire sizes above 1 ha in

582 records, which was marked near 2003. In the end, we considered the “Full” model satisfactory,
583 because tendencies for recent years -and especially those simulated after 2015 (validation
584 sample)- were in good agreement with historical observations.

585 Although moderate, the seasonal correction at the weekly scale enabled to match observations
586 closely, with a CP of 87% (Fig. 7b), which was fairly close to 95 %. The trends observed with
587 the “No seasonal” model showed that FWI explained a large part of the seasonal dynamics, but
588 that the escaped fire number was overestimated until the end of July and underestimated in late
589 August, which was consistent with the partial effect of the Week of Year shown in Fig. 3. When
590 the spatial model component was not included (“No spatial”), the occurrence component did
591 not simulate the spatial patterns of escaped fires well (Fig. 7c, right). In particular, hot spots
592 were missed, whereas the model predicted too many fires in the Alps and in the Camargue
593 region (coastal plain in the Rhône valley).

594 In general, burnt areas exhibited similar results (Fig. 8), albeit with notable differences. First,
595 the observed burnt area in 2003 was strongly underestimated, and was way above the upper
596 bounds of confidence intervals (Fig. 8a). This important point will be further analyzed in section
597 3.4. Second, the confidence interval widths, which expressed the amount of stochasticity, were
598 much larger for burnt areas than for escaped fire numbers, with model uncertainties on the order
599 of 35 % for both annual and seasonal predictions. Although such a high stochasticity was
600 expected due to the flat tail of the fire size distribution, one could argue that the randomness
601 was overestimated by the model. Two main clues indicated that it was not the case. Although
602 no obvious bias was evident in temporal and spatial trends, CP were on the order of 75-80 %,
603 which was not too far from the target (95 %), suggesting that stochasticity was on the right
604 order of magnitude. Moreover, observed mean weekly burnt areas (averaged over 1995-2018)
605 exhibited large fluctuations between consecutive weeks (between weeks 28 and 36, especially
606 between the last week of July and the first week of August: 13.6 km² for week 30; 4.0 km² for

607 week 31), whereas no obvious mechanisms except randomness could explain such a behavior
608 (Fig. 8b). The magnitude of these fluctuations seems to be consistent with the confident
609 intervals predicted by the model.

610 Expected temporal trends and spatial patterns in simulations looked like a smoothed expression
611 of observations, in which stochasticity would have been removed. However, one should notice
612 a few spurious differences. Simulations seemed to slightly overestimate burnt areas at the
613 beginning and the end of the season, and to exhibit less burnt areas than observed in the Corsica
614 and Var NUTS3 units, where most of the very large fires of the 2003 season occurred.
615 Interestingly, simulated burnt areas were only slightly better predicted when they were
616 simulated from escaped fire observations (using the fire size component only, see Appendix
617 S4: Fig. S1). This revealed that the limitation in burnt area simulations mostly arose from the
618 fire size model and that the full occurrence model performed well.

619 ***Sensitivity of response functions to explanatory variable selection.*** Beyond their limited
620 ability to reproduce observations, intermediate models also revealed that the accuracy and shape
621 of response functions could also be greatly impacted by modeling choices and the non-inclusion
622 of some key effects. The response function of FWI to escaped fire number for the intermediate
623 models were both limited in magnitude and exhibited spurious decreases, when compared to
624 the “Full” model (Fig. 9). In particular, the “Linear-FWI” model (for which the log number of
625 escaped fires has a linear response to FWI) was penalized by both low and high FWI, for which
626 the actual response to FWI was respectively stronger and lower than exponential. For other
627 intermediate models, the decrease observed above the FWI level of 65 could be explained by
628 confounding effects between FWI and space. Indeed, highest FWI values mostly occurred in
629 coastal populated areas where fire density was lower (at constant FWI). For the “Full” model,
630 a small decrease was also observed at 65, but its magnitude was much smaller and was followed
631 by slight increase above 70, thanks to the spatial model that considerably limited the impact of

632 the confounding effect. Hence, the inclusion of the cofactor (FA) and spatio-temporal
633 components in the occurrence model enabled to extract valuable information from FWI relative
634 variations, than what is available in absolute values in this fire danger index.

635

636 *3.3. Insights on an extreme year: the example of 2003*

637 Here, we examine in detail why the model underestimated burnt area for the year 2003. Because
638 most of the burnt area was caused by a small number of large fires, one might hypothesize that
639 i) observed burnt area for 2003 was unlikely considering fire weather, but possible with a low
640 probability (“bad luck”); ii) most fire observations were expected (i.e. consistent with the usual
641 fire-weather relationship), but the occurrence of a few very large fires that disproportionately
642 contributed to the total burnt area, leading to an underprediction of the total burnt area with the
643 model. In this context, arson is sometimes mentioned (and an arsonist was indeed involved in
644 a limited number of large fires in Var NUTS 3 division).

645 According to Fig. 8, the central tendency and the upper bound of the 95th CI (0.975 quantile)
646 for burnt areas predicted by the model were respectively of 213 and 357 km², which was well
647 below observations (610 km²). Similarly, the quantile 0.999, corresponding to a millennial
648 event according to the model was 469 km², still below observations. We can then conclude that
649 the model failed to simulate the likelihood of observed burnt area in 2003. We then analyzed
650 time series corresponding to 2003 seasonal fire activities in Fig. 10 (similar to Fig. 4, but with
651 99.9th confidence intervals added to show unlikely events). The predictions of escaped fires
652 were consistent with observations at both the daily and weekly scales, which shows that fires
653 did not escape more frequently than expected all along the season (without any exceptional
654 week or day). However, more than six weeks were largely above the central tendency in
655 numbers of fires larger than 100 ha and in burnt areas. Four weeks were above the 0.975
656 quantile and one was even above the 0.9995 quantile (week 35). This shows that 2003 was

657 atypical during several weeks, with an early start. The analysis of the distribution of fire size
658 (Fig. 11), showed that all fires larger than 10 ha occurred much more often than expected.
659 Hence, even if the presence of a few very large fire constituted most of the burnt area, most
660 fires (larger than 10 ha and during most of the season) were exceptionally large with respect to
661 observed FWI, which invalidates the “bad luck” or arson assumptions. The decrease in fire
662 suppression efficiency with increasing escaped fire number can be invoked to explain the 2003
663 observations as well. However, it is important to acknowledge that it had apparently not affected
664 the number of escaped fires, weakening this assumption, as their number was consistent with
665 expectations.

666

667 **3.4. Predictability of fire activity**

668 We proposed a detailed analysis of the predictability of fire activities at various temporal and
669 spatial aggregation scales to better understand the role of stochasticity in fire activity patterns.
670 In general, stochasticity in observations (fire counts and sizes) typically decreases when
671 aggregating them to larger scales, such that the nature of both observations and model
672 predictions becomes more deterministic. Slight biases of models arising at the voxel scale may
673 then lead to stronger biases at aggregated scales.

674 ***Predictability and confidence intervals at weekly scale.*** As shown in Fig. 4, aggregating fire
675 activity over the whole area at the weekly scale led to reasonable confidence intervals and MAE
676 for year 2001. More generally, the overall predictability of escaped fires at the weekly scale
677 was satisfactory for the whole period (1995-2018), with a MAE of 32% and a CP of 84%
678 (Appendix S3: Fig. S1A). However, the number of escaped fires out of confidence interval
679 (16%) was slightly larger than expected (5%). The majority of these weeks consisted in false
680 “high” fire numbers for small observed numbers, and false “low” fire numbers for high
681 observed numbers. They were explained by stochasticity (fortunate and unfortunate events),

682 Bayesian model smoothness, and over-dispersion of observations with respect to aggregated
683 Poisson laws (caused by the decrease in fire suppression efficiency with fire activity for
684 example). More explanations can be found in Appendix S3. Regarding weekly burnt areas, the
685 central tendencies (Appendix S3: Fig. S1B) were positively correlated with observed burnt area
686 for 1995-2018, but the MAE was high (76 %), mostly because of the width of the confidence
687 intervals (MU=91 %). This illustrates the huge role of stochasticity in observed burnt areas at
688 this scale. Most false “high” burnt areas occurred when observed occurrences were lower than
689 expected, whereas false “low” burnt areas mostly occurred in 2003. More details are available
690 in Appendix S3.

691

692 ***Predictability at other scales.*** The MAE and MU are presented in Fig. 12 for 42 spatio-temporal
693 levels of aggregation, ranging from one pixel-day to the whole area during the four years of the
694 validation sample. As expected, the MAE increased for smaller aggregations, and large fire
695 numbers and burnt areas were more uncertain than escaped fire number (higher MU). Beyond
696 this general trend, Fig. 12 allows us to identify which scales led to reasonable predictions
697 (typically, those with MAE -and MU- lower than 30 %) and which were, on the contrary,
698 subject to too much stochasticity for valuable predictions (typically, MAE and MU both above
699 60-70 %). In particular, the spatial aggregation drastically reduced the MAE, while sub-regional
700 predictions remained quite poor, even for escaped fire number, when predictions were made at
701 a shorter scale than the full season. This could be partly explained by the fact that spatial
702 patterns of ignitions have slightly evolved over the 24 years of the study period, resulting in a
703 small spatial bias of the model during recent years. This was suggested by the pattern followed
704 by MU, which was slightly smoother regarding the effect of spatial aggregation and by the
705 lower AUC of the occurrence model in recent years (Appendix S2: Table S1). In particular, less
706 fire activity than expected was observed in North Corsica and more escaped fires in the western

707 part of the basin during the recent years (Not shown). It should also be noted that the fire activity
708 was fairly limited during the validation period, which increased the magnitude of relative errors,
709 as model uncertainty becomes larger when central tendency decreases. It is hence expected that
710 the predictability of a larger number of fire events would be more accurate (even if the model
711 failed to predict 2003).

712

713 **4. DISCUSSION**

714 ***Predictability of fire activity.*** The wildfire phenomenon results from multiple interactions
715 between biophysical and human factors acting at various spatial and temporal scales, which
716 spawn individual events with a high degree of stochasticity. *Firelihood* is a probabilistic model
717 of regional fire activity that simulates replications of individual fires with their size (on a daily
718 basis and at 8km-pixel resolution) with a reasonable accuracy (for example see coverage
719 probabilities and AUC values in Fig. 4 and 5, respectively), thereby offering the opportunity to
720 study the predictability of fire activity, i.e. to determine to what extent observed patterns can
721 be deterministically predicted. This analysis was carried out by comparing the model
722 uncertainty and prediction errors (i.e., expected minus observed value) on data held out during
723 the estimation of the model.

724 Our results showed that the stochasticity of fire activity was quite high, especially for large fire
725 sizes, which exhibited large model uncertainties and equally large errors, unless aggregating
726 fire data at larger temporal and/or spatial scales (Fig. 12). The number of fires larger than small
727 thresholds (1 to 10 ha) were fairly deterministic for the whole study area on a weekly basis and
728 could be well predicted for years following the training period with limited uncertainties and
729 errors. However, the predictability of sub-regional fire activity decreased rapidly at finer spatial
730 scales, with model errors increasing faster than model uncertainties (Fig. 12). Refined analyses
731 are required to better understand the differences between spatial and temporal aggregations in

732 terms of predictability, but this suggests that there are prospects for improving the model spatial
733 predictions. Preliminary analysis suggested that time-variations in spatial effects would explain
734 this decrease in model performance.

735 Overall, our results highlighted that stochasticity was a major component of observed fire
736 activity, so that individual events, pixels, years or fire size class, etc. are often far from
737 deterministic. Hence, even long-term (>20 years) fire datasets that are used either for ecological
738 or operational purposes should be used with caution since they do not allow capturing the full
739 variability in fire disturbance. This major point is illustrated for instance by the high degree of
740 stochasticity observed in weekly burnt areas in Fig. 8b. Moreover, observed monthly and annual
741 burnt areas, which are often used as benchmarks in a number of studies, namely for damage
742 assessment exercises or for comparing efficiency of fire suppression strategies, were also shown
743 to be highly random. We recommend to use more robust metrics such as number of escaped
744 fires or fires larger than a given size threshold, instead (e.g. ≥ 100 ha in Southeastern France).

745 ***Factors controlling fire activity.*** The FWI and the forest area were included as explanatory
746 variables in the model to represent where and when weather conditions are conducive to fires,
747 and how much area is available for fire spread, respectively. Weather conditions are major
748 drivers of fire activity in Southeastern France and our results showed that FWI is an effective
749 metric to rate fire danger (e.g. Fig. 3a and 3b), as suggested by earlier studies based on FWI
750 subcomponents in the same region (Ruffault et al. 2016, Fréjaville and Curt 2017, Barbero et
751 al. 2019), and in accordance with studies using the FWI in other southern Mediterranean
752 countries (e.g. Padilla and Vega-Garcia 2011, Fernandes 2018, Dupuy et al. 2020). However,
753 our study also highlighted several limitations of the FWI. First and foremost, our results suggest
754 an inconsistent rating of actual fire danger by the FWI for different fire weather types (Ruffault
755 et al. 2020). Specifically, the relative sensitivity of the index to ranges of wind speed on the one
756 hand, and of temperature and drought on the other hand, might not be properly scaled in

757 southeastern France. Indeed, the FWI has an exponential response to wind, which might not be
758 the case of fire activity for high wind values, as suggested by the saturation of the FWI effect
759 in the fire occurrence ($\text{FWI} > 60$) and fire size ($\text{FWI} > 40$) models (Fig. 3), even if the saturation
760 was partly explained by spatial bias (Fig. 9). The FWI could overestimate actual fire danger
761 during these high wind days. By contrast, our results showed a systematic underestimation of
762 the numbers of fires with size larger than 10 ha during the whole fire season during the 2003
763 heatwave (Fig. 10 and 11), suggesting that the explanatory variable for fire danger (FWI) could
764 underestimate the actual fire danger during hot drought conditions. Another weakness of the
765 FWI could be its time lag with respect to seasonal fire observations. Indeed, with the version of
766 the probabilistic model without week correction (model “No seasonal” in Table 1), the fire
767 season predicted by the model starts and ends two to three weeks earlier than the observations
768 (Fig. 5b and 6b, blue line). Such a lag has already been reported for the KBDI in the
769 Mediterranean (Ganatsas et al. 2011), but never for the FWI to our knowledge. This could be
770 explained by the desiccation processes empirically modelled in the Drought Code (a
771 subcomponent of the FWI reflecting monthly variations in fuel moisture content), which only
772 poorly explains Live Fuel Moisture Content (Ruffault et al. 2018b), the latter being increasingly
773 recognized as an important factor of fire behavior (e.g. Pimont et al. 2019). The seasonality -
774 and potentially spatial patterns- of fire danger rating could be improved by the use of more
775 mechanistic models for fuel moisture assessment. Live fuel moisture content dynamics depends
776 on the processes of the water (soil water uptake, plant water storage and transpiration) and the
777 carbon (photosynthesis, respiration, carbon allocation and canopy phenology) cycles (Jolly and
778 Johnson 2018). Key water processes during an extreme drought and heat wave can be modeled
779 according to plant hydraulics, depending on plant traits (e.g. Martin-StPaul et al. 2020). As far
780 as the carbon cycle is concerned, the evolution of fuel moisture linked to the production of new
781 shoots could be taken into account thanks to tree phenological models (e.g. Vitasse et al. 2011).

782

783 Our results also confirmed that forest area is an important factor of spatial variations of fire
784 activity in southeastern France (Ruffault and Mouillot 2017, Ganteaume and Barbero 2019),
785 with less escaped fires in pixels with low forest area (typically below 20 %) than those with
786 moderate to high forest areas (typically higher than 40 %) (Fig. 3). A saturation effect or a slight
787 decrease was however observed above 40 %. This pattern is the result of two opposite
788 mechanisms explicitly accounted for in our model. First, fire numbers in each pixel are limited
789 by the area in which ignition “points” can occur (“offset” effect). Second, fire density (i.e.
790 number of fires per unit of forest area, f_{FA}) decreased with increasing forest area because human
791 activities, which are responsible for most fire ignitions in human-dominated landscapes
792 (Syphard et al. 2007, Hawbaker et al. 2013, Costafreda-Aumedes et al. 2018), are more limited
793 in these gridcells. This confirms that fire activity can be ignition-limited when forest area is
794 high but fuel-area-limited when forest area is low; the resulting effect of these two opposites
795 being likely due to some specificities of the studied area and scale-dependent (Parisien et al.
796 2011).

797 ***Methodological insights to fire activity modelling.*** One of the critical aspects of this work was
798 the determination of the appropriate voxel size. Typically, smaller voxels lead to issues related
799 to both data reliability, as well as computational and memory costs, but larger voxels result in
800 information loss, leading to a challenging trade-off. For example, we aimed at accounting for
801 fine spatio-temporal variations in fire weather, but had to ignore hourly variations in FWI and
802 spatial variations smaller than 8 km. Depending on the objective of a study and the specificity
803 of each region, an appropriate voxel size should be adapted, but the approach of the present
804 study is applicable with a sophisticated Bayesian method to fine scales at a reasonable cost. To
805 bypass prohibitively high computation costs, one critical device in our study was the
806 aggregation of escaped fire counts in classes of same predictor configurations. This aggregation

807 led to a reduction of the dataset's effective size by a factor close to 10, allowing to avoid the
808 resampling of non-fire observations, which can affect the accuracy of partial effect estimates
809 (Woolford et al. 2011).

810 Our study also confirmed the importance of accounting for non-linearities in FWI and co-
811 factors for fire activity modeling, in accordance with Woolford et al. (2011). We found the FWI
812 effect was either underestimated or inconsistent when non-linearities/co-factors were ignored
813 (Fig. 9). In particular, the use of the spatial model was critical to properly address fine scale
814 data in which spatial autocorrelation is present. This spatial model was only involved in the fire
815 occurrence component -not in the fire size, which simply included FWI and FA as explanatory
816 variables-, which was sufficient to obtain a general agreement with burnt area observations.
817 Although 1 ha fires (escaped fires) only represent a minor part of cumulated burnt areas, this
818 finding highlights their importance in explaining patterns of burnt areas. Regarding the fire size
819 component, an innovative aspect of the present work was the piecewise modelling framework
820 for fire size distribution, which allowed to model its dependency to explanatory variables with
821 flexible nonlinear response functions.

822 The ensemble approach allowed us to compute central tendencies, but also confidence intervals
823 and return intervals of specific events. This approach is hence purely probabilistic; in particular,
824 probabilistic statements about the uncertainty of specific components of the model (*e.g.*, the
825 response functions) are possible, and the goodness-of-fit of models can be formally compared
826 through probabilistic information criteria. These ensemble simulations can be evaluated against
827 observations thanks to coverage probabilities of the confidence intervals (Joseph et al. 2019).

828 ***Model limitations.*** A first limitation of the present approach was the limited number of Land
829 Use and Land Cover (LULC) predictors included in both models (Forest Area only). LULC
830 predictors are increasingly used in statistical models of fire activity, especially when intended
831 for long-term predictions (Costafreda-Aumedes et al. 2017). They usually relate to the presence

832 of human settlements through variables such as the presence of roads, urban land-uses and
833 housing or population densities, or to that of human activities with variables encompassing the
834 number of farms or that of touristic infrastructure. Other models also include variables related
835 to landscape composition, such as the amount of shrubland (compared to high forest) or the
836 proportion of coniferous trees, or to landscape structure, such as wildland-urban interfaces,
837 wildland-agriculture interfaces or landscape fragmentation metrics. The influence of such
838 variables on fire activity has been documented in France (Ager et al. 2014; Opitz et al. 2020;
839 Curt et al. 2016; Ruffault and Mouillot 2017; Ganteaume and Jappiot 2013) and other
840 Mediterranean countries (Moreira et al. 2011; Oliveira et al. 2012; Gallardo et al. 2016; Nunes
841 et al. 2016; Vilar et al. 2016; Papakosta and Straub 2017; Costafreda-Aumedes et al. 2017).
842 Other, less frequently encountered variables with similar effects include levels of preparedness
843 (Podschwit and Cullen 2020) or of unemployment and economic welfare metrics (Mancini et
844 al. 2018; González-Olabarria et al. 2015).

845 In the present study, we did not explicitly account for those factors, but relied on the SPDE
846 approach to model spatial variations in escaped fire density. We do not expect large
847 improvement from the inclusion of LULC variables (which are almost static over a decade) in
848 the occurrence model performance, but it would increase the genericity of the model, for a
849 better understanding of effective factors, or for extrapolated predictions to other areas of
850 Southern France where reliable calibration data are not available, for example. Larger benefits
851 could be expected from the inclusion of LULC variables into our fire size model in which no
852 spatial effect was included because of the small amount of data available. For example, large
853 fires are expected to happen more often in shrubland-dominated areas and further away from
854 cities and communication axes (Moreira et al. 2011; Ager et al. 2014; Ganteaume and Jappiot
855 2013). This perspective is all the more important as our results suggested that the main
856 limitations of the “Full” model were rooted in this fire size component. Hence, going this

857 direction appears promising and the inclusion of both LULC and socio-economic predictors is
858 part of our future research agenda. Based on high-resolution rasterized datasets of standard
859 LULC variables, we propose to construct derived predictor variables (e.g., proportions of
860 LULC categories around the location of interest for different sizes of spatial buffers, or
861 proportions of co-occurrence of several categories such as forest cover and buildings in such
862 buffers to represent interfaces), which may have higher predictive power. Since this may lead
863 to a relatively large number of potentially useful but also strongly correlated variables,
864 preliminary analyses (prior to constructing the full stochastic model) may consist of variable
865 selection algorithms, or of dimension reduction steps in the spirit of principal component
866 analysis. The resulting set of variables, identified as possessing relevant predictive potential, is
867 then included into the occurrence and size model components, either in a linear or nonlinear
868 way as for predictor variables in the current model. This approach is expected to allow for
869 attribution of wildfire occurrences to risk factors enclosed in LULC and socio-economic
870 variables. Moreover, it presents a promising lead for improving predictions since LULC
871 variables are available at higher spatial and temporal resolution than the random spatial effect
872 accounting for bias terms in our current model.

873 One challenging aspect of fire activity modelling is related to the changes in the nature and
874 strength of the fire-weather relationship not only over space but also over time, which can be
875 due to various co-factors, including variations in LU-LC factors, in suppression means,
876 detection efficiency (Higuera et al. 2015, Ruffault and Mouillot 2015, Xi et al. 2019). In the
877 present study, we used a sophisticated approach for spatial but static effects, and a crude
878 approach to account for annual evolution of the relationship by simply modelling the abrupt
879 shift in the relationship occurring between 2003 and 2005 (using a single global, not spatially
880 resolved regression coefficient). We noticed that spatial patterns have slightly evolved over
881 time resulting in a slight decrease in AUC after 2015. These elements might call for a reduction

882 of the temporal period used in fire activity studies to increase fire-weather relationship
883 consistency, and hence prediction performance. However, our study also highlights the need
884 for long time series to include exceptional events such as 2003. The best approach would hence
885 be to allow for temporal variation of response functions and spatial bias components in the
886 models. In that regard, the use of a spatio-temporal log-Gaussian Cox process model for fire
887 occurrence is particularly promising to account for time-varying spatial effects (Serra et al.
888 2014b; Opitz et al. 2020); but its implementation on a daily basis still poses considerable
889 methodological challenges due to prohibitively high computational and numerical
890 requirements.

891 Some studies proposed that fire numbers could be better represented with a negative binomial
892 model than with a Poisson model (Marchal et al. 2017; Joseph et al. 2019) as it accounts for the
893 overdispersion of the data, i.e., the situation where variance in observed count values can be
894 higher than the intrinsic variance of the estimated model. This situation can arise due to a too
895 low space-time resolution of the model and explanatory variables (such that important
896 variability within a pixel-time step unit is not properly taken into account), of missing
897 explanatory variables, and of spatio-temporal effects unaccounted for in the model (e.g., time-
898 varying spatial effect). In particular, we identified in section 3.4 that the decrease in suppression
899 efficiency when escaped fire numbers increase could be involved. In this context, preliminary
900 investigations (where we replaced the Poisson distribution with a negative binomial one)
901 confirmed the presence of overdispersion with respect to the Poisson model, but simulations
902 from a model fitted with a negative binomial response showed unrealistically high values for
903 the number of escaped fires per voxels, with simulated counts being up to 10 times larger than
904 the maximum of observed numbers. This implies that the model performance would deteriorate
905 by capturing overdispersion at the pixel-day scale. Therefore, we used the Poisson-based model
906 as the more realistic model for all our analyses, but confidence intervals based on the aggregated

907 simulations can be too narrow in some cases (with CP lower than 95) due to an excess of “false”
908 extremely high and low fire activity. A more robust, but highly challenging approach would be
909 to identify the spatial and temporal scales where overdispersion arises, and to include some
910 corresponding components in the model.

911 ***Model applications and perspectives.*** Beyond the developments and example cases covered in
912 the present study, the *Firelihood* modeling framework offers a variety of promising research
913 applications. Our modeling framework can be used to further investigate the effects of
914 biophysical and human factors on fire dynamics and the variations of these effects over time
915 and space. The model is also able to compute and map the return intervals of fire disturbance,
916 which can cover longer time spans than observations, and be used to increase our understanding
917 of the interactions between wildfire disturbance and vegetation dynamics (Keeley et al. 2012).
918 Another research avenue for *Firelihood* is to run the model for retrospective evaluation (e.g.
919 attribution studies, Barbero et al. 2020) or the anticipation (e.g. Wotton et al. 2003; Fargeon et
920 al. 2019) of the effects of climate change on wildfire activity. Statistical models of fire activity
921 may also help gain insight into the socio-economic impacts of changing fire regimes and drive
922 insurance company strategic prospects. At local scales, they can be used to estimate and forecast
923 suppression costs (Preisler et al. 2011). At larger scales, economic activity and climate
924 mitigation in the forest sector may be affected by disturbances (Lindner et al. 2010; Seidl et al.
925 2014), as well as smoke production (McKenzie et al. 2014). Long-term forecasts often rely on
926 deterministic simulators where the inclusion of risk is a methodological challenge (Chudy et al.
927 2016, Riviere et al. 2020): *Firelihood* may provide a way to consider fire activity in such
928 assessments, provided that they include relevant LULC factors for management.

929 Operational outcomes include short-term forecasts of fire activity across the landscape
930 (Woolford et al. 2011). Because weather forecasts are now quite accurate for periods up to
931 seven days, the present modelling approach could be used to anticipate the number of escaped

932 fires and large fires (50-100ha) and to organize suppression means, since the predictability of
933 fire activity was encouraging at weekly regional scales. It should however be acknowledged
934 that uncertainties arising from weather predictions were not included in our study and might
935 degrade the prediction performance, so that additional testing is required. Although this weekly
936 regional scale is relevant for many operational purposes, finer resolutions are also of interest
937 for managers. Our modeling framework offers opportunity for managers to select the temporal
938 and spatial aggregation scales of interest. In the present study, we used the NUTS3 spatial scale,
939 but other can be used, such as the forest massif, which is often used for detailed preparedness.
940 Our predictability study showed that the predictive performance remained high at finer
941 temporal scales, so that daily predictions can be envisioned as a reasonable lead time. Regarding
942 spatial predictions however, we found that the predictive performance of the model tended to
943 decrease faster than expected when the aggregation level was finer than the region (on the
944 evaluation dataset, period 2015-2018, Fig. 12). Since mapping daily expected burnt areas (e.g.
945 at a 8km-resolution) or predicting fire numbers inside forest massifs are of major interest for
946 operational services, we think incorporating temporal trends in spatial effects (i.e. time-varying
947 effects) would be the most promising option to improve operational applications of our model.
948 Another promising application of such probabilistic approaches is to help identify changes in
949 fire-weather relationship over time, related to operational aspects. This includes detection
950 efficiency variation, changes of local regulations and public awareness strategies for risk
951 mitigation, as well as the evolution in strategies, tools and techniques for fire suppression (Xi
952 et al 2019).

953 Finally, the probabilistic approach of *Firelihood* can be applied to many other areas, provided
954 that i) fire data are available; ii) the factors controlling fire activity are identified and
955 measurable; iii) voxel sizes are adjusted following guidelines mentioned above. In particular,
956 this methodology can be used to model occurrence in mixed models, which combine a

957 probabilistic approach for occurrence with a mechanistic approach for fire size (Parisien et al.
958 2013; Finney et al. 2011). The mechanistic approach for fire size is based on the spread of fire
959 contours on a landscape and may better account for fuel load and continuity, topography and
960 land use and cover. However, such mixed approaches could be refined by building on the
961 strengths of the occurrence model presented here (e.g. SPDE approach for spatial variations)
962 and on their mechanistic model for fire spread.

963

964 **Conclusion**

965 This study proposed a comprehensive probabilistic framework, *Firelihood*, for modeling fire
966 activity in Southeastern France. The hierarchically-structured Bayesian model used a space-
967 time Poisson model for fire occurrence and a piecewise-estimated distribution for fire size,
968 which enables the simulation of likely spatial-temporal explicit fire activities. The Bayesian
969 approach allows an accurate estimation of random components in these sophisticated
970 hierarchical models, which can be parametrized in a convenient and interpretable setting thanks
971 to INLA. This ensemble-based methodology is innovative and applicable to spatially-correlated
972 fire observations in other regions or landscapes. In Southeastern France, the model performance
973 was very encouraging, especially for escaped fire numbers, and allowed to better understand
974 the role of stochasticity in fire activity. Further effort is needed to elucidate the fire outbreak
975 that occurred during the 2003 heat wave as well as the limitations of the FWI in fire size
976 estimates during such conditions. We identified and discussed a few methodological challenges,
977 including the time variations in spatial effects or the proper integration of overdispersion in
978 data. We also suggest a variety of ecological, operational and economic applications of
979 *Firelihood*.

980

981 **Author contributions:**

982 HF led an earlier manuscript describing the model development in her PhD dissertation
983 (Fargeon 2019), supervised by FP, JLD and NM. TO, HF and FP built the models and ran the
984 simulations with RINLA. FP, TO and JR wrote the present version of the manuscript with the
985 help of other co-authors.

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991

992

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1285 **Tables**

1286 Table 1. List of probabilistic fire activity models (occurrence+size)

Probabilistic model name	Occurrence model	Size model
“Linear FWI”	Linear FWI	Linear FWI
“FWI only”	FWI	FWI
“No Seasonal”	FWI+2003+FA	FWI+FA
“No Spatial”	FWI+2003+FA+WEEK	FWI+FA
“Full”	FWI+2003+FA+WEEK+SPATIAL	FWI+FA

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1289 Table 2. Fire occurrence component (number of escaped fires, larger than 1 ha)

Occurrence model component	Effects
Null	No explanatory variable
Linear FWI	The predictor of fire counts in the Poisson model is a linear function of FWI
FWI	The predictor of fire counts in the Poisson model is a non-linear function of FWI
FWI+2003	As above + include also a fixed effect to account for post-2003 difference
FWI+2003+FA	As above + include the offset associated with FA and the non-linear effect of FA
FWI+2003+FA+WEEK	As above + include a weekly-based seasonal correction for occurrence
FWI+2003+FA+WEEK+SPATIAL	Full occurrence model described in section 2.1. As above + spatial model

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1292 Table 3. Fire size component (size of escaped fires)

Size model component	Effects
Null	No explanatory variable
Linear FWI	The predictor of fire-size-distribution parameters is a linear function of FWI
FWI	The predictor of fire-size-distribution parameters is a non-linear function of FWI
FWI+FA	As above + include a non-linear effect of FA ¹

1293 ¹ Except for the GPD which is a linear function of FWI only

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1295 **Figure legends**

1296 FIG. 1. Data site and description: a) Orography (elevation in m) of the study region; Fire activity
1297 (1995-2018): b) Monthly distribution of burnt areas; c) Spatial distribution of fires larger or
1298 equal to 1 ha; d) Yearly burnt areas. Data were extracted from the Prométhée fire database
1299 (<http://www.promethee.com/>).

1300 FIG. 2. Framework of the “full” probabilistic model of fire activity

1301 FIG. 3. Partial effects of the “Full” fire activity model: a) Occurrence component (number of
1302 escaped fires, i.e. larger than 1 ha): effects of FWI, Forest Area (including offset), Week of
1303 Year, and location; b) Size component (exceedance probabilities of escaped fires for a selection
1304 of thresholds ranging between 1 and 2000 ha): effects of FWI and FA, for a Forest Area of 30 %
1305 (top) and a FWI of 20 (bottom), respectively.

1306 FIG. 4. Simulated fire activity (in orange) and observations (black dots) for year 2001: daily
1307 and weekly escaped fire numbers, as well as weekly number of fires larger than 10, 50, 100 ha
1308 and weekly burnt areas added up over the whole study area. Central tendency (red line) was
1309 surrounded by the 95th confidence interval in orange and was based on averages computed over
1310 1000 simulations of fire activities for all voxels of year 2001.

1311 FIG. 5. Simulated fire size cumulative distribution and observations for year 2001: Central
1312 tendency (orange line) was surrounded by the 95th confidence interval in orange and the 99.9th
1313 confidence interval (light orange), computed from 1000 simulations of fire sizes for year 2001.
1314 The dotted line corresponds to the fire size distribution from 1995-2018.

1315 FIG. 6. “Areas Under the Curve” (AUCs) corresponding to the realization of events diagnosed
1316 according to the two components of the fire activity model. The different series correspond to
1317 the “full” model (on the subset used to fit data, 1995-2014; and for the subset used to test the
1318 model, 2015-2018) and to a more basic “Linear FWI” model (before 2014), which only
1319 implemented the linear effect of the FWI as explanatory variable.

1320 FIG. 7. Evaluation of the occurrence model component (escaped fire number) for a selection of
1321 aggregation scales. In each subplot, the “Full” model is compared to an intermediate model
1322 where one critical effect required for consistent simulations at this aggregation scale was not
1323 included: a) Yearly trends for the whole studied area (the dashed vertical line shows the
1324 separation between training and validation sample); b) Seasonal trends at the weekly scale; c)
1325 Spatial patterns in number of escaped fires.

1326 FIG. 8. Same as Fig. 7 for burnt area.

1327 FIG. 9. Partial effect of the FWI for the different occurrence models

1328 FIG. 10. Same as FIG. 4, for year 2003. Comparison of simulated fire activity (in red) with
1329 observation (black dots): daily and weekly escaped fire numbers, as well as weekly number of
1330 fire larger than 10, 50, 100 ha and weekly burnt areas were summed for the whole study area.
1331 Central tendency (red line) was surrounded by the 95th and 99.9th confidence intervals in orange
1332 and light orange (computed from 1000 simulations of fire activities).

1333 FIG. 11. Same as FIG. 5 for year 2003. Comparison of simulated fire size distribution with
1334 observation: Central tendency (red line) was surrounded by the 95th confidence interval in
1335 orange and the 99.9th confidence interval (light orange), computed from 1000 simulations of
1336 fire sizes for year 2003.

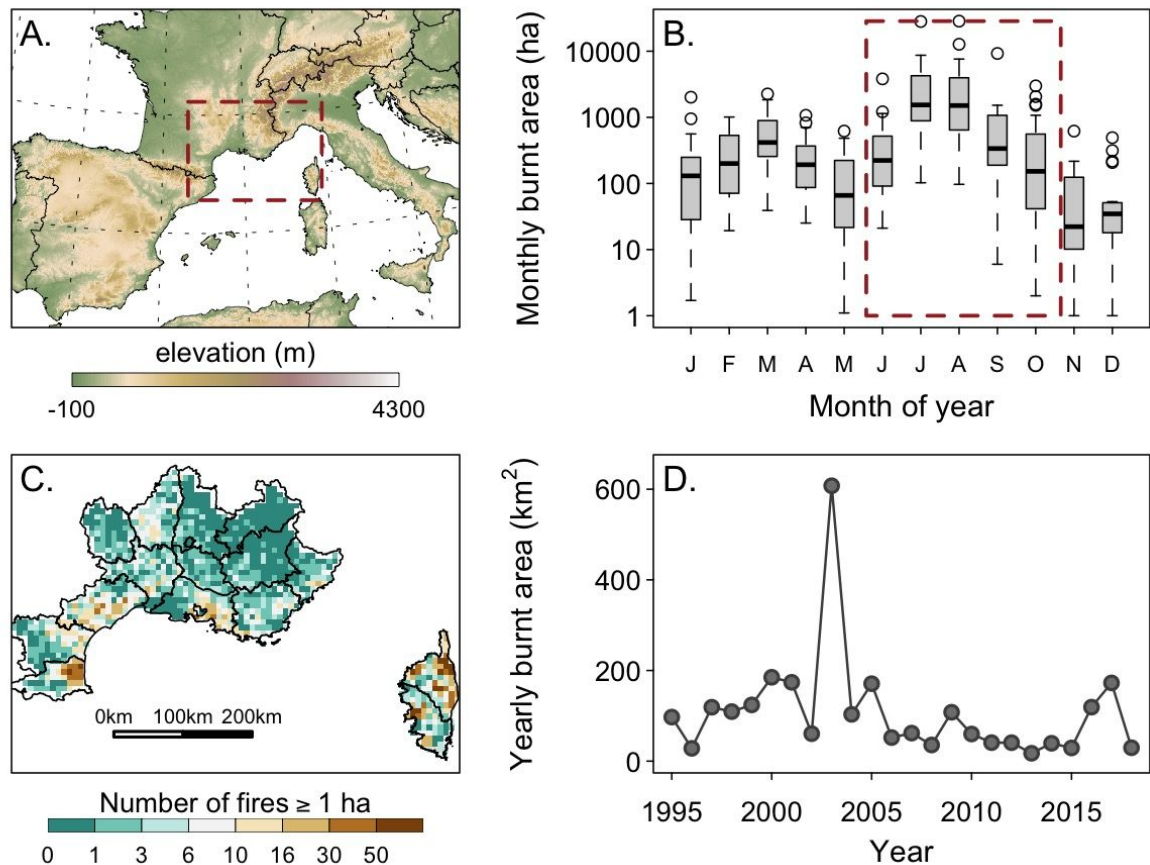
1337 FIG. 12. Mean Absolute Error (top) and Model Uncertainty (bottom) of the model at various
1338 spatial (1, 4, 16, 36 pixels, NUTS 3, all region, with size in km² in brackets) and temporal (1
1339 day, 1 week, two weeks, ..., one year, four years) aggregations for fire numbers of 1, 10, 100 ha
1340 and burnt area for the period 2015-2018.

1341

1342

1343 FIG. 1. Data site and description: a) Orography (elevation in m) of the study region; Fire activity
 1344 (1995-2018): b) Monthly distribution of burnt areas; c) Spatial distribution of fires larger or
 1345 equal to 1 ha; d) Yearly burnt areas. Data were extracted from the Prométhée fire database
 1346 (<http://www.promethee.com/>).

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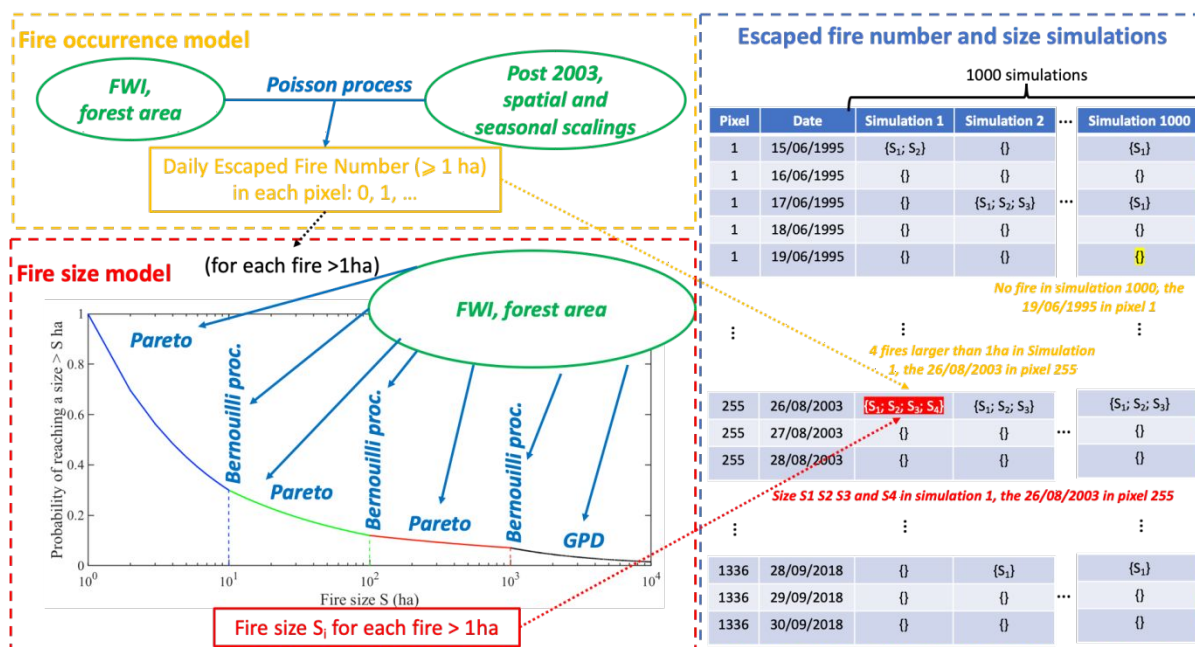


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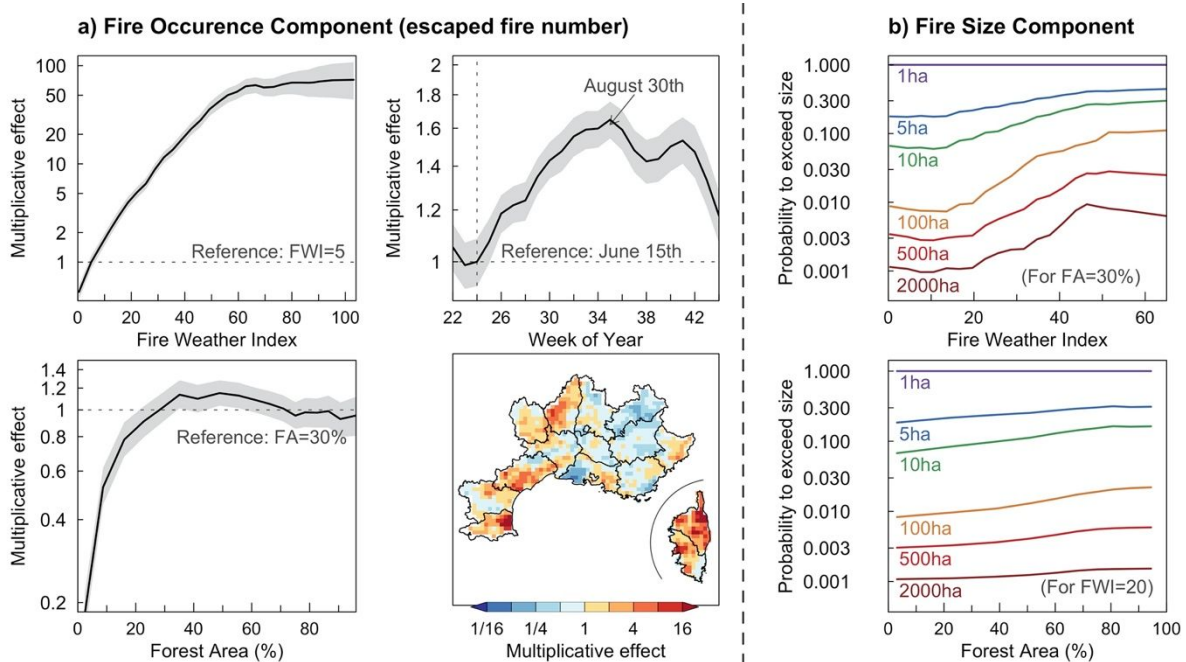
1351 FIG. 2. Framework of the “full” probabilistic model of fire activity. The occurrence and size
 1352 components of the model are presented in dashed boxes on the left in yellow and red,
 1353 respectively. Random effects are listed in green, whereas statistical processes involved are in
 1354 labelled in blue. The occurrence model (in yellow) used a space-time Poisson process to
 1355 simulate the daily number of escaped fires (i.e. larger than 1ha) in each pixel. The size of each
 1356 escaped fire is individually simulated from the 4-piece distribution estimated from the size
 1357 model (in red). The distribution model includes three exceedance thresholds (Bernoulli
 1358 process) and the 4 pieces corresponding to either Pareto or Generalized Pareto Distributions
 1359 (because fire size cannot be infinite). The blue box on the right illustrates ensemble simulations
 1360 that can be done with the model. For each pixel day, the models are used to simulate realizations
 1361 (here 1000) of the number of fires (which is most often 0) and their sizes (if any). The likely
 1362 fire activities can then be aggregated at larger scale to provide metrics and to compute
 1363 confidence intervals.



1364

1365

1366 FIG. 3. Partial effects of the “Full” fire activity model: a) Occurrence component (number of
 1367 escaped fires, i.e. larger than 1 ha): effects of FWI, Forest Area (including offset), Week of
 1368 Year, and location; Because the different effects are multiplicative, the partial effects represent
 1369 the multiplicative effect of each factor on the escape fire number, with respect to an arbitrary
 1370 reference. We respectively used FWI=5 (low danger value), week=24 (15th of June is the
 1371 beginning of the summer fire season), FA=30% (mean value in Mediterranean France), and
 1372 mean spatial effect for the spatial model. b) Size component (exceedance probabilities of
 1373 escaped fires for a selection of thresholds ranging between 1 and 2000 ha): effects of FWI and
 1374 FA, for a Forest Area of 30 % (top) and a FWI of 20 (bottom), respectively.



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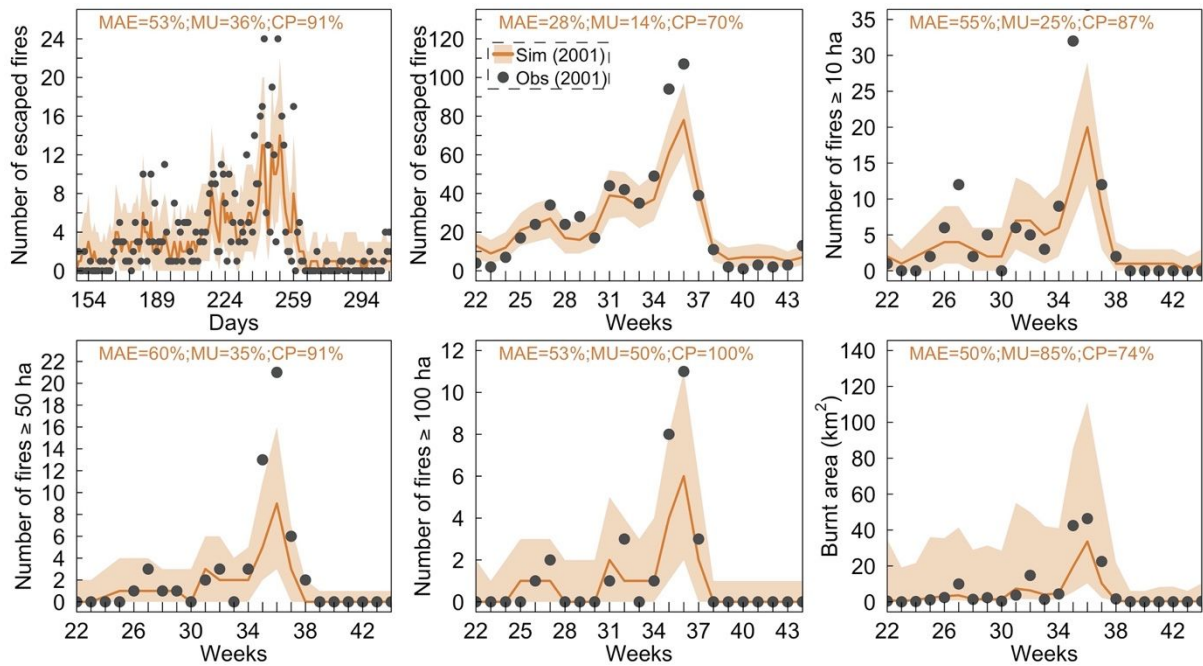
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1381 FIG. 4. Simulated fire activity (in orange) and observations (black dots) for year 2001: daily
 1382 and weekly escaped fire numbers, as well as weekly number of fires larger than 10, 50, 100 ha
 1383 and weekly burnt areas added up over the whole study area. Central tendency (red line) was
 1384 surrounded by the 95th confidence interval in orange and was based on averages computed over
 1385 1000 simulations of fire activities for all voxels of year 2001.



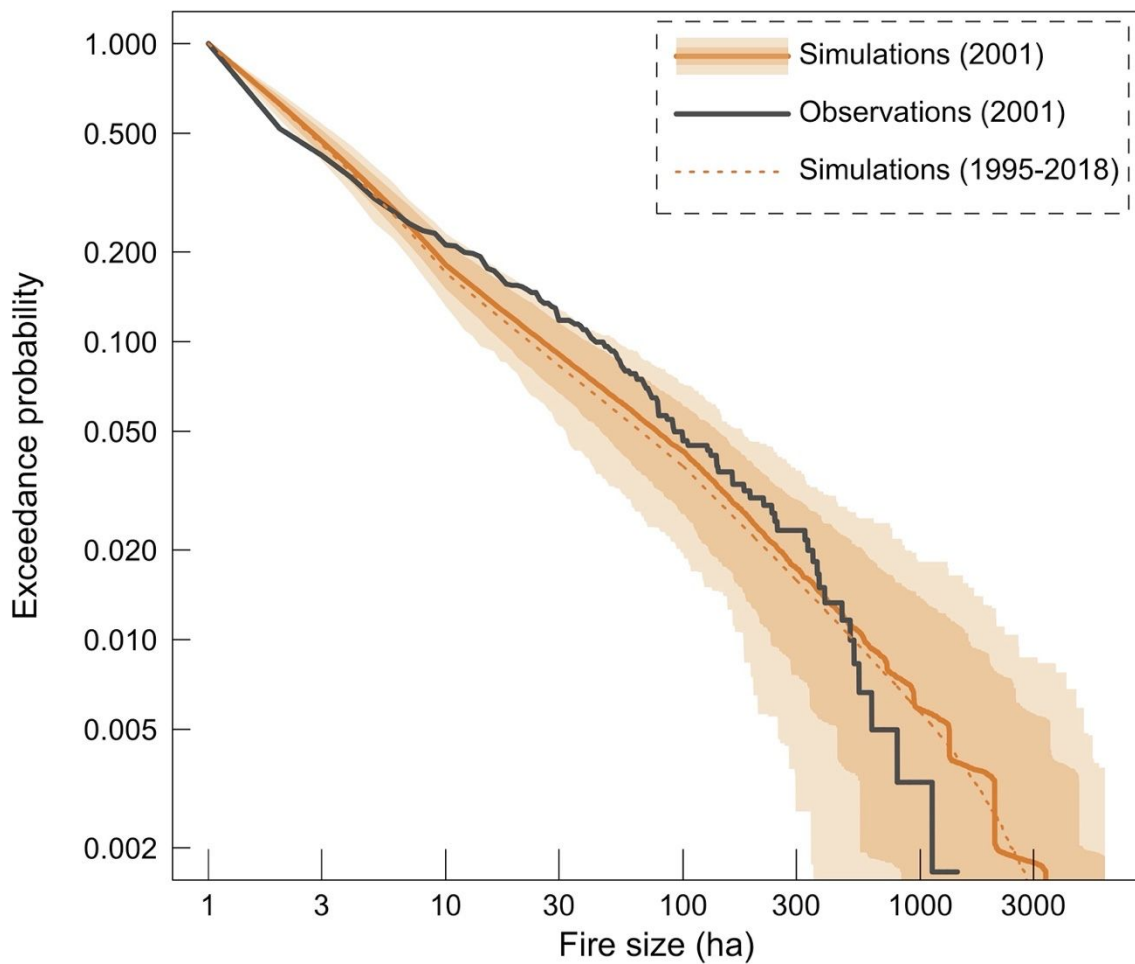
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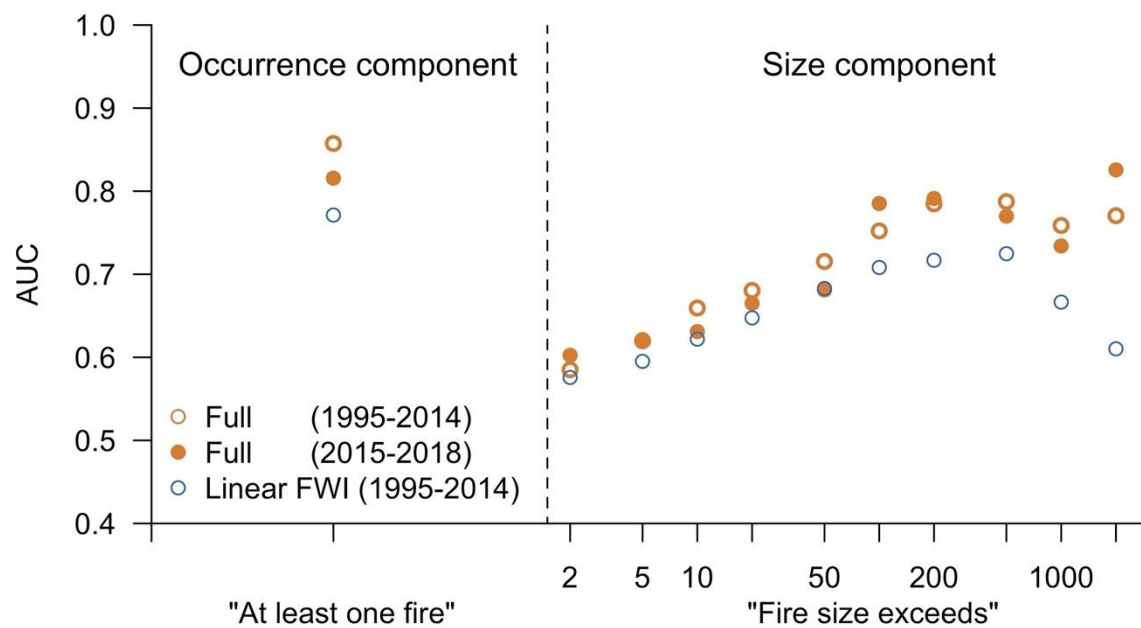
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1390 FIG. 5. Simulated fire size cumulative distribution and observations for year 2001: Central
1391 tendency (orange line) was surrounded by the 95th confidence interval in orange and the 99.9th
1392 confidence interval (light orange), computed from 1000 simulations of fire sizes for year 2001.
1393 The dotted line corresponds to the fire size distribution from 1995-2018.



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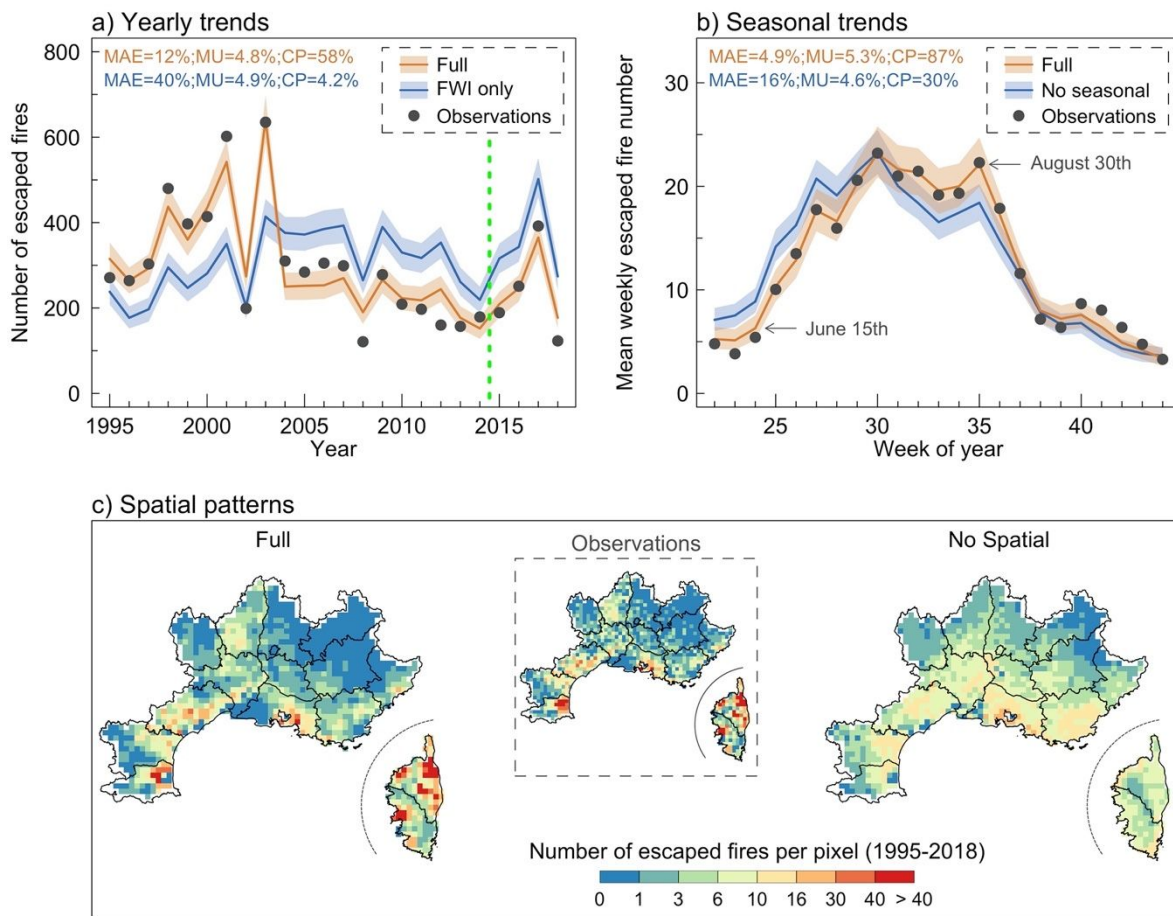
1396 FIG. 6. “Areas Under the Curve” (AUCs) corresponding to the realization of events diagnosed
 1397 according to the two components of the fire activity model. The different series correspond to
 1398 the “full” model (on the subset used to fit data, 1995-2014; and for the subset used to test the
 1399 model, 2015-2018) and to a more basic “Linear FWI” model (before 2014), which only
 1400 implemented the linear effect of the FWI as explanatory variable.



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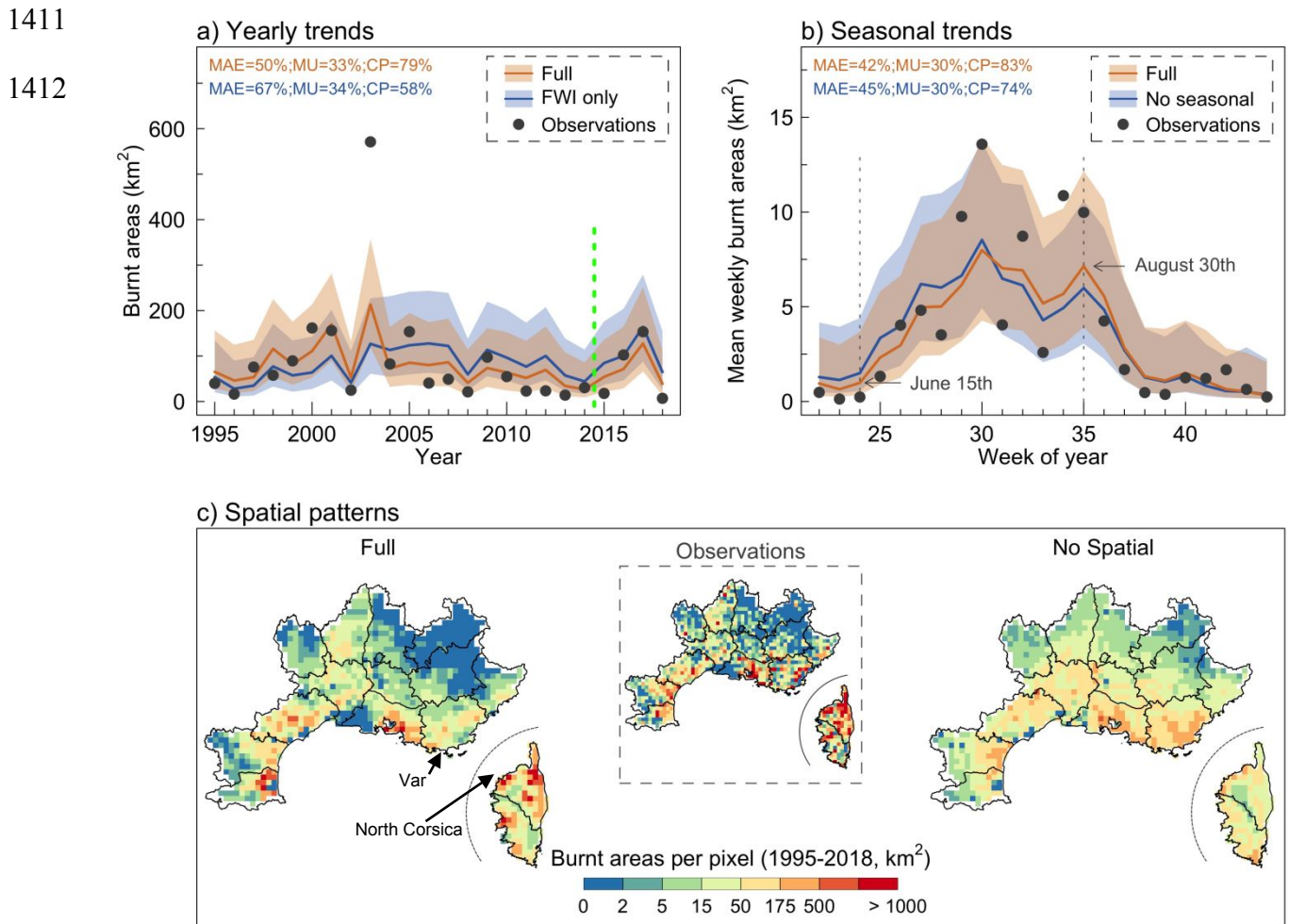
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1403 FIG. 7. Evaluation of the occurrence model component (escaped fire number) for a selection of
 1404 aggregation scales. In each subplot, the “Full” model is compared to an intermediate model
 1405 where one critical effect required for consistent simulations at this aggregation scale was not
 1406 included. a) Yearly trends for the whole studied area (the dashed vertical line shows the
 1407 separation between training and validation sample); b) Seasonal trends at the weekly scale; c)
 1408 Spatial patterns in number of escaped fires.

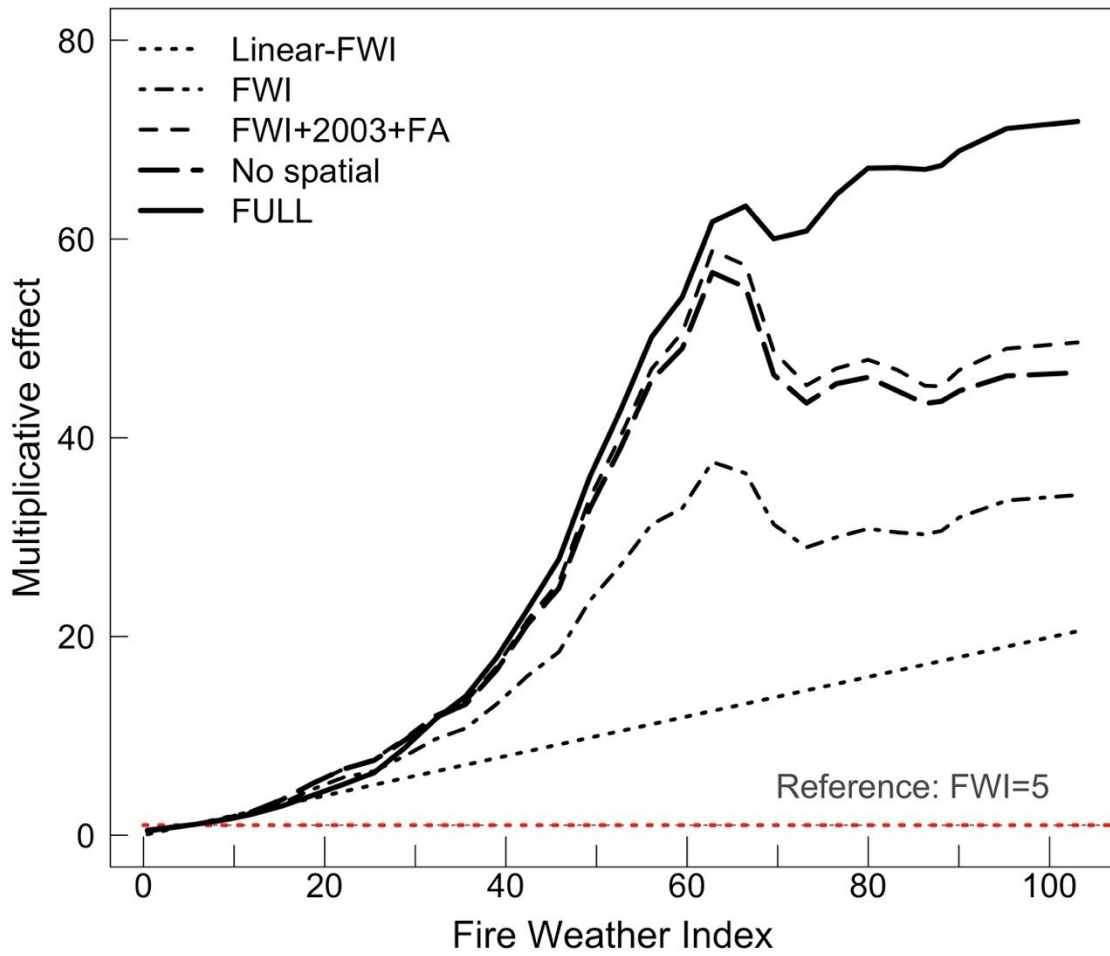


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1410 FIG. 8. Same as Fig. 7 for burnt area.



1413 FIG. 9. Partial effect of the FWI for the different occurrence models

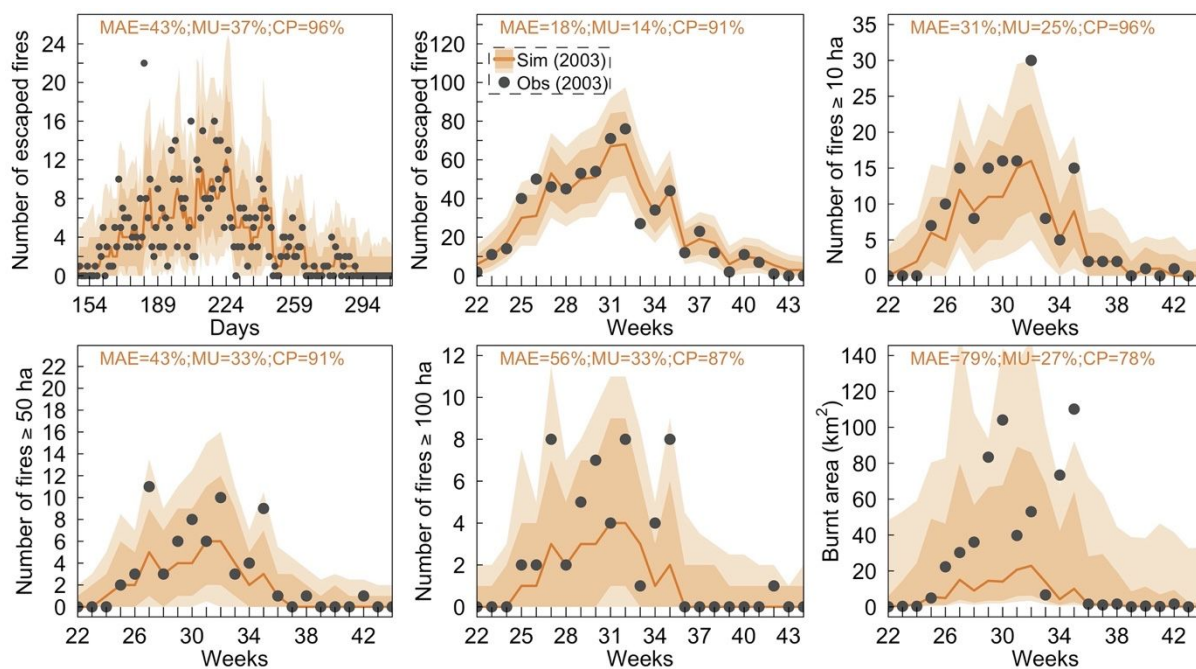


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1417 FIG. 10. Same as FIG. 4, for year 2003. Comparison of simulated fire activity (in red) with
 1418 observation (black dots): daily and weekly escaped fire numbers, as well as weekly number of
 1419 fire larger than 10, 50, 100 ha and weekly burnt areas were summed for the whole study area.
 1420 Central tendency (red line) was surrounded by the 95th and 99.9th confidence intervals in orange
 1421 and light orange (computed from 1000 simulations of fire activities).

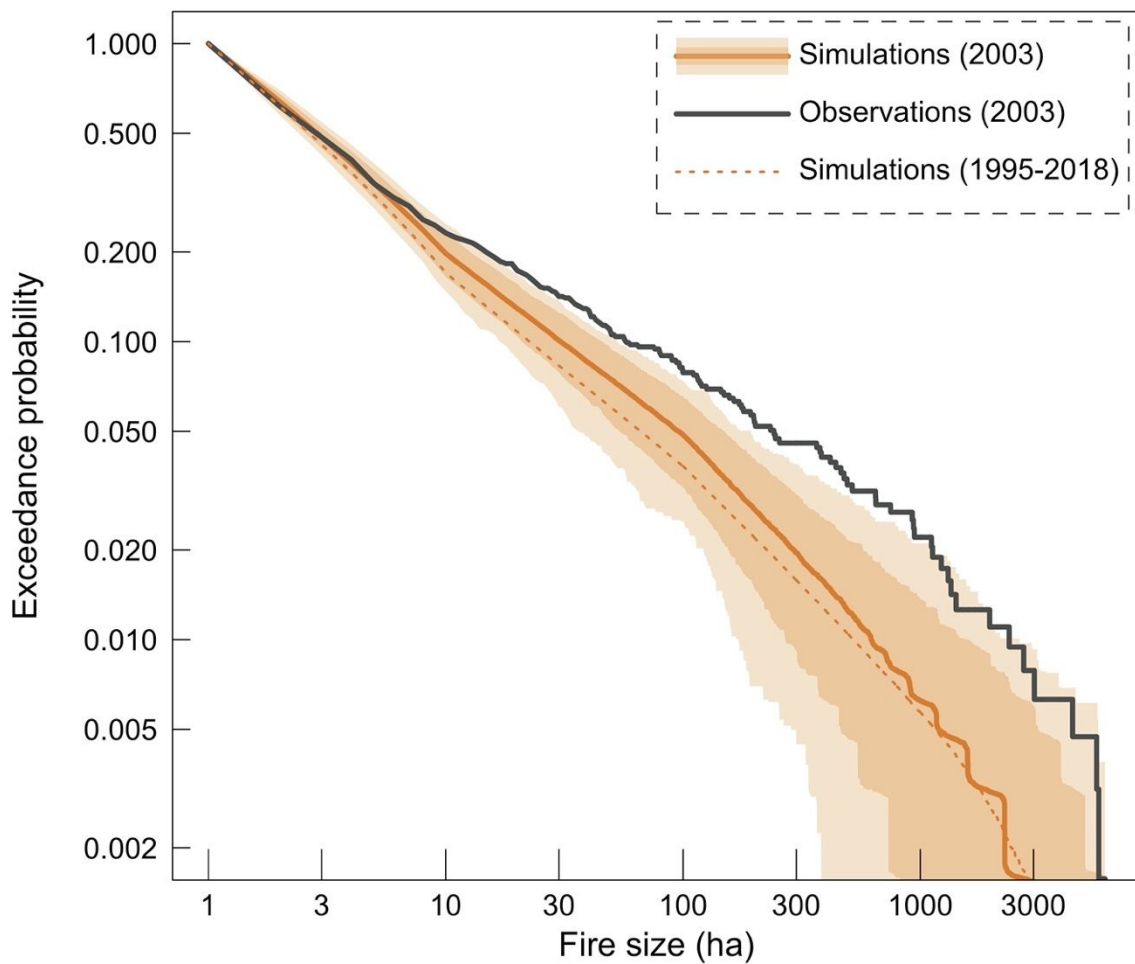


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1425 FIG. 11. Same as FIG. 5 for year 2003. Comparison of simulated fire size distribution with
1426 observation: Central tendency (red line) was surrounded by the 95th confidence interval in
1427 orange and the 99.9th confidence interval (light orange), computed from 1000 simulations of
1428 fire sizes for year 2003.

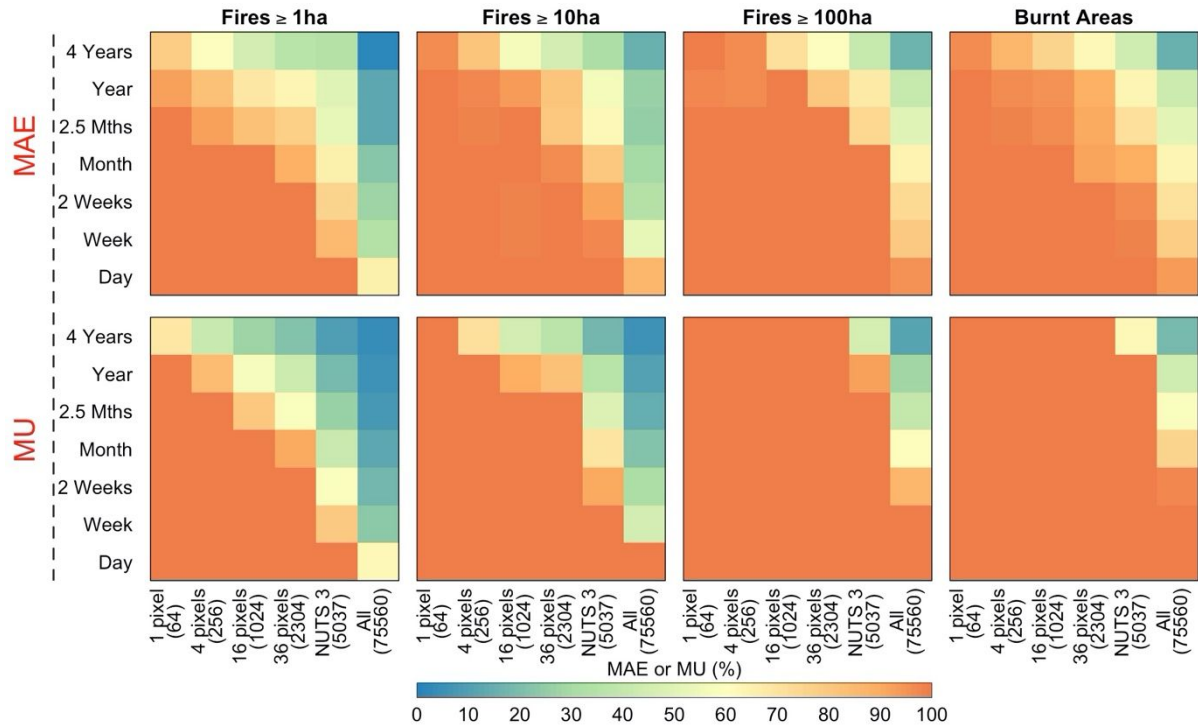


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1432 FIG. 12. Mean Absolute Error (top) and Model Uncertainty (bottom) of the model at various
 1433 spatial (1, 4, 16, 36 pixels, NUTS 3, all region, with size in km² in brackets) and temporal (1
 1434 day, 1 week, two weeks, ..., one year, four years) aggregations for fire numbers of 1, 10,
 1435 100 ha and burnt area for the period 2015-2018.



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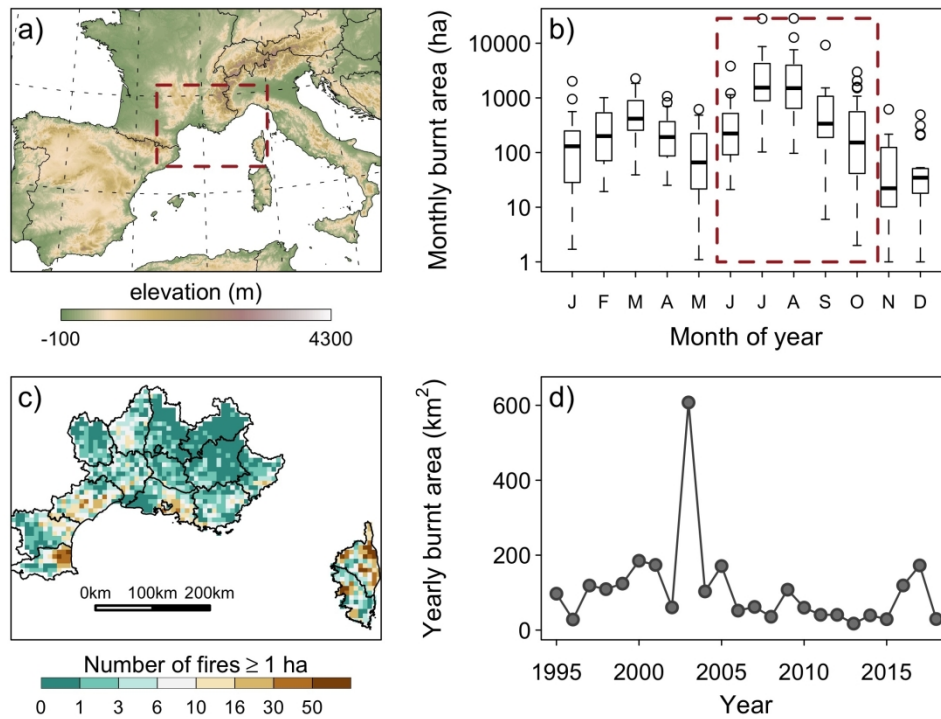
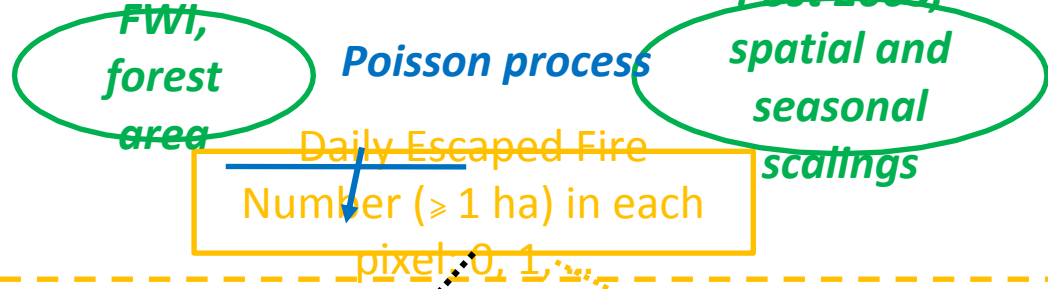


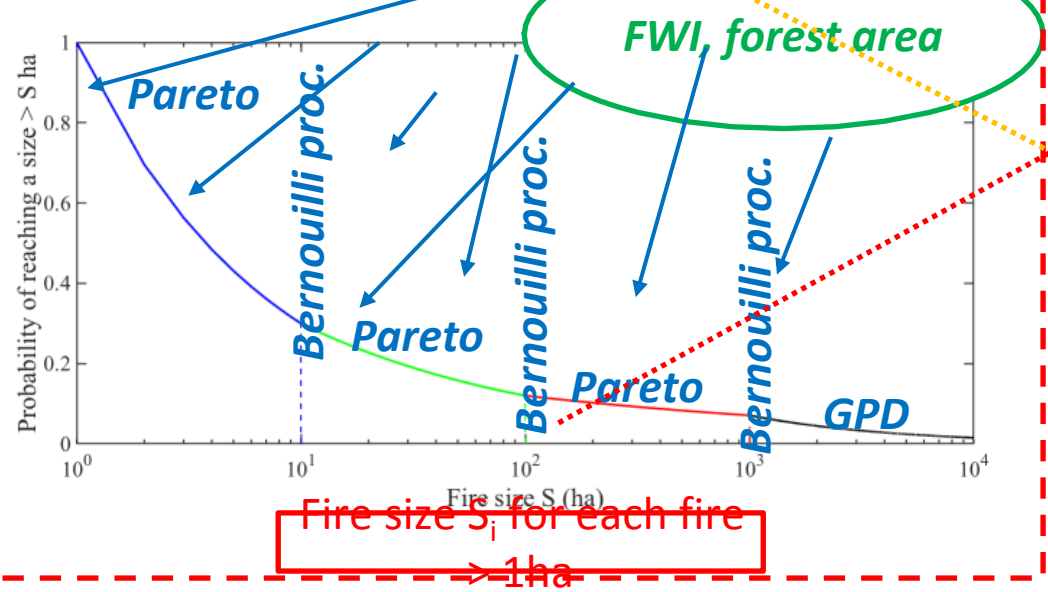
FIG. 1. Data site and description: a) Orography (elevation in m) of the study region; Fire activity (1995-2018): b) Monthly distribution of burnt areas; c) Spatial distribution of fires larger or equal to 1 ha; d) Yearly burnt areas. Data were extracted from the Prométhée fire database (<http://www.promethee.com/>).

846x634mm (72 x 72 DPI)

Fire occurrence model



Fire size model (for each fire >1ha)



Escaped fire number and size simulations

1000 simulations

Pixel	Date	Simulation 1	Simulation 2	...	Simulation 1000
1	15/06/1995	{S ₁ ; S ₂ }	{}	...	{S ₁ }
1	16/06/1995	{}	{}	...	{}
1	17/06/1995	{}	{S ₁ ; S ₂ ; S ₃ }	...	{S ₁ }
1	18/06/1995	{}	{}	...	{}
1	19/06/1995	{}	{}	...	{}
No fire in simulation 1000, the 19/06/1995 in pixel 1					
...
255	26/08/2003	{S ₁ ; S ₂ ; S ₃ ; S ₄ }	{S ₁ ; S ₂ ; S ₃ }	...	{S ₁ ; S ₂ ; S ₃ }
255	27/08/2003	{}	{}	...	{}
255	28/08/2003	{}	{}	...	{}
Size S ₁ S ₂ S ₃ and S ₄ in simulation 1, the 26/08/2003 in pixel 255					
...
1336	28/09/2018	{}	{S ₁ }	...	{S ₁ }
1336	29/09/2018	{}	{}	...	{}
1336	30/09/2018	{}	{}	...	{}

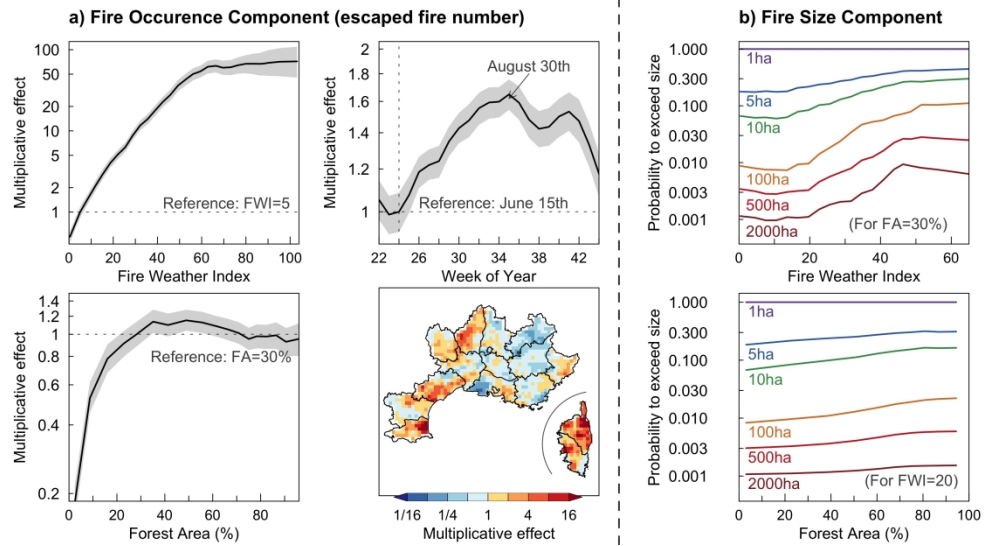


FIG. 3. Partial effects of the “Full” fire activity model: a) Occurrence component (number of escaped fires, i.e. larger than 1 ha): effects of FWI, Forest Area (including offset), Week of Year, and location; Because the different effects are multiplicative, the partial effects represent the multiplicative effect of each factor on the escape fire number, with respect to an arbitrary reference. We respectively used FWI=5 (low danger value), week=24 (15th of June is the beginning of the summer fire season), FA=30% (mean value in Mediterranean France), and mean spatial effect for the spatial model. b) Size component (exceedance probabilities of escaped fires for a selection of thresholds ranging between 1 and 2000 ha): effects of FWI and FA, for a Forest Area of 30 % (top) and a FWI of 20 (bottom), respectively.

1354x740mm (72 x 72 DPI)

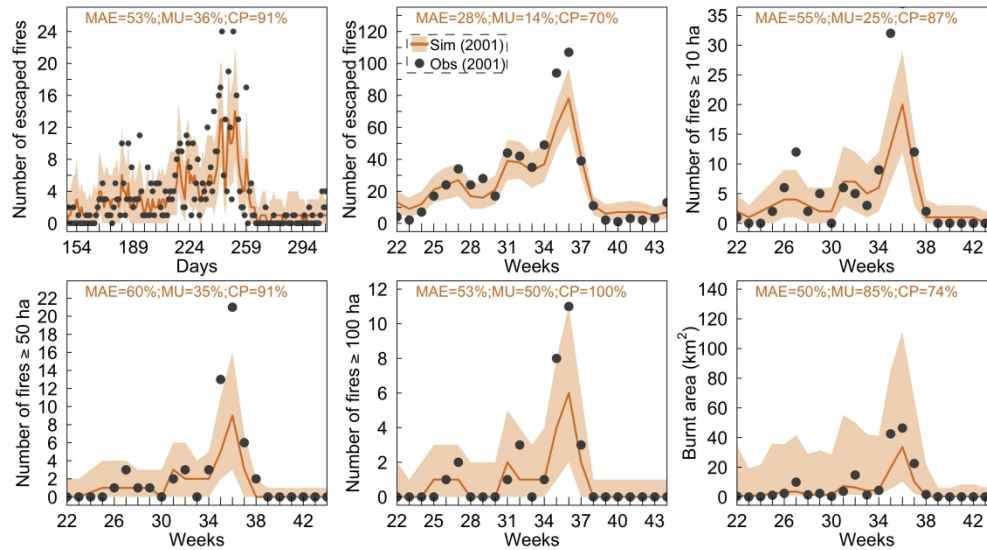


FIG. 4. Simulated fire activity (in orange) and observations (black dots) for year 2001: daily and weekly escaped fire numbers, as well as weekly number of fires larger than 10, 50, 100 ha and weekly burnt areas added up over the whole study area. Central tendency (red line) was surrounded by the 95th confidence interval in orange and was based on averages computed over 1000 simulations of fire activities for all voxels of year 2001.

1354x740mm (72 x 72 DPI)

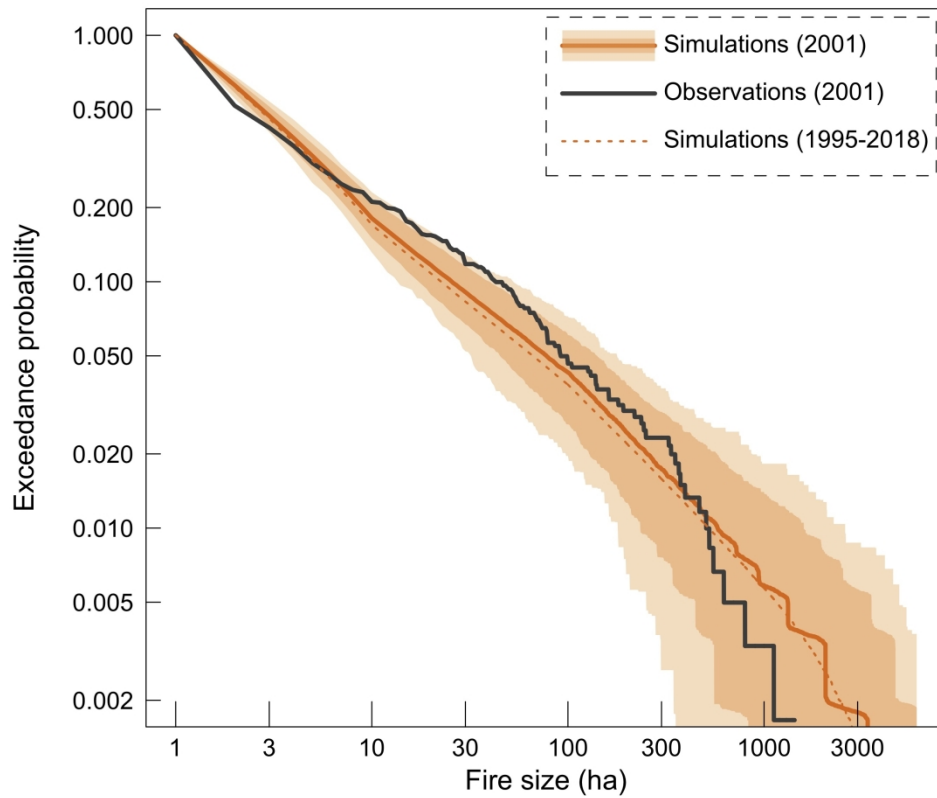


FIG. 5. Simulated fire size cumulative distribution and observations for year 2001: Central tendency (orange line) was surrounded by the 95th confidence interval in orange and the 99.9th confidence interval (light orange), computed from 1000 simulations of fire sizes for year 2001. The dotted line corresponds to the fire size distribution from 1995-2018.

1015x846mm (72 x 72 DPI)

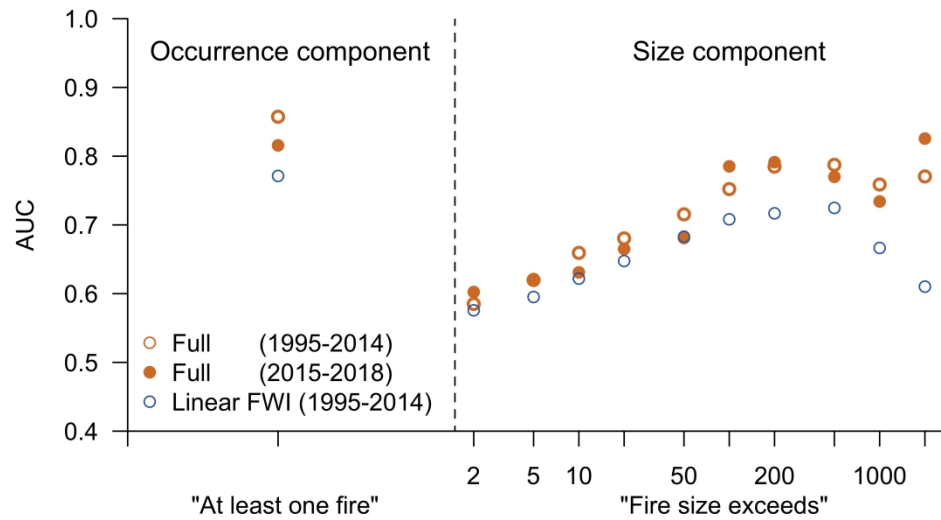


FIG. 6. "Areas Under the Curve" (AUCs) corresponding to the realization of events diagnosed according to the two components of the fire activity model. The different series correspond to the "full" model (on the subset used to fit data, 1995-2014; and for the subset used to test the model, 2015-2018) and to a more basic "Linear FWI" model (before 2014), which only implemented the linear effect of the FWI as explanatory variable.

1438x846mm (72 x 72 DPI)

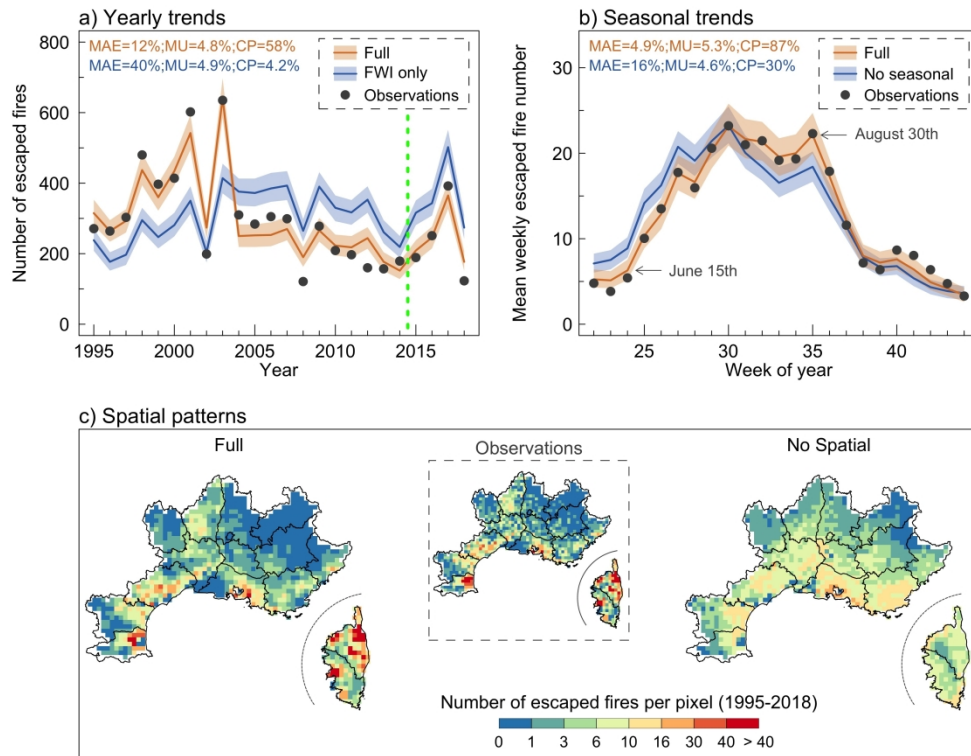
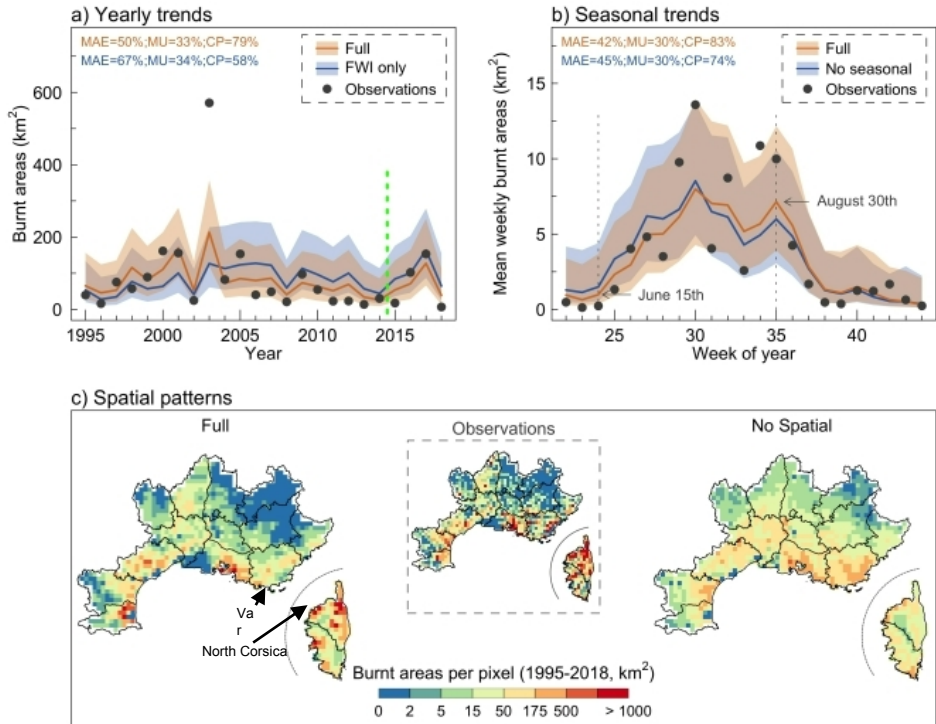


FIG. 7. Evaluation of the occurrence model component (escaped fire number) for a selection of aggregation scales. In each subplot, the "Full" model is compared to an intermediate model where one critical effect required for consistent simulations at this aggregation scale was not included. a) Yearly trends for the whole studied area (the dashed vertical line shows the separation between training and validation sample); b) Seasonal trends at the weekly scale; c) Spatial patterns in number of escaped fires.

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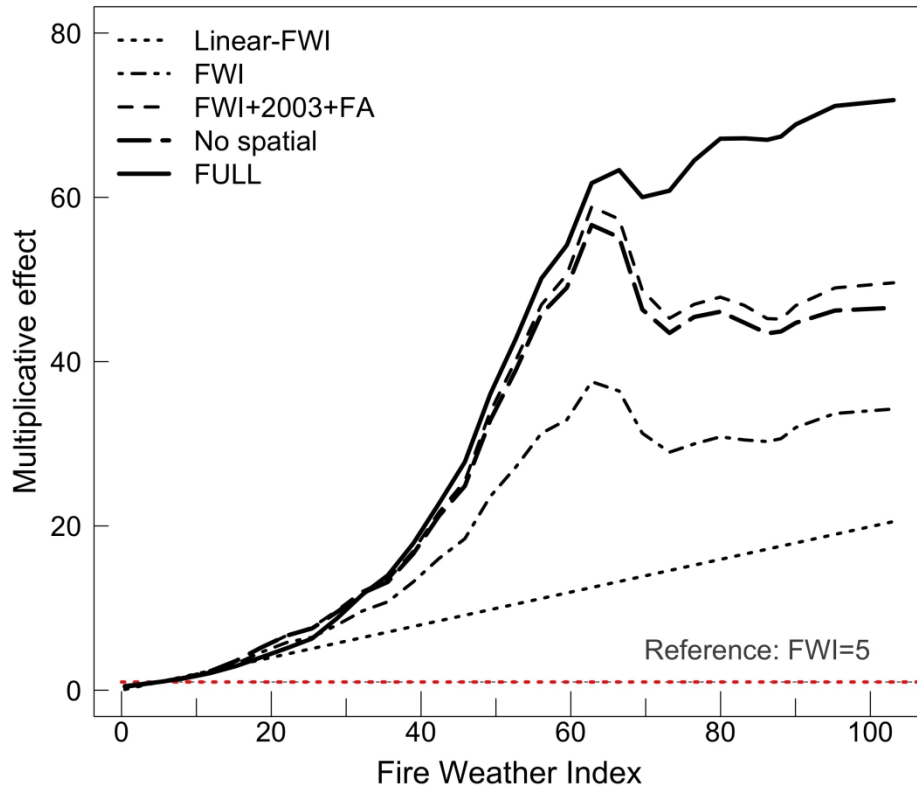


FIG. 9. Partial effect of the FWI for the different occurrence models

1015x846mm (72 x 72 DPI)

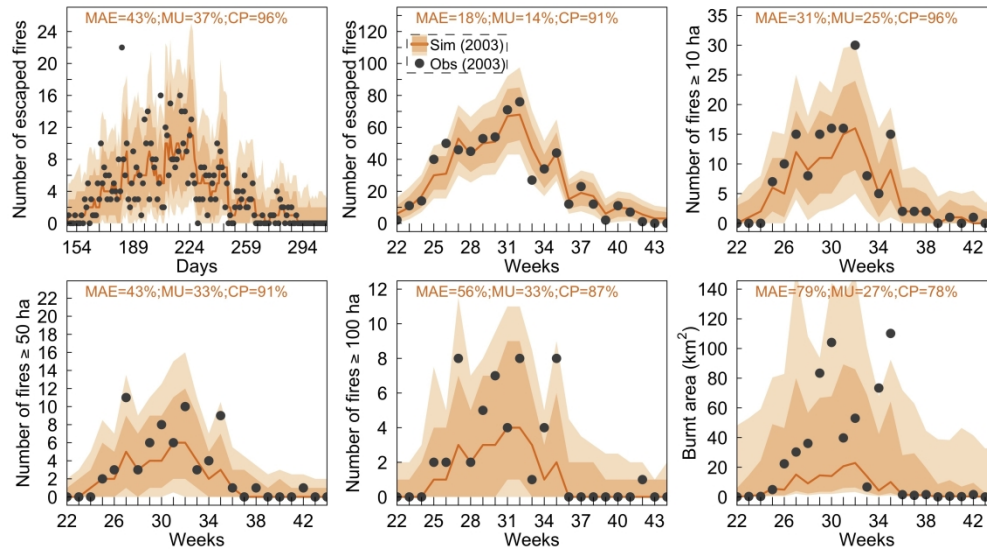


FIG. 10. Same as FIG. 4, for year 2003. Comparison of simulated fire activity (in red) with observation (black dots): daily and weekly escaped fire numbers, as well as weekly number of fire larger than 10, 50, 100 ha and weekly burnt areas were summed for the whole study area. Central tendency (red line) was surrounded by the 95th and 99.9th confidence intervals in orange and light orange (computed from 1000 simulations of fire activities).

1354x740mm (72 x 72 DPI)

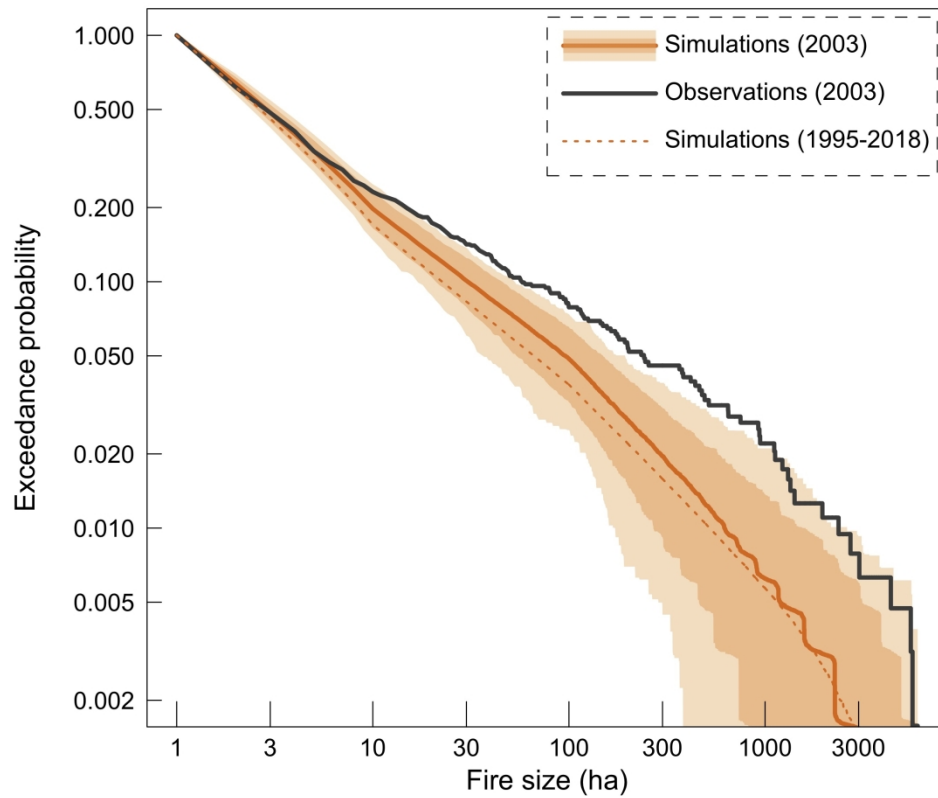


FIG. 11. Same as FIG. 5 for year 2003. Comparison of simulated fire size distribution with observation: Central tendency (red line) was surrounded by the 95th confidence interval in orange and the 99.9th confidence interval (light orange), computed from 1000 simulations of fire sizes for year 2003.

1015x846mm (72 x 72 DPI)

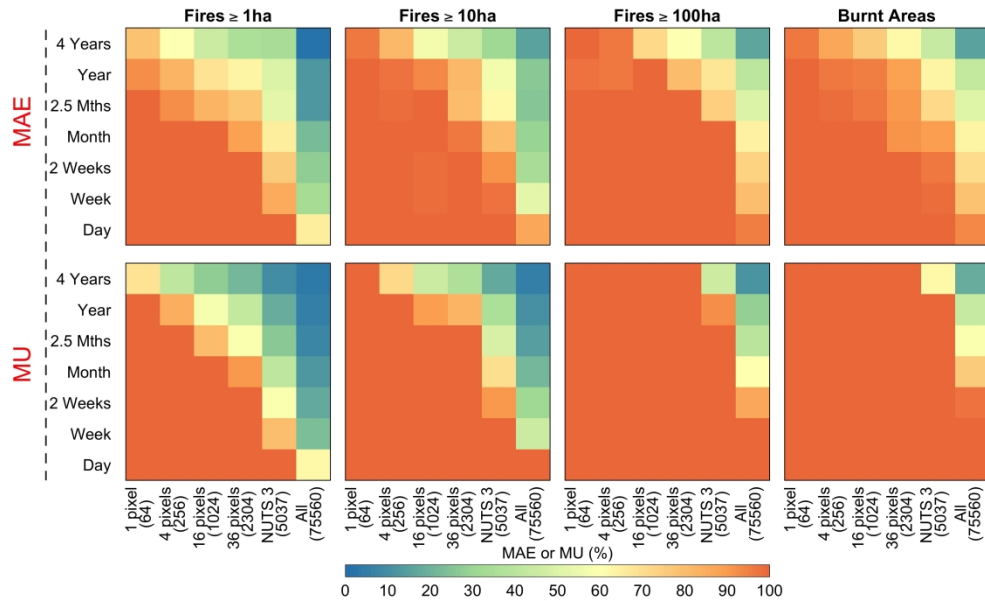


FIG. 12. Mean Absolute Error (top) and Model Uncertainty (bottom) of the model at various spatial (1, 4, 16, 36 pixels, NUTS 3, all region, with size in km² in brackets) and temporal (1 day, 1 week, two weeks, ..., one year, four years) aggregations for fire numbers of 1, 10, 100 ha and burnt area for the period 2015-2018.

1333x803mm (72 x 72 DPI)