

#### Simulation-based high resolution fire danger mapping using deep learning

Frédéric Allaire, Jean-Baptiste Filippi, Vivien Mallet, Florence Vaysse

#### ▶ To cite this version:

Frédéric Allaire, Jean-Baptiste Filippi, Vivien Mallet, Florence Vaysse. Simulation-based high resolution fire danger mapping using deep learning. International Journal of Wildland Fire, 2022, 31 (4), pp.379-394. 10.1071/WF21143 . hal-03189847

#### HAL Id: hal-03189847 https://inria.hal.science/hal-03189847

Submitted on 5 Apr 2021

**HAL** is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers. L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

# Simulation-based high resolution fire danger mapping using deep learning

Frédéric Allaire<sup>A</sup>, Jean-Baptiste Filippi<sup>B,\*</sup>, Vivien Mallet<sup>A</sup>, and Florence Vaysse<sup>C</sup>

<sup>4</sup> <sup>A</sup> Institut national de recherche en informatique et en automatique (INRIA), 2 rue

Simone Iff, Paris, France; Sorbonne Université, Laboratoire Jacques-Louis Lions,
France.

<sup>7</sup> <sup>B</sup> Centre national de la recherche scientifique (CNRS), Sciences pour l'Environnement

8 – Unité Mixte de Recherche 6134, Università di Corsica, Campus Grossetti, Corte,

<sup>9</sup> France.

3

<sup>10</sup> <sup>C</sup> Météo-France, Centre régional Sud-Est, 2 bd Château Double, Aix-en-Provence,
<sup>11</sup> France.

<sup>12</sup> \* Email: frederic.allaire@inria.fr; corresponding author.

Abstract: Wildfire occurrence and behavior are difficult to predict very locally for the next day. In the present work, we use an artificial neural network emulator called DeepFire, trained on the basis of simulated fire sizes, and study its application to fire danger mapping using actual weather fore-

casts. Experimental analysis is based on DeepFire forecasts for 13 relatively 17 big fires that occurred in Corsica and corresponding forecasts based on a 18 fire danger index used in operational conditions. A comparative analysis of 19 both indices is presented, highlighting the differences in terms of precision 20 and expected results of such predictions. Forcing weather forecasts used as 21 input have high spatial resolution and high frequency, which also applies to 22 the fire danger predictions. Additionally, input uncertainty is propagated 23 through DeepFire, resulting in ensembles of emulated fire size. Eventually, 24 several approaches are proposed to analyze the results and help in investing 25 assessment of next-day fire danger using this new simulation-based prediction 26 system. 27

<sup>28</sup> Keywords: wildfire simulation, deep learning, fire danger, potential fire size,

<sup>29</sup> fire weather, probability distributions

#### 30 1 Introduction

Wildfire occurrence and behavior is difficult to predict accurately. The environmental conditions such as weather and the type(s) of vegetation involved may be known to some extent, but the time, location, and cause of fire occurrence are rarely known ahead of time. A common approach in wildfire prediction consists in assessing fire danger, a general term that expresses both fixed and variable factors of the fire environment that influence the ease of ignition, rate of spread and difficulty of control.

Fire danger rating systems include assessment of one or several fire dan-38 ger indices, which are used among other information to provide a rating, i.e. 39 a class whose possible values may include "low", "moderate", "severe", "ex-40 treme", etc., but the notion of "rating" may also refer to the scalar indices 41 composing the system. Regardless of the type of quantity used to assess it, 42 fire danger relates to the proneness for ignition, spread and/or intensity of 43 a wildfire according to the state of the vegetation and its environment at a 44 given time, therefore reflecting how difficult it may be to control fire. De-45 velopment of fire danger rating methods has led to the implementation of 46 systems at the national scale about 50 years ago in Canada and in the US, 47 with the Canadian Forest Fire Danger Rating System (CFFDRS Lawson and 48 Armitage (2008), whose development started in 1968) and the National Fire 49 Danger Rating System (NFDRS Bradshaw et al. (1984), first published in 50 1972, but whose development as well as fire danger rating methods dates 51

<sup>52</sup> further back, see for instance Hardy and Hardy (2007)).

Maps of fire danger ratings are usually generated every day to assess 53 the situation of the current day and forecast the situation for the day(s)54 to come. Such maps may be available among other data via internet-based 55 information systems; for instance, covering the US as part of the Wildland 56 Fire Assessment System (WFAS Burgan et al. (1997))<sup>1</sup>, covering Canada as 57 part of the Canadian Wildland Fire Information System (CFWIS)<sup>2</sup>, covering 58 Europe and the Mediterranean area as part of the European Forest Fire 59 Information System  $(EFFIS)^3$ , or even covering the globe as part of the 60 Global Wildfire Information System (GWIS)<sup>4</sup>, which builds on activities of 61 EFFIS. 62

Calculation of the aforementioned fire danger indices mostly depends on 63 weather inputs and, to some extent, fuel moisture, which is generally derived 64 from weather information. In the CFFDRS, the final output is a composite 65 Fire Weather Index (FWI), that depends on such inputs, more precisely wind 66 speed, air temperature, relative humidity and rainfall over the previous 24 67 hours, as well as the values of the indices from the day before. Although one 68 could consider computing the indices at high temporal resolution, they are 69 generally computed to represent peak, or at least high, fire weather conditions 70 in a given day. Also, although the FWI was calibrated to describe fire behav-71

<sup>&</sup>lt;sup>1</sup>https://www.wfas.net/, last checked 2021.02.01 <sup>2</sup>https://cwfis.cfs.nrcan.gc.ca/maps/fw, last checked 2021.02.01 <sup>3</sup>https://effis.jrc.ec.europa.eu/, last checked 2021.02.01 <sup>4</sup>https://gwis.jrc.ec.europa.eu/, last checked 2021.02.01

ior in a jack pine stands, it has been implemented in many other countries
despite the differences in vegetation and climate where it showed reasonable
performance (see for instance Giuseppe et al. (2020) and references therein).
Forecasted maps of such indices generally have a temporal resolution of one
day even if the underlying weather forecasts have higher temporal resolution,
but the temporal extent and spatial resolution are generally the same.

Weather forecasts covering a smaller area may have higher spatial res-78 olution: for instance the regional AROME limited area model in use at 79 Météo-France has a spatial resolution of 1.3 km, covers France and part of 80 neighboring countries, and allows for the computation of fire danger index 81 at much higher resolution. AROME is also an operational system used as a 82 reference in this study. Meteorological assistance for forest fires started in 83 the 60s and the Météo-France methodology has been gradually evolving over 84 the years, depending on the research but also on the feedback of the various 85 departments of Civil Protection and the ONF who fight against forest fires. 86 In summer, the Mediterranean vegetation is evolving between a growth 87 phase in spring to a dormancy phase between mid-summer and early fall. 88

When the scrubland's shrubs are falling over to this vegetative state, there is a very small quantity of water in leaves and thus the Mediterranean vegetation is becoming extremely flammable by dry weather. The expertise of weather fire danger requires, firstly, the monitoring of drought to evaluate whether or not the vegetation is prone to big summer fires.

94

In this configuration, at Météo-France, the forecaster assesses weather fire

danger with 3 main indices; FWI: for vegetation in low or moderate drought, 95 IPse: a local rate of spread index for very dry vegetation and IEP (Indicateur 96 d'éclosion et Propagation, French for "Ignition and spread indicator"): for 97 dead or dormancy vegetation for which the water content is directly linked 98 with air moisture and therefore Fine Fuel Moisture Content (FFMC). All gc those indices are calculated at the maximum of the day based on hourly val-100 ues (in which case, they are post-fixed with an x, leading to FWIx, IPsex, 101 and IEPx). Weather fire danger depends on wind speed and highest temper-102 atures/lowest air moisture, which can happen at different moments during 103 the day depending on the local meteorological context; for instance, strong 104 and dry winds can happen at any moment in the day and even in the night 105 in Mediterranean areas. 106

Instead of relying on empirically calibrated formulas to compute indices 107 that are, for the most part, unitless, a promising strategy is to rely on a 108 large number of simulations of fire spread using weather forecasts as input, 109 therefore providing a more "concrete" representation of fire spread via sim-110 ulated burned surfaces. Two interesting methods following such a strategy, 111 although applied at different time scales than day to day predictions, are 112 burn probability (BP) modeling and ensembles of simulations for specific fire 113 cases. 114

<sup>115</sup> BP modeling consists in propagating input distributions of environmen-<sup>116</sup> tal characteristics (weather and fuels) and fire characteristics (ignition, fire <sup>117</sup> duration, number of fires in a year) via several simulations of wildland fire

ignition and spread, this process being repeated independently several times 118 via a MC method to represent potential scenarios of wildland fire activity in 119 a region and/or a country. In this context, the output BP maps represent the 120 probability of local areas to be burned by a fire (typically over the course of a 121 year). Notable implementations include Burn-P3 Parisien et al. (2005) which 122 relies on the Prometheus solver Tymstra et al. (2010) and FSim Finney et al. 123 (2011b) which relies on FARSITE Finney (1998). A large number of studies 124 have proposed and/or applied BP modeling (see for instance Parisien et al. 125 (2019) and references therein). 126

Similarly, ensembles of simulations for specific fire cases allow to assess "burn probabilities", following a Monte Carlo approach that accounts for input uncertainty in fire spread simulations, notably regarding weather variables. A notable implementation of this method is the FSPro system Finney et al. (2011a), which relies on an ensemble of FARSITE simulations. Due to knowledge of the ignition location, the burn probability maps resulting from such ensembles cover a much smaller area than maps of BP modeling.

From an operational perspective, BP modeling can be seen as a decision support tool for "long-term" planning, whereas ensembles of simulations for specific fire cases apply to "crisis" situations. In "short-term" predictions, however, the input distributions should be more representative of the expected weather conditions as in ensembles of simulations for specific fire cases, but should also account for the lack of knowledge regarding future ignitions over a vast territory, as in BP modeling. Although BP modeling methods could be adapted to account for daily weather forecasts, their computational requirement due to the large number of simulations involved is
too high for use in an operational context.

The approach developed in this work proposes to use wildland fire simulations as basis for short-term assessment of fire danger, while relying on deep learning to reduce the computational cost of running a high number of simulations. A deep neural network (DNN) referred to as *DeepFire* in the following is used to approximate the potential fire size returned by a fire spread simulator.

DeepFire is able to compute a high number of fire size estimations in 150 a short amount of time, and could generate fire danger maps at both high 151 spatial resolution (approximately 80 m) and high frequency (10-minute time 152 step) in a operational context. The fire size computations could be obtained 153 using a fire spread simulator, but would require several days in this context. 154 Compared to traditional fire danger indices, two major differences of Deep-155 Fire are that it accounts not only for weather but also for the influence of 156 terrain on fire spread, and that fire danger is expressed as a physical quan-157 tity, namely a surface area (in hectares). Its output and overall design are 158 therefore quite different from the CFFDRS, for instance. It is also possible 159 to run an ensemble of DeepFire predictions to quantify uncertainty, although 160 at lower spatial resolution (640 m). Compared to BP modeling, a noteworthy 161 difference is that DeepFire focuses on "sources" of fire spread (i.e. how large 162 will be the burned surface, assuming that an ignition will occur at a specific 163

location), while burn probabilities represent "sinks" of fire spread (i.e. how
often a specific location is likely to be burned, as a result of several scenarios
of fire spread each with variable ignition location).

A key aspect of this work is the the availability of high-resolution weather 167 forecasts, which is arguably a major limitation for application of a BP ap-168 proach to short-term predictions. In the frame of this study, a limited-169 area model running at 600-m resolution is used to generate a forecast of 170 surface wind, fuel moisture, and air temperature with a time extent of 42171 hours. In order to be representative of operational applications, this high-172 resolution weather forecast was run daily (at midnight) from 10/05/2017 and 173 was available around 11:00. To account for rapidly changing conditions, a 174 high-frequency simulation output with a time step of 10 minutes is provided, 175 resulting in time-series of 253 spatial fields of weather variables, which are 176 forecasted every day. 177

Section 2 details the method that is used to obtain predictions of fire 178 danger with DeepFire and with IEP. Analysis of forecasts for days were 179 relatively large fires occurred is presented in Section 3. A detailed analysis is 180 first provided for one fire, then more synthetically for 12 other fires. Section 4 181 addresses the question of generating daily maps that indicate the danger for 182 the coming day in order to summarize the high number of maps resulting 183 from the high forecast frequency. Finally, the main conclusions of this study 184 and some perspectives are given in Section 5. 185

#### $_{^{186}}$ 2 Method

### 187 2.1 DeepFire: fire size emulation using a deep neural 188 network

The new approach proposed to quantify fire danger consists in predicting, 189 for a given time and location, the size of the burned surface that would 190 result from one hour of free wildfire spread after an early stage where the 191 fire has already ignited and spread over about one acre. Ignition probability 192 is assumed homogeneous, except for locations without vegetation where it 193 is considered null. A duration of one hour is generally more than the time 194 necessary for the first attack on the fire to be carried out, even more so if one 195 assumes that the fire has been detected in the early stage. These simplifying 196 assumptions imply that fire danger mostly expresses potential for fire spread 197 if it is not attacked rather than potential for ignition. 198

In the present study, the one-hour fire size is estimated using the DNN 199 DeepFire. Its architecture is "hybrid" in the sense that it has two types of 200 input data. The first type is similar to an image: it is composed of four 201 rasters describing the landscape with a spatial resolution of about 80 m in a 202 square of  $20 \,\mathrm{km} \times 20 \,\mathrm{km}$  centered around the ignition location. One raster 203 represents elevation and the other three are derived from the same land cover 204 data. Aside from non-burnable areas, each type of land use is matched with 205 a fuel behavior model, for a total of 13 different fuel models. The three fields 206 other than elevation therefore represent the variable parameters of the fuel 207

Input	Symbol	Unit	Type	Range	Constraint
Wind speed	$(W_x, W_y)$	${\rm ms^{-1}}$	Raw	$[-35, 35]^2$	Euclidean norm $\leq 35$
Fuel moisture content (dead fuel)	$m_c$		Raw	[0.04, 0.3]	
Heat of combustion perturbation	$\Delta H$	$\rm MJkg^{-1}$	Additive	[-5, 5]	
Particle density perturbation	$ ho_p$	${\rm kg}{\rm m}^{-3}$	Additive	[-300, 300]	
Fuel height perturbations	h	m	Multiplicative	$[0.4, 1.6]^{13}$	
Fuel load perturbations	$\sigma_{f}$	${\rm kg}{\rm m}^{-2}$	Multiplicative	$[0.4, 1.6]^{13}$	
Surface-volume ratio perturbations	$S_v$	$\mathrm{m}^{-1}$	Multiplicative	$[0.4, 1.6]^{13}$	
Relative ignition point coordinates	$(\delta x, \delta y)$	m	Raw	In a fuel cell	

Table 1: Scalar inputs of DeepFire. In the case of perturbations, the symbol corresponds to the perturbed quantity, and the perturbation of this quantity can be either additive or multiplicative. The range indicates the boundaries of the domain of definition with two components for the wind and 13 components in the last three rows (one row per fuel type).

models, namely, the height h, the load  $\sigma_f$ , and the surface-volume ratio  $S_v$ . 208 The second type or inputs are scalars, listed in Table 1, that describe physi-209 cal quantities influencing fire behavior: the wind speed vector  $(W_x, W_y)$ , the 210 FMC  $m_c$ , and coefficients used to perturb the default values of fuel model 211 parameters. Two fuel parameters, namely the heat of combustion  $\Delta H$  and 212 the particle density  $\rho_p$ , have the same default value for all fuel models and 213 only have one additive perturbation coefficient each. The other parameters 214  $(h, \sigma_f, \text{ and } S_v)$  depend on the fuel model and each have one multiplicative 215 perturbation coefficient per fuel type, which, including the previous two coef-216 ficients, amounts to 41 perturbation coefficients. The remaining scalar inputs 217 are two coordinates that locate the ignition point inside the fuel cell of the 218 land cover raster where fire starts, but given the small size of the fuel cells, 219 these two inputs barely have any influence on fire size estimation. 220



Figure 1: Architecture of the DeepFire neural network.

Each type of input is first processed differently by DeepFire, a summarized 221 representation of the neural network architecture being shown in Figure 1. 222 Several convolutional layers and average pooling layers (among others) are 223 applied to the rasters while the scalars mostly go through a dense layer and 224 a rectified linear unit (ReLU) layer. This results in two intermediate vectors 225 of size 1024: the first vector only depends on the terrain around ignition 226 point, whereas the second vector depends on the scalar inputs. The rest 227 of the network consists in concatenating both vectors, and applying several 228 dense and ReLU layers, for finally providing an estimate of the fire size. 229 The parameters of the network were fitted so that DeepFire returns a good 230 approximation of the one-hour fire size that would be simulated by the fire 231 spread solver ForeFire Filippi et al. (2010) using the rate of spread model 232 of Rothermel Rothermel (1972) with the same inputs. In the simulations, 233 the initial burned surface is a 0.45-ha octagon, which is also the minimum 234 returned by both ForeFire and DeepFire (this generally happens when the 235 FMC is close to the moisture of extinction). DeepFire is an emulator (aka, 236 metamodel or surrogate model) of the one-hour fire size returned by ForeFire, 237 that is to say a model that computes this output considerably faster. The 238 first intermediate vector of "location" is pre-computed for each fuel cell in 239 the region studied (about 1.2 million fuel cells for Corsica island). Based 240 on these pre-computed vectors, the one-hour fire size can be computed for 241 all cells in about one minute for any ignition location, which is thousands 242 of times faster than with ForeFire and makes daily fire danger mapping 243

in operational conditions technically possible. More details on the neural
network and its use for emulation of fire spread simulation can be found
in Allaire et al. (2021a).

#### 247 2.2 Deterministic predictions of fire danger maps

The design of DeepFire allows for fire danger mapping of Corsica island at 248 high spatial resolution. First, for a given fuel cell, the intermediate location 249 vector (that was pre-computed) is used as input of the concatenate block. 250 The ignition point is assumed to be located at the center of the fuel cell, which 251 defines  $\delta_x$  and  $\delta_y$ . Then, scalar fuel parameters perturbations are set to 0 and 252 1 for additive and multiplicative coefficients, respectively, which corresponds 253 to no alteration of the default values of the fuel model parameters. Finally, 254 wind speed and FMC are quantities that vary during the day, so they are 255 estimated based on a weather forecast. A spatial interpolation can be carried 256 out to determine the value of these three inputs at the center of a given fuel 257 cell to address differences in spatial resolution and/or coordinate system (in 258 the present study, a barycentric interpolation is used). In extreme cases 259 where the wind speed norm is higher than  $35 \,\mathrm{m \, s^{-1}}$ , wind speed is reduced to 260 this threshold because DeepFire was not trained based on simulations outside 261 this scope. Similarly, when the FMC is lower than 0.04, this lower bound 262 is used as input of DeepFire. Also, the minimum output value (0.45 ha)263 is automatically returned when the FMC is higher than 0.3, which is the 264 moisture of extinction used in ForeFire simulations. The computation of the 265

DeepFire output with the aforementioned inputs corresponding to each fuel cell of the map and each forecast time of the weather forecast results in a time sequence of fire danger maps at high spatial resolution. Given that no perturbations are applied to the scalar inputs, this is referred to as a *deterministic prediction* of fire danger in the following.

Wind speed $\backslash$ FFMC	$\leq 80$	$\leq 80$ ]80, 85] ]85, 89] ]89, 93		]89, 93]	]93,  96]	> 96
$\leq 10  \mathrm{kt}$	low $(1)$	low $(1)$	minor $(2)$	moderate $(3)$	severe $(4)$	severe $(4)$
$]10{\rm kt},20{\rm kt}]$	low $(1)$	minor $(2)$	minor $(2)$ moderate $(3)$ severe $(4)$		severe $(4)$	very severe $(5)$
$]20{\rm kt},30{\rm kt}]$	low $(1)$	minor $(2)$	moderate $(3)$	severe $(4)$	very severe $(5)$	very severe $(5)$
$> 30  \mathrm{kt}$	minor $(2)$	moderate $(3)$	severe $(4)$	very severe $(5)$	very severe $(5)$	very severe $(5)$

Table 2: Computation of the IEP based on the norm of wind speed (in knots) and the FFMC.

Using the same weather forecast as for DeepFire, a time sequence of fire 271 danger maps at high spatial resolution based on the IEP can be obtained 272 similarly. IEP is one of the operational danger rating indicator in France 273 that serves for both summer and winter. The design of IEP is mostly em-274 pirical and based on phenological assumptions. In the autumn, as soon as 275 days become shorter and temperatures lower, the vegetation transforms it-276 self again. Deciduous trees lose their leaves which accumulate on soil and the 277 forest litter thicken. Other trees, shrubs and bushes 'hibernate' and become 278 in dormancy with a very low quantity of sap/water in their leaves. At the 279 same time, herbaceous are at the end of their cycle and die. In addition 280 to this traditional and seasonal dormancy, with climate warming, more and 281 more vegetation dies with huge and record summer drought. The dead or 282

dormancy vegetation water content is directly linked with air humidity (as 283 a sponge effect). In this case, the IEPx (daily maximum) is the most rele-284 vant indicator. In the 2010s, some huge fires occurred with moderate or just 285 severe weather fire conditions in places where dead vegetation were numer-286 ous. By studying indices and conditions in a file constituted by more than 287 5000 summer alerts from 2001, Météo-France set up an indicator by crossing 288 FFMC, correlated with outbreak potential, and wind. Since then, by em-289 piricism and following winter and summer situations, with Fire Brigades and 290 National Forest officers, it was concluded that this indicator was the most 291 relevant indicator for winter fires and a good complement in summer for dead 292 or dormancy vegetation in very dry conditions (as it was the case in summer 293 2017 in Corsica). 294

The IEP has five possible categories ranging from "low" to "very severe" 295 that only depend on the norm of wind speed and the FFMC as determined 296 from Table 2. Let us underline that both FMC and FFMC are diagnostic 297 variables of the weather forecast, i.e. they are deduced from the other vari-298 ables. The FFMC is generally based on the forecast for 12:00 in local time, 299 but this method does not account for variations of fuel moisture during the 300 day, whereas the forecasted FMC used as input of DeepFire may vary over 301 time. For consistency, we decided not to compute the input FFMC of the 302 IEP in the "standard" way but based on the value of FMC  $m_c$ , according to 303

 $_{304}$  Equation (2.1):

$$FFMC = 59.5 \times \frac{250 - m_c}{147.2 + m_c},$$
(2.1)

which is the final equation intervening in calculation of the FFMC in the Canadian system (cf. Equation (10) in Van Wagner and Pickett (1985), where the other equations are used to provide an estimate of  $m_c$ ).

Fire size (ha)	< 0.1	[0.1,  4.0[	[4.0,  40.5[	[40.5, 121.4[	[121.4,404.7[	[404.7,2023.4[	$\geq 2023.4$
Category	А	В	С	D	Е	F	G
Corresponding IEP	None	low $(1)$	minor $(2)$	moderate $(3)$	severe $(4)$	very severe $(5)$	very severe $(5)$

Table 3: Values of fire sizes used to determine a class of fire danger. The fire size classes follow the US classification and a correspondence of fire danger classes was made between DeepFire and IEP in the present study.

Categories of DeepFire values were determined based on thresholds of 308 burned surface area to provide maps with a categorical color scale for easier 309 interpretation. For simplicity, the thresholds of the US classification of fire 310 size<sup>5</sup> were chosen, providing seven categories ranging from A to G, as reported 311 in Table 3. This choice is not perfectly suited to DeepFire which estimates the 312 one-hour fire size of a freely spreading wildfire, whereas the US classification 313 accounts for all observed fires, even if there were firefighting actions or the 314 fire did not last one hour. The minimum value returned by ForeFire is 315 0.45 ha, which implies that class A will not be obtained in the present study 316 at all. Similarly, class G should be quite rare as it is only returned by 317

<sup>&</sup>lt;sup>5</sup>https://www.nwcg.gov/term/glossary/size-class-of-fire, last accessed on 2020.12.11

DeepFire given extreme input conditions (very high wind speed and very low FMC). Still, classes B to F should all contain at least a fair proportion of DeepFire predictions so this choice, although arbitrary, makes sense as a first approach. In practice, the thresholds should be calibrated in order to provide a fire danger indicator that is as relevant as possible. Finally, for qualitative comparison of danger class predicted by DeepFire and IEP, a correspondence reported in Table 3 was made.

### 2.3 Probabilistic predictions representing input uncer tainty

A major aspect that is not accounted for by the deterministic predictions 327 is the uncertainty associated to the modelling process, that could lead to a 328 difference between the "actual" one-hour fire size that would be observed and 329 its estimate. Although it may not be possible to determine the actual value 330 (firefighting actions usually occur, it can be difficult to measure, etc.), several 331 sources of uncertainty can be identified such as the error of approximation be-332 tween DeepFire and ForeFire and simplifying model assumptions. Arguably, 333 the main source of uncertainty regarding DeepFire predictions stems from 334 the weather predictions and values of fuel model parameters, that is to say 335 input uncertainty. 336

Previous studies Allaire et al. (2020,2) focused on the quantification of input uncertainty in simulations of wildland fire spread. To quantify the

uncertainty in the inputs of DeepFire, we use a *calibrated* probability dis-339 tribution associated to the inputs of ForeFire simulations. The calibration 340 method is detailed in Allaire et al. (2021b); its key aspect consists in using 341 an *a priori* distribution where the marginals of each individual input have 342 higher variance than in Allaire et al. (2020) and including the information 343 of observed burned surfaces of seven Corsican fires. The probability den-344 sity function (PDF) q of the calibrated distribution is intended to be higher 345 than the prior PDF f for a given input vector  $\boldsymbol{u}$  when there is good overall 346 agreement between observed burned surface  $S_{obs}$  and corresponding simu-347 lated burned surface  $\mathcal{S}_u$ . More precisely, the PDF g can be expressed as 348 follows: 349

$$g(\boldsymbol{u}) = \frac{e^{-\beta E(\boldsymbol{u})} f(\boldsymbol{u})}{\int e^{-\beta E(\boldsymbol{u})} f(\boldsymbol{u}) d\boldsymbol{u}},$$
(2.2)

where  $\beta > 0$  and E is a positive "energy" function that is equal to 0 when  $\mathcal{S}_{u} = \mathcal{S}_{obs}$  for each fire and increases with the dissimilarity between simulated and observed burned surfaces. Measurement of shape dissimilarity relies on the Wasserstein distance, which is a metric that appears in the field of optimal transport (see, for instance, Santambrogio (2015) for an extensive review), and E(u) can be understood as an energy that is required to transform  $\mathcal{S}_{u}$ into  $\mathcal{S}_{obs}$ . The definition of g is inspired from Bayes' rule:

$$p(\boldsymbol{u}|\mathcal{S}_{\text{obs}}) = \frac{\mathcal{L}(\mathcal{S}_{\text{obs}}|\boldsymbol{u})f(\boldsymbol{u})}{\int \mathcal{L}(\mathcal{S}_{\text{obs}}|\boldsymbol{u})f(\boldsymbol{u})d\boldsymbol{u}},$$
(2.3)

where  $p(.|\mathcal{S}_{obs})$  is the posterior PDF that would be obtained from  $\mathcal{L}(\mathcal{S}_{obs}|.)$ ,

the likelihood of the observation, and f, the prior PDF. The exponential in Equation (2.2) can therefore be seen as a pseudo-likelihood function, whose weight increases with the parameter  $\beta$ . When  $\beta = 0$ , the calibrated PDF gis equal to the prior PDF f.

In the present study, the calibrated input distribution obtained with 362  $\beta = 1/2$  is used. The components of the input vector  $\boldsymbol{u}$  are similar to 363 the scalar inputs of DeepFire listed in Table 1. The perturbations in fuel pa-364 rameters are exactly the same and can be used directly as input of DeepFire 365 instead of the values 0 and 1 used for the deterministic prediction. Regard-366 ing wind speed and FMC, however, the corresponding components of  $\boldsymbol{u}$  are 367 perturbation coefficients so that each value of  $W_x$ ,  $W_y$ , and  $m_c$  in the weather 368 forecast is perturbed using the corresponding components of  $\boldsymbol{u}$ . As for the 369 deterministic prediction, a threshold is applied so that the perturbed value 370 of wind speed norm and FMC fall in the range used to train DeepFire. By 371 sampling n independent sets of perturbation coefficients  $(\boldsymbol{u}_1,...,\boldsymbol{u}_n)$  follow-372 ing the calibrated distribution, one may obtain n replicas of the deterministic 373 DeepFire predictions but using perturbed inputs so that each of these n pre-374 dictions is different. The resulting ensemble of n DeepFire predictions is 375 referred to as a *probabilistic prediction* in the following. 376

A probabilistic prediction based on a large ensemble can be fairly easily obtained when one considers a single ignition location. However, computing an ensemble of M high-resolution maps requires M times more computational time, making the generation of a representative ensemble too long for

operational context conditions. To circumvent this issue, the spatial resolu-381 tion of the fire danger maps can be reduced. For each large cell and each 382 forecast time, we define a "representative cell": the small cell which has the 383 highest DeepFire value according to the deterministic prediction. For each 384 large cell, the computations of the probabilistic prediction is only carried out 385 for the small representative cell. In case the large cell contains a high number 386 of non-burnable cells, it may be considered as non-burnable as well (here, it 387 is considered to be the case when at least 90% of the cells are non-burnable). 388 It must also be noted that these ensembles are distinct from atmospheric 389 forecast ensembles, while the later may also be used as inputs for these sim-390 ulations to account for weather uncertainties, all fire danger predictions for 391 a given day in the present study, whether deterministic or probabilistic, were 392 based on a single deterministic weather forecast. 393

### <sup>394</sup> 2.4 Application to weather forecasts corresponding to <sup>395</sup> 13 Corsican fires

Daily forecasts are generated with a high-resolution run of the limited area model Meso-NH version 5.4 Lac et al. (2018). While being the support of coupled fire/weather simulations, Meso-NH is also the atmospheric research model of the French community, maintained and developed by two laboratories associated on the research program (Centre National de la Recherche Scientifique and Laboratoire d'Aérologie) that provided access to opera-

tional runs providing the boundary and initial conditions. Boundary and 402 initial conditions are gathered from the Météo-France archive of the AROME 403 model Amodei et al. (2015). The 00Z run is downloaded daily from the sys-404 tem and is available at around 3AM. The daily computation is performed 405 by Meso-NH on a Cartesian regular grid at 600 meter resolution and 46 at-406 mospheric levels (up to an altitude of 7000 meters). In the application over 407 Corsica this resulted in a horizontal grid of 300 by 180 points. Overall com-408 putation of the 42 hours of forecast takes an average of 2 hours on 360 CPU. 409 In these runs, Meso-NH is run coupled to ForeFireFilippi et al. (2010) code 410 in order to provide high frequency (2 minutes) model state outputs, resulting 411 in 252 output files containing water, temperature, cloud fraction, turbulence 412 and U,V and W wind fields. Such high frequency outputs is an important 413 point to, at the same time, display the complexity of local situations that 414 can locally be very perturbed by orography and rapidly changing situations 415 that may be critical on the field. 416

Still, as these forecasts cover more than one day, we focused more partic-417 ularly on the prediction between T+6h and T+30h. The spatial resolution 418 of the probabilistic DeepFire predictions is 640 m to reduce computational 419 time, instead of  $80 \,\mathrm{m}$  for the deterministic predictions (cf. Section 2.3). This 420 allows to compute an ensemble of 100 maps in a time that is about twice 421 as long as for computing a deterministic map (presented computed duration 422 for non-emulated maps are estimations based on a limited number of sim-423 ulations, full computations were not run). For specific ignition locations, a 424

larger ensemble of size 10,000 is computed as well. The characteristics of
both deterministic and probabilistic predictions are summarized in Table 4.

Type of	Ignition	Spatial	Total number	Number of time steps	Ensemble	
prediction	points	resolution	of time steps	in 24 hours	members	
Deterministic	$1.2 \times 10^{6}$	$80\mathrm{m}$	253	145	1	
Probabilistic	$2.0 \times 10^4$	$640\mathrm{m}$	253	145	100 (10,000 locally)	
Type of	Total number of	Computational time	Computational time	Computational time	Computational time	
prediction	fire danger estimations	DeepFire, total	ForeFire, total	DeepFire, 1 forecast step	ForeFire, 1 forecast step	
Deterministic	$3.0 \times 10^{8}$	2 hours	4 months	30 seconds	half a day	
	0.0 × 10	2 110415	4 шонено	00 0000000		

Table 4: Characteristics of deterministic and probabilistic predictions and estimation of computational time.

The predictions are carried out and analyzed for 13 daily weather fore-427 casts, each corresponding to the occurrence of a wildfire of 100 ha or more in 428 Corsica island. Data on these 13 fires are available in the French database 429 Prométhée (cf. https://www.promethee.com/, last accessed 2021.01.21) and 430 some are reported in Table 5. Regarding the "time of fire alert" reported 431 in Prométhée, one may assume that, before this time, the fire has ignited 432 and started spreading and, although its size at the time is unknown, it may 433 be close to the initial fire size of 0.45 ha assumed in DeepFire estimations. 434 The fire size in Table 5 corresponds to the final burned surface, which results 435 from firefighting actions and fire spread for generally more than one hour, 436 so it does not make much sense to compare it with DeepFire predictions. 437 Depending on the fire, the coordinates of the ignition point may be avail-438 able, and in any case, its estimated location is at least identified by a square 439 of  $2 \text{ km} \times 2 \text{ km}$ . When only the latter information is available, it will be 440

assumed that the ignition point is located at the center of the square. In 441 either situation, the ignition point coordinates may not be perfectly accurate 442 and one may assume that there could be an error ranging between 100 m 443 and 1 km. For the vil 2017 fire case, the fire started on 20-10-2017 (the date 444 indicated in Prométhée) and only spread a little then it started spreading 445 again two days later from which it burned most of the final observed burned 446 surface; therefore, corrected estimations of time of fire start and ignition 447 location are reported for this fire instead of the ones available in Prométhée. 448

Fire id	Town	Date and time of first alert (UTC)	Fire size (ha)	Fire season
bon_05-2017	Bonifacio	30-05-2017 11h43	380.0	summer
bon_07-2017	Bonifacio	17-07-2017 11h50	121.8	summer
olm_2017	Olmeta di Tuda	24-07-2017 10h49	2118.0	summer
pal_2017	Palneca	02-08-2017 13h48	185.5	summer
$cal_{2017}$	Calenzana	05-08-2017 15h42	124.6	summer
non_2017	Nonza	10-08-2017 22h45	1617.0	summer
man_2017	Manso	11-08-2017 13h10	109.0	summer
sai_2017	Sainte Lucie de Tallano	15-08-2017 09h42	130.0	summer
vil_2017	Ville di Paraso	22-10-2017 09h00	1517.8	summer
ghi_2017	Ghisoni	26-10-2017 13h37	526.0	winter
san_2018	Saint'Andrea di Cotone	01-02-2018 04h13	1317.2	winter
chi_2018	Chiatra	03-01-2018 18h44	565.7	winter
cal_2019	Calenzana	23-02-2019 19h03	1110.2	winter

Table 5: Information on the 13 fires studied, sorted in chronological order. The "Fire id" is used to identify the fires in the present study, the one in bold being the most detailed in the following sections.

The 13 fires studied all occurred between May 2017, date from which the weather forecasts were running, and late 2019. This relatively long data

collection period ensures a relative representativeness of high fire danger 451 meteorological conditions. Among these 13 fires, nine of them are considered 452 to have occurred during hot, windy and dry events in the summer fire season, 453 and the remaining four during windy events in winter fire season. In the 454 present study, no weather forecast corresponds to a day without at least one 455 big fire. In these situations, one may consider that fire danger was high at 456 least at some point during the event for a fire size of at least 100 ha to be 457 observed, especially during the summer fire season during for which more 458 firefighting forces are mobilized to carry out the initial attack as early as 459 possible. Availability of firefighting forces are obviously a strong factor in 460 having a reduced burned area, a notable example being bon 05-2017, a fire 461 happening on a low-danger day in May (no fire brigades were deployed in 462 the territory), yet in a rather remote area so that the fire propagated freely 463 for several hours and was barely fought. 464

Among those 13 fires, olm 2017, non 2017, vil 2017, chi 2018, san 2018 465 and cal 2019 are wind-driven fires, but with notable differences concerning 466 the last 3 winter fires that were the result of extremely high  $(>150 \,\mathrm{km}\,\mathrm{h}^{-1})$ 467 wind creating intense hot and dry down slope conditions. Ghi 2017 is a 468 different situation, with a rather high wind and dry day (not an unusual 469 situation in autumn) but a fire started in large areas of grounded deciduous 470 leaves that were not yet wet as no rain had fallen for a month. This created 471 a not very intense fire, but with a lot of spotting in a mountainous area that 472 were difficult to fight for several days. Other situations were typical of hot 473

dry day with some winds with less danger and resulted in smaller burnedarea due to the efficiency of fire fighting.

This database is yet representative of 3 years of active fire seasons with 476 unusual, mild and severe cases, chosen thereof as a first approach to evaluate 477 the ability to predict high danger and analyze predictions obtained using 478 DeepFire. Although this implies that the database is somewhat biased, both 479 winter and summer seasons are represented and the weather conditions are 480 quite diverse from a case to another. Also, given the time range of the 481 forecasts, there are also moments when the predicted weather conditions are 482 less prone to fire spread. 483

#### <sup>484</sup> 3 Analysis of predictions for specific fires

Although IEP and DeepFire serve similar purposes, results are not directly 485 comparable due to their different design. This section tries to tackle this 486 issue by analyzing fire danger predictions, illustrated by figures, that address 487 specific questions. Given the ability of the fire danger prediction system 488 to provide very local values, we first try analyze what is the predicted fire 489 danger in the neighborhood of the ignition location (cf. Figure 5). Then, 490 by leveraging the high temporal resolution, we investigate how the predicted 491 fire danger evolves over time, locally (cf. Figure 4 & 5), and for the whole 492 simulation domain Figure 6. Using ensembles it is also possible to estimate 493 how uncertain the prediction is (cf. Figure 8 at the ignition location and 494

time of fire alert, Figure 7 at the same location over time, Figure 9. and on the whole domain, cf. Figure 11, 12, 13 at the time of fire start).

Comparison with the IEP as a reference danger rating system is also of importance but not only as a pure numerical output. As being part of a differently designed system, the IEP does not address the same issues. While investigating the ability to forecast local danger, the following comparative analysis also tries to illustrate the interest of having model outputs that are both probabilistic and quantifiable in hectares.

The first part of this section illustrates this difference in designs with a detailed analysis a single case (Calenzana 2017) before a mode synthetic comparison is presented for the other 12 cases.

#### <sup>506</sup> 3.1 A detailed fire case: Calenzana 2017

Calenzana 2017 fire took place at 15h42 (UTC) on August 5th, and burned 507 a modest 119 ha but the most part was burned in less than two hours. Fig-508 ure 2 presents the meteorological situation that rapidly changed in the area, 500 thus creating a high weather fire danger. At 12:00 a sea breeze was keeping 510 temperatures and air relative humidity within a typical summer day, never-511 theless, south-westerly winds strengthened to more than  $10 \,\mathrm{m \, s^{-1}}$  at 12:30, 512 generating a down slope Foehn effect that took over the sea breeze with 513 higher temperatures and air moisture under 30% at 13:00, which persisted 514 up to the time of reported ignition at 15:40. The phenomenon was also ob-515 served at the nearby weather station of Calvi Airport Figure 3 although a 516



517 little later and more quickly than in forecast.

Figure 2: Model forecast at 12:00, 12:30, 13:00 and 15:00 on 08-05-2017 with surface temperature (color), wind (arrows) and area under 30% of relative humidity (dashed lines). Blue dot is the location of Calvi Airport, red dot is the fire ignition location.



Figure 3: Relative humidity (blue) and temperature (red) observations (plain lines) and forecasts (dashed lines) at Calvi airport (blue dot in Figure 2) on 08-05-2017.



Figure 4: Deterministic maps predicted based on the weather data of forecast time T+15:40 UTC (right before presumed fire start). In white are the locations that are not vegetation, where it is assumed that neither ignition nor spread is possible.

The black circle indicates the presumed location of the ignition point.



Figure 5: Same as Figure 4 but zoomed around the ignition point

The deterministic fire danger maps of both DeepFire and IEP predicted at the time of fire start, are represented in Figure 4. The DeepFire value in hectares is shown in Figure 4a with a continuous color scale. The locations in white indicate the absence of vegetation, where it is assumed that neither

ignition nor spread is possible. Among the locations where fuel is present, 522 the prediction ranges in three orders of magnitude in this specific map (from 523 less than 1 ha to several hundreds), making it difficult to highlight the differ-524 ences in fire danger with a continuous color scale. This appears more clearly 525 with the categorical color scale in Figure 4b, where most of the island is in 526 class D or E. Based on the correspondence between danger classes, the same 527 can be seen on the IEP map shown in Figure 4c. Although these two maps 528 do not perfectly match, their respective categories were determined indepen-529 dently, so we could expect more blatant differences. This overall similarity 530 is probably due to the fact both indices are very sensitive to wind speed 531 and FMC. A notable difference is that the map of IEP seems more regular 532 than that of DeepFire. This is most likely due to the fact that the "driving" 533 input field of IEP is the Meso-NH forecast whose original spatial resolution 534 is 600 m, while DeepFire also accounts for a terrain field at an original spa-535 tial resolution of 80 m. Another consequence of the sensitivity of DeepFire 536 to the terrain is more visible in Figure 5 which is zoomed around the ig-537 nition point. In Figure 5b, the ignition point is in class E, but slightly to 538 the north-east of this point, some locations are in class D or even C. This is 539 due to the forecasted wind in this region, which is oriented to the north-east 540 where there is a long area from north to south with no vegetation where the 541 fire cannot spread, hence the lower potential fire size at the aforementioned 542 locations. In Figure 5c, it clearly appears that the IEP does not account for 543 this characteristic, as these locations are in the same danger class as that of 544

<sup>545</sup> the ignition point (4: "severe").



Figure 6: Proportion of points on the island predicted in a given area/danger category as a function of forecast time between T+6 and T+30. The vertical line indicates the time of fire start.

(a) Categories of burned surface area range from A to G, cf. colorbar in Figure 4c.

(b) Categories of IEP range from "faible" to "très sévère", cf. colorbar in Figure 4b.

To summarize the overall of fire danger on the island, one may compute 546 the proportion of locations in each danger category. This "spatial" distribu-547 tion is represented between T+6 and T+30 in Figure 6 for both DeepFire 548 and IEP categories. The proportion of locations in DeepFire class E is lower 540 than the proportion for IEP class 4 at all times, but interestingly, they in-550 crease or decrease at almost the same times. For both indices, fire danger 551 seems to decrease on most of the island around the time of fire start, whereas 552 the evolution of both deterministic and probabilistic DeepFire predictions at 553 the ignition location represented in Figure 7 shows the opposite trend. At 554



Figure 7: Ensemble of 10,000 emulated burned area (in hectares) predicted at the ignition point as a function of forecast time between T+6 and T+30. The vertical line indicates the time of fire start.

Solid black line: deterministic prediction; solid blue line: mean; dotted blue line: median.

Shaded areas delineate quantiles: first and third quartiles (dark blue); and the first and ninth deciles (light blue).

this location, the DeepFire deterministic prediction is fairly low until T+13 where an abrupt increase by about 100 ha occurs in only one hour and stays in class E until it decreases at the end of the night. This sudden increase is yet well-connected with the local conditions and the sudden increase in temperature and lower relative humidity occurring locally near the ignition area as exposed in Figure 2.

Focusing on the distribution of DeepFire values, the histogram of the probabilistic prediction obtained at the ignition location at the time of fire start is represented in Figure 8. The raw histogram is right-skewed and has a



Figure 8: Distribution of the ensemble of 10,000 DeepFire values predicted at the time of fire start at the ignition location. The red curves are the PDFs obtained from fitting the parameters of a Johnson's  $S_U$  distribution to the logarithm of DeepFire values by maximum likelihood estimation.

single mode; it may resemble a log-normal distribution at first glance, but the 564 empirical distribution of its logarithm is fairly left-skewed instead of being 565 symmetrical. At several other time steps and/or locations, however, a log-566 normal distribution fits the predicted DeepFire ensemble quite well, as shown 567 in Figure 9a. A good agreement was obtained for most DeepFire ensembles 568 when fitting the parameters of a Johnson's  $S_U$  distribution to the logarithm 569 of DeepFire values by maximum likelihood estimation. This family includes 570 normal distribution, hence the good fit in several occasions, but is also well-571 suited to the left-skewed distribution obtained at the ignition location and 572 time of fire start. Still, although a Johnson's  $S_U$  distribution generally allows 573



Figure 9: Distribution of the ensemble of 10,000 logarithm of DeepFire values predicted for the cal\_2017 fire case. Contrary to Figure 8, the location is not the ignition point.

(a) The red curve is the PDF obtained from fitting the parameters of a normal distribution to the logarithm of DeepFire values by maximum likelihood estimation.

for a decent agreement, the shape of the fitted PDF associated to either the raw DeepFire value or its logarithm could match the histogram better around the PDF's mode when the distribution is skewed as in Figure 8. Also, the ensemble in Figure 9b shows that the minimum DeepFire value (0.45 ha) may be predicted for several ensemble members, resulting in a Dirac at this value that a Johnson's  $S_U$  distribution (which is continuous) cannot account for.

The distribution of DeepFire ensembles cannot be simply summarized by a simple distribution such as a log-normal. However, focusing on the ensemble mean and standard deviation reveals that over the time range of the forecast, the coefficient of variation of the DeepFire ensemble predicted at the ignition location remains between 0.7 and 1.1. For other times and/or



Figure 10: Predictions at the ignition point as a function of forecast time between T+6 and T+30. The vertical line indicates the time of fire start. Top most: DeepFire both deterministic (solid black) and 10,000-size ensemble mean (dotted blue).

Horizontal colorbars, from top to bottom: category of the DeepFire deterministic area; category of the DeepFire mean area; IEP

locations, the standard deviation of the ensemble is in the same order of 585 magnitude as its mean as well, so one may focus on the latter for simplicity. 586 The evolution of the ensemble mean at the ignition location is represented 587 in Figure 10 with the deterministic prediction, showing their respective fire 588 danger categories, as well as that of the deterministic IEP for comparison. 589 This "concise" plot reveals that the deterministic value and the ensemble 590 mean are predicted in the same category and match with those of IEP for 591 most of the forecast. 592

The probabilistic DeepFire prediction on the whole island consists in a smaller ensemble (100 members) than the local one that was analyzed previ-



Figure 11: "Probabilistic" predicted maps at forecast time 15h40 UTC (right before fire start). From left to right: mean (continuous), standard deviation, mean (categorical).

ously (10,000 members). The ensemble of DeepFire maps predicted for the 595 time of fire start is summarized in Figure 11 by the ensemble mean and stan-596 dard deviation computed for each location. Overall, the higher the mean, 597 the higher the standard deviation, which was also the case for the large en-598 semble at the ignition location. More precisely, the coefficient of variation is 599 close to unity and for almost all locations and forecast times, it is contained in 600 [1/5, 5] in this case. Focusing on the map of ensemble mean represented with 601 a categorical color scale, it appears similar to its deterministic counterpart 602 represented in Figure 4b and does not provide much additional information. 603 In order to show the uncertainty represented by the probabilistic predic-604 tion by means of maps, one may consider other quantities than the ensemble 605 mean and standard deviation. For instance, the fire size category with high-606 est probability (aka, "most likely category") is computed for each location 607



Figure 12: Most likely DeepFire size category in the ensemble (left) and associated probability (right)

and shown in Figure 12 together with the probability of this category. Like the ensemble mean, the map of most likely category is similar to its deterministic counterpart in Figure 4b. Regarding the associated probability, most locations have a probability ranging in [0.3, 0.7]. Locations whose most likely category is C tend to have probabilities closer to unity, so despite providing an intuitive representation of uncertainty, these maps do not seem to provide useful information.

Arguably, the probabilistic prediction is best represented by maps of quantiles computed for each location. Using the same quantiles as in Figure 7 as well as the ensemble minimum and maximum, the resulting map are shown in Figure 13. These maps can be understood as predicted scenarios that range from most optimistic (ensemble minimum at the left) to most



Figure 13: Statistics of the ensemble of DeepFire values predicted for the time of ignition mapped over Corsica island (Calenzana 2017.08.05) Upper row: continuous; lower row: categorical Q1 and Q3: first and third quartiles; D1 and D9: first and ninth deciles.

pessimistic (ensemble maximum at the right). It is arguably a more intuitive way to represent the uncertainty in the prediction than with the standard deviation or the probability of the most likely category. In this case, it seems that the map of minimum and, to some extent, the map of first decile show scenarios where fire danger categories are underestimated. Likewise, the map of maximum overestimates fire danger, but the other maps where fire danger is not as extreme seem fairly relevant.

#### <sup>627</sup> 3.2 Overview of predictions for all 13 fires

The fire danger predictions for fire case cal\_2017 that were presented in detail in Section 3.1 were also carried out for the 12 other fire cases listed in Table 5. The present section summarizes results for all 13 fire cases.

Fire id	IEP	DeepFire (ha)	Mean (ha)	[Q1, Q3] (ha)	$\mathbb{P}[B]$	$\mathbb{P}[\mathbf{C}]$	$\mathbb{P}[D]$	$\mathbb{P}[\mathbf{E}]$	$\mathbb{P}[F]$	$\mathbb{P}[G]$
bon_05-2017	3	72.6 (D)	67.2 (D)	[26.3, 86.2]	0.008	0.397	0.464	0.127	0.004	0
bon_07-2017	4	159.8 (E)	143.0 (E)	[60.5, 193.3]	0	0.126	0.422	0.415	0.037	0
$olm_{2017}$	4	368.3 (E)	272.5 (E)	[103.3, 362.5]	0	0.048	0.260	0.478	0.214	0.001
pal_2017	4	194.8 (E)	137.0 (E)	[54.5, 159.8]	0	0.139	0.489	0.324	0.048	$< 10^{-3}$
cal_2017	4	136.0 (E)	117.1 (D)	[47.8,  163.1]	$< 10^{-3}$	0.207	0.403	0.377	0.012	0
non_2017	3	118.9 (D)	106.7 (D)	[35.3, 130.8]	0.001	0.292	0.433	0.246	0.028	0
$man_{2017}$	2	38.7 (C)	27.9 (C)	[3.45, 32.8]	0.268	0.531	0.163	0.037	0.002	0
sai_2017	4	71.7 (D)	66.7 (D)	[25.3, 83.2]	$< 10^{-3}$	0.439	0.431	0.126	0.004	0
vil_2017	4	453.6~(F)	309.6 (E)	[59.6, 370.5]	$< 10^{-3}$	0.167	0.263	0.344	0.213	0.013
ghi_2017	3	55.9 (D)	63.6 (D)	[32.1, 77.6]	0	0.384	0.518	0.097	0.001	0
$\operatorname{san}_{2018}$	3	172.3~(E)	144.2 (E)	[49.6, 182.1]	0.003	0.198	0.369	0.378	0.052	$< 10^{-3}$
chi_2018	4	483.0 (F)	312.5 (E)	[79.1,  405.6]	0	0.099	0.272	0.378	0.245	0.005
cal_2019	5	431.9 (F)	450.1 (F)	[181.5, 578.9]	0	0.007	0.121	0.467	0.395	0.010

Table 6: Summary of the fire danger predictions on all 13 fire cases at the presumed location of fire start.

Q1 and Q3: first and third quantiles.

 $\mathbb{P}[X]$ : predicted probability of being into class X of burned surface area; in bold is the highest probability among all 6 classes.

631	The deterministic predictions of IEP and DeepFire at the ignition location
632	and time of fire start for each fire are listed in Table $6$ , together with some
633	statistics of the associated ensemble of 10,000 DeepFire predictions. The
634	DeepFire ensemble mean is generally a bit lower than the deterministic value,
635	except for two fires (ghi_2017 and cal_2019). Both ensemble mean and

deterministic value are generally slightly lower than the ensemble's third 636 quantile, except for man 2017 fire where the deterministic value is slightly 637 higher. In terms of fire size categories, whether we consider the deterministic 638 DeepFire value or the ensemble mean, the most likely category is either the 639 same or one level lower. The most likely category is either C, D, or E, and 640 in almost all cases, probabilities of being in category B and G are very low. 641 Comparing the deterministic predictions of IEP and DeepFire, there is an 642 agreement between fire danger categories for 9 out of 13 cases. Due to the 643 categorical nature of these ratings, difference of one category are expected 644 and require a more detailed analysis proposed thereafter. 645

Fire id	В	С	D	Е	F	G	1	2	3	4	5	E+	4 +
bon_05-2017	4.6%	39.0%	52.0%	4.3%	< 0.01%	0%	32.1%	40.5%	23.1%	4.3%	0%	4.3%	4.3%
bon_07-2017	< 0.01%	10.0%	52.8%	37.0%	0.2%	0%	0.1%	3.3%	33.0%	63.3%	0.2%	37.2%	63.5%
$olm\_2017$	5.1%	13.3%	39.7%	40.6%	1.3%	0%	9.1%	22.4%	39.8%	28.4%	0.3%	41.9%	28.7%
pal_2017	< 0.001%	13.1%	47.5%	38.9%	0.5%	0%	< 0.1%	2.1%	18.3%	76.1%	3.4%	39.4%	79.5%
$cal_{2017}$	< 0.01%	25.2%	52.6%	21.7%	0.5%	0%	1.1%	14.4%	47.5%	36.0%	1.0%	22.5%	37.0%
non_2017	0.8%	29.9%	34.5%	33.2%	1.6%	0%	14.2%	28.8%	33.9%	22.3%	0.8%	34.8%	23.1%
$man_{2017}$	7.9%	8.4%	32.1%	46.2%	5.4%	0%	8.8%	14.8%	41.8%	31.6%	3.0%	51.6%	34.6%
sai_2017	< 0.01%	23.6%	67.8%	8.7%	< 0.001%	0%	0%	5.6%	64.5%	29.9%	0%	8.7%	29.9%
vil_2017	28.6%	17.4%	33.1%	18.8%	2.0%	0%	36.4%	31.2%	26.7%	5.6%	< 0.1%	20.8%	5.6%
ghi_2017	< 0.01%	41.8%	52.6%	5.6%	0%	0%	4.9%	32.0%	53.3%	9.8%	0%	5.6%	9.8%
$\operatorname{san}_{2018}$	38.4%	11.6%	27.7%	22.3%	< 0.1%	0%	43.4%	39.6%	15.6%	1.5%	0%	22.3%	1.5%
$chi_{2018}$	35.0%	6.7%	16.4%	32.8%	9.0%	0%	26.4%	36.4%	18.4%	15.0%	3.8%	41.8%	18.8%
cal_2019	1.1%	9.7%	31.2%	43.2%	14.8%	< 0.1%	1.6%	4.9%	19.6%	55.6%	18.2%	58.0%	73.8%

Table 7: Summary of the fire danger predictions on all 13 fire cases over the whole island at the time of fire start: proportion of each class for both DeepFire (B to G) and IEP (1 to 5). In bold is the highest proportion among all classes.

Last two columns: proportion of locations in DeepFire class E or higher (E+) and proportion in IEP class 4 or higher (4+).

Focusing on deterministic prediction at the time of fire start for each 646 fire, the maps of both DeepFire and IEP are summarized in Table 7 by the 647 proportions of locations on the island predicted in either category of both 648 fire danger indices. In all fire cases, the proportion of the island that is in 649 class G is null or quasi-null and in most cases, the respective proportions of 650 class F and class 5 are also quite low. Proportion of class B is low in many 651 cases too, but there are 3 of them where it is higher than 25% because a 652 non-negligible part of the island is predicted with a FMC higher than 0.3. 653 This, together with the predicted probabilities listed in Table 6 reveals a 654 limit of using the fire size classes of the US system to quantify fire danger 655 with DeepFire. The thresholds of class B and G are very restrictive (upper 656 bound of 4 ha and lower bound of about 2000 ha, respectively) considering 657 that DeepFire estimates the potential fire size of a fire that spreads freely 658 during one hour. The same holds to some extent for class F (lower bound of 659 about 400 ha), explaining the lower representativeness of the extreme classes 660 in most cases. 661

Among the 13 cases, the fire danger category that has the highest proportion is generally class D for DeepFire and 3 for IEP. Comparison with the local deterministic predictions in Table 6 reveals that, in almost all cases, the deterministic prediction is in equal or higher danger class than the category with the highest proportion over the island for both IEP and DeepFire, the only exception being man\_2017 fire case. This means that using either index, the ignition point belongs to the areas that are "highlighted" at the time of fire start, which is a desirable property of a fire danger map. It would be even better to observe the same property at the sub-regional scale because the environmental conditions and values at stake can be quite different from one to another, and make more sense from an operational perspective than the average over the island.

The previous tables provide data regarding the prediction at the time of 674 fire start, but the evolution of fire danger over time needs to be assessed as 675 well. For simplicity, we decided to present only two of the figures that were 676 shown in the previous section regarding cal 2017 fire case, for the 12 other 677 cases. The zoom around ignition point of the DeepFire deterministic map 678 at the time of fire start with categorical color scale (cf. Figure 5c) provides 679 a prediction of fire danger at the sub-regional scale, while the "concise" plot 680 in Figure 10 shows the evolution at the ignition point of the deterministic 681 DeepFire prediction, the ensemble mean, and the IEP. These two figures 682 are shown for the 12 fire cases in Figure 14. Similarly to the cal 2017 fire 683 case, lower DeepFire values are obtained close to areas with no vegetation 684 that block fire spread in several instances, but this mainly depends on the 685 direction of wind speed. 686

In the case of bon\_07-2017 for instance, the wind comes from the east, so when getting closer to areas without vegetation, lower values (classes D and C) are obtained to the west of the ignition location, but higher values (class E) are obtained eastward. Regarding the DeepFire predictions over time at the ignition location, the deterministic value and the ensemble mean



Figure 14: For all 12 complementary fire cases: map of DeepFire predicted at the ignition time zoomed around the ignition location (left, cf. Figure 5c), as well as the "concise" plot for the ignition location (right, cf. Figure 10). Eight top-most: summer fires; four b44tom-most: winter fires.

are generally close and in the same fire danger category. The ensemble mean 692 seems to follow the same variations with equal or lower magnitude, resulting 693 in predictions in a smaller ranger than its deterministic counterpart, espe-694 cially when the latter is very high (> 200 ha). The category of IEP generally 695 matches that of DeepFire, but can be higher or lower by one level for a few 696 hours. There is a notable exception for Sainte Lucie de Tallano where IEP 697 is in the highest class (5) while DeepFire is in class D (2 levels lower), but it 698 can be observed as well that area nearby is only 1 level under (class E). 699

Looking at the DeepFire deterministic prediction more globally, one may 700 notice that close to the ignition point and/or in a few hours after fire start, 701 higher fire danger classes can be obtained. Five fire cases are concerned: 702 olm 2017 (eastward), non 2017 (eastward and about five hours after fire 703 start), man\_2017 (to the north-west), sai\_2017 (eastward and after about 704 two hours), and ghi\_2017 (about eight hours after fire start). Therefore, 705 considering the vicinity of the ignition point and/or a few hours after fire 706 start, class E or higher is predicted in most cases. This does not happen in 707 two cases: ghi 2017 (class D) where the fire burned slowly and several fire 708 starts occurred, and bon 05-2017 (class D), whose observed fire size (109 ha) 709 is the smallest among the 13 fires studied. 710

It may make more sense to focus on local predictions in time and space to evaluate predictions of ignition, but DeepFire estimates potential fire spread, so it should be analyzed over a larger range in time and space. For instance, some fires such as non\_2017 may spread slowly at first, yet become difficult to stop after some time due to a change in weather conditions and/or when they
reach locations with high slope or specific fuel type that are more favorable
to fire spread.

## <sup>718</sup> 4 Possible designs for daily fire danger map<sup>719</sup> ping

Focusing on the vicinity of the ignition location and the few hours after 720 fire start, the DeepFire predictions proved to be satisfactory. However, in 721 practice, information on the fires used in the previous section is not known 722 before making fire danger predictions. For the fire cases studied, we knew 723 what were the areas and times to focus on because the information was 724 known *a posteriori*. One could analyze the maps predicted for each time 725 step, but in an operational context one or a few maps that summarize the 726 daily predictions of fire danger. In the present section, we propose several 727 ways of summarizing the predicted fire danger maps and discuss how relevant 728 the resulting daily maps could be in an operational context. 729

The maps proposed in the present section attempt to address several questions. First, what are the locations and time where/when fire danger is highest for the day to come? (cf. deterministic: Figure 15 & 16, and probabilistic: Figure 17 & 18) Then, starting from when and for how long is there high fire danger? (cf. Figure 19 and Figure 20.) Regarding these aspects, the question of uncertainty in the prediction is also addressed to some extent <sup>736</sup> by comparing the deterministic maps to their probabilistic counterparts.

Similarly to Section 3, several maps are first proposed and detailed for
cal\_2017 fire case, then a summarized analysis is provided for all 13 fire
cases.

#### <sup>740</sup> 4.1 Focus on the day of Calenzana 2017 fire

From the deterministic prediction of either DeepFire or IEP, the maximum 741 over the day can be computed easily for each location. The maps of the 742 maximum between T+6 and T+30 of DeepFire (resp., IEP) and of the as-743 sociated time of maximum are shown in Figure 15 (resp., Figure 16). On 744 this fire day, relatively strong south-westerly wind was definitely the driv-745 ing factor, but this wind also brought some humidity, leaving area of high 746 danger either where a downslope effect was strong. By looking at the time 747 of the maximum of DeepFire on the right of Figure 15 it can be seen that 748 although there is a high danger potential (some areas in red in map on the 749 left), there is actually much contrast regarding time of highest danger in the 750 area of Calvi, suggesting that if there is an event, a detailed local analysis 751 is required. On the IEP map in Figure 16 such requirement is less obvious, 752 with large areas marked in orange and less contrast, indicating a dangerous 753 but more general situation (less discriminant) with an event having strong 754 probabilities of occurring in the morning. 755

<sup>756</sup> If the maximum is obtained at several forecast times, we show the ear-<sup>757</sup> liest one. Because the IEP has only 5 categories, the maximum value will



Figure 15: Maximum over the forecast between T+6 and T+30 (left) and time thereof (right) of the DeepFire prediction.



Figure 16: Same as Figure 15 but for IEP prediction

most likely be predicted at several times. Figure 16 shows that the time of maximum is T+6 for most locations, making it hard to tell when fire danger is highest. In practice, this issue can be avoided by identifying the time of maximum of another a continuous quantity, such as the FFMC which is one of the two components of IEP. In Figure 15, although the maximum is represented by a categorical color scale, it corresponds to a continuous index, so this issue does not occur. The time of maximum for DeepFire predictions is between T+8 and T+18 on the majority of the island, but for some locations (even among these predicted in class F) the time of maximum is after T+18, notably around the ignition location where the fire occurred at T+16 while the maximum is more around T+22.



Figure 17: Maximum over the forecast between T+6 and T+30 of the quantile for probability 0.8 in the ensemble of DeepFire predictions. From left to right: continuous scale; categorical scale; time of the maximum.

From the probabilistic forecast of DeepFire, the computation of a counterpart to Figure 15 is less direct. The ensemble can be summarized by a statistic such as the mean or a quantile. For either statistic, it makes more sense to first compute it for all locations and forecast times, then to identify the time of maximum. In the case of a quantile, for instance, the time of maximum can therefore be interpreted to that of a more or less optimistic predicted scenario. In Figure 17, the quantile for probability 0.8 was chosen.

According to the Prométhée database, about 80% of the fires in Corsica have 776 a final burned surface of 1 ha or less, which is quite low considering the range 777 of DeepFire predictions. Although it is intuitive to define quantile from a 778 meaningful fire size derived from a database of observations, it does not seem 779 relevant here, and it makes more sense to interpret the chosen quantile as a 780 quantity that represents a quite "pessimistic" scenario, yet not too extreme 781 given the previous analysis of Figure 13. However, as can be seen in Figure 17 782 (middle map) there are still many locations where fire danger is at least in 783 class D. It might be possible to make a distinction among the high-danger 784 areas by looking at the continuous value (left map) less intuitive. Regarding 785 the time of maximum, it is similar to that of the deterministic counterpart 786 in Figure 15. 787



Figure 18: Maximum over the forecast between T+6 and T+30 of the probability of being into class E or higher (left) and time thereof (right).

Alternatively, one may consider another maximum over time: that of the

probability (based on the ensemble) of being into class E or higher. The 789 resulting map for cal 2017 fire case is shown in Figure 18 together with 790 the associated time of maximum. Compared to Figure 17, the maximum 791 probability seems better suited to discriminate among locations with high 792 fire danger during the day, whereas the time of maximum appears similar 793 overall, except for some locations where the predicted probability is 0 over 794 all 24 hours, resulting in a time of maximum at the value of T+6 by default. 795 Among all the maps presented in the present section up to this point, 796 the maps of time of maximum to point out that the evolution of fire danger 797 over time does not necessarily result in a peak at a single given time (e.g., 798 midday) everywhere. Still, the time of maximum fire danger might not be 799 the most relevant information for daily predictions as there can be high fire 800 danger for an extended period of time. 801

Regarding the evolution of DeepFire predictions during the day, a more 802 relevant quantity could be the earliest time of being into class E or higher 803 if it happens at all. The associated maps resulting from the deterministic 804 and probabilistic predictions are represented in Figure 19. In the case of the 805 probabilistic version, the earliest time when class E is predicted may differ 806 from a member of the ensemble to another and the class may not be reached 807 for some of them, so the conditional mean among the sub-ensemble of mem-808 bers for which the class is reached is provided. According to the deterministic 809 version in Figure 19a, there is about a quarter of the island where class E 810 is never reached. However, according to its probabilistic counterpart in Fig-811



Figure 19: Earliest time between T+6 and T+30 of a location being predicted into class E or higher (in gray if it does not happen). The probabilistic version is the conditional mean among the ensemble of the time when class E is reached on the condition that it is reached (a gray area

<sup>812</sup> ure 19b, almost all locations have at least one member in the ensemble for <sup>813</sup> which class E is predicted at some point (but the amount of these members <sup>814</sup> may differ between locations), and the map is more homogeneous with fewer <sup>815</sup> extreme values.

is shown otherwise)

To complete the information provided by the previous maps, one may compute the total duration between T+6 and T+30 when a given location has a DeepFire prediction of class E or higher. In the case of the probabilistic prediction, there is no need to consider a conditional mean as the duration is null if class E is never reached. The deterministic version is shown in Figure 20a, while both mean and standard deviation of the ensemble are shown in Figure 20b to represent the probabilistic forecast. Once again, the map of



Figure 20: Total duration a location is predicted in class E or higher over the forecast between T+6 and T+30. The colorbar indicates the duration in hours.

(b) Mean (left) and standard deviation (right).

ensemble mean is more homogeneous than its deterministic counterpart and 823 the standard deviation seems higher in locations where the mean is higher. 824 The analysis of cal\_2017 fire case reveals that predicted time of maximum 825 fire danger is similar even when the input uncertainty is accounted for using 826 the calibrated distribution. However, based on the calibrated distribution, 827 the predicted duration of high fire danger is quite uncertain. Such quantity 828 may not serve as a daily fire danger index, but it appears interesting as a 829 complement, because the longer high fire danger conditions last, the more 830 severe the situation may be considered, even if the maximum fire danger 831 category over the day is the same. Still, in the case of DeepFire predictions, 832 not only is the prediction uncertain, but it is also quite sensitive to the choice 833

of the fire size threshold used to define high fire danger categories.

#### 4.2 Overview of the predictions for the 12 other fires

A number of numerical quantities that could serve as a daily indicator were 836 proposed. Due to its ability to discriminate between locations with high fire 837 danger in the cal 2017 fire case, the maximum over the forecast between 838 T+6 and T+30 of the probability of being into class E or higher is chosen as 839 a daily fire danger map for the 12 other fire cases. This map is shown for all 840 12 cases in Figure 21, together with the evolution of the proportion in the 841 island of each class for both DeepFire and IEP according to the deterministic 842 prediction (cf. Figure 6) to have an idea of how the overall spatial distribution 843 of fire danger evolves over time. 844

Overall there is a general agreement in variations between T+6 and T+30 between IEP and DeepFire, with a general trend of more "contrasted" Deep-Fire predictions, indicating a better ability to pinpoint high danger locations (i.e. it is more discriminant).

As in Section 3.2, one could present some scalar results regarding the overall spatial distribution of fire danger over time, but considering an average in time and space does not reflect the variations of fire danger and, therefore, does not seem very relevant. Arguably, a daily rating of fire danger based on DeepFire should be computed on a relatively large area, at the sub-regional level for Corsica island and the maximum value over the day can be considered. At this spatial scale, a representative fire danger rating could



Figure 21: For all 12 complementary fire cases: maximum between T+6 and T+30 of the probability of being into class E or higher (left, cf. Figure 18), together with the evolution of the proportions over the island of DeepFire (top right, cf. Figure 6a) and IEP (bottom right, cf. Figure 6b) classes. First two columns: summer fires; last column: winter fires.

<sup>856</sup> be the one associated to the DeepFire value that separates the 80% lower
<sup>857</sup> values from the 20% highest in a given area. As a complement to fire danger
<sup>858</sup> ratings, that are associated to a low spatial resolution, it makes sense to use
<sup>859</sup> the predictions with high spatial resolution and high frequency to analyze
<sup>860</sup> the situation in more detail.

#### **5** Conclusions and perspectives

We have shown a new method to compute fire danger predictions by esti-862 mating a potential fire size using the deep neural network DeepFire in a 863 reasonable computational time. This allows for the generation of a sequence 864 of high resolution maps of fire danger with high frequency, and an ensemble of 865 such predictions that account for input uncertainty, although at lower spatial 866 resolution. Several quantities derived from predictions of potential fire size 867 can be computed such as maximum fire danger over time, duration of high 868 fire danger, and probabilistic versions thereof using the ensemble. Analysis 869 of the predictions on 13 fire cases showed that, overall, DeepFire predicts 870 higher fire danger in the neighborhood of the ignition location and around 871 the time of fire start. The temporal variation over the day make it difficult 872 to summarize the predictions by a few daily fire danger indices. A few quan-873 tities were proposed to serve the purpose of providing a daily indicator, but 874 the evolution in time, the granularity, and the uncertainty of the predictions 875 can provide useful information to a forecaster. It is also important to note 876

that all these computations were actually run in a batch processing mode to ensures its potential to run in an operational context.

A major strength of the prediction using DeepFire seems to be its spatial 879 granularity allowing to be more discriminant. Compared to traditional fire 880 danger indices that mostly rely on weather forecasts, the potential fire size 881 estimated by DeepFire accounts for the influence of terrain on fire spread at 882 via the variability over space in type of vegetation, presence of non-burnable 883 areas, and slope. The high-resolution maps could be used as complement of 884 fire danger ratings, that generally attribute a single value to a large area, for 885 better anticipation but potentially to help to decide firefighting actions after 886 a fire has started spreading. For instance, the maps can be used to finely 887 identify locations that, if reached at a some point, the fire will spread even 888 faster and become harder to control. Moreover, another strength regarding 889 its design, compared to other fire danger rating systems, is that it is not 890 based on empirical knowledge, except for the actual choices of fire size for 891 each class, these results are not based on experience of past fires, nor on 892 expert analysis. 893

The present study allowed identifying several aspects that could be investigated further or improved. Regarding the DeepFire ensemble at a given time and location, it seems that the logarithm follows a Johnson's  $S_U$  distribution in several instances, although a more complex family of distribution could lead to a better fit in more instances. Statistical inference of the ensembles could also be analyzed at a larger scale, by considering several forecast times and locations, and even the predictions for several days. The analysis of the distribution of numerous potential fire sized predicted by DeepFire could lead to the definition of meaningful thresholds to define categories of fire danger that are better suited than the US classifications which pertains to all observed fires. Defining the thresholds based on observed fire sizes appears difficult in Corsica where a vast majority of fires are attacked early enough to spread far, even when fire danger is high.

Information on the intermediate sizes of the fires, rather than that of 907 the final burned surface, would be more relevant for comparison with Deep-908 Fire, but is difficult to measure. If DeepFire predictions were to be used in 909 operational conditions, the feedback would be very valuable to adjust the 910 thresholds, but also to evaluate the usefulness of such a prediction system. 911 Regarding uncertainty, only a deterministic weather forecasts were used, but 912 probabilistic weather forecasts could be used as an alternative or as a com-913 plement to represent the probabilistic distribution of wind and FMC inputs 914 of DeepFire. 915

DeepFire focuses on wildfire spread, and could be associated to predictions representing ignition probability for a better estimation of fire danger. A model of ignition probability should account at least for weather predictions, and other data sources such as proximity to roads or cities could be included to design such a model, which would result in a distribution that is not uniform among burnable locations. Ignition probability is also a major component of wildfire risk quantification frameworks, where DeepFire could

be used to estimate fire spread. Although the computational time constraints 923 of fire risk assessment are not as tight as for those of daily fire danger predic-924 tions, DeepFire could estimate a very large number of potential fire sizes in 925 a reasonable amount of time, much larger than it would be using traditional 926 fire spread simulators, allowing for better and/or more detailed risk quantifi-927 cation. For a complete assessment of risk, however, the values at stake are 928 not just hectares of land burned and should be accounted for more explicitly 929 than with DeepFire. A step in this direction could therefore be to train a 930 DNN in a similar fashion as DeepFire but based on an estimated cost. 931

Whether it be for fire danger or risk, DeepFire predictions should be also considered and evaluated over a long time period (e.g. a whole year) that includes both days with and without fires occurrence. Due to their ability to account for several types of data, and to carry out fast computations, deep neural networks appear promising to address the complexity of wildfires and design better prediction systems.

#### $\mathbf{Acknowledgments}$

<sup>939</sup> Funding: This work was supported by the Agence Nationale de la Recherche,
<sup>940</sup> France [grant number ANR-16-CE04-0006 FIRECASTER].

#### 941 Conflicts of interes

<sup>942</sup> The authors declare no conflicts of interest.

#### 943 **References**

- Allaire, F., Filippi, J.-B., and Mallet, V. (2020). Generation and evaluation
  of an ensemble of wildland fire simulations. *International Journal of Wildland Fire*, 29(2):160–173.
- Allaire, F., Mallet, V., and Filippi, J. B. (2021a). Emulation of wildland fire
  spread simulation using deep learning. preprint.
- Allaire, F., Mallet, V., and Filippi, J.-B. (2021b). Novel method for a posteriori uncertainty quantification in wildland fire spread simulation.
  Applied Mathematical Modelling, 90:527–546.
- Amodei, M., Isabelle, S., and Stein, J. (2015). Verification of the french operational high-resolution model arome with the regional brier probability
  score. *Meteorological Applications*, 22.
- Bradshaw, L. S., Deeming, J. E., Burgan, R. E., and Cohen, J. D. (1984).
  The 1978 national fire-danger rating system: technical documentation.
  Gen. Tech. Rep. INT-169. Ogden, UT: U.S. Department of Agriculture,
  Forest Service, Intermountain Forest and Range Experiment Station.
  44 pp.
- 960 Burgan, R. E., Andrews, P. L., Bradshaw, L. S., Chase, C. H., Hartford,

- R. A., and Latham, D. J. (1997). Current status of the wildland fire
  assessment system (wfas). *Fire Management Notes*, 57(2):14–17.
- Filippi, J.-B., Morandini, F., Balbi, J. H., and Hill, D. R. (2010). Discrete
  event front-tracking simulation of a physical fire-spread model. SIMU-*LATION*, 86(10):629–646.
- Finney, M. A. (1998). Farsite: Fire area simulator-model development and
  evaluation. Res. Pap. RMRS-RP-4, Revised 2004, Ogden, UT: U.S.
  Department of Agriculture, Forest Service, Rocky Mountain Research
  Station. 47 p.
- Finney, M. A., Grenfell, I. C., McHugh, C. W., Seli, R. C., Trethewey,
  D., Stratton, R. D., and Brittain, S. (2011a). A method for ensemble wildland fire simulation. *Environmental Modeling & Assessment*,
  16(2):153–167.
- Finney, M. A., McHugh, C. W., Grenfell, I. C., Riley, K. L., and Short, K. C.
  (2011b). A simulation of probabilistic wildfire risk components for the
  continental united states. *Stochastic Environmental Research and Risk Assessment*, 25(7):973–1000.
- Giuseppe, F. D., Vitolo, C., Krzeminski, B., Barnard, C., Maciel, P., and
  San-Miguel, J. (2020). Fire weather index: the skill provided by the european centre for medium-range weather forecasts ensemble prediction
  system. Natural Hazards and Earth System Sciences, 20(8):2365–2378.
- Hardy, C. C. and Hardy, C. E. (2007). Fire danger rating in the united states
  of america: an evolution since 1916. *International Journal of Wildland*

984 Fire, 16(2):217–231.

985	Lac, C., Chaboureau, JP., Masson, V., Pinty, JP., Tulet, P., Escobar,
986	J., Leriche, M., Barthe, C., Aouizerats, B., Augros, C., Aumond, P.,
987	Auguste, F., Bechtold, P., Berthet, S., Bielli, S., Bosseur, F., Cau-
988	mont, O., Cohard, JM., Colin, J., Couvreux, F., Cuxart, J., Delau-
989	tier, G., Dauhut, T., Ducrocq, V., Filippi, JB., Gazen, D., Geoffroy,
990	O., Gheusi, F., Honnert, R., Lafore, JP., Brossier, C. L., Libois, Q.,
991	Lunet, T., Mari, C., Maric, T., Mascart, P., Mogé, M., Molinié, G.,
992	Nuissier, O., Pantillon, F., Peyrillé, P., Pergaud, J., Perraud, E., Pi-
993	anezze, J., Redelsperger, JL., Ricard, D., Richard, E., Riette, S.,
994	Rodier, Q., Schoetter, R., Seyfried, L., Stein, J., Suhre, K., Taufour,
995	M., Thouron, O., Turner, S., Verrelle, A., Vié, B., Visentin, F., Vionnet,
996	V., and Wautelet, P. (2018). Overview of the meso-NH model version
997	5.4 and its applications. Geoscientific Model Development, $11(5)$ :1929–
998	1969.
999	Lawson, B. and Armitage, O. (2008). Weather guide for the canadian forest
1000	fire danger rating system. Natural Resources Canada, Canadian Forest

<sup>1001</sup> Service, Northern Forestry Centre, Edmonton, Alberta. 84 p.

Parisien, M., Kafka, V., Hirsch, K., Todd, J., Lavoie, S., and Maczek, P.
(2005). Mapping wildfire susceptibility with the BURN-P3 simulation
model. Natural Resources Canada, Information Report NOR-X-405,
Canadian Forest Service, Northern Forestry Centre, Edmonton, Alberta.

<sup>1007</sup> Parisien, M.-A., Dawe, D. A., Miller, C., Stockdale, C. A., and Armitage,

1008

1010

O. B. (2019). Applications of simulation-based burn probability modelling: a review. *International Journal of Wildland Fire*, 28(12):913– 926.

- Rothermel, R. C. (1972). A mathematical model for predicting fire spread
  in wildland fuels. Res. Pap. INT-115. Ogden, UT: U.S. Department of
  Agriculture, Intermountain Forest and Range Experiment Station. 40
  p.
- <sup>1015</sup> Santambrogio, F. (2015). Optimal Transport for Applied Mathematicians,
   <sup>1016</sup> volume 87 of Progress in Nonlinear Differential Equations and their
   <sup>1017</sup> Applications. Birkhäuser / Springer, Cham.
- Tymstra, C., Bryce, R., Wotton, B., Taylor, S., and Armitage, O. (2010).
  Development and structure of prometheus: the canadian wildland fire
  growth simulation model. Natural Resources Canada, Information Report NOR-X-417, Canadian Forest Service, Northern Forestry Centre,
  Edmonton, Alberta. 88 p.
- Van Wagner, C. E. and Pickett, T. L. (1985). Equations and fortran program
  for the canadian forest fire weather index system. Forestry Technical
  Report No. 33. Ottawa, Environment Canada, Canadian Forestry Service, Petawawa National Forestry Institute.