Fire-spotting modelling in operational wildfire simulators based on cellular automata: a comparison study.

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Abstract

One crucial mechanism in the spread of wildfires is the so-called fire-spotting: a random phenomenon which occurs when embers are transported over large distances. Fire-spotting speeds up the Rate of Spread and starts new ignitions which constitute a menace for fire fighting operations. Unfortunately, operational fire-spread simulators may not account for spotting effects, thus overlooking the harmful consequences associated with this phenomenon. In this work, several fire spotting methods are integrated in the operational wildfire simulator PROPAGATOR based on Cellular Automata (CA). RandomFront, a physics-based parametrization of fire-spotting, is tested for the first time in the context of CA simulators. RandomFront is compared with other two parametrizations already adopted in CA based simulators, the ones of Alexandridis et al. and Perryman et al. A wildfire occurred in the

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summer of 2021 in the municipality of Campomarino (Molise, Italy), and
where spotting effects were clearly reported, has been used as a study case.
RandomFront parametrization produced a more complex burnt probability
pattern than the other models. Moreover, it predicted higher burning proba-
bility in the area of the domain affected by spotting effects in the real wildfire
event.

*Keywords:* Fire-spotting, Spot-fires, Fire spread, RandomFront, Wildfires,
Cellular Automata.

*PACS:* 0000, 1111

*2000 MSC:* 0000, 1111

1. Introduction

Accurate predictions of wildfire behavior are essential for enhancing fire
risk assessment (Calkin et al., 2011), aiding fire management decision-making
and mitigating wildfire impacts (Stephenson et al., 2013). Unfortunately,
wildfire propagation is a complex and non-linear phenomenon that involves
multiple physical and chemical processes, leading to numerous sources of un-
certainty (Benali et al., 2016). One of this sources of non-linearity is the
so called *fire-spotting phenomenon*. Fire-spotting is strongly influenced by
atmospheric conditions and vegetation types and occurs when firebrands are
carried away from the original fire and ignite secondary fires, known as spot-
fires (Brown Davis, 1973; Werth et al., 2011). Those new fires can occur near
the fire propagation front, being able to increase the rate of spread (Storey
et al., 2021), or several kilometers away from the primary fire, leading to
new secondary ignitions. This situation increases the extinction difficulty,
given that both civilians and firefighters can potentially result captured by secondary fronts ignited by firebrands \cite{Koo2010, Storey2020}.

The research conducted to understanding and reproducing fire-spotting falls into two main approaches. On one hand, experimental studies have focused on characterizing firebrands (weight, size, generation mechanism...) and its transport process \cite{Manzello2007, Manzello2008, Suzuki2012, Thomas2017, Storey2021, Himoto2021}. However, the small scales of the experiments could limit their direct application in estimating landing distribution during real-world wildfires \cite{Perez2011, Sullivan2015, Egorova2022}. On the other hand, firebrand transport mathematical models have been developed to estimate the landing distribution and flight paths of firebrands \cite{Wadhwani2022a}. An early firebrand transport model was proposed by Tarifa et al. \cite{Tarifa1965, Tarifa1967}, who studied travel distances based on firebrand size, density, and shape, and by Albini \cite{Albini1979, Albini1983}, who estimated the maximum distance of new ignitions in terms of the burning area and mean wind. These models have been integrated into wildfire spread simulation models such as FARSITE \cite{Finney1998}, Phoenix Rapidfire \cite{Tolhurst2008} or Prometheus \cite{Tymstra2010}. Himoto Tanaka \cite{Himoto2005} proposed a transport model for disk-shaped firebrands. They suggested that the lognormal distribution is suitable for describing the landing distribution of firebrands in the downwind direction, while the normal distribution is appropriate for the perpendicular direction. Sardoy et al. \cite{Sardoy2007, Sardoy2008} conducted numerical experiments that incorporated atmospheric conditions, fire and fuel properties. As Hi-
moto Tanaka (2005), they found that the distribution of firebrands follows a log-normal distribution. Wang (2011) developed a mathematical model that derives the firebrand distribution and mass from a Rayleigh distribution function.

The physical parametrization of fire-spotting is a crucial aspect to consider when predictions are made (Fernandez-Pello 2017). However, spotting effects based on computational fluid dynamic simulations (Wadhwani et al. 2017, 2022b) can be computationally intensive, even infeasible, and exceed the time required for making management decisions. The fire-spotting parametrization RandomFront was developed to overcome this issue (Pagnini-Mentrelli 2014; Kaur et al. 2016; Trucchia et al. 2019). Such parametrization is independent of the rate of spread (ROS) formulation and the method utilized for the fire-line advancement (Level Set, marker methods...) and has been successfully implemented in the semi-physical model PhyFire, based on principles of energy and mass conservation (Asensio et al. 2021). Moreover, RandomFront includes the effects of the atmospheric stability by the height of the atmospheric boundary layer, as well as the effects of slope and flame geometry (Egorova et al. 2020, 2022).

In this work, the RandomFront parametrization was implemented for the first time within the operational wildfire spread simulator PROPAGATOR (Trucchia et al. 2020). Other two parametrizations are implemented as well in the simulator, namely the ones introduced by Alexandridis et al. (2008, 2011) and Perryman et al. (2013). The parametrization of Alexandridis et
al., Perryman et al., and RandomFront are characterized by an increasing complexity, retaining however operational feasibility. The effects of changing parametrization in a set of synthetic test cases, with uniform wind, fuel and topography, are analyzed, in order to depict the characteristic fire spotting patterns related to each formulation.

Finally, PROPAGATOR is used to simulate a wildfire which took place in 2021 in the municipality of Campomarino, Molise, Italy. The evolution of the fire saw two main fire perimeters separated by a water body, and fire spotting was clearly reported during the response phase. This real case study constitutes thus a good benchmark for assessing the performance boost of having a spotting module in a CA simulator, and to compare the fire evolution with the three tested fire spotting parametrizations.

The paper is organized as follows: in Section 2 a general description of the fire-spread models and the fire-spotting parametrizations are provided. In Section 3 the methodology of the study is described, and Section 4 reports the results of the simulations. Section 5 discusses the results and Section 6 conclude the paper.

2. Models description

In this section, the mathematical models utilized in this study are described. First, we introduce the operational fire spread model, PROPAGATOR, which is based on a cellular automaton scheme. Then, we present the three fire-spotting models that will be compared.
2.1. Mathematical modelling and wildfires

Several approaches have been developed to model and simulate the behavior of wildfires (Sullivan, 2009a,b,c), and a successful approach for operational simulators is based on the cellular automata approach. Formally, a two-dimensional cellular automaton is defined as an ultra-discrete dynamical system given by the 4-tuple $\mathcal{A} = (\mathcal{E}, \mathcal{S}, \mathcal{V}, f)$, where $\mathcal{E}$ arrangement of the cell set and is referred to as the cellular space, the set of states $\mathcal{S}$ represents the finite, or infinite, set of possible states in which each cell can be found at any given moment, $\mathcal{V}$ represents the set of neighboring cells surrounding a specific cell, whose states at time $t$ influence the state of the considered cell in subsequent time steps and $f$ denotes the transition rule between states.

In wildfire research, the computational domain $\mathcal{E}$ is usually discretized into square cells (Clarke et al., 1994), although hexagonal cells have also been utilized (Trunfio, 2004; Encinas et al., 2007). The rules governing fire spread from one cell to another, $f$, primarily depend on the states of neighboring cells, $\mathcal{V}$, and take into account various factors such as vegetation type, wind intensity and direction, terrain slope, as well as other physical parameters that contribute to the Rate of Spread (ROS) (Duarte, 1997; Hargrove et al., 2000). In this study, we use PROPAGATOR to simulate the spread of the fire. Previous work by Trucchia et al. (2020) discussed the performance of PROPAGATOR in reproducing the behavior of various wildfires that occurred in Mediterranean countries. However, their research did not consider at the time spotting effects. PROPAGATOR is an operational software developed for the Italian Civil Protection, it is based on a bidimensional...
cellular automaton approach and incorporates high-resolution data on topography and land fuel cover. The fire-spread is computed using a probabilistic approach that takes into account various factors, including the vegetation type, terrain slope, wind direction and speed, and fine fuel moisture content.

Given an ignited cell, wildfire can potentially spread on the Moore neighborhood with radius one of such cell, i.e., to the eight surrounding cells at each time step. The resulting burnt surface evolves stochastically. Given static maps accounting for elevation and fuel type, user input parameters for the simulation are the synoptic evolution of wind speed, wind direction, and fine fuel moisture content, as well as the ignition point. PROPAGATOR is specifically designed to generate a georeferenced map that indicates the probability of each cell being burnt. This burnt probability map follows a frequentist interpretation of probability, i.e., an ensemble of $N$ independent simulations is performed and the burnt probability assigned to cell $i$ at each step of time $t$ is calculated as

$$p_i^t = \frac{1}{N} \sum_{\omega=1}^{N} n_{i,\omega}^t,$$

where $\omega$ labels each independent realization $1 \leq \omega \leq N$ and

$$n_{i,\omega}^t = \begin{cases} 1 : & \text{Burned cell} \\ 0 : & \text{Unburned cell.} \end{cases}$$

2.2. Fire-spotting models

Despite the demonstrated ability of CA-based models to replicate wildfire behavior, fire-spotting remains not considered or, when it is included, it is based on pure probabilistic assumptions that disregard relevant physical
features. In this subsection, we present the fire-spotting models to be compared. The three models are presented in order of increasing complexity. The last two formulations (Perryman and RandomFront) include also a modeling for buoyancy and employ a lognormal function to model spotting distance. While the first two formulations are natively formulated in a CA framework, RandomFront is implemented for the first time in such a scheme.

2.2.1. The Alexandridis et al. fire-spotting parametrization

The fire-spotting model formulated by [Alexandridis et al. (2008, 2011)] was designed specifically for a CA framework. In the original model, the spotting module was another trigger of cell status change, in a CA model which relied on vegetation type and density, wind field, and topography. In their original works, simulations were focused on fires occurred in Greece: the Spetses island and the Attica region, showing satisfactory performance. Freire DaCamara (2019) slightly refactored the model to simulate a wildfire occurred in the Portuguese region of the Algarve.

The model computes the firebrand landing distance $d$ as follows:

$$d = r_n \cdot P_w = r_n \exp (U \cdot C_v (\cos(\varphi) - 1)),$$  

(3)

where $r_n$ is a random number drawn from a normal distribution, $\varphi$ is the angle between the wind direction and the direction of the ejected firebrand, $U$ is the mean-wind velocity, and $C_v$ is a vegetation-dependent fitted constant. The second part concerns the spot ignition, i.e., if an ejected firebrand will ignite or not a new spot-fire.
This probability is computed as:

\[
P_c = \begin{cases} 
P_{c0} (1 + P_{cd}) , & \text{if } P_{c0} (1 + P_{cd}) \leq 1 , \\
1 , & \text{if } P_{c0} (1 + P_{cd}) > 1 , 
\end{cases}
\]  

(4)

where \( P_{c0} \) is a constant probability corrected by \( P_{cd} \) which depends on the type and the density of the fuel. This model is similar to the SPOT module implemented in BEHAVE (Andrews, 1986, 2014).

2.2.2. The Perryman et al. fire-spotting parametrization

Perryman et al. (2013) developed a CA-based system and they studied how the spotting affects the ROS into a Pinus ponderosa ecosystem. The model consists in a suite of four sub-models adapted to a cellular automaton environment. These sub-models are used to compute the surface spread, tree torching probability, firebrand landing distribution and the spot ignition. The firebrand landing distance is calculated as the Euclidean distance between the firebrand landing distance parallel to the wind and the firebrand landing distance perpendicular to the wind. The distribution of firebrands in the direction parallel to the wind is implemented by following the statistical findings of Sardoy et al. (2008), where the landing distance follows a lognormal distribution function:

\[
P(d) = \frac{1}{\sqrt{2\pi}\sigma d} \exp \left( -\frac{\ln(d/\mu)^2}{2\sigma^2} \right) ,
\]  

(5)

where \( d \) is again the firebrand landing distance. Parameters \( \mu \) and \( \sigma \) are established according to buoyancy driven or wind driven regimes. To distinguish between both cases, the Froude number, \( Fr \), needs to be introduced.
It is defined as:

\[
Fr = \frac{U}{\sqrt{g \left( \frac{I_f}{\rho c_p T_A g^{1/3}} \right)^{2/3}}},
\]

where \( g \) is the acceleration of the gravity, \( I_f \) is the fire intensity, \( \rho \) is the ambient gas density, \( c_p \) is the specific heat of gas, \( T_A \) is the ambient temperature and \( U \) is the wind speed. For Froude number less or equal to 1, a buoyancy driven regime occurs, and we have:

\[
\begin{align*}
\sigma &= 0.86 \left( I_f^{-0.21} U^{0.44} \right) + 0.19, \\
\mu^* &= 1.47 \left( I_f^{0.54} U^{-0.55} \right) + 1.14,
\end{align*}
\]

and for Froude number greater than 1, wind driven regime occurs and we have:

\[
\begin{align*}
\sigma &= 4.95 \left( I_f^{-0.01} U^{0.02} \right) - 3.48, \\
\mu^* &= 1.32 \left( I_f^{0.26} U^{0.11} \right) + 0.02,
\end{align*}
\]

where \( \mu = e^{\mu^*} \). The assumption by Himoto Tanaka (2005) was followed for firebrands travelling perpendicular to the mean-wind direction, i.e., the firebrand landing distance is modelled by means of a normal distribution, assuming a zero mean and standard deviation equal to the half of the automata’s cell-size.

### 2.2.3. The RandomFront fire-spotting parametrization

In the RandomFront parametrization, the landing distance \( d \) is modelled by means of a log-normal distribution, see Equation (5), combined with the physics involved in the transport of the firebrands (Trucchia et al., 2019). Parameter \( \mu \) of the log-normal distribution takes into account the essential factors needed to describe the lifting mechanism inside the convective column.
of the firebrands, and depends on the Atmospheric Boundary Layer \cite{Egorova2020}:
\[
\mu = H \left( \frac{3 \rho C_d}{2 \rho_f} \right)^{1/2},
\]
(9)

where \( C_d \) is the Drag coefficient, \( \rho \) is the ambient gas density and \( \rho_f \) is the density of the wildland fuels. The maximum liftable height \( H \) is computed as a fraction of the injection height \( H = 0.4 \cdot H_{\text{smoke}} \). The injection height of the smoke \( H_{\text{smoke}} \) follows the formula developed by \cite{Sofiev2012}:
\[
H = 0.4 \cdot H_{\text{smoke}} = 0.4 \left[ \alpha H_{\text{ABL}} + \beta \left( \frac{I_f}{d P_f 0} \right)^\varsigma \exp \left( -\frac{\delta_{FT} N_{FT}^2}{N_0^2} \right) \right],
\]
(10)

where \( H_{\text{ABL}} \) is the height of the Atmospheric Boundary Layer, \( N_0^2 \) and \( N_{FT}^2 \) are the Brunt-Väisälä frequency at the current height and in the free troposphere respectively, \( I_f \) is the fire intensity and \( P_f 0 \) is the ratio of reference fire power. Parameter \( \sigma \) of the log-normal distribution involves the effects of the horizontal wind in the transport of the firebrands as well as how the flame geometry and the terrain slope affects. The flame length is defined as \cite{Egorova2022}:
\[
L_f = \left( \frac{1}{2g(c_p T_A)^2} \right)^{1/3} I_f^{2/3},
\]
(11)

and if we denote by \( \psi \) the angle of the slope, \( \varphi \) the angle between the wind direction and the direction of the ejected firebrand and define \( c_1(\psi) = \sqrt{g r (1 + \tan^2 \psi)} \), \( c_2 = \beta_2 \sqrt{\frac{2\rho_f}{3p \rho C_d}} \) and \( c_3 = \sqrt{g L_f} \), then \( \sigma \) it results to be \cite{Egorova2022}:
\[
\sigma = \frac{1}{z_p} \ln \left( \frac{U \cos \varphi}{c_1(\psi)} + c_2 \frac{1.4U \cos \varphi + c_3 \tan \psi}{c_3 - 1.4U \cos \varphi \tan \psi} \right).
\]
(12)
In the RandomFront parametrization fire-spotting is considered as a downwind phenomenon. Following this idea, a critical angle $\phi_0$ is defined when $\sigma = 0$ such that no firebrands are emitted when $\sigma \leq 0$.

3. Materials and Methods

To perform the simulations, two further processes need to be characterized for a complete integration of fire spotting modules in PROPAGATOR: firebrand generation and spot-fire ignition (Storey et al., 2020; Liu et al., 2021). Despite research experiments at laboratory scale, see Manzello et al. (2020) and Liu et al. (2021), there is a lack of statistical studies describing suitable distributions for both phenomena. Therefore, for simplicity, we stick to the modeling choices described in Alexandridis et al. (2008). That is, it is assumed that the number of firebrands ejected at each time-step follows a Poisson distribution, where the emission of one firebrand does not affect subsequent emissions. The Poisson distribution is well-suited to generate integer values of events that take place in a given time period. The probability of spot ignition, instead, is computed using Equation (4).

The comparison study of the presented fire spotting algorithms is divided in two steps. For a preliminary analysis, wildfire simulations were performed under a synthetic setting, with ideal conditions. This test allowed to study how the spread patterns may change under different wind conditions for each fire spotting formulation. After that, the case study of Campomarino fire, described in Section 3.2 was simulated with PROPAGATOR fed by realistic wind and fuel conditions, without fire spotting module and with the three analyzed fire spotting parametrizations. This particular wildfire pre-
presented a unique scenario, with fire brands flying over a water body to ignite
a secondary fire, with eyewitness accounts detailing the timing of spotting
occurrences. In this section we describe the experimental settings and the
evaluation methods.

3.1. The synthetic test case

We defined a quadrangular study area of 40 Km² such that long-range
spotting effects can be observed. Uniform vegetation cover is assumed, as
well as an uniform fine fuel moisture content (set to 5%). In particular,
the vegetation cover chosen is the PROPAGATOR calibrated class Fire-
Prone Conifers, see [Trucchia et al. (2020)] for further information. Plain
terrain as well as constant speed and direction of the wind are assumed
during the simulations. The comparison study is performed under different
constant wind speeds from South, without perturbations. In particular, we
have followed the so called Beaufort scale, where wind speed of 10 Km h⁻¹
is considered as weak and starting from 40 Km h⁻¹ is considered as strong.
The rest of the parameters used in the simulations are reported in Table 1.
To avoid the use of arbitrary parameters in this set of experiments, any other
parameter is set to be the same of the setting described in Subsection 3.2

3.2. The case study of Campomarino fire

The wildfire occurred in a fire-prone conifers forest situated in the municip-
ality of Campomarino, located in Molise region, along the Adriatic coast
of Italy, see Figure 1 on August 1st, 2021. The fire ignited around 12:00
p.m. and was extinguished at 5:00 p.m. The studied area is depicted before
and after the wildfire occurrence in Figure 2. A barrier to the spread of the
fire was introduced by a port, with a width of 190 meters. This effectively divided the computational domain into two separate areas and prevented the transmission of fire by surface spread, highlighting thus the role of spotting effects. For simplicity, we will refer to both areas in this paper as the West part of the port or secondary domain and East part of the port or main domain. Firefighting efforts were reported in the South-East and in the North-West zones. Squads of volunteers of the regional Civil Protection reported instances of fire-spotting from the East part of the port to the West part of the port approximately 3 hours after the fire started.

![Figure 1: Location of the studied area, in the Italian region of Molise, close to the municipality of Campomarino. Both pictures where obtained from the Google Earth and Google maps plugin in QGis.](image-url)
Figure 2: Satellite imagery of the studied area. Figure (a) shows the area before the wildfire occurred and was obtained from Google Earth through Qgis. Figure (b) shows the true color orthomosaic derived by UAV survey done after the wildfire occurs. The red line defines the burnt area, based on high resolution photo-interpretation. The blue dot indicates the approximate point in which the fire started. The wildfire burnt 5 hours.

To perform the simulations, we defined a computational domain covering 2.98 Km$^2$. The side of each cellular automaton cell represents a longitude of 20 m. For each fire-spotting parametrization, a PROPAGATOR run generates an ensemble of 100 independent realizations to calculate the burnt probabilities. The number of realizations performed was obtained from the Trucchia et al. (2020) research. The fuel types used were adapted from the Corine land cover classification (Feranec et al., 2016) to calibrated classes in PROPAGATOR (See Figure 3). The main burnt area predominantly consisted of a coniferous forest fuel type. Therefore, for the purposes of our study, we focused on fire-spotting phenomena resulting specifically from the fire-prone coniferous fuel type. In the studied area, the coniferous tree species associated with this fuel type is *Pinus Pinaster Aiton*. The data la-
beled as “non-burnable” have a low but non-zero probability of being burnt. The orography data were derived from a 20-meter Digital Elevation Model (DEM) provided by Italian Institute for Environmental Protection and Research (ISPRA).

Figure 3: Fuel type maps distribution over the simulated area. The data were obtained from the Corine land cover classification and adapted to the propagator classification. The resolution for each cell is 20 m x 20 m. Non-burnable classified areas stands for areas with very low probability of fire spreading, but they can suffer the spotting effects.

The weather conditions during the wildfire were reported as unstable and turbulent, with peaks speeds up to 70 Km h\(^{-1}\). To reproduce these conditions, we consider a constant wind speed of 40 Km h\(^{-1}\) and at every 15 minutes interval of simulated time a random perturbation is added to the
constant wind speed. The perturbation is derived by sampling a random variable from a normal distribution with zero mean and standard deviation of 20 Km h\(^{-1}\). Furthermore, we account for variations in the main wind direction, which was predominantly reported as flowing from South to North. The perturbations are also introduced at every 15 minutes, using another random variable drawn from a normal distribution with zero mean and standard deviation of \(\pi/8\) radians. The symmetry of the distributions avoids under- or over-estimation in the wind inputs. Parameters used in the simulation are presented in Table 1.

### 3.2.1. Burned area data acquisition

A drone survey was performed after fire to map the affected perimeter, see Figure 2(b). A quadcopter DJI Mavic Dual Enterprise equipped with FC2403 RGB digital camera (1/2.3” CMOS, 4056 X 3040 pixels, FOV 85°, focal length 35 mm equivalent: 24 mm) was used. Photos were taken from 80 m above ground level (3.8 cm pixel\(^{-1}\) of GSD) on the Western part and from 60 m (3.3 cm pixel\(^{-1}\) of GSD) on the Eastern part of the burnt area. The flight speed was 5.0 m s\(^{-1}\); the front lateral overlap 80% and 70% respectively. For the whole area 867 nadiral images were acquired. The images collected during the drone survey were processed into orthophotos and Digital Surface Models (DSMs) of the burnt area and direct surroundings using the Structure-from-Motion (SfM) workflow implemented in the commercial software Agisoft Metashape v.1.5.5. Details about the drone missions are reported in Table 2.
Table 1: List of the parameters and their values employed in the simulations.

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Name(units)</th>
<th>Value</th>
<th>source</th>
</tr>
</thead>
<tbody>
<tr>
<td>$C_d$</td>
<td>Drag coefficient.</td>
<td>0.47</td>
<td>Egorova et al. 2020</td>
</tr>
<tr>
<td>$c_p$</td>
<td>Specific heat (J Kg$^{-1}$ K$^{-1}$).</td>
<td>2017</td>
<td>Tihay et al. 2009</td>
</tr>
<tr>
<td>$C_v$</td>
<td>Wind parameter.</td>
<td>0.191</td>
<td>Alexandridis et al. 2011</td>
</tr>
<tr>
<td>$d$</td>
<td>Unit depth of combustion zone (m).</td>
<td>1</td>
<td>Egorova et al. 2020</td>
</tr>
<tr>
<td>$g$</td>
<td>Gravitational acceleration. (m s$^{-2}$)</td>
<td>9.81</td>
<td>-</td>
</tr>
<tr>
<td>$I_f$</td>
<td>Fireline intensity (MW m$^{-1}$).</td>
<td>20</td>
<td>Alexander 1982</td>
</tr>
<tr>
<td>$L$</td>
<td>Cell size (m)</td>
<td>20</td>
<td>Trucchia et al. 2020</td>
</tr>
<tr>
<td>$N_{FT}^2$</td>
<td>Brunt-Väisälä frequency at the current height (µs$^{-2}$).</td>
<td>250</td>
<td>Sofiev et al. 2012</td>
</tr>
<tr>
<td>$N_0^2$</td>
<td>Brunt-Väisälä frequency in the free troposphere (µs$^{-2}$).</td>
<td>278</td>
<td>Sofiev et al. 2012</td>
</tr>
<tr>
<td>$p$</td>
<td>Percentile from z-tables; $z_p = 0.45.$</td>
<td>67</td>
<td>Egorova et al. 2020</td>
</tr>
<tr>
<td>$P_{ld}$</td>
<td>Probability constant.</td>
<td>0.6</td>
<td>Alexandridis et al. 2011</td>
</tr>
<tr>
<td>$P_{cd}$</td>
<td>Fuel type and density factor.</td>
<td>0.4</td>
<td>Estimated</td>
</tr>
<tr>
<td>$r$</td>
<td>Mean firebrand radius (m).</td>
<td>0.015</td>
<td>Estimated</td>
</tr>
<tr>
<td>$T_A$</td>
<td>Ambient temperature (K).</td>
<td>308</td>
<td>Estimated</td>
</tr>
<tr>
<td>$\alpha$</td>
<td>Measure of stability.</td>
<td>0.24</td>
<td>Sofiev et al. 2012</td>
</tr>
<tr>
<td>$\beta$</td>
<td>Contribution of the fire intensity (m).</td>
<td>170</td>
<td>Sofiev et al. 2012</td>
</tr>
<tr>
<td>$\beta_2$</td>
<td>Correction factor.</td>
<td>0.7</td>
<td>Egorova et al. 2020</td>
</tr>
<tr>
<td>$\delta_{FT}$</td>
<td>Dependence on stability of the free troposphere.</td>
<td>0.6</td>
<td>Sofiev et al. 2012</td>
</tr>
<tr>
<td>$\eta$</td>
<td>Power-law dependence.</td>
<td>0.35</td>
<td>Sofiev et al. 2012</td>
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<tr>
<td>$\rho$</td>
<td>Ambient air mass density (kg m$^{-3}$).</td>
<td>1.1</td>
<td>Egorova et al. 2020</td>
</tr>
<tr>
<td>$\rho_f$</td>
<td>Density of spotting fuel (kg m$^{-3}$).</td>
<td>927</td>
<td>Tihay et al. 2009</td>
</tr>
</tbody>
</table>

Table 2: Data from the UAV surveys

<table>
<thead>
<tr>
<th>Sub-area</th>
<th>Num. of images</th>
<th>Ground sampling distance (cm/pixel)</th>
<th>Flight altitude (m)</th>
<th>Time (start-end)</th>
</tr>
</thead>
<tbody>
<tr>
<td>West</td>
<td>186</td>
<td>3.8</td>
<td>80</td>
<td>13:39 - 13:56</td>
</tr>
<tr>
<td>East</td>
<td>681</td>
<td>3.3</td>
<td>60</td>
<td>12:16 - 13:06</td>
</tr>
<tr>
<td>Total</td>
<td>867</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

18
3.2.2. Evaluation methods

Following an approach commonly used in literature (see e.g. Filippi et al., 2014; Price Germino, 2020), the Soersen’s coefficient and Cohen’s kappa were computed as measures of the agreement between the real and predicted burnt areas. Let denote $B$ as the burnt area in the real wildfire (i.e., the ground truth), and $B^{p_i'}$ as the predicted burnt surface. $p_i'$ denotes the possible threshold beyond the burning probability that can be considered by decision-makers. The Sorensen’s coefficient is defined as:

$$S^{p_i'} = \frac{2|B \cap B^{p_i'}|}{|B| + |B^{p_i'}|},$$

(13)

where $|\cdot|$ denotes the area of a surface. Cohen’s Kappa, instead, measures the agreement between forecasted and real areas after removing random agreements due to chance. It is defined as:

$$K^{p_i'} = \frac{P^{p_i'}_a - P^{p_i'}_e}{1 - P^{p_i'}_e},$$

(14)

where

$$P^{p_i'}_a = \frac{|B \cap B^{p_i'}|}{|E|} + \frac{|E \setminus (B \cup B^{p_i'})|}{|E|},$$

(15)

$$P^{p_i'}_e = \frac{|B||B^{p_i'}|}{|E|^2} + \frac{|E \setminus B||E \setminus B^{p_i'}|}{|E|^2},$$

(16)

and $E \setminus *$ denotes the computational domain area, i.e. the cellular space $E$, minus the surface *. Both scores range from 0 to 1. Values near 0 indicates low agreement and values close to 1 indicates good agreement.

Finally, the simulation results are studied also in the framework of probabilistic analysis (Filippi et al., 2014; Allaire et al., 2021). In particular,
routines for reliability and the distribution of the probabilities were implemented (Allaire et al., 2020). A forecast is reliable, i.e., is well calibrated, if $\forall p \in [0, 1], f(p) = p$, where $f(p)$ is the distribution of the conditional probability $o|p$, where $o$ stands for observation.

4. Analysis of the results

4.1. Synthetic test case results

Results under weak and strong wind conditions are provided. Figures 4, 5 and 6 portray the results of PROPAGATOR runs with the Alexandridis et al., Perryman et. al., RandomFront formulations, respectively. Those synthetic simulations where performed up to 150 minutes of simulated time. Figures 4, 5 and 6 retain the same extent even if some wildfire simulation, such as the one of Perryman et al., produced long range spotting effect since the first simulated hour. For synthesis purposes, the graphs depicting long-range effects, with varying extent of the plots, are shown in the Supplementary Material.

The outcome of this preliminary analysis shows the idealized spread patterns that different spotting algorithms cause, where other sources of uncertainty are removed from the analysis. Under such idealized conditions, the spread capacity of the RandomFront and Alexandridis et al. parametrizations were higher. Additionally, the spotting effects in Alexandridis et al. did not scale with the fire size, whereas in Perryman et al. model and the RandomFront formulation long-distance spotting effects were reported as the size of the wildfire grew. When strong winds are considered, we observed a “high-probability” area similar to the Alexandridis et al. and RandomFront
Figure 4: Alexandridis et al. spotting model. Plot (a) shows the results under weak wind field, and Plot (b) under strong winds. The wind direction originates from the south and remains unaltered for the entire duration of the simulation.

(a) Weak wind speed: 10 km h\(^{-1}\)  
(b) Strong wind speed: 40 km h\(^{-1}\).

Figure 5: Perryman et al. spotting model. Plot (a) shows the results under weak wind conditions, and Plot (b) under strong winds. The wind direction originates from the south and remains unaltered for the entire duration of the simulation.

(a) Weak wind speed: 10 km h\(^{-1}\)  
(b) Strong wind speed: 40 km h\(^{-1}\).
(a) Weak wind speed: 10 km h$^{-1}$ (b) Strong wind speed: 40 km h$^{-1}$.

Figure 6: RandomFront spotting model. Plot (a) shows the results under weak wind conditions, and Plot (b) under strong winds. The wind direction originates from the South and remains unaltered for the entire duration of the simulation.

Parametrizations at the end of the simulations. Weak winds made the fire-brands land near the fire-front when Alexandridis et al. parametrisation was implemented. The final burnt area (ha) is shown in Table 3. We provide the

<table>
<thead>
<tr>
<th>Model</th>
<th>Weak wind</th>
<th>Strong wind</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>25% 50% 75% 90% Average</td>
<td>25% 50% 75% 90% Average</td>
</tr>
<tr>
<td>Alexandridis</td>
<td>419.12 281.32 145.48 27.92 297.37</td>
<td>3099.24 2771.72 2333.96 1742.96 2637.81</td>
</tr>
<tr>
<td>Perryman</td>
<td>267.68 151.20 50.68 23.44 187.91</td>
<td>1236.08 1011.88 741.96 327.64 952.66</td>
</tr>
<tr>
<td>RandomFront</td>
<td>133.88 69.28 45.40 28.6 211.43</td>
<td>24345.72 8848.0 3027.56 1116.96 17861.62</td>
</tr>
<tr>
<td>Without spotting</td>
<td>58.64 47.96 33.64 13.44 44.49</td>
<td>208.52 173.92 1311.56 66.12 162.82</td>
</tr>
</tbody>
</table>

Table 3: Area (ha) comparison for both weak and strong wind speed cases. Results corresponds with the simulations showed in Figures 4, 5 and 6.

Burnt area held inside the 25%, 50%, 75% and 90% probability thresholds, as well as the averaged area. Averaged area was computed multiplying each burnt pixel by the burnt probability assigned to that pixel. As expected, the influence of spotting on the burnt area increased with wind speed. We
observed significant differences on the burnt area between models. These differences seem to depend on the wind speed, but also on the probability thresholds.

4.2. Real-wildfire simulations

Figures 7(a), 7(b) and 7(c) show the burnt probabilities obtained by the fire-spotting models. Figure 7(d) shows burnt probabilities predicted without spotting, but retaining the same run settings. The simulations with the Alexandridis et al. model in Figure 7(a) were implemented with the value of $r_n$, see Equation (3), as 190 m, and standard deviation as 25 m. This was motivated by the width of the water body equal to 190 m. Figure 7(b) shows the results with the model developed Perryman et al., and Figure 7(b) exhibits the burn probability map predicted by the RandomFront model.

All the adopted formulations are able to reproduce the actual fire spread inside the East reference area. However, differences in the area affected by the spotting effects are accounted. Alexandridis et al. model predicts an uniform and low-probability spotting pattern, while the parametrization proposed by Perryman et al. expresses an accurate burnt area, but probabilities in the pixels of the West reference area produced by spotting effects are still low. The pattern observed in Figure 7(b) appears to be changed with respect to that observed in Figures 7(a) and 7(b) due to stochastic perturbations in the main wind direction. RandomFront parametrization generates a large number of low-probability burnt cells, while assigning a higher density of probability in the West reference area. We define the averaged probability as the sum of the probabilities associated to each cell inside a domain.
Figure 7: Simulations with the Alexandridis et al., Perryman et al. and RandomFront firebrand landing models, and without spotting effects. All the plots are taken after 5 hours of simulated time after the fire ignition.
divided by the total number of cells of such domain. The resulting averaged
probabilities from each model are reported in Table 4.

<table>
<thead>
<tr>
<th>Sub-model</th>
<th>East</th>
<th>West</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Alexandridis et al.</td>
<td>0.7938</td>
<td>0.0358</td>
<td>0.7090</td>
</tr>
<tr>
<td>Perryman et al.</td>
<td>0.7370</td>
<td>0.1330</td>
<td>0.6695</td>
</tr>
<tr>
<td>RandomFront</td>
<td>0.7303</td>
<td>0.2868</td>
<td>0.6801</td>
</tr>
</tbody>
</table>

Table 4: Averaged probability inside the burnt areas. West reference area is the burnt area as consequence of the spotting effects and the East reference area is where the wildfire started. Total accounts for the whole burnt area observed.

West domain in Table 4 shows that the RandomFront parametrization forecasted probabilities one order of magnitude higher than the Alexandridis et al. parametrization, and twice than Perryman et al. Figure 4.2 illustrates the temporal evolution of the predicted burnt area, considering probabilities of at least 10%, 50%, and 75% likelihood of combustion occurring. Results showed the predictions for the nuclear zone of the wildfire were not significantly affected by the use of different fire-spotting parametrizations. However, the low probabilities were highly influenced.

Figure 9 show the evolution of the Sorenesen’s coefficient and Cohen’s Kappa defined in Equations (13, 14). We considered different probabilistic thresholds, observing strong dependence between both scores and the probability threshold. Figure 10(a) shows the reliability diagram for the three models. The three models seem to be well calibrated for high probabilities, but for probabilities lower than 0.15 only RandomFront showed good
Figure 8: Evolution of the burnt surface over time. The black dashed line represents the 37.9 ha burnt in the real wildfire. Plot (a) shows the evolution of the averaged burnt area and Plots (b), (c) and (d) the evolution of the area with at least 10%, 50% and 75% of chances of burning.

Figure 9: Soerenesen’s coefficient and cohen’s kappa for each probability threshold.
calibration. Finally, Figure 10(b) shows the distribution of the probabilities. Probabilities generated by RandomFront were mostly between 0 and 0.10, whereas Alexandridis et al. and Perryman et al. forecasted more high probabilities than RandomFront.

![Reliability Diagram](image1.png) ![Sharpness Diagram](image2.png)

(a) (b)

Figure 10: Statistical analysis of the ensembles. Plot (a) shows the reliability diagram and Plot (b) the sharpness diagram.

5. Discussion

In the simulations conducted within the ideal framework, see Subsection 4.1 distinct spread patterns of burn probability emerged due to the implementation of various spotting parametrizations. Among them, RandomFront exhibited the highest complexity, in the sense of spreading over longer ranges and in multiple directions. However, we also observed a notable risk of over-prediction in the wildfire evolution. The model proposed by Alexandridis et al. demonstrates limited capability in generating long-range spotting patterns. However, it exhibited a satisfactory spreading ability at short distances. On the other hand, simulations performed with the Perryman et al.
model successfully generated long-range spotting effects. Nevertheless, its spread capacity showed a high correlation with the main wind direction.

Regarding the real-world case study, Figure 7 highlights that the fire-spotting module causes significant deviation between simulations performed with the same input data. Among the analyzed fire-spotting parametrizations, RandomFront demonstrated the ability to generate more diverse spread patterns. While the probabilities of fire occurrence were similar within the East reference area for all parametrizations, RandomFront resulted in higher predicted burnt probabilities within the West reference area. However, we observed a risk of over-prediction in the number of spot fires at short distances. Figure 7(c) showed a significant number of cells with low burnt probabilities, which contrasts with the predictions from the other two parametrizations, see Figures 7(a) and 7(b). The spread capacity of RandomFront appears to impact the agreement scores for low thresholds of probability, see Figure 9.

Although fire spotting is challenging to predict and exhibits nonlinearity, quasi-physical models and parametrizations, built on sensible assumptions, can capture certain aspects of this phenomenon, as evident from Figure 7. The decision process based on the information obtained from each of the four PROPAGATOR setting of the aforementioned Figure varies significantly. Particularly, overlooking the effects of fire-spotting in simulations appears to be negligent (see Figure 7(d)). That is particularly true given the fact that the case study revolves around a conifer fire in presence of strong winds, and with the field characterized by detached patches of fire prone vegetation.
Moreover, the presence of fire-spotting patterns excessively concentrated almost exclusively in a specific areas, as exhibited by Perryman et al. and Alexandridis et al. parametrizations, does not accurately reflect the random nature of the studied phenomenon.

Table 4 gives food for thought on the behaviour of PROPAGATOR adopting different spotting modules. As also evident from Figure 7, RandomFront is the algorithm that associates the highest average probability of fire spread in the West reference area. Regarding the East reference area, it is evident that the other two algorithms put in place short-ranged spotting that raises the accumulated probability of fire spread in the eastern domain. Also RandomFront exhibits, up to a certain extent, short range spotting on the primary ignition area, as can be seen comparing the colors of the probability distribution of RandomFront and the no-spotting PROPAGATOR runs.

In operational terms, a spotting algorithm that highlights more possible areas that could potentially receive burning embers, however with a lower associated probability, can be useful for first responders since it adds more exposed assets to the list of priorities. For instance, Figure 7(c) highlights some spotting probability on both sides of the highway "SS 16 Adriatica". Such wider probability coverage based on low probabilities was satisfactorily provided by RandomFront. Giving more importance to other possible spotting candidate areas, did not prevent Randomfront to correctly assign a higher probability density to the West reference area, where fire spotting occurred in the real wildfire event.
6. Conclusions

Fire-spotting is one of the main sources of uncertainty that is not properly taken into account when simulating wildfires. In this paper, it has been further demonstrated how spotting effects may cause significant discrepancies between simulated wildfires and observed wildfires. Nevertheless, the challenge of accurately integrating spotting modules into existing simulators is a significant task that cannot be ignored, regardless of the complexity of the process. In this paper it is presented the first implementation of fire spotting modules in PROPAGATOR, an operational wildfire simulator based on CA. Event-based reconstruction of ember production and transport, as well as secondary fire ignitions, constituted a natural evolution of the grid based probabilistic algorithm that constitute the core of PROPAGATOR, instead of requiring major re-writings of the code. Three distinct parametrization of fire spotting have been tested, one of them, RandomFront, adapted to CA context for the first time. The results showed distinct spread patterns among the three studied parametrizations. A spread pattern based on low probabilities was observed with the RandomFront parametrization. Moreover, it predicted a higher likelihood of burning in the area where the real wildfire occurred than the other two fire-spotting parametrizations. We conclude that physical parametrizations, such as the model developed by Pagnini-Mentrelli (2014); Trucchia et al. (2019); Egorova et al. (2020, 2022), allow for long-range fluctuations of the burning probabilities and can increase the complexity of the fire spread patterns. The three proposed parametrization are characterized by growing complexity, and thus retaining the possibility to choose between them according to the available inputs can be a viable so-
olution for PROPAGATOR interface. This is also the first time when PROP-
AGATOR is analyzed not only for what regards the probability iso-contour
(that is, analyzing a sharp front advancing in time), since a comprehensive
analysis of all the cells interested by a non null probability of fire burning at a
given time is performed. This enabled an examination of areas characterized
by a low probability of fire spread, where it is uncertain whether the fire will
reach, but such zones are not entirely immune to potential harm.

PROPAGATOR fire spread simulator greatly benefited from the newly
introduced modules, since it can tackle a whole new class of scenarios where
spotting play a key role. The SAFERS platform (SAFERS Consortium
2020) already allows for adopting a fire spotting module while requesting a
new on-demand fire simulation run.

Further steps will involve improving the model’s robustness by calibrating
a suitable probabilistic density function for the firebrand generation process
and developing a physics-based probabilistic parametrization of the spot-
ignition mechanism.

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10.13039/501100011033 and through the national projects PID2019-107685RB-
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Data accessibility

Supplementary materials, full simulation results and the scripts of the analysis performed can be found here: https://gitlab.bcamath.org/malopez/fire-spotting

Declaration of competing interest

The authors declare no conflict of interest.
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Declaration of interests

☒ The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

☐ The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:
Click here to access/download
**Supplementary Interactive Plot Data (CSV)**
supplementary.pdf
# Reviewer 1

Dear Editor and co-authors,

This manuscript has a compelling scientific merit and I’d strongly encourage the authors to pursue publication. This piece of research is quite relevant to fire behavior modeling and the case study presented is an interesting and appropriate test case.

We would thank reviewer #1 for the time spent reviewing our manuscript, and its valuable comments and suggestions. This resubmission has been possible also thanks to the trust on the research findings expressed by the Reviewers. Following your advice in pursuing the publication of our research, we included all the changes suggested.

However, the manuscript needs further work. I recommend the authors to have this manuscript reviewed by a proficient English speaker. The narrative is challenging and I found it hard to comprehend, particularly the “denser” aspects of the analysis.

Also, I suggest some improvements to the analysis. I can see how the RandomFront model is better at predicting spotting across the water body over the east side of the port, however, the analysis used all probabilities > 0.1, which is not a realistic approach for operational use or research applications.

The authors perhaps intended to provide a comprehensive evaluation by calculating a number of different metrics but its presentation is disconnected and I wonder if some of these metrics aren’t redundant or even necessary. As I mentioned, the narrative was challenging, so perhaps I just didn’t understand the purpose. I’d suggest the authors select 1 to 3 conclusion bullets and reframe the analysis based on that. Provide figures/metrics that support the conclusion and trim down any excess.

In general, it’s better to clearly state the purpose of each session/segment upfront, and then build a narrative that objectively expands on that. For example, in Sec 2, the starting paragraph should clearly state the connection among the subsections. Very frequently the narrative abruptly shifts, without context or motivation.

The major improvements of the new manuscript reads as follows: we changed the structure of our manuscript to improve the narrative and avoid abrupt shifts, a deep check of the spelling was performed, and the quality of the pictures were improved. Moreover, we added new scores (as suggested by reviewers), and removed the redundant ones (also suggested by reviewers). Finally, we remade the analysis and discussion sections under a more operational point of view, implementing key probability thresholds.

The narrative is now clearer: the importance of having a fire spotting submodule in a real case scenario is assessed, and the effects of fire spotting parameterizations are studied. Such models range from the more “rule based” to a quasi-physical parameterization which tries to include all the mechanisms of such a nonlinear phenomenon. Also the importance of low probability spotting areas outside of the main downwind zone (as furnished by RandomFront parameterization) is emphasized, since it allows the first responders to have a glimpse on low probability but highly damaging scenarios.

Next, we give specific responses for the specific comments.

1. Define Moore neighborhood

The Moore neighborhood stands for the 8 cells that surround a cell on a cellular square grid. In line 142 we have included the sentence: “i.e., the eight surrounding cells at each time step” that we hope clarifies its meaning.

2. Explain what’s a cellular automata approach. There are numerous references to the method throughout the introduction, hence it’s important to include a brief description early on.
The new introduction of Section 2, where the mathematical models are described, now introduces the concept of cellular automaton from the mathematical point of view. Then, the concept is connected with wildfire research and simulation.

3. (99-100) What does this mean for a reader trying to decide if RandomFront is the right model for them? Also the paragraphs that follow are very disconnected.

We deleted this paragraph, and rephrased the concept we want to expose: RandomFront were previously used in wildfire simulators based on different mathematical approaches.

4. Define all variables in the equations

We thank the Anonymous Reviewer for his/her advice. We reviewed the equations and all variables are now defined. Some variables were defined in previous models since they retain the same meaning, and have not been defined again.

5. Fig 2: how many hours after ignition the red line perimeter represents?

a. Change the label from Contour to Fire Perimeter and include a label for the blue point.

b. Or, remove the red line label but leave the description for both in the caption.

We thank the Anonymous Reviewer for his/her comment. We implemented the option (a). We remade the picture. The burnt time was 5 hours as now correctly reported in the Image caption.

6. (211) why is the drone mission being described? Is it how the fire perimeter was obtained?

Yes, the drone mission provides us with the high-resolution data for contouring the fire perimeter, as specified in the main text (lines 314-317). We decided to describe the mission to strengthen the methodological procedure of the paper.

7. (224) I don’t understand this sentence. Is the “scenario” referring to this case study? I believe the author is trying to explain the following:

a. A drone surveyed the area after the fire, and the data collected enabled the creation of a fire perimeter. In this particular fire, in addition to eye witnesses reporting on the timing of observed spotting, there was a water body separating the burn area, which corroborates that the fire jumped over the water barrier through spotting. The evidence of spotting from this event makes it an ideal case study to investigate fire spotting parameterizations.

b. Please clarify or correct the narrative accordingly on the manuscript

We tried to communicate exactly what (a) says. Due to the changes made in the manuscript, the aforementioned paragraph no longer exists. We have included the clarification in the header of Section 3: Materials and Methods (lines 246-252).

8. Could the authors also include the grid spacing (in addition to the grid cell resolution) in the x and y direction? Does the 20m 2 cell area correspond to a grid spacing of 4.47m in each direction?
We deeply thank the Anonymous reviewer for pointing out the typo. The cells of the grid are squares with a 20 m side, as now correctly pointed out in line 286.

9. It would be helpful to include tables summarizing the idealized and real-case simulations.

Thank you very much for the suggestion. We have attempted to achieve the same effect as proposed by consolidating the simulation results into a reduced number of figures: specifically, Figures 4, 5, 6, and 7. Explanations in the headers of the subsections were also provided. We believe that this improvement, inspired by the advice provided, will enhance the narrative and readability of our article.

10. For an objective comparison, the author should calculate either the area or number of points with probabilities higher than a few key thresholds, e.g. 50%, 75%, 95%. It looks like the Alexandridis model predicts more points with high probability than the RandomFront, even though the area of probability > 0.01 is smaller. This is relevant information for the decision tree associated with fire spot ignitions.

Thank you for your advice. Our final goal is to contribute to decision-making strategies. We have included, for the ideal cases, the probability thresholds 25%, 50%, 75%, 90% and average (see Table 3). And in the real world case the evolution of the burnt area with 10%, 50% and 75% of probabilities of being burnt (Figure 8).

11. It would be interesting to include a brief analysis with respect to probabilities thresholds of spotting occurring at distances wider than the water barrier.

Thank you very much for your suggestion. Table 4 represents the contribution of all thresholds of the probability to each of the two domains, the East and the West ones. Concerning the synthetic case studies, the new Figures describing the synthetic results (Figs 4, 5, and 6) have all been set to a scale that allows us to understand the models’ behavior for distances greater than the width of the water body. Specifically, the fixed scale enables us to observe the performance of these models for units of kilometers (always remembering the ideal conditions under which this comparative synthetic study is conducted).

12. I’m confused with what the term “mean burnt area” represents. Is this the ensemble average of the member areas where the probability of fire is > 0 (i.e. continuous fire spread + spotting)? Is it realistic to assume that fire will occur for any P > 0?

We apologize for the confusion. We redefined “mean burnt area” by “average burnt area”, and defined it in lines 375-376. We thought that, if there are extensive regions of low probabilities, they ought to contribute to the average predicted probability in a proportional manner. The probability output of PROPAGATOR is thus used as a weight to each cell reached by any P>0, in order to sum up all the “burned area” in a way which reflects the probability of burning.

13. Is there a reason for using a gray scale? It’s very hard to distinguish. Could also use a nonlinear scale to emphasize higher probabilities

The Authors agree with the Anonymous Reviewer’s criterion. We remade all the figures again, improving their quality and adding a nonlinear color scale to better visualize the contrast between probabilities.
14. Can you overlay the observed fire perimeter in fig 14?

We removed Figure 14 and integrated the simulation without the fire-spotting effects into the new Figure 7-(d), with the burned area highlighted. We believe that this new arrangement contributes to enhancing the readability of the manuscript.

15. I think the discussion of fig 11-13 should be made based on probability thresholds. If one is considering that any value of \( P > 0 \) leads to spotting, the RandomFront model would be the worst of the models. However, that’s not the case. RandomFront is the only model indicating a higher probability to the NW, across the water barrier. I can’t see what the probability value is with the grayscale colormap but it’s clearly higher than the other models.

Thank you very much for your suggestion. In Figure 8, we have included the behavior of the burnt area over time for different probability thresholds. This, combined with the non-linear color scale, allows us to observe how the main differences that characterize the three models lies in their ability to generate low but distributed probabilities among the simulation domain.

16. It’s important that researchers take into account the application of their science. How can they break down the results in a way that it’s relevant to stakeholders who benefit (and sometimes fund) their science. Would firefighters consider \( P = 0.1 \) as a potential threat? This is an important aspect to be mentioned and considered in the analysis.

We have attempted to argue the importance of probability tails in lines 451 to 482. What sets apart the predicted probabilities by different Fire-spotting models are the tails of the probability distributions, namely, the behavior of low probabilities. We defend the idea that those making decisions in a real-life situation should have all the available information, and it is up to them to determine whether these probability tails are relevant or not. Moreover, in many formulations of the Risk equations, such as the standard \( R = H \times E \times V \), that is, Risk given by Hazard times Exposed asset value times their vulnerability to the hazardous event, Hazard can be broken down into potential intensity of the event (in our case, severity of the wildfire, fireline intensity…) and probability of the fire to reach such area. That is, an analysis which considers the fire embers not exclusively ballistically driven by the average wind, but also possibly dispersed in a more uniform manner, can help in having more realistic and comprehensive risk scenario assessments.

17. It’s not clear what’s the “reference” line in fig 15. Is this the observed area measured by the drone? Please clarify. It would be helpful to include the observed area and also the area predicted by the simulations without spotting.

Yes, the reference area is the burned area measured by the drone. We have attempted to clarify this in the new Figure 8.

18. (398) “we have implemented and studied reliability, sharpness diagram and rank histogram” Instead, state the specific points of conclusion given by each of these metrics. For example, was there any model statistically more reliable than the others? If not, is there a purpose to include the reliability analysis?

We deeply thank the Anonymous reviewer for pointing that out since it has motivated (together with comment 20) significant changes in this manuscript. Indeed, we have removed metrics that do not allow distinguishing clear differences between both models. However, reliability is a measure that helps us understand whether a model is well calibrated or not. We have implemented this measure following the
approach by Allaire et al (Allaire, F., Filippi, J.-B., Mallet, V., 2020. Generation and evaluation of an ensemble of wildland fire simulations. Int. J. Wildland Fire. 29, 160–173. https://doi.org/10.1071/WF19073.). As evident in Figure 10-(a), RandomFront is the only model that appears to predict low probabilities with proper calibration. For this reason, we believe this information could be of interest to the readers of the paper.

19. BSS is a measure of skill, it’s a relative metric.

We decided to delete this measurement because no relevant information can be extracted.

20. If I understand it correctly, the BSref value used in section 4.2.1 is dependent on the selected simulation domain, i.e., if the simulation was configured over a larger area, BSref would be lower. BSref seems to be the frequency of “positives” over the simulation area. That’s not a robust reference. According to Wilks 2016 (Statistical Methods in the Atmospheric Sciences, section 7.4.2); “ Usually the reference forecasts are the relevant climatological relative frequencies that may vary with location and/or time of year ”. I believe that using a set of various probabilities (0.5, 0.75, 0.95) would allow the author to best distinguish the model.

However, in my personal opinion, that’s a quite complex metric for the argument being made in this article. I’d strongly recommend the author use metrics that are more standard among firebehavior modelers, which would allow the results in this manuscript to be more frequently cited and referenced, such as the Sorensen’s coefficient and Cohen’s kappa. You could potentially plot the scores for various probability thresholds.


We thank the Anonymous reviewer for his/her comment. Following the referenced article, we have decided to include both similarity indices (Sorensen and Cohen) to align our work more closely with the metrics used in previous research within the field of study. Both indices have been computed and presented in Figure 9. They are expressed for different probability thresholds (x-axis). For instance, if the threshold (x-axis) is set to 0.5, all probabilities below 0.5 are evaluated as “non-fire,” and all probabilities above as “fire.” We hope that this change will increase confidence in the presented results and lead to a broader dissemination of this work.

21. Where are the metrics for the model simulations without spotting?

We thank the Anonymous reviewer for his/her comment. Since the focus of the paper is the comparison of different fire spotting techniques adapted to CA, and since no-spotting case leaves the West reference area completely devoid of burned pixels, we decided not to add no spotting metrics in most tables and figures.

22. Where’s the analysis for fig 18?

We believe that this index overloads and complicates the narrative of the article. Therefore, an optimized version will be presented in future works. We removed section 4.2.2.

23. (460) “ RandomFront is the fire-spotting parametrization which is able to generate the more complex spread pattern ” I’m not sure what “complexity” means in this context. Basically, RandomFront shows more embers spotting in a range of directions and over farther distances.

Thank you very much for the comment. We have attempted to "translate" the adjective "complexity" in line 429, so that readers from a wider community can understand at the first glance what we meant by this word.

24. (480) “ Due to the hazard degree that fire-spotting may imply, a higher spread capacity (in the sense of over-prediction due to the fire-spotting effects) must be regarded as an advantage ” This is not true. A Model that is not able to distinguish occurrences from non occurrences (i.e. predicting spotting when spotting does not occur) is not a better model than one that underpredicts but is able to discriminate between events.
We thank the Anonymous reviewer for his/her comment with which we agree. We have rewritten the entire discussion section to avoid errors like the one pointed out, and we have removed the unfortunate sentence. Thank you very much for bringing it to our attention.

We thank again the Reviewer #1 since its comments motivated a full scale rewriting of the paper, a more concise presentation of its narrative, a refactoring of the sections and a thorough spell check. The advancement made in this review can be attributed to the constructive questions raised, such as the one presented. Additionally, Reviewer #1's feedback has been invaluable in highlighting the merits of the research, which had previously lacked a clear and straightforward exposition.

Yours sincerely,

The Authors

# Reviewer 2

This paper considers three different models for spotting and applies them to a wildfire simulator called PROPAGATOR. The three different models are first compared in an idealized setting (uniform fuels, uniform wind speeds, etc.) at two different wind speeds. Then, they are applied to a wildfire that occurred in Campomarino, Italy in 2021. The results of the model are probabilities of each cell seeing fire, and these probabilities for each model are analyzed and compared using several different techniques. There is quite a few major changes that should be made before the paper is considered for publication.

Firstly, the Authors would also thank Anonymous Reviewer #2 for the time spent reviewing our manuscript, formulating insightful comments and suggestions. As you can see, profound changes have been made to the manuscript. These changes are aimed at enhancing the readability of the paper, incorporating new data, and removing redundant information. The narrative and grammar were improved. All the suggested changes by Anonymous Reviewer #2 were also included. Since practically every line of the paper has been written \textit{ex novo}, no track changes routines (e.g., with different colors of the newly introduced parts) have been put in charge.

Next we give specific responses for the specific comments.

- There are several typos and confusing sentences. For example, in the abstract: "Unfortunately, there are still poor parameterizations of fire-spotting based on the physics of the phenomenon that leads to overlook by operational fire-spread simulators the harmful consequences associated with it." In the first paragraph of the introduction: "These new fires can occur near the fire-front, such that to accelerate the spread of the fire (Storey et al., 2021), or kilometers away from the main burned area by causing new secondary ignitions that increase the extinction difficulty and in which civilians and firefighters can result in entrapment (Koo et al, 2010; Storey et al, 2021). The manuscript needs to be carefully edited for such mistakes before it is resubmitted.

Thank you very much for your comment. As mentioned above, we have reviewed all the sentences in our manuscript to prevent confusion like the one mentioned.

- On page 9, I think the parameter $\sigma$ should be $\alpha$

The parameter $\sigma$ is correct. With it, we refer to the standard deviation parameter in RandomFront, which is physically interpreted as the model's capacity to spread. We believe this is an example of the poor narrative in the previous version, and we want to offer our apologies for any confusion caused. We attempted to address it by adding "of the log-normal distribution" in line 218.

- Some of the assumptions are not justified. For instance, why is the number of emitted firebrands assumed to follow a Poisson distribution?
The Poisson distribution is typically employed when the occurrence of an event does not influence the probability of the same event happening subsequently. Moreover, the Poisson distribution is well-suited to generate integer values of events that take place in a given time period. We believe that this assumption aligns with the reality associated with the number of firebrands generated (see lines 237 and 240). Moreover, the ember production and secondary ignition phases have been aligned with the Alexandridis model, since it was already coincided for cellular automata, and has been kept the same for all model runs.

- The number of trials (100) seems small for such a high-dimensional problem. If the simulations can run in less than 2 minutes on a laptop, why not do 1000, or 10,000 simulations? My feeling is that this would significantly change Figures 4-9 that have sharp edges separating cells that did not burn (green) and cells that only burnt in one trial (black).

The reason why we have used 100 independent simulations is that the original PROPAGATOR operational code also employs the same number of simulations. The original developers of PROPAGATOR have informed us that the simulator is internally calibrated for an optimal number of simulations, considering both performance and memory constraints, and that number is set to 100. Furthermore, the abrupt jumps indicated allow us to quantify the different patterns that occur in each of the studied models. A higher number of simulations, in the ideal cases, would overshadow these patterns, preventing us from observing the complexity in the forecasted probability patterns. Of course, instead of isolated spots, wider areas characterized by a given probability “halo” would be visualized if the realization number is set to higher numbers.

- Based on the simulations in Figures 4-9, I would think that at least the Perryman model should not be considered further. The spread is completely unrealistic.

In the ideal scenario, where no wind direction perturbations occur, Perryman appears to be the worst of the models. However, when we employ more random meteorological conditions, it seems to offer better results. One of the reasons we decided to include the study under ideal conditions was to provide readers with a comprehensive understanding of how the models perform under different situations.

- The color scale used in Figures 11-13 is in black and white. This makes it very hard to see any kind of contrast. Why not use the same color map as those in Figures 4-9?

Following your helpful advice, the Authors have implemented the indicated change.

- Some of the metrics show little to no difference between the models. For example, Table 4 has basically the same values for all metrics of accuracy. To me, this means that the metric cannot be used to judge the pros and cons of each model.

We want to express our gratitude for your comment. We have removed all redundant metrics and added two new metrics suggested by reviewer #1 in Figure 9.

- I don't understand what Figure 17 means.

We decided to remove the metric presented in Figure 17 because we believe that the information it conveyed had a low relevance to the purpose of this study.

We thank again the Reviewer #2 since its comments motivated a full scale rewriting of the paper, a more concise presentation of its narrative, a refactoring of the sections and a thorough spell check. It is thanks to constructive questions as the one presented in this review that we could advance this far.

Yours sincerely,

The Authors