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Supplementary: Cellular Automata Based Simulators for the Design of Prescribed Fire Plans: the Case Study of Liguria, Italy

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Abstract

Background: Socio-economic changes of the last decades have led to fuel buildup in Mediterranean forests. In the context of Climate Change, this situation has resulted in the formation of potential fire traps that could lead to catastrophic events. Several wildfire management systems have therefore started to use prescribed fires for land management and wildfire risk mitigation. Prescribed fires are prepared by designing a plan, where specific objectives are identified, prescriptions are checked, and scenarios are defined. In the plan definition phase, simulation models can provide an additional decision-support tool, allowing the different scenarios to be qualitatively and quantitatively assessed. We used the well-established wildfire simulation tool `PROPAGATOR` to identify potential areas of treatment and to assess different scenarios of hypothetical prescribed fires. In the present work, we prepared the model for use in prescribed fires by changing the native space-time resolution to a finer scale. We selected a case study in the Liguria region, Italy, where the model is operationally used by the regional wildfire risk management system during emergencies.

Results: We first used the propagation model to simulate a wildfire event, to show the potentiality of the model as an emergency response tool. We selected the most important fire incident that occurred in the Liguria region in 2022. We then used `PROPAGATOR` to identify the optimal treatment areas to maximize wildfire risk mitigation effects and reduce the costs of treatment. In the identified areas, we used the model to simulate ignition scenarios in different weather conditions allowed by the regional regulation. The scenarios developed by the model made it possible to differentiate between situations that are under control and those that pose greater risks.

Conclusions: We showed how `PROPAGATOR` can provide quantitative and qualitative information that can be used in prescribed fire planning. Our methodology involved incorporating expert opinions throughout the process and providing scenarios based on this information. The possibility of evaluating different scenarios and having quantitative information helps make informed decisions, promoting safer and more efficient fire management practices.

Keywords: Prescribed fire planning; Cellular automata; Wildfire simulators; Wildfire scenarios

1 `PROPAGATOR` : from Early Warning to Early Action

In this section we briefly describe the model, highlighting the latest developments of the model. A detailed description of the model can be found in Trucchia et al.

(2020).

PROPAGATOR is a quasi-empirical stochastic Cellular Automata model based on a raster implementation. The model discretizes the space into a grid composed of square cells of arbitrary length $\Delta x = \Delta y = L$. Elevation and vegetation type are interpolated at the center of each cell from rasters given in input by users. The PROPAGATOR version operationally used has a spatial resolution of 20 meters. Every cell is characterized by one of these three states: the cell is burning; the cell is already burned; the cell is unburned. A burned cell cannot change its status and remain burned for the simulations, while a burning cell becomes burned after a computed burning time, propagating the fire at the end of its consumption. The unburned cell can change its status if a burning cell is in its neighborhood. It can become a burning cell or remain unburned, with a probability that depends on simulation settings. The evolution of the fire front is modeled by the rate of spread computed for each cell, from which the fire transition time is retrieved. The model then uses a fixed time step Δt, in which the burning cells are scheduled according to their burning time. The PROPAGATOR version operationally used has a time step of 1 hour. The fire propagation dynamics can then be thought of as a contamination process between adjacent cells, with spread probability that depends on cell conditions, and boundary conditions. A large ensemble of stochastic simulations is computed with identical settings in terms of ignitions, weather conditions, and static input rasters. A number $N = 100$ of realization is usually considered. On the basis of this simulations ensemble, the probability $u(\boldsymbol{x_P}, t)$ of being burnt at time t and for the center $\boldsymbol{x_P}$ of each cell is computed, using the fire frequency for each cell. This map is also used to compute the isochrones of wildfire evolution, corresponding to the iso-contour lines of the fire probability maps at different threshold values (typical thresholds are 50%, 75% and 90%). Further, mean and maximum values of the rate of spread and fire line intensity for each cell are computed. The simulation time required by PROPAGATOR model is usually less than 5 minutes (see Trucchia et al. 2020).

Propagation dynamics The model uses a Moore neighborhood of order one, which corresponds to a two-dimensional square lattice composed of a central cell (the ignited i-cell) and the eight cells surrounding it - we refer generically to one of them as the $j-$cell. The fire spreading probability between two cells p_{ij} is computed considering the directions between the cell centers. This probability is determined by modifying a *nominal fire spread probability* (referred to as p_n in the following) on the basis of topography, wind field, and fuel moisture content of the cell to be ignited. p_{ij} is computed using a formulation similar to the cumulative binomial probability (see Hargrove et al. 2000):

$$p_{ij} = (1 - (1 - p_n)^{\alpha_{wh}}) \cdot e_m \tag{1}$$

where α_{wh} is the topographic and wind correction factor on the spread probability and e_m is the correction due to fine fuel moisture content.

The nominal Fire Spread Probability p_n represents the probability of the fire to spread between two different fuel types. Fuel models are largely adopted by different wildfire propagation models (Finney 1998). PROPAGATOR uses a simplified custom model with seven fuel types corresponding to vegetation types: grasslands, shrubs, broadleaves, fire-prone conifers, agro-forestry areas, non fire-prone forests, and non-vegetated areas. The *Non-vegetated areas* class includes buildings and infrastructure, water bodies, and natural bare soil, where fire can not propagate. *Non fire-prone forest* class corresponds to the low-flammable forests. The *Broadleaves* class models tall vegetation with medium flammability, and highly flammable tall vegetation falls into *Fire-prone conifers* class. The medium-to-low vegetation is organized into three classes: *Agro-forestry areas* with a low vegetated density and low propagation probability; *Shrubs* with medium-flammable low vegetation; *Grassland* with highly-flammable very low vegetation. The p_n values are tabulated in Table 1. These values were defined by means of a continuous calibration throughout the years, with important inputs from experts and fire susceptibility mapping (Tonini et al. 2020, Trucchia et al. 2022).

The nominal Fire Spread Probability p_n is then modified by slope and the wind. The topography correction factor α_h increases the propagation probability in the uphill direction, decreasing it in the downhill direction. The wind correction factor α_w increases the burning probability in case of propagation direction aligned with the wind direction, while it is decreased in the opposite directions. The wind correction influence increases with wind speed. Wind speed and direction are considered homogeneous in the whole domain for each time step. However, these values are randomly perturbed in each cell independently with a uniform noise to consider wind inhomogeneity through the domain. The topographic and the wind factors are then multiplied, leading to the wind-slope factor α_{wh} shown in equation 1. The effect of fuel moisture content on the fire spread probability is enclosed by the moisture factor e_m. This factor has been implemented as reported by Burgan and Rothermel (1984). The moisture factor is a function of the ratio of the dead fuel moisture over the dead moisture of extinction. Applying a conservative estimate, a fixed value of 0.3 has been used as the moisture of extinction for all the fuel types considered.

Rate of spread The fire transition time t_{fire} is computed by combining the rate of spread v with the distance d between the center of the burning i-cell and the center of the newly ignited j-cell, following the equation 2:

$$t_{fire} = \frac{d}{v} \tag{2}$$

The Rate of Spread model is obtained by combining a *nominal fire spread velocity* (v_n in the following) and similarly modifying it on the basis of topography-wind-moisture conditions, following the equation 3:

$$v = v_n \cdot K_w \cdot K_s \cdot f_m \tag{3}$$

where K_w is the wind factor, K_s is the slope factor and f_m is the fuel moisture factor. The nominal fire spread velocity values for each fuel type are reported in Table 1. These values have been identified after years of consecutive developments and interaction with experts. The moisture factor f_m is computed with the formulation proposed by Marino et al. (2012), while wind and slope factors have been evaluated using the formulations proposed by Sun et al. (2013).

Fire-fighting operations In the latest releases of the model, fire-fighting actions have been added. Users can insert them as geometries in the domain where fuel moisture (in the case of *waterline*, *Canadair*, and *helicopter*) or vegetation type (in case of *heavy action*) is changed. In the first case, fuel moisture is set to a specific value depending on the firefighting actions implemented. A buffer around the firefighting areas and randomness in the locations is also introduced. In case of heavy actions, the vegetation type is changed to *non-vegetated areas* so that fire can not propagate. Fire-fighting actions and relative moisture values were selected based on experts' opinions in the field and subsequent calibrations.

Spotting dynamics A spotting dynamics has also been introduced. A stochastic paradigm of the spotting phenomenon has been adopted to be compliant with `PROPAGATOR` structure. A Poisson distribution is used to compute the number of embers randomly that can be emitted by each cell. Only the *conifers* fuel type is considered as an ember source. Then, the traveling angle and distance are computed for each ember, respectively, with a uniform distribution and using the formula of Alexandridis et al. (2011) considering wind speed and direction. Once the landing cells are identified, an ignition probability for each cell is computed by the formula:

$$P_i = P_{i,0}\,(1 + c_{fuel}) \tag{4}$$

where $P_{i,0}$ is the constant ignition probability and c_{fuel} is a correction term depending on fuel type. In particular, c_{fuel} has been set only for conifers due to their susceptibility to spotting phenomenon.

Rate of spread and fire line intensity maps In the latest release of the model, rate of spread and fire line intensity maps are given in output, producing mean and maximum values of both quantities for each cell. The rate of spread map is produced with the rate of spread model adopted to compute propagation dynamics. Fire line intensity is produced by equation used in the forest fire danger rating system `RISICO` (Fiorucci et al. 2008, Perello et al. 2022).

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Tables

Table 1: The first six rows show the nominal fire spread probability between all the fuel types considered in `PROPAGATOR` . The last row shows nominal fire spread velocity for each fuel type.

		Burning Cell					
		Broadleaves	**Shrubs**	**Grassland**	**Fire-Prone Conifers**	**Agro-Forestry Areas**	**Not Fire-Prone Forest**
neighbor cells	Broadleaves	0.3	0.375	0.25	0.275	0.25	0.25
	Shrubs	0.375	0.375	0.35	0.4	0.3	0.375
	Grassland	0.45	0.475	0.475	0.475	0.375	0.475
	Fire-prone conifers	0.225	0.325	0.10	0.35	0.2	0.35
	Agro-forestry areas	0.25	0.25	0.3	0.475	0.35	0.25
	Not fire-prone forest	0.075	0.1	0.075	0.275	0.075	0.075
Nominal Fire Spread Velocity [m/min]		140	140	120	200	120	60