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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 in recent decades have resulted in an accumulation of fuel within Mediterranean forests, creating conditions conducive to potential catastrophic wildfires intensified by climate change. Consequently, several wildfire management systems have integrated prescribed fires as a proactive strategy for land management and wildfire risk reduction. The preparation of prescribed fires involves meticulous planning, entailing the identification of specific objectives, verification of prescriptions, and the definition of various scenarios. During the planning phase, simulation models offer a valuable decision-support tool for the qualitative and quantitative assessment of different scenarios. In this study, we harnessed the capabilities of the well-established wildfire simulation tool `PROPAGATOR`, to identify areas where prescribed fires can be performed, optimizing the wildfire risk mitigation and the costs. We selected a case study in the Liguria region, Italy, where the model is utilized operationally by the regional wildfire risk management system in emergency situations.

Results Initially, we employed the propagation model to simulate a historical wildfire event, showcasing its potential as an emergency response tool. We focused on the most significant fire incident that occurred in the Liguria region in 2022. Subsequently, we employed `PROPAGATOR` to identify optimal areas for prescribed fires with the dual objectives of maximizing the mitigation of wildfire risk and minimizing treatment costs. The delineation of potential areas for prescribed fires has been established in accordance with regional regulations and expert-based insights. The methodology put forth in this study is capable of discerning the most suitable areas for the implementation of prescribed burns from a preselected set. A Monte Carlo simulation framework was employed to evaluate the efficacy of prescribed burns in mitigating the spread of wildfires. This assessment accounted for a variety of conditions, including fuel loads, ignition points, and meteorological patterns. The `PROPAGATOR` model was utilized to simulate the progression of wildfire spread.

Conclusions This study underscores the utility of `PROPAGATOR` in offering both quantitative and qualitative insights that can inform prescribed fire planning. Our methodology has been designed to involve active engagement with subject matter experts throughout the process, to develop scenarios grounded in their expert opinions. The ability to assess diverse scenarios and acquire quantitative information empowers decision-makers to make informed choices, thereby advancing safer and more efficient fire management practices.

Keywords Prescribed fire planning, Cellular automata, Wildfire simulators, Wildfire scenarios

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Resumen

Antecedentes Los cambios socioeconómicos en las recientes décadas han resultado en una acumulación de combustibles dentro de los bosques del Mediterráneo, creando condiciones favorables a fuegos catastróficos, empeoradas por el Cambio Climático. Consecuentemente, diversos sistemas de manejo del fuego han incluido también las quemas prescritas como estrategia proactiva para el manejo de tierras y la reducción del riesgo de incendios de vegetación. La preparación de las quemas prescritas necesita una meticulosa planificación, implicando la identificación de objetivos específicos, verificación de las prescripciones, y definición de varios escenarios. Durante la fase de planificación, los modelos de simulación ofrecen una herramienta valiosa de soporte de decisiones para la determinación cualitativa y cuantitativa de diferentes escenarios. En este estudio, aprovechamos las bien establecidas capacidades del simulador de incendios PROPAGATOR, para identificar áreas donde las quemas prescritas puedan ser llevadas a cabo, optimizando la mitigación del riesgo de incendios y sus costes. Seleccionamos un caso de estudio en la región de Liguria, en Italia, donde el modelo es utilizado operacionalmente por el sistema regional en situaciones de emergencia.

Resultados Inicialmente, empleamos el modelo de propagación para simular un evento de fuego histórico, mostrando su potencial como una herramienta de respuesta de emergencia. Nos enfocamos en el incendio más importante que ocurrió en la región de Liguria en 2022. Subsecuentemente, empleamos el modelo PROPAGATOR para identificar las áreas óptimas para quemas prescritas con el objetivo doble de maximizar la mitigación del riesgo de incendio y minimizar los costes de los tratamientos. La delineación de áreas potenciales para quemas prescritas fue establecida de acuerdo con regulaciones regionales y opiniones de los expertos. La metodología que empleamos en este estudio es capaz de discernir las áreas más oportunas para la implementación de quemas prescritas, elegidas de un conjunto preseleccionado. En ese marco conceptual, una simulación de tipo "Montecarlo" fue empleada para evaluar la eficacia de las quemas prescritas en la mitigación de la propagación del fuego. Este análisis tuvo en cuenta una variedad de condiciones, incluyendo la carga de combustibles, los puntos de ignición, y los patrones meteorológicos. El modelo PROPAGATOR fue utilizado para simular la progresión de la propagación del fuego en cada condición.

Conclusiones Este estudio subraya la utilidad del PROPAGATOR en que ofrece perspectivas tanto cuantitativas como cualitativas que pueden informar sobre el planeamiento de quemas prescritas. Nuestra metodología ha sido diseñada para involucrar el compromiso activo de expertos en la materia a lo largo del proceso, para desarrollar escenarios basados en sus opiniones expertas. La habilidad para determinar escenarios diversos y adquirir información cuantitativa, empodera a los tomadores de decisión a hacer elecciones basadas en información, y por lo tanto avanzar hacia prácticas de manejo del fuego más seguras y eficientes.

Background

Wildfires are a common occurrence on most continents. They hold global significance, constituting an integral part of numerous ecosystems and playing crucial roles in ecosystem dynamics, acting also on the preservation of species that have evolved in response to fire (Williams and Bradstock 2008, Pausas and Keeley 2009). Most wildfires are natural processes that confer various benefits to humankind. In ecosystems reliant on wildfires, disturbances in the natural fire regime often arise when fires are suppressed or their frequency increases (Pausas and Keeley 2019). In such instances, wildfires persist as an ongoing challenge, capable of significantly impacting wildlife, communities, and the environment due to their potential intensity and severity. Climate, ignition agents, fuels, and human activities all have a significant impact on fire activity (Flannigan et al. 2009). Among these factors, fuels provide the majority of the energy required for a fire to spread. As a result, fuel management can effectively reduce the intensity and severity of wildfires.

Prescribed burning is one of the most effective fuel management activities and it is recognized for reducing the risk and severity of wildfires (Keane et al. 2008). It refers to the intentional use of fire by experts in selected areas, under prescriptions and procedures, to achieve specific objectives (Bovio and Ascoli 2012). Prescribed burning entails reducing the fuel load in certain landscape areas, limiting the spread and severity of significant wildfires, and, as a result, the risk to human life and economic assets (Penman et al. 2011, Lydersen et al. 2017). Prescribed burning is used in most parts of the world for various land management purposes such as regenerating forests, clearing land for cultivation, managing pastureland, conserving fire-dependent plants and animals, and wildfire risk mitigation (Wade et al. 1989). The method's efficacy in managing wildfires through the reduction of fuel continuity—both vertical and horizontal—has been well-supported by research (Fernandes and Botelho 2003, Boer et al. 2009). Furthermore, prescribed burns have been recognized for their role in accomplishing other objectives, such as control of weeds, insects, and diseases; maintenance of biodiversity; site preparation for tree regeneration; and enhancements of silvicultural practices (Savage et al. 2011).

The integration of operations research into wildfire management dates back to the 1960s, focusing on fire detection, suppression, and prevention techniques, with its application in fuel management being a more recent development. In North America and Australia, as well as some Mediterranean countries such as France, Spain, and Portugal, prescribed burning is an integral part of fire prevention strategies, aiming to mitigate the risk of uncontrolled wildfires by managing fuel accumulation at key points across the landscape (Lázaro and Montiel 2010).

While Australia's modern history of prescribed burning began in the 1950s, the Aboriginal Australians' practice of using fire for land management predates this by centuries, underscoring a profound understanding of fire's role in ecological balance (McCaw 2013, Willman 2015). The acknowledgment of such traditional burning practices provides invaluable insights into the sustainable management of fire and has influenced contemporary approaches worldwide. Concerning the Mediterranean basin, although modern prescribed burning commenced in the latter half of the twentieth century, human use of fire has a long history in the region (Fernandes et al. 2022). The practice dates back to at least 1000/3000 BC (Connor et al. 2012). Initially employed for land reclamation, fire played a crucial role in sustaining ecosystem services related to grazing and agroforestry, such as maintaining grasslands for livestock and enhancing the growth of crops like blueberries (Keeley et al. 2012). Additionally, it served as a tool for rural protest and resistance (Tedim et al. 2015). However, it is important to note that depopulation of rural areas in recent decades, driven by socioeconomic changes, and fire use restrictions have led to the gradual loss of a *fire culture* in the region, along with the traditional knowledge of fire as a management tool (Ganteaume et al. 2013). Fire, now institutionalized in the form of prescribed burning, is emerging as a technology dedicated to fire hazard reduction and ecosystem maintenance and restoration goals (Fernandes et al. 2013). These institutional practices, rooted in science and technology, are taking up the challenge of preserving centuries-old knowledge and the cultural bond between mankind and the landscape.

The use of prescribed fire in France, Italy, Spain, and Portugal showcases a diverse array of practitioners, ranging from private forest associations and volunteer or professional fire brigades to municipalities, each with their unique approaches and historical experiences with fire management. This diversity is contrasted with the more limited number of active prescribed fire teams in these countries, indicating room for growth and greater adoption of these practices. When discussing "diversity," it is pertinent to consider the varied objectives, scales, and historical contexts within which these burning practices are situated. In comparison to the longstanding indigenous use of fire in regions like Australia, the Mediterranean's prescribed burning practices reflect a different spectrum of ecological, cultural, and fire management traditions.

Italy's exploration and adoption of prescribed fire have undergone phases of active implementation, research, and policy development, since its arose in the late 1970s. The National Forest Service recognized the positive impacts of prescribed burning (Calabri 1981) and, in the 1980s, supported experiments in pine forests (Tuscany region) and to maintain fuel breaks in Sardinia region under the management of the *Istituto Sperimentale di Selvicoltura* (Buresti and Sulli 1983). The experiments were abandoned despite good results (Calabri 1981). Italy's interest in the prescribed fire died off, unlike Portugal, France, and Spain. Focus on prescribed fire in Italy returned in the early twenty-first century, and several scientific studies (e.g., Giuditta et al. 2020), legislation training, initiatives, and burn programs have been led throughout the country (Bovio and Ascoli 2012). It is worth mentioning that in Italy prescribed fire legislation is a regional task (Italian law on wildfire No. 353/2000), leading to a fragmentation of the subject within the country. Both regional laws and regional fire management plans provide the legal framework for prescribed burning, mainly in the forestry sector, although not all the regions regulate prescribed burning in the fire management law. To date, 70% of Italian regions adjust prescribed burning in either a fire management plan or regional law. Nevertheless, many regulatory documents still lack precise information on critical issues such as liability and detailed authorization procedures (Bovio and Ascoli 2012). Consequently, many regions do not implement prescribed fires. To date, the effective use of prescribed burning for fire management purposes is restricted to Campania, Piedmont, Tuscany, and Sardinia regions.

Prescribed fire procedures and objectives are identified in the regional land management or wildfire management policies. The core of prescribed fires are the design indications concerning the season and frequency of the intervention, the time windows in which to operate according to weather conditions (e.g., fuel humidity, air humidity, temperature, wind speed, and direction), and the ignition techniques to be adopted (e.g., against the wind and slope), in order to conduct a flame front with a predicted intensity and rate of spread (Esposito et al. 2014). The use of prescribed fires is anticipated by the plan definition, in which prescriptions are checked and expected objectives are identified. The typical objectives of prescribed fires in Italy are wildfire risk mitigation in wildland-urban interfaces and forests, reducing fuel load, restoring the ecological role of fire in fire-adapted ecosystems, and managing agro-pastoral resources and in agro-forestry (Esposito et al. 2014). The objectives are, therefore, related to ecological purposes as well as wildfire risk mitigation (Bovio and Ascoli 2012).

Forest managers in Europe use various techniques for fuel modification, including prescribed burning (Rigolot et al. 2009). Even though mechanical treatment is the most common technique for fuel reduction in South European countries, prescribed burning is progressively being considered, with various acceptance levels among countries (Lázaro and Montiel 2010). In short, the practice of using fire as a tool for land management spans centuries and continents, with a rich diversity of traditional methods evolving into the prescribed burns widely implemented today. This evolution reflects a deepening understanding of fire's role in ecosystem dynamics and human safety, with an increasing emphasis on strategic, regulated, and science-based approaches to fire management.

As discussed before, prescribed burning is effective in managing wildfires and has emerged as a key fuel management strategy. It is important then to focus on improvement of modeling prescribed fire. The use of modeling tools and technologies could help the expert make informed decisions to evaluate different plans and assess the achievement of objectives in advance (Cassagne et al. 2011). Some uses of models in prescribed fire plans have been identified in the literature. Modeling tools could identify areas where actions can be more effective in reducing wildfire risk. In Wei et al. (2008), authors use mixed integer programming (MIP) in the framework of fuel management and wildfires to reduce the expected fire loss. In Matsypura et al. (2018), a network-based model has been developed to identify the areas where fuel treatment is more efficient in reducing fire spread. Fire simulation models can also be used to anticipate fire behavior during prescribed burning based on differences in fuels (fuel loads, moisture contents, and fuel types), topography (slope, aspect), and weather conditions such as temperature, wind speed, and humidity (Pearce 2009). Numerous authors also proposed utilizing fire simulators as an easy way to generate fire severity and probability maps based on various fuel reduction techniques and climatic factors (Ager et al. 2011, Finney et al. 2013). Several authors have discussed the effectiveness of using modeling tools. Fernandes and Botelho (2003) assessed the success of burning in reducing fire hazards and found that fire propagation models can be used to predict the effect of fuel reduction on potential fire hazard. Although several models have been established for basic fire behavior research or emergency response, only a handful have been designed for fuel management planning (Ager et al. 2011). Models created for fire behavior simulation in the USA, Canada, and Australia are also widely used in Europe (Mitsopoulos et al. 2017), becoming popular for prescribed fires. However, many aspects should be analyzed to reveal possible differences between wildfire and prescribed fire modeling. There is a need for developing a refined research agenda specifically adapted to prescribe fire to help with fuel management (Hiers et al. 2020).

Three model classes have been developed in the literature to assess fire behavior: empirical, quasi-physical, and physically based (Sullivan 2009a, Sullivan 2009b). Empirical models are built on the correlation between terrain characteristics, experimental fire spread rate, weather, and fuel. Their calibration requires many experimental fires, but they can quickly simulate fire spread. Their strength is the ability to explore numerous scenarios in a short time in different fire spread conditions. Quasi-physical and physical models are founded on an analysis of fire physics. These models require many parameters that are typically derived from laboratory experiments or modeling assumptions. One of the most famous models in this category is `BEHAVE` fire behavior prediction and fuel modeling system (Burgan and Rothermel 1984). Since it considers natural fuel characteristics, it can predict fire spread rate and intensity within any given fuel type when its main features are known. Other physically based fire models that openly take the spatial structure of the fuel have been constructed (Mell et al. 2007). These computational fluid dynamics models have established their ability to consider fuel structure when analyzing the impact of fuel treatment on fire propagation (Dupuy and Morvan 2005, Parsons 2007). However, physically based models are computationally heavy, leading to long simulation times and difficulty in simulating many scenarios. Complex fuel management and risk estimation planning demand refined fire behavior models from the stand to the landscape level to simulate fire behavior. At the same time, the need to explore numerous scenarios to make informed decisions poses an important limitation to fire modeling. In recent years, the cellular automata (CA) paradigm has raised attention in wildfire modeling, due to its modularity, its reduced computational costs, and its capacity to describe complex processes through simple rules (Alexandridis et al. 2011). The use of cellular automata models for prescribed fires has been recently explored in the literature by Linn et al. (2020), where the authors highlighted the potential use of CA models for prescribed fire simulation. Recently, the use of CA model to operationally support in prescribed burning has also been tested by Oliveira et al. (2023).

The model PROPAGATOR has been developed within the cellular automata paradigm (Trucchia et al. 2020). PROPAGATOR is a wildfire spread simulator developed in 2008 by the CIMA Research Foundation for the Italian Civil Protection Department. The main objective of the model is to quickly simulate the possible wildfire evolution, providing scenarios during the response phase to the ongoing emergency. Since its first release in 2008, the model has been implemented and tested in many national and European projects. In Italy, the model is currently available to the Italian Civil Protection Department in a user-friendly web application. Further, it is operationally available for the wildfire risk management system of the Liguria region (Lantero et al. 2022). The model has undergone continuous enhancements and functional expansions over time, largely driven by its dissemination and utilization in projects related to natural hazards, such as ANYWHERE (ANYWHERE Consortium 2019) and SAFERS (SAFERS Consortium 2020). Valuable feedback from stakeholders played a vital role in refining the model's performance and capabilities. However, PROPAGATOR remained mainly used as a rapid emergency response tool.

In this paper, we explored a possible use of PROPAGATOR for wildfire risk mitigation actions, in particular for prescribed fires. After many years of use of the model, this represents a necessary step in order to embrace all phases of the Wildfire Risk Management cycle.

Material and methods

In this section, we will present the PROPAGATOR model and the adopted case study as well as the methodology underlying the scenario-making process. We will start with its use as a wildfire simulation tool for emergencies and will then present a possible use of the model for prescribed fire planning. We selected a case study in the Liguria region (Italy) because of the operational use of the model by the regional wildfire risk management system. The region also has indications for prescribed fires in the regional regulation, although prescribed fires are not commonly used as a fuel management practice.

PROPAGATOR: from early warning to early action

PROPAGATOR is a quasi-empirical stochastic cellular automata model. It is described thoroughly in Trucchia et al. (2020), and a schematic description is also available in Supplementary Materials. The model discretizes the space into a square grid. Every grid cell is characterized by three possible states: burning, already burned and unburned. Each cell is also associated with some static (e.g., fuel type and elevation) and dynamic (e.g., wind and fuel moisture) conditions, given as inputs to the model.

The fire propagation dynamics is a contamination process between adjacent cells, with spread probability that depends on cell and boundary conditions. A burned cell cannot change its status and remains 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 the wind, topography, fuel type, and fuel moisture content of cells. The time evolution of the fire front is modeled by the rate of spread computed for each ignition process between two cells, depending as well on the wind, topography, fuel moisture, and fuel type. The time of ignition per each cell is consequently computed, and the simulation proceeds in time according to the next ignited cell. A large ensemble of stochastic simulations is computed with identical settings in terms of ignitions, weather conditions, and static inputs. Wind is stochastically perturbed in each simulation to consider local wind changes. 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 at different time steps, corresponding to the iso-contour lines of the fire probability maps at different threshold values (typical thresholds are 50%, 75% and 90%). From these isochrones, the simulated burned areas at different time steps and different probability thresholds are obtained. Further, mean and maximum values of the rate of spread and fire-line intensity for each cell are computed by means of empirical laws. In the last release of the model, a *fire spotting* module has been added. The module is based on a stochastic approach, keeping coherence with the stochastic paradigm used by PROPAGATOR. Further, in the last release, there is also the possibility of considering firefighting actions in the simulations. Four firefighting actions are available: *Canadair drops*, *helicopter drops*, *waterlines*, and *heavy actions*. The latter refers to the use of machines to cut the fuel or create strong barriers to wildfire propagation, so it acts in the model as a fuel type change during the simulation. The other implemented firefighting actions, which involve the use of water, increase the fuel moisture in the simulation. The simulation time required by PROPAGATOR model is usually less than 5 min (see Trucchia et al. 2020).

PROPAGATOR uses a simplified custom fuel 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 cannot propagate. *Non fire-prone forest* class corresponds to the low-flammable forests. The *Broadleaves* class models tall vegetation with medium flammability, while 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. Each fuel type is associated with different nominal fire spread probabilities and rate of spread values, each of them modified according to topography, wind, and fuel moisture conditions. The fuel parameters are reported in Table 1. These values were defined by means of continuous calibration throughout the years.

Albenga Fire: case study

We present the use of PROPAGATOR as an emergency response tool simulating the Albenga Fire, the main wildfire incident that occurred in the Liguria region in 2022. Albenga Fire was ignited on 6 August 2022 in the early afternoon in the municipality of Albenga, in the western part of the Liguria region (see Fig. 1). The wildfire was partially contained by the end of the day, 6 August. However, a strong wind reinforcement in the night between 6 and 7 made the wildfire uncontrolled. Most of the area burned on 7 August, with also a spotting activity on the neighborhood hill. The fire involved numerous fire brigades and aerial and ground vehicles. The operations lasted for 3 days. The total burned area obtained by satellite images with AUTOBAM algorithm (Pulvirenti et al. 2020) is 405.9 ha. The burned area is shown in Fig. 2.

We simulated the wildfire incident with PROPAGATOR. In the wildfire simulation, topography data has been obtained using the official Digital Elevation Model (DEM) of the Liguria region from the regional geographical data website (Regione Liguria, https://geoportal.regione.liguria.it/; see Fig. 2a). The native resolution of the DEM is around 5 m, which has been downgraded to 20 m to be compatible with the fuel map. The fuel map used (see Fig. 2b) has been obtained from the CORINE 2018 Land Cover and has been operationally used by the wildfire risk management system. To accurately represent the fire dynamics, we made some modifications to the operational fuel map: we incorporated the main roads into the map by designing them as non-vegetated fuel types; we also classified the burned area of the Cisano Fire that occurred in the same region in 2021 as non-vegetated. The weather data used was obtained from a weather station located about 5 km from the wildfire area (see Fig. 2c). Weather observations were available at 10-min resolution. We downgraded the resolution to 1 h as the resolution of the present simulation, computing mean values per each variable. Weather observations are then used to compute the fine fuel moisture content from the forest fire danger rating system RISICO (Fiorucci et al. 2008, Perello et al. 2022). The RISICO system provides fuel moisture computation in real-time through Italy, running with observed weather data from a selected weather station network. The system provides a proxy for fuel moisture modeled for grasslands. We used the fuel moisture computed on the weather station mentioned above. Due to the lack of an official ignition point location, we placed it in the area where the first reports of fire were received. The wildfire incident is simulated for the first 24 h, commencing from 12:00 UTC on 6 August 2022. We limited the simulation time to this duration since no firefighting actions were considered due to the

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

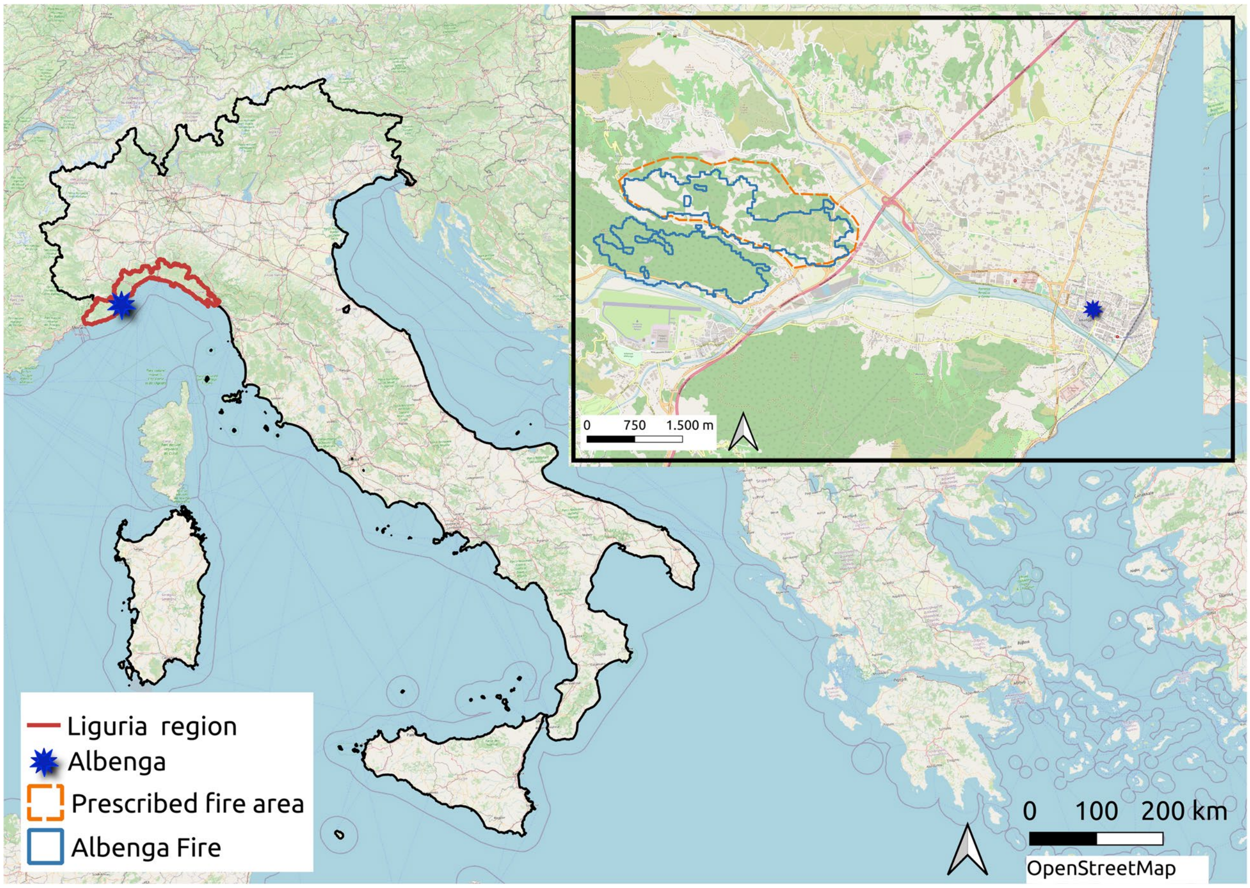

Fig. 1 Study area. In the main picture, Liguria region (in red) and Albenga municipality locations (the blue dot). In the overlay picture, the burned area of Albenga Fire (the light blue line) and the area considered for prescribed fires (the orange dashed line)

impossibility of having this information at present. The simulation was performed at a spatial resolution of 20 m, with a time resolution of 1 h. The simulation employed the spotting model adopted by PROPAGATOR.

Performance indicators To assess model performance, we adopted some indicators used by Trucchia et al. (2020) to compare simulation results with the real burned area. In particular, we used the Sorensens similarity index, the sensitivity, and the specificity. In order to compute the performance indicators, a computational cell is considered to be burned by PROPAGATOR when the computed probability of fire is greater than a threshold; we set the threshold to 75%. Based on this assumption, we compute the confusion matrix (Agresti 1990). The first entry of the confusion matrix, a, corresponds to the number of cells identified as burned in both observed and simulated fires; b corresponds to the number of cells coded as burned by PROPAGATOR but not in real fire; c corresponds to the number of cells that burned in the actual fire but coded as unburned by PROPAGATOR. Based on the confusion matrix entries, the performance indicators are computed. The Sorensen similarity index (S_c) (Sørensen et al. 1948) is a statistical index that computes the value of similarity between two samples, computed as follows:

$$S_c = \frac{2a}{2a + b + c} \tag{1}$$

The sensitivity (or *producer's accuracy*, Arca et al. 2019) is the ratio between cells correctly classified as burned by the simulation and the total number of burned cells in a real fire. The complementary measure is the *error of omission*, which is the probability of committing a false negative. The specificity (or *user's accuracy*, Montealegre et al. 2014) is the ratio between the number of cells correctly classified as unburned by the model and the total number of unburned cells from real fire. Its complementary measure is the *error of commission*, which is the probability of committing a false positive. All the performance indicators have values between 0 and 1, where 1

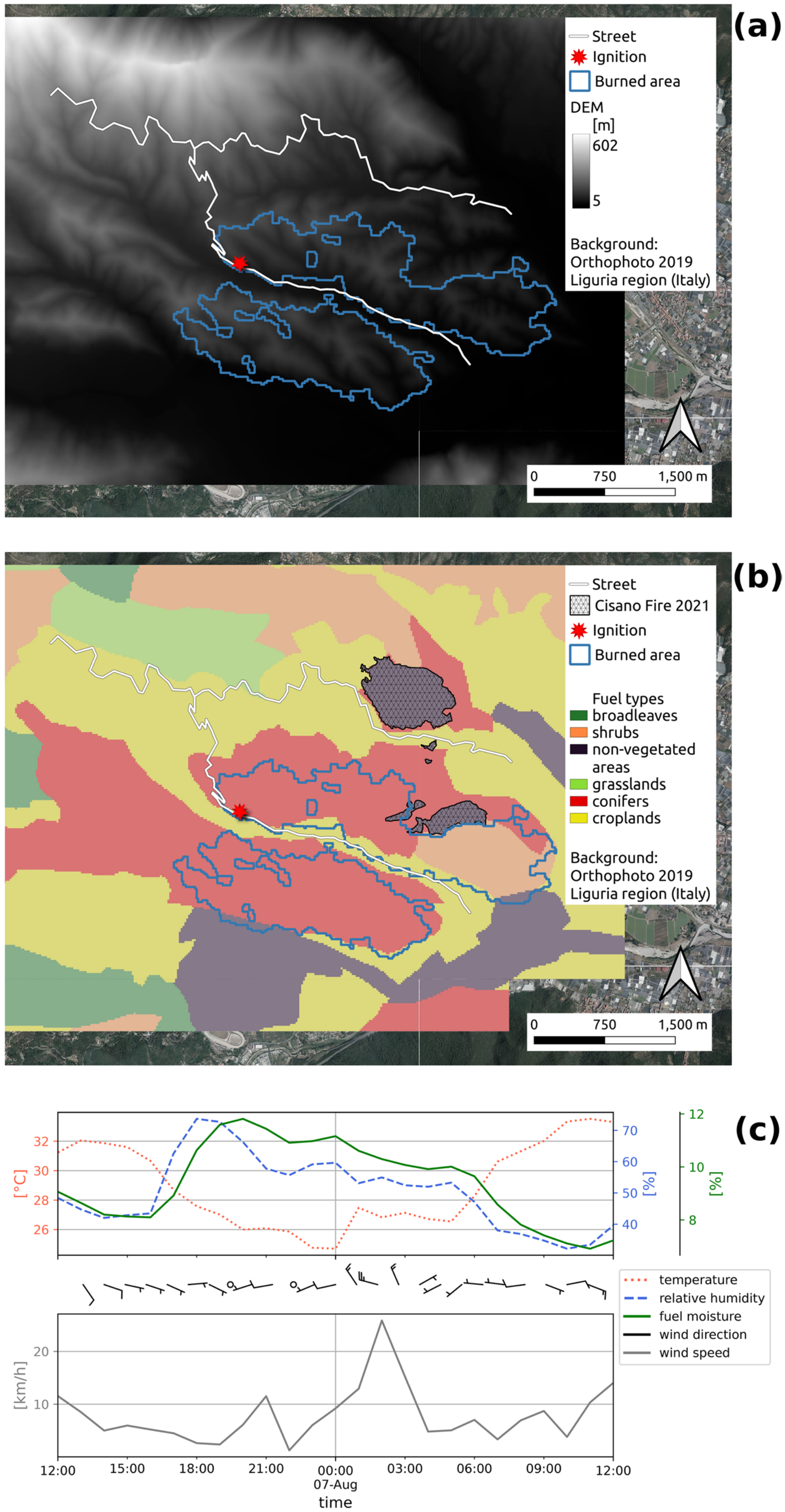

Fig. 2 Albenga Fire case study: **a** Digital Elevation Model map considered in the simulations, from official regional cartography; **b** fuel map considered for simulations, used for the regional implementation of PROPAGATOR model; **c** weather conditions (wind, relative humidity, temperature) during the first 24 h of the Albenga Fire. The fuel moisture reported in **c** is obtained by RISICO model based on the weather conditions reported

corresponds to a perfect agreement between observation and simulation, and 0 means no agreement.

`PROPAGATOR` for prescribed fires

We have identified a possible use of `PROPAGATOR` for prescribed fires, that is, the identification of optimal areas of intervention. The optimal areas are identified from a preselected set of areas, that can be input by the user. In our analysis, we selected these areas in accordance with regional regulation and expert opinion. The quantitative results given by the model can support the expert, helping to prepare the prescribed fire plan.

Area of interest and data retrieval

We used the area of the Albenga Fire as a study area in a hypothetical scenario where the fire did not occur. The Albenga Fire provided us with the opportunity to use the same study area, and its weather and ignition conditions as described in the following sections. All the fuel conditions are considered as just before the Albenga Fire in the following analysis. The study area corresponds to the hill where the Albenga Fire started, which is shown in Fig. 1. We selected the Albenga municipality area as it presents a low slope, then prescribed fire can more easily be carried out. The Albenga area has been used to present the methodology, which applies to any other area of interest. We used the official Digital Elevation Model (DEM) of the Liguria region as topographic input. We downgraded the original map resolution of 5 m to a resolution of 20 m to perform the simulations. We also created a detailed vegetation map of the study area for a total of 1 142 hectares (it is presented in Fig. 3a). We carried out the classification procedure through independent photo-interpretation of the following: the regional digital color orthophotos of Liguria from the year 2019; NDVI maps based on Sentinel-2 images acquired before Albenga Fire; high-resolution RGB orthomosaics derived from Unmanned Aerial Vehicle (UAV) survey of the study area in September 2022. The latter, being post-fire imagery, was considered only for the unburned vegetation. We classified vegetation into four main plant formations, also considering their use as fuel map in `PROPAGATOR` simulations: herbaceous vegetation, broadleaves forests, shrubs, and coniferous forests. The area presents a composition of mixed broadleaves forests (26.4%), mostly represented by downy oaks (*Quercus pubescens* Willd.), European hop-hornbeans (*Ostrya carpinifolia* Scop.), and common ashes (*Fraxinus excelsior* L.); shrubs (24%); herbaceous vegetation (17.4%); and coniferous forests (15.1%)—especially maritime pines (*Pinus pinaster* Ait.). Furthermore, we used the map to identify the plant formations most affected by the Albenga Fire which are broadleaves forests (41% of the total burned area) and shrubs (34%). Coniferous forests were less affected in terms of quantity (22%), but their damage severity is the highest, as well as for shrubs. We then rasterized the map into 20-m map and used in the following simulations.

Prescribed fires plans and Liguria regulation

In this part, we discuss the protocol to be followed for the prescribed fire as required by the Liguria regulations. In Liguria region, prescribed fire requirements are specified in the regional wildfire risk management ordinance[1]. As the first step in defining prescribed fire plans, specific objectives to be achieved by the prescribed fire are usually identified. In Liguria, the regulation identifies prescribed fire as a possible wildfire risk mitigation action. After, prescriptions on weather conditions have to be checked to identify proper time windows in which fire could be managed properly. In Liguria region, prescribed fires can be carried out when air humidity is in the range $30-50\%$, air temperature is in the range $0-10\,°C$, and wind speed is in the range $3-10\,km/h$. Further, fuel moisture has to be in the range $7-20\%$, although it is not specified to which type of fuel it refers. To adopt a conservative estimate, this constraint can be applied to fine fuel moisture content. The Liguria regional regulation identifies ignition techniques to be adopted, with some constraints of slope conditions concerning the technique used. In particular, the *heading fire* ignition can be applied with a slope of less than 20%.

Optimization of prescribed fire location

We propose a methodology to find the optimal areas for prescribed fires from a set of possible areas identified at the first stage from expert's opinion or user's choice. The objective is to identify which areas could, if subject to prescribed fires, maximize the effect of slowing wildfire propagation, thus enhancing wildfire risk mitigation. Also, the optimal areas have to be identified to reduce the overall area extent of prescribed fires to reduce costs. To simulate wildfire propagation, we adopted `PROPAGATOR` model.

First, we identify in the study area six possible areas where prescribed fires can be done based on regional regulations and expert opinions. Then, we consider the effect of prescribed fires performed in the areas by changing their fuel types based on different regrowth scenarios. We then identify possible ignitions and weather conditions for wildfire propagation. Finally,

[1] Regione Liguria, "Piano Regionale di Prevenzione, Previsione e Lotta Attiva contro gli Incendi Boschivi", 2022, available at the link: https://www.regione.liguria.it/component/publiccompetitions/document/49269:piano-regionale-incendi-boschivi-rev-2022.html?Itemid=11918.

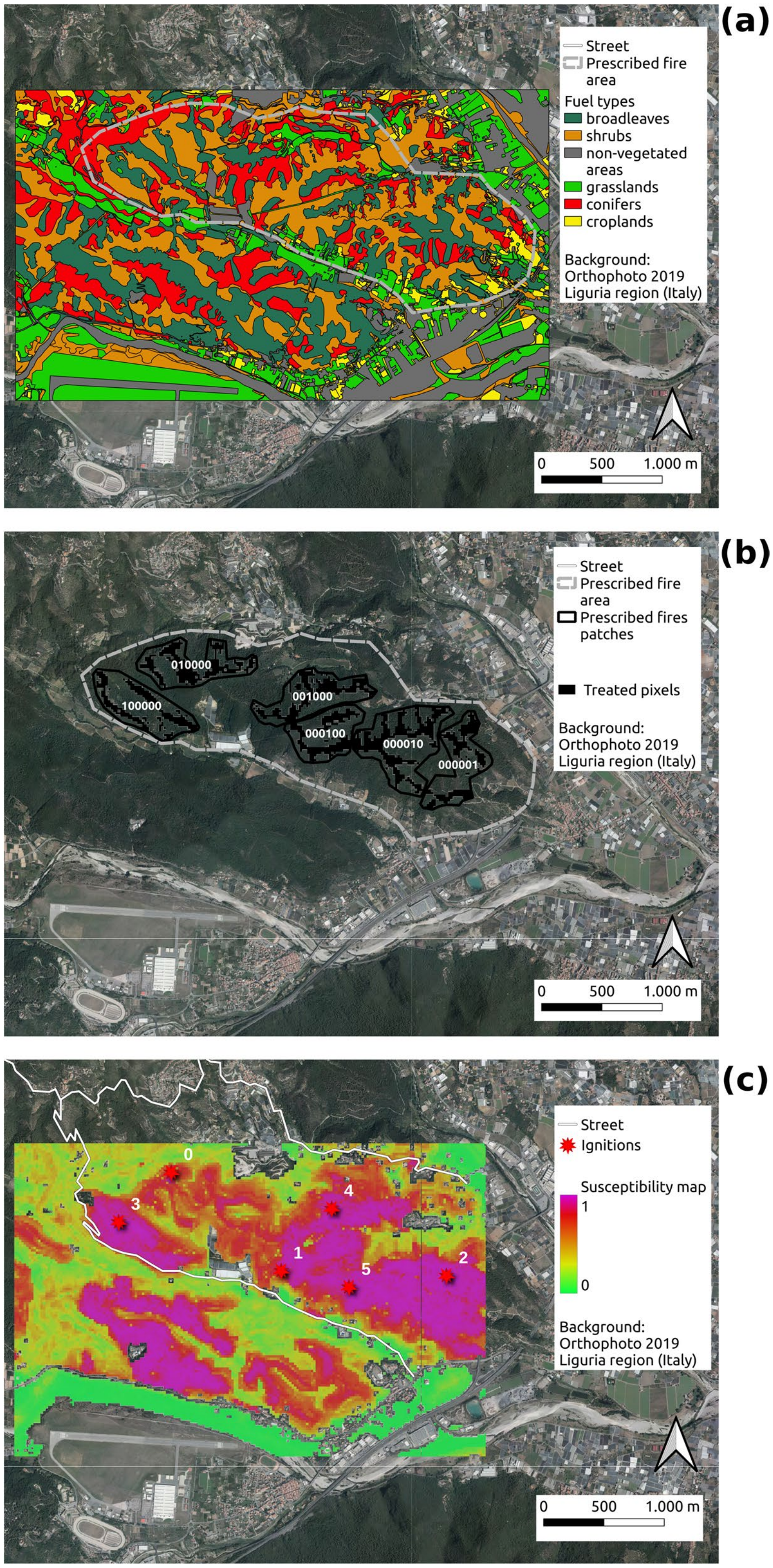

Fig. 3 In **a**, the detailed fuel map used for the prescribed fire simulations. In **b**, the six possible patches identified for prescribed fires. In **c**, the susceptibility map of the area obtained with machine learning techniques, and the six ignition points considered for the multiple ignitions case analysis

we simulate the wildfire propagation after the prescribed fires in all the possible combinations of the chosen areas and in all the scenarios, to assess the effect of prescribed fires in slowing wildfire propagation. As a result, the optimal areas for prescribed fires can be identified according to a specific cost-benefit function introduced below. The proposed methodology employs a Monte Carlo approach, performing an ensemble of simulations in various scenarios. All the simulations are computed for a fixed time of 48 h and without spotting or firefighting actions. In the following sections, we detailed the presented methodology.

Areas of prescribed fires The first step of the methdology is the definition of possible areas where prescribed fires can be done. Let call S the set of possible areas for prescribed fires. To identify these areas, from now on named *patches*, we used the regional slope constraint of 20% to perform *heading fire* ignition technique, as the most restrictive case. Further, we wanted to reduce shrubs in the area. As mentioned before, shrubs were one of the fuel types most affected by the Albenga Fire. Combining these two constraints, we identified six possible patches (see Fig. 3b) where quite large areas of shrubs and slopes less than 20% are present. Also, we identified patches with the presence of ridges that can help in performing prescribed fire. We have then to identify all the possible configurations of these patches for prescribed fires. With the term *configuration*, we refer to a specific choice of patches (one or more) where prescribed fire is performed. In fact, each of these patches can be either subject to prescribed fire or not. This leads to the *power set* of the initial areas set, $\mathcal{C} := \mathcal{P}(\mathcal{S})$. In doing so, we assess whether the implementation of prescribed fires across multiple patches could yield increased effectiveness. Let us call c an element of this set, i.e., a specific configuration. Considering the six patches defined in the present study, we have then $2^6 = 64$ possible configurations, ranging from none of the patches to all six patches involved in prescribed fires. For the sake of notation, we call each of the initial six prescribed fire patches with a sequence of six binary digits 0 or 1, and all the possible configurations as a digitwise sum of these initial configurations: the configuration $c = 001000$ refers to a specific patch; the configuration $c = 100100$ corresponds to the combination of patches 100000 and 000100; the configurations $c = 000000$ and $c = 111111$ correspond respectively to *no prescribed fires* (none of the patches are involved) and *all prescribed fires* (all the patches are involved) scenarios.

Regrowth scenarios We want to consider the condition of each configuration after the prescribed fire to simulate the effect on wildfire propagation. We mimic the effect of prescribed fires by changing fuel types. We modify the fuel from shrubs to different fuel types according to the different regrowth scenarios. As mentioned in the previous paragraph, we focus on modifying shrubs as one of the fuel types most affected by the Albenga Fire. The process of plant regrowth following the prescribed fire is widely studied in the literature (Quevedo et al. 2007, Catalanotti 2009, Potts et al. 2010, Fernández et al. 2013, Teshome and Glatzel 2018). The regrowth process varies depending on the type of vegetation, the intensity of the fire, and other environmental factors. We did not consider collecting field data on plant regrowth after the Albenga Fire because of the difference in plant regrowth conditions after a real fire with respect to prescribed fires. However, in the absence of field data, some hypotheses can be formulated in the model as a proxy for the plant regrowth process. In Matsypura et al. (2018), for example, the change in fuel load is considered in simulations without taking into consideration different fuel types. Given the complex nature of the regrowth process, we decided to assume a stochastic regrowth process by assigning a regrowth probability for each fuel type. We use a stochastic method to consider different possible regrowth processes. Let us call f_i the probability of regrowth for fuel type i in a single cell so that $\sum_i f_i = 1$, considering all fuel types. The regrowth scenario $\mathcal{F}$ can then be identified as the collection of these probabilities. As mentioned before, the values f_i could depend on different environmental conditions and prescribed fire conditions. Further, they can change over time. For the sake of simplicity, we limited the study to constant values of regrowth probabilities for two different regrowth scenarios:

- *scenario* $\mathcal{F}^1$: probability 100% to be non-vegetated areas, 0% otherwise, i.e., the prescribed fire prevents regrowth;
- *scenario* $\mathcal{F}^2$: probability 10% of shrubs, 50% of non-vegetated areas, 40% for grassland; 0% otherwise.

These two scenarios can be recognized as two post-prescribed fire scenarios at two different times: the former immediately after treatment, the latter at a later stage when shrubs are regrowing together with herbaceous species. This approach is similar to the one adopted in Cassagne et al. (2011). Let F_j^k, with $k \in \{1, 2\}$ and $j \in \{1, 2, ..., N_j\}$, be a realization of the regrowth scenario $\mathcal{F}^k$ and let N_j be the number of its realizations. We made ten independent realizations for each regrowth scenario, using a Monte Carlo approach.

Ignitions and weather conditions Let us define a set of ignition points $\mathcal{I}$ and let $\mathcal{W}$ be a set of weather conditions—we identify with i and w respectively a specific ignition point and weather condition. Expert-based knowledge and historical data can be used to identify the location of ignition points properly. Similarly, climatic data or weather conditions during past wildfire events in the area can be used to define weather conditions. In the present study, we split the analysis into two different cases. In the first *single ignition case*, we used the same ignition point of the Albenga Fire, perturbing weather conditions registered during the event of 0%, +50% and −50% respectively. In the second *multiple ignitions case*, we tested a random selection of ignition points and historical moisture conditions from past events. For the multiple ignitions case, we used the wildfire susceptibility map produced by CIMA Research Foundation for the Liguria region (Tonini et al. 2020) to randomly select six ignition points where fire susceptibility is over the 75^{th} percentile (see Fig. 3c). We impose a minimum distance of 500 m among them. Regarding the weather conditions, we focused on different fuel moisture conditions obtained by `RISICO` model in the areas of the wildfire incidents that occurred in Italy from 2007 to 2021. We identified three mean fuel moisture conditions: 8% (burned areas greater than 500 ha), 10% (burned areas between 50 ha and 500 ha), and 12% (burned areas smaller than 50 ha). We then obtained three weather scenarios for each case.

Objective function The objective of the methodology is to identify in which areas prescribed fires should be performed in order to both maximizes wildfire risk mitigation and minimizes the costs, i.e., which is the optimal areas configuration. We can identify an objective function G of the areas configuration, which encloses both effects. This function will depend on fuel regrowth, ignitions, and weather scenarios considered within the simulations. To find the optimal areas configuration, we should minimize this function:

$$c^*(\mathcal{F},\mathcal{I},\mathcal{W}) = \underset{c\in\mathcal{C}}{\arg\min} G(c,\mathcal{F},\mathcal{I},\mathcal{W}) \tag{2}$$

The optimal configuration c^* will be dependent on fuel regrowth, ignitions, and weather scenarios.

We used the simulated burned area as a proxy for considering the effect of performing prescribed fires in some areas on wildfire risk mitigation. Let $A(t; c, F_j, i, w)$ be the evolution of the simulated burned area in time, given the prescribed fire performed in the areas configuration c, a regrowth realization F_j from the regrowth scenario $\mathcal{F}$, ignition point i, and weather conditions w. $A(\cdot)$ is a non-negative increasing function of time. Since `PROPAGATOR` produces as output of each time step a scalar map corresponding to the fire arrival probabilities, we used the area enclosed by the isochrones of the 50% probability threshold to compute the burned area of a single simulation after a given time. We then computed the mean value of the burned area for each time, with respect to the different regrowth realizations, ignition points, and weather conditions of the considered scenarios:

$$\hat{A}(t; c, \mathcal{F}, \mathcal{I}, \mathcal{W}) = \frac{1}{|\mathcal{I}|\,|\mathcal{W}|\,N_j} \sum_{i\in\mathcal{I}} \sum_{w\in\mathcal{W}} \sum_{F_j} A(t; c, F_j, i, w) \tag{3}$$

where $|\cdot|$ is referred to the cardinality of the set and N_j is the selected number of regrowth realizations. To avoid the time dependency, we performed the integral of this function up to the final simulation time T:

$$\mathcal{A}(c; \mathcal{F}, \mathcal{I}, \mathcal{W}) = \int_0^T \hat{A}(t; c, \mathcal{F}, \mathcal{I}, \mathcal{W})\, dt \tag{4}$$

We chose the integral of the function to also take into consideration the shape of the function, i.e., the wildfire evolution. Finally, we normalized this value for the value obtained in the *no prescribed fires* configuration $c = 000000$:

$$\bar{\mathcal{A}}(c; \mathcal{F}, \mathcal{I}, \mathcal{W}) = \frac{\mathcal{A}(c; \mathcal{F}, \mathcal{I}, \mathcal{W})}{\mathcal{A}(c = 000000; \mathcal{F}, \mathcal{I}, \mathcal{W})} \tag{5}$$

To maximize the wildfire risk mitigation, we want to minimize function $\bar{\mathcal{A}}(\cdot)$, i.e., the simulated burned area from a wildfire that occurs after performing prescribed fires.

Then, we should consider the costs of prescribed burning. To simplify the analysis, we assumed a constant cost per hectare, which led to decrease the total area involved in prescribed fires $\mathcal{T}(c)$. We can then normalize this value according to the *all prescribed fires* configuration $c = 111111$ in order to have values between 0 (none of the patches are involved) and 1 (all the patches are involved):

$$\bar{\mathcal{T}}(c) = \frac{\mathcal{T}(c)}{\mathcal{T}(c = 111111)} \tag{6}$$

Due to the normalization of both functions with respect to the *no prescribed fires* or *all prescribed fires* scenarios, respectively, we can then minimize the sum of the two functions obtaining the optimal configuration (Miettinen and Mäkelä 2002). We can assign a relative weight a, b in (0, 1] to each function according to the importance assigned to each:

$$G(c; \mathcal{F}, \mathcal{I}, \mathcal{W}) = a\,\bar{\mathcal{A}}(c; \mathcal{F}, \mathcal{I}, \mathcal{W}) + b\,\bar{\mathcal{T}}(c) \qquad a, b \in (0, 1] \tag{7}$$

In the present study, we put $a = b = 1$.

Results

This section presents both the simulation results for the Albenga Fire and prescribed burning scenarios.

Albenga Fire simulation

In Fig. 4, we reported (from top to bottom) the probability map, with isochrones of 75% probability, mean rate of spread, and fire-line intensity maps. The probability, rate of spread and fire-line intensity maps are produced per each cell affected by the simulations, regardless of the probability value. This is reflected in a discrepancy between the isochrones, which enclose the areas with probability beyond a certain threshold, and the aforementioned maps. The final burned area, corresponding to a 75% probability threshold, is estimated to be 424.91 ha. The simulation yielded a mean intensity value of 3 458.95 kW/m, with a maximum value of 56 210 kW/m. The mean rate of spread is determined to be 256.7 m/h, with a maximum value of 3 789 m/h. Different patterns of high rate of spread and fire-line intensity values can be identified from the maps obtained. In the simulation, the fire remains confined in the hill where it was ignited for the first 14 h; after, the simulation identifies a spotting on the neighboring hill. We obtained the following performance indicator values: Sorensen's coefficient of 0.581, sensitivity of 0.635, and specificity of 0.536. Let us recall that the indicators are computed considering the 75% probability threshold. The computational time required for the simulation was about 2 min.

Optimization of prescribed fire location

The optimal configurations obtained for the analyzed cases are reported in Fig. 5. The results for the single and multiple ignitions cases are reported in Figs. 6 and 7, respectively. In these figures, we reported only the regrowth scenario $\mathcal{F}^2$ since the regrowth scenario $\mathcal{F}^1$ shows similar results. In the first plot (counted from top to bottom) of each figure, the mean burned area function obtained from Eq. 3 for the 64 areas configurations is reported. The reported curves $\hat{A}(t; c, \mathcal{F}, \mathcal{I}, \mathcal{W})$ can also be used to identify the effect of prescribed fires in slowing the fire propagation process since they describe fire evolution. In particular, the shape of each curve obtained for each area configuration can be compared with the *no prescribed fires* configuration $c = 000000$ (black line), representing the condition of a wildfire spreading without any action performed. In the second plot, each point represents a different area configuration, and its coordinates correspond to the normalized integral of the burned area ($\bar{\mathcal{A}}$ in the x–axis) and the normalized treated area ($\bar{\mathcal{T}}$ in the y–axis). In the third plot, each point is associated with a different area configuration while the y–axis corresponds to the objective function G. The values of the optimal configurations for each case are reported in Table 2.

For the single ignition case, the optimal configuration is $c^* = 100000$ for both the regrowth scenarios, with $\mathcal{A}(c^*; \mathcal{F}^1, \mathcal{I}, \mathcal{W}) = 0.0$ in the first regrowth scenario and $\mathcal{A}(c^*; \mathcal{F}^2, \mathcal{I}, \mathcal{W}) = 11.53$ in the second scenario. The null burned area for the regrowth scenario $\mathcal{F}^1$ is mainly due to the location of the ignition point in the patch $c = 100000$ and the fuel type changed to non-vegetated; in this condition, the wildfire simulation halts in its early stages due to the absence of fuel for propagation. In the multiple ignitions case, the optimal configuration depends on the regrowth scenario. In $\mathcal{F}^1$, we have $c^* = 001000$ and $\mathcal{A}(c^*; \mathcal{F}^1, \mathcal{I}, \mathcal{W}) = 185.94$. In the second scenario $\mathcal{F}^2$, we have $c^* = 001100$ and $\mathcal{A}(c^*; \mathcal{F}^2, \mathcal{I}, \mathcal{W}) = 113.61$.

The burned area curves $\hat{A}(t; c, \mathcal{F}, \mathcal{I}, \mathcal{W})$ show very different behavior in the single ignition and multiple ignitions cases (let us compare the first plot of Figs. 6 and 7). In the single ignition case, the curves are grouped depending on which treated patch is included first in the configuration, counting the patches from West to East in Fig. 3b. In particular, the configurations where patch 100000 is included are characterized by zero or few burned areas (green lines in Fig. 6). The configurations where 010000 is the first patch included show the effect in fire propagation later (blue lines in Fig. 6), followed by the configurations where patch 001000 is the first treated (red lines in Fig. 6). The other configurations show a small impact on slowing fire propagation. The black line corresponds to the *no prescribed fires* scenario ($c = 000000$), while the yellow line corresponds to the *all prescribed fires* scenario ($c = 111111$). The color palette remains consistent across all the plots. The result pattern presented before is absent in the multiple ignitions case, showing a more complex behavior where no simple patterns are highlighted.

Discussion

The subsequent section will delve into a comprehensive discussion of these results, offering a detailed examination and interpretation of the findings.

The `PROPAGATOR` model was designed specifically as a tool to be used during the emergency response. The limited amount of data required by the model and its rapidity of simulation make it suitable for this purpose. Thus, the user can explore numerous scenarios quickly, making informed decisions. We presented the Albenga Fire case study as an example of using the model for emergency response. All the data used in terms of topography, fuel map, and weather conditions are potentially available for the operational use of the model. We used weather conditions retrieved from real observations, while weather forecasts can be used to provide scenarios of an upcoming fire evolution. The model efficiently provided possible fire scenarios in few minutes by providing a preliminary hypothesis on the ignition location. The model provided an indication of the potential burned area of the same order of magnitude as the real one.

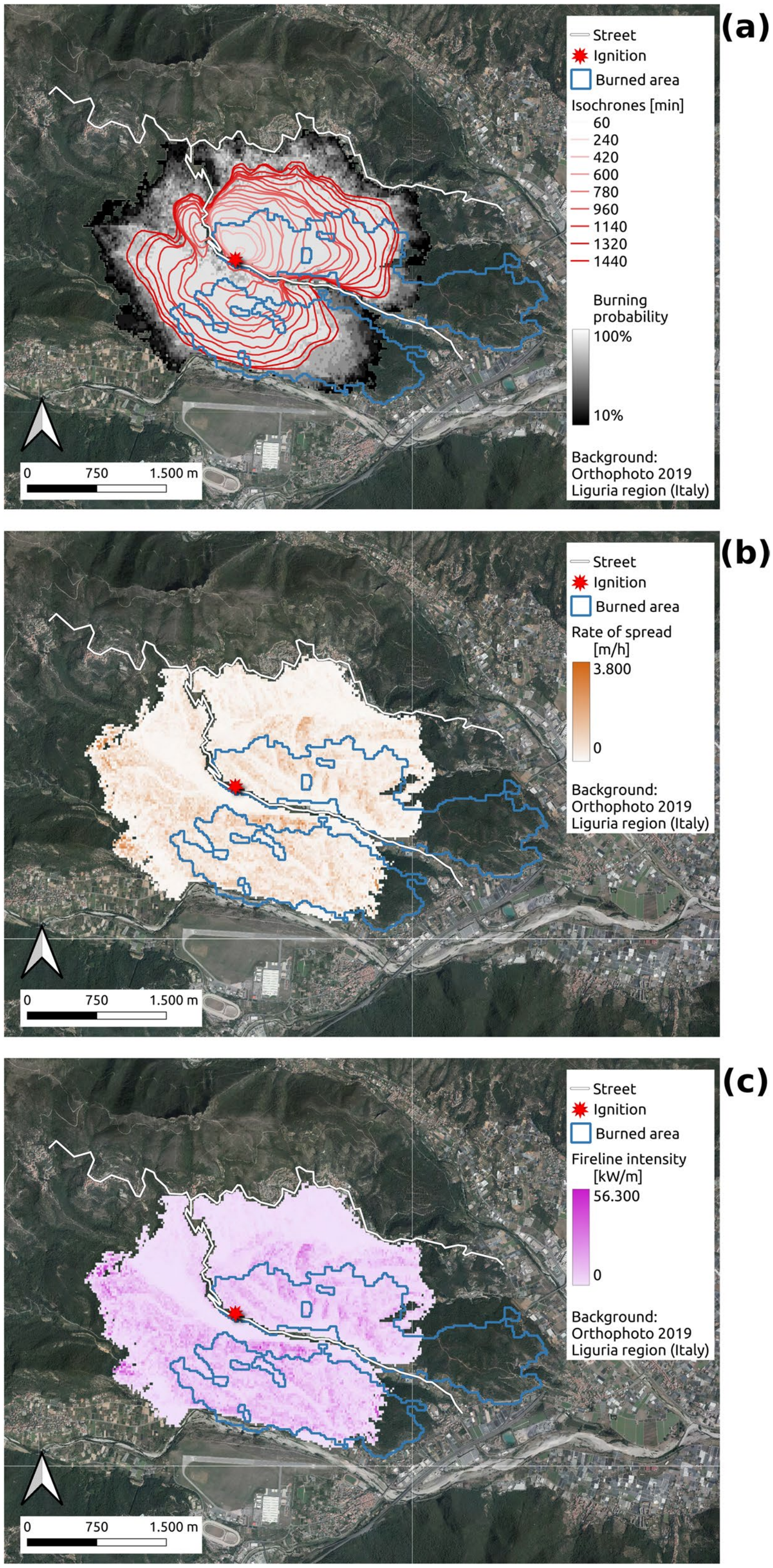

Fig. 4 Results from Albenga Fire simulation: **a** probability map and isochrones related to the 75% probability threshold; **b** mean rate of spread; **c** mean fire-line intensity

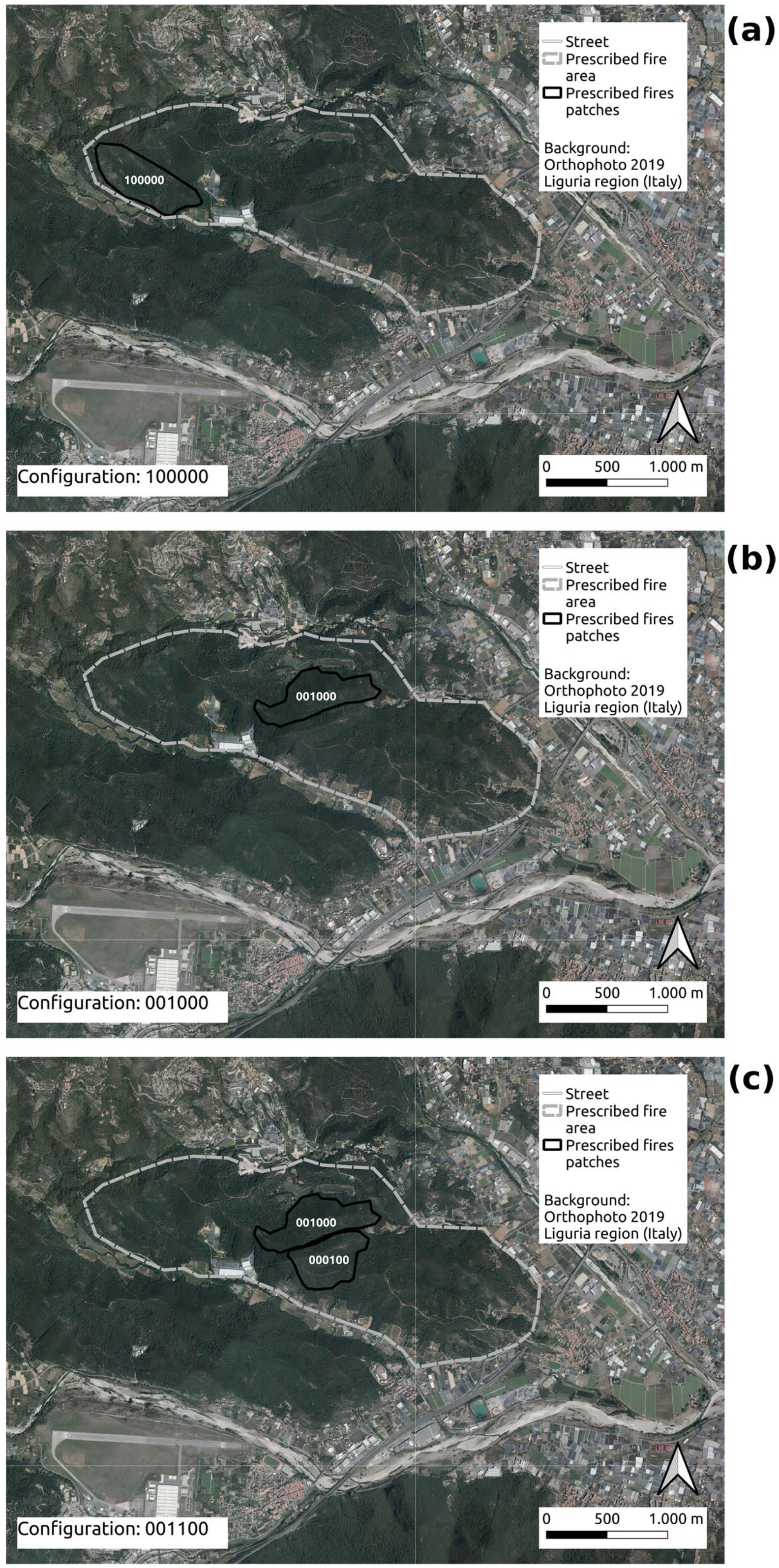

Fig. 5 The optimal area configurations obtained for the optimization of location problem: **a** optimal configuration $c = 100000$ obtained for the single ignition case, in both regrowth scenarios considered; **b** optimal configuration $c = 001000$ obtained for the multiple ignitions case and regrowth scenario $\mathcal{F}^1$; **c** optimal configuration $c = 001100$ obtained for the multiple ignitions case and regrowth scenario $\mathcal{F}^2$

Table 2 Optimal areas configuration for single ignition and multiple ignitions cases, for the two regrowth scenarios $\mathcal{F}^1$ and $\mathcal{F}^2$. For each optimal configuration, there are also reported: values of the integral of the burned area function $\mathcal{A}$ and its normalized value $\bar{\mathcal{A}}$ with respect to the *no prescribed fires* configuration $c = 000000$; values of treatment area $\mathcal{T}$ and the normalized value $\bar{\mathcal{T}}$ with respect to the *all prescribed fires* configuration $c = 111111$; values of the objective function G

	Regrowth scenario	Optimal configuration	$\mathcal{A}$	$\bar{\mathcal{A}}$	$\mathcal{T}$	$\bar{\mathcal{T}}$	G
Single ignition	$\mathcal{F}_1$	100000	0.0	0.0	9.04	0.15	0.15
	$\mathcal{F}_2$	100000	11.53	0.01	9.04	0.15	0.16
Multiple ignitions	$\mathcal{F}_1$	001000	185.94	0.48	10.28	0.17	0.65
	$\mathcal{F}_2$	001100	113.61	0.28	18.0	0.3	0.58

This is an essential information for firefighters, allowing them to modulate their response based on the potential extent of the fire. Further, the model identified a spotting phenomenon in the neighboring hill. This was due to the presence of conifers in the area for which the spotting model was triggered. Highlighting this potential fire behavior is important to take preventive measures and avoid enlarging the area where operations must be performed. The performance indicators obtained in the present study show smaller values as compared with respect to the other test cases presented in Trucchia et al. (2020). There are several reasons for this. The quantity and entity of firefighting operations during the Albenga Fire make it difficult to simulate it without including them. The effect of firefighting operations on simulation results will be taken into consideration in future studies. Another source of uncertainty is associated with the location of the ignition point, for which a hypothesis has been made.

Furthermore, we used weather conditions registered 5 km from the fire location. Given the large burned area involved, the local topography and fire-induced convection could have affected the local wind conditions (Liu et al. 2021). Considering local wind conditions could improve model performance.

In the last release of PROPAGATOR, the rate of spread and fire-line intensity maps have been introduced as additional output from simulations. These maps can be used to assess potential fire behavior during its spreading, highlighting areas where firefighting actions are more effective. Considering the maps obtained from the Albenga Fire, we can observe different patterns of areas characterized by high fire-line intensity due to topography conditions and the presence of conifers. Firefighting actions can eventually be placed in predicted locations where fire-line intensity is lower to make them more efficient.

In the present study, we then analyzed the possible use of PROPAGATOR for the optimization of prescribed fire location. The objective was to identify areas where the effect of slowing wildfire propagation could be maximized, thus enhancing wildfire risk mitigation. Also, another objective is to reduce the area of treatment to contain costs. We made assumptions regarding regrowth scenarios, ignitions, and weather conditions to demonstrate the methodology's use. However, expert opinions can be incorporated in to any step of the process.

We split the analysis into two main cases. In the case of single ignition, we observed a strong dependence of the optimal configuration on the ignition point location and weather scenarios. We observed different wildfire behaviors among various configurations based on the included areas. Configurations that included patch 100000 exhibited significant reductions in wildfire propagation from the initial stages due to their proximity to the ignition point. The wildfire simulation then is influenced from the beginning by the effect of prescribed fires, i.e., the change in fuel type. Other configurations displayed delayed effects on wildfire propagation. In the single ignition case, weather conditions from the Albenga Fire are considered. Fire spread is then expected to move from West to East as for the fire incident. Consequently, the

(See figure on next page.)

Fig. 6 Results of the optimization of location problem, for the single ignition case and regrowth scenario $\mathcal{F}^2$. In the first plot (from top to bottom), the mean burned area curves $\hat{A}(t; c, \mathcal{F}^2, \mathcal{I}, \mathcal{W})$ for each areas configuration. In the second row, each point is associated with a different configuration, with *x*-coordinate corresponding to normalized integral of burned area curve $\bar{\mathcal{A}}$ and *y*-coordinate corresponding to the normalized treated area $\bar{\mathcal{T}}$. In the third plot, each point is associated to a different configuration, with the *y*-coordinate corresponding to the objective function value *G*. The color palette has been chosen according to which patch has been considered first in the configuration (counting from West to East): green palette for configurations in which patch 100000 has been considered first; blue palette for patch 010000 as first; red palette for patch 001000; magenta palette for patch 000100; purple palette for patch 000010; orange palette for patch 000001. Black color corresponds to *no prescribed fires* configuration 000000; yellow color corresponds to the *all prescribed fires* configuration 111111

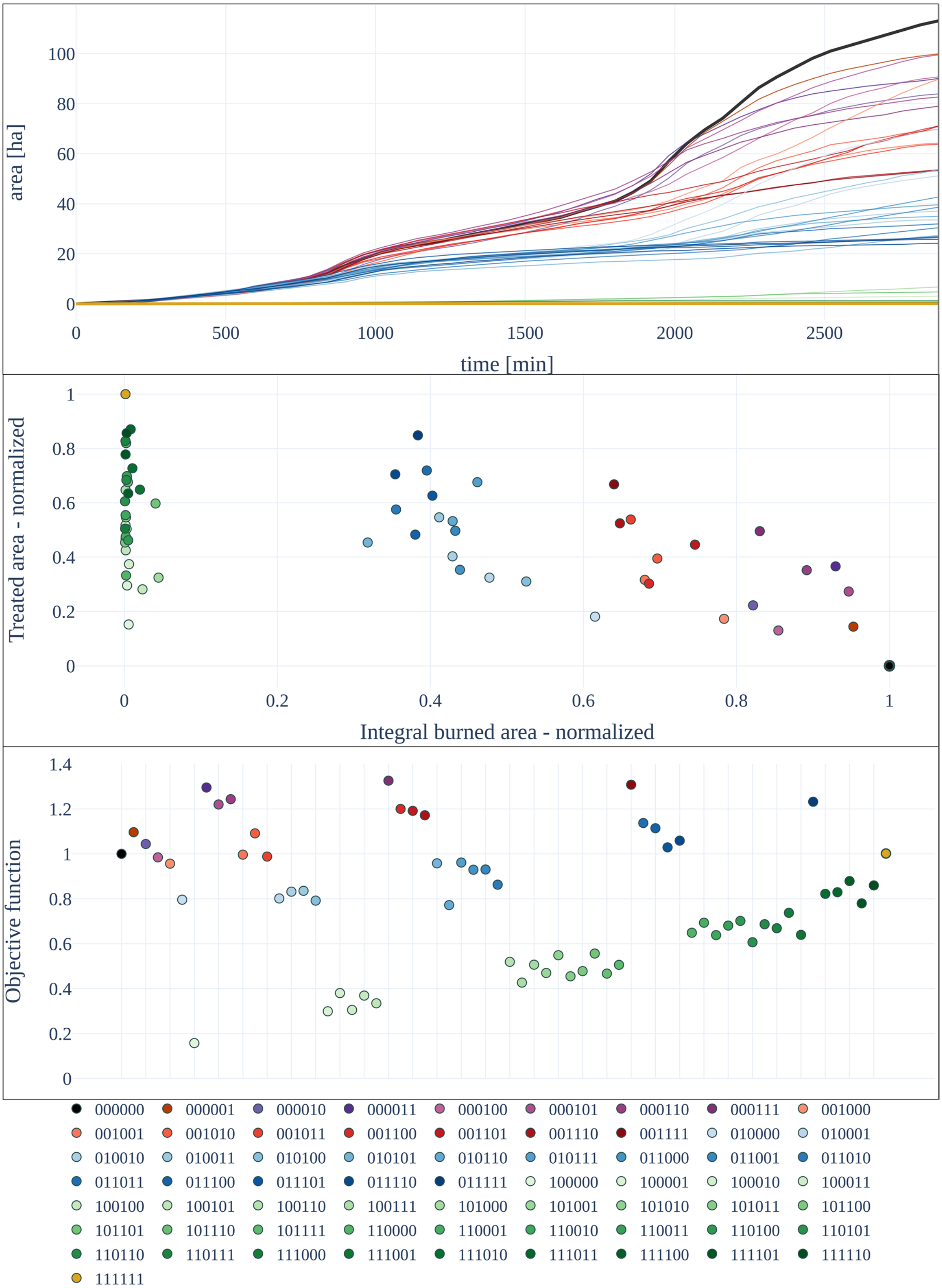

Fig. 6 (See legend on previous page.)

effect in slowing fire propagation is delayed accordingly to the distance of the first patch considered in the configuration from the ignition point moving toward East. The optimal configuration was found among those including the 100000 patch, particularly the configuration with the smallest treated area (i.e., the 100000 configuration) because of the smallest associated cost with respect to the other possible configurations. The same behavior is observed with both regrowth scenarios, leading to the same optimal configuration.

We then adopted a distribution of points in the multiple ignitions case to avoid a strong dependence on the ignition point. At this stage, the expert opinion can provide valuable information on possible ignition areas, given the area's wildfire history. In this study, we used the susceptibility map to locate ignition points. The multiple ignitions case emphasized the role of certain patches in limiting the fire propagation, regardless of the ignition point location. In particular, the optimal configurations for both regrowth scenarios included the patches 001000 and 000100. These patches divide the domain considered for prescribed fires into two smaller domains, limiting then fire propagation. The optimal configuration associated with regrowth scenario $\mathcal{F}^1$ consists of less treated area (10.28 hectares) than the one related to scenario $\mathcal{F}^2$ (18 hectares), including only one patch. In the former, the effect of prescribed fires in wildfire propagation is stronger with respect to the latter due to the change of shrubs to non-vegetated areas. In fact, `PROPAGATOR` does not allow wildfire propagation in pixels whose fuel is set to "non vegetated". Consequently, to obtain the same effects in reducing wildfire propagation, the total area of prescribed fires should be increased in regrowth scenario $\mathcal{F}^2$ with respect to $\mathcal{F}^1$.

The proposed analysis presents some similarities with the work of Matsypura et al. (2018). However, in the mentioned work, the authors use the graph theory, and the objective was to identify the right node to treat to disconnect the graph and slow fire propagation. We adopted the idea of identifying critical areas in a different modeling framework, considering directly the fire propagation simulations in different ignitions and weather scenarios.

It should be noted that defining regrowth scenarios remains a critical aspect of the methodology. Ongoing research aims to establish more specific regrowth scenarios based on experimental results, considering different prescribed fire intensities or fuel types. In Cassagne et al. (2011), authors used data from past prescribed fires to consider different regrowth scenarios in different time frames after treatment. However, the authors used these data to simulate the effect of a single prescribed fire in reducing fire risk. To the best of our knowledge, these scenarios have not been used to identify the optimal prescribed fire location. The multiple ignitions case highlights the impact of these scenarios on post-prescribed fire effects and their influence on the optimal configuration. This aspect will be further explored in future studies. Likewise, it would be beneficial to consider more detailed objective functions that incorporate not only the burned area but also fire behavior such as fire-line intensity. Prescribed fires aim to reduce the intensity of future wildfires, facilitate management efforts, and minimize negative effects on ecosystems. Additionally, incorporating more detailed cost-of-treatment information can be advantageous. These aspects will be taken into account for future studies.

Another critical aspect is the computational costs of simulations. As already mentioned, `PROPAGATOR` model offers a limited computation cost thanks to the Cellular Automata framework adopted. However, the number of simulations performed considering all areas configurations increase exponentially with the number of patches involved. Future study will assess the feasibility of increasing the patches number, and if some strategies could be adopted to reduce the computational cost.

The methodology proposed to find the optimal prescribed fire locations allows for the incorporation of expert opinions or prescribed fire regulations in each step of the process. This was demonstrated, for instance, in the selection of the six possible patches. The same could be done in defining ignition points and weather scenarios. We chose this approach so that the methodology can serve as an additional tool for the users, complementing their expertise. Starting from some choices made by the expert, the methodology indeed provides

(See figure on next page.)

Fig. 7 Results of the optimization of location problem, for the multiple ignitions case and regrowth scenario $\mathcal{F}^2$. In the first plot (from top to bottom) the mean burned area curves $\hat{A}(t; c, \mathcal{F}^2, \mathcal{I}, \mathcal{W})$ for each areas configuration. In the second row, each point is associated with a different configuration, with *x*-coordinate corresponding to normalized integral of burned area curve $\bar{\mathcal{A}}$ and *y*-coordinate corresponding to the normalized treated area $\bar{\mathcal{T}}$. In the third plot, each point is associated to a different configuration, with the *y*-coordinate corresponding to the objective function value *G*. The color palette has been chosen according to which patch has been considered first in the configuration (counting from West to East): green palette for configurations in which patch 100000 has been considered first; blue palette for patch 010000 as first; red palette for patch 001000; magenta palette for patch 000100; purple palette for patch 000010; orange palette for patch 000001. Black color corresponds to *no prescribed fires* configuration 000000; yellow color corresponds to the *all prescribed fires* configuration 111111

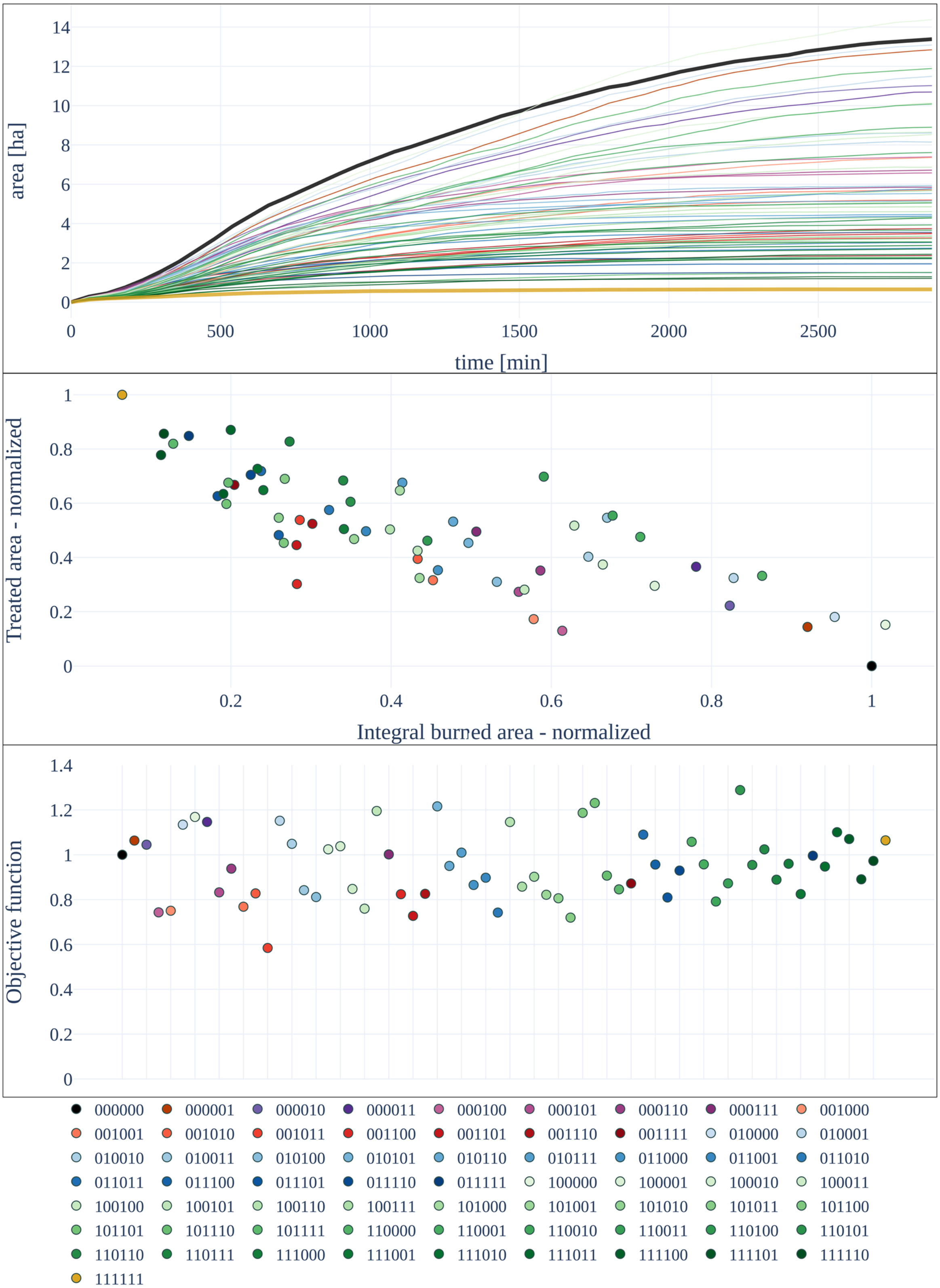

Fig. 7 (See legend on previous page.)

quantitative information on which are the optimal areas for prescribed burning. This approach can, however, undermine the portability of the methodology for a comparative study among different study areas. A future study is required to understand which aspects of the proposed methodology can potentially be generalized and which are necessarily based on expert opinion.

Furthermore, we believe that the proposed methodology can be adapted to various fire simulators (e.g., BEHAVE) with some adjustments to tailor it to the chosen simulator's characteristics. In fact, the Monte Carlo approach for the different scenarios and the assessment of prescribed fire effects in wildfire propagation remains valid, regardless of the simulator used for the fire propagation scenarios. Future research will be conducted to identify the portability of the methodology employing different wildfire simulators.

Once the locations for prescribed fires are identified, the next step would be the actual simulation of performing prescribed fires to support the definition of the prescribed fire plan. Considering different scenarios, eventually incorporating local prescribed fire regulations, the expert could use the quantitative information from simulations to make informed decisions regarding the fire management strategies to be performed. Similar assessments can be performed during prescribed fire execution. Given the actual state of the prescribed fire and the subsequent hours of weather forecast, fire propagation scenarios can help properly manage the fire. Some tests on the use of PROPAGATOR to simulate prescribed fires in Liguria region can be found in the Supplementary Material.

PROPAGATOR can offer some notable advantages when simulating prescribed fires. First, the model is not affected by a change in temporal resolution. The flexibility in changing the temporal resolution of simulations is helpful for prescribed fires. A more detailed simulation can be required because of the higher vigilance required to manage the fire and prevent it from getting out of control. The users can then simulate rapid changes in weather conditions to assess the prescribed fire behavior. The rapid simulation time required by PROPAGATOR is important to simulate many fire propagation scenarios in different conditions. The comparison of multiple scenarios helps the expert to make informed decisions. Further, PROPAGATOR makes it possible to consider different ignition patterns, as usually used in prescribed fires. Last, the model can include firefighting actions, such as the ones performed during prescribed fires.

However, some important changes should be made to make PROPAGATOR able to simulate prescribed fires properly. A good opportunity to assess PROPAGATOR limitations in simulating prescribed fires is provided by the comparison with QUIC-fire (Linn et al. 2020), developed specifically for prescribed fires. In Linn et al. (2020), authors highlighted the importance of considering fire-wind interactions and the effect of fuel structure on wind to simulate prescribed fires. The fire-wind interaction can play an important role, especially when multi-ignitions patterns are performed. Also, the role of topography in changing wind locally can play a remarkable role, especially in areas characterized by a complex topography. In the current release of PROPAGATOR, the fire-wind interaction is not considered, as well as the interaction of the wind field with topography. A proper wind-fire and wind-topography interaction module could be considered in a future release of PROPAGATOR, to make it able to simulate prescribed fires properly.

Last, a study on the effect of changing spatial resolution in PROPAGATOR could be performed. As already mentioned, a detailed simulation can be valuable to properly manage the fire and prevent it from getting out of control. In Linn et al. (2020), the simulation resolution corresponds to 2 m, while the native PROPAGATOR model adopts a 20-m resolution. The underlying technology of the model can handle the same propagation dynamics by changing its resolution. However, it remains an open question whether the probabilities of propagation should be adjusted with the change in scale. This question will be addressed in future studies.

Conclusion

In conclusion, our study utilized the PROPAGATOR model to investigate its applicability in both the emergency phase and the planning of prescribed fires. Through the case study of the Albenga Fire, we demonstrated the model's effectiveness in generating fire scenarios during the emergency phase, providing valuable information for firefighters in modulating their response based on the potential behavior of the fire. The performance indicators obtained in this study showed promising results, albeit with smaller values compared to other test cases, highlighting the unique challenges posed by highly anthropized fires such as the Albenga case study.

Furthermore, we explored the use of PROPAGATOR for planning prescribed fire, addressing the key problem of optimizing prescribed fire location. Our methodology involved incorporating expert opinions throughout the process, allowing for a comprehensive approach to defining prescribed fire plans. The optimization of prescribed fire location revealed the significance of ignition point location and regrowth scenarios, with different configurations exhibiting varying effects on wildfire propagation. We demonstrated the role of specific areas in limiting fire spread, regardless of the point of ignition, and identified optimal configurations for both regrowth scenarios. However, future studies should focus on refining regrowth scenarios based on experimental results. Further, a more complex formulation of the objective function should be tested to consider better the positive effects of prescribed fires and the resources they require.

Overall, our findings highlight the potential of PROPAGATOR as a valuable tool for both the emergency phase and planning of prescribed fires. We decided to show a case study in the Liguria region because the model is already embedded in the regional wildfire risk management system as an emergency response tool. Its role already in the system can also facilitate its operational use for other purposes, such as prescribed fires, as shown in the paper.

While further research is necessary to address specific challenges and refine the methodology, PROPAGATOR offers significant advantages in assessing fire behavior, optimizing prescribed fire locations, and facilitating informed decision-making by experts. These advancements can contribute to more effective wildfire risk mitigation strategies and promote safer and more efficient fire management practices in the future.

Supplementary information

The online version contains supplementary material available at https://doi.org/10.1186/s42408-023-00239-7.

Additional file 1.

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Authors' contributions

NP, AT, and PF conceived research. NP and FB contributed to the development of the PROPAGATOR model. NP contributed with simulations. LP contributed with fuel data retrieval. The literature review was conducted by BSA and NP. NP and BSA were mainly responsible for writing with major contributions by LP and AT. The manuscript was reviewed during multiple rounds by NP, BSA, AT, and FB. PF, NR, and AT were responsible for the supervision of the research. All authors have read and agreed to the published version of the manuscript.

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Availability of data and materials

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

Declarations

Ethics approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

Competing interests

The authors declare that they have no competing interests.

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References

Ager, A. A., N. M. Vaillant, and M. A. Finney. 2011. Integrating fire behavior models and geospatial analysis for wildland fire risk assessment and fuel management planning. *Journal of Combustion*, 19.

Agresti, A. 1996, An Introduction to Categorical Data Analysis, New York: John Wiley & Sons, Inc.

Alexandridis, A., L. Russo, D. Vakalis, G.V. Bafas, and C.I. Siettos. 2011. Wildland fire spread modelling using cellular automata: Evolution in large-scale spatially heterogeneous environments under fire suppression tactics. *International Journal of Wildland Fire* 20 (5): 633–647.

ANYWHERE Consortium. 2019. EnhANCing emergencY management and response to extreme WeatHER and climate Events (ANYWHERE). https://cordis.europa.eu/project/id/700099. Accessed 31 Dec 2019.

Arca, B., T. Ghisu, M. Casula, M. Salis, and P. Duce. 2019. A web-based wildfire simulator for operational applications. *International Journal of Wildland Fire* 28(2), 99-112.

Boer, M.M., R.J. Sadler, R.S. Wittkuhn, L. McCaw, and P.F. Grierson. 2009. Long-term impacts of prescribed burning on regional extent and incidence of wildfires–evidence from 50 years of active fire management in sw australian forests. *Forest Ecology and Management* 259 (1): 139–142.

Bovio, G., and D. Ascoli. 2012. Fuoco prescritto: stato dell'arte della normativa in italia. *L'Italia Forestale e Montana* 67 (4): 347–358.

Buresti, E., and M. Sulli. 1983. Il fuoco strumento colturale? *Annali dell'Istituto Sperimentale per la Selvicoltura* 16: 355–385.

Burgan, R. E., and R. C. Rothermel. 1984. *BEHAVE: fire behavior prediction and fuel modeling system, fuel subsystem*. General Technical Report INT-167. Ogden, UT: U. S. Department of Agriculture, Forest Service, Intermountain Forest and Range Experiment Station. 126 p.

Calabri, G. 1981. Il fuoco prescritto, una discussa tecnica per la gestione dei boschi. *Monti e Boschi* 32 (1): 35–42.

Cassagne, N., F. Pimont, J.L. Dupuy, R.R. Linn, A. Mårell, C. Oliveri, and E. Rigolot. 2011. Using a fire propagation model to assess the efficiency of prescribed burning in reducing the fire hazard. *Ecological Modelling* 222 (8): 1502–1514.

Catalanotti, A. 2009. Effects of prescribed burning on soil and vegetation. Ph.D. thesis. University of Naples Federico II.

Connor, S.E., J. Araújo, W.O. van der Knaap, and J.F.N. van Leeuwen. 2012. A long-term perspective on biomass burning in the Serra da Estrela, Portugal. *Quaternary Science Reviews* 55: 114–124.

Dupuy, J.L., and D. Morvan. 2005. Numerical study of a crown fire spreading toward a fuel break using a multiphase physical model. *International Journal of Wildland Fire* 14 (2): 141–151.

Esposito, A., D. Ascoli, and S. Mazzoleni. 2014. Il fuoco prescritto nella prevenzione degli incendi boschivi. In *Ingegneria antincendio, tecnologie dell'informazione e pianificazione dell'emergenza nel sistema integrato di videosorveglianza e telerilevamento degli incendi boschivi nelle regioni Puglia e Calabria*. Rome, Italy: Ministero dell'Interno, Dipartimento dei Vigili del Fuoco, del Soccorso Pubblico e della Difesa Civile. Chapter 12, 1–22.

Fernandes, P., G. Davies, D. Ascoli, C. Fernandez, F. Moreira, E. Rigolot, C. Stoof, J. Vega, and D. Molina. 2013. Prescribed burning in southern europe: developing fire management in a dynamic landscape. *Frontiers in Ecology and the Environment* 11 (s1): e4–e14.

Fernandes, P., C. Rossa, J. Madrigal, E. Rigolot, D. Ascoli, C. Hernando, N. Guiomar, and M. Guijarro. 2022. *Prescribed burning in the European Mediterranean Basin*, In: Weir, J.R., Scasta, D. (Eds.), Global application of prescribed fire. Clayton South: CSIRO Publishing. Chapter 13, 230–248

Fernandes, P.M., and H.S. Botelho. 2003. A review of prescribed burning effectiveness in fire hazard reduction. *International Journal of Wildland Fire* 12 (2): 117–128.

Fernández, C., J.A. Vega, and T. Fonturbel. 2013. Does fire severity influence shrub resprouting after spring prescribed burning? *Acta Oecologica* 48: 30–36.
Finney, M.A., J.D. Cohen, S.S. McAllister, and W.M. Jolly. 2013. On the need for a theory of wildland fire spread. *International Journal of Wildland Fire* 22 (1): 25–36.
Fiorucci, P., F. Gaetani, and R. Minciardi. 2008. Development and application of a system for dynamic wildfire risk assessment in italy. *Environmental Modelling and Software* 23 (6): 690–702.
Flannigan, M., B. Stocks, M. Turetsky, and M. Wotton. 2009. Impacts of climate change on fire activity and fire management in the circumboreal forest. *Global Change Biology* 15 (3): 549–560.
Ganteaume, A., A. Camia, M. Jappiot, J. San-Miguel-Ayanz, M. Long-Fournel, and C. Lampin. 2013. A review of the main driving factors of forest fire ignition over europe. *Environmental Management* 51 (3): 651–662.
Giuditta, E., R. Marzaioli, A. Esposito, D. Ascoli, A. Stinca, S. Mazzoleni, and F. Rutigliano. 2020. Soil microbial diversity, biomass, and activity in two pine plantations of southern italy treated with prescribed burning. *Forests 11*(1), 19.
Hiers, J. K., J. J. O'Brien, J. M. Varner, B. W. Butler, M. Dickinson, J. Furman, M. Gallagher, D. Godwin, S. L. Goodrick, S. M. Hood, A. Hudak, L. N. Kobziar, R. Linn, E. L. Loudermilk, S. McCaffrey, K. Robertson, E. M. Rowell, N. Skowronski, A. C. Watts, and K. M. Yedinak. 2020. Prescribed fire science: the case for a refined research agenda. *Fire Ecology 16*(1), 11.
Keane, R.E., J.K. Agee, P. Fulé, J.E. Keeley, C. Key, S.G. Kitchen, R. Miller, and L.A. Schulte. 2008. Ecological effects of large fires on us landscapes: benefit or catastrophe? *International Journal of Wildland Fire* 17 (6): 696–712.
Keeley, J., W. Bond, R. Bradstock, J. Pausas, and P. Rundel. 2012. *Fire in Mediterranean Ecosystems: Ecology, Evolution and Management*. Cambridge: Cambridge University Press.
Lantero, F., P. D. Jardin, F. C. Pesle, V. Parodi, S. Vergante, and M. Galardi. 2022. The medcoopfire project. *Environmental Sciences Proceedings 17*(1), 102.
Lázaro, A., and C. Montiel. 2010. Overview of prescribed burning policies and practices in Europe and other countries. In *Towards Integrated Fire Management – Outcomes of the European Project Fire Paradox*, ed. F Silva, JS Rego, P Fernandes, and E Rigolo, Number 23, 137–150. Joensuu, Finnland: European Forest Institute.
Linn, R.R., S.L. Goodrick, S. Brambilla, M.J. Brown, R.S. Middleton, J.J. O'Brien, and J.K. Hiers. 2020. Quic-fire: A fast-running simulation tool for prescribed fire planning. *Environmental Modelling and Software* 125 (2019): 104616.
Liu, N., Lei, J., Gao, W., Chen, H., Xie, X. 2021. Combustion dynamics of large-scale wildfires. Proceedings of the Combustion Institute 38(1):157-198.
Lydersen, J.M., B.M. Collins, M.L. Brooks, J.R. Matchett, K.L. Shive, N.A. Povak, V.R. Kane, and D.F. Smith. 2017. Evidence of fuels management and fire weather influencing fire severity in an extreme fire event. *Ecological Application* 27 (7): 2013–2030.
Matsypura, D., O.A. Prokopyev, and A. Zahar. 2018. Wildfire fuel management: Network-based models and optimization of prescribed burning. *European Journal of Operational Research* 264 (2): 774–796.
McCaw, W.L. 2013. Managing forest fuels using prescribed fire-a perspective from southern australia. *Forest Ecology and Management* 294: 217–224.
Mell, W., M.A. Jenkins, J. Gould, and N. Cheney. 2007. A physics-based approachto modelling grassland fires. *International Journal of Wildland Fire* 16: 1–22.
Miettinen, K., and M. Mäkelä. 2002. On scalarizing functions in multiobjective optimization. *OR Spectrum* 24: 193–213.
Mitsopoulos, I., G. Mallinis, S. Zibtsev, M. Yavuz, B. Saglam, O. Kucuk, V. Bogomolov, A. Borsuk, and G. Zaimes. 2017. An integrated approach for mapping fire suppression difficulty in three different ecosystems of eastern europe. *Journal of Spatial Science* 62 (1): 139–155.
Montealegre, A.L., M.T. Lamelas, M.A. Tanase, and J. de la Riva. 2014. Forest fire severity assessment using als data in a mediterranean environment. *Remote Sensing* 6: 4240–4265.
Oliveira, U., B. Soares-Filho, H. Rodrigues, D. Figueira, L. Gomes, W. Leles, C. Berlinck, F. Morelli, M. Bustamante, J. Ometto, and H. Miranda. 2023. A near real-time web-system for predicting fire spread across the cerrado biome. *Scientific Reports 13, 4829*.
Parsons, R. A. 2007. *Spatial variability in forest fuels: simulation modeling and effects on fire behavior*. Ph.D. thesis, University of Montana.
Pausas, J.G., and J.E. Keeley. 2009. A burning story: The role of fire in the history of life. *BioScience* 59 (7): 593–601.
Pausas, J.G., and J.E. Keeley. 2019. Wildfires as an ecosystem service. *Frontiers in Ecology and the Environment* 17 (5): 289–295.
Pearce, H. G. 2009. Review of fire growth simulation models for application in New Zealand. Client report, Christchurch.
Penman, T.D., F.J. Christie, A. Andersen, R.A. Bradstock, G. Cary, M.K. Henderson, O. Price, C. Tran, G.M. Wardle, and R. Williams. 2011. Prescribed burning: How can it work to conserve the things we value? *International Journal of Wildland Fire* 20 (6): 721–733.
Perello, N., A. Trucchia, M. D'Andrea, S. Degli Esposti, and P. Fiorucci. 2022. RISICO, an enhanced forest fire danger rating system: Validation on 2021 extreme wildfire season in southern Italy. Environmental Sciences Proceedings 17(1), 37.
Potts, J.B., E. Marino, and S.L. Stephens. 2010. Chaparral shrub recovery after fuel reduction: A comparison of prescribed fire and mastication techniques. *Plant Ecology* 210 (2): 303–315.
Pulvirenti, L., G. Squicciarino, E. Fiori, P. Fiorucci, L. Ferraris, D. Negro, A. Gollini, M. Severino, and S. Puca. 2020. An automatic processing chain for near real-time mapping of burned forest areas using sentinel-2 data. *Remote Sensing 12*(4), 674.
Quevedo, L., A. Rodrigo, and J.M. Espelta. 2007. Post-fire resprouting ability of 15 non-dominant shrub and tree species in Mediterranean areas of NE Spain. *Annals of Forest Science* 64 (8): 883–890.
Rigolot, E., P. Fernandes, and F. Rego. 2009. Managing wildfire risk: Prevention, suppression. In *Living with Wildfires: What Science can Tell Us. A Contribution of the Science-policy Dialogue*, ed. Y Birot. Joensuu, Finland: European Forest Institute.
SAFERS Consortium. 2020. Structured Approaches for Forest fire Emergencies in Resilient Societies (SAFERS). https://cordis.europa.eu/project/id/869353. Accessed 15 Nov 2023.
Savage, D.W., D.L. Martell, and B.M. Wotton. 2011. Forest management strategies for dealing with fire-related uncertainty when managing two forest seral stages. *Canadian Journal of Forest Research* 41 (2): 309–320.
Sørensen, T., T. Sørensen, T. Biering-Sørensen, T. Sørensen, and J. T. Sorensen. 1948. A method of establishing group of equal amplitude in plant sociobiology based on similarity of species content and its application to analyses of the vegetation on danish commons. Biologiske Skrifter/Kongelige Danske Videnskabernes Selskab, 5, 1-34
Sullivan, A. L. 2009a. Wildland surface fire spread modelling, 1990-2007. 1: phys-ical and quasi-physical models. *International Journal of Wildland Fire 18* (4): 349–368.
Sullivan, A. L. 2009b. Wildland surface fire spread modelling, 1990–2007. 2: Empirical and quasi-empirical models. *International Journal of Wildland Fire 18* (4): 369–386.
Tedim, F., G. Xanthopoulos, and V. Leone. 2015. *Forest fires in Europe: Facts and challenges*, 77–99. Amsterdam: Elsevier.
Teshome, E., and G. Glatzel. 2018. The effect of wildfire on Erica arborea L. (Ericaceae) in Simien Mountains National Park, Northwest Ethiopia. *Proceedings of the International Academy of Ecology and Environmental Sciences* 8 (3): 151–161.
Tonini, M., M. D'Andrea, G. Biondi, S. Degli Esposti, A. Trucchia, and P. Fiorucci. 2020. A machine learning-based approach for wildfire susceptibility mapping. The case study of the Liguria region in Italy. *Geosciences* 10(3), 105.
Trucchia, A., M. D'andrea, F. Baghino, P. Fiorucci, L. Ferraris, D. Negro, A. Gollini, and M. Severino. 2020. Propagator: An operational cellular-automata based wildfire simulator. *Fire* 3: 1–24.
Wade, Dale D.; Lunsford, James D. 1989. A guide for prescribed fire in southern forests. Technical Publication R8-TP-11. Atlanta, GA: USDA Forest Service, Southern Region. 56 p.
Wei, Y., D. Rideout, and A. Kirsch. 2008. An optimization model for locating fuel treatments across a landscape to reduce expected fire losses. *Canadian Journal of Forest Research* 38 (4): 868–877.
Williams, R.J., and R.A. Bradstock. 2008. Large fires and their ecological consequences: Introduction to the special issue. *International Journal of Wildland Fire* 17 (6): 685–687.
Willman, E.A. 2015. An economic model of aboriginal fire-stick farming. *Australian Journal of Agricultural and Resource Economics* 59 (1): 39–60.

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