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ORIGINAL PAPER

Operational flexibility in forest fire prevention and suppression: a spatially explicit intra-annual optimization analysis, considering prevention, (pre)suppression, and escape costs

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Abstract
Increasing wildfire threats and costs escalate the complexity of forest fire management challenges, which is grounded in complex interactions between ecological, social, economic, and policy factors. It is immersed in this difficult context that decision-makers must settle on an investment mix within a portfolio of available options, subject to limited funds and under great uncertainty. We model intra-annual fire management as a problem of multistage capacity investment in a portfolio of management resources, enabling fuel treatments and fire preparedness. We consider wildfires as the demand, with uncertainty in the severity of the fire season and in the occurrence, time, place, and severity of specific fires. We focus our analysis on the influence of changes in the volatility of wildfires and in the costs of escaped wildfires, on the postponement of capacity investment along the year, on the optimal budget, and on the investment mix. Using a hypothetical test landscape, we verify that the value of postponement increases significantly for scenarios of increased uncertainty (higher volatility) and higher escape costs, as also does the optimal budget (although not proportionally to the changes in the escape costs). Additionally, the suppression/prevention budget ratio is highly sensitive to changes in escape costs, while it remains mostly insensitive to changes in volatility. Furthermore, we show the policy implications of these findings at operational (e.g., spatial solutions) and strategic levels (e.g., climate change). Exploring the impact of increasing escape costs in the optimal investment mix, we identified in our instances four qualitative system stages, which can be related to specific socioecological contexts and used as the basis for policy (re)design. In addition to questioning some popular myths, our results highlight the value of fuel treatments and the contextual nature of the optimal portfolio mix.

Keywords Forest fire management · Risk management · Multi-resource investment · Stochastic optimization · Socioecological context

Introduction

Ever-increasing wildfire incidence and costs have relentlessly been challenging forest fire management (FFM). Over the last decades, areas burned by wildfires have increased significantly, together with suppression costs (Fischer et al. 2016; Lee et al. 2012) and other indirect societal costs (e.g., real estate devaluation, post-fire rehabilitation, losses in timber and non-timber products, and in recreation and tourism assets). More lives, natural resources (soils, watersheds, and other ecosystem services), and property values have been put at risk, and cultural resources and some ecosystems have been affected substantially (Schoennagel et al. 2017; Thompson et al. 2017). These increasing costs and threats to biodiversity, community safety, and human health, and the escalation of substantial losses are a global trend, affecting

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Australia, the countries of North America, and the Mediterranean Basin (Fernandes et al. 2016; Fischer et al. 2016; Lee et al. 2012; Salis et al. 2014), and raise complex challenges to FFM (Lee et al. 2012; O'Connor et al. 2016).

The escalating complexity of FFM is grounded in complex interactions between ecological, social, economic, and policy factors. Fire regimes altered by changing climate conditions and land use—e.g., afforestation and agriculture abandonment (Alcasena et al. 2016; Fernandes et al. 2016)—interact with the expanded development of the wildland–urban interface (WUI), as populations grow and residential development increases, causing changes in fuel density and composition (O'Connor et al. 2016; Thompson et al. 2017). In many temperate forest ecosystems, fire is an essential ecological process, playing a critical role in maintaining wildlife diversity and native plants (Fischer et al. 2016). Furthermore, sometimes the direction of fire consequences is also difficult to discern, e.g., over time, as sites recover from fire effects changes in value tends to attenuate (Thompson et al. 2017), but in the first years after a fire, some types of recreation activities can see their value increased while others can see their value decreased (Loomis et al. 2001). The absence of adequate policies—e.g., on WUI expansion (Keiter 2012), or the traditional use of fire in land management (Tedim et al. 2016)—or their unintended consequences—e.g., the "firefighting trap" of a suppression focused policy (Collins et al. 2013), or the fuel build-up in result of a mandatory aggressive fire suppression policy (Rönnqvist et al. 2015; Tedim et al. 2016)—spur these gradually changing variables (climate change, fuel build-up, and human pressure) and interact with the susceptibility to rapid combustion, substantially increasing the stress on ecosystems and the length of the fire season (Fischer et al. 2016), contributing to heightening the risks of wildfires for society and several ecosystems (Schoennagel et al. 2017; Thompson et al. 2017). FFM decision-making is framed by the interactions between all the factors above, modulated by local circumstances such as the available response options and the relative magnitude of the uncertainties—e.g., Thompson et al. (2017) illustrates this context variability by comparing Andalusia (Spain) with Montana (USA).

Understanding how to mitigate wildfires with the available local options, in particular within the constraints of a limited budget, is thus an important issue. In the last decades, fire suppression costs have escalated rapidly (O'Connor et al. 2016), e.g., between 2003 and 2012, in the USA, comparing with the previous decade, economic losses doubled and suppression costs tripled (Fischer et al. 2016), with indirect societal costs, especially near the WUI, growing to 30 times the direct costs of firefighting (Schoennagel et al. 2017). The investment in fire suppression has not been able to decrease the number of large fires, with mega-fires becoming more frequent (Fernandes et al. 2016), WUI fires (where people and property values are at risk) account for as much as 95% of the suppression costs, when compared with remote fires (Schoennagel et al. 2017), and the synchronous occurrence of fires across broad geographic regions has also increased (Lee et al. 2012), all leading to permanent budget shortfalls.

Managing with a limited fire budget under uncertainty

Decision-makers must decide how to apply limited funds to an investment mix chosen from a portfolio of available options. Constrained by limited financial funds and faced with imperfect information, policy makers (PM) and fire managers (FM), at different levels and scales, must decide the most efficient and effective allocation of funds to alternative FFM choices (Pacheco et al. 2015). Limited financial funds require budget balancing at both policy—e.g., prevention vs suppression (Collins et al. 2013) and restoration—and operational—e.g., equipment and human resources—levels. Overall, these decisions, usually made under considerable uncertainty, include options such as community prevention, fuel management, pre-suppression, suppression, and restoration (Pacheco et al. 2015), and more broadly, social interventions, as well as biodiversity, soil, water, ecosystems, and productivity conservation interventions, in the context of a sustainable forest management (Rönnqvist et al. 2015). Both PMs and FMs face difficult trade-offs in choosing among all of these inter-related alternatives (Thompson et al. 2017).

In the presence of uncertainty, operational flexibility is of great value for most FFM decisions. "Flexibility is the ability to adapt to change and may take many forms" (Chod et al. 2010); thus, the flexible design of a system, using a range of alternative sources of flexibility, strengthens its capability to adapt to different potential future unfoldings, dependent on multiple sources of uncertainty, and consequently its ability to achieve its proposed objective (Cardin et al. 2015). It is precisely to address the challenges raised by the complexity and the large uncertainties present in FFM systems that we propose in this paper a Stochastic Mixed Integer Programming model to study the relationship between different types of operational flexibility, when used to mitigate exposure to the highly unpredictable factors that are at the basis of most FFM decisions (e.g., weather, suppression performance, fire behavior, spread, and effects in the landscape), focusing on the decisions made by FMs along the year. Because of path dependencies, a frequent characteristic of complex engineering systems (Cardin et al. 2017), we chose not to use Dynamic Programming. We then use the model to explore patterns of decisions under changes in the costs of escaped fires and derive implications for both FMs and PMs from this analysis.

In order to explore more efficiently the design space under uncertainty, we adopt a screening approach (Cardin et al. 2015). A screening model is a mid-fidelity representation of an entire system which includes the essential details of the system's interconnected sub-domains and produces a relatively stable ranking order for different strategies or design alternatives. Precisely because it connects the system's sub-domains at a mid-fidelity level, a screening model requires less computational and set-up time than high-fidelity but disconnected models in each sub-domain (Lin et al. 2009, 2013).

Our goal specifically is to study how to manage an integrated portfolio of forest fire management options along the fire year, under a finite budget, considering uncertainties in weather, economic conditions, and the impact of the different options on each other, in order to mitigate fire effects. Our model focuses on a portfolio of three management alternatives on which FMs can apply their budget along the year: fuel treatment, pre-suppression planning, and suppression. We model this intra-annual fire management problem as a multistage capacity investment problem (Chod et al. 2010), considering a portfolio of fire management resources, and fires as the demand. We focus our analysis on mismatch risk, i.e., the risk related to the cost of supply differing from demand: overinvestment in fire management capacity will lead to costs related to unused capacity, whereas underinvestment will lead to costs related to not being able to satisfy the demand, i.e., to value loss in the forest.

Literature review

Recently, Pacheco et al. (2015) reviewed key systems created to support FFM decision-making, and the evolution of their focus from risk assessment, to risk management, to risk governance, as a result of a simultaneous pull of methodological progresses in risk handling and push from technological progress. Martell (2015) reviewed the use of operational research and management science in the development and implementation of FFM decision support systems (DSS). Thompson et al. (2017), in the context of large fire management, highlight the need for a framework with the ability to describe credible relationships between FFM activities and avoided losses, to evaluate efficient strategies and the consequences of suppression, accounting for factors like probabilities, economic efficiency, and intertemporal feedbacks and trade-offs, adjustable to different socioecological contexts.

Valuable research has been carried out and published along the years, focusing on major aspects of FFM (e.g., fuel management and suppression, among others), a part of it explicitly exploring the trade-offs between post-fire impacts in valued resources and assets, and pre-fire management through risk mitigation investments, seeking to minimize FFM costs and detrimental fire impacts (Hand et al. 2014). In fact, there is a considerable body of fundamental literature concerned with the optimization, in some way, e.g., of fuel management, broadly speaking, or of some aspect of it, in particular. The same happens with suppression activities. Examples for the latter are the works of Calkin et al. (2011), Kirsch and Rideout (2003), Pacheco (2011), and Chow and Regan (2011), and for the former, Minas et al. (2014), Butry et al. (2010), and Ager et al. (2007).

Calkin et al. (2011) described how the primary components of a geospatial DSS for wildfire suppression fit in the current state of art for risk assessment tools. Focusing on initial-attack preparedness planning, Kirsch and Rideout (2003) presented an integer programming model capable of addressing multiple simultaneous ignitions. Pacheco et al. (2013) proposed a discrete-event simulation optimization approach for the sizing of suppression systems (considering rekindles and false alarms), with the system's "point of collapse" as a constrain. Chow and Regan (2011) applied dynamic server relocation under uncertainty to the (re-)allocation of air tankers to bases in California, introducing flexibility to adapt the home-basing strategy over time by re-deploying air tankers within air bases as the fire season progresses, according to the daily changes in fire weather.

Minas et al. (2014) developed a set of integer programming models to schedule fuel treatments across multiple periods, considering operational and ecological constraints, with the goal of breaking the connectivity of high risk fuel treatment units in a landscape, and applied them to representative hypothetical cases. Butry et al. (2010) examined the trade-offs between wildfire prevention education (to lower ignition risk), prescribed fire (to lower ignition risk and burnt area), and fire suppression, seeking to minimize FFM costs and societal losses. Ager et al. (2007) used wildfire simulation methods to study the efficacy of fuel treatments in decreasing the probabilistic risk of northern spotted owl habitat loss.

Considering the well-established interaction between fuel treatments and fire suppression, studies including both in the same model are scarce, and even more in the case of mixed integer programming, as in the works of Minas et al. (2015) or Mercer et al. (2008). The latter inspired our intra-annual model, which in turn modifies the standard-response model of Haight and Fried (2007) to include the effects of fuel treatments. In addition, we use insights from our previous studies and field work (Collins et al. 2013; Pacheco et al. 2014a) to set up our proof of concept instances.

Haight and Fried (2007) developed a daily dispatching optimization model using a scenario-based standard response model with two objective functions, the number of (1) suppression resources deployed and (2) escaped fires, defined as the fires that did not receive a desired number of resources within a pre-defined response time. The expected number of escaped fires is obtained with an initial-attack stochastic simulation model (CFES2) using the fire perimeter to determine whether the initial attack fails or not, assuming multiple simultaneous fires. The weighted sum of the two objective functions is minimized, and the weights are ramped to generate trade-offs between deployment levels and a standard response objective.

Later, with the goal of evaluating trade-offs between investments in fuel treatment and fire suppression resources, and damages from wildfire, Mercer et al. (2008) extended the model of Haight and Fried (2007) to include fuel treatments in an integer programming model. However, in this first attempt at including elements of both fuel management and fire suppression in their approach, the elements were not fully integrated, requiring one-at-a-time adjustments of the parameters used in the model to incorporate the joint effect of deployment levels and the alternative locations of fuel treatments.

Our model extends the work of Mercer et al. (2008), by (a) preceding the fire scenarios (each representing the micro-uncertainty in fire locations during a single day) with a scenario tree representing intra-annual weather variability, (b) introducing the notion of dispatch class (which can include more than one type of resource), and (c) including the cost of fuel treatments in the objective function. We then minimize the sum of the investments in fire mitigation (fuel treatments) and suppression and the expected value lost as a result of escaped fires—but with the decisions about resource contracting and fuel treatment implementation taken along the year (as the future unfolds and the uncertainty about the fire season severity decreases), instead of minimizing the weighted sum of the cost of initial-attack resource deployments and the expected cost of escaped fires. With the latter, the authors generate a trade-off curve representing the decision-maker's preference (minimizing initial-attack costs or minimizing expected escaped costs) in order to show how the intensity of the investment in initial attack resources affects the consequent cost of suppressing escaped fires, while we focus our analysis on flexibility (e.g., postponement of the investment in capacity) and budget balance (e.g., mitigation vs suppression), as weather uncertainty (volatility) and escaped fire losses change.

Independently, Minas et al. (2015) published a different approach, with a single-period integer programming model incorporating fuel management and suppression preparedness decisions, aiming at maximizing the coverage area, with the main decisions being where to base suppression resources and undertake fuel treatments. The model does not directly consider a fire (spread or) escape probability, and instead, a pre-calculated location-specific (cell) "fire escape time", defined as the time a fire takes to reach a pre-defined threshold size (a certain number of burnt hectares, e.g., five), is used to classify a fire as escaped.

As an additional contribution to the framing of our research in the literature, considering the enumeration by Rönnqvist et al. (2015) of 33 open operations research problems in forestry, our work is directly related with the 26th (planning for uncertainty) and the 20th (FFM tractable models), and indirectly with the 10th (coordinate and synchronize a set of stakeholders with individual agendas).

The rest of the manuscript is organized as follows: the second section describes how we address uncertainty, presents our theoretical model, and introduces the set of instances used for the model's proof of concept; the third section presents the results of the optimization analysis, together with the discussion of their implications; the conclusion, including some policy implications, is provided in the fourth section. All the parameters and results considered not to be essential for the reader are provided as electronic supplementary material (henceforth referred to as "supplementary Table/Fig. A *n*," or just as "Table/Fig. A *n*").

Methods and data

In this research, we study the relationship between three types of operational flexibility, when used to mitigate exposure to demand uncertainty, in the context of forest fire management. Considering fires as the demand, we model intra-annual fire management as a multistage capacity investment problem, considering a portfolio of fire management resources, enabling (1) fuel management and (1) fire suppression preparedness.

Viewing flexibility as the ability to adapt to change (Chod et al. 2010), we address in our analysis two types of flexibility:

- *postponement* of the commitment to each type of capacity (fuel treatment and suppression preparedness), fine-tuning the capacity mix as the year evolves, in a trade-off between the changing weather conditional probabilities, an eventual decrease in the capacity cap, and increasing capacity costs;
- and *spatial flexibility,* in a trade-off between the costs of different suppression resources types (e.g., helicopters and ground crews) and their flexibility (e.g., helicopters have higher flexibility than ground crews, but also an additional cost). In contrast to suppression resources, which are able to reach multiple locations, fuel treatments do not feature directly spatial flexibility.

Lower up-front capacity costs and higher up-front capacity caps mean lower postponement flexibility (Chod et al. 2010). Spatial flexibility, in turn, may be measured by the ratio of the unit cost of the more flexible resources (the helicopter) to the unit cost of the more dedicated resources (the ground crew). As this ratio decreases, spatial flexibility increases from low (only ground crews) to high (only helicopters).

About the relationship between the three sources of flexibility considered in the model, we intuitively expect the following:

- Suppression investment postponement and suppression spatial flexibility are substitutes, i.e., higher (lower) postponement flexibility will decrease (increase) the value of spatial flexibility, which is constrained to be exercised only at a later stage, in the beginning of the fire season.
- A direct relationship of substitution also exists between fuel treatment postponement flexibility and suppression spatial flexibility, with an argument similar to the relationship between suppression investment postponement and spatial flexibility.
- Higher (lower) postponement flexibility in fuel treatment reduces (increases) the value of suppression postponement flexibility, because each type of decision (either treatment locations or suppression investment), when occurring at a later stage, can best adapt to the other earlier decision.

The relative values of these three sources of flexibility will interact to determine which type of relationships between them will dominate: the direct substitution relationships or the indirect complementarity relationships.

In this paper, we gave priority to the study of how changes in the cost of an escaped fire and in the volatility of the demand, influence the postponement of capacity investments along the year, the total expenditures, and the investment mix. Next, we study the qualitative relations between the extended escape costs and the (un)balance between fuel treatments and suppression resource (type) investments, when minimizing the total system cost. With the support of these qualitative relations, we identify four typical socioecological contexts, each with a characteristic investment mix, according to the values at risk, corresponding to different management policies.

Our model and findings about flexibility will be mostly relevant for FMs, whereas the categorization according to the socioecological context will mostly be of interest for PMs.

Dealing with uncertainty

In general, fuel management (i.e., controlling flammability through fire, mechanical, chemical, biological, or by manual means) and fire suppression preparedness or pre-suppression planning (e.g., recruiting and training, equipment and supplies procurement, mutual aid agreements negotiation) make up the portfolio of management alternatives that FMs can apply their budgets to along the year. The decisions about, e.g., where and when to apply fuel treatments and locate suppression resources, and about the level, timing, and mix of suppression resources contracted, condition the success of suppression (i.e., the work of extinguishing a fire, beginning with its discovery) and thus the burnt area, later in the fire season. All these decisions and their outcomes interact with each other and are made under uncertainty.

In our model, the uncertainty in the demand has two origins: (1) the intra-annual weather variability, which leads to oscillations in the overall severity of the fire season and (2) a confluence of micro-scale factors (micro-uncertainty) that lead to uncertainty in the occurrence, time, place, severity, and escape probability of specific fires.

The uncertainty related to intra-annual weather variability is modeled with a scenario tree, similar to the one displayed in Fig. 1. In this case, the structure of the tree considers the conditions for the winter, spring and summer seasons, as well as different conditions for the Fire Weather Index (FWI), with the corresponding conditional probabilities. Each leaf node in this part of the tree corresponds to a fire season scenario. Each scenario consists of the path between the root of the tree and a leaf node.

The micro-uncertainty is modeled with a spatial grid of forest districts, each characterized by an ignition probability. One such matrix, similar to the one presented in Fig. 2, will characterize each fire season scenario. From each of these matrices, multiple fire scenarios will be derived, which will become the ultimate leaf nodes of the scenario tree.

The uncertainty is thus modeled jointly (Fig. 3) with a scenario tree for the part related to intra-annual weather variability and a spatial grid of forest districts (each characterized by a maximum ignition probability) for the part related to micro-uncertainty. These probabilities can be obtained from historic data or expert elicitation (the values in the figures are merely illustrative).

Model formulation

Our formulation of a stochastic integer programming model for fuel management planning and intra-annual suppression preparedness is presented below. We consider a landscape divided into a number of cells representing candidate locations for fuel treatment, potential temporary bases for suppression resource deployment, and potential fire locations. The shape and size of these cells does not need to be uniform, and indeed the landscape partition should be done on logical fuel treatment units. The main decisions to be considered are where and when to apply fuel treatment, where to locate temporary suppression bases, and how many resources to contract of each type, and when. The model uses an explicit tree structure, with each node modeled uniquely, as part of the tree, and scenarios modeled as paths in the tree from the root node to a leaf node, i.e., as subsets

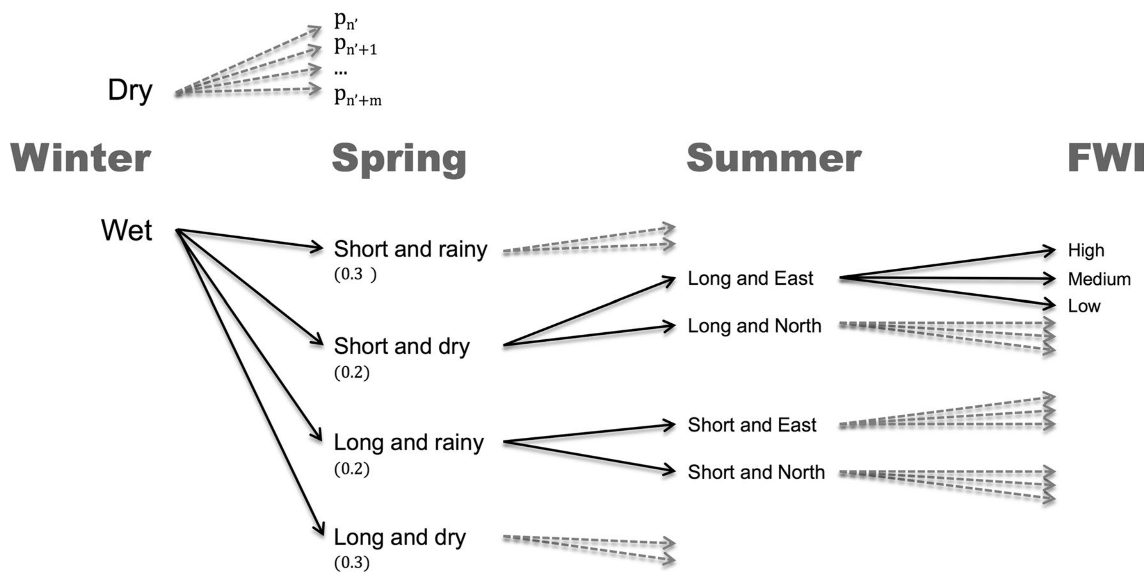

Fig. 1 Scenario tree—part related to intra-annual weather variability. $n', n'+1, \cdots, n'+m$ are $m+1$ nodes that share a same immediate ancestor, each with an assigned probability such that $p_{n'} + p_{n'+1} + \cdots + p_{n'+m} = 1$

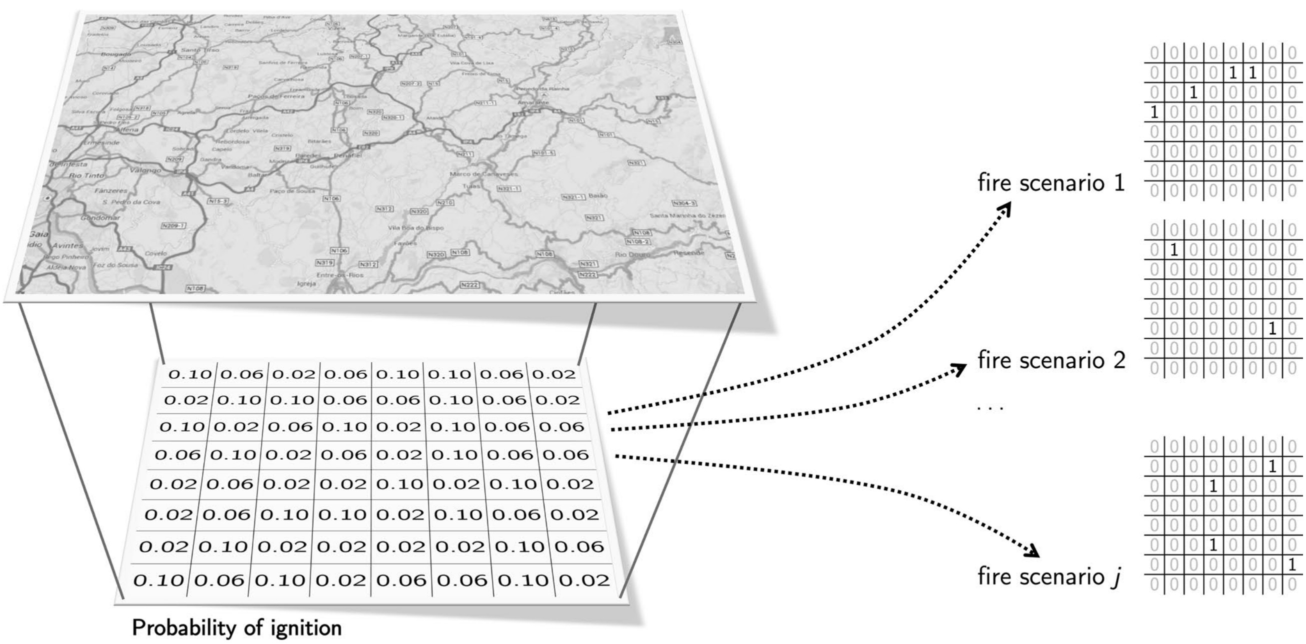

Fig. 2 Scenario tree—part related to the micro-uncertainty in fire occurrence, location, and severity

of nodes, thus not requiring non-anticipativity constraints. The model is formulated with the following notation:

Indices and sets:

i, I index and set of potential fire stations;
j, J index and set of potential fire locations;
k, K index and set of suppression resource dispatch classes (class 0 is no resources dispatched);
r, R index and set of types of suppression resources;
q, Q index and set of types of treatment (0 or 1);
n, N index and set of nodes in scenario tree;
P_n path in the scenario tree from the root node ($n=0$) to the parent of node n;
s, S index and set of fire season scenarios, i.e., parents (direct ancestors) of the leaf nodes in the scenario tree;

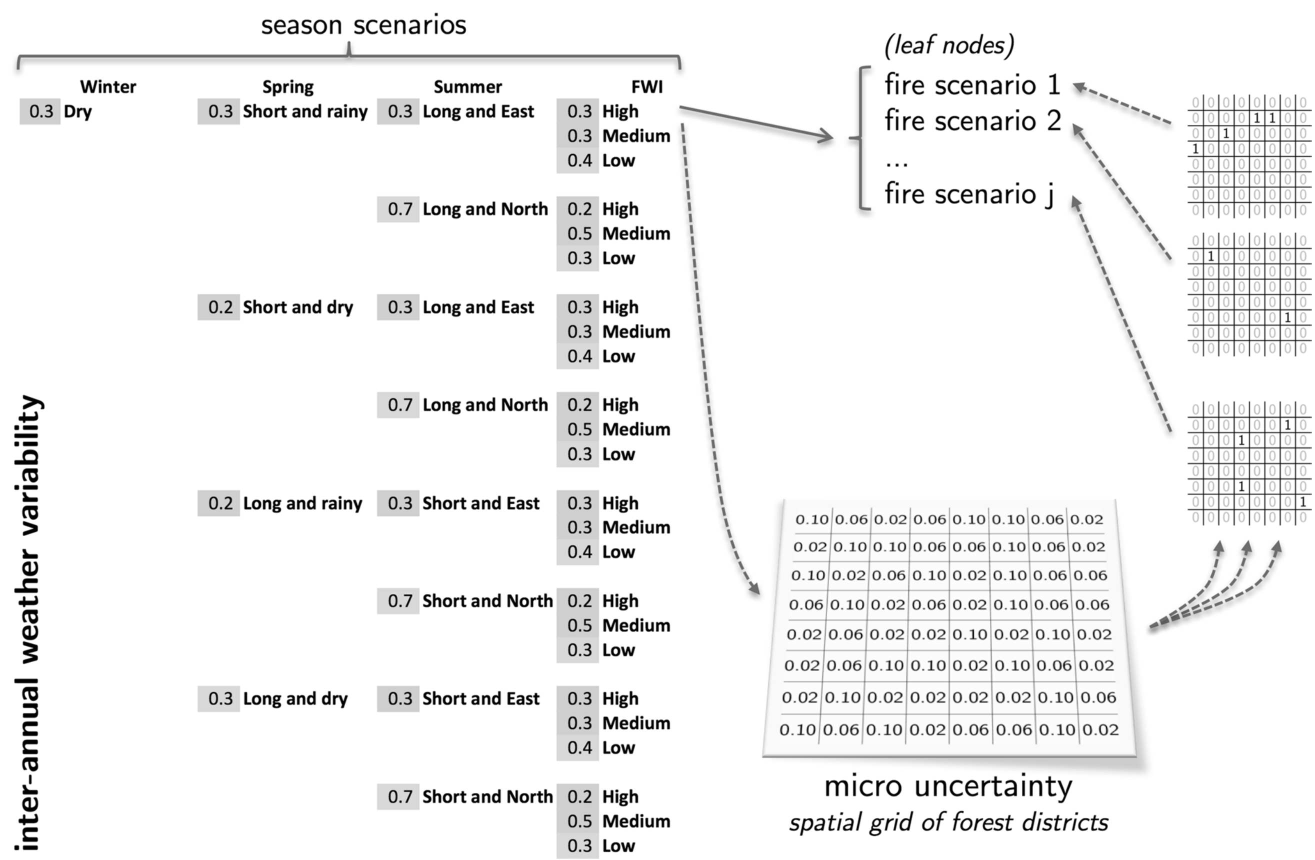

Fig. 3 Model uncertainty overview: scenario tree joining intra-annual weather variability with micro-uncertainty

s', S' index and set of fire scenarios, i.e., leaf nodes in the scenario tree
A set of season scenarios, i.e., (all) ancestors to the leaf nodes in the scenario tree (decision nodes);
a_n parent (direct ancestor) of node n.

Parameters:

c^1_{rn} cost of contracting one unit of resource type r in node n;
c^2_i fixed cost of opening a station at location i;
c^3_j extended cost of an escaped fire (including lost value and restoration) at location j;
c^0_{jn} annualized cost of treating location j in node n;
$f_{js'}$ binary parameter; 1 if fire occurs in location j in fire scenario s', 0 otherwise;
p_n probability of node n;
M_{ir} upper bound on the number of suppression resources of type r deployed at station i;
B budget
T_n upper bound on the number of treatments that are possible at decision node n;
d_{rk} number of resources of type r deployed in dispatch class k ($d_{r0} = 0$);
v_{qjks} probability of escape for a fire in location j in fire season scenario s under dispatch class k and treatment q ($v_{qj0s} = 1$);
O_{rij} set of stations i from where resources of type r can reach location j within the maximum permissible response time.

Variables:

u_{rn} number of suppression resources of type r contracted in node n;
x_{irs} number of suppression resources of type r deployed at station i in fire season scenario s;
$y_{ijrs'}$ number of suppression resources of type r dispatched from station i to location j in fire scenario s';
t_{jn} binary variable; 1 if location j is treated in node n, 0 otherwise;
w_{ia_s} binary variable; 1 if station i is open in season scenario a_s, 0 otherwise;
$z_{qjks'}$ binary variable; 1 if dispatch class k is used at location j in fire scenario s' under treatment q, 0 otherwise;

b_s budget allocated to treatments, suppression resources, and opening of stations in season scenario *s*

$$\text{Minimize} \sum_{s \in S} p_s b_s + \sum_{s' \in S'} \sum_j \sum_q \sum_k p_{s'} f_{js'} v_{qjka_{s'}} c_j^3 z_{qjks'} \quad (1)$$

$$\text{Subject to}: \sum_{n \in P_s} \sum_{j \in J} t_{jn} c_{jn}^0 + \sum_{n \in P_s} \sum_{r \in R} u_{rn} c_{rn}^1 + w_{ia_s} c_i^2 = b_s \quad \forall s \in S \quad (2)$$

$$b_s \le B \quad \forall s \in S \quad (3)$$

$$x_{irs} \le M_{ir} w_{ia_s} \quad \forall s \in S, i \in I, r \in R \quad (4)$$

$$\sum_{i \in I} x_{irs} \le \sum_{n \in P_s} u_{rn} \quad \forall s \in S, r \in R \quad (5)$$

$$\sum_{j \in O_{ri}} y_{ijrs'} \le x_{ira_{s'}} \quad \forall s' \in S', i \in I, r \in R \quad (6)$$

$$\sum_{i \in O_{rj}} y_{ijrs'} = \sum_{k \in K} \sum_{q \in Q} z_{qjks'} d_{rk} \quad \forall s' \in S', j \in J, r \in R \quad (7)$$

$$\sum_{j \in J} t_{jn} \le T_n \quad \forall n \in N \backslash (S \cup S') \quad (8)$$

$$\sum_{n \in P_s} t_{jn} \le 1 \quad \forall s \in S, j \in J \quad (9)$$

$$\sum_{k \in K} z_{0jks'} = 1 - \sum_{n \in P_{a_{s'}}} t_{jn} \quad \forall s' \in S', j \in J \quad (10)$$

$$\sum_{k \in K} z_{1jks'} = \sum_{n \in P_{a_{s'}}} t_{jn} \quad \forall s' \in S', j \in J \quad (11)$$

Our objective function (1) consists of the minimization of the expected value of the investment mix and the escape costs. The budget allocated to treatments, suppression resource contracting, and opening of temporary stations in new locations, by fire season scenario, is defined in Eqs. (2). Multiplying the investment mix by the probability of each fire season scenario, we obtain the expected value of the investment mix. For each location, if a fire occurs, we have an escape probability according to the fuel treatment applied, the suppression class dispatched, and the fire scenario, and also the extended cost of an escaped fire at that particular location. By adding, for all locations, the product of the escape probability by the extend cost of such escape we evaluate the costs of all escapes under each fire scenario. Finally, with the probability of each fire scenario, we obtain the expected value of the extended cost of all escapes. As the escape costs under each fire scenario depend on the investment mix for the corresponding fire season scenario, we define our objective function as the sum of the two expected values, which we want to minimize.

Constraints (3) define budget limits (for any season scenario) and constraints (4) upper bounds on resources deployed, by location, season scenario, and resource type. Please note that the location of the temporary fire stations is chosen in a_s, the parent (direct ancestor) of node *s*. Once the decision is made, the stations remain open in the fire season scenario *s*.

The overall suppression capacities, by season scenario and resource type are defined in constraints (5), which ensure that the overall suppression capacity (sum of resources, by each type, deployed to all the stations) does not exceed the actually contracted suppression resources (of that type), in each season scenario. The decision to contract resources is only possible along the path in the scenario tree, from the root node to node *s*, i.e., in the decision nodes of the season scenarios except the last (node *s* or the fire season scenario).

Constraints (6) define the dispatch capacities, by station, fire scenario and resource type: the suppression resources (of each type) deployed at each station in the corresponding season scenario limit the sum of the resources dispatched to all the fires covered by that station (in each fire scenario). This formulation of the dispatch capacity constraint contains an implicit worst-case assumption for each season scenario, in the sense that the decisions cover the simultaneous occurrence of the maximum number of fires in all the cells covered by each particular station, in every fire scenario of each season scenario. The use of the maximum number of fires is a very conservative approach and can lead to overinvestment. As an alternative, in practical applications, it would be advisable to use measures such as the Value-at-Risk or the Conditional Value-at-Risk (also known as "Conditional Tail Expectation") for a given probability.

Our model assumes that FMs at the fire incident command and control level can define a set of initial-attack dispatch policies or "dispatch classes", which, according to the fuel load and the meteorological conditions in a certain location, feature an associated probability of escape for a fire in that location. Constraints (7) define the dispatch demand, by location, fire scenario, and resource type. In every fire scenario and location, the total suppression resources of each type, dispatched from any station that covers that location (left hand side) must equal the total resources of that type involved in the dispatch class (equation right side) actually employed for that location. When the probability of escape cannot be estimated from historical data (e.g., due to insufficient data for all combinations, in the presence of new dispatch policies), expert elicitation is an alternative to be considered.

The number of treatments that can be performed at each node along the fire season can be limited by several reasons (e.g., existing equipment, specialized personal availability); thus, constraints (8) define an upper bound (maximum) on the number of treatments that can be done, considering all the landscape (all locations), at each node of the alternative scenarios under consideration. Furthermore, constraints (9) assure that each location cannot be treated more than once, in each alternative season scenario. Because our model is intra-annual, we are interested in the short-term effect of fuel treatments. However, as fuel treatments have a multi-year impact, the cost of treatments in c^0_{jn} is annualized.

Finally, constraints (10) and (11) impose that only one dispatch class is assigned to each location under a fire scenario and set the appropriate corresponding fuel treatment status. In both constraints, the right-hand side imposes that only one dispatch class is assigned to each fire location. In addition, for each fire scenario, constraints (10) set a no fuel treatment status for locations that did not receive any fuel treatment along the year for the corresponding fire season scenario. The same holds for treated locations in constraints (11).

Model proof of concept

To demonstrate the types of analysis that our model enables and carry out our two studies on the role of flexibility and socioecological contexts, we synthesized an appropriate 25-cell test landscape, that we then used with several values for the extended cost (direct and indirect values lost and restoration costs) of an escaped fire. We considered values of 4 and 12 million euros for the study on the role of flexibility and values from 0 to 20 million euros for the study on socioecological contexts (further details are provided in "Investment mix, volatility, *EFeC*, and flexibility" and "Investment mix and socioecological contexts" sections, respectively).

The dimension of the test landscape and the parameterization of the costs were inspired in the case of Portugal, where forest fires are a critical problem. They account for more than half of the fires in the EU Mediterranean region (San-Miguel-Ayanz et al. 2013), and over the years, the consequences of forest fires in the country have been particularly severe, with successive catastrophic fire seasons. In half of the past thirty years (1987–2016), the total burnt area was larger than 110,000 ha, and in 2 years it was larger than 310,000 ha—please see the work of Fernandes et al. (2016) on extremely large (≥ 2500 ha) fires in the country between 2003 and 2013. Every year, on average about 2.5% of forestland is burnt, with total direct losses near €250MM, and more than €120MM spent in fire prevention and suppression (Pacheco and Claro 2014). Worse than the ecological and economic losses, almost every year there are casualties[1] resulting from forest fires.

In the remainder of this subsection, following an overview of the values of the parameters for the test landscape, summarized in Table 1, we detail the parameterization of the (a) scenario tree, (b) dispatch classes, and (c) costs.

Scenario tree parameterization

The instances used for the proof of concept have four decision stages, with two or three branches for each node of the scenario tree (please see Fig. 4) and Table A4, with the overall season probabilities). The stages correspond roughly to the seasons of the year, except for the last stage, for which the micro-uncertainty is modeled using four fire scenarios for each season scenario. Furthermore, we chose not to consider any decisions in the fall season.

Our model was designed for a worst case in which the suppression resources are needed to attend the maximum possible number of fires simultaneously. A rapid, aggressive, and vigorous initial attack—a policy that has been followed in Portugal (Pacheco et al. 2014a)—can prevent an ignition from becoming a large fire with associated substantial costly damages (Parks 1964). The initial attack can be generally defined as the first 1–8 h (90 min, in Portugal) of the fire suppression effort, when the fundamental objective is the containment in the shortest possible time of the fire at a small size, by using ground crews (fire engines, hand crews, and eventually bulldozers) and aerial means (e.g., water-dropping helicopters) (Lee et al. 2012).

The unconditional probability of ignition decreases from north-west to south-east in all fire scenarios (Fig. 5). For each of the 12 fire season scenarios, we generated four fire scenarios with the same probability (25%), obtaining a total of 48 season scenarios (probabilities in supplementary Table A4). For proof of concept purposes, we constructed the fire scenarios in order to obtain the same average, but different standard deviations, for the total number of ignitions (the detailed maps of ignitions, for each of the 48 fire scenarios, are provided in supplementary Table A5 and Table A6).

Dispatch classes parameterization

The fire escape probability is influenced by the season scenario, namely by the FWI (in the last stage, the fire season

[1] For example, in June 17, 2017, five escaped fires that later became one large fire in the center of Portugal caused 64 deaths and more than 250 injuries. With a total burnt area of about 46,000 ha (e.g., "Pedrogão Grande", one of the seven severely affected municipalities, had its forest reduced by 82%); the fire destroyed over 491 houses and jeopardized 49 companies, causing estimated losses of €497MM (CCDRC 2017).

Table 1 Test landscape parameter values

Parameters	Values
Set of cells and of potential fire stations: *I*	25 cells (5×5 grid), with 10 by 10 km each
Set of potential fire locations: *J*	Matches the set of cells *I*
Set of suppression resource dispatch classes: *K*	Two classes (and class 0, for no resources dispatched)
Set of types of suppression resources: *R*	Two types (helicopters and ground crews)
Set of types of treatment: *Q*	Treatment/no-treatment (1/0)
Set of nodes in scenario tree: *N*	#N = 70 (please see Fig. 4)
Set of fire season scenarios: S	#S = 12 (please see Fig. 4)
Set of fire scenarios: S'	#S′ = 48 (please see Fig. 4)
Set of season scenarios (decision nodes): A	#A = 10 (please see Fig. 4)
Cost of contracting one unit of resource type r in node n: c^1_{rn}	€700,000 and €22,000 for aerial and ground crews, respectively; increasing 4% at each decision stage along the branch but equal in parallel nodes
Fixed cost of opening a station at location *i*:c^2_i	€8000 (temporary stations) for any location
Extended cost of an escaped fire (containing, lost value and restoration) at location *j*: c^3_j	Equal in all locations; 4 and 12 million euros (Table 2, 3, supplementary Table A1 and A2) for the study on the role of flexibility, and from 0 to 20 million euros (Fig. 9 and 10) for the study on the socioecological contexts—details in Investment mix, volatility, *EFeC*, and flexibility" and "Investment mix and socioecological contexts" sections
Cost of treating location *j* in node *n*: c^0_{jn}	€100,000 increasing 4% at each decision stage along the branch but equal in parallel nodes for all locations
Ignitions location (binary); 1 if fire occurs in location *j* in fire scenario *s*′, 0 otherwise: $f_{js'}$	Ignitions location probability decreases from north-west to south-east in all fire scenarios; two distributions with the same average, but different standard deviations, for the total number of ignitions – details in Fig. 5, Table A5, and Table A6
Probability of node *n*: p_n	Please see Fig. 4)
Upper bound on the number of suppression resources of type *r* deployed at station *i*: M_{ir}	Not limited (large number: 5000 in each location)
Budget: B	Not limited (large number: €99,999,000)
Upper bound on the number of treatments that are possible at decision node *n*: T_n	Not limited (large number: 50 for 25 maximum possible locations, in each decision node)
Number of resources of type *r* used in a *k* dispatch class ($d_{r0} = 0$): d_{rk}	Helicopters/ground crews: 1/2, 0/6 and 0/0 for classes 2, 1, and 0, respectively
Escape probability for a fire in location *j* in season scenario *s* under dispatch class *k* and treatment *q* ($v_{qj0s} = 1$): v_{qjks}	Same in all locations and all scenarios; always 1 for dispatch class 0 by definition; decreases by a half if a cell is treated, and a fifth if class 2 (instead of 1) is dispatched; as the FWI goes from "low" to "medium" or "high", the escape probability grows by a factor of 1.3 or 2, respectively—please see Table A3
Set of stations *i* from where resources of type *r* can reach location *j* within the maximum response time: O_{rij}	Helicopters and ground crews cover the cell where they are located and all cells reachable within 15 min of travel time at a speed of 170 and 40 km/h, respectively—please see Fig. 6

scenario), in addition to the class of suppression resources dispatched, and the fuel treatment of the cell where the fire occurs, as detailed below in this section. *Ceteris paribus*, a fire in a season with the highest FWI has an escape probability that is twice the escape probability for the same fire in the season with the lowest FWI, and in the season with moderate FWI, the escape probability increases by a factor of 1.3 relative to the season with the lowest FWI (please see supplementary Table A3).

In all instances, we defined two dispatch classes, $k = 2$ with one helicopter and two ground crews, and a less effective $k = 1$ with only (six) ground crews. The effectivenesses were defined by the escape probability, which increases 5 times if dispatch class 1 is used instead of 2 (supplementary Table A3). If there are no suppression resources available to attend a fire, the escape probability is 1 ($k = 0$). Helicopter and ground crews have different spatial flexibility, determined by a threshold of 15 min of travel time, considering speeds of 170 and 40 km/h, respectively. Figure 6 shows three examples of resource coverage.

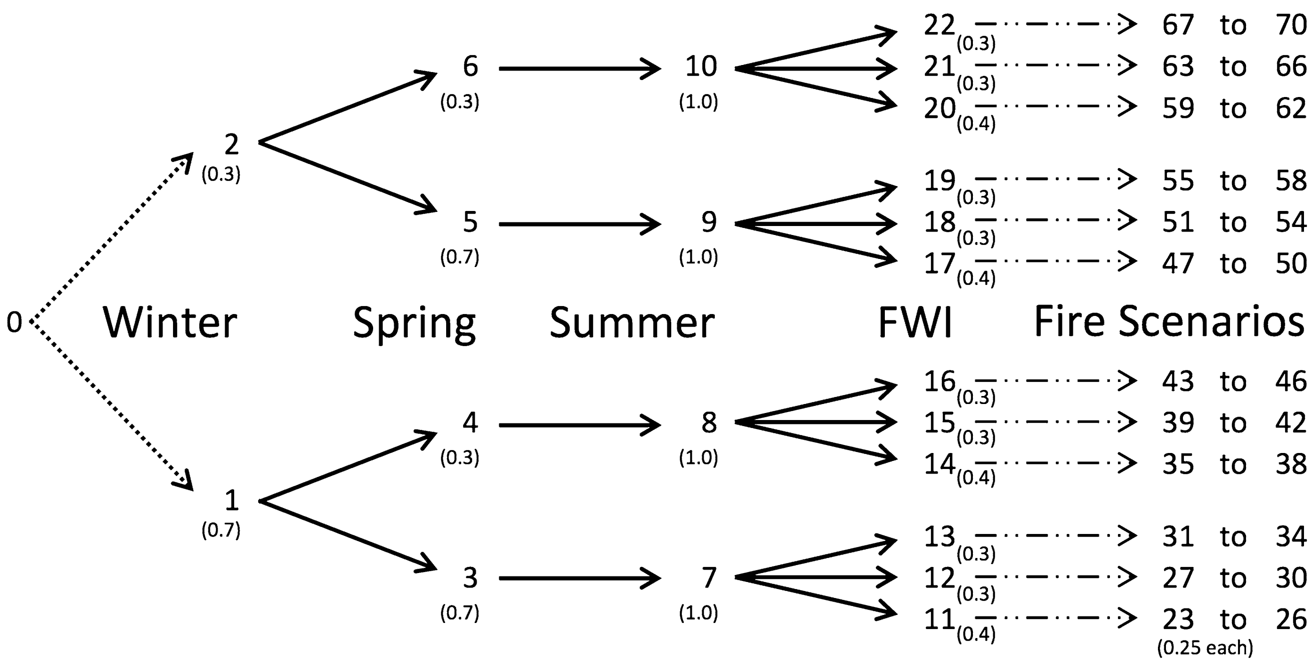

Fig. 4 Scenario tree used in the model proof of concept (please see also supplementary Table A4)

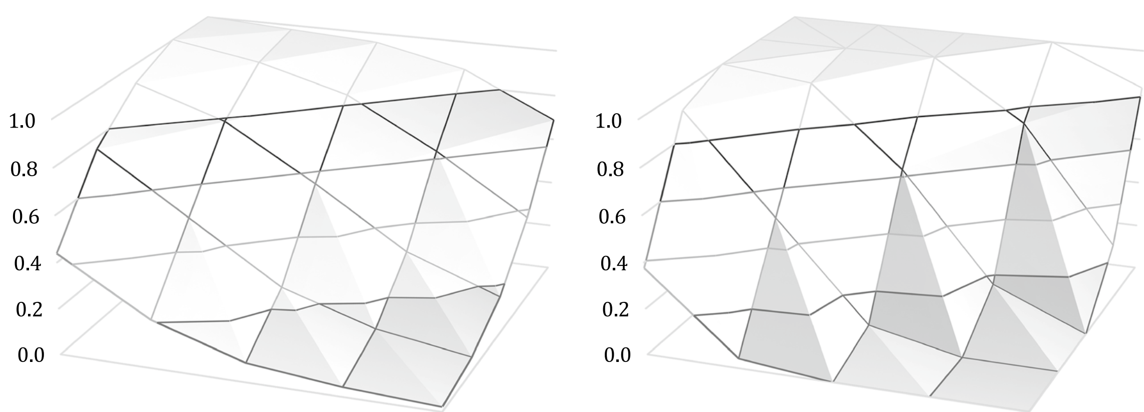

Fig. 5 Representation of the two sample (unconditional) probability distributions used to generate ignition locations (Table A5 and Table A6, respectively), with the same average, but different higher (left) and lower (right) volatilities, for the fire scenario total number of ignitions (*fstni*)

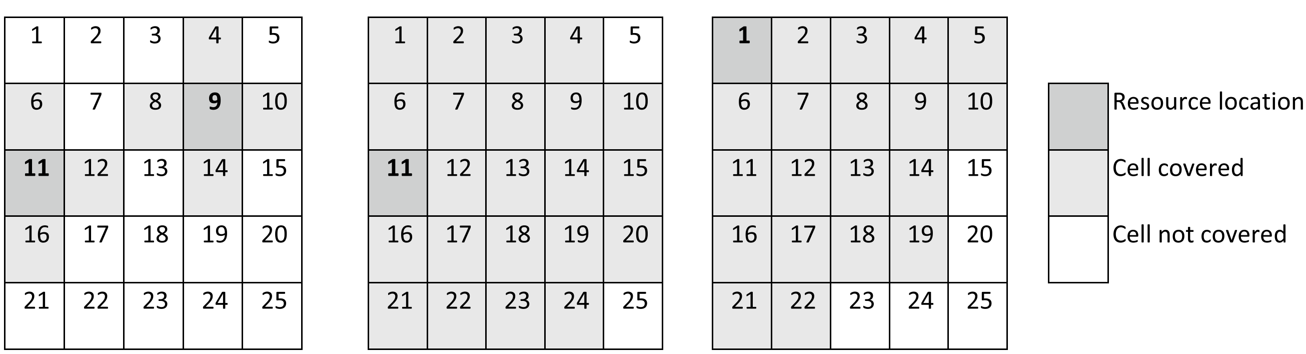

Fig. 6 Suppression resource 15 min ranges (examples): cells covered by ground crews located in cells 11 and 9 (left) and cells covered by a helicopter located in cells 11 (middle) and 1 (right)

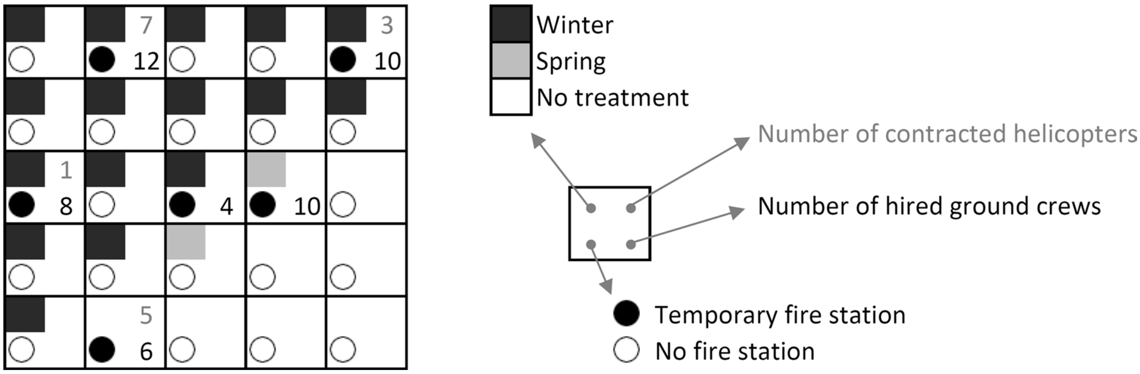

Fig. 7 Spatial view of the solution for branches 1–3, for an escaped fire extended cost (EFeC) of 12,000 M, with lower volatility in the set of fire scenarios (see Table 3). For the solution with higher volatility, please see supplementary Fig. A1

Costs parameterization

The test landscape was built using realistic values. The costs were inspired by the Portuguese case, and the dimension of the test landscape specifically by the district of Porto, analyzed in two previous published studies (Pacheco et al. 2014a, b).

For the cost of contracting aerial resources ($r = 1$), we considered the unit cost of renting a helicopter during the entire season (i.e., the 92 days from the beginning of July to the end of September) including 635 h of flight at a cost of €788/h (an average utilization of about 7 h per day) and a fixed cost of €200,000, obtaining the total of €700,000. Renting a helicopter fleet, instead of purchasing, is a common practice in Portugal, both by public authorities and private companies (e.g., pulp and paper companies which own large areas of planted eucalyptus forests). For the unit cost of contracting ground crews ($r = 2$), we considered teams of five firefighters, also during the entire fire season, at a cost of €240 per day, obtaining the rounded total of €22,000. Each crew operates a truck with a small water tank which is not included in our cost calculations as we assume a preexisting truck fleet, as is usually the case in Portugal. Both costs increase 4% at each decision stage along the year (i.e., winter, spring, and summer), similarly for all the nodes at the same level of the scenario tree.

Because fire stations are located in populated areas, the temporary relocation of fire crews to strategic locations in forested areas is a common practice. That is the reason why, for the fixed cost of opening a temporary station, we considered an expenditure of €2500 for its preparation, and a maintenance cost of €60 per day, obtaining a rounded total of €8000. These costs are assumed to be the same in all cells and do not change along the year.

We considered the same treatment cost for all locations and assumed that the effects of the treatments last 4 years, annualizing the cost at 25% per year. With an area of 10,000 ha per cell of our test landscape, assuming that on average only 10% need to be treated, i.e., 1000 ha, at a cost of €400 per hectare, the total treatment cost for each cell is €100,000. The evolution of this cost along the year is identical to the evolution of the cost for suppression resources. Treatments also influence the escape probability, by decreasing it to half (please see supplementary Table A3).

Finally, for the escape fire cost (EFC), we considered an overall value that includes several fire-related losses (e.g., timber and non-timber products, recreational activities, indirect use, and other values of non-market resources), which we named "escaped fire extended cost" (EFeC). We assumed that an escaped fire would burn 20% of the area of the cell, and that half of the value of the burnt area would be lost. Thus, e.g., for a hectare value of €2000 (€0.2/m^2), the cell value is €20,000,000 and an escaped fire would cause an EFeC of 2000 M/cell (where "thousands of euros" are denoted simply by "M"). Similarly to other costs, we consider the EFeC to be identical in all locations.

Results and discussion

In addition to how much should be invested, in what options, and when (according to the evolution of weather conditions), the model's spatially explicit solutions (Fig. 7) indicate where the investments should be carried out, except for the temporary fire stations, whose locations, w_{ia_s} are decided at the last moment (Summer; Fig. 4).

In this section, the escaped fire extended cost (EFeC) is assumed to be the same for all the cells of the test landscape, i.e., c_j^3, which for simplicity we denote c^3, is the same in all locations, and thus, $EFeC = c^3$.

In "Investment mix, volatility, *EFeC*, and flexibility" section, we start by analyzing how changes in EFeC and in the volatility of the demand (total number of ignitions in the fire

Table 2 Budget allocation (absolute and percentage) for an escaped fire extended cost (EFeC) of 4000 M, with low and high volatility in the set of fire scenarios, overall and per decision node (Winter and Spring)—branch 1–3 (for branch 2–5, please see Table A1)

Portfolio options	Volatility					
	Low			High		
	Winter [1]	Spring [3]	Total	Winter [1]	Spring [3]	Total
Fuel treatments	16	2	18	19	4	23
Suppression (ground crews)	102	12	114	126	24	150
Suppression (helicopters)	0	0	0	0	0	0
Fire stations	5	1	6	6	1	7
	Investment balance (%)		Bdgt Prt (%)	Investment balance (%)		Bdgt Prt (%)
Fuel treatments	88	12	41.3	82	18	40.7
Suppression (ground crews)	89	11	58.7	83	17	59.3
Suppression (helicopters)	-	-		-	-	
Fire stations	83	17		86	14	

scenarios) influence (1) the postponement of capacity investments along the year, (2) the total expenditures, and the (3) investment mix. The observation that the budget increases about proportionally to EFeC leads us to further exploring this issue later; in "Investment mix and socioecological contexts" section, we analyze the behavior of the system in the presence of different values at risk, i.e., different EFeC values, related with different socioecological contexts. More specifically, we analyze how the balance between prevention and suppression in optimal budgets behaves as a function of EFeC.

Investment mix, volatility, *EFeC*, and flexibility

To model the volatility in weather conditions, we maintain the probabilities associated with the intra-annual weather variability, and change only the segment of the 48 fire scenarios (the ultimate leaf nodes of the scenario tree), i.e., the micro-uncertainty (in fire occurrence, location, and severity) associated with the 12 fire season scenarios. As mentioned previously (in "Model proof of concept" section), the total number of ignitions in the fire scenarios feature the same average (13.5 ignitions per fire scenario) but different standard deviations: in the lower (higher) volatility case, the total number of ignitions in the fire scenarios varies between 8 and 19 (2 and 25), with a standard deviation of 2.84 (5.71)—supplementary Table A5 and Table A6 show the locations of the ignitions for each fire scenario, for the higher and lower volatility cases, respectively, and Fig. 5, left and right respectively, the two sample (unconditional) probability distributions that generated them.

In this subsection, we use two values for the EFeC, 4 and 12 million euros (4000 M and 12,000 M, with "M" denoting *thousands of euros*) which we name C4 and C12, respectively. We have thus four instances—C4L, C4H, C12L, and C12H, with L and H standing for the low- and high-volatility cases, respectively.

From the "Spring" decision stage to the "Summer" decision stage, there is only one branch (Fig. 4) and an increase of 4% in costs (please recall the c^1_{rn} parameterization for the model proof of concept in Table 1). Thus, there are no decisions in the latter, only in "Winter" and in "Spring"—the information available in "Spring" is the same as in "Summer" and the decisions can be made at a lower cost.

In addition, in the alternative branches (Fig. 4) sharing 1 (2) as the first decision node, i.e., in the paths starting with 1–3 (2–5) and 1–4 (2–6), the latter represent less hazardous situations than the former. Fire scenarios 35–46 (59–70) feature less ignitions than fire scenarios 23–34 (47–58)—please see supplementary Table A5 and Table A6—and thus no decisions are made in node 4 (6). Accordingly, for the main text, from the initial alternative branches we focused our attention only on the paths starting by 1–3, i.e., 1–3–7–11–23[to 26], 1–3–7–12–27[to 30], and 1–3–7–13–31[to 34] (and present in the supplementary material the results of the paths starting with 2–5).

The results for branch 1–3 can be seen in Table 2, for C4L and C4H, and Table 3, for C12L and C12H. (For branch 2–5, the results are presented in the supplementary Table A1, for C4L and C4H, and Table A2, for C12L and C12H.)

I. How volatility in the demand and EFeC influence the timing of capacity investment

The study of the evolution of investment decisions along the year confirms what was intuitively expected: *ceteris paribus*, for a higher (lower) volatility in the weather conditions, i.e., a higher (lower) uncertainty about the future, a higher (lower) proportion of the total optimal investment is postponed. Indeed, e.g., for C4, in branch 1–3 (Table 4),

Table 3 Budget allocation (absolute and percentage) for an escaped fire extended cost (EFeC) of 12,000 M, with low and high volatility in the set of fire scenarios, overall and per decision node (Winter and Spring)—branch 1–3 (for branch 2–5, please see Table A2)

Portfolio options	Volatility					
	Low			High		
	Winter [1]	Spring [3]	Total	Winter [1]	Spring [3]	Total
Fuel treatments	16	2	18	18	4	22
Suppression (ground crews)	46	4	50	66	8	74
Suppression (helicopters)	14	2	16	15	4	19
Fire stations	5	1	6	6	1	7
	Investment balance (%)		Bdgt Prt (%)	Investment balance (%)		Bdgt Prt (%)
Fuel treatments	88	12	12.7	81	19	12.8
Suppression (ground crews)	92	8	87.3	89	11	87.2
Suppression (helicopters)	87	13		78	22	
Fire stations	83	17		86	14	

Table 4 Budget allocation decisions in 1 (Winter) and 3 (Spring) for an escaped fire extended cost (EFeC) of 4000 M (values in thousands of euros, M)—for branches starting with 2–5, please see Table A7

Portfolio options	Volatility					
	Low			High		
	Winter	Spring	Total	Winter	Spring	Total
Fuel treatments	1600	208	1808	1900	416	2316
Suppression (ground crews)	2244	275	2519	2772	549	3321
Suppression (helicopters)	0	0	0	0	0	0
Fire stations	40	8	48	48	8	56
Suppression total	2284	283	2567	2820	557	3377
Total (prevention + suppression)	3884	491	4375	4720	973	5693
Ratio (suppression/prevention)	1.43	1.36	1.42	1.48	1.34	1.46

Table 5 Budget allocation decisions in 1 (Winter) and 3 (Spring) for an escaped fire extended cost (EFeC) of 12,000 M (values in thousands of euros, M)—for branches starting with 2–5, please see Table A8

Portfolio options	Volatility					
	Low			High		
	Winter	Spring	Total	Winter	Spring	Total
Fuel treatments	1600	208	1808	1800	416	2216
Suppression (ground crews)	1012	92	1104	1452	183	1635
Suppression (helicopters)	9800	1456	11,256	10,500	2912	13,412
Fire Stations	40	8	48	48	8	56
Suppression total	10,852	1556	12,408	12,000	3103	15,103
Total (prevention + suppression)	12,452	1764	14,216	13,800	3519	17,319
Ratio (suppression/prevention)	6.78	7.48	6.86	6.67	7.46	6.82

with a lower volatility, the percentage of the total investment (prevention and suppression) postponed to the Spring is 11.2% (490, 560/4, 374, 560), whereas with a higher volatility it is 17.1%: a high/low volatility postponement ratio of 1.52 (17.1%/11.2%). From C4 to C12, the EFeC triples and the total investment about triples also, from 4375 M (Table 4) to 14,216 M (Table 5), and from 5693 M (Table 4) to 17,319 M (Table 5), for the lower and higher volatilities, respectively. In this case, the pressure to postpone the investments increases, as shown by the increase in the postponement ratio from 1.52 to 1.64.

Table 6 Summary of total budget (please see Table s4 and 5, Table A7, and Table A8). "Vlt" and "var" stand for volatility and variation, respectively. All values are in thousands of euros

Branch	EFeC				EFeC (var)		Vlt (var)	
	4,000 M		12,000 M		C4–C12		Low–High	
	Low	High	Low	High	Low	High	C4	C12
2–6	2948	2848	9068	7032	3.1	2.5	1.0	0.8
2–5	3439	3821	10,832	10,551	3.2	2.8	1.1	1.0
1–4	3884	4720	12,452	13,800	3.2	2.9	1.2	1.1
1–3	4375	5693	14,216	17,319	3.2	3.0	1.3	1.2
0–2–5	3326	3713	10,484	10,282	3.2	2.8	1.1	1.0
0–1–3	4262	5585	13,868	17,050	3.3	3.1	1.3	1.2
0 (fall)	2836	2740	8720	6763	3.1	2.5	1.0	0.8

II. How volatility in the demand and EFeC influence the optimal budget

Dispatch class 2 is more effective than dispatch class 1 (please see the escape probability in supplementary Table A3) but has a higher cost (744 M vs 132 M), as it involves the hiring of one helicopter (1 × 700 M) and two ground crews (2 × 22 M) instead of six ground crews (6 × 22 M). In addition, the increased spatial flexibility of the helicopter, to be useful, must be compensated by the presence of other ground crews, spread by the area it covers, because the helicopter cannot work alone (from the dispatch class 2 definition, in Table 1).

From C4 to C12, the EFeC increases enough to justify contracting helicopters (in order to use dispatch class 2), and, as observed in Table 6, the optimal budget increases also (in about the same-triple-proportion). An increase in the volatility also has a significant impact on the optimal budget—in C4 the expected value of the optimal budget increases 22.6%, and in C12 it increases 12.3%, from the low to the high-volatility instance.

III. How volatility in the demand and EFeC influence the investment mix

A similar pattern is observed in branch 2–5 (please see supplementary Table A7 and Table A8), for which the proportion of investment postponed to the Spring in C4 is 14.3% and 25.5% for the lower and higher volatility, respectively. The postponement ratio of 1.79 also increases to 2.05, from C4 to C12, as the total investment grows from 3439 M to 10,832 M for the lower volatility, and from 3821 M to 10,551 M for the higher volatility.

The postponements of the commitments to each type of capacity, fuel treatments, and suppression preparedness (ground crews, helicopters, and temporary fire stations) have about the same ratio, respectively 1.56 and 1.50 in C4(1–3), 1.86 and 1.74 in C4(2–5), 1.63 and 1.64 in C12(1–3), and 1.99 and 2.06 in C12(2–5). However, looking at the portfolio with more detail (please see supplementary Fig. A2)—except for temporary fire stations (please see Fig. A3 and supplementary Note A1, right below)—higher volatility and then higher EFeC cause increasing differences in the investment postponement within the suppression options. Increasing uncertainty about fire locations (volatility) with an EFeC that justifies contracting helicopters, which have more spatial flexibility and efficacy although at an increased cost, leads to a higher postponement in the commitment to their acquisition.

Unlike ground crews and helicopters, fuel treatments do not feature spatial flexibility directly, because their effect is restricted to the region where they are applied. In addition, consisting of increasing the probability of containment by initial attack (see Table A3), their effect is only realized through the deployment of suppression efforts. This interaction, jointly with the fact that dispatch class 2 also brings together the two types of suppression resources, greatly complicates the relationships between the different portfolio options.

In fact, although the number and location of fuel treatments are sensitive to volatility (Fig. 8), their proportion of the annual budget remains constant. Almost in opposition, the number and location of fuel treatments are fairly insensitive to the EFeC, but their proportion in the annual budget decreases more than 2/3 from C4 to C12 (from about 41% to 13%), as a consequence of the shift from no investment to a large investment in helicopters.

Suppression resources are highly sensitive to changes in the EFeC. Indeed, *ceteris paribus*, increasing EFeC from C4 to C12, the number of ground crews (Table 2, Table 3, Table A1 and Table A2) is reduced to about half (44–57% reduction) but their weight in the budget (Tables 4, 5, Table A7, and Table A8) is reduced from 58% to about 1/7 to 1/5 (13–21%) of the total budget—a proportion roughly 1/3 lower.

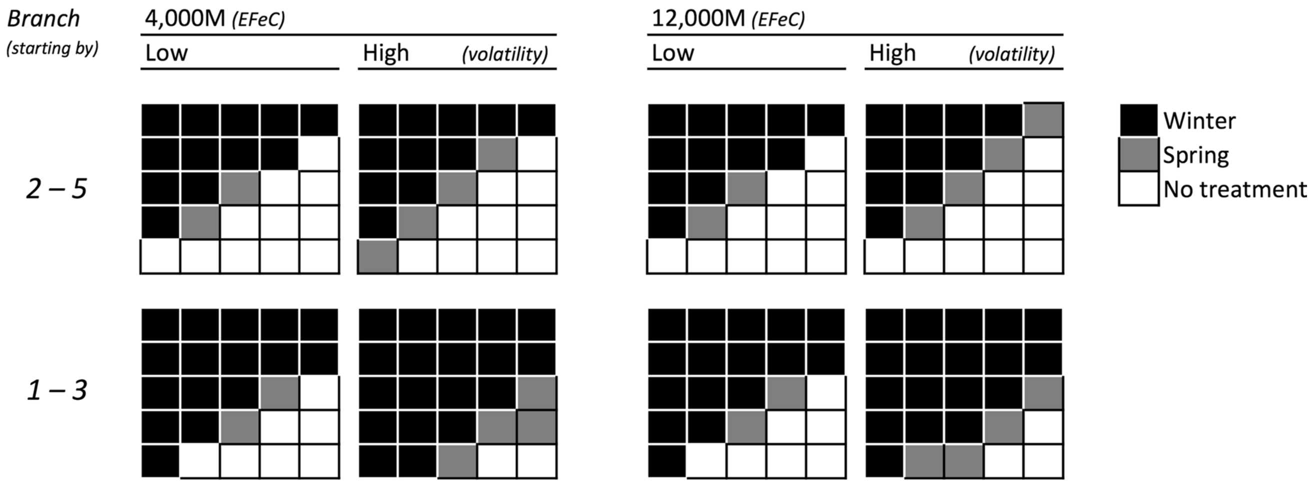

Fig. 8 Spatial view of the cells chosen for the application of fuel treatments in winter and spring, in the two branches of the test landscape, for a low and a high volatility in the set of fire scenarios, with a fire escape extended cost of 4 and 12 thousands euros (see Table A10, for the number of fuel treatments and percentage of treated cells)

However, from lower to higher volatility, *ceteris paribus*, despite the increase in the number of total ground crews (13% and 32% in C4, and 38% and 48% and C12, respectively for 2–4 and 1–3), the proportion of the budget allocated to ground crews is quite stable, about 58% and 10% (8–12%, more precisely) of the optimal budget, in C4 and C12, respectively. In C12, almost unresponsive to volatility, helicopters absorb 77% of the optimum budget (74–79%).

The suppression/prevention budget ratio (Table 4, Table 5, Table A7, and Table A8) grows nearly five times, from 1.46 in C4 to 6.71 in C12, while remaining almost insensitive to changes in volatility.

Investment mix and socioecological contexts

The length of the fire season is increasing in several regions worldwide (Fischer et al. 2016) and, as referred before ("Introduction" section), decision-making processes need to be framed in terms of the relative magnitude of uncertainties and the response options available for each particular context. The context relates to fire regimes, policy (e.g., relative cost of fire suppression), and the values at risk—e.g., the extent of the WUI, forested areas (and the type of terrain where they are), degree of economic dependence on forest resources, or existence of protected natural parks (Thompson et al. 2017). In this subsection, we study the sensitivity of the portfolio mix to changes in the values at risk, expressed as different EFeC values, i.e., how the optimal budget balance (between prevention and suppression) reacts to increases in EFeC.

We found that the prevention/suppression balance changes smoothly within four regions, limited by δ_1, δ_2, and δ_3, but features leaps at these EFeC thresholds. The regions (A, B, C, and D, in supplementary Table A11), or system stages, reflect qualitative changes in the system equilibrium. Furthermore, the change in weather volatility considered in our analysis did not affect system stages (supplementary Table A11 and Fig. A4), as the threshold values remained exactly the same—in our test landscape, 169, 960, and 6490 (€/ha or M/cell), respectively. The leaps were, however, more abrupt with the lower volatility (e.g., at δ_2, from 959 to 960, the suppression budget falls from 100 to 67% with the lower volatility, whereas with the higher volatility, it falls to 82%, reductions of 33 and 18% respectively). It should be noted that values higher than 6490 are not unreachable. Indeed, at the WUI, they can be far larger: e.g., the reported losses in the recent Pedrogão Grande fires (CCDRC 2017), mentioned in "Model proof of concept" section above, are of about €10,804/ha (€1.08/m^2).

A global view of the system equilibrium qualitative behavior changes, as the hectare value or the escaped forest fire losses (M) rise, for the high-volatility scenario, is provided above, in Fig. 9, with the horizontal axis consisting of log-transformed values (base 2), to provide visibility to the first stage. A similar overview without log-transformed values is provided in supplementary Fig. A5, with the detail for values below 1600, presented in supplementary Fig. A6. The complete results for the lower and higher volatility cases are provided in supplementary Table A11.

These qualitative stage changes are caused by a rational successive inclusion of available options in the portfolio mix, as soon as they become economically efficient. It is worth noting that the order of inclusion—dispatch class 1, fuel treatments, dispatch class 2—does not follow the intrinsic cost of the options—the cost of treating one location, and the costs of the resources needed to use dispatch class 1 and

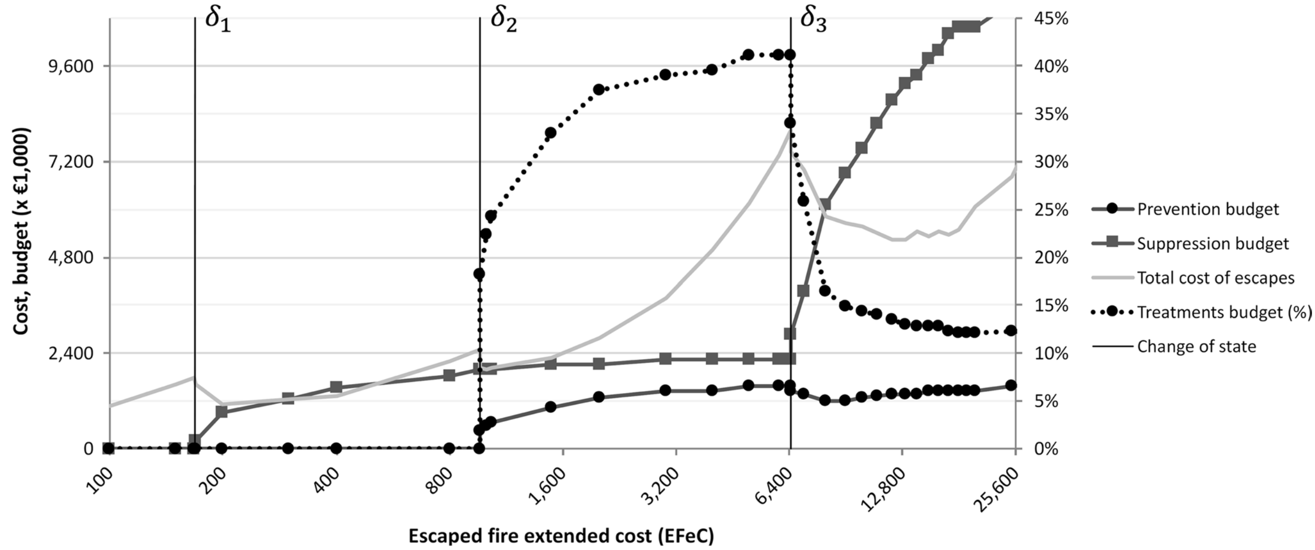

Fig. 9 Global system behavior (high volatility) and stages (*let burn*, *no prevention*, *prevention focus*, and *suppression dominance*) according to the hectare value or escaped forest fire loss (M)—please see supplementary Table A11; horizontal axis with log-transformed values (base 2)—for a similar overview without log-transformed values, please see supplementary Fig. A5)

2, start at (Table 1) 100 M, 140 M (6 × 22 M + 1 × 8 M), and 752 M (1 × 700 M + 2 × 22 M + 1 × 8 M), respectively. As observed previously, the interactions between the options complicate this analysis.

In the lowest system stage (or region), for an EFeC < δ_1, which we call it "*let burn,*" the optimal expected budget is zero because no positive portfolio mix of investments is low enough to be compensated by the decrease in escape costs, i.e., the optimal investment in both prevention and suppression options is zero. The second stage, until δ_2 ($\left[\delta_1, \delta_2\right[$), has a positive optimal budget, 100% allocated to suppression (ground crews and temporary fire stations), and we name it "*no prevention.*" Next, in the third stage ($\left[\delta_2, \delta_3\right[$), which we call "*prevention focus,*" prevention jumps from 0 to 33% (18%) and grows smoothly until 43% (41%) for the lower (higher) volatility, while suppression falls from 100 to 67% (82%) and continues to fall to 57% (59%). Indeed, at δ_2, fuel treatments start to pay-off with the decreased escape probability they provide.

Finally, in the last stage, termed "*suppression dominance,*" for an EFeC ≥ δ_3, the value lost with the burnt area is sufficiently high to justify investing in helicopters. Consequently, prevention drops, for the lower (higher) volatility, from 43% (41%) to 35% (34%) and then smoothly falls to 12% (12%), while suppression jumps from 57% (59%) to 65% (66%) and continues rising until about 88% (88%). However, despite the low and decreasing proportion of the prevention budget, its absolute value remains quite stable: 1382 and 1465 for the lower and higher volatility, respectively. We emphasize the enduring importance of fuel treatments (above the δ_2 threshold), in the face of the dominance of fire suppression policies in contemporary fire management (Schoennagel et al. 2017). Fire management in Europe, e.g., is still strongly focused on fire suppression (Fernandes et al. 2016), in spite of the, now well understood, impacts of fire suppression on fuel build-up (Schoennagel et al. 2017). In Portugal, expenditures with firefighting are three times larger than expenditures with fire prevention, fuel management, and pre-suppression (Mateus and Fernandes 2014), i.e., suppression accounts for 75% of the total budget available for FFM.

The stages also reflect shifts in behavior for the expected burnt area. The investment in the portfolio increases (with decreasing gains) up to a point at which further investments cost more than the avoided escaped fires. So, there is always a probability distribution for a certain number of escaped fires and thus for burnt area associated with the optimal portfolio mix. Unless society is willing to pay a suboptimal price, there will always exist some (positive) expected burnt area.

In the case of our test landscape, for the higher volatility, along the four regions (Fig. 10), the expected proportion of escaped fires goes from being always 100%, to a variation from 88.9 to 24.2%, then from 19.9 to 11.5%, and finally from 10.7 to 2.4% (achieved at an EFeC of 50,000 M). Similarly, the expected burnt area is at first always 8.6% and then goes from 7.6 to 2.1%, from 1.7 to 1.0%, and from 0.9 to 0.20%. The thresholds are included in Table 7 (values in supplementary Table A11). In our model, burnt area and escaped fires have a linear relationship. For this reason, with the appropriate scales, the two lines displayed in Fig. 10

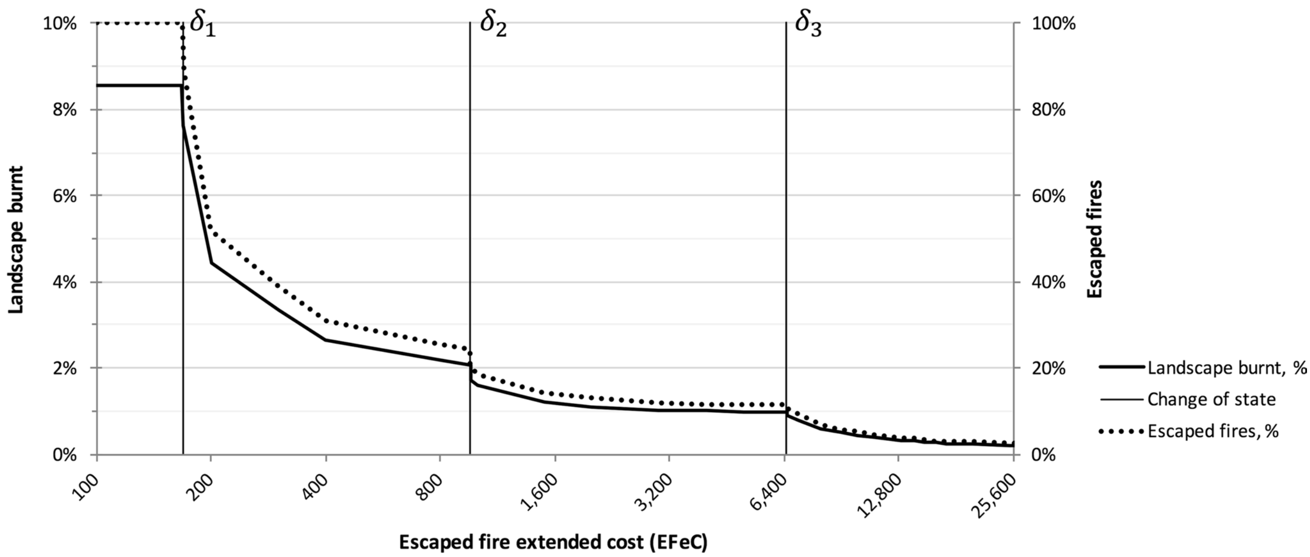

Fig. 10 Socioecological context and changes in the percentage of landscape burnt and escaped fires (high volatility), as EFeC rises (values in supplementary Table A11—horizontal axis with log-transformed values (base 2)

Table 7 Characterization of test landscape system stages and connected socioecological contexts, with their values at risk and policy concerns

	System stages (EFeC thresholds)			
	Let burn $< \delta_1$	No prevention $[\delta_1, \delta_2[$	Prevention focus $[\delta_2, \delta_3[$	Suppression dominance $\geq \delta_3$
Fuel treatments	No	No	Yes	Yes
Ground crews	No	Yes	Yes	Yes
Helicopters	No	No	No	Yes
Escaped fires[a] (%)	100	88.9–24.2 (22.6)	19.9 (14.6)–11.5 (10.8)	10.7 (10.2)–2.36[b]
Landscape burnt[a] %	8.6 (9.7)	7.6–2.1 (2.2)	1.7 (1.4)–1.0	0.9 (1.0)–0.20 (0.23)[b]
	Socioecological contexts			
	Shrubland	Abandoned forest	Planted forest (stands)	WUI and forest reserves
Values at risk ordered list (suggestion)	Forest biomass Recreational activities	Indirect use Pellets Pulpwood	Timber products Non-timber products Forest prod. and services Birch logs Sawlogs	Non-market resources[c] WUI related values Human lives
Policy concerns	Promote mix with more valued activities	Wood prices	Aerial resources ineffective utilization	"Firefighting trap" (Collins et al. 2013)

[a]Lower volatility values within brackets

[b]At an EFeC of 50,000 (20,000)

[c]Cultural heritage, ecological values, and others

would be the same—in order to improve readability, we show them separate.

An actual landscape can exhibit one (or more) of the stages we identified, depending on the relationships between its values at risk, the cost, effectiveness, and spatial flexibility of the suppression resources in each dispatch class, and the cost and effectiveness of the fuel treatments. In the face of a (rational) optimal portfolio that leads to a number of expected escaped fires (and burnt area) considered to be excessive according to some point of view, policies can be designed in order to change the *status quo*. These policies can assume forms such as direct subsidization, market regulation, or consent to suboptimal fire responses.

These successive stages can also be seen as a ladder of ascending value. At the top of such value ladder will certainly be the WUI with its associated higher fire protection costs, requiring restrictions to further residential growth in fire-prone landscapes, a policy that is harder to implement today, but promises to yield future benefits to society (Schoennagel et al. 2017). Also, as in many temperate forest ecosystems, fire has a critical role and is an essential ecological process in order to preserve native plants and wildlife diversity (Fischer et al. 2016), a context that we can associate to the bottom of this ladder. In between these extremes, there may exist other system stages, that can be associated with particular (local) contexts, altogether calling for the rational utilization of resources and the design of contextual policies.

The optimal response is always context dependent, and indeed, our results challenge some popular "one-size-fits-all" ideas, e.g., (a) investing in prevention is always worthwhile, (b) the proportion of the fire budget spent with fuel treatments should always be at least one-third, (c) the utilization of helicopters is always a waste, and (d) the idea that large fires can be totally eradicated. The fact that at the bottom of the ladder ("*let burn*") it does not make sense to invest in any kind of option (even suppression) challenges (a), the budget allocated to fuel treatments varies significantly, featuring proportions both above and below the one-third referred in (b), the utilization of helicopters in the upper stages challenges (c), and in order to achieve (d), society must be willing to pay a suboptimal price, as referred above.

Using our test landscape as an application exercise, we can relate the observed stages with different socioecological contexts (Table 7) in Portugal. "No prevention" can be associated with the "abandoned forest" (typical of the center and north of Portugal, where most forest, and old agricultural lands now forested due to rural abandonment, is divided among numerous small owners), "prevention focus" with the "planted forest" (owned or rented, but managed by companies for timber production), and "suppression dominance" with the WUI, because of the related EFeC high values. In line with the analysis described in the next paragraph, and although Portuguese law requires every fire to be fought, we relate "let burn" with shrublands (distant from populated areas).

In order to assign the assets presented in Table 7 (bottom) to each stage, we used Netto (2008) and Pinto et al. (2013) for the valuation of "forest biomass", AFN (2011) for the overall "losses in (forest) products and services" (€1435/ha), and ISA (2005) for the "value losses" in "timber products" (€917/stand-ha), "non-timber products" (€1045/stand-ha), "recreational activities" (€47/forest-ha), and "indirect use" (€191/forest-ha)—all in 2017 values, accounting for the official inflation rate (PORDATA 2017). The values for the other assets in the first three stages (pellets, pulpwood, birch logs, sawlogs) were obtained in Sathre and Gustavsson (2009) and FOEX (2017) price indices. For the last stage, we chose to list the value of "non-market resources" (cultural heritage, ecological values, and others) below the losses in "WUI related values" and "human lives" (above all). A final note concerns "timber products", whose current value is slightly above δ_2, but can sometimes, according to experts, be below. For this reason, we chose to classify "pulpwood" ("timber products") as the asset with higher (lower) value in the second (third) stage.

The optimal investment mix in some of the system stages resembles some behaviors actually observed in Portugal. A wood price below δ_2 can justify why small forest landowners implement no fire mitigation actions (e.g., fuel treatments). The sometimes criticized investment in aerial suppression resources can be understood in the face of the extension of the WUI in the country, and more broadly also explain part of the observed increase in suppression costs worldwide, related to the high costs of protecting the WUI from the increasing number of fires, due to global warming.

Schoennagel et al. (2017) stress the difficulties in recognizing and addressing significantly the impacts of wildfires on ecosystems and society, aggravated by gradual (but significant) changes in climate, fuels, and the WUI, and often worsened by a lack of political will to change ineffective long-standing policies and implement new policies with long-term value but short-term costs. Nevertheless, society has a unique opportunity to change the course of its response to wildfires and related policies, in the face of the projected global warming for the coming decades.

Our imaginary region (the test landscape) provides an example of how the model can be used to raise awareness to some deficits in system governance and support the design of new policies. In the bottom row of Table 7, we provide some examples of such "policy concerns", focused on placing assets in the appropriate stage of the ladder of value, or avoiding inappropriate, out-of-context, suppression options. For instance, desirable (isolated) economic activities with a value so low that they do not even justify suppression could benefit from policies to promote their mix with other valuable activities, to reinforce the area's value at risk (e.g., promoting forest biomass exploitation together with pulpwood or recreational activities in national parks). Market regulation (or direct subsidization) policies can prevent the values of some timber products from falling below δ_2 and thus favor the option to invest in fuel treatments. The observed inappropriate utilization of aerial resources in stages below the upper stage (WUI and forest reserves) can also be avoided. In addition, at that upper stage, the "firefighting trap" of a suppression focused policy (Collins et al. 2013), where apparently sound management can result in several unintended consequences, is a major concern. Finally, it should be noted that, in some cases, policies can be designed to protect some assets at a suboptimal price, by supporting investment options that in normal conditions would be avoided (e.g., the utilization of aerial resources to protect the "let burn" stage).

Conclusion

In this paper, we used a stochastic MIP model grounded in the literature, considering options related to fuel treatments and fire suppression, and weather variability and micro-scale factors, as sources of uncertainty, to show how an integrated intra-annual FFM can lead to a cost-effective budget allocation. We focused our analysis on mismatch risk, addressing two types of flexibility (investment postponement and spatial flexibility) and analyzing, first ("Investment mix, volatility, *EFeC*, and flexibility" section), how the optimal investment mix responds to weather volatility and the values at risk (EFeC), through system-endogenous flexibilities, and then ("Investment mix and socioecological contexts" section), how the optimal budget composition changes as the values at risk rise.

We found that (1) the value of postponement flexibility is evidenced in scenarios of increased uncertainty (higher volatility) and at a higher EFeC, to the point of almost 40% of the total optimum budget being postponed to the next decision node; (2) the optimum budget is affected by changes in demand volatility (impacting also the spatial solution) and is sensitive (but not proportionally) to changes in EFeC; and (3) the number and location of fuel treatments are sensitive to volatility, but their proportion of the annual budget remains constant, being fairly insensitive to changes in the EFeC (but impacting their proportion in the annual budget); suppression resources are sensitive to changes in the EFeC and in the volatility (without affecting the proportion of the budget allocated to ground crews); and the suppression/prevention budget ratio is sensitive to changes in the EFeC, and almost insensitive to changes in volatility—e.g., if climate change is leading to an increase in weather volatility, the optimal budget and the proportion allocated to each of the feasible options will be affected, namely the number and location of fuel treatments and the number of suppression resources (but not the suppression/prevention budget ratio), and the postponement of capacity investment will play an important role. Thus, policy makers should introduce this kind of flexibility in the design of the system.

The finding, in "Investment mix, volatility, *EFeC*, and flexibility" section, that the optimal budget and the proportion of the budget allocated to each option are highly sensitive to changes in the values at risk, was exhaustively explored in "Investment mix and socioecological contexts" section. For the instances that we analyzed, we found that the changes in budget composition and total value occur along four qualitative system stages that can be related to specific socioecological contexts and used as the basis for policy (re) design. Furthermore, even if—as we have seen—the investment mix changes qualitatively in the system, fuel treatments are always of value above a certain cost per hectare (δ_2). Also, independently of how the escape cost rises, after our δ_3 threshold, the optimal absolute value of the budget for fuel treatments is stable, with almost no changes, the policy implication being that, above a certain value at risk threshold (δ_2), investments in fuel treatments are always needed. These stages and their inherent proprieties can thus be conceptually useful in terms of defining regions.

As solutions are spatially explicit, the model is useful also at the operational level and the results show that an integrated intra-annual FFM leads to a cost-effective allocation of the budget, which in turn, contributes to mitigating the losses with catastrophic fires.

We believe our model contributes to (a) a strategic and operational problem in forestry by representing the underlying uncertainty in a solvable and tractable model; (b) that can be used also to help determine when and where to implement fuel treatments; and somehow (c) be used to motivate the interaction (and hopefully, later the coordination) of a set of stakeholders with individual agendas—a contribution to, respectively, the open problems 26, 20, and 10, in Rönnqvist et al. (2015).

There are apparent limitations in our model formulation, e.g., the fact that a fuel-treated cell does not impact its neighboring cells, or that if a fire escapes, all (and only) the cell where the fire ignites, burns. If the former is consistent with the latter, the latter, in turn, at some point can be partially addressed in the model parametrization—as we did, when we assumed, in our test landscape, that an escaped fire would burn 20% of the cell area, and that half of the value of the burnt area, would be salvaged.

It should also be noticed that the application of the model to a real forest implies the parameterization of the probabilities of the scenario tree, the ignition probability in all landscape cells, and the costs due to escaped fires. Defining these probabilities and costs with meaningful values is not an easy task, but can be grounded in analyses of historical data and/or expert elicitation. However, as we have demonstrated, the insights obtained as the result of a "what if" approach, with a test landscape, can be of value.

Finally, our preliminary results, despite being based on a test landscape, point in promising directions. The application of the model to an actual landscape, in addition to removing this limitation, can better explore the policy implications of the outlined qualitative system stages. The multi-year effect of fuel treatments (which we included in our analysis by way of a simple estimation of their expected value for subsequent years) suggests the extension of our intra-annual model to a long-term inter-annual portfolio management model, as future work.

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