flexible design of forest fire management systems

Abílio Pereira Pacheco

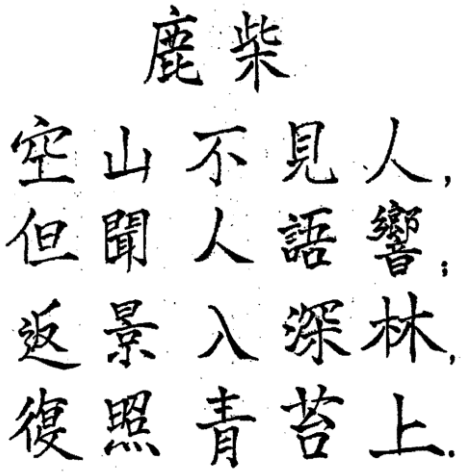
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a existência humana é curta e relativa
o pensamento harmonizado
pode conduzir ao silencio

Carlos César Pacheco



Wang Wei[1]

La Forêt

Dans la montagne tout est solitaire,
On entend de bien loin l'écho des voix humaines,
Le soleil qui pénètre au fond de la forêt
Reflete son éclat sur la mousee vert.
[G. Margoulies, 1948]

En la Ermita del Parque de los Venados

No se ve gente en este monte.
Sólo se oyen, lejos, voces.
Por hos ramajes las luz rompe.
Tendida entre las yerba brilla verde.
[Octavio Paz, 1974]

Empty mountains:
no one to be seen.
Yet – hear –
human sounds and echoes.
Returning sunlight
enters the dark woods;
Again shining
on the green moss, above.
[Gary Snyder, 1978]

[1] Three alternative translations of a poem of Wang Wei (701-761AD). Source: *19 Ways of Looking at Wang Wei*, by Eliot Weinberger, Moyer Bell Limited; 1995 (1st edition, July 1987).

to my mother

Maria Rosa Pereira Ferreira

to my true fathers, my uncles

Vitorino Pereira Ferreira

Manuel Augusto da Cunha Teixeira

to my other mothers

Maria Aurora Pereira Coelho (my grandmother)

Margarida Cidália Pereira Ferreira (my aunt)

to my father

Joaquim Moreira Pacheco (whose negative incentive was unfortunately really powerful)

to my other fathers

Carl Sagan, Jacob Bronowsky, Jorge Almeida, Noam Chomsky, Christopher Hitchens

Alberto Pimenta, Carlos César Pacheco, Alvaro de Campos, Walt Wittman, Han-Shan, Herberto Helder, Isabel de Sá, António José Forte, António Botto

Franz Kafka, Robert Musil, Hermann Hesse, Friedrich Nietzsche, Jorge Luís Borges, Nikolai Gogol, Thomas Mann, Almeida Faria, Maria Gabriela Llansol

Luigi Nono, John Cage, Steve Reich, Luc Ferrari, Horațiu Rădulescu, Morton Feldman, New Phonic Art, Giacinto Scelsi, Terry Riley, Walter Marchetti, Pierre Henri, Alvin Lucier, Christian Wolff, Tomasz Sikorski, Iannis Xenakis, Dietrich Buxtehude, Juan Hidalgo Codorniu, James Tenney, Telectu, Miso Ensemble, Morton Subotnick, Erik Satie, Jean-Claude Risset, Constança Capdeville, Iancu Dumitrescu, Earle Brown, Alvin Curran

Yves Klein, Helena Almeida, Jean Tinguely, Mark Rothko, Wolf Vostell, Marcel Duchamp, Alexander Calder, Alberto Giacometti, René Magritte

Andrei Tarkovski, Michelangelo Antonioni, Wim Wenders, Edgar Reitz, Jacques Tati, Šarūnas Bartas, F. W. Murnau, Pier Paolo Pasolini, Bernardo Bertolucci

to my unique sister and her daughter, my favorite niece

Paulinha e Francisca

(Elsa Paula Pereira Pacheco e Francisca Bianca Pereira Ferreira Pacheco)

to my beloved wife, Lúcia

(Lúcia Maria Meireles Bessa Costa)

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FLEXIBLE DESIGN OF FOREST FIRE MANAGEMENT SYSTEMS

ABSTRACT: Forest fires have become a major threat to the prosperity and well-being of many communities, with severe consequences also for many ecosystems. The understanding of how to mitigate those consequences with finite resources, and how to apply such resources efficiently is receiving increasing attention from academics, practitioners, and policy makers concerned with forest fire management (FFM). There is, however, a lack of systematic studies about inefficiencies present in the FFM system, their impact on system behavior, and how methodological progresses in risk handling and flexibility can contribute to improve the system's redesign, in the different socioecological contexts where forest fires are a threat, and under the immense and pervasive uncertainty always associated with them. Framed by the fundamental research question, *How can flexibility in system design and management, framed by an engineering systems holistic perspective, aid in improving the FFM system (of systems)?*, this thesis asks: (1) What major inefficiencies can be found in the suppression system in Portugal?, (2) Does the development of the decision support systems that have actually been used worldwide reflect methodological progresses in risk handling?, (3) What is the impact of inefficiencies in the behavior of the suppression system and how can the system be redesigned in order to mitigate them?, and (4) How should a limited budget for prevention and suppression be managed along the year and in different socioecological contexts, under conditions of uncertainty?

The FFM system is exposed to critical uncertainties and characterized by complex dynamics, as it is a 'messy' complex system, involving nature, people and technology. Driven by the broad nature of the research questions, several methods were adopted. Namely, we used statistical analysis, discrete event simulation, and, in order to include flexibility in the system design and management, location analysis and simulation, and stochastic optimization – framed by a literature review of decision support systems (actually used worldwide) and methodological progresses in risk handling. This research is mostly focused on the suppression system and its interconnection with the prevention system. We start by identifying and characterizing some sources of inefficiency in the suppression subsystem (Chapter 2) and presenting a review of the advancements in risk handling and their interconnection with the evolution of the decision support systems (Chapter 3). Then, in two studies (Chapter 4), we expand the analysis about the impact of inefficiencies and propose tools to address them, including the measurement of their impact and the inclusion and explicit consideration of flexibility in the redesign of the system. Finally (Chapter 5), we extend the latter to the integrated design of the suppression and prevention systems.

This thesis contributes to the body of knowledge on the FFM field of research, and also provides some insights for fire managers and policy makers. Our findings stress the need for a backbone of professional firefighters, frequent strategic reassessment of the suppression resources, investment in large-fire suppression intelligence and organization, and the integration with forest fire prevention (which in turn leverages fire suppression). The significant variation in fire challenges across different socioecological contexts requires a regional specialization of FFM policies. Furthermore, the high-risk exposure and the level of interdependence between the actors and systems of the FFM system suggest that socially preferable policies may have to be favored, even if being economically sub-optimal. Altogether, our findings suggest an ample opportunity for infusing science and technology at all system levels.

KEYWORDS: forest fire management, forest fire suppression, economic efficiency, engineering systems, flexibility, risk handling, uncertainty, decision support systems, false alarms, initial attack, mediterranean-type ecosystems, mop-up operations, natural resources, rekindles, fire weather, fuel hazard, discrete event simulation, location analysis, simulation, stochastic optimization

CONCEPTION FLEXIBLE DE SYSTEMES DE GESTION DES INCENDIES DE FORET

RÉSUMÉ: Les incendies de forêt sont devenus une menace majeure pour la prospérité et le bien-être de nombreuses communautés, avec de graves conséquences pour de nombreux écosystèmes. La compréhension de la façon d'atténuer ces conséquences avec des ressources limitées, et les moyens pour appliquer efficacement ces ressources reçoivent une attention croissante de la part des universitaires, des opérationnels et des décideurs concernés par la Gestion des Incendies de Forêt (GeIF). Il y a cependant un manque d'études systématiques sur les inefficacités présentes dans le système de la GeIF, leurs impacts sur le comportement du système, et comment pouvant être amélioré l'intégration des progrès méthodologiques dans la gestion des risques et de la flexibilité dans la refonte du système, en prenant en compte les différents contextes socio-écologiques où les feux de forêt sont une menace, et l'incertitude immense et omniprésente toujours associée à eux. Encadrée par la question de recherche fondamentale, *Comment la flexibilité dans la conception et la gestion des systèmes, encadrée par une perspective holistique des systèmes d'ingénierie, aide-t-elle à améliorer le système (des systèmes)?*, cette thèse propose de répondre aux questions suivantes: (1) Quelles sont les principales inefficacités? (2) Le développement des systèmes d'aide à la décision utilisés dans le monde reflète-t-il les progrès méthodologiques dans la gestion des risques? (3) Quel est l'impact des inefficacités dans le comportement du système d'extinction et (4) Comment un budget limité pour la prévention et la suppression devrait-il être géré tout au long de l'année et dans différents contextes socio-écologiques, dans des conditions d'incertitude?

Le système de la GeIF est exposé à des incertitudes critiques et caractérisé par une dynamique complexe, car il s'agit d'un système complexe «désordonné» impliquant la nature, les personnes et la technologie. Poussé par la nature large des questions de recherche, plusieurs méthodes ont été adoptées. Nous avons utilisé l'analyse statistique, la simulation d'événements discrets et la flexibilité dans la conception et la gestion du système, l'analyse et la simulation de l'emplacement, et l'optimisation stochastique. Ces différentes méthodes ont été couplées à une revue des systèmes d'aide à la décision (actuellement utilisés dans le monde) et aux progrès méthodologiques de la gestion des risques. Cette recherche est principalement axée sur le système de suppression et son interconnexion avec le système de prévention. Nous commençons par identifier et caractériser certaines sources d'inefficacité dans le sous-système de suppression (Chapitre 2) et présenter un examen des progrès dans la gestion des risques et leur interconnexion avec l'évolution des systèmes d'aide à la décision (Chapitre 3). Puis, dans deux études (Chapitre 4), nous étendons l'analyse de l'impact des inefficacités et proposons des outils pour y remédier, y compris la mesure de leur impact et l'inclusion et la prise en compte explicite de la flexibilité dans la refonte du système. Enfin (Chapitre 5), nous étendons ce dernier à la conception intégrée des systèmes de suppression et de prévention.

Cette thèse contribue à l'ensemble des connaissances sur le champ de recherche de la GeIF, et fournit également quelques idées pour les gestionnaires de feux et les décideurs politiques. Nos conclusions soulignent la nécessité d'une colonne vertébrale de pompiers professionnels, une réévaluation stratégique fréquente des ressources de suppression, l'investissement dans l'intelligence et l'organisation de la lutte contre les incendies et l'intégration avec la prévention des feux de forêt. La variation significative des défis du feu dans différents contextes socio-écologiques nécessite une spécialisation régionale des politiques de GeIF. En outre, l'exposition à haut risque et le degré d'interdépendance entre les acteurs et les systèmes de la GeIF suggèrent que des politiques socialement préférables peuvent être privilégiées, même si elles sont économiquement sous-optimales. En conclusion, nos résultats suggèrent qu'il existe une grande possibilité d'infuser la science et la technologie à tous les niveaux du système.

MOTS-CLEFS: gestion des incendies, suppression des feux de forêt, efficacité économique, systèmes d'ingénierie, flexibilité, gestion des risques, incertitude, systèmes d'aide à la décision, fausses alarmes, attaque initiale, écosystèmes de type méditerranéen, opérations de nettoyage, ressources naturelles, reprises de feu, météorologie du feu, charge de carburant, simulation d'événements discrets, analyse de localisation, simulation, optimisation stochastique

DESIGN FLEXÍVEL DE SISTEMAS DE GESTÃO DE INCÊNDIOS FLORESTAIS

RESUMO: Os incêndios florestais tornaram-se uma ameaça à prosperidade e ao bem-estar de muitas comunidades, com graves consequências também para muitos ecossistemas. A compreensão sobre a forma de mitigar essas consequências com recursos finitos e como aplicar esses recursos de forma eficiente, está a ser alvo de atenção crescente por parte de acadêmicos, profissionais e decisores políticos preocupados com a Gestão de Incêndios Florestais (GIF). Há, no entanto, um défice de estudos sistemáticos sobre ineficiências existentes no sistema de GIF, sobre o seu impacto no comportamento do sistema e sobre como os avanços metodológicos no tratamento do risco e flexibilidade, podem contribuir para melhorar o redesenho do sistema, nos diferentes contextos socio-ecológicos onde os incêndios florestais são uma ameaça, e na imensa e penetrante incerteza sempre associada a eles. Enquadrado numa questão fundamental de investigação, *Como é que a flexibilidade na conceção e gestão do sistema, enquadrada pela perspetiva holística de sistemas de engenharia, pode melhorar o sistema (de sistemas) de GIF?*, a presente tese questiona: (1) Que ineficiências podem ser encontradas no sistema de combate em Portugal?, (2) O desenvolvimento dos sistemas de apoio à decisão que são realmente utilizados em todo o mundo refletem progressos metodológicos no tratamento do risco?, (3) Qual o impacto das ineficiências no sistema de combate e como é que o sistema pode ser redesenhado para o mitigar? e (4) Como deve um orçamento finito, para prevenção e combate, ser gerido ao longo do ano e em diferentes contextos socio-ecológicos, em condições de incerteza?

O sistema de GIF é exposto a incertezas críticas e é caracterizado por dinâmicas complexas, sendo um sistema intrincado e "confuso", que envolve natureza, pessoas e tecnologia. Em consequência da natureza ampla das questões de investigação, foram adotados vários métodos. Nomeadamente, utilizamos análise estatística, simulação de eventos discretos e, para incluir flexibilidade na conceção e gestão do sistema, análise de localização e simulação, e otimização estocástica – enquadrados por uma revisão de literatura sobre sistemas de apoio à decisão e progressos metodológicos no tratamento do risco. Esta investigação é principalmente focada no sistema de combate e na sua interconexão com o sistema de prevenção. Começamos por identificar e caracterizar algumas fontes de ineficiência no sistema de combate (Capítulo 2) e apresentar uma revisão da literatura sobre os avanços no tratamento do risco e sua conexão com a evolução dos sistemas de suporte à decisão (Capítulo 3). Seguidamente, em dois estudos (Capítulo 4), expandimos a análise do impacto das ineficiências, propondo ferramentas para as abordar, incluindo a medição do seu impacto e a consideração explícita de flexibilidade no redesenho do sistema. Finalmente (Capítulo 5), estendemos esta última à conceção integrada dos sistemas de prevenção e combate.

Esta tese contribui para o corpo de conhecimento da área de investigação de GIF e também fornece algumas ideias para gestores do sistema e decisores políticos. Os nossos resultados enfatizam a necessidade de bombeiros profissionais, de reavaliar frequentemente os recursos de combate, de investir em conhecimento e organização no combate a grandes incêndios florestais e de integrar o combate com a prevenção (o que, por sua vez, alavanca a eficácia do combate). A significativa variação dos desafios da GIF em diferentes contextos socio-ecológicos requer uma especialização regional nas políticas de GIF. Além disso, a exposição a riscos elevados e o nível de interdependência entre os atores e os sistemas incluídos na GIF, sugerem que políticas socialmente preferíveis podem ter que ser favorecidas, mesmo que sejam economicamente subótimas. Globalmente, os nossos resultados sugerem a existência de uma ampla oportunidade para infundir ciência e tecnologia em todos os níveis do sistema.

Palavras-chave: gestão de incêndios florestais, supressão de incêndios florestais, eficiência econômica, sistemas de engenharia, flexibilidade, gestão de risco, incerteza, sistemas de apoio à decisão, falsos alarmes, ataque inicial, ecossistemas mediterrâneos, operações de limpeza, recursos naturais, reacendimentos, meteorologia do fogo, carga de combustível, simulação de eventos discretos, análise de localização, simulação, otimização estocástica

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Nothing is built on stone; all is built on sand, but
we must build as if the sand were stone.
Jorge Luis Borges

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List of abbreviations and acronyms

AFN	Autoridade Florestal Nacional (National Forest Authority), currently ICNF
AFOCELCA	Private firefighting company owned by a group of Portuguese cellulose companies
ANPC	Autoridade Nacional de Proteção Civil (National Civil Protection Authority)
CAP	Confederação dos Agricultores de Portugal (Portuguese Farmers Confederation)
CM	Câmara Municipal (Municipal Council)
CDOS	Centro Distrital de Operações de Socorro (District Relief Operations Center)
CNOS	Centro Nacional de Operações de Socorro (National Relief Operations Center)
CODIS	Comandante Operacional Distrital (the coordinator of CDOS)
ES	Engineering Systems
FCT	Fundação para a Ciência e a Tecnologia (Foundation for Science and Technology)
FFM	Forest Fire Management
Florest	Associação dos Produtores Agrícolas e Florestais da Estremadura (Association of Agricultural and Forestry Producers of Extremadura)
Forestis	Associação Florestal de Portugal (Portuguese Forestry Association)
GIPS	Grupo de Intervenção de Proteção e Socorro (GNR, Protection and Relief Intervention Group)
GNR	Guarda Nacional Republicana (National Republican Guard)
gPS	Grupo PortucelSoporcel, currently TNC
GTF	Gabinete técnico florestal (Municipal forestry technical office)
ICNF	Institute for nature conservation and forestry
ISA	Instituto Superior de Agronomia (School of Agronomy, University of Lisbon)
LPN	Liga para a Protecção da Natureza (League for the Protection of Nature)
MIT	Massachusetts Institute of Technology
PNDFCI	Plano Nacional de Defesa da Floresta Contra Incêndios (National plan of forest protection against fires)
SEPNA	Serviço de Proteção da Natureza e do Ambiente (GNR, Protection of Nature and Environment Service)
SGIF	Sistema de Gestão de Informação de Incêndios Florestais (Forest fire management information system)
SMPC	Serviço Municipal de Protecção Civil (Municipal Civil Protection Service)
TNC	The Navigator Company
UNAC	União da Floresta Mediterrânica (Union of the Mediterranean Forest)
UTAD	Universidade de Trás-os-Montes e Alto Douro (University of Trás-os-Montes and Alto Douro)

Pocket glossary of forest fire terminology

(Adapted from: "*Glossary of Wildland Fire Terminology*", NWCG[1])

Economic Fire Protection Theory

A concept postulating that the object of fire protection is to minimize total cost (i.e. the sum of the costs of fire prevention, fire pre-suppression, fire detection, fire suppression, and net costs of fire damage/benefits).

Fire Weather Index (FWI)

A numerical rating in the Canadian fire danger rating system, based on meteorological measurements of fire intensity in a standard fuel type.

The system is comprised of three fuel moisture codes (FFMC, DMC, and DC), covering classes of forest fuel of different drying rates, and three fire behavior indices (ISI, BUI, and FWI), that represent rate of spread, amount of available fuel, and potential fire intensity.

Fuel Management

Act or practice of controlling flammability and reducing resistance to control of forest fuels through mechanical, chemical, biological, manual means, or by fire, in support of land management objectives.

Mop Up

Extinguishing or removing burning material near control lines, felling snags, and trenching logs to prevent rolling after an area has burned, to make a fire safe, or to reduce residual smoke ("rescaldo" in Portuguese).

Pre-suppression

Activities in advance of fire occurrence to ensure effective suppression action.

Includes planning the organization, recruiting, and training, procuring equipment and supplies, maintaining fire equipment and fire control improvements, and negotiating cooperative and/or mutual aid agreements.

Prevention

Activities directed at reducing the incidence of fires, including public education, law enforcement, personal contact, and reduction of fuel hazards (fuels management).

Rekindle

Reignition due to latent heat, sparks, or embers or due to presence of smoke or steam.

Restoration

The continuation of rehabilitation beyond the initial three years or the repair or replacement of major facilities damaged by the fire.

Suppression

All the work of extinguishing or confining a fire beginning with its discovery.

[1] NWCG, National Wildfire Coordinating Group (U.S.A.).

Chapter 1
Introduction

Even a thought, even a possibility,
can shatter us and transform us.
Friedrich Nietzsche

1.1. Background

In recent decades, forest fires have become a major threat to the prosperity and well-being of communities, with severe ecosystem consequences. Understanding how to mitigate those consequences with a finite budget, and how to spend such a budget efficiently is of great importance.

Uncertain and highly unpredictable factors, such as weather, suppression performance, or fire behavior, spread and effects, interacting in complex ways, are at the basis of most forest fire management (FFM) decisions. Theoretical and computing advances in the last four decades have enabled the development of risk-sensitive Decision Support Systems (DSS), capable of contributing to an improved active FFM by allowing structured assessments of the outcomes and costs associated with alternative policies, budgets, and suppression resource mixes.

With a limited amount of financial funds, equipment, and human resources, forest managers must decide the most efficient and effective distribution of such resources among alternative FFM options, and apply them efficiently. FFM options include, namely, community prevention (e.g., education, public campaigns), fuel treatment (e.g., prescribed burning, thinning, mechanical fuel removal), pre-suppression (e.g., firefighter recruitment and training, maintenance of fuel breaks and water sources), suppression, and restoration (Mavsar, Cabán, and Farreras 2010).

Recent catastrophic fires, not only in Portugal (2003, 2005, 2010, 2012, 2013, 2016, and 2017) but also worldwide, seem to be occurring regardless of the substantial increase in prevention and suppression budgets. This calls for the study of the inefficiencies that are present in FFM systems, and for their redesign, both at the operational and at the strategic level. In this research, we adopt an engineering systems (ES) perspective to study how such challenges, largely associated with the presence of complexity and uncertainty, can be addressed by fire managers and policy makers with the inclusion and use of flexibility in the design of FFM systems.

1.2. Research gaps and questions

The story of the development of this research is also the story of an adventure. Guided by the belief that, for successful wildfire management modeling, analysts must closely interact with wildfire experts (from operational staff to decision makers), as highlighted by Martell (1982), we started out with a main objective of studying how to include and use flexibility in the design of FFM systems, and along the way discovered new problems which led to new research questions.

Our research started in the scope of project FIRE-ENGINE, which provided us the opportunity to develop a close collaboration with leading scholars (ISA, MIT, UTAD), public organizations (ANPC, GIPS, GNR, ICNF, SEPNA), private companies (AFOCELCA, The Navigator Company), and other key stakeholders in areas of relevance to FFM, namely, forest related associations (CAP, Florest, Forestis, LPN, UNAC) and key municipalities, through their forestry technical offices (GTF) and/or civil protection services (SMPC): CM Gondomar, CM Mafra, CM Odemira, CM Paredes, CM Penafiel, CM Torres Vedras, and CM Valongo. In our initial field work, we collected references to several sources of inefficiency, which directed us to the literature and available data, which in turn led us to the discovery of new problems, in a reinforcing loop.

Motivated by the conviction that the careful analysis of a system's deficiencies can always result in the identification of potential opportunities for improvement, which can then be validated and exploited with field work and mathematical models, we formulated our fundamental research question (*RQ0*) as follows:

> *How can flexibility in system design and management, framed by an engineering systems holistic perspective, aid in improving the FFM system (of systems)?*

Next, we present the set of higher-level and subordinate research questions (RQ) derived from RQ0, also sketched in Figure 1 (below), which guided the development of our contributions to the body of knowledge in the FFM field.

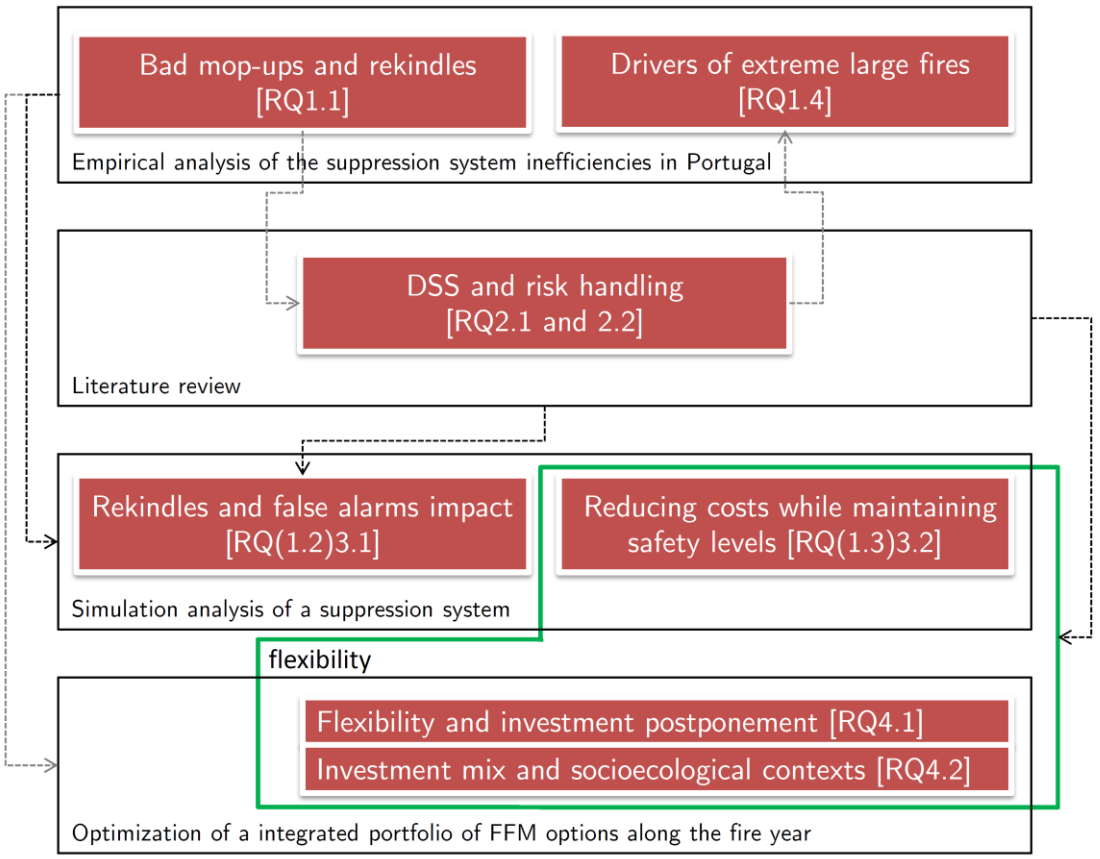


Figure 1: Overview of our research questions and the strongest connections between them (the four dark border squares represent the higher-level research questions, and also the next four chapters of this thesis).

RQ1: What major inefficiencies can be found in the suppression system in Portugal?

A massive volume of data about forest fires and related activities has been collected in the last decades. In Portugal, for instance, ICNF has the largest database (ICNFdb) in Europe in terms of total number of recorded fires, and one of the most comprehensive worldwide (Pereira et al. 2011). It features data relative to more than half a million individual fires, collected since 1980, a number that unfortunately is increasing significantly every year. Paulo Fernandes (UTADdb) has complemented this information with the compilation of the meteorological conditions (FWI and other fundamental indicators) observed by the nearest weather station at the beginning of each fire between 2001 and 2010. Finally, also for each individual fire, but only after 2006, ANPC has a database (ANPCdb) of all used resources, and Rui Almeida (ICNFdb*) completed this database for the prior period of 2003-2005.

With access to these data, to address RQ1, we formulated RQ1.1, to study one of the most well-known inefficiencies in the Portuguese suppression system, RQ1.2 and RQ1.3, to study respectively the excessive number of false alarms and the waste in expensive and outdated although valuable suppression equipment that is used only rarely, and RQ1.4 to better understand the suppression system as a whole.

RQ1.1: Is the pressure to immediately attack starting fires causing more fires?
RQ1.2: Should false alarms be managed?
RQ1.3: Is the fleet mostly used in extended attack managed efficiently?
RQ1.4: Which are the drivers of extreme large fires in Portugal?

The improved understanding obtained about FFM in Portugal, jointly with the observation of the lack of utilization of decision support tools, even the most basic such as forest fire simulations, directed us to the next high-level research question.

RQ2: Does the development of the DSSs that have actually been used worldwide reflect methodological progresses in risk handling?

In recent years, several authors have updated the state of the art related to the challenges of FFM. Minas, Hearne, and Handmer (2012) updated the review of Martell, Gunn, and Weintraub (1998) about operations research methods applicable to wildfire management. Thompson and Calkin (2011) systematically aligned decision support tools methodologies with wildfire risk assessment in face of uncertainty, in order to facilitate cost-effective, risk-based wildfire management and planning efforts. Mavsar, González Cabán, and Varela (2013) described the economic efficiency analysis theory of fire management measures and reviewed four fire management DSSs actually applied in America and Europe. There was however a lack of a systematic study about the relation between the successive developments of DSSs actually used operationally, at some point, and the evolution of risk handling perspectives, which resulted in the following RQs:

RQ2.1: Which FFM DSSs have actually been used worldwide?
RQ2.2: Is there a trend in the evolution of FFM DSSs related to the broadening of FFM concerns from risk assessment, to risk management, to risk governance?

As a natural sequence to the two previous high-level research questions, the following two high-level research questions express the need to better understand the impact of some inefficiencies in the suppression system, and how they can be dealt with by including and explicitly considering flexibility in system redesign and planning.

RQ3: What is the impact of inefficiencies in the behavior of the suppression system and how can the system be redesigned in order to mitigate them?

Analytical solutions obtained using standard mathematical methods are always preferable, but when the application of these methods is not possible, as is almost always the case when working with complex systems (White and Ingalls 2009), simulation is arguably the most robust alternative method that can be applied to analyze real-life stochastic systems that evolve probabilistically over time (Minas, Hearne, and Handmer 2012). We formulated the following RQs, that we addressed using simulation:

RQ3.1: How do rekindles and false alarms impact the behavior of the suppression system?
RQ3.2: How can suppression costs be reduced while maintaining safety levels?

RQ4: How should a limited budget for prevention and suppression be managed along the year and in different socioecological contexts, under conditions of uncertainty?

The appropriate allocation of a finite budget to suppression and prevention efforts is a complex challenge. Considering its relevance, studies addressing prevention and fire suppression in the same model are scarce (Rideout et al. 2008).

We co-authored a paper[1] (Collins et al. 2013) in which we report how, using a system dynamics model, we found that apparently sound management can have unintended consequences. Indeed, an instinctive management response to periods of worsening fire severity is to increase fire suppression investments, an approach with immediate appeal as it directly treats the symptom of devastating fires and appeases the public. However, the analysis of the results indicates that a policy emphasizing suppression can degrade the long-run effectiveness of FFM[2].

In the context of this dissertation, we turned our attention to the study of the optimal allocation of the budget along the year and in different socioecological contexts, formulating the following final two RQs:

RQ4.1: How should an integrated portfolio of FFM options be managed along the fire year, considering the economic conditions, the impact of the different options on each other, and key uncertainties in weather and fire location?
RQ4.2: What is the optimal mix of investment in prevention and suppression in different socioecological contexts?

We used Mixed Integer Programming (MIP) to address these two RQs, contributing to a promising but still underdeveloped line of research that includes namely the works of Mercer, Haight, and Prestemon (2008), and Minas, Hearne, and Martell (2015).

1.3. Thesis structure and synopsis

Our adoption of an ES perspective was motivated by the existence of multiple interacting elements within the FFM system (e.g., community prevention, fuel treatment, pre-suppression, suppression, and restoration, among others), as well as multiple relevant interactions between other systems and the FFM system (e.g., socioeconomic, political, weather and climate, among

[1] Not included in this thesis.
[2] Ironically (or not) the business management literature refers to this problem as the firefighting trap, wherein focus on fixing problems diverts attention from preventing them, and thus leads to inferior outcomes.

others). Our choice of methods was influenced by the adoption of this perspective, in the sense that the methods should be able to address those interactions. The scopes of the case studies and applications were also established with the same concern. Our specific interest in the challenges raised by the complexity and the large uncertainties present in FFM systems, with a focus on better understanding the sources of inefficiency in fire suppression activities, and the potential of flexibility to improve the design of FFM systems, led us to use multiple methods, chosen according to the features of each specific research question, which included regression analysis, simulation, and stochastic optimization, framed with field work with experts and stakeholders of the Portuguese fire system, and national and international researchers in the area of FFM.

This thesis is written as a cumulative thesis, comprising research papers already published, under review, or submitted, which are aligned with the RQs presented above. The organization of the chapters of the thesis thus follows the structure outlined by the high-level research questions. In the remainder of this section we present the references included in each chapter and their main contributions.

In Chapter 2 we include our investigation of RQ1.1 with a study of rekindle dynamics in Portugal. Using regression analysis, we found that rekindle proportions increase in days with more fire occurrences, supporting the hypothesis of premature abandonment of mop-up operations, as a result from the pressure to attack starting fires with the same crews. We detailed the analysis for two representative districts, providing further evidence of rekindle hazardousness. RQ1.2 and RQ1.3, concerning the excessive number of false alarms and the dimension of the extended attack fleet, are addressed later (with a positive answer) together with the related research questions of Chapter 4. Both issues were discovered during the initial database analysis (ICNFdb and ANPCdb, respectively) and their importance was later confirmed with experts.

After the study of the previously described sources of inefficiency in the suppression system, we directed our attention to the context in which the system operates, focusing on the study of the combinations of inputs that characterize large fires – the small portion of fires that escape initial attack and are responsible for most of the burnt area (e.g., in Ontario, Canada, according to Podur and Martell (2007), 98% of the area burned comes from roughly 3% of the fires). Such inputs can be purchased or free. Free (i.e., non-market) inputs to an escaped fire include geographical surroundings, natural fuels (vegetation) and weather conditions. Purchased inputs include anything employed by fire managers to affect the fire extent and intensity (e.g., suppression resources or firefighter training). When an initial attack fails, it is followed by an extended attack, with a much larger expected burnt area, and more suppression resources mobilized, in an effort to mitigate major losses. Additionally, fire managers operate under a finite budget that places constraints on their actions, so their decisions are typically choices among competing means to intervene in the wildfire processes (Butry et al. 2010). To address RQ1.4, we studied the drivers of extreme large fires in Portugal, between 2003 and 2013[3], using the ICNFdb and UTADdb databases of fire and weather historical data, together with the ICNFdb* (2003-2005) and ANPCdb (2006-2013) databases of suppression resources used in fires.

[3] The period between 1998 and 2002 was studied trough old ANPC handwritten fire reports. The lack of detail, however, restricted the studied period.

This chapter consists of the following two research papers:

- *Pacheco, Abílio Pereira, João Claro, and Tiago M. Oliveira. 2012. "Rekindle dynamics: validating the pressure on wildland fire suppression resources and implications for fire management in Portugal." In Modelling, Monitoring and Management of Forest Fires III, 258. Ashurst, Southampton, UK: Wessex Institute of Technology. Doi:* 10.2495/FIVA120191.
- *Fernandes, Paulo M., Abílio Pereira Pacheco, Rui Almeida, and João Claro. 2016. "The role of fire-suppression force in limiting the spread of extremely large forest fires in Portugal." European Journal of Forest Research:1-10. Doi:* 10.1007/s10342-015-0933-8.

Chapter 3 includes our examination of RQ2.1 with a literature review of the operational and strategic DSSs t*hat have been* developed over time and actually used worldwide. We studied their characteristics and the contexts in which they have been applied. In doing so, and addressing RQ2.2, we found a clear trend enabled by increasing computational capability that has guided DSS development – the broadening of risk handling concerns, from risk assessment to risk management, and from risk management to risk governance. The chapter consists of a single research paper that addresses the two RQs:

- *Pacheco, A. P., J. Claro, P. M. Fernandes, R. de Neufville, T. M. Oliveira, J. G. Borges, and J. C. Rodrigues. 2015. "Cohesive fire management within an uncertain environment: A review of risk handling and decision support systems." Forest Ecology and Management no. 347 (0):1-17. doi:* 10.1016/j.foreco.2015.02.033.

In Chapter 4, guided by the empirical studies of Chapter 2, and by the set of concepts and models found in the literature and detailed in Chapter 3, we present two models developed with the goal of contributing to improve the design of FFM systems, together with case studies illustrating their application. We used discrete event simulation (DES) to address RQ3.1, by modeling [4] the impact of non-value-added fire suppression activities such as rekindles (defects, inappropriate processing) and false alarms (motion) on the fire suppression system. Building on earlier work, in the scope of this thesis we extended the literature review, performed an extensive non-parametric data analysis, improved the definition of the system's "point of collapse", re-ran the 240 simulations (increasing the number of replications in each simulation to 2000), re-did the analysis of the results, and further elaborated the policy implications.

To address RQ3.2, we developed, as part of a one-semester (fall 2012) research visit to MIT, a spatially explicit screening model, integrating optimization and simulation, to support decisions regarding spatial allocation of a set of firefighting vehicles to centralized depots, seeking to preserve security levels while reducing investment costs and increasing vehicle utilization. We used two-dimensional distributions (obtained from historical data) of fire occurrences in a 20-year simulation, with an Ornstein–Uhlenbeck process driving the impact of the weather in the number of escaped fire occurrences, and ran the model under four scenarios ("as-is", Wildland-Urban-Interface expansion or climate change, surveillance policy, and law enforcement). The analysis confirmed the safety of partially concentrating the part of the suppression fleet that is mostly used in extended attacks, under a new policy that implements a flexible design.

[4] This research started in March 2011 in the scope of a master's thesis and resulted in a peer reviewed conference paper published in the proceedings of a conference organized by the US Forest Services (Pacheco, Claro, and Oliveira 2012) which is not included in this thesis. In addition to being available in English, this paper is also available in Spanish from the Pacific Southwest Research Station website.

The two research papers (which also address RQ1.2 and RQ1.3, respectively) included in this chapter are the following:

- *Pacheco, Abílio Pereira, João Claro, and Tiago M. Oliveira. 2014. "Simulation analysis of the impact of ignitions, rekindles, and false alarms on forest fire suppression." Canadian Journal of Forest Research no. 44 (1):45-55. doi:* 10.1139/cjfr-2013-0257.
- *Pacheco, Abílio Pereira, Richard de Neufville, João Claro, and Hèctor Fornés. 2017. A risk analysis methodology for spatial flexible design of a network of fire-fighting depots.*

In Chapter 5, we extend our analysis of the role and value of flexibility in FFM systems to intra-annual fire management budgeting and planning, using a spatially explicit MIP model developed with the goal of addressing RQ4.1. With this model, we studied the relationship between different types of operational flexibility, when used to mitigate exposure to weather and fire location uncertainty, in the context of FFM. Modeling intra-annual FFM as a multistage capacity investment problem, we considered a portfolio of FFM resources, enabling fuel treatment and fire suppression, and fires as the demand. The model was inspired by the work of Mercer, Haight, and Prestemon (2008), which in turn modified the standard-response model of Haight and Fried (2007) to include the effects of fuel treatment. The uncertainty in fire demand was considered to have two origins, inter-annual weather variability (oscillations in the fire season severity), and uncertainty of micro-scale factors (ignition, time, place, escape probability, and specific fire severity). We focused our analysis on mismatch risk (the cost of supply differing from demand[5]). The uncertainty related to inter-annual weather variability was modeled with a scenario tree (considering conditions for winter, spring, and summer) and the micro-uncertainty with a spatial grid of forest regions (with each cell characterized by an ignition probability).

We addressed two types of flexibility, considered as the ability to adapt to change: the postponement of the commitment to each type of capacity (prevention and suppression), fine-tuning the capacity mix as the year evolves (and the weather conditional probabilities change); and the spatial flexibility of different types of suppression resources (helicopters and ground crews), in a trade-off with their costs. Finally, to address RQ4.2, by analyzing the results and implications from the application of the model to instances representative of different socioecological contexts, we found that the dynamic interactions between prevention and suppression lead to different optimal budget partition patterns for different contexts. Similar to Chapter 3, this chapter also consists of a single research paper that addresses the two RQs:

- *Pacheco, Abílio Pereira, and João Claro. 2017. Operational flexibility in forest fire prevention and suppression: a spatially-explicit intra-annual optimization analysis, considering prevention, (pre)suppression, and escape costs.*

In the last chapter (Chapter 6), we conclude the thesis with the presentation of empirical findings, theoretical implications, and policy insights, as well as the limitations of our research and future research directions. Our contributions can help fire managers and policy makers better appreciate the impact and the effectiveness of alternative resource allocations within the FFM interconnected subsystems (e.g., reactive suppression and proactive prevention) and the dynamics and apparently minor details that may undermine seemingly rational management decisions, often in unexpected and unintended ways.

[5] An over-investment in FFM capacity will lead to costs related to unused capacity, whereas under-investment will lead to costs related to value loss in the forest (not being able to satisfy the demand).

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Chapter 2

Empirical analysis of suppression effectiveness in Portugal: rekindles and extremely large forest fires

When the winds of change blow,
some people raise barriers while others build windmills.
Érico Veríssimo

1st (conference) paper and book chapter

Pacheco, Abílio Pereira, João Claro, and Tiago M. Oliveira. 2012. "Rekindle dynamics: validating the pressure on wildland fire suppression resources and implications for fire management in Portugal." In Modelling, Monitoring and Management of Forest Fires III, 258. Ashurst, Southampton, UK: Wessex Institute of Technology. doi: 10.2495/FIVA120191.

2nd paper

Fernandes, Paulo M., Abílio Pereira Pacheco, Rui Almeida, and João Claro. 2016. "The role of fire-suppression force in limiting the spread of extremely large forest fires in Portugal." European Journal of Forest Research:1-10. doi: 10.1007/s10342-015-0933-8.

Rekindle dynamics: validating the pressure on wildland fire suppression resources and implications for fire management in Portugal

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Abstract

Rekindles can represent a high burden on wildland fire suppression resources, but despite the relevance of this phenomenon in Portugal, related research is still scarce. Seeking to contribute to address this gap, the purpose of this study was to organize and provide an overview of the problem of rekindles in Portugal, and to verify whether evidence exists that the high proportion of rekindles in Portugal is related to the double duty of Portuguese firefighters to perform initial attack and mop-up operations. Our study included informal meetings, formal recorded interviews, dispatch centre visits, actual rekindle observation, and an analysis of the National Forest Authority database. From the study of genealogies of rekindles, we concluded that 17.2% additional forest fires (rekindles in successive generations) had their origin in only 7.4% of primary fires. Through linear regression analysis, we found that their proportions increase in days with more occurrences, preliminarily supporting the hypothesis of premature abandonment of mop-up operations, as a result from the pressure to immediately attack starting fires by the same crews. A more detailed analysis of two representative districts highlighted specific organizational and natural challenges to successful mop-up efforts and provided further evidence of the hazardousness of rekindles.
Keywords: wildfire, rekindle, mop-up operations, reburn, initial attack, suppression.



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1 Introduction

There are few natural phenomena with the scope and complexity of a forest fire (Van Wagner [1]). An intricate part of that phenomena are rekindles, or reignitions, that reburn an area over which a previous fire has passed, but has left fuel that later ignites due to latent heat, sparks, or embers (NWCG [2]). Throughout the 2010 summer, Portugal had 14,551 primary wildfires, of which 17.2% rekindled into an additional 2,497 fires, leading to a total of 17,048. That summer accounted for 94.7% of the wildland annual burnt area of 132,241 ha. However these figures may be worse. Several authors suggest that the amount of rekindled forest fires is higher than officially reported (ANIF [3], Lourenço and Rainha [4]). Expert-judgment elicitation in our interviews points to the double. Even assuming that the available information is correct, there are too many rekindles (Beighley and Hyde [5]). This is a concerning situation that has gotten worse over the years (ANIF [3]), and results from ineffective mop-up operations (ANIF [3], Lourenço and Rainha [4], Beighley and Hyde [5], ISA [6], Lourenço [7], Murdock *et al.* [8]) despite the effective initial attack (ANIF [3], Lourenço and Rainha [4], Lourenço [7]). Although there is a danger of fatalities during the mop-up stage (Alexander *et al.* [9]), this danger is even higher in a rekindle scenario (NWCG [10]). Finally, this ineffective mop-up and lack of surveillance (Lourenço [7]) results in rekindles that often become large fires (ANIF [3], Lourenço and Rainha [4], Lourenço [7]). These are usually bigger than the wrongly judged extinguished primary fire, with large burnt areas and considerable damage (ANIF [3]), even when the initial perimeter was just tens of meters (Lourenço and Rainha [4]).

During the suppression effort, as soon as the fire slows to a point where it can be fought safely, the fire crews establish control lines around the perimeter of the fire. They solidify it and gradually work from the perimeter towards the interior of the fire, extinguishing flames farther and farther from the fire's edge (Martell [11]). Once the fire is declared under control, the essential job of mopping up begins; afterwards, the area must be patrolled before it is declared truly "out" (Murdock *et al.* [8], Martell [11], Alexander [12]). Done along the fire control line, mop-up involves eliminating all hot areas and removing burning material. Hot spots can be found by visible signs, smoke smell, audible signs or by touch. A small spark left near a control line can cause a later rekindle (Murdock *et al.* [8]). This mop-up stage may proceed for days or weeks (Martell [11]). Being an exceedingly time-consuming stage, it is also very costly (González-Cabán [13]). Several studies found considerable regional variation in costs, significantly influenced by site-specific factors. Physical site characteristics, however, do not fully explain the observed variation in mop-up costs (Donovan and Brown [14]). Thus natural (weather conditions, spatial-temporal concentration) and organizational (human resources and equipment management) factors must be considered (AFN [15]). This is the case of Portuguese mainland, where across the 18 districts the proportions of rekindles varied from zero to 85%, with half of the districts featuring proportions above 9.3%.

After the disastrous fires of 2003 (Fernandes [16]), repeated two years later, the government commissioned a technical strategy (ISA [6]) to address this problem. In 2006, a modified version (shifting the emphasis from prevention to an increase in suppression capability) was approved and published (CM [17]) as the national strategy for forest protection against fires (Beighley and Hyde [5]). The plan recognizes the impact of rekindles and establishes mitigation as one of the priorities, with a goal of 1% by 2010 defined as an accepted value for the rekindle rate (Oliveira [18]). However, this goal was not ever achieved (AFN [15]) and could be too ambitious. Compared, for instance, to the USA 2004-2008 rekindle annual averages, which vary between 2 and 6% (Ahrens [19]), it is known that the local rate is still higher (Pacheco [20]).

Many of these rekindles occur in inaccessible areas where fires are not properly mopped up (Beighley and Hyde [5]). Fire lines are often constructed using existing roads (Lourenço and Rainha [4], Beighley and Hyde [5]) or near houses (Lourenço and Rainha [4]). Between these infrastructures and the burnt areas remain fuels with low moisture due to the pre-heating, which later may rekindle (Lourenço and Rainha [4]). Meanwhile, mop-up is made exclusively with water in most cases, without the appropriate tools to consolidate the perimeter safely (ANIF [3], Lourenço and Rainha [4], Beighley and Hyde [5]). In short, the lack of specialized crews in firefighting with hand tools is a huge tactical limitation (ISA [21]). In fact, mop-up should be done with hand tools, working with water as a complement (ANIF [3], Beighley and Hyde [5]). Tools are used to rake, chop, scrape and dig out hot fuels (Murdock *et al.* [8]), making a trench up to the mineral soil (Oliveira [18]), or regolith, where water does not penetrate until a discontinuity is created (Lourenço and Rainha [4]). Water, if available, is used to cool down these fuels mixed with hand tools in the hot spots (Murdock *et al.* [8]). Also with hand tools or machines, it is critical to create a break in continuity between the contiguous burnt and non-burnt areas (Lourenço and Rainha [4]). Otherwise, hot spots may not be extinguished and can rekindle (Murdock *et al.* [8]).

The high level of rekindles may indicate that there were problems in post-fire management and active surveillance (AFN [15]). Some authors suggest the need for specialized extended attack hand crew brigades (Beighley and Hyde [5]) and complementary crews properly trained in mop-up operations, in particular if spatiotemporal concentration of primary fires occurs (ISA [6]). In practice, the crews that need to remain on the mop-up are often the same that need to be available for new fires – primary or rekindled. This double-duty weakens the system. It is pointed to as one of the reasons why the percentage of rekindles is so high. In other words, firefighters are often pulled away from a fire prematurely, to respond to new initial attack demands (Beighley and Hyde [5]).

This research analyses the latter hypothesis. In days with a higher number of occurrences, the pressure to abandon mop-up operations prematurely may increase. This leads to future rekindles that further increase the number of active fires. We study rekindle genealogies and use linear regression across Portuguese districts. The results can provide useful information that could enhance the effectiveness of suppression activities. The paper is organised as follows. In the



next section, we present data sources, describe the regression and briefly explain how we constructed the rekindle genealogies and the number of daily active fires. Subsequently, we present the results, highlighting some of their aspects. The final section discusses main points, and offers some conclusions.

2 Data and methods

For this study we use data kindly provided by *Autoridade Florestal Nacional* (AFN). This wildfire dataset, although having undergone several changes throughout the years, has been relatively stable in the last 12 years. The current version gathers information regarding the location of the fire, date and time (i.e. alert, ignition and extinction), burnt area, type of event, and causes. The events could be false alerts, fires in agricultural lands, or wildland fires (forests and shrublands). Information about the nature of the fire (single or reignition) is recorded since 1984 (Pereira *et al.* [22]). We focused our attention on 2010 because this is the first year for which appropriate data on rekindles is available. For instance, it is now possible to know, for each rekindle, the specific fire whose bad mop-up originated it.

The country mainland is divided in 18 main administrative regions (districts), their corresponding municipalities (278 counties,) and 4,050 parishes. There are significant geomorphologic, climatic and demographic differences between the northern and southern parts of Portugal (Pereira *et al.* [22]). Fire policies, suppression and prevention efforts are organized at the district level. They are therefore too heterogeneous, and we chose them as unit of analysis.

Rekindles represent a high burden on suppression resources. Our goal (and hypothesis) is to find whether there is any evidence that in days with more ignitions, the firefighters are compelled to prematurely abandon the fire mop-up operations, thus promoting even more rekindles. In other words, we want to know if the high number of rekindles results from the pressure to immediately combat all the new fires, preventing them from becoming big fires. To accomplish this, we conducted a linear regression analysis study, considering two variables. We consider the explanatory variable as the number of fires that were simultaneously fought in each day (active fires). For the first component of the dependent variable, we count the number of fires with bad mop-up in that same day, i.e., the fires erroneously declared extinct and origin of some later rekindle. However, because it is expected that bad mop-ups increase with adverse climatic conditions and the number of fires in each day, we divided this component by the number of active fires in that day. To count the number of fires with bad mop-up in a particular day, we performed a detailed treatment of the database to uncover the genealogies of rekindles, identifying for each rekindle the bad mop-up that originated it. We used Microsoft Excel® and MapPoint Europe 2011® for the pivot tables and maps, IBM SPSS Statistics 19® for descriptive statistics, and STATA/IC 12® for regression analysis.

3 Results

3.1 Overview of forest fires and rekindles in Portugal

From the point of view of the suppression system, a false alert or a fire in agricultural lands produces the same pressure as a wildland fire (Pacheco [20]). Firefighters do not know beforehand which type of event they are being called to, and they need to get to the site as fast as possible. For this reason, we include all these events, and not only forest fires, in our analysis. Also, because of the temporal concentration of fires in Portugal (Table 1), we focus on the critical period between July and August called the "Charlie" phase.

Table 1: Number of occurrences, rekindles and burnt area (Summer, 2010).

	All events			Wildland fires		
	All year	July - August		All year	July - August	
		All	Time data		All	Time data
Wildland burnt area (ha)	133,091	125,859	125,688	132,241	125,173	125,003
Total burnt area (ha)	141,840	133,487	133,294	139,121	131,716	131,545
Events/fires	32,357	24,036	23,232	22,026	17,048	16,965
Rekindles	2,733	2,543	2,532	2,687	2,497	2,486

For some chains of successive rekindled fires, the database holds information about the burnt area for each individual rekindled fire. But for most cases, because of measurement difficulties when there is a high number of active fires, only the total area measured at the end is registered, in the ancestor fire (the first fire whose bad mop-up starts that particular chain), with all the successive rekindles attributed a zero burnt area. For this reason, we were unable to directly assess the impact of bad mop-ups on burnt area. However, an examination of the districts with more than (on average) five new ignitions per day (Figure 1) provides some evidence of the expert-judgment assessment that most of burnt area comes from rekindles. Indeed, the proportion of rekindles to active events (bubble area) appears to be greater in districts with more burnt area.

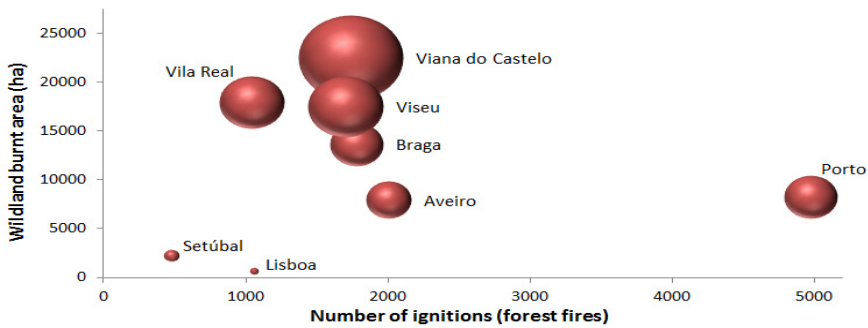


Figure 1: Relationship between ignitions, burnt area, and rekindles; bubble area represents the proportion of rekindles to forest fires.

Figure 2 shows the density of rekindles (number of rekindles per 1000 km^2 of forest area) in each municipality. In short, rekindles are spatially concentrated in seven districts (in the north near the coastline): Aveiro, Braga, Coimbra, Porto, Viana do Castelo, Vila Real and Viseu.

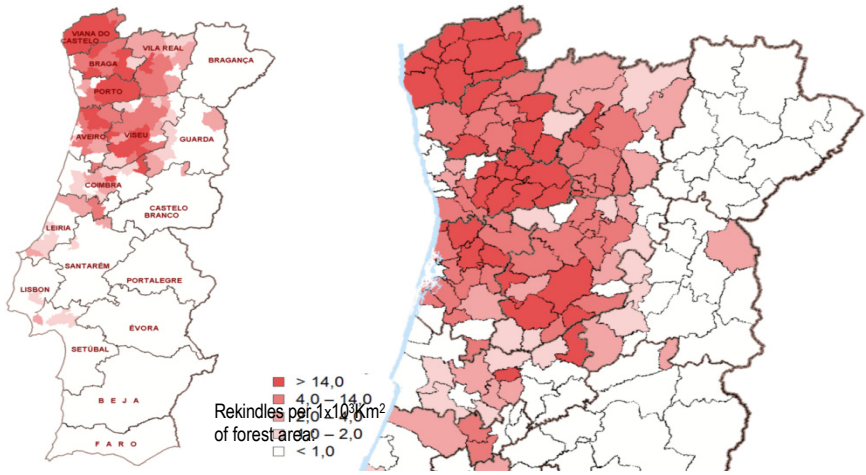


Figure 2: Spatial concentration of rekindles in mainland Portugal.

3.2 Active events

To determine the number of simultaneous (active) events, the alert and finish times of each event are required. This forced us to remove from our analysis 171 fires, less than 0.14% of all the data (see Table 1). Processing the information in the database with the help of pivot tables, and using a daily balance of entries and exits, we were able to compute the number of fires actually being fought each day. Half of the districts have more than nine active fires, with the presence of extremes quite superior to the mean, and outliers in four of them (Figure 3).

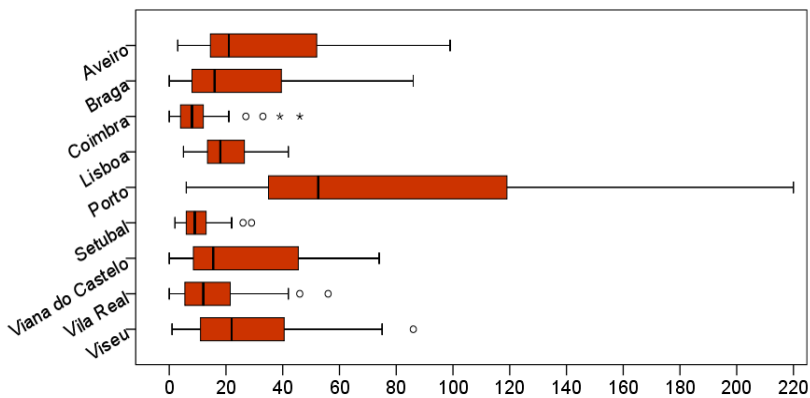


Figure 3: Box plot of active fires in the more devastated districts.

On any given day, there will usually be a difference between new and active events, as a consequence of fire durations that are higher than one day (Figure 4). These numbers show very high oscillations along the season, across all districts.

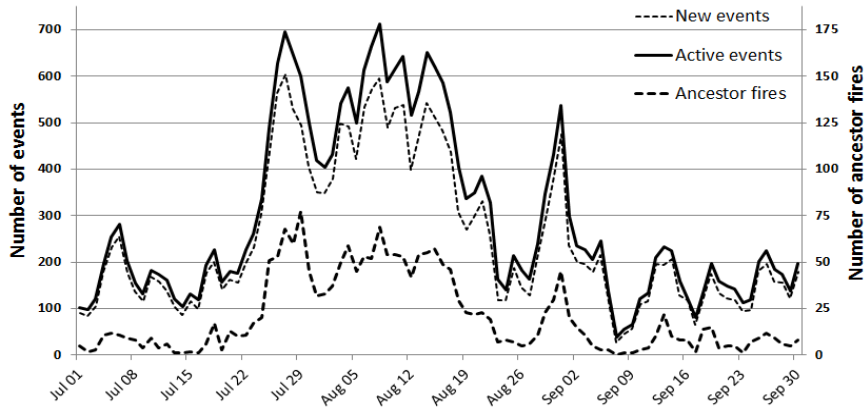


Figure 4: Daily panorama of new and active events, and primary bad mop-ups.

3.3 Bad mop-ups and rekindles

To uncover the genealogy of each rekindle, we started by identifying all the ancestor fires (new fires with bad mop-ups). We extended this analysis to the whole year because a restriction to the summer period would exclude bad mop-ups in the final days of June. In Portugal, the year begins in the coldest season without any active fires. Table 2 shows an interval of 1 to 28 rekindles originated from ancestor fires. For the 786 ancestors with one rekindle, no additional data processing was required. For the remaining 479 chain events, we collected and identified all the intermediate fires with bad mop-ups in the chain. The diagram at the bottom of Table 3 graphically outlines this idea that some rekindles also rekindle and must be considered as part of the set of bad mop-ups.

Table 2: Ancestor fires organized by the number of rekindles originated.

Times rekindled	1	2	3	4	5	6	7	8	9	10	11	12	13	15	16	18	22	25	28
Ancestor events/fires	786	189	100	65	39	20	13	13	10	8	5	4	4	1	3	2	1	1	1
Rekindled	786	378	300	260	195	120	91	104	90	80	55	48	52	15	48	36	22	25	28

We built an SQL query to identify, for each chain, the groups of fires with the same geographic coordinates, excluding the fires with successful mop-ups (whose end occurs after any of the beginnings in that group). As a result, we identified an additional 855 bad mop-ups, leading to an annual total of 2,120

(Table 3). Figure 5 illustrates this process for an extreme case in the district of Viseu, for which 99.3% of the burnt area was due to successive rekindled fires.

Table 3: Results from the analysis of rekindle genealogies.

	All events			Wildland fires		
	All year	July - August		All year	July - August	
		All	Time data		All	Time data
Events/fires	32,357	24,036	23,232	22,026	17,048	16,965
Primary events/fires	29,624	21,493	20,700	19,339	14,551	14,479
Rekindles	2,733	2,543	2,532	2,687	2,497	2,486
Ancestor events/fires	1,265	1,131	1,121	1,204	1,083	1,074
Bad mop-ups (next generations)	855	801	797	846	792	789
Bad mop-ups (total)	2,120	1,932	1,918	2,050	1,875	1,863
Rekindles/ancestors rate	2.2	2.2	2.3	2.2	2.3	2.3

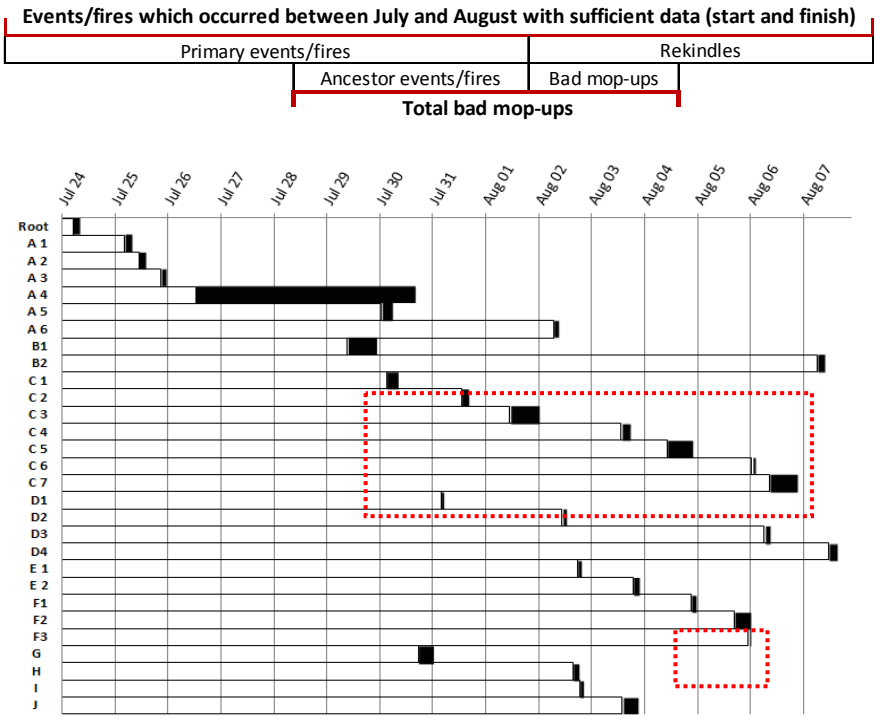


Figure 5: A case study of a tree of 28 rekindles of the same fire in Viseu with seven sub-chains (letters A to J), and seventeen intermediate fires with a bad mop-up; notice that fires F2 and F3 occur at the same time and thus are not counted as bad mop-ups.

We excluded from our analysis districts with few or no rekindles. A criterion of considering only districts with a daily average of rekindles above 0.5

concentrated the analysis on seven districts: Aveiro, Braga, Coimbra, Porto, Viana do Castelo, Vila Real and Viseu.

3.4 Regression analysis

With the data on proportion of bad mop-ups and number of active fires for the selected districts, we were able to perform our regression analysis study. The correlation coefficients, as well as the p-values for the regressions, are shown on Table 4. The results provide statistical support to our hypothesis that the proportion of bad mop-ups increases with the number of active events. The only exception is the district of Viana do Castelo, which is discussed in the final section of this paper.

Table 4: Regression results for the seven selected districts.

	R	Prob > F	Active events (daily mean)	New events (daily mean)	Ancestors	Bad mop-ups	Rekindles
V. Castelo	+0.1575	0.1406	26	21	311	580	796
Coimbra	+0.2405	0.0224	9	9	35	48	63
Aveiro	+0.2607	0.0121	34	31	125	149	174
Braga	+0.2736	0.0108	26	22	110	148	205
Viseu	+0.4691	0.0000	27	23	136	312	410
Vila Real	+0.5120	0.0000	15	13	103	153	184
Porto	+0.7256	0.0000	79	63	220	431	581

3.5 Rekindle generations

As Porto is the district with the highest correlation, we conducted a more detailed analysis of the rekindle dynamics inside this district. As shown in Figure 6, in the first generation of 5,118 wildfires, 197 had bad mop-ups and thus rekindled (3.85%). These 197 rekindles originated 500 additional fires (254% more). 22 fires of that second generation (4.4%) had again bad mop-ups and rekindled into 51 other fires (232% more) on the third and successive rekindle generations. As a matter of fact, 551 wildfires could have been avoided if 197 primary fires had had a successful mop-up in first place. These rekindle/ancestor ratios of 254% and 232% are consistent with the national averages (see Table 3).

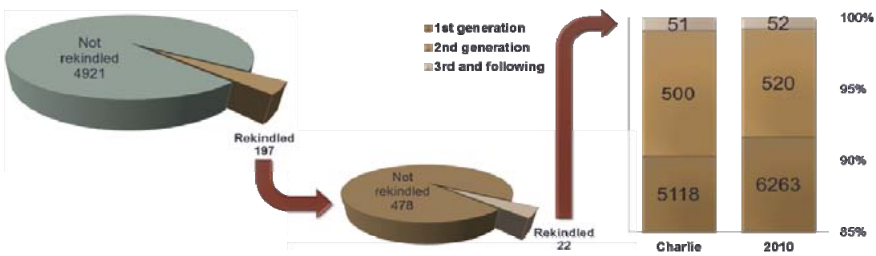


Figure 6: Rekindle genealogies in the district of Porto (Pacheco [20]).

Finally, crossing the database of AFN and the database of the Dispatch Center of the district of Porto (CDOS Porto), which registers the assignment of suppression resources to each event, we determined that, on average, rekindles have initial and extended attacks longer than primary fires, 19.2% and 51.3% respectively (Pacheco [20]). This underlines the hazardousness of rekindles in the district of Porto, and provides further evidence of the impact of bad mop-ups on burnt area.

4 Discussion and conclusions

Among the districts with a relevant number of rekindles, only one – Viana do Castelo – did not present a statistically significant positive correlation between the proportion of bad mop-ups and the number of active fires. The plot of the relationship between the two variables (Figure 7) displays no discernible trend; however it shows very clearly a persistently very high proportion of bad mop-ups. In our contacts with experts, a key explanation that was put forward for this result was the fact that this is the district in the country with the lowest ability to mobilize volunteer firefighting efforts, which leaves mop-up activities permanently understaffed. Another potential cause is the fact that the district has a very large mountain area, where wildfires are more difficult to control, resulting in higher burnt areas and perimeters, and therefore higher probabilities of rekindling.

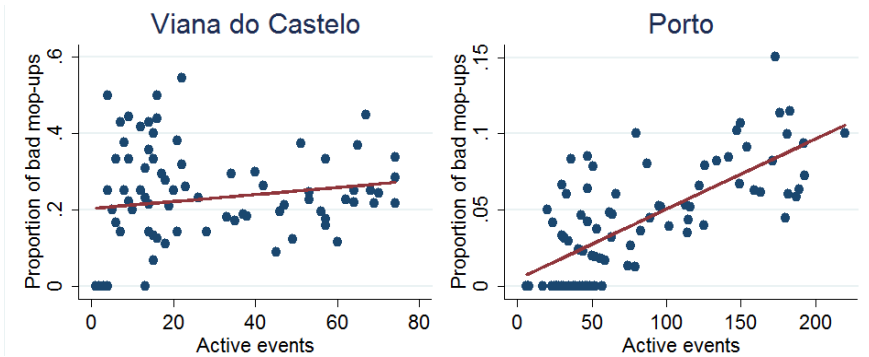


Figure 7: Plots of values and fitted values for Viana do Castelo and Porto.

The district where the effect of suppression pressure on bad mop-ups is clearer is the district of Porto. The correlation is high and the plot (Figure 7) shows a distinct trend of increase in the proportion of bad mop-ups with the increase in active events. The district of Porto has a historical trend of a very high number of forest fires, which remained through 2010, with a very high proportion of forest fires with a burnt area below 1 ha – 90.6% of the six thousand incidents (Pacheco [20]). This very high number of incidents puts a huge pressure on the suppression system, which not only works at constantly very high levels of capacity utilization, but also is constantly being requested for initial attack of new fires or rekindles.

The research presented in this paper initially uses the literature review and the results of our fieldwork to identify, organize, and relate the set of physical, natural, technical and organizational factors that influence the occurrence of rekindles. We then use data analysis and descriptive statistics to present evidence of the size and impact of the problem of rekindles in Portugal. A key contribution of our work results from a simple linear regression analysis of the relationship between active events and the proportion of bad mop-ups to active events. A statistically significant positive relationship was found for six of the seven districts with a relevant number of rekindles. Finally, a more detailed view of rekindle dynamics in the districts of Viana do Castelo (the only district with a non-significant regression) and Porto (the district with the higher significant correlation) highlights specific organizational and natural challenges to a successful mop-up effort and provides further evidence of the hazardousness of rekindles. Among future work, we plan to extend this study to new data that is becoming available for more recent fire seasons, and analyse the performance of alternative organizational architectures for suppression efforts, with specialized teams assigned to the different suppression tasks.

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ORIGINAL PAPER

The role of fire-suppression force in limiting the spread of extremely large forest fires in Portugal

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Abstract Large forest fires are notorious for their environmental and socio-economic impacts and are assigned a disproportionately high percentage of the fire management budget. This study addresses extremely large fires (ELF, ≥2500 ha) in Portugal (2003–2013). We analysed the effect of fire-suppression force variation on ELF duration, size and growth rate, versus the effect of the concomitant fire environment (namely fuel and weather) conditions. ELF occurred in highly flammable landscapes and typically were impelled by extreme fire weather conditions. Allocation of suppression resources (normalized per unit of burned area or perimeter length) was disparate among fires, suggesting inadequate incident management. Fire-suppression effort did not affect time to containment modelled by survival analysis. Regression tree analysis indicated ELF spread to be negatively affected by higher fire-suppression resourcing, less severe fire weather, lower time to containment and higher presence of <9-year-old fuels, by decreasing order of importance; regional variability was relevant. Fire environment-to-fire suppression ratios of influence were 3:1 for fire size and 1:1 for fire growth rate, respectively, explaining 76 and 60 % of the existing variability. Results highlight the opportunistic nature of large-fire containment. To minimize the area burned by ELF, management and operational improvements leading to faster containment are recommended, rather than higher fire-suppression resourcing; more effective identification and exploration of containment opportunities are preferable to the accumulation of suppression resources.

Keywords Fire management · Fire suppression · Fire weather · Fuel hazard · Mediterranean-type ecosystems

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Introduction

Large-fire events constitute a small percentage of the total number of fires but are responsible for a disproportionately high fraction of area burned and the consequent effects (Strauss et al. 1989). Depending on the country, fires larger than 500 ha represented 0.3–2.1 % of the total number of ignitions >0.01 ha in size in southern Europe (2001–2011), but accounted for 16–48 % of total area burned (Mateus and Fernandes 2014). Large fires, and especially the so-called megafires, can be highly disruptive from both the environmental and societal perspective (Beverly and Martell 2005; Gill and Allan 2008) and apparently are gaining importance in certain parts of the world due to ongoing modification in climate and fuel patterns (Attiwill and Binkley 2013).

Fire suppression has been effective at changing fire regimes, e.g. Martell and Sun (2008). In the presence of organized and systematic (as in Europe) fire suppression, significant or large fires develop when initial attack is either not fast or strong enough to overcome the fire environment (Martell 2001), i.e. the joint influences of weather, fuel and topography on fire behaviour characteristics (Countryman

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1972). Hence, fire suppression decreases burned area by reducing the number of potentially large fires through initial attack and by decreasing the size of large fires through extended attack. Empirical studies have shown the probability of initial attack failure to vary with fire danger rating and fuel hazard or forest type (Arienti et al. 2006; Plucinski 2012), and area burned to increase with the integration of those variables as a fire control difficulty index (Martell and Sun 2008). The suppression effort (manpower and equipment) required to contain a wildfire is a function of time since ignition, rate of perimeter increase (a function of fire spread rate), resource production rates and fireline intensity, which determines suppression effectiveness in relation to resource type (Alexander 2000). Access difficulties, simultaneous fires and focus on asset protection rather than on perimeter control additionally complicate the suppression of large fires (Gill and Allan 2008). Controlling large fires is then a complex, dynamic and demanding task (Thompson 2013) for which the available suppression resources often are insufficient (e.g. McCarthy et al. 2012) and that greatly benefits from dedicated decision-support systems (Pacheco et al. 2015).

Fire management in Europe is strongly focused on fire suppression (Fernandes 2008), e.g. expenditures with fire fighting in Portugal exceed by a factor of three those with fire prevention, fuel management and pre-suppression (Mateus and Fernandes 2014). The current policy developed as a response to increased fire activity in the 1970s following forest and shrubland expansion as a result of afforestation and agriculture abandonment (Fernandes et al. 2014; Pausas and Fernández-Muñoz 2012). While fire-suppression investment did mitigate area burned (Fréjaville and Curt 2015; Moreno et al. 2014), it did not succeed in decreasing the number of large (>500 ha) fires (San-Miguel-Ayanz et al. 2013), with the largest events (e.g. >5000 ha in Spain) becoming more frequent in the last two decades (Marques et al. 2011; Cardil et al. 2014).

Empirical analysis of fire suppression–fire activity relationships can produce substantial insights and has been actively pursued in Canada, the USA and Australia (Podur and Martell 2007; Finney et al. 2009; Plucinski 2012), but has seldom been attempted in Europe. Marchi et al. (2014) analysed the impact of helicopter resourcing in fire-suppression effectiveness in a central Italy region. In Spain, Costafreda-Aumedes et al. (2015) related the fire-suppression resources allocated to >100-ha individual fires with fire duration and fire size, among other variables.

Despite the relevance of large fires and the expenditures involved, currently it is not understood how the level of fire-suppression resourcing affects large fires in Europe and elsewhere (Rönnqvist et al. 2015). Quantitative linkages between fire-suppression force and fire characteristics are useful to optimize resource allocation, assess the functional and cost-effectiveness of fire suppression, examine trade-offs between fire management strategies and alternatives, and inform future policy-making (McCarthy et al. 2003; Plucinski 2012; Finney et al. 2009; Holmes and Calkin 2013). The objective of this study is to quantify how fire-suppression force contributes to mitigate the duration, development and size of the largest fires occurring in Portugal, under the tenet that the fire environment is the dominant influence.

Materials and methods

Wildfire and fire-suppression data

Our subject of study was the upper end of the fire size distribution in mainland Portugal (89,100 km^2) from 2003 to 2013. Exploratory analysis of the Portuguese rural fires database (http://www.icnf.pt/portal/florestas/dfci/inc/estat-sgif) indicated that approximately 0.1 % of fires >1 ha exceeded 2500 ha (1998–2013), which we termed extremely large fires (ELF). ELF identified in the database were located in the digital fire atlas of Portugal (http://www.icnf.pt/portal/florestas/dfci/inc/info-geo), a combined result of high-resolution Landsat imagery and ground inspection. Fire scars >2500 ha resulting from two or more near-simultaneous ignitions were included.

We retrieved fire-suppression data from ANPC (Civil Protection National Authority) to build a database of the resources (personnel and equipment type, time on the fire) allocated to each ELF and the multiple date–times when it was declared contained, as sometimes it would resume spreading and escape (Pacheco et al. 2012, 2014). We trialled two approaches to estimate time to containment (T), here defined as the time elapsed between detection and the moment the fire is classed as being held and ceases to increase in size. We used as proxies for containment date–time either (1) the maximum number of resources sent, or (2) the maximum accumulation of suppression resources. The rationale for (1) is the reduction in the need for new suppression resources, i.e. their rate of arrival, when the fire has been held; and for (2) the life cycle of a wildfire and the assumption that resources demobilization begins as soon as the fire is contained (Martell 2001; Pacheco et al. 2012).

Given the temporal inaccuracy inherent to manually recorded resources arrival, we calculated (1) either using time windows of 1 and 30 min, respectively, to represent near-instantaneous arrivals and to depict arrival density and remove potentially spurious irregularity. As an example, we show the resources arrival history for the 2012 Tavira ELF, the largest fire in the database originated by a single ignition (Fig. 1). To assist in the decision of choosing

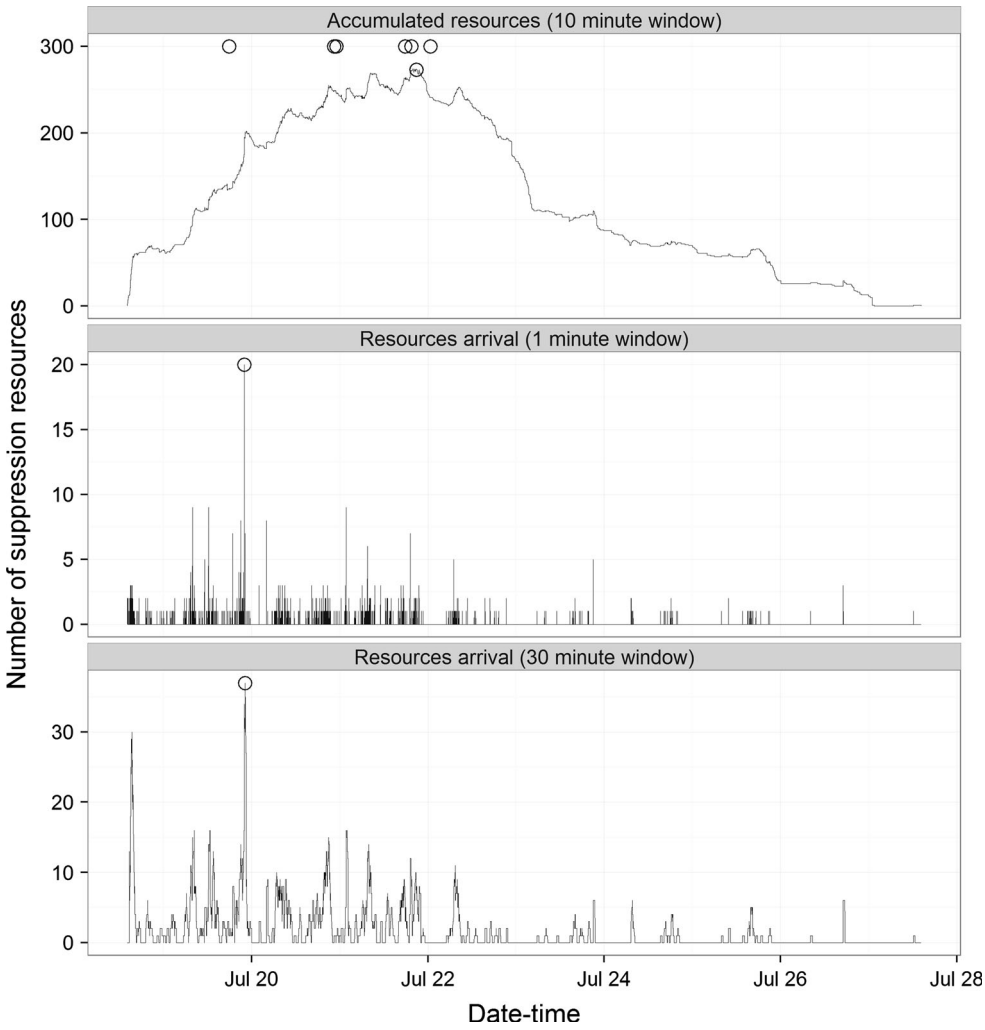


Fig. 1 Accumulation and arrival of fire-fighting resources (vehicles, aircraft and personnel) in the 24,843-ha Tavira ELF: on the *top panel* the accumulated resources on a 10-min time window basis, the maximum or estimated *T* (*circle*, *on top of the line*), and the six times at which the fire was declared 'being held' (*circles aligned at the top*); in the *middle and bottom panels*, the number of dispatched resources, calculated using, respectively, one- and 30-min time windows and their maxima (*circles on top of each line*)

between methods (1) and (2), we examined ANPC records for the reported date–time of the change of state to 'fire being held'; these text records transcribing communications with the national coordination centre were available for 67 ELF. Results differed largely between the estimates of resources arrival and reported containment (e.g. Fig. 1), in spite of the expectation that additional suppression resources would not be asked for once a fire is apparently contained. A possible explanation for the discrepancies is the fact that all locally available, but limited resources are deployed when initial attack fails and extended attack begins, following the 'muscled attack' dispatch policy (Pacheco et al. 2014). The second approach was finally adopted to estimate *T* using a time window of 10 min; other time windows (5, 15, 30 min) were experimented with very similar results. The evolution of accumulated resources in Fig. 1 is typical of ELF development, as it mirrors a fire's life cycle (Martell 2001): a fast initial attack response is followed by a strong gradual increase in resources during extended attack, levelling off when the fire is contained and then gradually decreasing as the fire is brought under control and subsequently is declared out.

ELF *size* from the fire atlas and *T* were used to calculate the average growth rate (*FGR*) of each ELF as *size*/*T*, in units of ha h^{-1}.

Each observation in the ANPC database contained the type of suppression resource (e.g. fire engine, tanker, helicopter), its registration plate and fire department (if applicable), location of the fire, the date–time of departure and return, travel distance and the associated personnel, from which we built an ELF database with the resources used in each fire. The single or multiple date–times a ELF was declared contained (up to seven) were obtained in the text records (e.g. Fig. 1). The resulting database included data on all suppression resources used (11,662 observations) for 100 ELF. Its analysis was carried out using R (http://CRAN.R-project.org/) version 3.1.0 ×64 (R Development Core Team 2014) in RStudio version 0.98.1028 (Racine 2012), and the packages: 'zoo' version 1.7–11 (Zeileis and Grothendieck 2005); 'ggplot2' version

1.0.0 (Wickham 2009); 'gridExtra' version 0.9.1 (Auguie 2014); 'scales' version 0.2.4 (Wickham 2014); 'doBy' version 4.5–10 (Højsgaard 2006); and 'pscl' version 1.4.6 (Jackman 2014).

We calculated a set of variables characterizing suppression resources usage from beginning to end of each ELF and the resources present at the time of containment (Table 1): total used suppression resources (the number of observations) (*Mt*); total number of fire fighters (*Ht*); ground tankers (*WTV*) and total (*WT*) water capacities (litres); and water power (*WpTV* and *WpT*) as the product of duration on the fire and *WTV* or *WT*. Duration on the fire is the difference between the date–times of return and departure from the fire station, measured in minutes and calculated for each suppression resource. In addition to *Mt* and *Ht*, we calculated the following variants: (1) excluding observations with zero or negative duration or without recorded date–time of departure or return (*M*, *H*) and (2) calculated at *T* (x*M*, x*H*, x*WpT*, x*WpTV*) using the 10-min time window inherent to *T* estimates. Regarding aircraft, only the number of resources and water capacity were available. To control for the potential association between dispatched resources and *size* or *T* (e.g. Costafreda-Aumedes et al. 2015) and account for the dispersion of resources, all suppression effort variables were expressed both per unit area and per unit length of the final fire perimeter.

Fire environment data

Assessment of the fire environment associated with ELF considered fire weather and fuel hazard metrics. Fire weather conditions were described by components of the Canadian Fire Weather Index (FWI) System (Wotton 2009), adopted in Portugal for fire danger rating purposes. We used the Initial Spread Index (ISI) and the Buildup Index (BUI) of the FWI system to, respectively, describe the atmospheric and drought components of fire weather. The ISI reflects the influences of wind speed, relative humidity, air temperature and recent rainfall on potential fire spread rate. The BUI is primarily a function of precipitation history and expresses fuel consumption. The combination of the ISI and the BUI into the Fire Weather Index (FWI) indicates potential fireline intensity. Daily FWI system codes from the nearest weather station were averaged for the duration of individual ELF.

We described fuel hazard through fuel age as a simple proxy for fuel accumulation and structure, influent on fire spread rate (e.g. Cheney et al. 2012) and proportional to fireline intensity (Byram 1959). In Portugal, the effect of area burned in decreasing subsequent area burned extends for 8 years (Price et al. 2015), and increasingly larger fires select increasingly older fuels (Fernandes et al. 2012). Based on these antecedents, we used the mapped time since fire to calculate the fractions of each fire occupied by low and high fuel hazard patches, corresponding to fuel ages <9 years (*LoHaz*) and >20 years (*HiHaz*). Additionally, we considered the rural fires database record of ELF fraction with forest cover, because fire behaviour in forests is potentially more extreme and extinction is more difficult (Finney et al. 2009). Each ELF was also assigned the corresponding ecoregion (Albuquerque 1961) because fire–environment relationships are expected to respond to the biophysical setting, e.g. Parisien and Moritz (2009).

Statistical analysis

ELF characteristics, fire-suppression metrics and fire environment descriptors were generally not normally

Table 1 Complete list of the variables describing fire-suppression effort calculated for each ELF

Variable type	ELF All data (n = 11,662)	ELF, date–time Data with valid[b] date–time (n = 11,494)	ELF, *T* Calculated at the estimated fire containment date–time, *T* (n = 5574)
Total suppression resources (no. observations)	*Mt*	*M*	*xM*
Total no. firefighters	*Ht*	*H*	*xH*
Tanker water capacity	*WTV*		
Tanker water power (*WTV* multiplied by duration[a])		*WpTV*	*xWpTV*
Total water capacity (all vehicles)	*WT*		
Total water power (*WT* multiplied by duration[a])		*WpT*	*xWpT*

[a] Duration is the difference between the date–time of return and departure from the fire-fighting headquarters, measured in days, calculated for each suppression resource (observation)

[b] Excluding observations with zero or negative duration[a] and without recorded date–time of departure or return, respectively, 93 and 75 out of 11,662 (1.4 % of the total)

distributed and hence were summarized by their median, range and interquartile range. Spearman's rank correlation coefficient (ρ) was used to assess association between variables.

The statistical analysis sought to model *T*, *size* and *FGR* from the available fire environment and fire-suppression descriptors. We used maximum-likelihood parametric survival analysis to model *T*, including fire environment and fire-suppression effort metrics as covariates and assuming the Weibull and the log-normal as alternative distributions. Survival analysis models time-to-event distributions and is the customary method to analyse fire frequency (e.g. Johnson and Gutsell 1994), but it suits the analysis of time to fire containment as well (Morin et al. 2015).

We used regression tree analysis (RTA) to model *size* and *FGR* from fire environment and fire-suppression metrics. We considered the explanatory power of both the average and the maximum observed values of fire weather metrics (ISI and BUI), as in a multi-day fire most of the increment in area burned can occur in a single day. We also included *T* as a potential explanatory variable of *size* as a proxy for unobserved fire environment effects. RTA splits continuous response variables into gradually more homogeneous subsets through recursive partitioning on categorical or numerical independent variables. RTA, among other convenient features, is nonlinear, nonparametric and handles missing observations, complex data structures and interaction between predictor variables (Death and Fabricius 2000). RTA is not immune to collinearity, which can affect the partitioning variables chosen and produce unstable and biased partitions (Berk 2008). This was a minor concern because our objective was to quantify aggregate effects through a descriptive, rather than predictive, model. Nonetheless, we examined the relationships between fire-suppression force metrics, potentially multicollinear and ELF characteristics (*size* and *FGR*). The putative independent variables were allocated to one of the three types of variables (number of resources, number of firefighters, water-related metrics), and the best univariate predictors (Dormann et al. 2013) were kept for the RTA, one per each type of variable.

Because nonconstant variation was expressive, the analysis was done on natural log-transforms of the dependent variables to avoid giving more weight to more variable data (Death and Fabricius 2000). Splitting was carried out to the maximum extent possible, and then, the resulting tree was pruned to the ideal size as determined by tenfold cross-validation combined with the minimum AICc criteria. The influence of each variable on ELF characteristics was assessed by its relative contribution (%) in explaining variability out of the total variation accounted for by the model.

Results

Fire characteristics, fire environment and fire-suppression effort

The study sample contained 100 ELF, of which eight were the outcomes of two or more ignitions. ELF *size* covered two orders of magnitude, up to 43,766 ha, but most fires extended over three to seven thousand hectares (Table 2). The remaining fire metrics, *T* and *FGR*, were more variable than *size* and spanned three orders of magnitude, with the typical ELF lasting for 24 h and expanding at 260 ha h^{-1}. Fire danger rating based on the *FWI* index as per Palheiro et al. (2006) included the classes high ($n = 1$), very high ($n = 8$) and extreme ($n = 91$). Hence, fire weather conditions were generally favourable to fast spreading fires, nearly complete fuel consumption and fireline intensities hindering effective and safe control by direct attack at the head of the fire (Palheiro et al. 2006). Forests were usually more represented than open vegetation types in ELF. Fuel hazard was potentially high, given the residual presence of <9-year-old fuels and dominance by >20-year-old-fuels (Table 2).

The relative allocation of fire control resources varied also more than *size*, up to four orders of magnitude (Table 3). We report fire-suppression force metrics per unit of ELF area but not per unit of ELF perimeter length, whose subsequent analysis (see below) proved to be less relevant. The number of fire fighters (*Ht, H, xH*) was greater than the number of tankers and other resources (*Mt, M, xM*) by an approximate ratio of 4:1. These quantities were lower at *T* (*xM*; *xH*) than overall (*Mt*, *M*; *Ht*, *H*). Association between the different fire-suppression effort metrics was always strong, the minimum ρ being 0.75 and highly significant ($p < 0.0001$).

Table 2 Variation in ELF characteristics and corresponding fire environment descriptors

Variable	Range	Median	Interquartile range
Fire characteristics			
size (ha)	2500–43,766	4208	2981–7395
T (h)	3.7–140.1	24.1	11.1–42.0
FGR (ha h^{-1})	31.7–1244.2	260.3	108.3–415.6
Fire weather			
ISI	6–45	15	13–19
BUI	75–601	227	165–289
FWI	23–99	50	43–58
Vegetation and fuel			
Forest fraction	0–1	0.56	0.30–0.87
LoHaz	0–0.84	0.06	0–0.22
HiHaz	0.02–1	0.73	0.46–0.95

Table 3 Variation in the fire-suppression resources per unit of ELF area (ha)

Variable	Range	Median	Interquartile range
Mt	0.0002–0.1293	0.0161	0.0059–0.0360
M	0.0002–0.1203	0.0161	0.0058–0.0353
xM	0.0001–0.0675	0.0068	0.0030–0.0176
Ht	0.0011–0.4454	0.0609	0.0223–0.1314
H	0.0011–0.4202	0.0600	0.0217–0.1248
xH	0.0004–0.2088	0.0258	0.0106–0.0634
WTV (l)	1.8–359.2	40.8	15.9–85.9
WpTV (l)	0.9–1027.1	76.2	26.4–170.4
xWpTV (l)	1.5–948.2	52.0	22.0–127.7
WT (l)	0.6–422.5	54.6	21.4–119.8
WpT (l)	0.1–1202.2	90.2	30.9–209.9
xWpT (l)	0.3–1113.2	59.9	26.2–151.0

Table 1 defines each variable

Role of fire-suppression resources on ELF characteristics

Survival analysis using the log-normal distribution (Fig. 2) fitted ELF time to containment, *T*, better than the Weibull distribution, consistent with previous work (Pacheco et al. 2014). The distribution of *T* was marginally affected by fire weather in the form of the BUI ($p = 0.0453$), reducing the AICc from 866.0 to 864.2, but not by the ISI ($p = 0.1936$) or the FWI ($p = 0.6817$). Vegetation and fuel hazard metrics did not influence *T*. The trend in fire-suppression force metrics was to increase with increasing *T* and BUI. Either in km^{-1} or in ha^{-1}, none of the fire-suppression effort metrics was significant in the parametric survival model.

Fire-suppression effort per unit of area always outperformed its per unit of perimeter length equivalent in explaining variation in *size* and *FGR*. Likewise, RTA selected mean values of fire weather indices as independent variables, rather than their maxima, possibly because half of the fires did not differ in their mean and maximum fire weather—those ELF that did not spread for more than 24 h (Table 2). Pre-RTA screening leads to the selection of *H*, *M* and *WT* as fire-suppression metrics for inclusion in the RTA. RTA indicated log-transformed ELF *size* to be a primary and balanced function of fire-suppression force (*H* and *WT*) and fire weather (the BUI), both accounting for 26 % of the amount of variation explained (Table 4). Higher density of fire control resources, essentially manpower, decreased *size*, while higher BUI increased it. *T* (19 %) and *LoHaz* (15 %) were also relevant influences, respectively, positive and negative, and ecoregion further absorbed 12 % of the variation; forest fraction exerted a minor (2 %) positive influence. Overall, the analysis accounted for 76 % the observed variability and indicated a 3:1 fire environment-to-fire suppression ratio of influence on *size*.

Fire-suppression force through *H* and *M* prevailed in the explanation of log-transformed *FGR* variation (47 % of the total effect), followed by ecoregion (27 %), fire weather (both the *ISI* and the *BUI*, 14 %), forest fraction (8 %) and *LoHaz* (5 %). The signs of the effects were the same as in the case of *size*. The independent variables captured 60 % of the variation, with a fire environment-to-fire suppression ratio of influence of 1:1.

Discussion

ELF occurred in landscapes characterized by high fuel hazard, primarily under severe fire weather conditions generally conducive to extreme fire behaviour and hence ineffective fire control operations. Large fires in Portugal occur mostly where population density is lower and forest and shrubland dominate land cover (Moreira et al. 2010), largely coinciding with mountainous areas and probably denoting combined effects of high fuel hazard, adverse

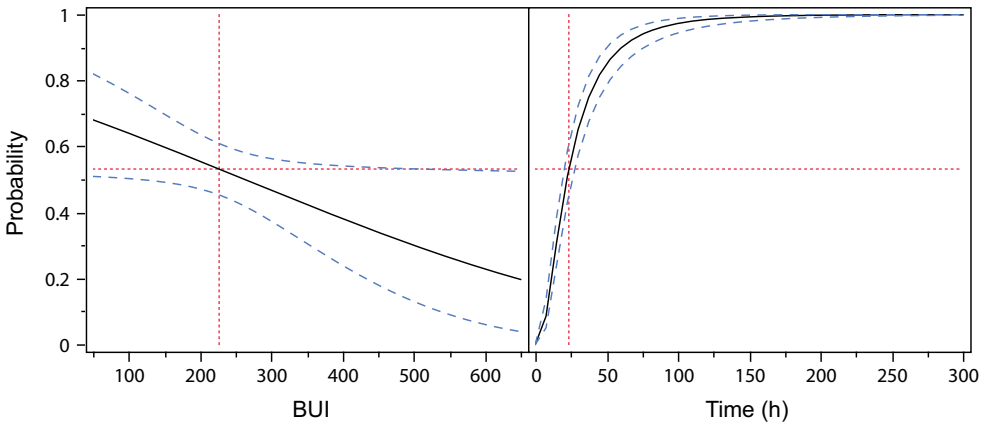


Fig. 2 Probability (with 95 % confidence intervals) of ELF containment modelled by survival analysis as function of time and the BUI, exemplified ($p = 0.52$) for the median values of the independent variables, respectively, 24.1 h and 227

Table 4 Relative influences (%) of fire environment and fire-suppression variables on log-transformed ELF *size* ($R^2 = 0.76$, AICc = 79.9) and *FGR* ($R^2 = 0.60$, AICc = 190.6)

Variables	*size*	*FGR*
T	19.3 (+)	–
ISI	–	4.0 (+)
BUI	26.4 (+)	9.8 (+)
Ecoregion	11.9	26.8
Forest fraction	2.2 (+)	7.9 (+)
LoHaz	14.6 (−)	4.7 (−)
H	24.2 (−)	35.6 (−)
M	–	11.3 (−)
WT	1.5 (−)	–

Variables with increasing and decreasing effects are denoted, respectively, by (+) and (−)

topography and deficient pre-suppression preparedness. The provision of normalized fire-suppression resources was extremely variable among ELF (Table 3). Such variation is inherent to the influences of seasonal preparedness level, assets at risk, regional variation in fire-fighting staffing and the amount of simultaneous large incidents competing for resources. Nevertheless, discrepancies in the fire-suppression effort of this magnitude (sixfold to eightfold variation considering the interquartile range) can signal inadequate resourcing, poor size-up of fire growth potential and the need to improve ELF management, including rekindle potential (Pacheco et al. 2012). The human and equipment resources per unit area in large fires (>100 ha) in Spain are typically higher, respectively, by factors of two and four (Costafreda-Aumedes et al. 2015). Such difference can be attributed to lower resource scarcity in Spain versus the relatively informal and substandard Portuguese fire-fighting system (Beighley and Quesinberry 2004), given the extremely large budget of fire suppression in Spain, which is comparable to US expenditures (Seijo and Gray 2012).

We found no evidence that allocating increasingly higher levels of fire-suppression resources decreases the lifespan of ELF. Large-fire control is opportunistic, by taking advantage of the intermittent periods during which weather conditions allow effective containment (Finney et al. 2009; Podur and Martell 2007). Because gradual or abrupt changes in the fire environment (not considered in the study) contribute decisively to fire spread cessation, ELF likely expanded as long as the combined effects of weather, fuel and terrain overwhelmed the fire control capacity, regardless of the available resources; as an example, ELF in southern Portugal in 2003 were contained when nighttime relative humidity approached 100 % (Tedim et al. 2013). However, suppression resources and organization and contained sections accrue as the fire expands, enabling more effective control as opportunities arise (Finney et al. 2009) due to economies of scale (Holmes and Calkin 2013).

Modelling ELF *size* and *FGR* from empirical data is a notable challenge considering the multiple variables and interactions involved. Sorting out the relative weight of fire environment components and fire control efforts is inherently complicated, and more so when fire weather and fuel hazard are not limiting factors and constrain what can realistically be expected from fire suppression. The fire environment and fire-suppression variables controlling ELF *size* and *FGR* differed in relative influence but were essentially the same. While more extreme fire weather favoured fire spread, higher *LoHaz* representation in the landscape and the allocation of more fire-suppression resources exerted the opposite effect.

The fire environment control over ELF *size*, explicit and implicit (through *T*), was modestly offset (1:3) by the amount of allocated fire-fighting resources. This was expected given the need to prioritize human protection over fire control (Moritz 1997) and because effective suppression requires moderate fire weather (Finney et al. 2009; San-Miguel-Ayanz et al. 2013). *T* absorbed a significant fraction of the explained variation in *size*, reflecting fire environment influences not captured by the independent variables and the persistence of conditions impeding successful fire containment. Changes in the fire environment leading to fire control can be detected by comparing fuel and topography (including discontinuities) across the edge of the fire, which allowed Viedma et al. (2009) to increase the explanation of fire size variability from 16 to 57 % in a central Spain area.

The contribution of fire-suppression force to *FGR* nearly doubled in relation to *size*. This was in part an outcome of the influence of *T* on *size*, as *FGR* is independent of *T*. Fire spread rate, hence potential *FGR*, is a function of the fire environment, but the presence of more resources will restrict fire expansion by increasing the length of attacked fire perimeter and the strength of the attack, provided that fireline intensity—highly variable around the fire perimeter (Catchpole et al. 1982)—is within suppression capacity. Still, even when fire behaviour precludes effective suppression action, i.e. the fire remains uncontained, fire growth can be slowed, e.g. through aircraft drops.

A number of caveats are apparent in the study besides not identifying the conditions that actually determined the end of active spread. We did not consider the effects of topography, which in part is justified because the average rate of spread of a large fire in complex terrain tends to approach that of a fire in flat ground (Sullivan et al. 2014). Metrics of landscape fuel connectivity and diversity would have likely improved the fuel-related explanation of ELF characteristics (Curt et al. 2013; Loepfe et al. 2010;

Viedma et al. 2009). To some extent, these effects may have been captured through regional variation, which was a relevant influence, especially on *FGR*. The presence of ecoregion in the regression trees probably integrates a combination of effects on fire spread through terrain characteristics such as slope, topographic complexity and dissection and wind–landform interactions (Barros et al. 2012), as well as differences in vegetation composition and continuity. Fire danger rating is not expected to portray local fire behaviour (Alexander 1994) and conditions at the fire location differ from those indicated by the nearest weather station, depending on distance, elevation, hour of the day and weather–topography interactions (Schroeder and Buck 1970).

Despite our effort to describe the fire-suppression effort through more sophisticated metrics, namely by taking into account the time during which resources were available, overall and at *T*, only the simplest variables (*H*, *M*, *WT*) ended up in the regression tree. In fact, it is difficult to establish quantitative relationships between available suppression resources and large-fire expansion because of equivocal links between suppression resources and tactics (Finney et al. 2009). Additionally, aircraft resources were incompletely considered here. Aerial fire fighting is perceived to diminish time to containment (Plucinski et al. 2012) and decreases the likelihood of large fires (Holmes et al. 2008; Moritz 1997), but expectations on its effectiveness often are too high, especially regarding use in extended rather than in initial attack (Calkin et al. 2014; San-Miguel-Ayanz et al. 2013). Given these limitations, the RTA succeeded in explaining relatively high amounts of variation in *size* and *FGR*, respectively, 76 and 60 %. The value of wildfire case studies to understand fire-suppression relationships cannot be emphasized enough (Alexander and Thomas 2003). Future observational studies should quantify the distribution of fire-suppression resources among operational strategies and tactics (e.g. civil protection, direct and indirect attack, mop-up); assess the operational outcomes; consider fire crews qualification and specialization; and register fire environment and fire behaviour characteristics in relation to fire control operations and fireline production rates.

The primary functional objective of fire management in Portugal is to minimize the area burned (Lourenço 2005). As the effect of fire-suppression force on ELF *size* was modest in relation to the fire environment influence, our results suggest that further investment on large-fire suppression should be focused on intelligence and organization rather than on resource availability. Improvement of large-fire management should integrate fire behaviour analysis and expand fire-fighting options to enable effective perimeter control through more manual and mechanized fireline construction—versus line-holding with water, prevalent in Portugal (Beighley and Quesinberry 2004)—and indirect control (Castellnou et al. 2010). ELF *T* and *size* will decrease by better identifying and exploring the opportunities for fire containment, including those offered by fuel treatments, rather than by accumulating suppression resources.

Conclusion

In Portugal, and in comparison with the effect the fire environment exerts, the size response of ELF to variation in fire-suppression force is weak, which in part reflects lack of influence of fire suppression on time to containment. Nevertheless, the rate at which ELF develop in area is equally affected by the fire environment and by fire resourcing. Our findings are indicative of the need to improve current large-fire management and operations to take better advantage of weather, fuel and topographic changes that create containment opportunities and are conducive to effective fire control. The latter can be fostered through landscape-scale fuel treatment projects and by increasing community fire awareness to increase the level of self-protection, hence lowering fire-suppression resources deviation to the wildland–urban interface.

We have quantified to what extent the fire control effort impacts *size* and *FGR* by using data on the available suppression resources, not on their actual activity and effectiveness, as this would have required an observational study. Further understanding of the role played by fire suppression on fire characteristics should also target more thorough descriptions of the fire environment by including topographic metrics and assessing changes at the fire edge, and should consider the putative influences of anthropogenic features, e.g. the wildland–urban interface.

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Chapter 3

Advancing risk handling through decision support systems within an imperfect information environment

There are occasions when it pays better to fight
and be beaten than not to fight at all.
George Orwell

3rd paper

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Review

Cohesive fire management within an uncertain environment: A review of risk handling and decision support systems

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ABSTRACT

Wildfire management has been struggling in recent years with escalating devastation, expenditures, and complexity. Given the copious factors involved and the complexity of their interactions, uncertainty in the outcomes is a prominent feature of wildfire management strategies, at both policy and operational levels. Improvements in risk handling and in risk-based decision support tools have therefore a key role in addressing these challenges. In this paper, we review key systems created to support wildfire management decision-making at different levels and scales, and describe their evolution from an initial focus on landscape-level fire growth simulation and burn probability assessment, to the incorporation of exposure and economic loss potential (allowing the translation of ignition likelihood, fire environment – terrain, fuels, and weather – and suppression efficacy into potential fire effects), the integration with forest management and planning, and more recently, to developments in the assessment of values at risk, including real-time assessment. This evolution is linked to a progressive widening of the scope of usage of these systems, from an initial more limited application to risk assessment, to the subsequent inclusion of functionality enabling their utilization in the context of risk management, and more recently, to their explicit casting in the broader societal context of risks and decisions, from a risk governance perspective. This joint evolution can be seen as the result of a simultaneous pull from methodological progresses in risk handling, and push from technological progress in wildfire management decision support tools, as well as more broadly in computational power. We identify the key benefits and challenges in the development and adoption of these systems, as well as future plausible research trends.

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1. Introduction

Uncertain and highly unpredictable factors, such as weather forecasts, performance of suppression resources, and fire behavior, spread and effects, are the basis of fire management and policy decisions, across multiple levels and scales. Theoretical and computational progress in the last four decades has enabled the development of risk-based Decision Support Systems (DSS) that contribute to improve those decisions, namely by facilitating a structured assessment of the outcomes and costs associated with alternative policies, budgets, and suppression resource mixes.

In recent years, several authors have updated the state of the art on these tools and related challenges. Minas et al. (2012) have updated the review of Martell et al. (1998) on operations research methods applicable to wildfire management. Thompson and Calkin (2011) organize and align sources of uncertainty with decision support tools and methodologies, in order to facilitate cost-effective, risk-based wildfire management and planning efforts. Mavsar et al. (2013) present the economic efficiency analysis theory of fire management measures and use it as a framework to review four fire management DSS in use in America and Europe. Papadopoulos and Pavlidou (2011) make a comparative review of wildfire simulators and Sullivan (2009b) presents a comprehensive survey and review of surface fire spread simulation models. Indeed, some pre-defined spread model is incorporated in most of wildfire simulation models to simulate the behavior of fire across a landscape (Thompson and Calkin, 2011). Bettinger (2010) describes the methods used to integrate wildfires into forest planning models, using operations research techniques, going back to the seminal work of Van Wagner (1979), while more recently Pasalodos-Tato et al. (2013) review the use of decision support tools to address risk and uncertainty in forest management planning.

Our review adopts a higher-level perspective to provide a broader and more complete view of the evolution of the field. We concisely present several important risk-based decision support models for fire management, on the one hand highlighting their usefulness within the scope and the purposes that guided their development, but on the other rendering explicit a number of limitations that they present. Some of these limitations have also been discussed recently, although in a fragmented way, in the literature on challenges in the development and deployment of risk-based decision support systems. We bring together this set of observations, and highlight what seems to us to be an important trend of broadening of concerns from risk assessment, to risk management, to risk governance. This trend frames an increasingly ambitious utilization of these systems, gradually and successively broadened to address each of those areas of concern. This overall evolution pattern is the result of simultaneous methodological progress in risk handling, as well as specific technological progress in wildfire management decision support tools, and generic technological progresses in computation.

The remainder of the paper is structured as follows: in Section 2, we describe several fire growth simulators developed in recent decades in multiple parts of the world, and their connections with different wildfire management DSS based on economic models, as well as developments in the integration of forest and fire management, and more recent efforts aiming at going beyond economic models; in Section 3, we characterize the trend of broadening of risk handling concerns from risk assessment, through risk management, to risk governance, in close connection with the previous section; in Sections 4 and 5 we close the paper, with a discussion and with the presentation of conclusions and suggestions for future work, respectively.

2. From fire growth simulation to economic models and beyond

2.1. Fire growth simulation models

A number of wildfire growth simulation models have been developed over the years (Table 1). Explicit spatial simulation of fire growth requires a fire spread model and the description and mapping of vegetation (fuel) as per the typology required by the spread model. Consequently, spatial fire modeling has been preceded by the ability to estimate fire behavior characteristics for a given point or location from a set of static fuel, weather and slope conditions. Fire spread models usable by fire managers are either semi-physical or empirical in nature. The Rothermel (1972) model is the best known of the former type and is widely used, being at the core of the U.S. fire modeling systems, from the stand – e.g., BEHAVE (Andrews, 1986), now BehavePlus (Andrews, 2014) – to the landscape-level – e.g., FARSITE (Finney, 1993, 2004). Rothermel's model has also been adopted for fire growth simulation elsewhere, e.g., CARDIN (initially based on BEHAVE and later named "Visual Cardin") in Spain (Millan et al., 1991; Martin-Fernández et al., 2002; Rodríguez y Silva and González-Cabán, 2010) and in the module of fire simulation of the KITRAL system in Chile (Julio et al., 1995).

Canadian and Australian fire growth simulators depend on empirical fire spread models and systems (Noble et al., 1980; Forestry Canada, 1992). The Canadian Prometheus has been in development since 1999 (Tymstra et al., 2010). The Australian SiroFire was launched in 1994 (Coleman and Sullivan, 1996) and has now been replaced (Sullivan, 2009b) by PHOENIX Rapidfire (Saeedian et al., 2010; Duff et al., 2012) at the University of Melbourne as a component of a risk management model, being developed by the Bushfire CRC for southern Australia (Tolhurst et al., 2008; Taylor and Freeman, 2010).

Vector-based simulation approaches for fire growth like those based on Huygens principle produce much more realistic fire shapes than raster-based simulations, or cellular automata, among other alternatives (French, 1992; Sullivan, 2009b; Tymstra et al., 2010). Raster-based models deal with heterogeneous fuels and weather better than vector-based models (French et al., 1990). Nevertheless, and although the procedure varies, all the existing North American and Australian fire growth simulators implement Huygens approach (Cechet et al., 2014). Given our focus on systems used by practitioners, there are several other important models

Table 1
Review of the characteristics of cited fire modeling systems (fire behavior, fire spread, and probabilistic fire spread simulators).

Name	Origin/ year	Primary attributes	Inputs	Outputs	Spread model/math. models	Deterministic/ stochastic	Planning context and decisions supported	Duration	Fires considered	Simulation type	Type of burn probability	Source of variation[1]	References
BehavePlus[b]	USA 1983[c]	Fire behavior prediction and fuel modeling – Constant variation in time – Uniform variation in space (runs in a PC or Smartphone)	Interactive user input (generally ranges of values)	– Tables – Graphs – Simple diagrams	Over 40 mathematical fire models for ignition and tree mortality probability, crown scorch height, surface and crown fire behavior, maximum spotting distance, safety zone size, point source fire size and shape, and fire containment	D	– Predicting the behavior of an ongoing fire – Fuel treatment planning – Training (fuel hazard, fire behavior) – Post-fire analysis	Elapsed time for size or spread distance	Individual fire	One fire, one constant weather scenario	NA	None	Andrews (2007) Andrews (2014)
Visual-Cardin used by SINAMI[d,e]	Spain 1989[f]	– Fire growth and behavior simulation modeling system – Initially based on BEHAVE, applies its algorithms in a discreet way to each pixel using raster maps (runs in a PC)	– Ignition area or line (set of pixels) with maximum slope and direction values, calculated from terrain topography (GIS) information – Fuel model in each pixel (cell) – Tree height, crown base height, and crown density – Fuel moisture and degree of protection – Wind speed and direction – Ambient temperature and humidity – Suppression resources spatiotemporal allocation	Maps of flame length and residence, directions, wind, fire line intensity, heat by unit area, and rate of spread (Rodríguez y Silva, 1999)	– 13 BEHAVE fuel models adapted to the Mediterranean ecosystems – Fire expansion is assumed to occur in a cardioid way (Cassini ovals), instead of elliptical as in BEHAVE – Simulation model through cellular automata (CA) using the more nearest neighbor (Rodríguez y Silva et al., 2014)	D[g]	– Predicting the behavior of an ongoing fire – Air and ground suppression actions planning – Fuel treatment planning – Post-fire analysis – Preventive forestry strategies design (Rodríguez y Silva, 1999)	–Minutes/hours of active burning with or without suppression –Proved to accurate for time intervals of 20 min (simulation/ reality emerged small discrepancies mean that the system should be updated every 20 min)	Individual fire (pixels ranging 20–50 m)	One fire, one weather scenario	NA	– Uniform wind speed and direction* – Air and live/ dead fuel moisture content, and wind protection* – Fuelscape[ax] *These values can be updated during the simulation	Millan et al. (1991) Rodríguez y Silva (1999) Martin-Fernández et al. (2002) Rodríguez y Silva and González-Cabán (2010) Rodríguez y Silva et al. (2014)
FARSITE[h]	USA 1993	– Fire growth and behavior simulation modeling system – Variation in time, diurnally and by day – Variation in space across the landscape – Heterogeneous conditions of terrain, fuels, and weather (runs in a PC)	– Spatial (GIS) fuel, terrain, etc. data – User-defined fuel moisture and wind	Maps of fire growth, perimeter, intensity, etc.	– Richards partial differential equations to propagate each vertex along the fire perimeter[i] – Mathematical fire models for surface fire spread, crown fire initiation and spread, spotting, and dead fuel moisture[j,k]	D[g]	– Fire and land management decisions – Air and ground suppression actions simulation	Long time periods: hours/day of active burning or number of days for the simulation	Individual fire	One fire, one weather scenario	NA	– Wind speed – Wind direction – Fuel moisture content – Fuelscape[ax]	Finney (2004) and Andrews (2007)
SiroFire[l,m]	Australia 1994	– Real-time bushfire spread simulator to help fire control officers predict the probable spread of a fire – Can consider suppressed sections of fire perimeter	– Topography (proprietary format with data derived from several GIS platforms) – Spatial fuel types (unburnable, other) – Fuel load and condition – Grass curing – Slope	– Map of the wildfire predicted spread across the landscape – Fire perimeter predicted at regular intervals – Wind direction changes can be incorporated in the prediction	– Rothermel's model (ellipse based on local fuel fire growth) configured for Australian grass and forest litter fuel – McArthur Forest and Grassland Fire Danger Rating meters – CSIRO Grassland Fire Spread Meter	D	– Predicting the behavior of an ongoing fire – Suppression actions planning (e.g., applying firebreaks) – Used mostly as fire-suppression training tool	One day[n] (from one day 9am until next day 9am)	Individual fire	Up to ten fires over the landscape, one weather scenario	NA	Throughout the day: – Temperature – Relative humidity – Wind speed and direction Does not: – make corrections for elevation of temperature and humidity	Coleman and Sullivan (1995) Coleman and Sullivan (1996) Sullivan (2009b) Papadopoulos and Pavlidou (2011)

(*continued on next page*)

Table 1 (*continued*)

Name	Origin/ year	Primary attributes	Inputs	Outputs	Spread model/math. models	Deterministic/ stochastic	Planning context and decisions supported	Duration	Fires considered	Simulation type	Type of burn probability	Source of variation[1]	References
		– Subsumed into PHOENIX Rapidfire (runs in a PC)	– Weather (temperature, relative humidity) – Wind speed/ direction – Selected fire spread models (one for forests, one for grasslands)	– Spotting distance prediction[as] (not used to ignite new fires)	– Does not simulate crown fires – Does not simulate Spotfires							– incorporate fuel moisture lag time	
Prometheus[o,p] used by Burn-P3[q]	Canada 1999[r]	– Spatially explicit, deterministic fire growth simulation model – Complex fire environment and modeling parameters managed as scenarios – Modular design eases the integration with external applications[s] (runs in a PC)	– Spatial (GIS) topography (slope, aspect, and elevation) – Spatial fuel types (required) – Weather streams[t] – Spatial landscape grids[u] (option) – Wind speed/direction grids[v] (option) – Foliar moisture content – Fire type and duration – Fuel breaks (spotting is allowed[w])	– Statistics and map (vector and raster) views – Spread rate – Fuel consumption fraction burned and total (crown and surface) – Fire intensity – Spread distance – Fire area – Fire perimeter (at user-specified time step intervals)	– Richards partial differential equations to propagate each vertex along the fire perimeter[l] – FBP and FWI Systems (sub-systems of the CFFDRS[x])	D[y]	– Fire behavior training tool – Evaluate fire management alternatives/costs – Design of fuel management strategies for values at risk or in protected areas[z] – Fuel treatment planning[aa] – Large fires management – Post-fire analysis – Recovery planning[ab]	– One or many daily burning periods – Type and duration (only limited by the length of weather data) of the simulation	Individual or multi-fire simulation (Alberta generally uses 100 m grids (sometimes 25 m) for operational purposes)	One or multiple ignitions, under one or more scenarios	NA	Spatially across the landscape: – Fuelscape[a,x,u] – Topographic conditions Spatially and temporally: – Weather conditions	Johnston et al. (2005) Opperman et al. (2006) Sullivan (2009b) Tymstra et al. (2010) Papadopoulos and Pavlidou (2011)
FSPro[a,c] used by WFDSS[ad,ae] as RAVAR[af]	USA 2006	– Variation in time, by day – Variation in space across the landscape – Runs remotely for authorized analysts with internet access	– Spatial (GIS) fuel and terrain data – Current fire perimeter – Weather stations for fire danger and wind climatology	Map of probability of the fire reaching each point by the end of the simulation period	Minimum travel time (MTT) fire spread algorithm (Finney, 2002)	S	Suppression strategy development	Days to weeks of active burning or number of days for the simulation	Individual escaped fire	One fire, many weather scenarios	Conditional on current fire location and specified time period	– Wind speed – Wind direction – Fuel moisture content – Fuelscape[a,x]	Scott et al. (2013) Finney et al. (2011a) Andrews (2007)
FSim[a,g,ah] used by FPA [ai,ae]	USA 2008	Large-fire simulation system	– Landscape characteristics: Surface fuel model, aspect, elevation, slope, and canopy coverage – Historic Energy Release Component (ERC) – Wind Data from a representative weather station or from NARR GRID data (BAH, 2012)	– Spatially explicit burn probability maps and fire size distributions (Pacheco et al., 2013) – Intensity (via flame length), size, and impacts of escaped ignitions[o]) (BAH, 2012; Thompson et al., 2013b) – Fire intensity level table for each fuel model and percentage of treated surrounding area (-control and fuel treatment runs)[aj] (BAH, 2012)	– Minimum travel time (MTT) fire spread algorithm (Finney, 2002) – Combines weather influences, ignition probability, fire spread, and containment success submodels (Thompson et al., 2013a)	S	– Fire management plan development – Preparedness and response planning – Fuel treatment planning	Entire fire season	All large fire ignitions	All fires, all weather scenarios	Annual (full fire season)	– Wind speed – Wind direction – Fuel moisture content – Fuelscape[a,x] – Ignition location and probability – Containment probability – Fire duration	Scott et al. (2013) Finney et al. (2011b) Finney (2007) BAH (2012) Thompson et al. (2013a) Thompson et al. (2013b) Notes[ah] (about FlamMap alternative): Finney (2006) Ager et al. (2007) Ager et al. (2011) Ager et al. (2013)
PHOENIX Rapidfire[ak] used[a] by FireDST[am]	Australia 2006[an]	Spatially and temporally explicit dynamic fire behavior and characterization model[ao] used operationally:	– Fuel types[ap] – Wind reduction factors – Fire history – Topography – Assets and values – Road proximity – Linear disruptions – Weather – Suppression resources	Maps of:	– CSIRO grass[ar], McArthur MK5[as] fire behavior models – Models for the effects of short to long distance spotting[aq] (<200 m to 30 km) by upper level winds	D	Component of the Bushfire risk management model[av], for use by fire agencies, land managers, town and land planners, and policy makers to explore the strength and the interaction[aw] of:	– Short to long periods of active burning (minutes to days) – 1/15 min time interval between perimeter spread cal-	Individual or multi-fire simulation	One fire and multi-fire under several management scenarios, from the Bushfire risk management model[av]	Fire likelihood at each cell location (when in multi-fire simulation) which can include the probability of a fire starting at the ignition point from	– Weather (wind speed/ direction, temperature, humidity) – Fuelscape[a,x] – Ignition location and probability – Suppression effects	Tolhurst et al. (2006)

Table 1 (*continued*)

Name	Origin/ year	Primary attributes	Inputs	Outputs	Spread model/math. models	Deterministic/ stochastic	Planning context and decisions supported	Duration	Fires considered	Simulation type	Type of burn probability	Source of variation[1]	References
		– to estimate the fire impact on specified values or assets – for training purposes – in real-time – for post-fire analysis (runs in a PC)		– Fire origin, extent, intensity, and frequency – Flame height and depth – Rate of spread – Ember density – Size (area) – Time to impact (in each cell) – Spotting[aq] (explicitly and deterministically modeled) – Convective output	– WindNinja[at] wind field – Wind-slope interactions, fuel accumulation rates, fuel moisture models, road impact, self-extinction and fire suppression – Fuel accumulation (time since fire) – Point spread modeling (Huygen's[au], discrete event CA)		– Prevention – Disaster preparedness and response – Recovery – Fire regime management	culations for fast/slow moving fires – 100–200 m grid size is usually sufficient for operational purposes (as small as 5 m for very detailed analysis)			historic data	– Fire conditions (e.g., spotfires increase the rate of spread, different fuel strata included or excluded as fire changes in intensity and over time)	Tolhurst et al. (2008) Sullivan (2009b) Tolhurst and Chong (2009) Saeedian et al. (2010) Taylor and Freeman (2010) Duff et al. (2012) Pugnet et al. (2013) Cechet et al. (2014)

[a] Relates to variability modeled with probabilities, or aspects which can vary in the course of the simulation, according to the system stochastic or deterministic nature.
[b] http://www.frames.gov/partner-sites/behaveplus.
[c] Considering the predecessor BEHAVE; BehavePlus 1.0 was released in 2001.
[d] SINAMI, Sistema Nacional para el Manejo de Incendios Forestales.
[e] ARCAR41 developed since late 1990s was abandoned.
[f] Cardin first version (used with ARCAR41[e] in the late 1990s in a strategic model for forest fire simulation and economic planning).
[g] Spotting has a stochastic component.
[h] http://www.firelab.org/project/farsite.
[i] Prometheus and FARSITE use the same method to propagate each vertex along the fire perimeter under heterogeneous conditions, but the models differ in the fire behavior modelling approaches and fuel typologies; Prometheus uses fuel types and the fire danger rating codes and equations of the CFFDRS,[x] whereas FARSITE uses fuel models[k] and is driven by Rothermel's model and related models[j] (Tymstra et al., 2010); both were compared by Opperman et al. (2006).
[j] FARSITE fire behavior models: Rothermel's (1972) surface fire spread model, Wagner's (1977) crown fire initiation model, Rothermel's (1991) crown fire spread model, Albini's (1979) spotting model, and Nelson's (2000) dead fuel moisture model.
[k] A complete reference can be found on the technical documentation: http://ced.berkeley.edu/faculty/ratt/tool_time/fire_lab/lab7/farsite_stuff/ ("FARSITE Technical References").
[l] The CSIRO bushfire spread simulator (http://www.csiro.au/Outcomes/Safeguarding-Australia/SiroFire-Overview.aspx).
[m] CSIRO has been working on a replacement for SiroFire called Spark, intended to be an open-source fire perimeter propagation engine that is platform independent and scalable across processors (Hilton et al., 2015).
[n] The output of one simulation could be used as the input for the next, to overcome this limitation.
[o] Developed by the Canadian Interagency Forest Fire Centre (http://www.ciffc.ca/) and led by the Alberta Environment and Sustainable Resource Development (http://esrd.alberta.ca/).
[p] Canadian Wildland Fire Growth Simulation Model (http://www.firegrowthmodel.ca/).
[q] Burn-P3 (Probability, Prediction, and Planning), simulation model for the evaluation of the burn probability in a large fire-prone landscape (http://www.firegrowthmodel.ca/burnp3/overview_e.php).
[r] Version 1.0 released in May of 2002 and used operationally for the first time in the same month to provide fire management decision support for the House River fire, a classic boreal wind-driven fire (248,243 ha), which became the second-largest fire in Alberta since 1961.
[s] E.g., Pandora (to run any number of Prometheus simulations in a batch operation, also included in the Spatial Fire Management System), Pegasus (for fire management staff remotely access Prometheus via the internet), and Burn-P3 (a simulation model used to assess burn probability over a landscape).
[t] Streams can be obtained from observations, forecasts or generated from the time of year and latitude average conditions;
[u] Spatial landscape grids (an optional input) include degree of curing (grass), percent greenup (for mixedwood fuel types), percent conifer (for mixedwood fuel types), percent dead fir, crown base height, and tree height.
[v] Prometheus optionally allows users to input wind direction and wind speed grids; these are usually derived from WindNinja.[at]
[w] Long-range spotting is not natively modeled in Prometheus: it includes a breaching function (for fuel breaks) but does not include spotting over features (usually long range spotting); spotting is implicitly included in the FBP sub-systems of the CFFDRS[x] (i.e., ROS equations) because the FBP System is an empirically based model (Sullivan, 2009a); however, spotting can be added manually.
[x] CFFDRS, Canadian Forest Fire Danger Rating System (http://cwfis.cfs.nrcan.gc.ca/background/summary/fdr).
[y] Spotting and gusting winds are modeled as stochastic processes.
[z] Fuel isolation and conversion.
[aa] Including spatiotemporal smoke emissions estimates.
[ab] Also less operational decisions supported as long-term projections (e.g., climate change);
[ac] FSPro, Geospatial Fire Spread Probability model.
[ad] WFDSS, Wildland Fire Decision Support System.
[ae] WFDSS and FPA, both use LANDFIRE (Landscape Fire and Resource Management Planning Tools).
[af] RAVAR, Rapid Assessment of Values at Risk.
[ag] FSim is the FPA[ai] implementation of FSPro,[ac] included in the Large Fire Module (LFM).
[ah] FlamMap (Finney, 2006), widely used for planning fuel treatments (Ager et al., 2011), is an alternative to FSim because the access to it is not restricted to authorized personal; it can input fire lists that can be generated from statistical models, thereby making it quite advanced and simpler to use; the first paper (Ager et al., 2007) published on wildfire risk from simulation models uses FlamMap; Randig (Ager et al., 2013), the model first used for risk analysis, is a kind of command line version of FlamMap (as Pandora with Prometheus [see s]).
[ai] FPA, Fire Program Analysis.

[aj] Output of the Large Fire Module (LFM) of FPA[ai] where FSim is included.
[ak] http://www.bushfirecrc.com/projects/a41/fire-management-business-model.
[al] http://www.bushfirecrc.com/projects/2-2/enhancement-fire-behaviour-models.
[am] FireDST, Fire Impact and Risk Evaluation Decision Support Tool (http://www.bushfirecrc.com/projects/2-1/risk-assessment-decision-toolbox); development (as prototype) started in 2011, see Cechet et al. (2014).
[an] The state of Victoria began using it operationally for the 2010–2011 fire season;
[ao] PHOENIX Rapidfire was initially one component of a scenario based (non-spatially explicit) bushfire risk management and mitigation model[ak] (developed by the University of Melbourne within the Bushfire CRC, Cooperative Research Centre) to quantify the impact[aw] of several management choices[av] in the resulting fire characteristics.
[ap] Fuel moisture, flammability (heat absorption, combustion), embers (abundance, lofting, burnout, ignition), plume (energy release rate, total heat output, emissions), and suppression (radiation, embers, ease of extinction).
[aq] Spotfires are created by burning embers and occurs when a fire produces firebrands that carried by the wind starts new fires beyond the main fire (Saeedian et al., 2010); this phenomenon happens in most bushfires, especially in eucalypt forests in Australia where large numbers of embers are produced (Tolhurst and Chong, 2009).
[ar] CSIRO southern grassland fire spread model.
[as] McArthur MK5 forest fire behavior model.
[at] WindNinja is a computer program that computes spatially varying wind fields for wildland fire and other applications requiring high resolution wind prediction in complex terrain (http://www.firelab.org/project/windninja).
[au] The Huygens approach used in PHOENIX Rapidfire has been taken from SiroFire.
[av] 54 elements of bushfire management options, grouped in: prevention, preparedness, response, recovery, and fire regime management; these elements cover several management activities including: legislation, planning, public education, firefighter training, equipment development, prescribed burning, fuel management, fire detection, firefighting, use of aircraft, post-fire recovery, environmental rehabilitation and others.
[aw] There are two types of interaction included in the model, the interchangeability and the interdependence between the elements.
[ax] Fuelscape: «A raster-format geospatial characterization of ground, surface and canopy fuel across a landscape, typically consisting of one or more fuel characteristics data layers. For fire behavior modeling, a fuelscape consists of geospatial data layers representing surface fuel model, canopy base height and canopy bulk density. Other geospatial data layers required for geospatial fire modeling include topography characteristics (slope, aspect, elevation) and vegetation characteristics (forest canopy cover and height)», Scott et al. (2013).

that we do not consider, e.g., HFire (Highly Optimized Tolerance Fire Spread Model), a raster-based and computationally efficient model, which was designed to simulate long-term shrubland fire regimes but can be used for single fires (Peterson et al., 2011).

Prometheus and FARSITE are deterministic models with similar functionalities (Dupuy and Alexandrian, 2010). Both adopt the partial differential equations of Richards to propagate each vertex along the fire perimeter but differ in the fuel classification typology, weather-related inputs and fire behavior models used. Prometheus is based on the Canadian Fire Behavior Prediction System (Forestry Canada, 1992) that estimates fire behavior (adjusted for specific fuel types) from fire danger rating codes. FARSITE is part of the suite of U.S. landscape-level fire modeling systems, that also includes FlamMap (Finney, 2006) and the geospatial Fire Spread Probability (FSPro) model (Andrews, 2007), and relies on Rothermel's spread model and associated fuel models. Opperman et al. (2006) compared the two models for wildfires in grass, scrub, and forests, in New Zealand and Australia. Both performed very well. Despite the lack of site-specific fuel models and weather data, local users concluded that the fuel model choice was less important than expected, but having local wind data was imperative because local winds influence the final fire shape. Local users also concluded that the most important criteria in the choice of an application are usability and configuration flexibility.

SiroFire (Coleman and Sullivan, 1996) has been used in Australia as a fire-suppression training tool, using McArthur's fire spread models for grassland and forest as well as Rothermel's model (Sullivan, 2009b). Similarly, fire behavior characteristics in PHOENIX are derived from the CSIRO southern grassland fire spread model and the McArthur MK5 forest fire behavior model (Saeedian et al., 2010). PHOENIX does not adopt state-of-the art fire spread models (e.g., (Cheney et al., 2012)) but incorporates additional models that enhance its dynamic ability, namely for the effects of spotting (also present in FARSITE), wind-slope interactions, fuel accumulation rates, fuel moisture models, self-extinction and fire suppression (Tolhurst and Chong, 2009; Saeedian et al., 2010; Papadopoulos and Pavlidou, 2011; Cechet et al., 2014).

The fire behavior module FSPro (Finney et al., 2011a) uses a computationally efficient form of the FARSITE calculations to simulate 2-D fire growth across the landscape, without suppression. It differs from FARSITE in that it simulates fire growth for thousands of possible weather scenarios, statistically derived from local weather stations data using the latest recorded fire perimeters. FSPro assigns a burn probability to each cell in the landscape by dividing the number of runs of the simulation in which the cell burns by the total number of runs (Calkin et al., 2007). FSim is an implementation of FSPro that simulates thousands of possible fire seasons, varying fuels, weather, suppression and treatments, to estimate burn probabilities and fire size distributions. It uses the minimum travel time fire spread algorithm (similarly to FlamMap), whose extensive application has established that it can be effectively used in heterogeneous landscapes, as is the case of the wildlands in the U.S. (Calkin et al., 2011a; Finney et al., 2011b).

Used for land-management planning (and also for fire research), Burn-P3 (probability, prediction, and planning) is a spatial fire simulation model that uses the Prometheus engine to simulate the ignition and spread of a very large number of fires. The inputs are topography, fuels, weather, and fire ignitions patterns (drawn from a probability density grid with Monte Carlo methods). Fire spread is driven by the weather conditions and fire length is modeled stochastically from user-supplied distributions. Burn-P3's main output is a burn probability map (Parisien et al., 2005, 2010).

Table 1 summarize a set of primary attributes (name, origin, year, primary attributes, inputs, outputs, spread model/mathematical models, deterministic/stochastic, planning context and decisions supported, duration, fires considered, simulation type, type of burn probability, source of variation, and selected references) for the fire behavior, fire spread, and probabilistic fire spread simulators mentioned in this section.

2.2. Fire suppression models

The development of risk-based decision support tools has largely been directed to the management of active fires, especially during initial attack, aiming at preventing fires from escaping and causing damage, since the seminal paper of Fried and Fried (1996). Using some form of simulation, the fire is considered contained when the constructed length of fireline, dependent on the capacity of the firefighting resources employed, equals the fire perimeter determined by its rate of spread; in addition, other factors could be considered, like containment probability, interactions between fireline production and fire growth, fire danger rating, rate of spread, fuel type, or the diversion of resources for structure protection (Thompson and Calkin, 2011). Furthermore, to handle the lack of objective data about some aspects of suppression, expert judgment elicitation has been used by several authors to inform the modeling of the initial attack, e.g. Martell et al. (1999) and Hirsch et al. (2004).

The amount of resources to dispatch to each fire and how to prioritize scarce resources in a multiple fires scenario, are some of the dispatching decisions included in the initial attack and that often must be taken quickly and with limited information (Collins, 2012). The skills, experience, and intuition of the firefighters could be enhanced with this kind of DSS, potentiated by advances in computing power and geospatial data acquisition that enables massive geo-processing, rapid simulations, projection of fire behavior across the landscape and increases the accuracy of fuel conditions (Thompson and Calkin, 2011). Despite these advances, the modeling of escaped large wildfires is still an immature field with significant knowledge gaps since the factors contributing to suppression success remain poorly understood (Finney et al., 2009) and very little is known about the relationship between suppression inputs and fireline construction along the duration of extended attack episodes (Holmes and Calkin, 2013).

2.3. Wildfire management DSS based on economic models

With a limited amount of funding, equipment, and human resources, forest managers must decide the most efficient distribution among alternative fire management options such as prevention (e.g., education, public campaigns), fuel treatments (e.g., prescribed burning, mechanical treatments), pre-suppression (e.g., planning and preparedness, firefighters recruitment and training, maintenance of fuelbreaks and water points), suppression, and restoration measures (Mavsar et al., 2010). Accomplishing that requires the ability to evaluate how wildfires spread with and without suppression and their effects on the monetary value of the destroyed or damaged assets (Mendes, 2010). It further requires being able to assess stand-level prescriptions, including fuel treatments, as wildfire risk is related to stand structure and flammability, and the spatial allocation of prescriptions (e.g., harvest and fuel treatment decisions) in the forested landscape and its impact on the spread and intensity of wildfires.

The evaluation of fire spread and its effects, with and without suppression, requires an extensive amount of information, which is in many cases unavailable, especially concerning the overall social (e.g., ecological values, air pollution) and private (e.g., destroyed assets) costs associated with wildfires. The resulting knowledge uncertainty and substantial gap in the scientific understanding of both short and long-run effects (Brillinger et al., 2009)

lead to a lack of resource value measures to guide prioritization across fires and resources at risk (Thompson and Calkin, 2011). Even so, considerable theoretical progress has been achieved (Gorte and Gorte, 1979; González-Cabán, 2007; Mavsar et al., 2013), since the early work of Headley (1916), Lovejoy (1916) and Sparhawk (1925), until the more recent contributions of Donovan and Rideout (2003), including Simard (1976), Mills and Bratten (1982) and Rideout and Omi (1990). Generally, the economic analysis of fire management efficiency makes use of the "cost plus net-value-change" concept, C + NVC (Mavsar et al., 2010).

Starting with FEES, the Fire Economics Evaluation System (Mills and Bratten, 1982; González-Cabán et al., 1986), and even though not always adequately considering the effects on non-market resources (e.g., recreation, flora and fauna, soil, air and water quality, or cultural heritage) (Brillinger et al., 2009), the combination of computer simulation and Geographic Information Systems (GIS) with the economic evaluation of losses and wildfire fighting costs has enabled substantial advances toward the goal of providing *"sufficient data to enable the efficient economic choice of the best combination of fire combat resources per fire type, the integration of cost–benefit analysis, modeling incidence probability as well as the spread of fires lines with and without intervention, per intervention and fire type"* (Mendes, 2010).

Even if this goal has not yet been fully achieved, especially for the management of escaped large wildfires (Finney et al., 2009; Holmes and Calkin, 2013), examples of these systems currently in use include the Canadian "Level of Protection Analysis System", LEOPARDS, the Chilean KITRAL ("fire" in the indigenous Mapuche language), U.S.A.'s "Fire Protection Analysis", FPA, and the Spanish "Sistema Nacional para el Manejo de Incendios Florestales", SINAMI. The latter is a more advanced and updated version of U.S.A.'s "California Fire Economics Simulation Model", FPPS/CFES, operating under the same principles (Mavsar et al., 2013).

2.3.1. LEOPARDS

LEOPARDS (Martell and Boychuk, 1994, 1997) has been in use in Ontario, Canada, since 1995 (McAlpine and Hirsch, 1999a,b). It can model daily fire-suppression activities (Minas et al., 2012), emulating them with inputs that include historical fire weather, fire incidence data, land-use objectives, operational rules, infrastructure and suppression resource information. The system estimates three forms of outputs: physical outcomes (e.g., response time, escaped fires, burnt area), fixed and variable costs, and resource utilization information (McAlpine and Hirsch, 1999a,b; Podur and Wotton, 2010).

LEOPARDS is based on the initial attack model developed by Martell et al. (1983, 1984) and considers temporal queuing conflicts and spatial realities (multiple fire ignitions over a large area or a large number of fires in a small area and in a short time period) of forest fire suppression, situations that often lead to delays in initial attack resulting in more escaped fires (McAlpine and Hirsch, 1999a,b). Podur and Martell (2007) have used it in an attempt to model the more complex problem of the containment of large wildfires (Thompson and Calkin, 2011), wherein the combat is typically opportunistic and meteorologically driven (Martell, 2007; Finney et al., 2009). Currently, with the key improvements focused on the fire behavior simulator and the suppression deployment model, a second version of LEOPARDS is being prepared (Mavsar et al., 2013).

2.3.2. KITRAL

In development since 1993, and in usage after 1996, KITRAL uses simulation models to predict fire behavior including risk, danger, spread rate, wind velocity, flame length and priorities at several time and space scales, using an extensive geographical database (Pedernera and Alvear, 1999). By evaluating different fire management alternatives, for pre-suppression and suppression, KITRAL enables daily (real time) allocation of resources, and strategic planning of activities (Mavsar et al., 2013).

For dispatch, the system locates the areas of reported fires, simulates the spread and the competing needs of simultaneous fires, and calculates the quantities and types of resources that should be sent to efficiently fight each fire (Pedernera and Alvear, 1999).

Tested under real conditions, the results reveal 90% accuracy in forecasts of fires larger than 60 ha, but less reliability in fires affecting less than 2 ha, probably because its grid has a minimum size of 25 m^2. However the system is fast, being capable of simulating a period of twelve hours in three minutes (Soto et al., 2004), and its use may lead to savings in the range of 15–50% of direct losses (Pedernera and Alvear, 1999).

More recently, an optimization model, using integer linear programming, aiming at minimizing the cost of fire control has also been developed and integrated with the system (Musa, 2004; Pedernera et al., 2004).

Soto et al. (2013) have used KITRAL to obtain a global territorial model of economic vulnerability to forest fire (considering direct costs), integrating risk, danger and damage potential, to facilitate the prioritization of suppression activities, even in the wildland urban interface (WUI), where fires are mainly caused by humans.

2.3.3. SINAMI

The research design of the SINAMI model, which includes CARDIN as a calculating tool, was presented in 2004 (Rodríguez y Silva, 2004) and finished in 2006 together with ECONOSINAMI, its module for economic analysis (Rodríguez y Silva, 2007).

SINAMI is a model exclusively intended for strategic fire management planning, using marginal analysis and the economic criterion of C + NVC to determine the most efficient fire management programs and budget levels, and considering a true representation of the historical analysis of the last 10-year average conditions. It enables managers to quantitatively explore the tradeoffs among budget levels and potential losses, and justify budget requests by easily identifying the potential consequences of a budget reduction or relocation. Furthermore, the model provides fire management program compositions and the number of necessary resources (Rodríguez y Silva and González-Cabán, 2010).

The model has continued to evolve, and by 2012 it had already included the impact of wildfires on a variety of tangible and intangible natural resources, such as timber, forage, underbrush, fruits, water, fishing, fauna, recreation, hunting and landscape (Mavsar et al., 2013). In that same year, a pilot project was implemented in two forest areas of Mexico (Rodríguez y Silva, 2010).

SINAMI has been applied to the evaluation of economic losses in Iberian swine production, which depends on privately held pasture lands that may be affected by wildfires, and more broadly, of the direct negative economic impact on rural development (Martínez et al., 2011). In a different application, SINAMI has been used to validate an extension of the thirteen Rothermel fuel models to better represent the Mediterranean ecosystems (Rodríguez y Silva and Molina-Martínez, 2012). The system has also been employed, in an extension of the principle of economic valuation to the concept of economic vulnerability, to provide a cartography of economic vulnerability and value of forest ecosystems, which may provide fundamental inputs for temporal and spatial budget optimization (Rodríguez y Silva et al., 2012).

2.3.4. Fire Program Analysis

In the U.S., in response to the National Fire Plan (Babbitt and Glickman, 2000), a report commissioned by President Clinton after the severe wildfires of 2000, and to the updated Federal Wildland Fire Policy (Interagency Working Group, 2001), the Hubbard report (Hubbard, 2001) proposed that the five federal wildland

firefighting agencies should develop and implement a single, common, uniform and performance-based interagency analysis process, including a software application tool to support wildland fire budgeting and planning decisions (Fairbanks et al., 2002).

To evaluate the effectiveness of alternative fire management strategies in time, that system should be objective-driven, performance-based, and should find the most cost-effective program encompassing the full scope of fire management activities (protecting life and property, using fire and other treatments to maintain and restore the health of ecosystems, and reducing hazardous fuels in fire-prone ecosystems), identifying resource needs and sharing opportunities across all jurisdictions. This endeavor was thereafter supported by the Congress, which further required that the resources sharing mechanism should also include non-federal partners (BAH, 2012).

The development of this system, called Fire Program Analysis (FPA), was initiated in 2002 (Rideout and Botti, 2002; Botti et al., 2004) and should have been completed by 2006. However, after the conclusion of the first part of the model in 2004, as the agencies began to use it, officials started raising concerns about the underlying science. As a result, in 2006 the agencies conducted a review, which questioned the basic modeling approach and led to a change from an optimization paradigm (which evaluated all possible combinations and locations of firefighting assets to identify the optimal combination for a given budget level) to a simulation paradigm, incorporating a tradeoff analysis. This change caused a delay of three years in the development of the system, with its expected cost rising from $40 million to close to $54 million (GAO, 2008).

This change on the modeling approach originated an important "knowledge fight" (Buuren and Edelenbos, 2004), i.e., a scientific disagreement featuring intellectual arguments stemming from different approaches to knowledge representation, in both arenas: public (e.g., Fried (2007), wildlandfire.com (2012), Olinger and Gorski (2012)) and academic (e.g., Rideout et al. (2008a,b), Yu et al. (2008), Bruins et al. (2010), Calkin et al. (2011a), Thompson et al. (2012)). The Government Accountability Office (GAO), the audit, evaluation, and investigative arm of Congress, expressed concerns about the simulation-based approach, since it provides considerable discretion to the agencies' decision makers, and in doing so, requires full transparency in those decision processes (GAO, 2008, 2009b,a).

The FPA shares the fire simulation model, FSim, and the Landscape Fire and Resource Management Planning Tools Project, LANDFIRE, with the Wildland Fire Decision Support System (WFDSS) (BAH, 2012; Ryan and Opperman, 2013). These modules are applied independently to each of the 134 Fire Planning Units that cover the continental U.S., and compared with historical data (Finney et al., 2011b), requiring a total simulation time of approximately four months to complete (BAH, 2012).

The required spatial information on fuel structure and topography are provided by LANDFIRE at a 30 m resolution (Finney et al., 2011b). These data are available on-line and are subject to continuous updating (Ryan and Opperman, 2013). However, the full set of simulations only needs to be run after a major LANDFIRE update (BAH, 2012).

After a decade, the FPA development has continued to be characterized by delays and revisions (GAO, 2011a, 2011b). The first results were intended to be used to develop the budget for the fiscal year of 2011 (GAO, 2009a,b), however the scope of usage in that year was limited to supporting the development of the budget request for 2013 (GAO, 2009a,b; BAH, 2012). The system was expected to be fine-tuned, calibrated and fully implemented in 2012 to inform the 2014 fiscal year budget (BAH, 2012), but in its current state, it is not yet suitable for field-level use (BAH, 2012; Thorsen and Hubbard, 2012).

The perception remains, for some stakeholders, that FPA has not achieved the goals set in the Hubbard report, and its current objectives have shifted from the original intent (BAH, 2012). However, FPA promises to achieve some of the key objectives established originally (GAO, 2008, 2009a) and there is no current alternative in the U.S. for the coordination of national fire investments (BAH, 2012).

2.4. Integrating forest and fire management

Recent research has been conducted to develop decision support tools to help integrate forest and fire management planning activities that are currently carried out mostly independently of each other. These tools focus on the support to wildfire prevention planning rather than the management and suppression of active fires. Bettinger (2010) discussed the potential of a wide range of techniques to enhance the integration of forest and wildfire management processes. Borges et al. (2014) presented and discussed the world-wide experience of developing forest management DSS. Packalen et al. (2013) provided a brief overview of this experience. In this section the reader is provided with additional detail about a typical forest management DSS (SADfLOR) to highlight the key functionalities needed to address efficiently and effectively the integration of forest and fire management.

The Portuguese SADfLOR is a DSS with a modular structure that encompasses an information management system, a prescription writer, a model base, a methods base, and a graphical user interface (Borges et al., 2003). Reynolds et al. (2008) provide a detailed description of its architecture. The system was developed with the participation of forest stakeholders ranging from the Forest Service to the forest industry and non-industrial forest owners. Its model base includes growth and yield models for the most important Portuguese species and its methods base includes both exact and heuristic approaches to forest management planning (Garcia-Gonzalo et al., 2013). The system supports strategic and tactical forest management planning and among its applications we may list the development of strategic management plans for the Portuguese pulp and paper industry (Borges and Falcão, 1998), or more recently the Leiria National Forest management plan (Garcia-Gonzalo et al., 2013).

This web-based multiple criteria spatial decision support system has recently been updated with tools to integrate forest and fire management planning. Emphasis was on integrating stand-level fuel treatment scheduling and landscape-level management planning to target socio-economic and ecological objectives while sustaining effective fire prevention levels. Specifically, the SADfLOR model base was updated with models to estimate the probability of stand-level wildfire occurrence according to composition, vertical structure and biometric variables. This is instrumental to understand the effect of stand characteristics on wildfire occurrence probability. The model base was further updated with models to estimate the proportion of trees in a given stand that will die as a consequence of a wildfire event and to understand how stand-level variables impact mortality. These models provide information about the impact of management options on wildfire occurrence probability (Botequim et al., 2013) and on wildfire damage (Marques et al., 2011) in the main forest cover types in Portugal. The new SADfLOR model base thus provides the functionality needed to project conditions and outcomes of interest (e.g., timber flows, carbon stocks) associated with each stand-level prescription under wildfire risk and generate the resulting feasible sets in the criteria space.

The SADfLOR methods base was updated to include management scheduling techniques that might process decision spaces under scenarios of wildfire risk. Specifically, non-linear optimization algorithms (e.g., Hook and Jeeves and populations methods)

and stochastic dynamic programming approaches (Ferreira et al., 2012) to stand-level management planning were developed to help managers and landowners: select the sequence of management activities, including fuel treatment and timber harvests, that maximizes soil expectation value for a stand where wildfire risk is related to stand structure and fuel loads; and assess trade-offs between objectives, as well as estimate opportunity costs of non-optimal prescriptions in a wildfire risk context. The methods base was also updated to include a mixed integer programming technique that maximizes the forest value while addressing timber even-flow and landscape wildfire resistance concerns (Ferreira et al., 2014). For this purpose the updated model base was used further to develop a stand-level wildfire resistance index.

2.5. Beyond economic models

Recent developments in near real-time risk-informed decision support (Zimmerman, 2012) for incident management feature a broader scope of concerns, addressing not only economic aspects, but also the likelihood of fire impact on the values at risk.

The Wildland Fire Decision Support System, WFDSS (Calkin et al., 2011b; Noonan-Wright et al., 2011; NFAEB, 2012; Zimmerman, 2012) and the Fire Impact and Risk Evaluation Decision Support Tool, FireDST (Cechet et al., 2014), have been developed as support tools for risk-informed decisions on the management of escaped fires, in the U.S. and Australia respectively.

Developed with the combined effort of several U.S. federal fire management agencies, to reduce redundancy, and in operation since 2009, WFDSS has replaced the former Wildland Fire Situation Analysis (WFSA), Wildland Fire Implementation Plan (WFIP), and Long-Term Incident Planning (LTIP) processes, in a scalable and flexible web based environment (Noonan-Wright et al., 2011; NFAEB, 2012; Zimmerman, 2012). Being a real-time system like Prometheus (Tymstra et al., 2010), Phoenix (Tolhurst et al., 2008) and CARDIN (Martin-Fernández et al., 2002; Rodríguez y Silva, 2004), WFDSS improves the management of escaped large wildfires by supporting integrated risk assessment and the communication between analysts and decision makers (Calkin et al., 2011b).

However, WFDSS differs in a fundamental way. Recognizing the limited understanding of suppression efficacy (Thompson and Calkin, 2011) and the opportunistic nature of suppression effects on large fires (Martell, 2007; Finney et al., 2009), WFDSS does not attempt to model the effectiveness of various alternatives of firefighting resources or suppression tactics, leaving that evaluation to the decision maker in the field. Instead, the system enables usable real-time exposure analysis of the likelihood of fire impact on the values at risk (Calkin et al., 2011b; Thompson and Calkin, 2011).

The two fundamental primary components of WFDSS are the fire behavior module FSPro (Finney et al., 2011a), and the resource impact model RAVAR, Rapid Assessment of Values at Risk (Thompson et al., 2012). Together they provide appropriate fire behavior modeling, overlaid with geospatial identification of human and ecological threatened values (Calkin et al., 2011b; Thompson and Calkin, 2011).

RAVAR identifies the critical infrastructures (private structures, hazardous waste sites, public infrastructure and reserve areas) and the natural and cultural resources (sensitive wildlife habitat, natural resources, recreation zones, and restoration priority areas) within the threatened areas previously identified by FSPro (Thompson and Calkin, 2011; Thompson et al., 2012). This allows WFDSS to support management decisions regarding where and when to perform aggressive suppression or allow the fire to burn, protecting and enhancing ecosystem values (Thompson and Calkin, 2011).

The result of more recent developments in Australia, FireDST is a prototype simulation system based on PHOENIX, that provides an integrated fire risk-assessment framework (Cechet et al., 2014). The intrinsic uncertainty in fire weather (modeled with high-resolution 3-D forecasts), fire spread, exposure to fire and likely impact, are addressed probabilistically through the output of an ensemble of scenarios. By simulating the impacts of fire on community assets, infrastructure and people, FireDST delivers crucial fire-planning information that aids the allocation and prioritization of fire-fighting resources, enabling fast decisions in highly complex situations.

3. From risk assessment to management to governance

The developments described in the previous section have not followed a strictly linear path. This is naturally due in part to the parallel development efforts taking place in different parts of the world, focusing also on applications beyond broad, flexible and integrated forest fire management systems, e.g., emergency evacuation planning (Taylor and Freeman, 2010). Additionally, the decreasing costs of computer storage and computing power are defying well established paradigms, causing a swing in favor of raster-based models, more proficient at dealing with heterogeneous fuels than vector-based models, but requiring geographic data at a high enough resolution to obtain meaningful simulations results – rendering moot the decision between the two (Sullivan, 2009b). Also, as has become apparent in major developments such as the case of FPA, the path between science and practical implementation, involving multiple stakeholders, is often not clear and provides room for "knowledge fights".

Nevertheless, starting from a scientific approach to establish fire spread models, with the early efforts related to the development of BEHAVE (Andrews, 1986) and CARDIN (Millan et al., 1991; Martin-Fernández et al., 2002), we identify in our review a broadening of focus from risk assessment to risk management, and then to risk governance (Fig. 1).

IRGC defines risk governance as the "identification, assessment, management and communication of risks in a broad context", including "the totality of actors, rules, conventions, processes and

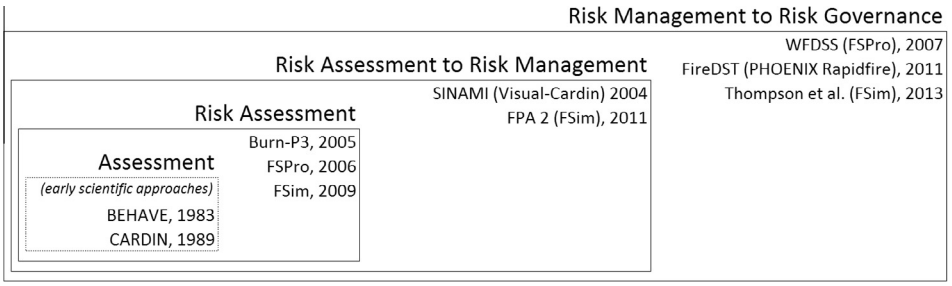


Fig. 1. Conceptual outline of the expanded focus, from risk assessment to management to governance, with examples.

mechanisms concerned with how relevant risk information is collected, analyzed and communicated, and how and by whom management decisions are taken and implemented" (IRGC, 2009). Risk governance's broad picture of risk includes risk management, but also looks at coordination or reconciliation requirements when a variety of actors is present, and in an enhanced way at context to consider "historical and legal background, guiding principles, value systems and perceptions as well as organisational imperatives" (IRGC, 2005). In this context, the role of risk-based decision support is also challenged to be widened and encompass these additional aspects.

Bachmann and Allgöwer (2000) stressed early on the need for a consistent wildfire risk terminology, with a truly modern definition of fire risk, including fire behavior probabilities and fire effects. (Hardy, 2005) noted that at the time there was widespread ambiguity over the term "fire risk", often used to mean only the probability of ignition. Considering the quantitative fire risk model of Finney (2005), incidentally published in the same year as the IRGC Risk Governance Framework (IRGC, 2005), the aim of the early fire spread models cannot be strictly described as being risk assessment, since the basic elements of risk (probability and effects) were largely absent from them. However, the fire behavior "assessment" that they provide became the basis for later true risk assessment systems, such as FSPro and FSim (and the systems using them, WFDSS and FPA, respectively), or any system using a deterministic simulation model together with probabilities (e.g., Burn-P3 with Prometheus, SINAMI with Visual-Cardin, or FireDST with PHOENIX RapidFire).

The progress at that level, together with the development of more effective models capable of taking into account large numbers of alternative scenarios, additionally supported by the availability of increasing computing power, have enabled more sophisticated analyses that could not be performed earlier. Indeed, we can establish a parallel, throughout the last decades, between the increasing comprehensiveness of risk handling and the developments from fire science (§2.1), to economic evaluation (§2.2, §2.3 and §2.4), and then to broader perspectives (§2.5).

3.1. Aligning decision support tools and practitioners

The evolution in these two trajectories, the development of more effective models enabling more sophisticated analyses and the broadening of focus to risk governance, has naturally led to misalignments between decision support tools and the practitioners adopting and implementing them, a fact that has been reflected in lower than expected levels of adoption (Calkin et al., 2011a). This is in fact also perceptible in the broader area of forest management and planning DSSs (Stewart et al., 2013).

On the social and organizational domains, difficulties have in part been linked with low levels of stakeholder engagement in the development and implementation of the DSSs, suggesting the need for improved interactions at the science–policy–practice interface, and the need to expand the absorbing capacity of user communities (Reis and Oliveira, 2007). In the specific case of risk assessment, Borchers (2005) highlights its incompatibility with an unwarranted desire for certainty that managers and policymakers often have, advocating an "embrace" of uncertainty, within a framework that considers the risk "marketplace" while addressing the challenge of "deciding how to decide". Calkin et al. (2011a) also accentuate this organizational perspective, defending the implementation of a continuous improvement process, appropriate incentives, risk management training, and communication with stakeholders who have important socio-political influence. Pasalodos-Tato et al. (2013) add the difficulty in explaining methods for decision support under uncertainty to non-specialists, including difficulties in admitting certain outcomes, unfamiliarity with concepts, and technical difficulties such as: large-scale problems, time-consuming analysis, managing the trade-off between simplicity and accuracy, knowledge about the uncertainties and risks, risk attitude, and interpretation difficulties.

But a focus on risk handling also brings added scientific challenges to the area of fire behavior and effects. Finney (2005) highlights the complexity associated with determining a location's burning probability, related to its dependence on "ignitions occurring off-site and the fuels, topography, weather, and relative fire direction allowing each fire to reach that location", and argues for a common scale to evaluate impacts on the diversity of fire-susceptible values.

Thompson and Calkin (2011) identify multiple sources of uncertainty, ranging from the unpredictability of wildfire behavior, to inaccurate or missing data, limited resource value measures, and an incomplete scientific understanding of ecological response to fire, fire behavior response to treatments, and spatiotemporal dynamics involving disturbance regimes and climate change. Using an uncertainty topology, the authors review decision support approaches for each class of uncertainty. Wildfire effects analysis and value uncertainty are identified as primary challenges to integrated wildfire risk assessment and wildfire management. Minas et al. (2012) also review Operations Research methods and discuss their ability to address some of the major challenges of wildfire management, including complexity, multiple conflicting objectives and uncertainty.

Calkin et al. (2011a) mention the need to address temporal considerations, the challenges that arise from the local scale of resource values, the uncertainty in resource response, aggravated by temporal and spatial concerns, and the social preferences for non-commensurate resources. Yousefpour et al. (2012), referring more broadly to adaptive forest management under climate change, stress the need to handle non-stationary and perhaps even belief-based parameters of stochastic processes to model climate change, and forest growth models that can estimate the production of timber and other resources, incorporate changes in climate, work across multiple scales, and feature a computational complexity that is commensurate with the evaluation of numerous scenarios and alternatives.

Mavsar et al. (2013) review four decision support systems aimed at improving the efficiency of the allocation of resources for fire protection programs, and conclude that in spite of improvements in the theoretical economic model, the advances are still not fully implemented in practice, in particular, the net value change component of the C + NVC model. This is mainly due to lacking knowledge about the impacts of different fire management measures on fire behavior and the resulting damages, and economic impacts, including market and nonmarket goods and services.

Hyde et al. (2013) point out the complexity and multidimensionality of the processes that drive ecosystem changes, and thus the need for tools that account for highly variable effects on multiple values-at-risk and balance competing objectives, and for an analysis framework that works across the range of fire-management activities. Miller and Ager (2013) state that quantitative frameworks are increasingly supporting multiple planning scales, from individual incidents or fuel treatments, to national and higher levels, but also placing a higher importance on the evaluation of multiple resource values, and the consideration of more than one risk factor at a time.

3.2. A holistic, risk-governance perspective

A more holistic view, integrating decision support and risk handling in the context of wildfire management and policymaking, and considering a broader spectrum of concerns and approaches to address the escalating costs and increasing threat to human and

ecological values posed by wildfires, has recently been emphasized by Calkin et al. (2011a), Thompson et al. (2013a), and Calkin et al. (2014).

Thompson et al. (2013a) suggest a framework for systematic risk assessment, integrating wildfire simulation and burn probability modeling, expert-based modeling of fire effects and multicriteria analysis addressing multiple sources of value, to be extended to include additional activities in the wildfire management spectrum, such as prefire planning.

Calkin et al. (2011a) point to the need of considering a broad spectrum of approaches, including communication with communities, partnerships with insurers, and engagement with planning boards on zoning and development standards, as has been the case of the "Firewise Communities Program" (www.firewise.org) or the "FireSmart Canada" (www.firesmartcanada.ca) initiatives. A view of fire management as a coupled human-natural system (Moritz et al., 2014; Spies et al., 2014) calls for the search for more than technical solutions alone. As suggested by Busenberg (2004), for this type of systems the use of an adaptive policy design framework (public participatory and learning process) may be useful to tackle uncertainties in wildland fuel reduction prescription, solving some fragilities in models, data and economic assumptions. For these purposes, Marcot et al. (2012) suggest the use of formal decision science procedures and tools in a context of structured decision making, and Calkin et al. (2014) suggest a strategic risk assessment framework to enable the evaluation of the impact of multiple strategic options on various risk factors, describing the advantages of approaching problems with a structured decision process, that allows for a well-structured problem statement and the integration of decisions made at varying spatial scales, at different points in time, by different individuals and organizations in the face of substantial uncertainty and complexity.

This resonates with the adoption of a broader view of risk governance, encompassing risk management in a broader scope, highlighting the coordination efforts among stakeholders to overcome societal challenges. In complex coupled human-environment systems with multi-stakeholder and multi-level decision-making, sound governance approaches are needed to deliver effective risk handling outcomes. In wildfire prone countries, wildfire hazard has been dealt with in ways that have evolved in time from simple risk management routines to integrated fire management frameworks, that address social, economic, cultural and environmental concerns, as well as the complexity and uncertainty in forest fire management systems (Aguilar and Montiel, 2011).

Muller and Yin (2010) have illustrated policy alternatives and their effects using low fidelity scenario prototypes for regional governance of wildfires, stressing the need to account for the multiple and interacting influences over risk that shape voluntary decision making by local authorities and management (Muller and Schulte, 2011). When DSSs are used in a broader framework, with multiple stakeholders who have different perceived values at risk, wildfire hazard mitigation must be regarded as a complex problem, characterized by uncertainty and ambiguity, thus reinforcing the importance of the governance side of risk handling. The scientific and technical support provided by DSSs may be distrusted, as they do not incorporate socio-cultural dimensions. However, if wisely utilized and communicated in the scope of participatory frameworks, DSSs can pave the way to consensus and acceptance of solutions, improving the robustness of management and policymaking.

4. Discussion

Uncertainty arises when physical or biological processes are not fully understood or behavior is not easily describe or predicted, and so, it is unavoidably linked to risk (Morgan and Small, 1992). In the wildfire management decision making process, framed in the scope of coupled human-environment systems, uncertainty about fire behavior, e.g., due to the role of fuel or weather, amplifies ambiguity when social agents or time dependent variables tag along in modeling. Uncertainty challenges both analytical and organizational innovation for participants in risk governance and management process, because complexity and ambiguity change the way the decision making entities or agents perceive the risk or value at risk, thus conditioning their decisions (IRGC, 2009).

In this paper we present the state of the art of DSS available in Australia, Europe and America. The allocation of resources to prevent and suppress fire has gained sophistication with the availability of DSSs to help the national, state and local level managers decide where and how many hectares should be treated, building effective fire-risk reduction programs. The available reliable knowledge and tools can provide useful insights to incident commanders or can illustrate the potential consequences of alternative risk management strategies to managers or policymakers. Despite limitations, they can reliably inform fire management policies and activities such that trade-offs are addressed and resources are rationally allocated and result in effective risk mitigation.

However, despite all the efforts put into risk-based DSS for fire management applications, their adoption by policymakers and managers has been generally feeble, in part because of the perceived inherent uncertainty and ambiguity in the outputs, but probably also because of insufficient stakeholder involvement in DSS conception and development. It must be recalled that decision-making aids enhance but do not replace the experience and intuition of the decision makers (Martell, 1982; Mavsar et al., 2013). A large number of factors must be considered, many of which cannot be measured quantitatively, and fire programs must be placed within their institutional context and constraints. A DSS only quantifies some of the relevant factors in fire management planning, helping to trace complex interactions and relationships, too numerous to be easily followed by one person (Mavsar et al., 2013).

Decision-making aids require a careful implementation process for a successful assimilation in the routine operations of their adopters. In the context of fire management, these implementations are particularly complex, since they involve several stakeholders with very diverse levels and natures of concerns, as evidenced throughout this paper. It is also clear from the fire management DSS literature that these systems must be adapted to local contexts, and that their development is strongly affected by institutional and external pressures (Collins et al., 2013). The success of their implementation depends deeply on opinion leaders, who are affected by the perceptions that they develop about the DSSs. Furthermore, the use of these systems requires certain capabilities, sometimes absent from the operational field.

A framework systematizing the challenges of fire management DSS implementations could substantially benefit the outcomes of these implementations. Drawing from the implementation literature (Rogers, 2003; Greenhalgh et al., 2004), this framework would uncover factors concerning the systems, the context where they are being implemented, and their adopters, and how these factors influence the perceptions, decisions and actions related to the implementation process, which in turn have an impact on the outcome of the implementation. Empirical studies should verify whether the claims from the implementation literature, such as those outlined in the paragraphs below, apply to fire management DSSs.

The implementation literature suggests that the involvement of stakeholders and users in the decisions develops commitment, increases motivation, and helps internalize norms associated to

the system (Leonard-Barton, 1988; Rogers, 2003). Furthermore, most of the decisions and the perceptions of adopters are the result of contamination from external influences (Rogers, 2003). Perceptions are mostly related to the personal and global risk of adoption, specifically concerning the impact of the system on the activities of the adopters (Leonard-Barton, 1988; Greenhalgh et al., 2004). Moreover, the compatibility of the system with values, norms, past experiences, and needs of adopters affects their perceptions of the uncertainty related to the system (Rogers, 2003).

The alignment between the capabilities of the adopter and the capabilities required to use the system has also a key influence on perceptions about the system's complexity (Linton, 2002). The lack of that alignment usually leads to initial losses of productivity, which are overcome throughout the implementation project as the system's and the adopter's capabilities, and eventually their structures, are aligned with each other through mutual and dynamic adaptation cycles (Leonard-Barton, 1988). The implementation literature also shows that the flow of the implementation process and specifically its management throughout the adaptation cycles, are strongly influenced by: the characteristics of the technology, such as its complexity, triability, demonstrability, flexibility, and compatibility (Leonard-Barton, 1988; Rogers, 2003; Greenhalgh et al., 2004); the characteristics of the adopter, such as its structure, capabilities, culture, and strategy (Leonard-Barton, 1988; Edmondson et al., 2001; Rogers, 2003; Greenhalgh et al., 2004); the characteristics of the users, such as their perceptions, motivations, and capabilities (Leonard-Barton, 1988; Edmondson et al., 2001; Greenhalgh et al., 2004); and the characteristics of the context of the implementation, such as contamination of outer systems, specific policies, and market pressures (Rogers, 2003; Greenhalgh et al., 2004).

Other important challenges for implementations of fire management DSSs concern their management. Further research should therefore also focus on gathering important managerial insights from fire management DSS implementations that can be useful for later implementations. A main management challenge pointed out by the implementation literature is how to efficiently overcome misalignments between the system and the adopter. Addressing this type of challenge would most likely include systematizing information about the factors that influence a particular implementation project, identifying the misalignments, and promoting the adequate adaptation cycles while carefully managing user perceptions and motivations (Leonard-Barton, 1988; Edmondson et al., 2001; Rogers, 2003).

Additionally, a systematized framework can provide evidence on whether, in the course of fire management DSS implementations, delivery systems and the performance criteria of the adopters adapt to fit the system (Leonard-Barton, 1988), and the targeted users become more skilful, consistent, and committed to its use (Klein and Sorra, 1996). Or whether this transition is a period of strong inertia to change, favouring established routines (Greenhalgh et al., 2004). As several stakeholders are involved, many implementation decisions may have to be orchestrated between them, with dynamics that depend not only on each of them, but also on their mutual alignment (Linton, 2002). The framework should consider how the relations between stakeholders are managed during the implementation of the system. Studies of implementations of fire management DSSs should also explore which managerial practices help enhance the perceptions of the positive impacts, and reduce the negative impacts, and the importance of implementation management complying with the culture and the overall strategy of the multiple stakeholders.

Research on these topics should provide a global perspective about the implementation of fire management DSSs, and allow a systematization of the knowledge about implementations in this particular and complex context.

5. Conclusions

A myriad of interacting social and ecological factors influence the severity of forest fires (Tedim et al., 2013). Thus, we need to understand the non-linear relationships between interconnected physical, biological, and cultural systems to be able to effectively reduce the vulnerability of ecosystems and human societies, through improved and proactive risk governance.

To perform an economic evaluation of the investment in a fire management program, an effective DSS to assist assessing alternatives and making decisions must consider multiple conflicting management options, subject to several sources of uncertainty, and their economic impact in the stream of goods and services disrupted by fire occurrence, establishing the ratio between prevention and suppression expenditures, in face of always present budgetary constraints.

The integration of forest fire risk concerns into forest planning processes is a significant step (Bettinger, 2010). However, more research is needed characterizing the impacts of alternative fire management options on market and nonmarket values at risk, and on the economic losses in goods and services triggered by the fire consequences that they try to mitigate (Thompson and Calkin, 2011; Mavsar et al., 2013). This is particularly important regarding the integration of suppression preparedness planning and fuel management (Minas et al., 2013) considering operational and ecological constrains (Minas et al., 2014).

As research evolves and the available computational power increases, it will be possible to tackle increasingly complex challenges raised by more frequent and destructive fires that threaten lives and homes, in particular in an expanding WUI. Problem structuring methods, system dynamics, simulation, decision analysis, and optimization (Minas et al., 2012), together with qualitative methods such as expert elicitation (e.g., Martell et al. (1999), Hirsch et al. (2004), or Rideout et al. (2008b)), open interviews, questionnaires, and surveys (e.g., Tedim et al. (2013)), can help model the dynamics and advance the understanding of these complex systems, gaining insight into problem structures, and better enabling the exploration of alternative management options. Guidelines on how these techniques may help improve specific aspects of decision-making are provided by Minas et al. (2012), on applications of operations research to wildfire management, and Thompson and Calkin (2011), on the alignment of sources of uncertainty with decision support tools and methodologies. Nevertheless, the performance of even the most accurate DSS will be limited by the quality of the input data. Indeed, the balance between input data errors and models accuracy should inform the need for greater precision since it increases the cost of data acquisition (Sullivan, 2009b). A good understanding of the different sources of uncertainty and their potential impact on losses, should guide the development of a DSS sufficiently easy to implement and use, and parsimonious in the amount of information decision makers need to consider (Pasalodos-Tato et al., 2013).

The implementation of DSSs raises other important challenges that emerge from our literature review, namely the involvement of multiple stakeholders who must be considered in the decision-making processes, the need for adaptation to local contexts (e.g., Opperman et al. (2006)), and the strong influence of external pressures and opinion leaders on adoption decisions and on how users perceive the system. It is vital that these and other implementation challenges are carefully managed. Research aiming at the development of a framework that systematizes knowledge about implementation challenges, and how to efficiently manage them, may

significantly benefit such management efforts, and the outcomes of implementation processes.

Risk-based analysis is required for the integration of risk handling and fire management, in order to improve the prioritization of future efforts to mitigate the risks associated with these natural and human caused disturbances. This asks for more research in biophysical and social sciences with a dynamic spatiotemporal perspective, from fire spread and effects models to fuel treatment effectiveness, climate change impacts, and social preferences. Risk assessment should also identify and characterize the importance and weight of uncertainties to improve the management of human and ecological resources at risk, in areas ranging from fuel mapping to how society values those resources (Thompson and Calkin, 2011).

Our review of DSSs in current use stresses the importance of the integration between risk handling and DSS development, to facilitate and improve the quality of decisions under uncertainty, and enable a cohesive fire management in an uncertain environment. It also points out the importance of understanding the institutional constraints of management programs within which forest fire mitigation programs develop, that along with ecological constraints and the need to engage stakeholders, need to be reflected in the usability and flexibility of these systems.

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Chapter 4

Flexible redesign of the suppression system to mitigate the impact of inefficiencies

If you wish to make an apple pie from scratch,
you must first invent the universe.
Carl Sagan

4th paper

Pacheco, Abílio Pereira, João Claro, and Tiago M. Oliveira. 2014. "Simulation analysis of the impact of ignitions, rekindles, and false alarms on forest fire suppression." Canadian Journal of Forest Research no. 44 (1):45-55. doi: 10.1139/cjfr-2013-0257.

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ARTICLE

Simulation analysis of the impact of ignitions, rekindles, and false alarms on forest fire suppression

Abílio P. Pacheco, João Claro, and Tiago Oliveira

Abstract: Rekindles and false alarms are phenomena that have a significant presence in the Portuguese forest fire management system and an important impact on suppression resources in particular and fire management resources in general. In this paper, we propose a discrete-event simulation model of a forest fire suppression system designed to analyze the joint impact of ignitions, rekindles, and false alarms on the performance of the system. The model is applied to a case study of the district of Porto, Portugal, for the critical period of the forest fire season, between July and September 2010. We study the behavior of the system's point of collapse, comparing the real base scenario with a benchmark scenario built with reference values for rekindles and false alarms, and also as a function of the number of fire incidents, considering historical variations. The results of the analysis are useful for operational decision-making and provide relevant information on the trade-off between prevention and suppression efforts.

Key words: forest fire suppression, rekindles, false alarms, discrete event simulation.

Résumé : Les reprises de feu et les fausses alarmes sont des phénomènes qui occupent une place importante dans le système portugais de gestion des feux de forêt et qui ont un impact important particulièrement sur les ressources allouées à la suppression et de façon générale sur les ressources responsables de la gestion des feux. Dans cet article, nous proposons un modèle de simulation d'événements discrets d'un système de suppression des feux de forêt, conçu pour analyser l'impact conjoint des allumages, des reprises et des fausses alarmes sur la performance du système. Le modèle a été appliqué à une étude de cas dans le district de Porto, au Portugal, durant la période critique de la saison des feux de forêt, entre les mois de juillet et septembre 2010. Nous avons étudié le comportement du point de rupture du système en comparant le scénario de base réel à un scénario étalon élaboré avec des valeurs de référence pour les reprises de feu et les fausses alarmes et également en fonction du nombre de feux en tenant compte des variations historiques. Les résultats de l'analyse sont utiles pour prendre des décisions opérationnelles et fournissent des informations pertinentes au sujet des compromis entre les efforts de prévention et de suppression. [Traduit par la Rédaction]

Mots-clés : suppression des feux de forêt, reprises de feu, fausses alarmes, simulation d'événements discrets.

1. Introduction

In this paper, we propose a discrete-event simulation model of a forest fire suppression system designed to analyze the joint impact of ignitions, rekindles (re-starts), and false alarms (FAs) on the performance of the system. The application of the model is illustrated with a case study of the district of Porto, Portugal, for the critical period of the forest fire season, between July and September 2010.

Our motivation for this work comes from the perception that rekindles and FAs (malicious or good-intent calls) have unusually high values in the Portuguese forest fire management system, a quarter of all occurrences (Autoridade Florestal Nacional (AFN) 2011*a*), with potential positive feedback loops wherein suppression resources are used unnecessarily or inefficiently, leading to further degradation of system performance. Accordingly, rekindles and FAs represent an unusually high burden on the suppression resources in particular and fire management resources in general.

Because fire departments cannot presume that a call is an FA and must respond as they would to a fire (Ahrens 2003), the high values for this proportion are strenuous for initial attack (IA) crews, who get deployed to nonexistent fires, become unavailable for real fires, are deprived of time to rest and recover, or are hastily redeployed from other incidents, prematurely abandoning mop-up efforts and possibly creating conditions for fires to rekindle. In the little research available about FA performance measures (Flynn 2009), we have found values for FA calls as a proportion of all emergency calls for the US (4.4% of all calls in 2009 and 4.1% in 2010; Karter 2011), New Zealand (between 4.6% and 5.4%; Tu 2002), and the UK (5.0% in Derbyshire (Yang et al. 2003) and 6.2% in South Wales (Corcoran et al. 2007)). These numbers, when compared with the 12.3% observed in 2010 (AFN 2011*a*), suggest that there is still room for improvements regarding FAs in Portugal.

The 13.0% of rekindles registered in the same year is also an extremely high proportion, still very much above the target of 1% defined in the "Technical Proposal for a National Plan of Defense of the Forest against Fires" (Instituto Superior de Agronomia (ISA) 2005) and reveals futile suppression efforts that contribute to an overload of the suppression system. Incidentally, the 1% target may be too ambitious. Indeed, in a report on the factors that contribute to ignition, Ahrens (2010) mentions rekindles as responsible for 3% and 6% of the US local fire department responses

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to "brush, grass, and forest fires" and to "forest, woods, or wildland fires", respectively, between 2004 and 2008.

In the remainder of this section, we review the literature, presenting an overview of the state of the art in forest fire simulation and the IA response time as a performance measure.

1.1. Forest fire simulation

Uncertain factors such as the weather, the performance of suppression resources, and fire behavior, spread, and effects are at the basis of most fire management decisions. Theoretical and computing advances in the last four decades have enabled the development of risk-based decision support systems (DSS) that provide improved active fire management through a structured assessment of the outcomes and costs associated with alternative fire management policies, budgets, and suppression resource portfolios.

In recent years, several authors have updated reviews of the state of the art in this field. Minas et al. (2012) updated the review of Martell et al. (1998) on operations research methods applied to wildfire management. Thompson and Calkin (2011) describe available decision support tools and methodologies, addressing wildfire risk assessment in face of uncertainty to facilitate cost-effective, risk-based wildfire management and planning. Mavsar et al. (2013) describe the economic efficiency analysis theory of fire management and review four fire management DSS currently applied in America and Europe. Papadopoulos and Pavlidou (2011) offer a comparative review of wildfire simulators, and Sullivan (2009) provides a comprehensive survey and review of surface fire spread simulation models. Indeed, some predefined spread model is incorporated into most wildfire simulation models to simulate the behavior of fire across a landscape (Thompson and Calkin 2011). Finally, Bettinger (2010) reviews the methods used to integrate wildfires into forest planning models using operations research techniques, starting with the seminal work of Van Wagner (1979).

A number of wildfire growth simulation models have been developed in different countries and throughout the years. Some examples are the Canadian Prometheus (Tymstra et al. 2010), in development since 1999, and, starting in the early nineties, FARSITE in the US (Finney 2004), Visual Cardin in Spain (Rodríguez y Silva and González-Cabán 2010), and the Australian SiroFire launched in 1994 — the latter has now been subsumed in the more recent and promising Phoenix RapidFire, developed by the University of Melbourne as part of a risk management model (Sullivan 2009). Finally and with a different approach, the Wildland Fire Decision Support System (WFDSS) has been in development since 2004 in the US as a support tool for risk-informed decisions on the management of escaped fires (Calkin et al. 2011; Noonan-Wright et al. 2011) using FSPro as a fire spread probability model (Finney et al. 2011*a*).

With limited financial funds, equipment, and human resources, forest managers must decide how to build a portfolio of alternative fire management options such as community prevention (e.g., education, public campaigns), fuel treatment (e.g., prescribed burning, thinning, mechanical fuel removal), presuppression (e.g., firefighter recruitment and training, maintenance of fuel breaks and water sources), suppression, and restoration (Mavsar et al. 2010). This requires an evaluation of how wildfires spread, with and without suppression, and their impact in terms of the monetary value of destroyed or damaged assets (Mendes 2010). Since FEES, the Fire Economics Evaluation System (González-Cabán et al. 1986; Mills and Bratten 1982), and even though sometimes not considering adequately the effects of nonmarket resources (e.g., recreation, flora and fauna, soil, air and water quality, or cultural heritage) (Brillinger et al. 2009), computer simulation, geographic information systems, and the economic evaluation of losses and wildfire fighting costs have been successfully combined in some integrated systems that "provide sufficient data to enable the efficient economic choice of the best combination of fire combat resources per fire type, the integration of cost–benefit analysis, modeling incidence probability as well as the spread of fires lines with and without intervention, per intervention and fire type" (Mendes 2010).

Examples of these systems currently in use include the Canadian LEOPARDS (Level of Protection Analysis System; McAlpine and Hirsch 1999), the Chilean KITRAL ("fire" in the indigenous Mapuche language; Mavsar et al. 2013), the US FPA (Fire Program Analysis; http://www.forestsandrangelands.gov/FPA/index.shtml), which includes the large-fire simulation system FSim to estimate average burn probabilities and fire size distributions (Finney et al. 2011*b*), and the Spanish SINAMI (Sistema Nacional para el Manejo de Incendios Florestales; Rodríguez y Silva and González-Cabán 2010). The latter is a more advanced and updated version of the US California Fire Economics Simulation Model (FPPS/CFES), operating under the same principles (Mavsar et al. 2013).

As the previous review highlights, the existing fire spread simulators and wildfire DSS based on economic models are very detailed and powerful. In contrast, our system is a screening model that, with less fidelity, explicitly considers rekindles and FAs, phenomena that have not been captured in previous simulation work. Our modeling efforts aim at evaluating their impact on the performance of fire management operations in a season and deriving additional implications for strategic fire management planning.

Analytical solutions using standard mathematical methods are always a preferred approach, but when their application is not possible, as is almost always the case when working with complex systems (White and Ingalls 2009), simulation is arguably the most robust method applied to model real-life stochastic systems that evolve probabilistically over time (Minas et al. 2012). Discrete event simulation (DES), system dynamics, and agent-based modeling are three of the most used systems modeling approaches in the simulation field. DES mimics the dynamics of a real system as a chronological sequence of events and was the approach that we chose for our analysis.

1.2. Response time as a performance measure

Fire occurrence rates vary over both time and space (Martell 2001), and an increased response time is considered intrinsically linked to a decreased probability of containment of new fires (Quince 2009) and a larger intensity-weighted area burned (Mercer et al. 2008). That is the reason why, in forest fire management organizations, fire managers must minimize IA response times (Martell 2001). Indeed, it is reasonable to assume that the longer that it takes to attack a fire, the larger the fire size will be at attack (Islam 1998) because the fire grows as it waits (Islam et al. 2009; Martell 2001). Accordingly, the larger the fire is at the beginning of the IA, the more likely it is that the fire will escape (Islam 1998). In addition, IA resources will be there for a longer period of time, so the next occurring fire may have to wait even longer and therefore that delayed response can ripple over time and affect the ability of the suppression system to respond to fires occurring even several days later (Martell 2001).

Hence, it is reasonable to use response time as a performance measure to evaluate an IA and for operational decision-making, as it is well understood by fire managers (Islam 1998). Minimizing fire crew response time is crucial to minimizing the number of fires that escape IA (Islam et al. 2009). Therefore, the use of response time as a proxy of suppression effort is meaningful because it is related to available suppression resources (Butry 2007) and most strategic fire management planning models use this simple performance measure of effectiveness to reflect suppression cost effectiveness (Martell 2007; Quince 2009).

For any fixed quantity of mobile suppression resources such as IA crews, as the occurrence rate increases, so do response times, and thus, daily IA effectiveness will saturate at some rate, beyond which the proportion of fire escapes will increase (Cumming

2005). The limit at which the system starts to fail is what we call "point of collapse", the performance measure that we chose to evaluate the joint impact of ignitions, rekindles, and FAs on forest fire suppression.

The remainder of the paper is structured as follows: in section 2, we describe the study site, the data and methods used in this study, the conceptual model, and its implementation as a DES model; in section 3, we present the parameterization of the model and the results for the base case and for the sensitivity analyses; in section 4, we discuss the results; and in section 5, we offer some conclusions and suggestions for future work.

2. Materials and methods

In this paper, we present an exploratory case study. The impact of rekindles and FAs on the performance of suppression systems has been given scarce attention by research in forest fire management. At such a preliminary research phase, we chose to focus our work on describing a revelatory case and developing initial insights about that impact, based on a combination of observation, data analysis, and simulation modeling and analysis.

In this section, we start by providing an overview of the study site, the sources of information, and the analysis methods that we have used. We then describe our conceptual model of the operation of a suppression system and its implementation as a discrete-event simulation model.

2.1. Study site

In 2010, according to data provided by Autoridade Florestal Nacional (National Forest Authority) (AFN 2011*a*), the Portuguese suppression system handled 32 357 incidents, of which 12.3% were FAs and 13.0% were rekindles. At the district level, the proportion of rekindles and FAs varied from 0% to 41% and from 5% to 26%, respectively. There are four key motives for the choice of the district of Porto in the critical period between July and September 2010 as a case study: the district is particularly interesting as it has a high number of fire occurrences and available data about deployed resources; the proportion of rekindles and FAs is slightly below but still in line with national figures; 84% of the ignitions, corresponding to 96% of the burnt area, occur in the 3-month period considered; and 2010 is a year with appropriate data on FAs (see subsection 2.4.3 below).

The district of Porto is located in northwestern Portugal and is home to 1.82 million people in an area of 2331 km^2 (Supplementary Table S1).[1] The population density is 781 people·km^{-2}, ranging from 1587·km^{-2} near the coastline to 366·km^{-2} in the interior and extremes in the 18 municipalities of 119 and 5786·km^{-2}, the maximum corresponding to the district capital, Porto (the second-largest city in Portugal after Lisbon, the capital). This kind of variation is typical in the European Mediterranean region (San-Miguel-Ayanz et al. 2013).

Forest accounts for 48% of the land use in the district, with a total area of 111 347 ha, divided between 60 081 ha of stands, 40 089 ha of shrubs, and 11 177 ha of burnt areas in recent years. Seventy-five percent of the forest area is located in the rural interior, distant from the sea (Supplementary Table S2). In 2010, the district had 3785 registered firefighting volunteers, with a density of about 30 ha of forest per volunteer, ranging from 14 in the seaside to almost 47 in the interior, where, in fact, they are also most needed.

The district has a historical trend of a very high number of forest fires, which remained through 2010, with a very high proportion of forest fires with a burnt area less than 1 ha (90.6% of the approximately 6000 incidents) (Supplementary Table S3).

This trend is consistent with the wildfire ignition risk map for Portugal (Catry et al. 2009), which relates the high number of fires in the district to human presence and activity, in particular, population density, human accessibility, land cover, and elevation. In fact, the district of Porto, besides the referred high population density with an extended wildland–urban interface (WUI) between the coastline and the interior, features a high road density, agriculture-related burning practices, and shepherding-related burning practices.

In the critical period of 2010, approximately 9% of the incidents in the district of Porto were FAs, and 10% were rekindles (Fig. 1).

Every year, the national authorities define the number of contracted firefighting crews (formed by two teams of men working 12 h daily each) for each district. In 2010, the number was 76 for the district of Porto. These contracted crews are supplemented with crews of volunteers and, when necessary, crews from neighboring districts (in an unspecified number). In 2010, each contracted crewmember received a wage of 41 euros per 24 h of work, paid by the central government. The fuel spent in the operations was paid at the end of the season. A helicopter was rented for this part of the year.

2.2. Data and analysis methods

Our work involved the development of a conceptual model, its implementation as a discrete-event simulation model, the parameterization of the model, a base-case simulation analysis, and simulation sensitivity analyses. The conceptual and discrete-event simulation models were developed through an iterative process of literature review, field trips, informal meetings, formal recorded interviews, and statistical analysis of a database of fire suppression interventions.

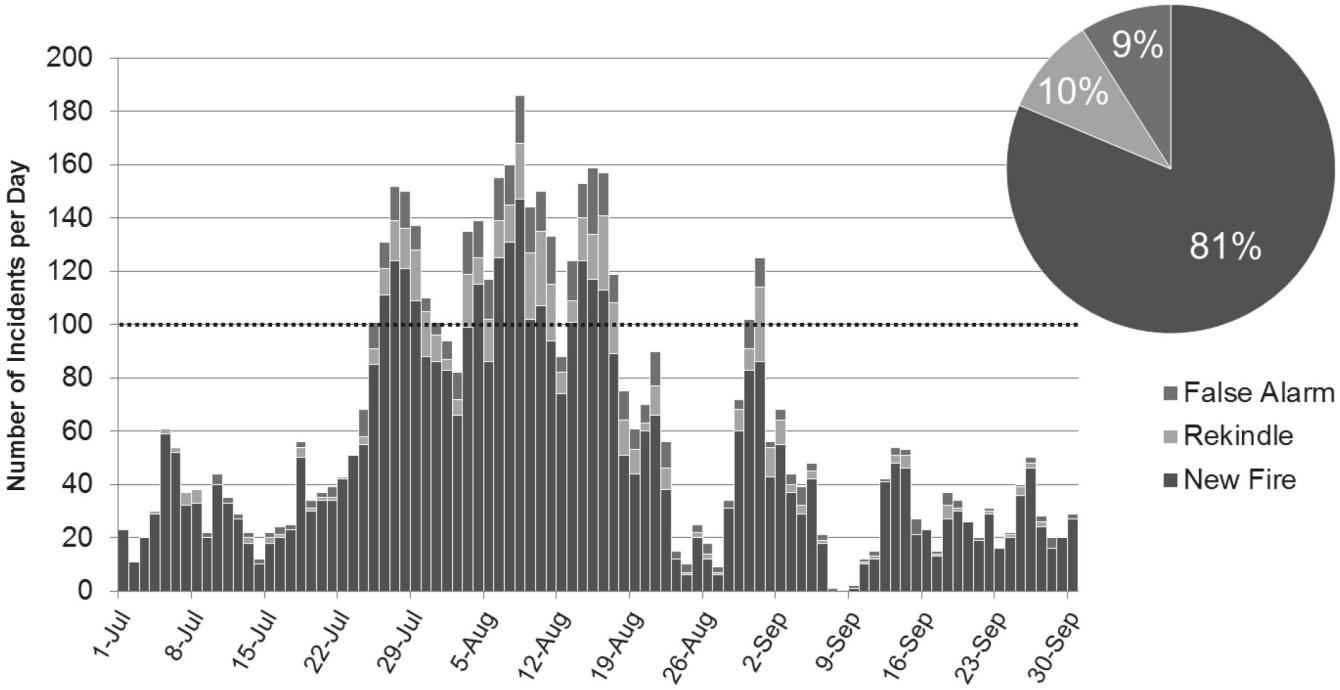
The meetings and interviews were held with public and private stakeholders. In the public sector, they were held with the district office of rescue operations (Centro Distrital de Operações de Socorro, CDOS) of two different districts (Lisbon and Porto), where the dispatch centers at the district level are located, with the forest fire first intervention special police force (Grupo de Intervenção de Proteção e Socorro, GIPS), and with the Portuguese forest authority (Autoridade Florestal Nacional, AFN). For the private sector, contacts were made with the Portuguese farmers' confederation (Confederação dos Agricultores de Portugal, CAP), with a private firefighting force (AFOCELCA), and with a Portuguese pulp company (grupo Portucel Soporcel). These meetings and interviews were useful for understanding the suppression system and the data recorded in the official databases and for comparing the operational standards with the field reality and to have a first-hand impression of the system operation under pressure.

For the case study of the district of Porto in the critical period, between July and September 2010, we combined and jointly analyzed two databases: one from AFN, with the dimension, duration, causes, and locations of forest fires (Tedim et al. 2013); and the other from the Porto CDOS, with the type and number of resources used in firefighting operations. The joint database was used to parameterize and validate the model. Multiple descriptive statistics analyses and statistical tests were used to derive the parameters of the simulation model, as described later in Results subsection 3.1.

Whenever our data did not comply with some of the parametric tests assumptions, we performed nonparametric tests such as the Kruskal–Wallis H test and the Mann–Whitney U test (Wilcoxon rank-sum test) (Fagerland and Sandvik 2009), with the homogeneity of variance assumption validated in both cases through a nonparametric Levene's test (Nordstokke and Zumbo 2010) at the 5% level of significance. These nonparametric tests and other

[1]Supplementary materials are available with the article through the journal Web site at http://nrcresearchpress.com/doi/suppl/10.1139/cjfr-2013-0257.

Fig. 1. Ignitions, rekindles, and false alarms in the district of Porto between July and September 2010.



analyses such as 2 × 2 contingency tables and pairwise comparisons of means were performed in IBM SPSS software.

Finally, the simulation model was implemented in Arena (Rockwell Automation, Inc., Wexford, Pennsylvania). In its parameterization, goodness-of-fit tests (Kolmogorov–Smirnov, Anderson-Darling, and chi-square) were used in EasyFit (MathWave Technologies, http://www.mathwave.com) to guide the choice among the classic probability distributions available in Arena, and base-case simulation analysis was used to validate the model.

The model was subsequently used with sensitivity analyses to understand the impact of ignitions, rekindles, and FAs on the performance of the suppression system, particularly on the "point of collapse". For this indicator, we chose an average waiting time of 10 min. The value emerged from our interviews as the limit beyond which the system starts to fail for lack of capacity to respond to all simultaneous occurrences.

The combination of sensitivity analysis with simulation analysis allowed us to directly address the two main research questions in this work.

- How do rekindles and FAs influence the average waiting time of an incident (ignition, rekindle, or FA) until suppression resources are available to be dispatched?
- How does the total number of incidents influence the point of collapse of the suppression system?

2.3. A conceptual model of the operation of a suppression system

Figure 2 displays the conceptual model that was created. The suppression operation starts with the communication of the incident to the dispatch center. The incident may or may not be an FA, but the operator has no way of distinguishing, so an IA crew will always be dispatched to the site:

- In the case of an ignition or a rekindle, the fire may be suppressed with the IA or escape and require an extended attack (EA) operation. In both cases, a rekindle may occur after a delay (represented in Fig. 2 as "//").
- In the case of an FA, the operation consists of the discovery and confirmation that there is no ignition. This operation, even with shorter duration than IAs in the case of a confirmed ignition, takes time, which needs to be considered.

Since 2006, Portugal has adopted a "muscled attack" dispatch policy. According to the operational standards, for an IA, a CDOS should dispatch a team with two engine crews (two vehicles with a water tank and three to five firefighters each), a third large vehicle with extra water supply (which has a driver and an assistant), and a helicopter, if available. If the fire is not contained after 90 min, an EA should start, with the dispatch of more resources.

2.4. A discrete-event simulation model

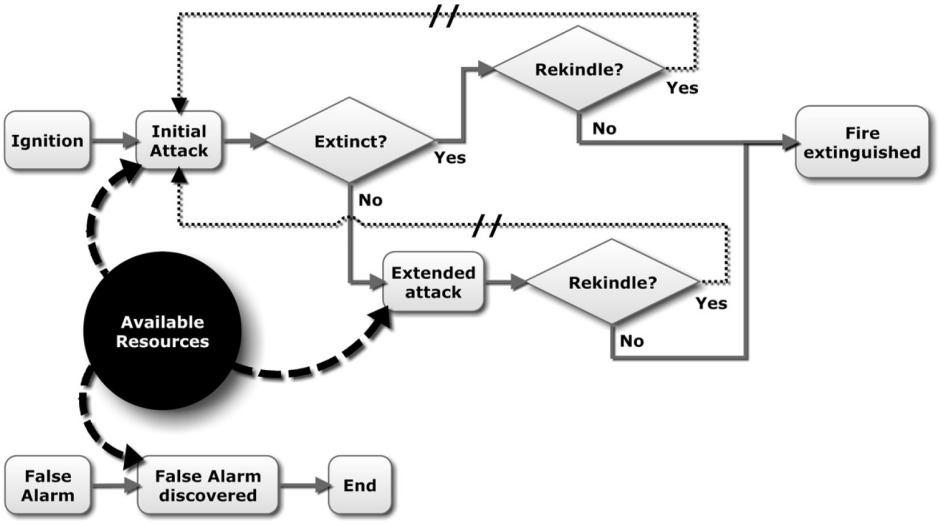
The discrete-event simulation model has five main components: (1) incident occurrence and communication ("arrival", using queuing theory terminology), generating ignitions, rekindles, and FAs; (2) ignition and rekindle attack, simulating IA, fire escape, EA, and resource allocation; (3) FAs, simulating the verification operation, and the corresponding resource allocation; (4) statistics collection; and (5) simulation control logic. Definitions of the Arena modules used are provided in Supplementary Table S4, and the implementation of the simulation model is presented in Supplementary Figs. S1 to S5.

2.4.1. Incident arrival

The correlation between the number of forest fires (and burnt area) and the weather (concerning the ignition and propagation conditions) is well established (Finney 2005; Wotton 2009). Different levels of daily severity rating (DSR) thus present different operational challenges for the suppression system. Accordingly, in the construction of the model, we differentiate days in two classes of daily incident frequency (DIF).

We modeled the arrivals of ignitions, rekindles, and FAs as nonstationary Poisson processes (Bookbinder and Martell 1979). As the numbers of incidents can change significantly during the day, we implemented a nonstationary process for the arrivals in our model, considering rates of arrival that change hourly

Fig. 2. Conceptual model of the operation of a forest fire suppression system.



throughout the day. In Arena, this was accomplished by using the piecewise-constant method that divides the time frame of the simulation into subintervals of 1 h over which a flat arrival rate is assumed. Specifically, the incidents (entities) are created in a "create" module with the time between arrivals controlled by a "schedule" module containing the means for each of the 24 hourly intervals. These 24 parameters are configurable in the model and can easily be changed later after obtaining the expected number of arrivals per hour through data analysis of the incidents of interest.

In this component (Supplementary Fig. S1), the numbers of occurrences in each day are differentiated in classes of DIF, "class A" and "class B". We used two "create" modules, one for each of the two classes of DIF considered. A "decide" module filters the arrivals according to the DIF class of the current day in the simulation. This process is similar, and replicated, for ignitions, rekindles, and FAs.

2.4.2. Ignition and rekindle attack

This component (Supplementary Fig. S2) includes the definition of the fire duration, the assignment of resources for IA, the transition to EA, and the assignment of resources for EA. The logic is similar for ignitions and rekindles. Because the available resources (ground crews and helicopters) have an associated cost, at the end of the simulation, Arena is able to compute suppression costs.

Setting the duration of a fire incident, according to a probability distribution, is the first step in this module. The following step is a "process" module, which will seize (reserve) the parameterized ground crews and, if available, an aircraft. For all of the modules of our model, the queue discipline is "first in first out" (FIFO), and the resources have the same allocation priority. The resources are seized for the minimum time between the fire duration and the maximum duration for an IA, i.e., the resources sent to the fire are the resources required for an IA.

A "decide" module will consider the fire extinguished if the duration is less than the maximum duration for an IA, and the resources will subsequently be released. Otherwise, the EA phase starts and additional resources are required. If the required resources are available, the fire goes into EA immediately, seizing all of the resources (the ones initially seized for the IA, as well as the additional ones later seized for the EA) for its remaining duration.

In very extreme situations, the required additional resources may not be available, and to avoid leading the simulation into a deadlock, the resources that were allocated to the fire's IA are released, and the fire waits for enough resources to become available, growing freely.

2.4.3. False alarms

When the resources of the forest fire suppression system are deployed to an incident that is found not to be a forest fire but still a fire (e.g., a garbage can burning) or not to be a fire at all, the incident is classified as a "false alarm" in the database; indeed, with the exception of 2010, it is not possible to distinguish between FAs and no forest fires. For the sake of detail, in the false alarm component, we separately modeled non-forest fires (also called "false" false alarms, FFA) and FA (truly nonexistent fires). With FA (Supplementary Fig. S3, top), similarly to an IA, the parameterized ground crews and, if available, an aircraft will be dispatched. The resources are seized for the duration of the operation of checking that there is no fire, according to its probability distribution.

With FFA (Supplementary Fig. S3, bottom), the parameterized ground crews will be seized for a time interval following the respective probability distribution. With considerably less information about these incidents, we decided to implement only one class of DIF.

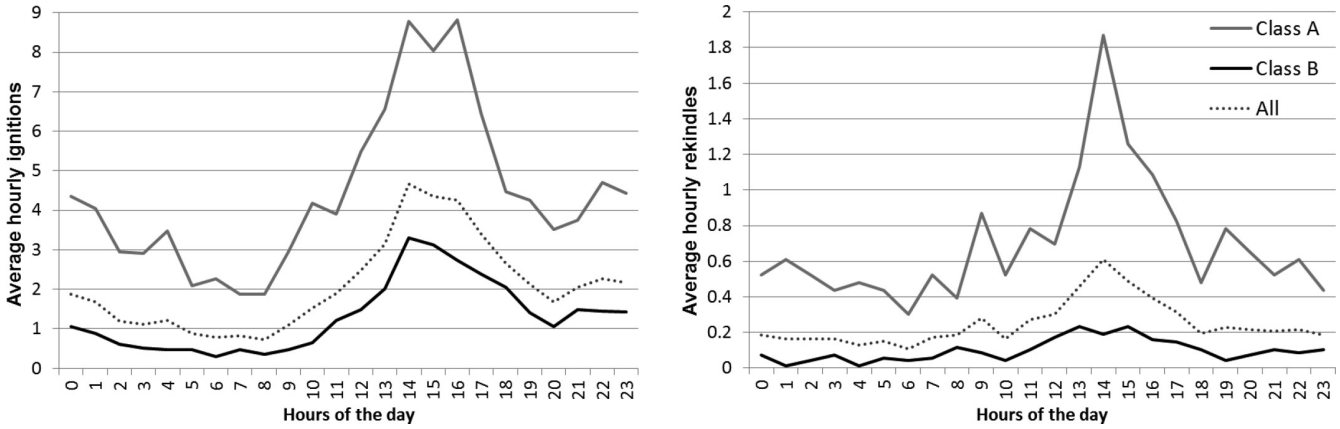
2.4.4. Statistics collection and simulation control logic

At a final processing stage, a statistics collection component (Supplementary Fig. S4) computes the total numbers of incidents, and the duration of the fire (the sum of waiting and service times) is also available.

The multiple effects that influence the burnt area (e.g., weather conditions, fuel type and level of accumulation, wind speed and direction, or whether the fire spreads downhill or uphill) are not all reflected in its duration. However, if we were able to find statistically significant relationships (by analyzing historical data) between the fire duration in each of the DIF classes and the burnt area in stands and burnt area in forest (stands plus shrublands), the model is prepared to be parameterized with such (four) relationships and compute the burnt area for each fire. With the burnt area for each fire, the model can also calculate the associated value losses by multiplying the burnt areas by parameterized constants with the monetary lost value for each burnt hectare.

Finally, CO_2 emissions are computed using the official guidelines of AFN (AFN 2011*b*), which follow Narayan et al. (2007), distinguishing between stand and shrubland burnt areas, each with a specific emission factor. As the model computes, for each fire, forest burnt area and stand burnt area, the shrubland area is

Fig. 3. Average hourly ignitions (left) and rekindles (right) in Porto between July and September 2010.



computed by subtracting burnt stand area from burnt forest area. However, because this part of the model is not needed for the analysis presented in this paper, we will not describe its parameterization in subsection 3.1.

The simulation control logic component (Supplementary Fig. S5) controls the change of day, the DIF class, and the end of the process of creation of new incidents. "Days" are created at a constant daily rate and assigned to an appropriate DIF class. After the last day of the simulation, the ignitions are stopped. Nevertheless, all of the fires that are ongoing in the last day of the simulation are allowed to end.

All modules of the model were implemented with parameters that are defined externally, enabling much simpler debugging, reconfiguration, or extended analysis processes. For a comprehensive list of all configurable variables and expressions, see Supplementary Table S5.

3. Results

In this section, we present two sets of results: (*i*) in subsection 3.1, the results from the statistical analysis of the combined AFN and Porto CDOS databases, used to parameterize the simulation; and (*ii*) in subsection 3.2, the results of the combined simulation and sensitivity analyses.

3.1. Model parameterization

Throughout this subsection, we illustrate the parameterization of our simulation model using analysis of historical data for the study site.

3.1.1. DIF classes

Through observation of the histogram of the daily number of incidents, there seems to be a division at around 100 incidents. Our interviews with the district dispatch center confirmed this threshold — for a lower number of incidents, the response capability is easily sufficient. Accordingly, we decided to consider a DIF class A as above 100 incidents/day and a DIF class B as below that threshold (horizontal line in Fig. 1).

We further tested the differences between these classes, as well as the rest of the year, concerning fire duration. The Kruskal–Wallis H test revealed that fire durations (in minutes) are significantly affected by the DIF class of the day, with $H(2) = 248.34$, $p < 0.001$, and mean ranks of 3421.25 (median = 121.00), 2848.72 (median = 100.00), and 2518.20 (median = 89.00) for classes A, B, and the rest of the year, respectively. Pairwise comparisons using Mann–Whitney tests, with adjusted p values, revealed significant differences between the fire durations for all classes ($p < 0.001$).

In our analysis, we consider several stochastic elements such as the number of fires and the duration of each fire. However, the daily weather conditions that drive the simulation are deterministic (Podur and Martell 2007) and follow the 2010 historical sequence of daily class of DIF.

3.1.2. Ignitions, rekindles, and false alarms

The evolution of both the rates of ignitions and the rates of rekindles (Fig. 3) during the day follows an expected pattern (Bookbinder and Martell 1979), with a peak in mid-afternoon.

The evolutions of FA and FFA are presented in Supplementary Fig. S6. FFAs have behavior similar to that of ignitions and rekindles. With the exception of a peak at the beginning of the night, FAs also follow a pattern described in the literature (Tu 2002), with a valley during the night.

3.1.3. Duration of interventions

The histogram with the duration of interventions, jointly considering ignitions, rekindles, and FAs, is presented in Fig. 4, and individual histograms for each type of intervention are included in Supplementary Figs. S7 and S8. The shapes for new fires and rekindles are very similar, with fewer fires extinct in the first hour than in the second but decreasing in number after that, with a long tail; on the contrary, the bar height for FA is always descending. The durations of the interventions associated with each type were modeled with individual probability distributions for each of the DIF classes.

In all analyses — ignitions, rekindles, and FAs (DIF classes A and B) and FFAs — we used an empirical distribution when the distribution with highest fit in EasyFit, and significant at 0.01, was not available in Arena; in the other cases, the lognormal distribution was always the selected distribution.

3.1.4. Initial attack and extended attack

To differentiate between fires that were suppressed in the IA and those that escaped and required EA, we sought to identify the threshold in the duration of the fire at which this transition occurs.

As a maximum of two engine crews and one aircraft are allocated to the IA (according to operational standards), we obtained an initial lower bound for this threshold as the average duration of the fires with a number of allocated resources within that interval. Then we used a multiplicative factor to perform a sensitivity analysis with the simulation and obtain a threshold consistent with our field data.

As suggested by Fig. 5, rekindles present higher adversity — in all conditions, IA and EA have higher average durations than for fires directly resulting from ignitions. Furthermore, these values are evidence that the operational rule that places this threshold at 90 min is not being strictly followed, a fact that in some of our interviews was attributed to insufficiencies in resource capacity during the critical period. To check if these differences are signif-

Fig. 4. Histogram of the duration of interventions (all incidents) in Porto between July and September 2010.

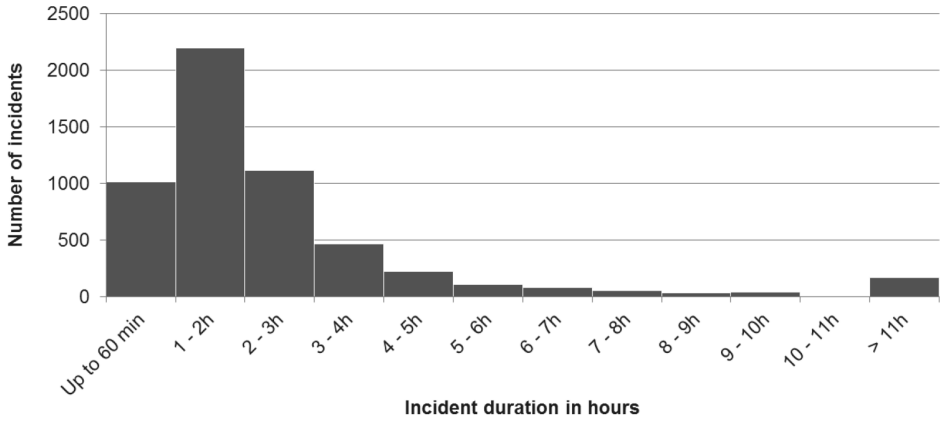
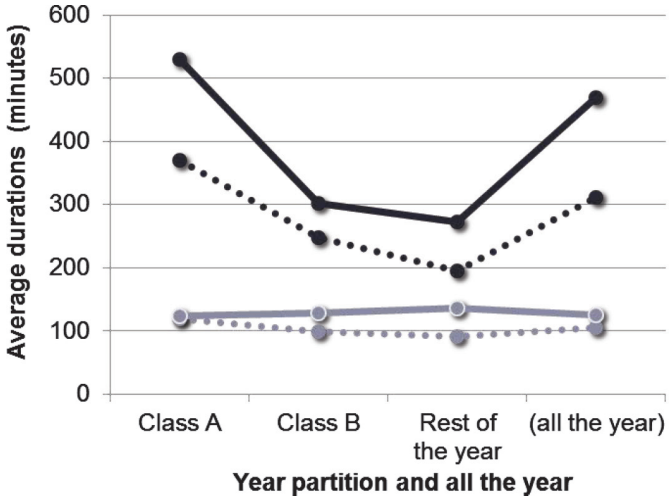


Fig. 5. Average durations of initial and extended attacks for new fires and rekindles in Porto for 2010.



	Class A	Class B	Rest of the year	(all the year)
New Fire Initial Attack	118	99	91	105
New Fire Extended Attack	370	248	195	311
Rekindle Initial Attack	123	128	136	125
Rekindle Extended Attack	529	302	271	470

icant, we tested the differences between fire durations belonging to different classes of incidents and DIFs with a series of Mann–Whitney *U* tests.

In days of class A, the duration of new fires (median = 99.00 min) does not differ significantly from that of rekindles (median = 102.00 min) if the fire is contained during the IA, with U = 201 026.50, z = –1.49, and $p > 0.05$. However, if they escape, the duration of new fires (median = 212.00 min) is significantly less than that of rekindles (median = 334.00 min), with U = 29 950.50, z = –4.44, and $p < 0.001$.

In days of class B, the opposite happens, with the duration of new fires (median = 86.50 min) being significantly less than that of rekindles (median = 109.00 min) if the fire is contained during the IA, with U = 87 675.00, z = –3.65, and $p < 0.001$. For fires that escape, the duration of new fires (median = 171.50 min) does not differ significantly from that of rekindles (median = 203.00 min), with U = 6111.50, z = –1.40, and $p > 0.05$.

Nevertheless, it should be noted that the differences for both new fires in days of class A and rekindles in days of class B become statistically significant at 0.10.

Furthermore, we tested this difference for the rest of the year, which has fewer ignitions per day than the critical period. We found that the duration of new fires (median = 82.00 min) does not differ significantly from that of rekindles (median = 97.50 min) for fires contained during the IA, with U = 6077.00, z = –0.95, and $p > 0.05$; and if they escape, the duration of new fires (median = 178.00 min) also does not differ significantly from that of rekindles (median = 219.00 min), with U = 26.50, z = –1.04, and $p > 0.05$.

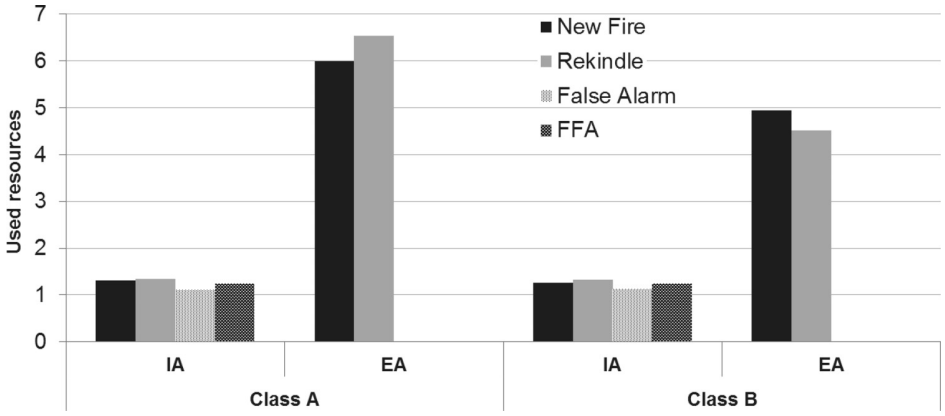
These results seem to point to the duration of rekindles in days with higher number of incidents being greater than the duration of new fires. In fact, overall, the duration of new fires (median = 120.00 min) is significantly lower than that of rekindles (median = 125.00 min) in days of class A (U = 488 391.50, z = 2.20, $p < 0.05$), as well as in days of class B (new fires, median = 99.00 min; rekindles, median = 120.05 min; U = 198 865.00, z = 3.38, $p < 0.001$) and in the rest of the year (new fires, median = 89.00 min; rekindles, median = 111.00 min; U = 13 185.50, z = 1.76, $p < 0.05$).

Finally, we checked if the proportion of escaped fires is different between new fires and rekindles in the three cases (class A, class B, and rest of the year). For each case, a 2 × 2 contingency table analysis was conducted to evaluate whether "fire escaping (no, yes)" was associated with "rekindle (no, yes)". The analysis yielded Pearson χ^2 values of (1, N = 2777) = 0.58, (1, N = 2280) = 0.001, and (1, N = 1047) = 1.57, respectively, which are less than the critical value of 3.84 at the 5% level of significance in all cases. Thus, despite the differences observed in our sample, the proportions of escaped fires are not significantly different ($p > 0.05$).

3.1.5. Allocated resources and costs

Using the same logic of analysis, we were able to estimate the resources allocated to IA and EA, again considering the two DIF classes (Fig. 6). In this case, the data also provided evidence that

Fig. 6. Average number of crews dispatched to initial and extended attacks in Porto between July and September 2010.



the operational standards IA dispatch rule is not being strictly applied in practice.

The data do not discriminate between contracted and volunteer crews or between district and out-of-district crews; they simply include the number of engines present in each incident. Thus, we parameterized the model only with the average number of engine crews, without loss of generality, because there should be one vehicle with extra water supply for each two engine crews according to operational standards. Regarding costs, in the model, we assign to each engine crew a fixed contract cost of €10 per hour (rounded up from €8.54) and do not consider other costs (e.g., firefighter training, food, fuel spent, engine maintenance, and others). The rented helicopter is assigned a variable cost of €788 per hour of usage.

Throughout the process of model construction and parameterization, we made sure that the results of the model were consistent with the real data, paying particular attention to the evolution of the number of ignitions and crews involved in suppression operations, as well as the number of aircraft missions.

3.2. Sensitivity analysis

After parameterizing the model using data from the study site, the district of Porto, we present in this subsection the actual simulation results.

3.2.1. Benchmark levels for rekindles and false alarms

We ran the simulation for different levels of daily occurrences and also compared benchmark conditions with the base scenario (the current conditions), varying the number of available crews. With eight scenarios (40%, 60%, 80%, 120%, 140%, and 160% of the current level of daily occurrences, as well as the benchmark and base scenarios), each analyzed with 30 different levels for the number of suppression crews available, we ran 240 fires–crews scenarios, with 2000 replications each. In the literature, we found studies using 500 replications (e.g., Podur and Martell (2007) or Podur and Wotton (2010)); however, after a sensitivity analysis, we concluded that with our simulation, we should use at least 1000 replications, and in fact, we chose to use twice that number.

We started by assessing the average waiting time for different levels of crew capacity, under the base scenario and under a benchmark scenario in which the number of rekindles is reduced from 10% to 1%, the target in the "Technical Proposal for a National Plan of Defense of the Forest against Fires" (ISA 2005), and the number of false alarms is reduced from 9% to 4.5%, in line with international levels (Corcoran et al. 2007; Karter 2011; Killalea 1998; Tu 2002; Yang et al. 2003). The results of this analysis are presented in Fig. 7.

3.2.2. Point of collapse and the number of incidents

Between 2001 and 2009, the average number of daily incidents in the critical period ranged from 39.2% to 162.6% of the value of 2010. We analyzed seven points in this range — 40%, 60%, 80%, 100%, 120%, 140%, and 160% — using the same experimental design as in subsection 3.2.1. For each level, Fig. 8 illustrates the point of collapse, which was determined as the minimum level of crews that keeps the average waiting time below 10 min. The points of collapse were determined using exponential regressions adjusted to the relationships between mean waiting time and crew capacity, considering all positive values for the mean waiting times.

4. Discussion

Our data analysis of forest fire incidents in the district of Porto, between July and September 2010, highlights the importance of addressing the phenomena of rekindles and false alarms. Jointly, rekindles and false alarms represent almost 20% of the incidents, with daily peaks that are exactly coincident with the peaks of requests of suppression resources for real new forest fires. Although, on average, FAs use resources for a time interval less than that of an IA, there is a very high opportunity cost to that time. In the case of rekindles, this is worsened by the fact that rekindle suppression operations are much harder, as made clear from the fact that both IA and EA durations are higher for rekindles.

The extra pressure that these additional classes of incidents put on the suppression system raises difficult challenges to its management. We believe that the deviations from operational standards that we found in our data analysis (e.g., that the IA often extends beyond 90 min and that the average number of engine crews dispatched to IAs is approximately 1, instead of the recommended 2) are evidence of this pressure. In a fire-prone country with an extensive WUI, where the average number of fires in the last decade corresponds to over 50% of the whole EU Mediterranean region (San-Miguel-Ayanz et al. 2013), increasing suppression effectiveness is particularly important to avoid small fires becoming mega-fires in days of critical fire danger (Tedim et al. 2013).

Using our simulation analysis to study the impact of rekindles and false alarms on the performance of the suppression system, we found that bringing them down to benchmark levels, with a joint reduction of approximately 13.5% in the number of incidents (9.0% from rekindles and 4.5% from false alarms), would lead to a reduction in the number of crews required to keep the average waiting time under 10 min from 112 to 101; in short, bringing them down to benchmark levels would lead to a reduction in the point of collapse of approximately 9.8%. This reduction in the number of engine crews translates to a reduction of €236 500 in suppression costs per year (€283 800 when adding the proportional number of water supply vehicles).

Fig. 7. Average waiting times as a function of crew capacity for base and benchmark scenarios.

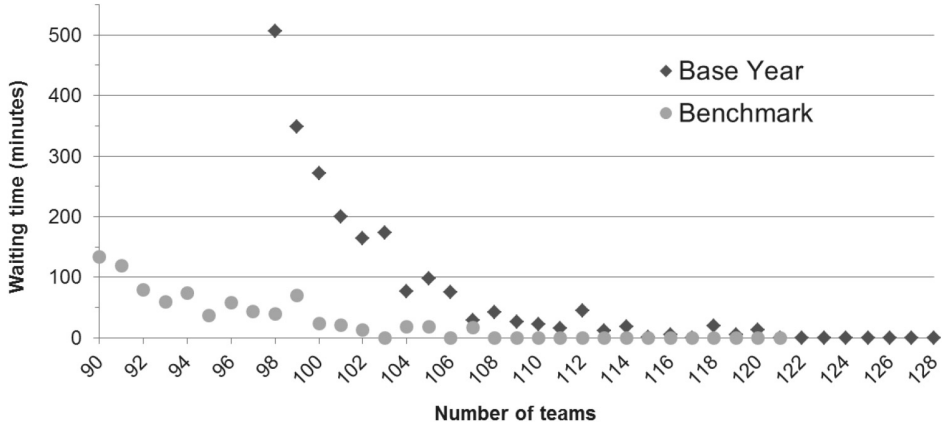
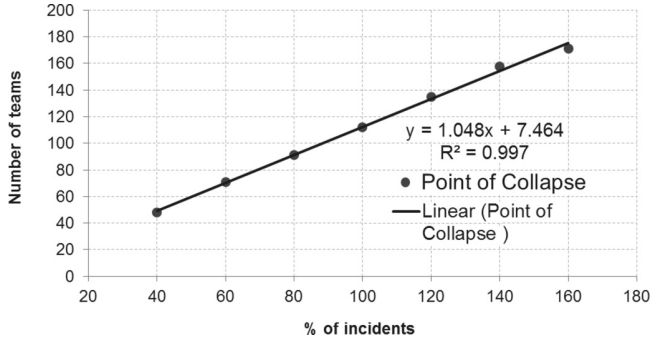


Fig. 8. Point of collapse as a function of the average number of daily incidents (with 2010 value as base).



This means that managing false alarms, for instance, will lead to a lower number of incidents in the system, which reduces pressure and releases resources that become available for real fires and to invest more time in mop-up operations, thus reducing the number of rekindles, contributing again to reduce the number of incidents, and so on, in a positive feedback loop (Pacheco 2011).

Effective management of false alarms requires proper recording of these incidents to understand the phenomenon and take appropriate measures (Corcoran et al. 2011; Flynn 2009; Pacheco 2011). Studies evidence that the motivations behind malicious false alarms may differ from place to place (Corcoran et al. 2007, 2011). Identifying the calling number (Killalea 1998), clustering high-risk zones by phone prefix (Yang et al. 2003), returning a call when it sounds suspicious (e.g., school sound behind), and asking to talk with an adult if a child's voice is heard are some of the actions that can be taken. The last two measures were implemented by Porto CDOS and were pointed out in our interviews as part of the reason why the district has fewer false alarms. As for the good-intent false alarms, the public can be informed about what should be reported, and overall, publicizing the real costs of false alarms is also an option that may be considered (Killalea 1998).

To reduce rekindles, some authors suggest improvements in post-fire management by enhancing suppression effectiveness (e.g., properly training firefighters in mop-up operations) and active surveillance, as firefighters often leave a fire prematurely to respond to new IA demands (Pacheco et al. 2012). Increasing crew capacity and adjusting dispatch rules are also options that could be considered. For instance, if an active crew is dispatched to a new fire (to minimize waiting time), another crew (the first available) should later return to the fire site just vacated to ensure sufficient mop-up and prevent rekindles. Overall, contracted crews could always be out of the headquarters, either fighting a fire or engaged in active surveillance and prevention.

Another very important challenge for the suppression system is the huge interannual variability in the number of ignitions. We sought to characterize the impact of overall ignitions on the point of collapse, and for the range of values observed between 2001 and 2010, we found a linear relationship between the number of ignitions and the point of collapse, with a decrease of 1.00% in the daily rates of ignitions leading to between 0.85% and 0.96% reduction in the number of required suppression teams in the range that we studied. Because 98% of ignitions are of human origin (arson, negligence, or accidental), this indicator provides a relevant threshold for the investment in prevention: a reduction of 1% in ignitions allows for a reduction of the point of collapse of one firefighting team, inverting the vicious circle of more fire, more teams.

Our results support the relevance of the point of collapse as a useful indicator in capacity decisions for a suppression system. Arriving early increases the probability of containing the fire in its initial stage, and additionally, if the resources are insufficient, the pressure to attack starting fires increases the premature abandonment of mop-up operations of already controlled fires, leading later to more rekindles and thus even more fires (Collins 2012; Pacheco et al. 2012).

There are several limitations in our model that do not challenge the essence of our analysis but limit its applicability to study other important aspects of the operation and the management of a suppression system.

- The sequence of daily classes of DIF is not stochastic.
- We did not analyze and model weekly patterns for occurrences, but they were mentioned in our fieldwork and identified in the literature. As an example, in New Zealand, false alarms grow approximately 50% on weekends (Tu 2002).
- The queue disciplines are always FIFO and do not differentiate in terms of priority, for instance, between IA and EA.
- The fire durations depend on the daily class of DIF and depend on the resources allocated only indirectly (the scarcity of resources increases the waiting time, thus the fire duration).
- Very large forest fires do not have a differentiated treatment.
- The loss of productivity that results from the overload in consecutive high DIF days, or from relocating crews to less familiar sites, has not been modeled (Podur and Martell 2007; Wallace 1978).
- The study was confined to a single district and a single year.

We believe that these limitations do not have a qualitative impact on the results of the analysis that we conducted in this paper.

However, overcoming the first two can add more precision to the model; addressing the third can be useful to analyzing alternative dispatch policies; and the last three may become more significant if the model evolves to a simulation of the suppression system over a larger region (a set of districts). Regarding the fourth, having a direct dependence also on the number of deployed suppression crews will perhaps increase the accuracy of the computation of the burnt area.

Our model is prepared to compute value losses and CO_2 emissions, relating the impact of a fire with the variables present in the model, namely the burnt area, which in turn may be computed from the duration of the fire through regression analysis of historical data (see subsection 2.4.4). Value losses and CO_2 emissions depend directly on burnt area, and burnt area depends directly on the probability distribution of the duration of the interventions (related with ignitions and rekindles) and indirectly on the number of crews. Thus, the consistence of such results depends on the reliability of the regression, which will increase with more independent variables. If parameterized with that information, the model is currently prepared to evaluate the impact in terms of value losses and CO_2 emissions of different levels of crew capacity, false alarms, and rekindles.

Moreover, because we have suppression cost data available to compute value losses, we can use OptQuest, the simulation optimization module of Arena, to determine the number of crews that minimizes the sum of suppression costs and value losses (the system total cost), or we can plot the evolution of costs and losses with the number of engine crews available.

5. Conclusion

In this paper, we describe a discrete-event simulation model of a forest fire suppression system, which we use to analyze the joint impact of ignitions, rekindles, and false alarms on system performance. The model has been created and applied with a screening logic, i.e., it has lower fidelity than previously proposed models, but it considers additional factors not captured in prior work such as rekindles and false alarms, and it enables a wider exploration of the suppression system's design space.

The results of an analysis based on the case of the district of Porto in Portugal for the critical period between July and September 2010 show how a joint reduction of rekindles and false alarms to benchmark levels leads to a significant improvement of the system's point of collapse and provide useful information on the trade-off between prevention and suppression efforts.

The model can be applied to other regions, and because the model considers dispatch decisions and the performance of the IA response system (which represents approximately 90% of suppression activity), it can be used by managers to improve the effectiveness of the suppression system and, at the same time, reduce its costs.

With the perspective of more severe fire seasons in the future and because we cannot change the weather, one of the remaining options is to reduce the human impact (Flannigan et al. 2013). Our results point to the importance of managing false alarms and diminishing rekindles, which can be achieved through changes to current policies, namely through education programs, law enforcement, and the use of more effective suppression techniques.

Ongoing work, largely stimulated by this analysis, aims at exploring the relationship between IA efforts and fire escape probabilities and at optimizing the timing, sizing, and location of different types of prevention and suppression resources and activities from intra- and inter-annual perspectives.

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Simulation analysis of the impact of ignitions, rekindles and false alarms on forest fire suppression

Supplementary Material

Table S.1. Demographic, suppression system (number of volunteer firefighters), and forest fire (number and burnt area) data of the study site (district of Porto) in the year 2010. Prepared by the authors using PORDATA (http://www.pordata.pt/). "Littoral" aggregates data of the municipalities near the coastline and "Interior" the others.

	Population [1]	**Area** [2]	**Population density** [3]	**Firefighters** [4]	**Forest fires** [5]	**Forest burnt area** [5]		
						Total	Stands	Shrubs
	(n)	*(Km²)*	*(n/Km²)*	*(n)*	*(n)*	*(ha)*	*(ha)*	*(ha)*
Littoral*	1,257,034	792	1,587	1,990	1,767	1,272	817	455
Interior†	562,862	1,539	366	1,795	4,240	7,279	2,602	4,678
Porto	1,819,896	2,331	781	3,785	6,007	8,551	3,419	5,133

* Gondomar, Maia, Matosinhos, Porto, Póvoa de Varzim, Valongo, Vila do Conde, Vila Nova de Gaia.
† Paços de Ferreira, Lousada, Trofa, Felgueiras, Baião, Santo Tirso, Paredes, Marco de Canaveses, Penafiel, Amarante.

Data Sources:

1) "*INE - Estimativas Anuais da População Residente*"; Last Update: 2013-06-18 11:46:17.
2) "*IGP - Série Cartográfica Nacional à escala 1:50 000*" and "*Carta Administrativa Oficial de Portugal – CAOP 2009.0*"; Last Update: 2012-12-20 16:49:03.
3) "*IGP - Série Cartográfica Nacional à escala 1:50 000*" and "*Carta Administrativa Oficial de Portugal – CAOP 2009.0*"; "*INE - Estimativas Anuais da População Residente*"; Last Update: 2013-06-18 12:25:30.
4) "*INE - Inquérito ao Ambiente - Acções dos Corpos de Bombeiros*"; Last Update: 2013-07-26 18:33:29.
5) AFN/MAMAOT; Last Update: 2012-04-16 15:16:33.

Table S.2. Study site (district of Porto) land cover data. Prepared by the authors using FloreStat (http://www.icnf.pt/portal/florestas/ifn/ifn5/florestat), an application to query the results of the 5th National Forestry Inventory (http://www.icnf.pt/portal/florestas/ifn/ifn5); the data was taken between 2005 and 2006 and the final report (AFN/DNGF 2010) published in 2010.

	Portugal mainland		**Porto District**		**Littoral***		**Interior†**	
Land use	*(ha)*	*(%)*	*(ha)*	*(%)*	*(ha)*	*(%)*	*(ha)*	*(%)*
Aagriculture	2,929,544	33%	68,564	29%	22,720	29%	45,844	30%
Shrubs	1,926,630	22%	40,089	17%	7,247	9%	32,842	21%
Forest	3,458,557	39%	71,892	31%	20,782	26%	51,110	33%
Inland waters	161,653	2%	2,804	1%	1,354	2%	1,450	1%
Other uses	432,050	5%	49,757	21%	27,200	34%	22,557	15%
Total	8,908,434		233,106		79,303		153,803	
Forest categories								
Burnt areas	100,472	3%	11,177	16%	1,875	9%	9,302	18%
Cut areas	34,328	1%	574	1%	249	1%	325	1%
Other wooded land	148,409	4%	56	0%	-	0%	56	0%
Stands	3,175,348	92%	60,081	84%	18,657	90%	41,424	81%
Total	3,458,557		71,888		20,781		51,107	
Dominant tree species								
Acacia sp.	4,098	0%	200	0%	25	0%	175	0%
Castanea sativa	30,029	1%	-	0%	-	0%	-	0%
Eucalyptus sp.	739,515	23%	30,820	51%	12,175	65%	18,645	45%
Pinus pinaster	885,019	28%	21,463	36%	5,493	29%	15,970	39%
Pinus pinea	130,386	4%	150	0%	-	0%	150	0%
Quercus rotundifolia	412,878	13%	-	0%	-	0%	-	0%
Quercus suber	715,922	23%	25	0%	-	0%	25	0%
Other Quercus sp.	150,020	5%	2,093	3%	25	0%	2,068	5%
other broadleaves	82,383	3%	5,306	9%	938	5%	4,368	11%
other coniferous	25,099	1%	25	0%	-	0%	25	0%
Total	3,175,349		60,082		18,656		41,426	

* Gondomar, Maia, Matosinhos, Porto, Póvoa de Varzim, Valongo, Vila do Conde, Vila Nova de Gaia.
† Paços de Ferreira, Lousada, Trofa, Felgueiras, Baião, Santo Tirso, Paredes, Marco de Canaveses, Penafiel, Amarante.

Table S.3. Number of forest fires and burnt forest area in the district of Porto, between 2001 and 2010

	Frequency of forest fires				Burnt forest area (*ha*)		
Year	**Total** (*n*)	**≤ 1*ha*** (%)	**>1*ha* and ≤100*ha*** (%)	**> 100*ha*** (*n*)	**Total area** (*ha*)	**Average area** (*ha*)	**Largest fire** (*ha*)
2001	5,823	85.2%	14.8%	4	5,342	0.92	282
2002	5,976	84.7%	15.2%	4	5,032	0.84	260
2003	7,715	88.4%	11.5%	10	7,947	1.03	792
2004	4,598	86.9%	12.9%	9	6,574	1.43	780
2005	7,628	82.9%	16.6%	39	25,510	3.34	1,859
2006	4,590	89.0%	10.8%	8	7,007	1.53	1,132
2007	3,489	90.4%	9.6%	1	1,419	0.41	280
2008	2,353	93.7%	6.3%	0	573	0.24	35
2009	6,819	87.0%	12.8%	11	9,161	1.34	879
2010	6,007	90.6%	9.1%	15	8,551	1.42	639
Minimum	2,353	83%	6%	0	573	0.24	35
Mean	5,500	88%	12%	10.1	7,712	1.25	694
Maximum	7,715	94%	17%	39	25,510	3.34	1,859

Table S.4. Rockwell Arena® simulation flowchart module description (Kelton et al. 2010; Rossetti 2010)

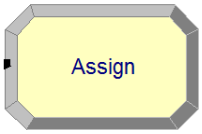
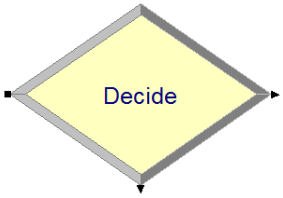
Name	Symbol	Module Description
Create		Entry for entities in the model, specifying their type and scheduling their entry based on a schedule or a time between arrivals.
Assign		Assignment of values to variables, including system variables, and entity attributes, types, and pictures.
Decide		Decisions based on logical conditions or probabilities.
Process		Processing method, with functions to seize and release resources, and the ability to define logic processes. Process time and costs are allocated to entities.
Release		Releasing of resource units previously seized by an entity.
Record		Statistics collection, including time between exits, and entity processing times or costs, among others.
Dispose		Exit for entities in the model, with option to record entity statistics.

Table S.5. Comprehensive list of all the configurable variables and expressions of the discrete-event simulation (DES) model.

Group	Incident type	DIF class	Parameters quantity	Notes
Arrivals	New Fire	Class A	24 parameters	(hourly)
		Class B	24 parameters	(hourly)
	Rekindle	Class A	24 parameters	(hourly)
		Class B	24 parameters	(hourly)
	False Alert	Class A	24 parameters	(hourly)
		Class B	24 parameters	(hourly)
	FFA	One class	24 parameters	(hourly)
Durations	New Fire	Class A	1 parameter	Probability distribution
		Class B	1 parameter	Probability distribution
	Rekindle	Class A	1 parameter	Probability distribution
		Class B	1 parameter	Probability distribution
	False Alert	Class A	1 parameter	Probability distribution
		Class B	1 parameter	Probability distribution
	FFA	One class	1 parameter	Probability distribution
Initial Attack (End)	New Fire	Class A	2 parameters	end, tuning
		Class B	2 parameters	end, tuning
	Rekindle	Class A	2 parameters	end, tuning
		Class B	2 parameters	end, tuning
Resources	New Fire	Class A	2 parameters	(IA / EA)
		Class B	2 parameters	(IA / EA)
	Rekindle	Class A	2 parameters	(IA / EA)
		Class B	2 parameters	(IA / EA)
	False Alert	Class A	1 parameter	Initial Attack only
		Class B	1 parameter	Initial Attack only
	FFA	One class	1 parameter	Initial Attack only
Burned Area	Stands	Class A	1 parameter	formula
		Class B	1 parameter	formula
	Forest	Class A	1 parameter	formula
		Class B	1 parameter	formula

Other variables:

Group	Name	Parameters quantity	Notes
Resource costs	ground crews	2 parameters	number, value/h
	helicopters	2 parameters	number, value/h
Value Losses	*in* Products and Services (AFN)	1 parameter	value/ha
	in Timber Products	1 parameter	value/ha
	in Non-Timber Products	1 parameter	value/ha
	in Recreational Activities	1 parameter	value/ha
	in Indirect Use	1 parameter	value/ha

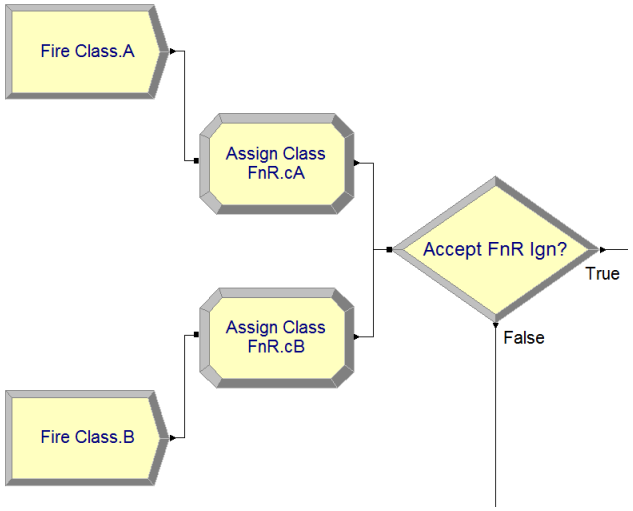


Figure S.1. Incident arrival component of the DES model in the case of a new fire (similar for rekindles and false alarms). The flowchart legend is in Table S.4. Shortenings: **FnR**, fire not rekindled, i.e. new fire; **cA/B** (DIF class); **Ign**, ignition.

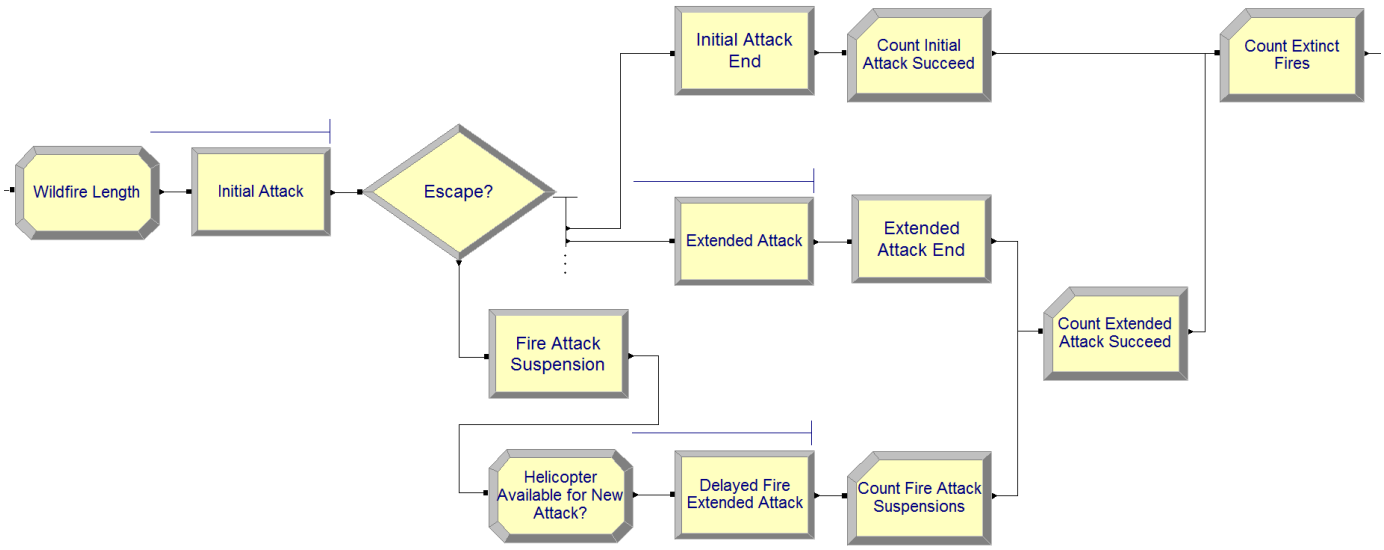


Figure S.2. Ignition and rekindle attack component of the DES model. The flowchart legend is in Table S.4.

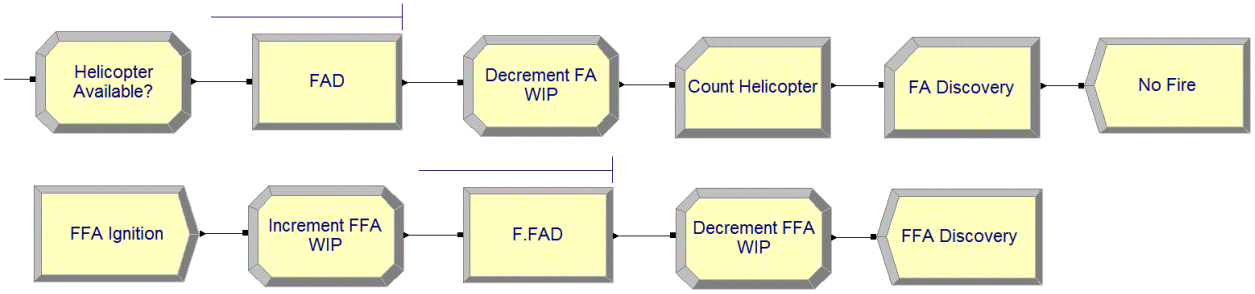


Figure S.3. False alarm component of the DES model with FA (nonexistent fire false alarm) on the top and FFA (non-forest fire false alarm, e.g., a garbage can burning) on the bottom. The flowchart legend is in Table S.4. Shortenings: **FAD/F.FAD**, FA/FFA discovering and confirmation; **WiP**, work in progress, i.e., the number of false alarms (FA or FFA) in process.

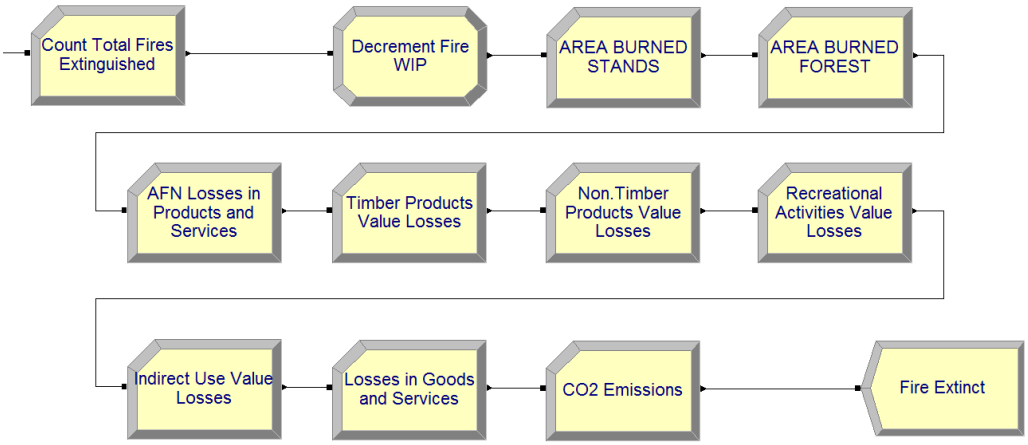


Figure S.4. Statistics collection component of the DES model. The flowchart legend is in Table S.4. **WiP**, is a shortening for work in progress, i.e., the number of fires (new fires and rekindles) in process. Value losses are computed in two alternative ways. Following the official guidelines of AFN (AFN 2011) "AFN Losses in Products and Services" multiply each burnt hectare of forest (stands plus shrublands) by € 1,435. Following the guidelines of the "Portuguese National Plan for Prevention and Protection of Forest against Fires" (ISA 2005): "Timber Products Value Losses" and "Non-Timber Products Value Losses" multiply each stand burnt hectare by € 917 and €1,045, respectively; "Recreational Activities Value Losses" and "Indirect Use Value

Losses" multiply each forest burnt hectare by € 47 and € 191, respectively; Finally "Losses in Goods and Services" sum the four values for each fire.

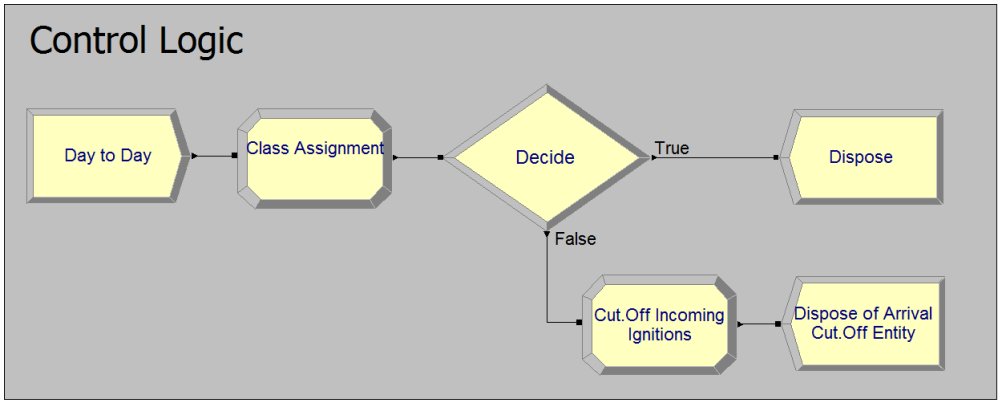


Figure S.5. Control logic component of the DES model. The flowchart legend is in Table S.4.

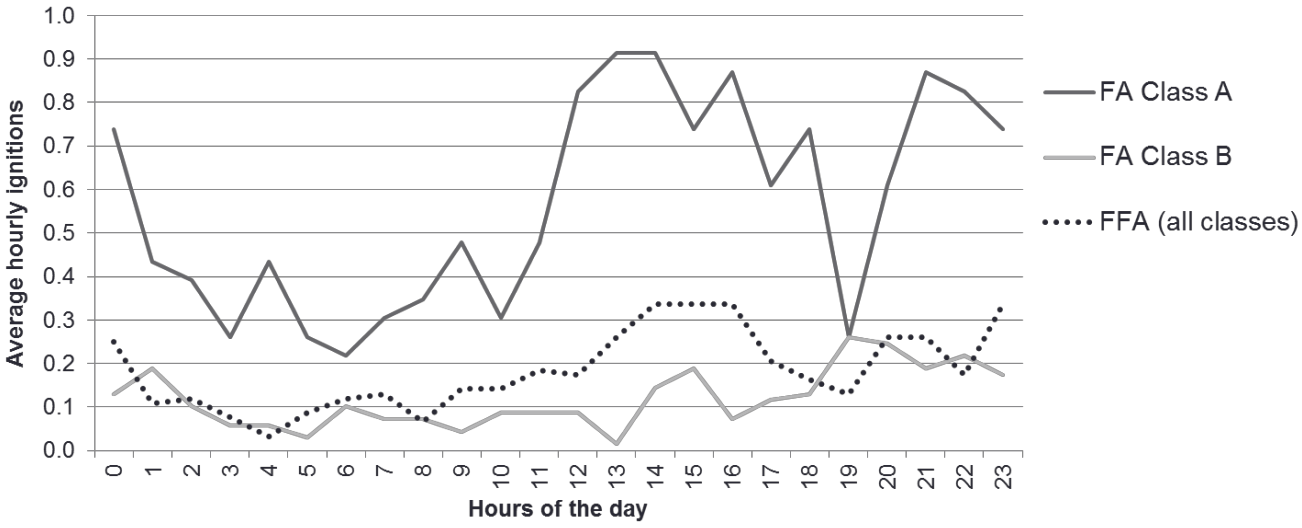


Figure S.6. Average hourly alarms for nonexistent (FA) and non-forest (FFA) fires in Porto, July – September 2010

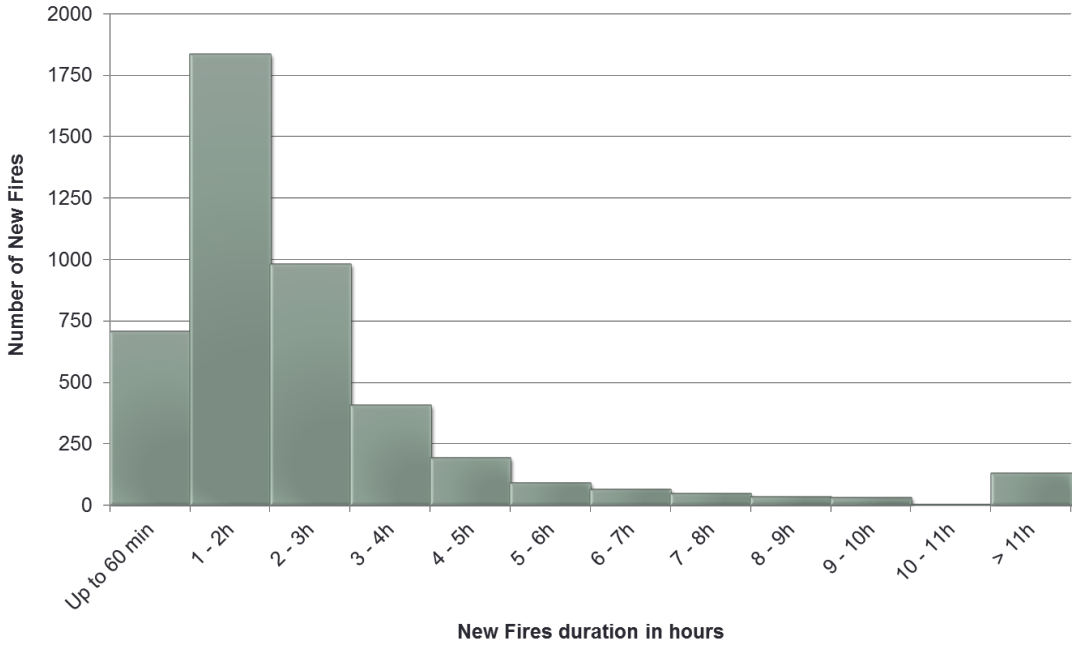


Figure S.7. Histogram of the duration of interventions in New Fires, Porto, July – September 2010

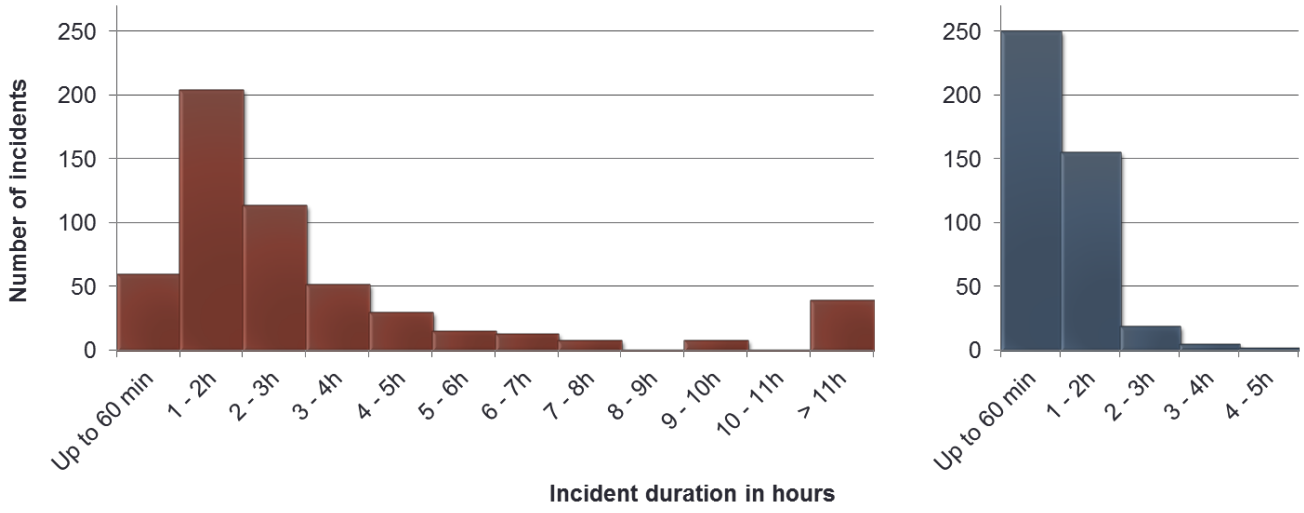


Figure S.8. Histograms of durations of interventions in Rekindles (left) and False Alarms (right), Porto, July – September 2010

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A risk analysis methodology for spatial flexible design of a network of fire-fighting depots

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ABSTRACT

This paper proposes an approach for allocating fire-fighting vehicles over a region. By considering uncertainties in fire location and intensity, it develops a plan more cost-effective than that from the traditional deterministic approach, reducing the number of required vehicles.

The approach recognizes that while small fires occur regularly and call for 'first response' equipment available close to fire-prone areas, large fires occur rarely and take time to develop. Thus, extended attack resources needed for the latter can be held in reserve over a larger area, as insurance against rare events. The approach consists of a layered strategy that moves specialized equipment from front lines to Flexible Regional Depots (FRDs).

The analysis introduces a combination of optimization and simulation into fire-fighting management. It first solves location problems to calculate optimal placements for FRDs, and then uses a twenty-year simulation to determine probability distributions for four vehicle performance measures: two types of run distances, utilization, and fire access time. A flexible decision rule adjusts the number of open FRDs annually, adopting the corresponding pre-obtained optimal solution, according to safety and efficiency performance in the previous year.

A case study of Porto, Portugal, demonstrates the approach, suggesting expected savings of 7.4 Million € in investment, while maintaining safety expressed by reasonable access times.

Keywords: Fire-fighting, location analysis, uncertainty, simulation, distribution of outcomes, regional allocation

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1. Introduction

Large fires pose significant challenges to forest fire management. The small portion of fires that escape initial attack (e.g., roughly 3% in Ontario, Canada) can grow and become extremely threatening very fast, and are responsible for most of the burned area, and most of the damages in general. The control strategies for such large fires are designed and implemented in a challenging context of uncertainty in weather, fire behavior, and suppression performance, seeking to balance fire damages and risks for firefighters. Suppression performance, in particular, depends on the availability and productivity of suppression resources (Rönnqvist *et al.* 2015), which in turn are greatly determined by key strategic operations decisions such as the prepositioning of the resources.

The traditional organization of fire suppression systems can lead to inefficiencies in equipment procurement and location, key activities associated with prepositioning. A typical system is often just an amalgamation of independent local entities, most of them volunteer fire departments – 88.5% in the US – (Yarnal and Dowler 2002), bounded by the political and geographical borders of the territory that they protect. In Portugal and in the United States, for example, these local fire departments procure and locate their equipment independently of other urban or regional authorities. In addition, their operations are autonomous and they do not routinely coordinate the operation of their equipment, even if they help each other in emergency situations (Perkins and Benoit 1997). These arrangements and practices are very likely to lead to wasteful duplication, as each individual organization seeks to procure expensive and needed specialized equipment (SE), especially in the case of equipment that is only rarely used. This duplication of capital equipment has several undesirable knock-on consequences: duplication of operational costs, difficulty in maintaining proficiency due to low utilization and lack of practice, inability to afford fleet renovation, and the foregoing of economies of scale and scope as regards procurement and operations.

The static nature of the traditional organization of fire suppression systems aggravates these inefficiencies. Indeed, fire departments and their locations are typically a legacy of past generations, maintained by the will and self-interest of local firefighting organizations (Perkins and Benoit 1997; Yarnal and Dowler 2002). But the regional distribution of wildfire risk can evolve dramatically over just a couple of decades, influenced by changes in areas as diverse as agriculture, demography, or climate. In Portugal, for example, rural abandonment of farming and emigration to the coastal cities after the 1960s, reinforced by European Union policies (Collins *et al.* 2013) and agricultural modernization, led to the accumulation of fuels in no longer needed, forested areas. Other examples of changes are the spread of urban areas into forested suburbs, which has increased the wildland urban interface (WUI) and the risk of human ignitions, and changes in patterns of wind and rainfall, which have shifted the location and intensity of potential fires. Simply put, a static firefighting system rooted in local control necessarily has trouble keeping up with the changing behavior of fire threats.

This paper proposes a new approach to locating the bases of firefighting equipment across a region, combining simulation and optimization methods. The main concept of the approach is a partial centralization of specialized equipment in Flexible Regional Depots (FRDs), to serve a wider zone comprising the areas of several local firehouses. These FRDs can be viewed as reserve centers for the front-line local units of first response to new wildfires. This layered organization of resources increases the cost-effectiveness of the system. Specifically, it can reduce overall costs while maintaining the safety level.

The concentration of resources creates the possibility of negative side effects that must be evaluated. Relocating equipment from local firehouses to FRDs inevitably places at least some of the equipment farther away from potential fires, and thus increases its response times. This could threaten to diminish

the system's capacity to contain and promptly extinguish fires. Any policy to concentrate fire-fighting equipment thus needs to study carefully its prospective effect on response times. In fact, selective choice of which equipment to centralize can eliminate this potential problem. The concern about immediate response applies to the vehicles deployed to the initial attack – these are the ones that need to be closest to potential fires. It applies much less to the kind of equipment that is always held in reserve to combat the fires that escape the initial containment efforts and become large. In particular, to vehicles mostly used in extended attack and in large fires (SE vehicles). Indeed, the response time of the specialized equipment used to combat escaped fires depends to a great degree on the operating procedures that define when this secondary equipment is dispatched. If the standard operating procedure (SOP) is to call on this additional equipment later, only when the initial attack fails, the effect of a greater distance between the FRD and a fire can be counterbalanced by changing the SOP to call for the equipment earlier. In Portugal, for example, the SOP dictates that a fire escapes when it has not been declared under control 90 minutes after the initial attack begins (Pacheco *et al.* 2014). The equipment used in escaped fires can thus be concentrated in more distant central locations (FRDs), without compromising the overall response time.

The paper demonstrates the feasibility and impact of the approach by applying it to a case study of the District of Porto, Portugal. Porto's firefighting system consists of a large number of local firehouses located regionally for historical reasons, collectively struggling with the problem of how to procure and use their equipment efficiently. The results show that a network of FRDs could significantly reduce the cost of investment in equipment while maintaining current levels of safety.

To establish the context for our analysis, the following section provides a brief literature review, covering key studies that address the challenges of emergency service facility location, and how to balance the need for economic efficiency with the requirement to keep services at an acceptable quality level. The section also presents the classical approaches to measure location performance, and establishes the need for an explicit consideration of flexibility in system design to appropriately address uncertainty, specifically in location problems. The remainder of the manuscript is organized as follows. We first describe our methods of analysis, which required a preliminary examination of the Portuguese forest service's official fire incident records and the Portuguese civil protection authority's firefighting vehicle utilization database, as well as contacts with experts (on financial data, and system organization and behavior), in order to categorize and understand the use of the firefighting resources. This section is then followed by the presentation of our findings and the discussion of their implications. Finally, we close the paper with a summary of our conclusions and suggestions for future research.

2. Literature review

Every day, fire managers must decide when and where to pre-position suppression resources in order to anticipate critical incidents and minimize the time required to reach them. With response time as a critical success factor, forest fire management agencies have much in common with first responder organizations, such as urban fire departments, emergency medical response agencies, and others (Martell 2015). If time is vital in emergency situations, it is critical that emergency vehicles are located in such a way that a quick response time is guaranteed and an adequate coverage is ensured, sometimes with the need to comply with some standard, e.g., in the case of the US emergency medical services, to serve 95% of the requests within 10 and 30 minutes for urban and rural areas, respectively. In this context, emergency vehicle location and relocation algorithms and models play a key role (Brotcorne *et al.* 2003).

Facility location often involves difficult spatial resource allocation decisions, and is a critical aspect of strategic planning for both private firms and public authorities (Owen and Daskin 1998), although fire, police, ambulance services, and other Emergency Response Organizations (ERO), are almost exclusively part of the public sector (Papageorgiou 1994; Simpson and Hancock 2009). An effective planning of the locations of fire brigades, in particular, is of vital importance to avoid fatalities caused by fire related disasters, and achieve effectiveness and reliability in the emergency response system (Başar *et al.* 2012). Because facilities are typically long-lived, their location decisions are usually difficult and costly to reverse (Snyder 2006). Finding robust facility locations is thus a challenging task – decision makers must select sites that perform well for the current state of the system, as well as for uncertain future events (Owen and Daskin 1998). Although ERO location problems have attracted substantial research in the past four decades, the vast published literature focuses more on the siting of emergency medical stations and ambulances, than in the seemingly similar problem for fire stations (Başar *et al.* 2012).

From the early works of Valinsky (1955) and Hogg (1968), to the RAND-New York City fire project collaboration (Green and Kolesar 2004), most ERO location studies can be characterized as "management engineering" (Simpson and Hancock 2009), defined by Corbett and Van Wassenhove (1993) as addressing the kind of practical problems whose solution requires the adaptation or the use of existing tools in a novel way – the essence of Operations Research (OR) (Altay and Green III 2006). The work of RAND in New York took place between January 1968 and September 1975 (Green and Kolesar 2004), the year that delimits the so called "golden age" of management science (Denizel *et al.* 2003; Simpson and Hancock 2009). Addressing macro issues that involved millions of dollars, such as the number of fire stations needed and their location, at times using simple deterministic models such as the "firehouse-siting model" (Green and Kolesar 2004), at other times developing more sophisticated models such as the stochastic integer linear programming formulation of the fire brigades relocation problem (Kolesar and Walker 1974), it had a lasting impact. Indeed, three decades later, the relocation algorithm was used again on September 11, 2001, when the World Trade Center attack emptied most of the fire protection in Manhattan and Brooklyn (Green and Kolesar 2004; Simpson and Hancock 2009).

2.1. The quest for efficiency

The redesign of public service systems in order to ensure the provisioning of appropriate quality levels while containing costs (Eiselt and Marianov 2015) is an ancient quest, with several cases of significant success. Throughout the eight years of the fire project, and despite all the adoption adversities (Chaiken 1978; Lawless 1987), the research work of RAND cost the city of New York about $500,000/year (less than a single fire company), and resulted in annual cost savings of $5 million (on a budget of $375 million). In 1972, six fire stations were closed and seven others were permanently relocated, and three years later, the dynamic relocation algorithm (Kolesar and Walker 1974) was successfully implemented as part of a new computer-based fire management and control system, enabling a real-time "adaptive response" of the initial dispatch policy to alleviate the workload in regions with high fire-incidence rates (Green and Kolesar 2004).

Later, recognizing that less than 25% of the emergency medical calls in Austin, Texas, required the advanced skills of paramedics, Eaton *et al.* (1985) reformulated the maximal covering location model (Church and Velle 1974) to analyze the redesign of the ERO system to include a two-tiered response capability – less trained personnel in lower-cost basic life-support vehicles would be dispatched to non-life-threatening events, while highly trained paramedics in advanced life support vehicles would respond to critical calls. The new design, in which the ERO resources were housed in existing fire stations or in new facilities built on city-owned lands, was adopted in 1980 and saved the city $3.4

million dollars in construction costs, and $1.2 million dollars/year in operating costs, at the same time that it reduced the average response time, even after an increase in the volume of emergency calls. This simultaneous improvement in quality of service and cost was achieved with about $30,000 spent in research by the city.

Swersey *et al.* (1993) described an application of the RAND-New York City "firehouse-siting model" (Dormont *et al.* 1975) and a spatial queuing model, to the redesign of the fire/medical ERO in New Haven, Connecticut. Implemented since 1991, the new design improved public safety by cross-training firefighters for the first response to medical emergencies, to be followed, if needed, by an ambulance service with highly trained paramedics. The system redesign led to savings of $1.4 million/year, 10% of the budget, achieved with a very small loss of fire protection, offset in turn by a large decrease in medical response time. This services integration approach, based on providing existing firefighters with dual training also as paramedics, enabling the delivery of additional emergency medical services without an increase in labor cost, appears to show promise (Eiselt and Marianov 2015).

2.2. Location performance measures

Response time translated into travel time or travel distance (representing the "cost" of traveling between locations) can be used as a performance measure for facility location effectiveness. Indeed, as the average travel distance increases, facility accessibility, and thus location effectiveness, decreases. This relationship holds for facilities for which proximity is desirable, both when customers need to travel to the facility to be served (e.g., schools, distribution centers) and when servers need to travel to the customers to serve them, as in the case of EROs.

To measure location effectiveness, there are three classical mathematical formulations: *p*-median, covering, and *p*-center. In the *p*-median formulation, the distances between demand locations and *p* given facilities are weighted by the associated demand quantities, and the total weighted travel distance is minimized. The problem can be traced back to Fermat, with several authors rediscovering the same iterative solution algorithm for it between 1937 and 1963 (Kuhn 1973). However, in this formulation, minimum service level requirements, expressed as maximum travel distances or times, as in the case of EROs, are ignored. To account for minimum service levels, minimizing the average traveled distance is not sufficient, and alternative measures of location effectiveness are required, considering a demand location to be covered only if the traveling distance or time to the nearest facility is below a given threshold. In the corresponding simple decision problem known as "location set covering problem", the demand quantity at each location is not taken into account, and the number of facilities is determined endogenously once the service level threshold is specified. As a consequence, the number of needed facilities *p* can be influenced by outlying small demand locations with high cost/benefit covering ratios, and can require investments larger than an available budget.

To avoid considering desired levels of coverage that are unfeasible for a certain available level of resources, in the "maximal covering problem" the maximum number of facilities is fixed, and the goal is the maximization of the number of demand locations for which the desired level of service (coverage) is satisfied, i.e., the maximization of demand coverage for a fixed number of facilities. Alternatively, to avoid the potential infeasibility of set covering problem instances, in the *p*-center formulation ("minimax problem") the coverage distance associated with locating *p* facilities can be determined endogenously, by requiring all demands to be covered, and seeking to minimize the maximum distance between demand locations and the nearest facility. Owen and Daskin (1998) provide a review on strategic aspects of facility location and their mathematical translation, from static deterministic formulations to dynamic and stochastic models, including queueing and scenario planning approaches.

2.3. System flexibility under uncertainty

Deterministic perspectives for system assessments use expected values of inputs, ignoring their variability. Moreover, they often do not account for the fact that, in general, "average inputs" do not produce a system's "average outcome", and therefore when using "average inputs" we might be optimizing the design of the system for a scenario that does not correspond to the central tendency of its performance. This pitfall, known as "flaw of averages", is described in detail by Savage (2009). In order to assess and improve the expected performance of a system, as regards both the input values and the ranking of design choices, in uncertain environments, the model should evaluate the "average outcome" as the average system performance under all potential scenarios corresponding to the many unfolding futures in which the system might exist (de Neufville and Scholtes 2011).

The proper analysis of the different choices related with the design of a system requires the recognition and the understanding of the effects of uncertainty. In order to accomplish that, a model should mimic the existence of many contingent decisions as the future unfolds, granting flexibility to the system. Indeed, a flexible design is useful to address uncertainty, by enabling the adaptation to potential changes in diverse sources of uncertainty – economic, technological, and regulatory, among others – and thus the conservation of the system's ability to meet its proposed requirements (Cardin *et al.* 2015).

Target curves (i.e., cumulative distributions) representing the uncertainty in the input values, and decision rules that model different management decisions in different futures, jointly translated into performance outcomes expressed also as target curves, provide an effective and systematic tool to gain insight into the behavior of different system designs, highlighting their risks and opportunities (de Neufville and Scholtes 2011).

2.4. Flexible location under uncertainty

As communities and surrounding conditions change, the parameters of location problems (costs, demands, distances) may fluctuate widely, and it may become necessary to increase, decrease, or relocate existing facilities (Snyder 2006; Başar *et al.* 2012). The uncertainty in future political conditions, economic trends, demographic changes, or other developments, can be represented by a set of scenarios associated with these driving forces, which influence the inputs of the model. Defining these scenarios is a relevant problem by itself (Correia and da Gama 2015).

Optimization and simulation, as noted by Aboueljinane *et al.* (2013) in their review of simulation models applied to emergency medical service operations, have been used multiple times in combination in these contexts. Uyeno and Seeberg (1984) applied a simulation model to the emergency medical services of Victoria, Canada, to evaluate and refine optimal locations previously obtained with a *p*-median model which minimized the total travel time required to respond to the demand from the closest base, assigning a fixed number of vehicles to each potential base. An earlier approach, developed by Berlin and Liebman (1974), used simulation to evaluate the performance of the system (mean response time and vehicle utilization) for different sets of base locations providing different target response times. These candidate solutions were previously obtained with a deterministic mathematical model which minimized the required number (cost) of bases in order to cover all the demand points within alternative target response times.

In our approach, we first optimize the location of p regional depots for different values of p, and then apply simulation to evaluate the performance of the system over a period of twenty years, using target curves in the input parameters, and decision rules to eventually adapt the number of regional depots (and consequently their location) as the future unfolds. The key novelty of our approach consists precisely on the use of (nonlinear) decision rules as a way to introduce flexibility in the design of the

system, mimicking adaptive management decisions seeking to guarantee a predetermined service level. The outcomes, in the form of target curves, allow the evaluation of the performance of the system with flexibility explicitly considered in its design.

3. Materials and methods

In order to address uncertainty in the number of deployments and in the location and intensity of fires over time, our analysis first solves location problems to calculate optimal sets of placements of FRDs, and then uses simulation to determine the probability distributions of several relevant measures of system performance, comparing the performances of the current and flexible designs over a period of 20 years. This analysis was carried out, independently, for four different future scenarios.

We used the district of Porto, Portugal, in 2006, to develop a case study, taking historical forest fire and suppression resource usage data from the previous three years as input.

We start this section by presenting the study site and the data and analysis methods used, followed by our modeling approach and the sources of uncertainty considered. Next, we explain how we obtained the sets of optimal depot locations, the spatial distribution of vehicle deployments, and the four future scenarios used in the simulation model. The section ends with the presentation of the simulation model, which is guided along the years by a mean-reverting process, and a description of how costs are evaluated.

3.1. Study Site

We used Porto, one of the eighteen districts of mainland Portugal, to develop our case study. As expected, the annual number and locations of fires in the district vary considerably, as Collins *et al.* (2013) have described for Portugal, and Pacheco *et al.* (2014) for the district of Porto in particular.

In Portugal, at the time of this analysis (and currently, as a matter of fact), independent local firefighting departments, called "Corporações de Bombeiros" (CB), are responsible for carrying out the majority of firefighting tasks. Each CB has its own firehouse, suppression equipment fleet, and crews. These CBs are volunteer humanitarian nonprofit associations – they are neither public entities exclusively funded by government, nor private profit-oriented companies. Their funding comes from many sources: the national government, the European Union, and other miscellaneous sources, such as municipal authorities, private donations, and fees from various services that they provide, including emergency medical services (ambulances).

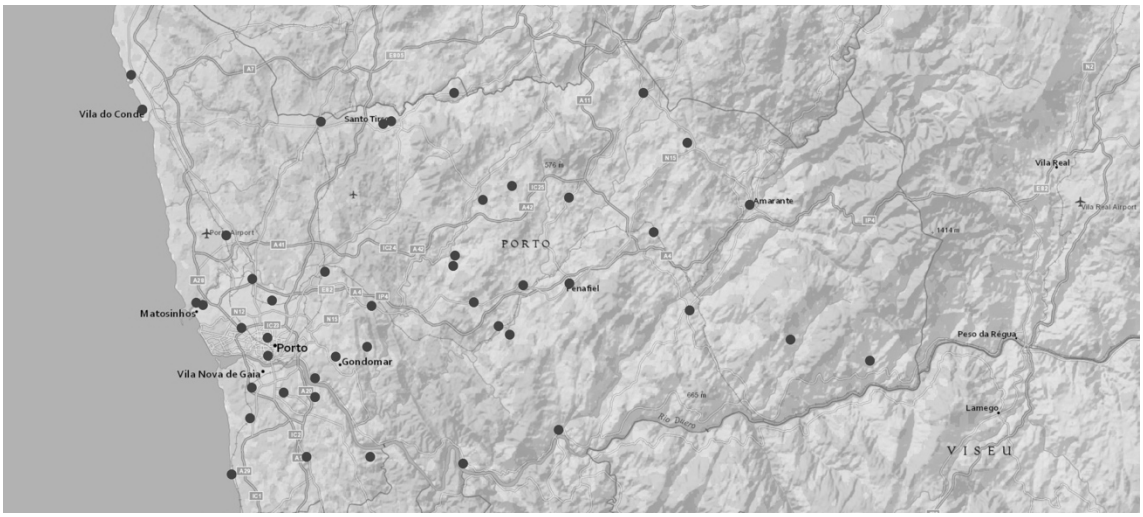


Fig. 1 Location of the 45 firehouses (CBs) in the District of Porto, Portugal (Barros *et al.* 2014)

Portugal has an extended network of CBs. For instance, the district of Porto has 45 CBs (Fig. 1 and supplementary Table S1), each with its own jurisdiction. They cover a total area of 2,395 km^2, with eighteen municipalities, and a population of about 2 million inhabitants. This translates into one independent CB for about every 53 km^2 and 44 thousand inhabitants, which means that the firefighting system is highly fragmented. The district combines a highly-populated area in the littoral (about one third of the population) with a forested area in the interior. For detailed data about demographics, number of volunteer firefighters, land cover, and forest fires (number and burnt area) between 2001 and 2010, we refer interested readers to the supplementary materials provided by Pacheco *et al.* (2014).

The state of fragmentation that the system evolved into, in the course of its historical development, leads to an inefficient resource allocation. The local CBs have sought to own the full range of required equipment, from first response (initial attack) to extended attack equipment. Nominally, they have collectively achieved this goal, but the local CBs do not have sufficient funds on their own to renew their fleets with modern equipment, and overall, the district of Porto has had an obsolete fleet. Analysis of the available detailed data about the fleet shows that the majority of the vehicles had an old age and also a very low utilization: about 40% of the existing fleet (Table 1) is utilized in less than 4% of the fires (supplementary Table S2). The district of Porto thus offers opportunities for an improved allocation of fire-fighting equipment, and for the establishment of a flexible network of FRDs, in a subset of the existing facilities (CBs), and these results can be extrapolated to the whole country.

3.2. Data and analysis methods

The case example used historical data of forest fires and the suppression system between 2003 and 2005, available from two different databases.

The fire database (ICNF 2016), publicly available from the Portuguese forest authority, ICNF (Institute for Conservation of Nature and Forestry, "*Instituto da Conservação da Natureza e das Florestas*"), was used for the characterization of the occurrences and for the analysis of the number of simultaneous fires. This database is the largest among European equivalents in terms of the total number of fires recorded between 1980 and 2005, and is fully described in Pereira *et al.* (2011).

For the suppression resources used in each fire, we used a database (Fernandes *et al.* 2016) originated in the Portuguese civil protection authority, ANPC ("*Autoridade Nacional de Protecção Civil*"), which assembles information collected separately until the beginning of 2006 and since 2003 (the year when this kind of data started to be collected). The original scattered data were recorded locally by the no longer existing SNBPC (National Firefighters and Civil Protection Service, "*Serviço Nacional de Bombeiros e Protecção Civil*"). Indeed, between 2003 and 2005, the suppression data were collected by 29 regional rescue coordination centers (CCS, "*Centros de Coordenação de Socorros*") where the local operational commands (CCO, "*Centro de Comando Operacional*") were located, all around the country.

This dataset contains highly detailed information about all the suppression resources used in Portugal during that period. Each observation contains the type of suppression resource (e.g., fire-engine, water tank vehicle, helicopter, or chainsaw), its license plate, its CB owner, the date-time of departure and return to the CB firehouse, the travel distance, the associated crew, and the fire location. We used this second data source to obtain detailed performance indicators for the suppression system in terms of distances covered, and number and types of vehicles sent to each fire.

The fire codes (ID) in the two databases did not match, and no correspondence was available. Moreover, during this period each CCO also recorded the suppression resources sent to fires in other regions, meaning that each fire in the ICNF database typically had several associated IDs on the suppression database: one for each CCO that supplied suppression resources for that particular fire. However, this

was not a problem for our analysis, because unlike Fernandes *et al.* (2016) we did not need to relate the suppression resources with the burnt areas. Finally, it is worth mentioning that 2003, 2004, and 2005 were years with different fire intensities. The years of 2003 and 2005 were particularly intense, indeed the worse in recorded fire history (Pereira *et al.* 2011), but 2004 presented an average pattern. These data, therefore, are a good reflection of a somewhat extreme wildfire season.

The statistical analysis of the two databases was carried out using the R system for statistical computing, version 3.1.0 x64 (R Development Core Team 2014), in RStudio, version 0.98.1028 (Racine 2012), and packages 'ggplot2', version 1.0.0 (Wickham 2009), and 'doBy', version 4.5-10 (Højsgaard 2006). R itself and the packages are freely available under the terms of the general public license (GPL) from the Comprehensive R Archive Network (CRAN) at http://CRAN.R-project.org/. The linear regressions were also carried out with R, using distances between locations obtained from Google Maps.

We built the simulation model in Microsoft® Excel and performed the Monte Carlo analysis using @RISK version 6.0, included in a software package available from Palisade®. @RISK is a Microsoft Excel add-on that facilitates uncertainty and risk analysis with Monte Carlo simulation, and provides a selection of probability distributions and sensitivity analysis options. We chose readily available "off the-shelf" commercial software packages for ordinary desktop computers, in order to maximize the likelihood that practitioners adopt our approach. These software packages have been on the market since the 80s, with frequent updates, and online detailed instructions, expansive examples, and help.

Monte Carlo simulation is valuable because it allows the analysis of a range of future conditions over multiple iterations. Using the @RISK software add-on, we ran a Monte Carlo simulation of 10,000 iterations of the static (inflexible) and flexible designs along a period of twenty years, in four independent future scenarios. The simulation results consisted of the cumulative distribution functions (CDFs) of the system performance indicators.

For optimization, we also used Microsoft® Excel, specifically the Evolutionary Solving Method, one of the algorithms available in "Solver" (a tool included in the package as an *add-in*).

3.3. Modeling approach and sources of uncertainty

In our approach, the number of vehicles deployed to a particular fire was considered as a proxy for that fire's intensity. While this assumption may be questionable for resources used in the initial attack (the fire intensity is unknown until the suppression means get there), the simplification holds for specialized vehicles sent to the fire well after the first emergency call. Moreover, this assumption is sound because, in fact, the larger the fire, the larger the number of resources that are deployed to it, conveniently or not (Fernandes *et al.* 2016). We can therefore think of a fire as a group of vehicle deployments to the same location. This measure is thus a valid indicator of the demand for this kind of firefighting vehicles, and the number of deployments is well-suited to our focus, which is related to dispatching policies. The same rationale holds for the entire season, for which we used the annual number of deployments instead of the annual number of fires as a proxy for season severity.

Forecasts are always wrong (de Neufville and Scholtes 2011), so for our goal of providing forest fire decision makers with solutions that cost-effectively allocate less used fire equipment, it is useful to adopt a probabilistic approach to address uncertainty in the inputs. We accomplished that by combining optimization with simulation:

- First, we solve p-median integer programming problems, to determine for each p ($p < \#CBs$) the optimal set of regional depot locations, a step which requires a non-negligible computational time;

- With these optimal sets of FRD locations, one set for each p ($p < \#CBs$), we then use Monte Carlo simulation, with the severity of the seasons determined over time by a probabilistic process, to obtain probability distribution functions for several performance indicators.

In the simulation, we compare over twenty years the performance of the current static design, with the less used vehicles scattered by all the CBs, with the proposed plastic network of FRDs, in which the bases belonging to a subset of the existing potential bases are chosen annually as depots for this kind of equipment.

The decision on the CBs to be used as depots each year, allows addressing the uncertainty in the number of fires and their geographical location. In each simulation run, the annual choice of CBs results from a flexible approach (implemented as a decision rule) that opens or closes each possible depot location (among all the existing CBs) according to the recent observation of efficiency and safety parameters, the severity of the last critical period, and the number of FRDs open in the previous year.

We evaluated the two designs independently for four alternative future scenarios. In a first "as-is" scenario, we assumed that over the time the currently observed conditions regarding the number and probabilistic location of fires did not change; in a second scenario, we considered an expansion of the WUI; a third scenario reflected an investment in surveillance actions; and a fourth, an increase in law enforcement.

As mentioned above, before running the simulation, we needed two pre-calculations, to (1) identify the best CBs to be used as depots, and (2) define the spatial (2D) distribution of the locations of fires, where the considered suppression resources are needed. We describe these steps in the following sections, and the simulation model in section 3.6, including the main probabilistic process that drives the simulation in time.

3.4. Optimal depot location

The overall goal of our allocation model is to divide the region into influence areas or clusters around regional depots, in order to minimize the sum of the distances cover by the vehicles (*minisum*). Clustering is a general solution approach that has been implemented for many types of allocation problems, with different optimization objectives (Tryfos 1998; Mooi and Sarstedt 2011), and in particular using spatial division and the Euclidean distance as a cost function, as in the case of our approach.

While the origins (the set of FRDs) are the output of the location problem – what it seeks to determine – the destinations (fires) are its input. The latter need to be determined a priori, which we do using historical data – the uncertain location of future ignitions, in turn, is appropriately (probabilistically) addressed by the simulation model (section 3.6).

The model uses fire deployments (to each possible fire location) as a proxy for fire events, and accounts for the possibility that more than one fire occurs in the same location. As a result, the input to the problem consists of a set of locations with an associated number of vehicle deployments required by all the fires that occur in the same location during the period of analysis. Consistent with our option for a mid-resolution spatial model (and the simulation model), instead of using precise locations we use the closest cell center (^{ccc}), from the spatial grid used for scenario generation.

We restrict the sources (FRDs) to places fixed in advance, namely to existing facilities (firehouses of CBs), rather than allowing full leeway in their location. Limiting the set of feasible locations is likely to reduce demand coverage, but this drawback is counterbalanced by the absence of costs in the construction of new infrastructures, and by exploiting the flexibility to change the location of FRDs to

adapt to future conditions. Furthermore, in the specific case of the deployment of emergency vehicles, existing firehouses are already conveniently located close to main roads.

Considering the above, our modified *p*-median location problem statement is the following: *given a number of depots (#FRD), a set of fire*[ccc] *locations, each weighted by a number of deployments, and a set of potential depot locations (CBs), determine the best set of depot locations (FRDs)*. Our formulation assumes that the number of FRDs is an input rather than a result because the decision about the required number of regional depots is taken (and changed) throughout the simulation. Eq. 1 provides the formulation for the problem's objective function as the minimization of the weighted distance run in all deployments (*minisum*).

$$Z = \sum_{i=1}^{m} \sum_{k=1}^{n} \rho_k \cdot [(x_{D\,k} - x_i)^2 + (y_{D\,k} - y_i)^2]^{1/2} \cdot \propto_{ki}. \qquad \text{Eq. 1}$$

In Eq. 1, index $k = 1, \dots, n$ refers to the destinations (fires[ccc]), and $i = 1, \dots, m$ to the potential origins (CBs). ρ_k is the weight of each destination, i.e., the number of deployments required by destination k, according to our formulation. The x, y coordinates are $x_{D\,k}$ and $y_{D\,k}$ for destination k, and x_i and y_i for origin i. Finally, $\propto_{ki}$ is a binary variable that takes the value 1 if i is the (open) depot closest to destination k, and 0 otherwise.

"Fixing" the potential locations of the FRDs introduces a combinatorial aspect into the problem, with the solutions indicating through the binary optimization variables whether each destination is assigned to a particular FRD. The combinatorial nature of the problem requires a specific mathematical treatment, different from problems purely in continuous domains. In our approach, we use genetic algorithms and local search methods (the Evolutionary Solving Method for non-smooth optimization, included with Excel's Solver) to address that combinatorial nature.

After defining the interval of acceptable numbers of FRDs, between N_{min} and N_{max}, we calculate the optimal sets of FRD locations, selected among the network of existing CBs, for each $n \in \{N_{min}, N_{min} + 1, \cdots, N_{max}\}$ and each scenario. All the solutions are obtained by solving the location problem described above, with the computation naturally becoming more time-consuming as the $N_{max} - N_{min}$ amplitude increases.

Minas *et al.* (2012) and, more recently, Martell (2015) provide examples of Integer Programming applied to wildfire management. Pacheco *et al.* (2015) also cover Integer Programming applications in the context of their review of wildfire risk handling and decision support systems actually in use. Among these examples, a reference of particular relevance for our work is the approach of Kirsch and Rideout (2005) to optimize the effectiveness and performance of initial attack. Among more generic references of relevance for our work, the following are worthy of note: ReVelle and Swain (1970) provide the location problem mathematical formulation that we adopted; Baker and Camm (2005) discuss integer programming in a spreadsheet environment, as opposed to stand-alone software, acknowledging that practitioners tend to use "off the-shelf" software packages; and Mooi and Sarstedt (2011), Tryfos (1998), and Aravind *et al.* (2010), guided our implementation of the *minisum* formulation in Excel.

Our objective function is the minimization of the sum of all the distances that the vehicles cover when deployed from the FRDs. Alternative objective functions, focusing for example on non-Euclidean distances (e.g., Manhattan distance), could be used and possibly lead to alternative optimal solutions. Kotian (2005) and Kotian *et al.* (2009) studied the planar *k*-central location problem, which seeks to minimize the sum of the distances to some of the farthest destinations, ignoring irrelevant calculations related to deployments closest to the origins, and could be particularly interesting in situations in which outliers play an important role in allocation.

3.5. Spatial distribution of vehicle deployments and scenario generation

In order to model the uncertainty in the locations where these kinds of vehicles are needed, we used a two-dimensional distribution defined after a frequentist analysis of empirical data. To reflect the spatial pattern and intensity of the ignitions that escape initial attack, whose extended attack these kinds of vehicles are used for, we discretized the region with a grid of square cells, assigning each cell a value (variable of interest) consisting of the number of deployments that were made to that particular cell during the historical time interval considered (Fig. 2). The rationale for this model is the assumption that the spatial distributions of the vehicle deployments always present a "similar" shape, regardless of the randomness in the probabilistic process used in the simulation model to model the severity of each season (the total number of vehicle deployments).

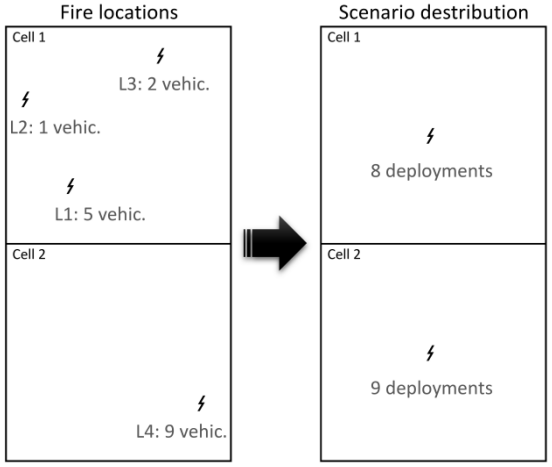


Fig. 2 This simplified map (left), with a grid of two cells, illustrates the generation of a base scenario for the distribution of deployments (right) from historical fire locations (L1, L2, L3, L4).

After the described probabilistic analysis of historical data, the obtained historical spatial distribution of vehicle deployments defines the base scenario "1", which reflects the current "as is" situation.

We used the reference distribution used in the base scenario, to calculate the distributions for each of the other three scenarios, each reflecting a different threat, trend or policy change, and characterized by a specific modification of the reference distribution (a benchmark against which we assess the alternative policies). For each of the derived scenarios there is thus a set of rules that transform the reference distribution in the distribution of the scenario of interest. Specifically, in each cell of the grid of the new scenario, the number of deployments is a function of the state of that particular cell and/or the states of its neighboring cells in the reference distribution. In the following paragraphs, we describe the three derived scenarios.

Scenario 2, which we call "*WUI expansion*", reflects a variation due to changes in the WUI, with its spatial deployments distribution generated from a prediction about the WUI evolution (changes in population density, new physical barriers, etc.). The underlying rationale is the higher likelihood of fire ignitions (and thus escaped fires and the use of the kind of vehicles we are considering) in the WUI than in wildland areas, as Radeloff *et al.* (2005), Catry *et al.* (2009), and Silva *et al.* (2010) in chapters 2.3, 3.3, 3.5, and 5.2, show respectively for the US, Portugal, and EU in general, and, e.g., Silva *et al.* (2014) is a recent application.

The evolution of the WUI is implemented assigning a new value to each cell as a function of the values of that cell and its neighboring cells in the reference distribution. For example, with a purely eastbound evolution of the WUI, the future state of each cell depends on the current values of its left

(western) neighboring cells (visually, a deformation/displacement of the original distribution to the right). In the function parameterization, other specific scenario parameters can be used (e.g., static or dynamic WUI evolution, and WUI spreading speed, among others).

Scenario 3, "*increased surveillance*", emulates the effects of a surveillance policy applied to areas where the number of escaped fires is higher than a certain threshold. The expected consequence of such policy is a reduction of fire ignitions by preventing a part of the arson and negligent unintended fire incidents. The rationale behind this policy is the influence of surveillance investment on the reduction of both intended and accidental fire ignitions due to human activity (Radeloff *et al.* 2005; Catry *et al.* 2009).

To understand the procedure to generate the distribution for this scenario, it may be useful to visualize the reference spatial distribution of deployments – inherently likely to be heterogeneous, i.e., to have some cells with many more deployments than others – and a smoothing of its peaks, as the intensified surveillance actions (e.g., active patrol) are directed to the most affected areas. The distribution depends on threshold and surveillance efficiency parameters. The former determines the cells in the reference distribution that will have their values reduced, while the latter defines the expected reduction. For the cells with values below the threshold, the values remain unchanged. For practical reasons, we use the same efficiency factor for all the cells with deployment values above the chosen threshold.

Scenario 4, "*law enforcement*", reflects the effect of a law enforcement policy on the number of vehicle deployments. Increasing the punishment for arson and neglectful ignitions is expected to decrease the number of fires in all cells (we assume a constant rate of reduction), resulting in a proportionally lower distribution. The effect is analogous to the effect observed in the previous scenario, with the key difference that "increased surveillance" only affects targeted areas, whereas "law enforcement" is a generalized policy that affects the entire region.

3.6. Simulation model

The simulation model evaluates whether a flexible strategy based on the centralization of vehicles in FRDs is able to reduce costs through an increase in vehicle utilization, while maintaining the level of safety, when compared with the current situation (vehicles spread throughout all the CBs). The evaluation is carried out over time, in the face of annual variations in the season severity, and independently under several scenarios.

We use the total number of deployments tnd in each year y as a proxy for the number and intensity of escaped fires, in order to emulate a season's severity, with tnd_y determined by a mean-reverting (Ornstein–Uhlenbeck) process. In each scenario, we obtain the spatial distribution of deployments for a particular year by applying this factor to the respective distribution: for each cell, we multiply its value by tnd_y to obtain the number of deployments into that particular cell (for that particular year).

The decision to be made every year concerns the number (level) of FRDs. Seeking to achieve a high performance for the system, by maximizing vehicle utilization, subject to a minimum safety level, a flexible decision rule determines every year whether and how the number of FRDs should be altered. The exact location of the FRDs is then obtained using the corresponding pre-computed optimal set. It should be noted that changing the number of FRDs by one may require closing and opening several depots (e.g., Fig. 11).

The four different scenarios are studied independently with the purpose of showing that the advantages of a flexible design policy are also present therein, even with such diverse patterns of fire occurrences.

As the output of the simulation model, for each performance indicator, we obtain eight CDFs, for the current design and for the flexible design, under the four scenarios considered. General views of the approach and the simulation model are presented in Fig. 3 and Fig. 4, respectively.

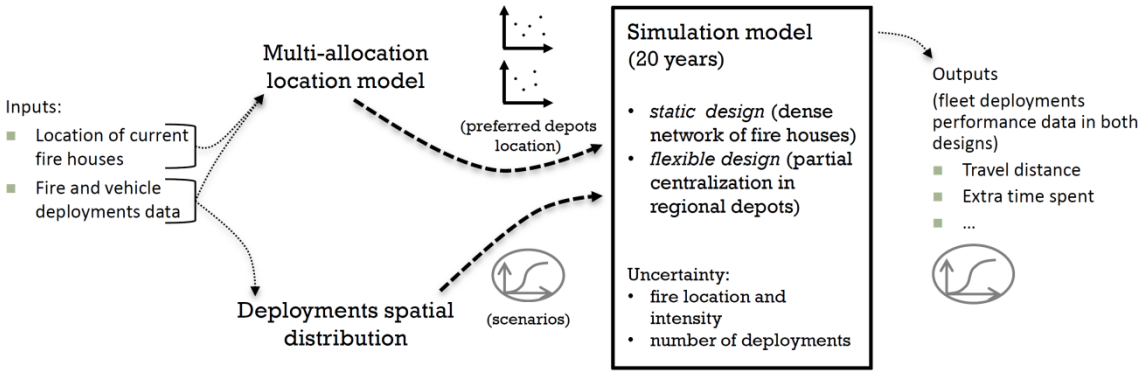


Fig. 3 General view of the approach.

Next, we will look with more detail into: (a) the evolution of the number of deployments as a mean-reverting process; (b) the decision rule; (c) how, for each year, the system is considered in the model; and finally (d) the performance indicators and how they are measured:

a) In order to model the annual total number of vehicle deployments along the simulated period as a stochastic variable, we used a discretized mean-reverting process, analytically expressed in Eq. 2 (Uhlenbeck and Ornstein 1930), similar to, e.g., Chow and Regan (2011). The main characteristic of a variable described by mean reversion is its tendency to move back (to "revert") to the average value after having assumed distant values. In other words, despite the presence of volatility, after a certain time with high (low) values, the variable tends to take on lower (higher) values towards the mean.

$$\frac{dS}{S} = \mu dt + \sigma dz \qquad \text{Eq. 2}$$

In Eq. 2, S represents the uncertain variable, and μ and σ represent its long-term mean and volatility, respectively; dz is the standard Wiener process (also called Brownian motion), which adds randomness (fluctuation) to the mean. A relative change in S thus has a constant expected value, μdt, and also a constant variance, $\sigma^2 var(dz) = \sigma^2 dt$ (dz expresses the change during dt). In our model, S is the annual total number of deployments (tnd_y), which guides the simulation, with μ and σ parameterized with historical data.

The rationale for adopting of a mean-reverting process is the fact that large burnt areas need some time to regenerate and accumulate fuel before they can burn again. This happens when fuel is withdrawn essentially by the occurrence of fires and not in a planned way in the context of prevention programs, such as fuel treatments by controlled fire, use of chemicals, or use of manual or mechanical equipment (e.g., Collins *et al.* (2013)). Hence, years with fewer fires favor the accumulation of fuel, which in turn will favor escapes in subsequent years, maintaining the average burnt area in the long term. Consequently, after years with a low (high) number of vehicle deployments, the number of total deployments is expected to be higher (lower).

b) Flexibility is included in the model through a decision rule with two conditions. Taking the results of year y (independently for each scenario) as input, a decision to decrease, maintain, or increase the number of FRDs is made for year $y + 1$. The depot locations cannot be long-term decisions. Because of the uncertainty in fire locations and number of deployments over time, it may be necessary to relocate the depots as time evolves. In the adjustment of the location of the depots, within the set of existing facilities, we used the previously determined optimal sets of depots, which means that we

allow the opening (closing) of some depots closed (open) in the previous year. Later, in section 4.2 (Fig. 11) we provide a concrete example of the implications of a one unit change in $\#FRDs$ on the simultaneous opening and closing of several depots.

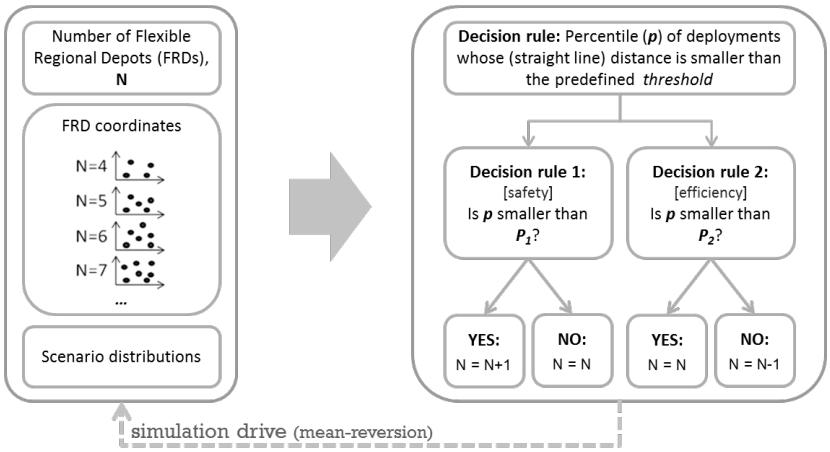


Fig. 4 General view of the simulation model with next year inputs (left) influenced by the decision rule (right).

The criterion to change the set of FRDs (by opening or closing several depots located in the existing CBs) in year $y+1$ is mainly concerned with the value in the previous year y of the simulation, for a percentile p relative to a predefined threshold distance L in the distribution of the straight-line distances travelled by the deployed vehicles (Fig. 4, right):

$$\#FRD(y+1) = \begin{cases} N-1, & p > P_2 \\ N, & P_1 \le p \le P_2 \\ N+1, & p < P_1 \end{cases} \qquad \text{where } N = \#FRD(y) \qquad \text{Eq. 3}$$

The first condition, "*safety*", aims at ensuring that the straight-line distance is lower than that predefined threshold L for at least a proportion P_1 of the deployments; if not ($p < P_1$), the number of FRDs is increased by one. A minimum percentile threshold (e.g., $P80$) thus guarantees that the system maintains its safety by seeking to allow only a small percentage of deployments to be longer than a certain distance (e.g., $L = 11km$).

On the other hand, the second condition, "*efficiency*", aims at ensuring that the straight-line distance is not lower than the same predefined threshold L for more than a proportion P_2 ($P_1 < P_2$) of the deployments; if not ($p > P_2$), the number of FRDs is decreased by one. The maximum percentile value (e.g., $P90$) is thus part of a complementary condition that seeks to ensure that the proportion of deployments shorter than a certain distance is not excessive. Both conditions are expressed by the decision rule defined in Eq. 3.

c) Within each year y^* the system is considered in the simulation as follows. For each scenario, we have the locations of all the CBs (*static design*) and the N FRDs (*flexible design*), XY_i^{sd} and XY_j^{fd} respectively, and a grid of cells C_k, each with its number of deployments ρ_k (obtained from the distribution for that scenario and the mean-reversion process). To obtain the XY_k^d coordinates for the location of each deployment, we use a uniform distribution inside each cell (Fig. 5).

Then, for each deployment location ($XY_{k'}^d$), the simulation finds the nearest CB ($XY_{i'}^{sd}$) and FRD ($XY_{j'}^{fd}$), and calculates the two respective (Euclidean) straight line distances $d_{k'}^{sd}$ and $d_{k'}^{fd}$. From the straight-line distances, we estimate the real distances covered by the vehicles, hereafter referred to as "travel distances", and the related extra time spent (ETS) in the deployment.

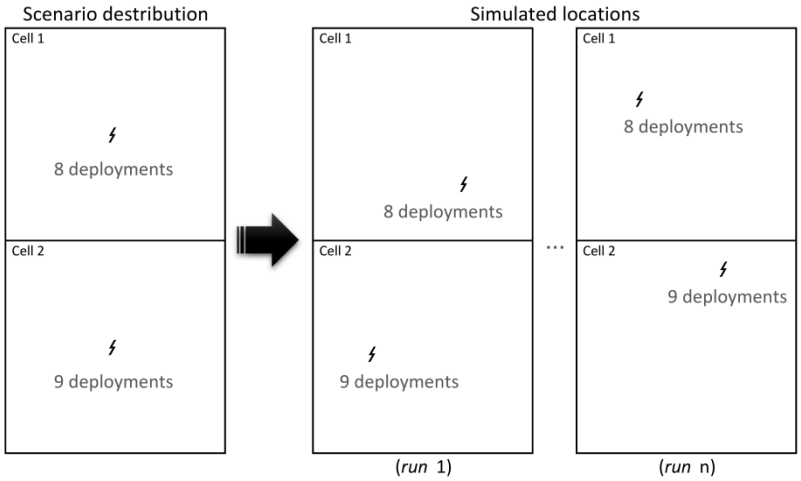


Fig. 5 From a distribution of deployments for a base scenario (left), two hypothetical random instances, run 1 and run n (right), are derived for two different simulation replications (please revisit Fig. 2, to see the map of fire locations used to generate this scenario distribution).

It should be noted (Fig. 6) that if the CB closest to a fire location also happens to be an FRD, then the straight-line distance is the same in both designs, and thus the travel distance and the ETS are zero.



Fig. 6 A deployment to a fire location l_1 will be served by CB_A in the old design and by CB_B in the new design because CB_A is not an FRD. However, in a location l_2 it will be served by CB_B in both designs.

d) With this structure in place we start computing the performance indicators. To estimate the travel distance in the old design, we use a linear transformation, $2\alpha d_{k'}^{sd} + \beta$, with parameters α and β estimated from field data, where α stands for the proportion of the distance run in the primary or secondary roads near the closest CB, and β for the trips (in curvy and narrow off-road forest paths) near and inside the burnt area, and for refilling purposes (in the case of water tanks).

If the closest CB is not an FRD, then we compute an additional travel distance by multiplying the difference between the straight-line distances $d_{k'}^{fd} - d_{k'}^{sd}$ ($d_1^{fd} - d_1^{sd}$ in Fig. 6) by 2γ ($\gamma < \propto$), with the parameter γ also estimated from field data, and accounting for the conversion of a straight-line distance into a primary road trip. The rationale for this conversion considers that CBs are located near the forest, and that the traveling between CBs can be done in primary roads. In this case, we will also have an ETS in the flexible design, which is estimated from an average speed v (again, obtained from field data and the assistance of experts) for vehicles in primary roads (because the location of a vehicle in a more distant FRD increases the time traveled on paved roads, but does not really change the distance traveled in the forest, near the fire). The four parameters $(\propto, \beta, \gamma, v)$ can be obtained with regression analyses and the assistance of a geographical information system.

With the straight-line distance $d_{k'}^{fd}$ and the number of deployments $\rho_{k\prime}$ for each cell $C_{k\prime}$, we compute the percentage of deployments into the cell, $p_{k\prime} = {}^{\rho_{k\prime}}/_{tnd_{y^*}}$, and after sorting all pairs $(d_{k'}^{fd}, p_{k\prime})$ by

distance, build the CDF and find the percentile p of distances not greater than the predefined threshold L, later used by the decision rule (described above) to determine the $\#FRD$ for the next year.

After obtaining the ETS for each deployment, we compute the average, the median, and the percentile (e.g., P80) t of the ETSs for that year. Our interest in this value is due to our concern, for security reasons, with what happens in "almost all" the cases. The average and even the median of the ETS are thus not appropriate metrics for this purpose.

Adding the straight-line and travel distances for all the locations, in the static and in the flexible designs, we obtain the respective annual totals. Finally, dividing the annual total traveled distance by the number of deployments in the year tnd_{y^*}, and by the exogenous number of vehicles (please see next section), we obtain, respectively, the average trip distance (km/trip) and the average fleet utilization (km/vehicle), in the flexible design.

The preceding calculations are repeated for each year along the simulation's twenty-year time span, and separately for each independent scenario. For each scenario, at the end of the simulation, we have a set of twenty values for each performance indicator. In order to evaluate both designs for each scenario, using distributions functions for the results, the simulation should be replicated at least 1,000 times.

3.7. Fleet dimension and system costs

We used a simple approach to compare the costs of the two designs, enabled by the fact that in our model the number of vehicles is exogenous. We defined the dimension of the fleet in the flexible design (an input to the simulation, used to compute the average fleet utilization for each year – please see the previous section) by analyzing historical data to find the maximum number of vehicles used at the same time (simultaneity factor).

Computing this figure for a particular period required, for each ignition, data on the dates when it started and was put out, as well as on its number of deployed vehicles (Fernandes *et al.* 2016). To perform this calculation we applied the technique described in Pacheco *et al.* (2012), using paired pivot tables to compute the balance of entries and exits, and the daily numbers of vehicles in use simultaneously by the suppression system, from which the maximum is retained.

The daily number of escaped fires active simultaneously and the number of vehicles deployed to each of them are our focus, so the maximum daily number of vehicles in simultaneous use can be applied as a simultaneity factor for the fleet dimension. Using data from severe seasons in terms of number of ignitions and burned area (a proxy for the number of escaped fires), e.g., 2003 or 2005 in Portugal, we can be confident that the simultaneity factor is conservative enough, and a sound estimate of the number of required and non-required vehicles. The latter are the main opportunity for a fleet and suppression system cost reduction in the flexible design proposal under evaluation.

4. Results and discussion

In this section, we present three sets of results: (i) in subsection 4.1, results from the statistical analysis of ICNF and ANPC databases, and other sources, used to parameterize the model; (ii) in subsections 4.2 and 4.3, the results of the combined optimization and simulation analyses; and (iii) in subsection 4.4, the evaluation of the capital expenditure savings.

4.1. Model parametrization

The size of the forest fire suppression fleet decreased from 401 to 365 vehicles in the analyzed three-year period, and the number of the less used suppression resources that we focus on for centralization

in FRDs (SE), ranged from 138 to 157. It should be noted that their percentage of utilization was slightly higher than fifty percent, in contrast to almost one hundred percent for the rest of the fleet (Table 1). Indeed, the fleet of SE vehicles appears to be too large for the current needs, and according to experts, the available human resources are not even enough to use all the existing vehicles. Their utilization is very low, between about 52 and 93 km/vehicle/year, depending on whether we consider the entire SE fleet or only the SE vehicles actually used, and the analysis of the registration plates shows that the SE fleet had an average of 33 years of age at the time of our analysis.

Table 1: Existing and actually utilized suppression fleet vehicles (also as percentage), from 2003 to 2005.

	Existing fleet			Utilized fleet			Utilized fleet (%)		
	2003	2004	2005	2003	2004	2005	2003	2004	2005
Total	401	366	365	312	303	300	78%	83%	82%
SE	157	138	142	83	77	79	53%	56%	56%
IA	244	228	223	229	226	221	94%	99%	99%

The SE fleet can actually be even older because some of the vehicles are donations from foreign fire organizations, which received a new Portuguese plate when they entered the country. In addition, some vehicles were second-hand and the majority of the CBs have maintenance staff that extends their lifetime. The old age of SE vehicles, also according to experts, is one of the factors that contributes to the existence of unused vehicles, as is their role as insurance against the possibility of break-downs, and their exemption from taxes.

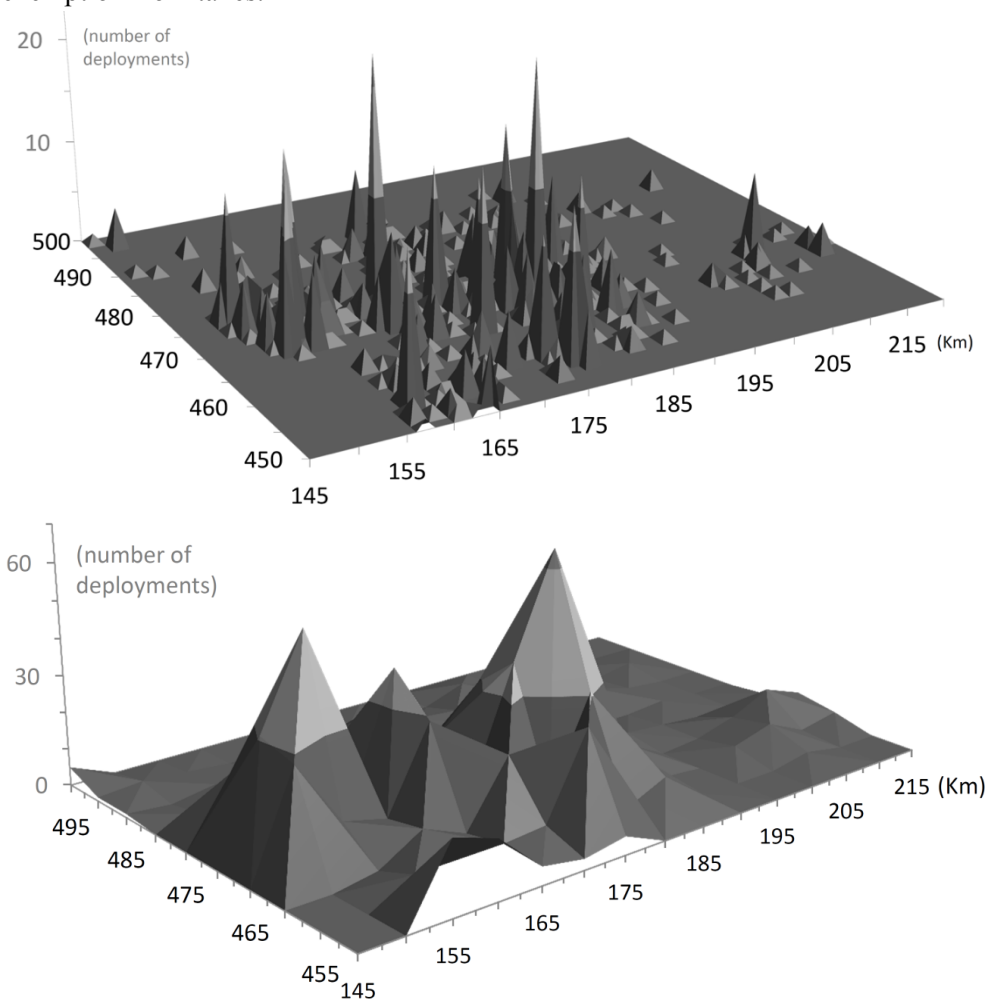


Fig. 7 Graphical representation of the spatial (2D) frequency distribution of deployments to locations in the Porto district, with a grid scale of one (top) and five (bottom) square kilometers (supplementary Table S4).

Specifically, the kind of SE vehicles that we analyzed (whose figures for 2005 are reported in brackets) are capacity water tank trucks and technical assistance vehicles [63], logistics support (technical equipment and food) and personnel and firefighter transportation vehicles [61], strategic operations command and communications vehicles (except tactical command, [2]), and special fire-fighting vehicles (with extinguishing agents other than water and above 4,000 liters of capacity, [16]) – in a total of 142 for 2005. All the other types of vehicles were, and continue to be, distributed by all the CBs for rapid initial attack (e.g., fighting vehicles, rural tactical water tanks, and tactical command vehicles).

During the 2003-2005 period, there were 843 SE vehicle deployments to 689 different fires (with the number of vehicles per fire ranging from 1 to 8), less than 1.2% (10) from fleets belonging to other districts, namely Vila Real (6) and Lisbon (4), which were used in four fires and mostly (7) for logistics support and firefighter transportation. These fires occurred in 399 different locations, with the number of deployments to each location ranging from 1 to 23 (supplementary Table S3), and they represent a small fraction (3.6%) of all the fires (supplementary Table S2).

Considering a grid of one (five) kilometer cells, we obtain from 0 to 23 (0 to 65) SE vehicle deployments to each of the 3700 (150) cells that cover the district, 330 (88) non-null. Fig. 7 shows a spatial representation of the frequency distribution for deployments in both grid scales applied to the region (exact values in supplementary Table S4).

Table 2: Parameters used for scenario generation.

Scenario	**Parameter**	**Value**
WUI expansion	Random effect [0=No,1=Yes]	1
	Maximum number of deployments (per cell)	65
	Influence from north-west, west, and south-west (# cells)	1, 3, 1
Increased surveillance	Apply to cells with more than (decision rule)	30 dep.
	Reduction efficiency	60%
Law enforcement	Law enforcement reduction efficiency	20%

Table 3: Overview of the characteristics of the scenarios.

Scenario	**Statistics**	
As-is	Total number of cells in the grid	150
	Cell area (5x5)	25 km²
	Total deployments	843
WUI expansion	Influencing area	225 km²
	Maximum total deployments in the generated grid (random effect = 0)	1253
	Generated grid (total deployments)	1115
	Expansion impact on deployments	+32%
Increased surveillance	Number of cells under surveillance	7
	Percentage of cells under surveillance	4.7%
	Generated grid (total deployments)	666
	Overall deployments reduction	21%
Law enforcement	Generated grid (total deployments)	709
	Overall deployments reduction	16%

The spatial frequency distribution of vehicle deployments at a five-kilometer scale was used to define the base scenario ("as-is") and derive the other three scenarios. Table 2 presents the parameters that were used, and provides an overview of the assumptions that were made and the order of magnitude of their values. It is worth noting that in the second scenario, which represents the expansion of the WUI, the expansion develops eastward, from the littoral to the afforested interior of the district, as it is taking place today.

The overall statistics for the scenarios are presented in Table 3, and some descriptive statistics about the deployments for each case in Table 4 (including figures for positive cell values). The generated grids are used in the simulation model as the base-grid for each scenario.

Table 4: Deployments statistics for the base-grid generated for the simulation of each scenario (figures for positive cell values in brackets).

	As-is	WUI expansion	Increased surveillance	Law enforcement	*unit*
# cells	150	150	150	150	*cells*
# cells, positive	88	109	88	88	
Sum	843	1115	666	709	*deployments*
Minimum	0 (1)	0 (1)	0 (1)	0 (1)	
Maximum	65	65	29	52	
Median	1 (5)	3 (6)	1 (5)	1 (4)	
Average	5.6 (9.6)	7.4 (10.2)	4.4 (7.6)	4.7 (8.1)	
Std. deviation	10.6 (12.4)	11.1 (11.8)	6.9 (7.5)	8.6 (9.9)	

The mean-reverting process uses 281 deployments as the long-term mean (μ) and 70 deployments as the annual standard deviation (σ) with a speed of mean reversion (η) of 0.5. We use μ also as starting value (first year) and consider 30 and 532 as respectively the lower and upper limits. The results obtained with these parameters are consistent with the available data. Fig. 8 shows, as an example, three realizations of the regression to the mean of the annual value of vehicle deployments, parameterized as described.

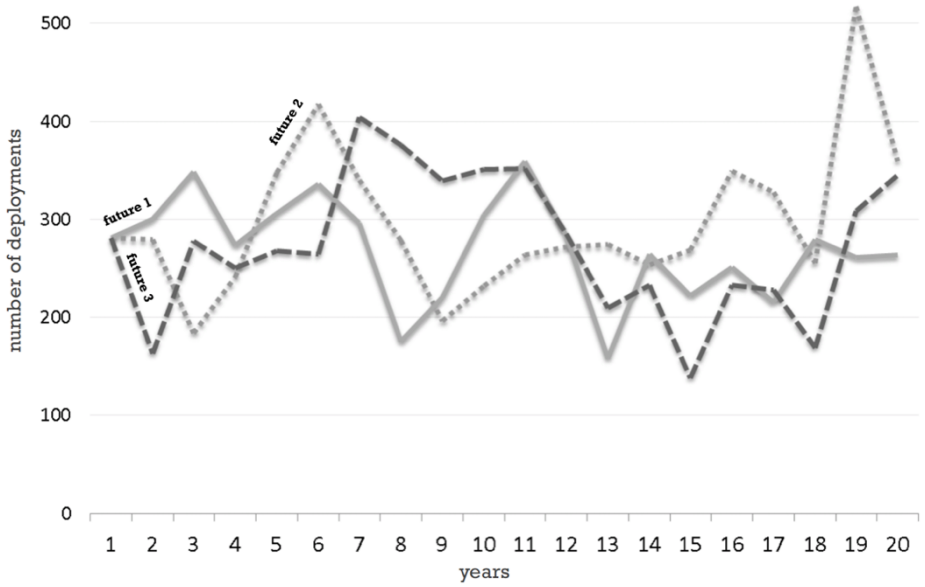


Fig. 8 Three realizations of the regression to the mean parameterized for the case study (annual values).

For the definition of the sets of FRDs we optimize their locations for 1 to 16 sites, chosen from the 45 available firehouses (supplementary Table S1). Fig. 9 shows the results for the instances with four and five sites, considering the aggregated deployments for the 2003-2005 period in the district.

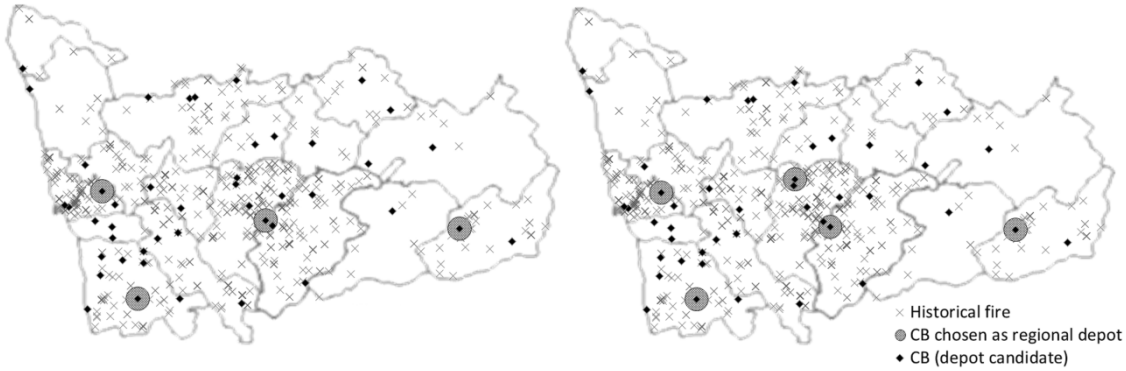


Fig. 9 Optimal locations of regional depots in the "as-is" scenario, for four (left) and five (right) sites.

In order to implement the decision rule, we adopted a cautious decision profile and defined a low value for the threshold L, 10 km, and high percentiles of P90 and P95 for the thresholds in the two conditions, P_1 (*safety*) and P_2 (*efficiency*) respectively.

To convert straight-line distances to travel distances, and evaluate the ETS when the FRD is not the closest CB, we used the parameters in Table 5. The distance conversion parameters $(\propto, \beta, \gamma)$ were obtained with regression analyses and the assistance of Google Maps. For the ETS parameters (v, t), based on the input of experts, we chose very conservative values.

Table 5: Parameters for straight-line distance to travel distance conversion and extra time spent (ETS) computation.

Parameters		**Design where applied**	**Value**
Straight-line to travel distance conversion	Straight-line to "roadway" factor	*static* (α)	x 3.5
		*flexible** (γ)	x 2
	Fixed distance per deployment (β)	*static*	6.6 km
Extra time spent	Average speed in good roads (v)	*flexible*	40 km/h
	Security percentile (t)	*flexible*	P90

* additional distance

Finally, to compare the average SE vehicle utilization and system costs in both designs, we studied the fleet utilization through time by evaluating the number of SE vehicles utilized simultaneously in the same day (supplementary Table S5) and in each fire (supplementary Table S6, and also supplementary Table S7 and Table S2).

Analyzing the fires in which SE vehicles are utilized (SE fires), we observed that they have a higher utilization in days with a larger number of simultaneous fires (supplementary Table S2). This is in line with the perception that more fires will typically escape initial attack in those days, but is also a sign, according to experts, that they are used as well as urban firefighting vehicles (mainly in the WUI) in the initial attack when the IA fleet (heavily used – Table 1) is already deployed or resting. When vehicles of this kind are deployed to an SE fire (up to 28, simultaneously, in the same day), roughly 2/3 (1/3) are deployed for more than two (eight) hours, and only about 13% for less than one hour (supplementary Table S7). However, the probability of not having any deployments in a given day (supplementary Table S5), and the probability of not having any deployments to the same SE fire (supplementary Table S6), which is the same by definition, is very high, with a value of 74%. The

overall probability of having more than two deployments in a given day is 11%, and 5% for more than six deployments. Regarding the deployments to the same SE fire, the overall probability of having more than two is 9%, and 3% for more than six. The previous figures show that the simultaneous use of SE vehicles is low, both in quantity and in deployment duration, although both with a long tail.

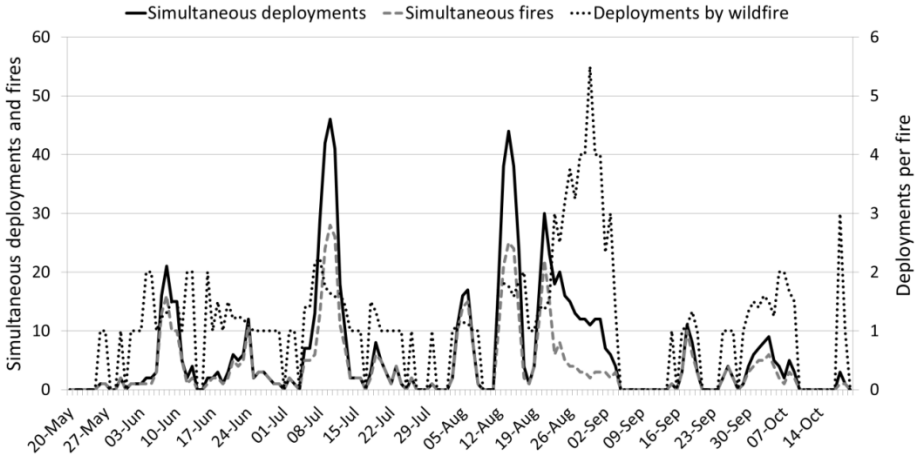


Fig. 10 Number of simultaneous deployments and fires per day, and deployments/fire ratio during the critical period of 2005, in the district of Porto.

Fig. 10, which includes the analysis of the simultaneous deployments per day for the 2005 season, shows a maximum value (Table S5) of 46 vehicles for July 10, which was also the maximum observed for the whole period of analysis. This value was taken as the minimum fleet size in the flexible design. For the static design, we used 142 and 79, the number of existing and actually utilized SE vehicles (also in 2005), respectively. For the average cost of each SE unit we used €77,007 the weighted average cost of the existing fleet (again in 2005), based on the input from an expert on the individual prices of each class of SE vehicles.

4.2. Optimization results

For the application of the simulation model, we optimized a priori the set of depots for each scenario and for $n \in \{1, \cdots, 16\}$, i.e., for a total of 64 instances. The computation took about four days in a computer (Dell Precision T5500) with six Intel Xeon X5650 2.67GHz processors, 24GB of RAM, running Windows 7 (64 bits version).

The results for the four scenarios are presented in supplementary Table S8 to Table S11. The values for the objective function (minimum total straight-line distance) are included in Table S12 and are well approximated by a power function ax^b (the parameters a and b, and the R^2 are provided in Table 6). This result has the practical interest of avoiding a time-consuming calculation, allowing the objective function value for a new n' to be estimated from a smaller set (e.g., $n \in \{5, \cdots, 9\}$) of previously calculated values.

Table 6: Parameters a and b of a power function ax^b approximating the values of the objective function for the 16 instances of each scenario, and the corresponding R^2.

Scenario	a	b	R^2
As-is	12,614,550	-0.49970	0.9972
WUI expansion	17,194,507	-0.45282	0.9991
Increased surveillance	11,249,545	-0.52230	0.9942
Law enforcement	10,885,606	-0.50305	0.9972

As mentioned in section 3.6 (b), flexibility is incorporated in the model through a decision rule with two conditions, which can leave the number of depots (n) unchanged, or increase or decrease them by one, for the following year according to the results of a specific year. We provide a concrete example (Fig. 11) of the implications of a one unit variation, in the simultaneous opening and closing of several depots, specifically showing what happens when the $\#FRDs$ changes from 4 to 5, and from 5 to 6 (the complete set of changes in the four scenarios is provided in supplementary Table S8 to Table S11).

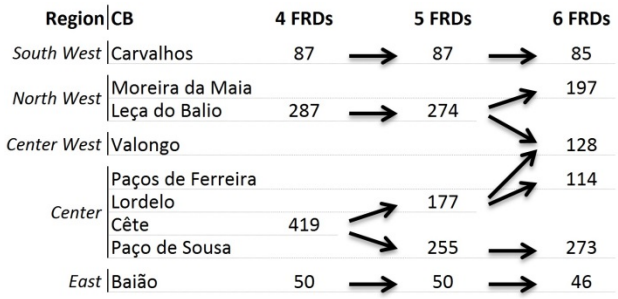


Fig. 11 Changes in open and closed depots in the "*as is*" scenario, when the number of FRDs (n) increases from 4 to 5, and from 5 to 6 depots (the matrix distances between CBs are provided in Table 7 and the sets of open depots for 4 and 5 FRDs are shown in Fig. 9).

With the increase from 4 to 5 depots, one regional depot is closed ("Côte") and two others ("Paço de Sousa" and "Lordelo") are open nearby (Fig. 11), at distances of 1.3 and 7.6 km, respectively (Table 7). With the change from 5 to 6 depots, two depots are closed ("Lordelo" and "Leça do Balio") and three are open, two nearby ("Paços de Ferreira", 5.7 km from "Lordelo", and "Moreira da Maia", 4.7 km from "Leça do Balio") and the third ("Valongo") in a central position, covering part of the regions previously covered by the former two (9 and 11.3 km from "Lordelo" and "Leça do Balio", respectively).

The observed behavior was expected, given the fact that the change in the number of locations leads to a different optimization problem. In addition, the fact that a depot is closed for some n' does not imply that it cannot be reopened later (for some $m' > n'$), e.g., the "Leça do Balio" depot, closed when $n = 6$, is opened for $n = 7$, closed for $n = 9$, and opened again for $n = 14$. In addition, most depot changes occur in the center littoral (center west / center) of the district, as expected given the pattern of fire locations.

Table 7: Matrix of distances (km) between the CBs selected in at least one of the sets of FRDs, when $n \in \{4, 5, 6\}$, in the "*as is*" scenario (please see Fig. 11).

		Carvalhos	Moreira da Maia	Leça do Balio	Valongo	Paços de Ferreira	Lordelo	Côte	Paço de Sousa	Baião
South West	Carvalhos		21,7	17,1	**15,1**	28,7	23,0	21,4	21,9	46,0
North West	Moreira da Maia	21,7		**4,7**	14,9	23,9	21,2	26,5	27,7	52,9
	Leça do Balio	17,1	4,7		11,3	22,5	18,8	23,2	24,3	50,0
Center West	Valongo	15,1	14,9	11,3		14,1	**9,0**	11,9	13,0	38,8
Center	Paços de Ferreira	28,7	23,9	22,5	14,1		**5,7**	11,7	12,6	31,1
	Lordelo	23,0	21,2	18,8	9,0	5,7		**7,6**	8,8	31,9
	Côte	21,4	26,5	23,2	11,9	11,7	7,6		**1,3**	27,0
	Paço de Sousa	21,9	27,7	24,3	13,0	12,6	8,8	1,3		**25,9**
East	Baião	46,0	52,9	50,0	38,8	31,1	31,9	27,0	25,9	
		South West	*North West*		*Center West*	*Center*				*East*

4.3. Simulation results

The simulation was replicated (run) 10,000 times for each scenario, taking about 20 hours (7.3'' per iteration, with the computational platform described at the beginning of the previous subsection), in order to obtain the performance indicator measures as accurate distribution functions. Consistent with

inputs described as probability distributions (e.g., the location and intensity of fires), probability distributions are also appropriate to describe outputs, and are presented as cumulative distributions, or target curves. These graphs are convenient to compare the effect of different strategies and identify their corresponding values at risk and gain, typically set at the 5 and 95% values of the cumulative distribution (e.g., Fig. 12). Target curves are especially useful when the curves of two (or more) strategies cross each other, e.g., hypothetically, the static and flexible approaches in the "as-is" scenario. This was not the case in our analysis (the flexible design outperforms the static design in all four scenarios), so we present our results mostly using summary tables.

As shown in Table 8, the results of the simulation model for the static design in the "as-is" scenario are in line with the data – about 52 and 93 km/vehicle/year for the total (142 vehicles) and the actually utilized (79 vehicles) fleet (please see Table 1). It is worth noting that we calibrated the simulation for the "as-is" scenario with all the deployments for the three years, not just 2005, which explains the small discrepancy.

The changes in utilization, presented in Table 8, are the same for 142 and 79 vehicles, and the means change only by a proportional factor. Using this factor, the expected mean for the fleet minimum size of 46 (obtained from the simultaneity analyses) is 166.1 km/vehicle/year in the current design ("as-is" scenario, static design). This figure, as expected, is reasonably below the value of about 230 km/vehicle/year, obtained under the flexible design for the same fleet size.

Table 8: Simulation statistics for vehicle utilization (in km/vehicle/year) with the static design, for the total (142 vehicles) and utilized (79 vehicles) SE fleet. The lower and upper 5% (5^{th} and 95^{th}) percentiles for the "as-is" scenario determine the thresholds (e.g., 48.2 and 59.6 km in the total fleet section of the table) for which the corresponding percentiles are determined in the other three scenarios (e.g., in the "WUI expansion" scenario, 42.5% of the replications had results above 59.6 and 107.1 km for the total and utilized fleet, respectively).

	Scenario	Percentiles			Mean	Std. Dev.
total fleet	As-is	5.0%	90.0%	5.0%	53.8	3.5
	WUI expansion	0.3%	57.2%	42.5%	58.8	4.0
	Increased surveillance	1.1%	78.2%	20.7%	56.6	3.8
	Law Enforcement	3.4%	88.5%	8.1%	54.6	3.6
		< 48.2 km	*between*	*> 59.6 km*		
utilized fleet	As-is	*< 86.6 km*	*between*	*> 107.1 km*	96.7	6.2
	WUI expansion				105.8	7.2
	Increased surveillance				101.7	6.8
	Law enforcement				98.1	6.4

As expected, the centralization of resources leads to an increase in travel distances, due to (some) farther firehouse locations. Table 9 presents this result for our case study, as obtained from the simulation.

Comparing the static and flexible designs, the mean deployment straight-line distance increases between 71 and 86% (in the "WUI expansion" and the "as-is" scenarios, respectively), and the mean deployment travel distance between 32 and 37%, with an increase in the SE fleet efficiency of about one third for all the scenarios. At the same time that the flexible strategy reduces the $\#FRDs$, it increases the individual vehicle utilization, for a constant fire distribution and number of vehicles.

It is worth mentioning that the increase in deployment straight-line distances is above 80%, however this larger difference can be explained by two factors that affect the calculation of the additional travel distance (when it exists) introduced by the flexible approach. Recalling that the additional distance is assumed to be traveled in primary roads and thus obtained by multiplying the straight-line difference $d_{k'}^{fd} - d_{k'}^{sd}$ by 2γ (please revisit parts c and d of subsection 3.6, and Fig. 6), first, the γ parameter has

a relatively lower impact than the $\propto$ and β parameters ($\times 2$ with $\times 3.5$ and $6.6Km$, see Table 5) previously (and always) applied to the straight-line to travel distance conversion in the static design, and second, when the closest CB is also a FRD then the travel distance is the same.

Table 9: Average deployment straight-line and travel distances (km). The lower and upper 5% (5th and 95th) percentiles for the "as-is" scenario determine the straight-line and travel distance thresholds (e.g., 22.8 and 34.3 km in the travel distance table section) for which the corresponding percentiles are determined in the other three scenarios (e.g., in the "law enforcement" scenario, 4.2% of the replications had travel distances below 22.8 km and 6.1% above 34.3 km).

	Scenario	Percentiles			Mean	
straight-line	As-is	5.0%	90.0%	5.0%	3.0	5.6
	WUI expansion	0.5%	77.2%	22.4%	3.4	5.8
	Increased surveillance	1.8%	86.7%	11.5%	3.2	5.9
	Law enforcement	4.2%	89.5%	6.3%	3.1	5.7
		< 2.5 km	*between*	*> 3.7 km*		
travel distance	As-is	5.0%	90.0%	5.0%	27.9	38.3
	WUI expansion	1.0%	82.0%	17.1%	30.6	40.3
	Increased surveillance	2.5%	87.8%	9.7%	29.3	39.8
	Law enforcement	4.2%	89.7%	6.1%	28.3	38.6
		< 22.8 km	*between*	*> 34.3 km*		
		static design				***flexible***

However, to be fair, we should compare the gains in efficiency between the total fleet or at least the utilized fleet in the static design, with the performance under a flexible design, for which we obtain an improvement greater than a factor of 4 or 2, respectively. Over a normal three-month fire season, this amounts to an average daily use of 2 to 3 km/SE vehicle per day, which appears to be low but even so an improvement over the 0.6 or 1.1 in the current situation.

Next, we present the results for the extra time spent with the change from the current static system to a flexible configuration. Fig. 12 shows, for each scenario, the 90th percentile of the increase in access time under the current dispatch policies.

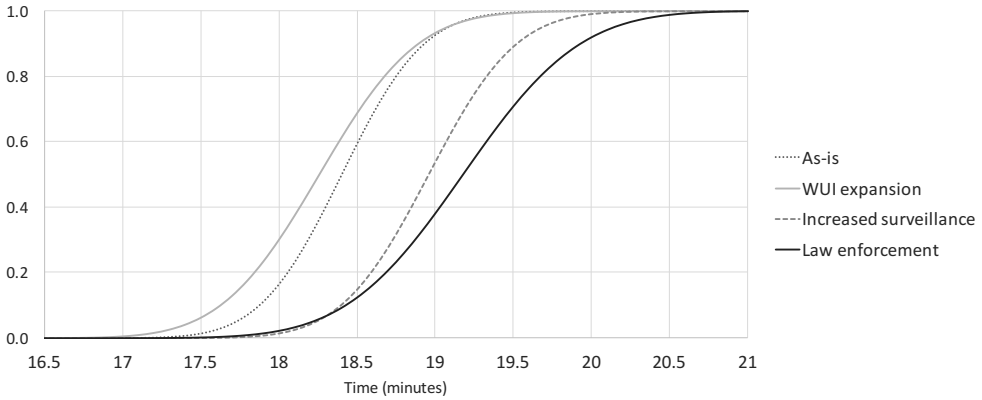


Fig. 12 Distribution of the 90th percentile of the increase in access time due to centralization (in minutes).

Table 10 shows the results in greater detail, also for the average and median ETS.

In all scenarios, the annual volatility is low along the 20 years of the simulation, with higher values for the median and the 90th percentile than for the average. The median is always lower than the average, reflecting the presence of a few years with higher values. This effect is smaller in the "WUI expansion" scenario than in the "as-is" scenario (the mean of 7'09" is lower than the 7'13" threshold)

because in the former the deployments are more spread, the required #FRDs is larger (Table 9), and the spatial distribution has 32% more deployments (Table 3), for the same maximum (Table 4).

Table 10: Extra time spent (ETS) average, median and 90th percentile in minutes (') and seconds ('). In each section of the table (ETS average, median, and 90th percentile), the lower and upper 5% (5th and 95th percentiles) percentiles for the "as-is" scenario determine the thresholds (e.g., 3'40'' and 5'28'' in the median table section) for which the corresponding percentiles are determined in the other three scenarios (e.g., in the "law enforcement" scenario, 95.9% of the replications featured a median ETS between 3'40'' and 5'28'').

	Scenario	Percentiles			Mean	Std. Dev.
average	As-is	5.0%	90.0%	5.0%	7'40''	14''
	WUI expansion	62.1%	37.9%	0.0%	7'09''	13''
	Increased surveillance	3.1%	78.3%	18.7%	7'46''	17''
	Law enforcement	6.6%	89.5%	3.9%	7'36''	15''
		< 7'13''	*between*	*> 8'01''*		
median	As-is	5.0%	90.0%	5.0%	4'39''	33''
	WUI expansion	2.9%	96.9%	0.2%	4'22''	22''
	Increased surveillance	1.1%	78.5%	18.7%	5'04''	30''
	Law enforcement	1.8%	95.9%	2.3%	4'35''	26''
		< 3'40''	*between*	*> 5'28''*		
90th percentile	As-is	5.0%	90.0%	5.0%	18'24''	25''
	WUI expansion	14.3%	81.0%	4.7%	18'16''	29''
	Increased surveillance	10.0%	62.3%	18.7%	18'58''	26''
	Law enforcement	1.2%	39.9%	58.9%	19'11''	35''
		< 17'44''	*between*	*> 19'05''*		

In order to assess the outcomes for most cases, and for the worst cases (in the right tail), we focus our analysis on the median and the 90th percentile. Considering a reasonably prudent average speed of 40 km/h in primary roads (between CBs), in 50% and 90% of the replications the new strategy causes a mean increase in the access time of less than 5 and 20 minutes, respectively, whichever the scenario (considering 60 km/h instead, the values would fall to less than 4 and 13 minutes, respectively).

Such a delay would not be acceptable for initial attack deployments. However, in the case that we are considering, of SE vehicles mostly used in extended attack, we can mitigate the impact of the delay by adopting a policy to dispatch these vehicles earlier.

Table 11: Minimum and maximum number of FRDs during the simulations.

	Scenario	Min	Median	Max
minimum	As-is	5	7	8
	WUI expansion	6	8	8
	Increased surveillance	6	8	8
	Law enforcement	5	7	8
maximum	As-is	8	8	10
	WUI expansion	9	10	12
	Increased surveillance	8	9	11
	Law enforcement	8	9	10

It is useful to look into the range of the number of FRDs during the simulations. For each scenario, Table 11 shows the median (and also the minimum and maximum) for the minimum and the maximum number of regional depots. In the "as-is" scenario, the number of FRDs range from 5 to 10, being typically around 7 or 8. As expected, due the heaviest deployment distribution, the "WUI expansion" scenario is the more demanding, requiring 6 to 12 regional depots (typically around 8 to

10). Overall, considering all the scenarios, the number of required depots varies between 5 and 12 (supplementary Table S8 to Table S11 present an overview of these figures).

It is also worthwhile examining the spatial location of the sets of FRDs selected during the simulation (and previously defined in the optimization stage). To avoid the cost of new construction, the FRDs are constrained in our model to be located in current firehouses (CBs), which in turn are historically located near populations. When a populated area is located in the WUI, the probability of occurrence of ignitions increases, and thus the probability of escaped fires and the number of SE deployments. At first, the depot locations are chosen in areas with large intensity of deployments (so as to minimize the sum of the distances run), but as n increases, some depots begin to be located in less deployment dense areas.

In the "as-is" scenario, the extreme cases (5 and 10) are showed in Fig. 9 (right) and in the supplementary Fig. S1, respectively, and the most typical (7 and 8) in Fig. 13. The comparison of the two solutions indicates that the sites are remarkably stable. The increase from 7 to 8 does not, in this case, change the optimal location of any of the previous sites: only a new depot is added, near the center-south district border. In general, the overall performance is insensitive to marginal perturbations: a move closer to one need, is a move away from other needs, and these benefits and costs tend to cancel each other. In practice, the policy of using only existing sites (CBs) implies that an optimal site would only change in the presence of an important advantage, which is increasingly less likely to occur as n increases.

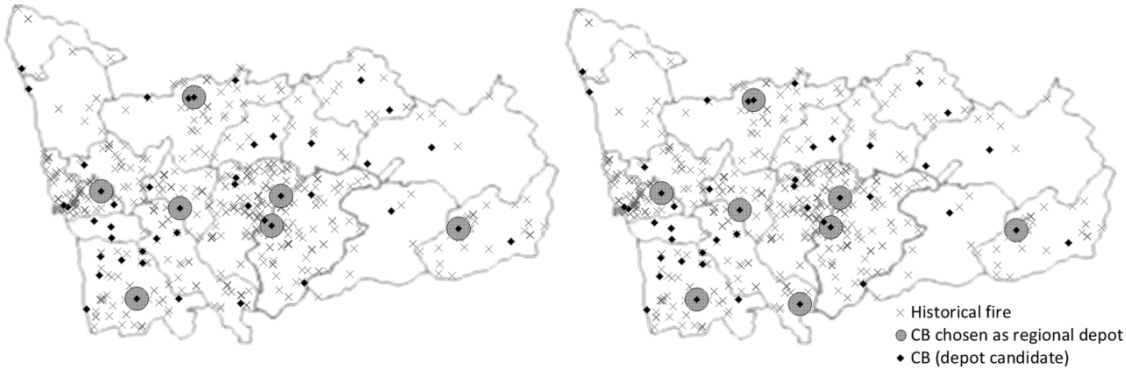


Fig. 13 Optimal networks of sites selected as regional depots, in the "as-is" scenario, for $n = 7$ (left) and $n = 8$ (right).

The stability of optimal sites is relevant from a policy perspective. It should be relatively easy to agree on a core set of sites (such as those represented by the solution for 7 depots) and focus the discussion and political maneuvering around whether or not to add or subtract sites.

4.4. Capital expenditures savings

The proposed approach avoids about 7.39 M€ in fleet renovation costs, with a reduction of over two-thirds (96 vehicles, or 67.6%) of the current fleet, from 142 to 46 SE vehicles. This value can be reasonably extrapolated for the entire country, corresponding to substantial savings of more than seventy million euros.

We estimate the reduction in the investment to modernize the SE fleet for the entire mainland Portugal (Table 12) with a proportional calculation (country/district), using as criteria the number of CBs (A1), the number of SE vehicles (A2), and the number of SE vehicles in each class (B). The SE fleets of different districts have different class compositions, and criterion B considers these variations, estimating a level of savings that is probably higher than eighty five million euros.

If we ignore, contrary to the views of experts, that the fleet may simply be oversized, and consider the ratio of the existing to the utilized fleet (142 to 79) as a proxy for insurance against vehicle breakdowns and seasons even worse than 2005 (the worst season so far in Portugal), the system would need 83 instead of 46 SE vehicles. Even so, the fleet reduction would be of about 42% (59 vehicles) and the corresponding savings would be about 4.54 M€ for the district and probably more than fifty million euros for the entire country (please see supplementary Table S13).

Table 12: Gains for the entire country extrapolated (a) as a proportion of the number of CBs (criterion A1) and the size of the SE fleet (criterion A2), and (b) directly by the number and corresponding cost of each SE vehicle class (criterion B), from the gains estimated for the Porto district (€7.39 million) achieved with a 67.6% SE fleet (2005) reduction (cost for each SE vehicle class obtained from an expert).

		Criterion A1	Criterion A2	Criterion B
		proportional by		*directly by*
		# CBs	# SE vehicles	number/class value
Porto	number	45	142	n. a.
	estimated	€ 7.39 million	€ 7.39 million	€ 7.39 million
Portugal	number	434	1589	n. a.
	extrapolated	€ 71.3 million	€ 82.7 million	€ 85.78 million

It is worth mentioning that these savings are only for the capital cost of periodic fleet renovation (e.g., each twenty years) and do not account for the impact of the proposed flexible approach in operational expenses. The reduction of the size and dispersion of the SE fleet, from all the 45 CBs to at most 12 regional depots, would have a significant impact in the decrease of annual maintenance and repair costs, and travel and vehicle expenses. In addition, the associated firefighting personnel (a crew with two firefighters, at least, in each SE vehicle not used) could be assigned to other important suppression-related tasks, e.g., mop-up operations, helping to control the excessive number of rekindles in the country (Pacheco *et al.* 2012, 2014).

5. Conclusion

This paper presents a new approach for policy analysis of the allocation and deployment of the wildfire-fighting specialized vehicles mostly used in extended attack and in large fires. The approach considers the centralization of these vehicles in a flexible set of locations for regional depots (FRDs), to serve a range of front-line firehouses (with the mission of responding to initial attack) as insurance against rare events. To avoid the typical rigidity in long term decisions associated to emergency services location, we design and assess, using simulation, a flexible strategy to adapt the set of regional depots selected as bases among existing facilities (CBs) over the years. We applied the approach to a realistic problem instance, considering an appropriate time horizon (twenty years) and uncertainty (under several scenarios, in the number and location of fires, and in season severity).

The spatially explicit screening approach, created to find a high-quality flexible centralization solution for fire-fighting specialized vehicles, uses two models: a location model for the optimization of the spatial position of the FRDs, and a simulation model to address the uncertainty in the number of fires, and adapt the location of the FRDs in time, seeking to preserve security levels, while reducing costs by increasing vehicle utilization. To analyze the trade-off between the proximity of the depots to the fires, and the number of depots required, under fire location uncertainty, we use two-dimensional distributions of fire occurrences (obtained from historical data), with an Ornstein–Uhlenbeck process driving the global severity of the weather in each year of a 20-year simulation, under four macro scenarios.

The analysis confirms the safety of partial concentration with the proposed flexible design policy, with the distances run by vehicles kept within reasonable limits. It reduces substantially the number of required specialized vehicles (up to two thirds lower), and increases their utilization, with an increased access time in the range of 0 to 20 minutes (time regarded as how long in advance these kinds of vehicles should be deployed, rather than as a delay).

The proposed method can result in significant system-wide cost reductions maintaining similar levels of safety. In the case of the district of Porto, Portugal, the analysis showed that it would be possible to reduce the number of specialized vehicles by a factor of three and thus save over seven million euros of capital expenditure in this small geographical area, even without considering the annual reduction in operational costs. Although many of the vehicles of interest are purchased by the CBs themselves, using funds obtained from the populations they serve (through public collection of private donations), a substantial part of the amount needed to acquire such vehicles is subsidized by the State (through City Hall or EU funds). These savings should thus be viewed as an increase in the social surplus (total welfare or economic surplus) and not as direct savings.

Authorities may consider using this new design as part of a management plan for this type of specialized equipment, as it facilitates the modernization of the existing fleet. Indeed, the implementation of an FRD policy can be effected gradually, with neither great expense (no new firehouses) nor political upheaval (no closing of firehouses). It would proceed by locating newly acquired modern, replacement specialized equipment in the designated depots, while not replacing the obsolete equipment as local firehouses withdraw it from use (e.g., instead of responding to a subsidy request for a new vehicle, conditionally offering every year a set of new vehicles under this new public policy).

The firefighting sector is resilient to changes, which is desirable in some aspects but makes it difficult to implement new strategies. Indeed, such resilience would complicate the application of a strategy intended to move existing resources to new FRDs. Therefore, it is tactically favorable to combine both existing and new networks during the transition process.

The State already has a model for resource distribution among the CBs that takes into account the number of ignitions in each CB area. This model can be expanded to district scale in line with the centralization in regional depots. In addition, vehicle replacement should not be done automatically (e.g., the operational need should be verified, and the approval of any subsidies should be conditional upon a CB accepting that its vehicle might eventually be parked at a depot located in another CB) and the exemption of taxes should be revised, in order to promote vehicle retirement. Also, it is advisable to evaluate every year the best choice and number of FRDs required, using the last 3 to 8 years of historical deployment data (depending on the time that the vegetation needs to grow to be ready to burn again, in each district).

In summary, besides the novelty in the combination of optimization with simulation, our contribution for practitioners also includes (i) a method to randomly generate a spatially explicit ignitions pattern according to a two-dimensional distribution obtained from historical data, (ii) three scenarios that can be used to carry out sensitivity analysis of changes resulting from the WUI expansion (which can also be seen as a climate change scenario), increased surveillance, or law enforcement, (iii) a method to determine the maximum simultaneity of wildfires in a given time interval, and (iv) a method to dynamically choose new locations.

In general, our approach should be useful for other problems in which decentralization of resources drives inefficiency. Within fire-fighting, it could also be applied to the allocation of fire-fighting helicopters to existing heliports, the storage of fire-prevention agents, the allocation of suppression crews to CBs, and the rationalization of initial attack vehicles. Beyond these applications, it could also

be useful in the location of all kinds of emergency supplies, such as those to deploy for earthquakes, floods and other recurring disasters, contributing to address an important current problem in emergency supply-chain management. Future research could explore such extensions.

Future research could also explore the current limitations in the structure of the models, and in the data. The models, e.g., currently assume that the system can only deploy vehicles to areas within its jurisdiction. However, vehicles used in extended attack often travel to neighboring jurisdictions to collaborate in the extinction of large fires. Another limitation concerns the use of a maximum straight line distance, instead of a real distance run by vehicles, as a limit for the FRD influence area. Constraints imposing a realistic maximum number of deployments associated to each depot could also be added. Further work could benefit from the analysis of longer time series of the number of fires and vehicle deployments to improve the estimates of the spatial distribution of deployments, the mean reversion process, and straight-line to trip distance conversion parameters.

However, we should always carefully consider the trade-offs between model complexity and implementation challenges, i.e., by increasing the complexity of the models, more sophisticated approaches could amplify the implementation challenge, namely by decreasing practitioners' willingness to adopt, and increasing their resistance to change (Chaiken 1978; Lawless 1987), undermining desired policy shifts, as in the case of the frustrations associated to the practical impacts of the Fire Project in New York City (Green and Kolesar 2004).

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Supplementary material

Table S1: Planar coordinates (meters) of the candidate depot (CB) XY locations ("V." stands for "Volunteers").

	CB name	CB location X	CB location Y
1	Sapadores do Porto	159,698	466,092
2	V. Aguda	156,323	453,560
3	V. Amarante	204,234	478,175
4	V. Areosa	159,747	464,439
5	V. Avintes	164,074	460,604
6	V. Baião	207,974	465,810
7	V. Baltar	178,750	469,255
8	V. Carvalhos	163,245	455,116
9	V. Cête	181,031	467,050
10	V. Coimbrões	158,211	461,516
11	V. Crestuma	169,142	455,092
12	V. Entre-os-Rios	186,584	457,524
13	V. Ermesinde	165,029	472,100
14	V. Felgueiras	194,435	488,439
15	V. Freamunde	182,286	479,917
16	V. Gondomar	165,997	464,322
17	V. Leça do Balio	158,304	471,492
18	V. Leixões	153,737	469,132
19	V. Lixa	198,458	483,871
20	V. Lordelo	177,043	473,534
21	V. Lousada	187,540	478,829
22	V. Marco Canaveses	198,685	468,494
23	V. Matosinhos-Leça	153,148	469,349
24	V. Melres	177,702	454,452
25	V. Moreira da Maia	155,947	475,504
26	V. Paço de Sousa	182,061	466,267
27	V. Paços de Ferreira	179,598	478,648
28	V. Paredes	183,323	470,831
29	V. Penafiel	187,562	470,950
30	V. Póvoa do Varzim	147,265	490,244
31	V. Rebordosa	176,875	472,605
32	V. S. Mamede de Infesta	160,128	469,501
33	V. S. Pedro da Cova	168,893	465,224
34	V. S.ª Marinha do Zêzere	215,309	463,869
35	V. Santo Tirso	170,467	485,660
36	V. Tirsenses	171,210	485,871
37	V. Trofa	164,712	485,885
38	V. Valadares	158,056	458,689
39	V. Valbom	164,073	462,353
40	V. Valongo	169,315	468,941
41	V. Vila das Aves	176,998	488,455
42	V. Vila do Conde	148,298	487,100
43	V. Vila Meã	195,378	475,660
44	Sapadores de Gaia	161,155	461,040
45	V. Portuenses	157,320	466,990

Table S2: Number of fires, and new and simultaneous daily maximum numbers per type of fire, i.e., all fires, and only fires in which SE vehicles were utilized – SE fires (Porto district, 2003-05).

Type of fire	Number of fires	Daily maximum	
		new	simultaneous
All fires	19,281	186	209
SE fires	689 (3.6%)	18 (9.7%)	28 (13.4%)

Table S3: Number of SE deployments ($\#d$) to each XY location (planar coordinates, in meters) and the closest CB id (c); the CB ids are in the first column of supplementary Table S1.

	X	Y	$\#d$	c		X	Y	$\#d$	c		X	Y	$\#d$	c		X	Y	$\#d$	c
L1	167,061	474,034	23	13	L101	181,755	471,955	2	28	L201	161,636	454,973	1	8	L301	159,498	452,482	1	2
L2	183,365	469,021	21	28	L102	176,388	456,189	2	24	L202	184,467	469,689	1	28	L302	171,264	482,395	1	35
L3	180,192	470,798	16	7	L103	179,176	472,998	2	20	L203	170,502	465,398	1	33	L303	190,812	471,994	1	29
L4	177,787	455,682	14	24	L104	166,931	454,971	2	11	L204	200,018	469,416	1	22	L304	175,335	469,342	1	7
L5	158,276	454,968	13	2	L105	181,559	469,431	2	28	L205	183,967	469,342	1	28	L305	180,223	475,283	1	27
L6	172,394	471,545	13	40	L106	156,354	472,698	2	17	L206	166,469	471,346	1	13	L306	152,627	474,592	1	25
L7	156,862	472,984	12	17	L107	184,362	465,928	2	26	L207	177,315	468,485	1	7	L307	159,928	454,045	1	8
L8	151,033	476,715	12	25	L108	200,794	484,346	2	19	L208	157,567	452,501	1	2	L308	174,863	469,748	1	31
L9	176,730	469,028	11	7	L109	184,076	473,093	2	28	L209	169,203	470,583	1	40	L309	167,559	461,073	1	5
L10	175,879	457,210	11	24	L110	154,537	473,505	2	25	L210	183,636	466,763	1	26	L310	178,389	464,591	1	9
L11	188,421	473,402	9	29	L111	167,734	457,276	2	11	L211	155,013	468,036	1	18	L311	161,714	483,864	1	37
L12	184,333	463,546	9	26	L112	165,682	456,353	2	8	L212	165,458	473,729	1	13	L312	158,592	477,999	1	25
L13	165,670	468,548	9	13	L113	161,784	452,752	2	8	L213	163,647	473,068	1	13	L313	183,084	456,489	1	12
L14	173,683	464,423	9	33	L114	179,665	474,572	2	20	L214	153,381	471,021	1	23	L314	151,788	472,758	1	23
L15	153,177	468,545	8	23	L115	217,973	464,838	2	34	L215	164,939	455,082	1	8	L315	174,049	454,040	1	24
L16	155,357	471,281	8	18	L116	172,556	483,281	2	36	L216	169,460	484,286	1	35	L316	207,923	478,345	1	3
L17	159,485	478,665	8	25	L117	184,356	455,429	2	12	L217	209,723	465,807	1	6	L317	201,401	471,039	1	22
L18	158,650	471,627	7	17	L118	183,379	463,069	2	26	L218	159,793	458,459	1	38	L318	189,852	459,323	1	12
L19	178,598	473,948	7	20	L119	178,171	484,937	2	41	L219	157,587	452,310	1	2	L319	171,626	471,875	1	40
L20	210,008	467,983	7	6	L120	182,323	474,404	2	28	L220	157,703	468,759	1	45	L320	191,271	471,461	1	29
L21	173,020	488,412	7	36	L121	217,776	466,675	2	34	L221	157,586	473,208	1	17	L321	185,815	465,472	1	26
L22	178,977	467,834	6	7	L122	175,824	479,720	2	27	L222	209,120	467,333	1	6	L322	173,239	474,120	1	20
L23	179,946	465,748	6	9	L123	182,351	475,819	2	27	L223	158,296	468,896	1	32	L323	186,831	461,398	1	12
L24	156,023	468,706	6	45	L124	182,362	475,795	2	27	L224	187,088	459,387	1	12	L324	176,097	484,654	1	41
L25	173,062	484,452	6	36	L125	178,296	482,437	2	27	L225	177,795	490,216	1	41	L325	160,289	474,897	1	17
L26	168,078	472,127	6	13	L126	173,150	482,277	2	36	L226	187,872	480,757	1	21	L326	162,923	451,155	1	8
L27	164,040	450,973	6	8	L127	151,986	473,829	2	25	L227	176,959	475,509	1	20	L327	205,807	481,832	1	3
L28	173,840	464,628	6	33	L128	191,552	472,570	2	29	L228	176,776	469,515	1	7	L328	162,344	475,086	1	13
L29	187,630	462,614	6	12	L129	164,205	476,464	2	13	L229	177,633	478,321	1	27	L329	205,221	462,886	1	6
L30	182,217	460,380	6	12	L130	151,765	473,657	2	23	L230	175,039	473,658	1	20	L330	182,683	458,578	1	12
L31	178,524	454,169	5	24	L131	152,399	484,064	2	42	L231	186,210	459,510	1	12	L331	185,857	464,786	1	26
L32	180,011	467,473	5	9	L132	161,098	475,990	2	25	L232	177,530	490,408	1	41	L332	190,734	486,703	1	14
L33	180,408	468,015	5	9	L133	201,713	463,482	2	22	L233	174,926	473,221	1	31	L333	191,717	477,483	1	43
L34	154,736	469,718	5	18	L134	177,760	460,349	2	24	L234	154,012	471,236	1	23	L334	181,090	474,583	1	20
L35	164,241	469,986	5	13	L135	183,357	486,943	2	41	L235	189,235	469,705	1	29	L335	192,952	492,353	1	14
L36	171,539	457,095	5	11	L136	157,669	485,669	2	37	L236	196,474	483,178	1	19	L336	173,265	470,459	1	31
L37	184,157	474,866	5	28	L137	154,332	492,798	2	30	L237	185,680	471,886	1	29	L337	192,974	472,212	1	43
L38	164,073	462,353	4	39	L138	212,318	486,050	2	3	L238	164,244	465,482	1	16	L338	181,785	474,991	1	27
L39	168,893	465,224	4	33	L139	177,043	473,534	1	20	L239	180,271	465,083	1	9	L339	168,526	474,564	1	13
L40	164,223	454,878	4	8	L140	163,366	455,210	1	8	L240	185,142	469,718	1	28	L340	181,993	474,904	1	28
L41	169,426	467,697	4	40	L141	163,962	460,709	1	5	L241	156,522	470,314	1	17	L341	164,769	476,385	1	13
L42	180,036	469,322	4	7	L142	176,984	472,440	1	31	L242	169,828	487,699	1	35	L342	174,100	476,719	1	20
L43	183,566	465,887	4	26	L143	147,459	490,045	1	30	L243	178,900	456,249	1	24	L343	202,686	482,882	1	19
L44	166,868	466,451	4	16	L144	177,133	488,772	1	41	L244	162,298	457,070	1	8	L344	161,222	451,113	1	8
L45	155,549	471,588	4	17	L145	166,137	463,955	1	16	L245	156,261	470,749	1	17	L345	174,402	468,090	1	7
L46	153,885	473,475	4	25	L146	164,974	485,545	1	37	L246	166,935	473,168	1	13	L346	151,244	473,463	1	23
L47	155,321	471,609	4	18	L147	186,213	457,849	1	12	L247	167,780	453,373	1	11	L347	163,883	450,620	1	8
L48	181,567	475,615	4	27	L148	164,597	460,549	1	5	L248	162,325	457,114	1	8	L348	184,784	475,190	1	21
L49	184,363	463,417	4	26	L149	152,568	469,314	1	23	L249	209,292	467,713	1	6	L349	184,185	475,732	1	21
L50	152,113	474,405	4	25	L150	154,290	469,412	1	18	L250	179,358	473,250	1	20	L350	180,549	485,547	1	41
L51	173,375	469,316	4	40	L151	164,805	460,686	1	5	L251	149,639	489,103	1	42	L351	186,341	464,430	1	26
L52	159,357	478,096	4	25	L152	180,486	467,580	1	9	L252	217,176	465,473	1	34	L352	160,306	477,166	1	25
L53	161,177	475,217	4	17	L153	154,394	469,596	1	18	L253	183,950	468,432	1	28	L353	174,769	458,174	1	24
L54	170,532	460,750	4	33	L154	155,606	476,256	1	25	L254	171,613	467,973	1	40	L354	160,565	476,779	1	25
L55	148,171	497,750	4	30	L155	154,462	468,718	1	18	L255	155,404	470,994	1	18	L355	170,825	480,882	1	35
L56	181,084	465,713	3	26	L156	188,183	470,367	1	29	L256	160,701	458,528	1	44	L356	169,275	460,436	1	33
L57	152,391	470,368	3	23	L157	176,238	473,815	1	20	L257	158,530	454,902	1	2	L357	180,676	461,657	1	26
L58	183,379	466,217	3	26	L158	177,896	469,252	1	7	L258	178,962	475,301	1	20	L358	169,556	460,289	1	33
L59	170,630	484,324	3	35	L159	154,402	469,693	1	18	L259	184,317	464,957	1	26	L359	171,072	480,703	1	35
L60	177,614	470,481	3	7	L160	164,155	472,002	1	13	L260	210,303	467,000	1	6	L360	171,703	480,719	1	35
L61	154,826	470,494	3	18	L161	153,965	468,271	1	18	L261	175,653	456,108	1	24	L361	219,919	466,155	1	34
L62	194,568	490,353	3	14	L162	178,302	468,458	1	7	L262	169,947	488,258	1	35	L362	204,324	483,324	1	3
L63	180,679	469,677	3	7	L163	154,528	469,633	1	18	L263	167,601	452,902	1	11	L363	175,572	483,127	1	36
L64	178,671	474,772	3	20	L164	160,751	470,234	1	32	L264	180,862	471,912	1	28	L364	194,267	465,805	1	22
L65	167,680	467,256	3	40	L165	181,971	467,422	1	9	L265	185,782	472,969	1	29	L365	187,831	465,764	1	29
L66	181,225	472,397	3	28	L166	154,484	469,823	1	18	L266	158,499	455,162	1	2	L366	175,360	482,719	1	36
L67	188,599	459,305	3	12	L167	177,886	472,911	1	20	L267	196,370	482,150	1	19	L367	174,994	458,971	1	24

	X	Y	$\#d$	c
L68	165,756	469,272	3	13
L69	179,335	464,618	3	9
L70	155,068	472,595	3	25
L71	175,696	468,288	3	7
L72	181,790	462,945	3	26
L73	183,454	474,640	3	28
L74	190,486	467,003	3	29
L75	150,809	476,113	3	25
L76	189,285	463,407	3	12
L77	178,201	469,306	2	7
L78	158,361	462,164	2	10
L79	154,403	469,343	2	18
L80	164,206	472,049	2	13
L81	158,887	470,772	2	17
L82	157,739	470,729	2	17
L83	178,325	468,291	2	7
L84	154,462	469,964	2	18
L85	154,903	469,164	2	18
L86	159,596	470,544	2	32
L87	152,341	470,332	2	23
L88	175,652	472,203	2	31
L89	186,694	471,999	2	29
L90	208,181	464,386	2	6
L91	166,382	472,623	2	13
L92	159,698	471,075	2	17
L93	184,438	469,818	2	28
L94	181,735	464,778	2	26
L95	188,171	469,414	2	29
L96	166,815	471,822	2	13
L97	195,166	473,810	2	43
L98	167,439	469,059	2	40
L99	180,531	469,966	2	7
L100	178,864	474,152	2	20

	X	Y	$\#d$	c
L168	162,214	455,471	1	8
L169	176,056	487,901	1	41
L170	180,091	467,630	1	9
L171	158,313	459,771	1	38
L172	185,428	457,593	1	12
L173	155,414	476,546	1	25
L174	161,878	461,965	1	44
L175	175,945	474,021	1	20
L176	182,225	471,318	1	28
L177	179,499	468,284	1	7
L178	159,288	458,784	1	38
L179	188,692	470,441	1	29
L180	158,401	470,254	1	17
L181	178,734	470,502	1	7
L182	177,251	487,204	1	41
L183	188,132	472,118	1	29
L184	154,640	470,085	1	18
L185	184,580	470,439	1	28
L186	157,597	453,216	1	2
L187	178,876	479,812	1	27
L188	169,510	456,415	1	11
L189	184,449	471,623	1	28
L190	159,601	470,807	1	32
L191	181,599	464,936	1	26
L192	187,842	480,211	1	21
L193	160,600	462,360	1	44
L194	179,593	466,930	1	9
L195	156,416	468,162	1	45
L196	209,455	465,719	1	6
L197	154,676	470,367	1	18
L198	206,838	464,709	1	6
L199	154,748	470,368	1	18
L200	154,542	467,739	1	18

	X	Y	$\#d$	c
L268	174,931	486,652	1	41
L269	182,604	482,666	1	15
L270	162,879	469,824	1	32
L271	217,929	464,845	1	34
L272	171,494	470,739	1	40
L273	174,935	453,851	1	24
L274	188,509	455,415	1	12
L275	166,343	454,505	1	11
L276	164,020	474,810	1	13
L277	157,365	450,853	1	2
L278	184,931	466,688	1	26
L279	194,073	473,065	1	43
L280	174,902	453,621	1	24
L281	162,093	472,242	1	13
L282	178,522	465,462	1	9
L283	158,645	455,420	1	2
L284	185,942	473,473	1	29
L285	208,814	462,930	1	6
L286	161,519	472,165	1	32
L287	184,867	481,457	1	15
L288	195,513	483,248	1	19
L289	155,257	471,928	1	17
L290	168,373	487,936	1	35
L291	169,760	472,006	1	40
L292	191,371	487,812	1	14
L293	181,853	473,596	1	28
L294	172,004	464,624	1	33
L295	197,590	488,799	1	14
L296	159,141	455,660	1	38
L297	192,289	476,744	1	43
L298	212,252	462,679	1	34
L299	169,038	458,377	1	11
L300	178,488	464,885	1	9

	X	Y	$\#d$	c
L368	150,707	474,847	1	25
L369	211,903	469,368	1	6
L370	150,737	476,502	1	25
L371	182,298	460,934	1	26
L372	174,248	466,133	1	33
L373	172,877	477,159	1	20
L374	188,795	488,530	1	14
L375	215,886	469,504	1	34
L376	180,914	460,664	1	26
L377	158,442	480,662	1	25
L378	189,622	485,281	1	14
L379	150,393	477,201	1	25
L380	174,980	464,735	1	7
L381	182,944	487,703	1	41
L382	205,404	460,360	1	6
L383	192,848	466,977	1	22
L384	190,803	465,697	1	29
L385	202,662	462,363	1	6
L386	169,587	476,521	1	13
L387	161,683	478,410	1	25
L388	192,889	458,836	1	12
L389	185,722	485,497	1	15
L390	172,043	477,974	1	20
L391	156,066	482,223	1	25
L392	217,544	470,233	1	34
L393	171,329	477,514	1	20
L394	207,082	458,590	1	6
L395	205,206	458,964	1	6
L396	193,444	462,763	1	22
L397	159,635	491,777	1	37
L398	156,704	484,245	1	37
L399	146,818	499,352	1	30

Table S4: Number of SE deployments to each cell in the 5 km grid (basis of the "as-is" scenario). XY axes are in kilometers (planar coordinates).

Y	145	150	155	160	165	170	175	180	185	190	195	200	205	210	215
495	5	0	0	0	0	0	0	0	0	0	0	0	0	0	0
490	1	2	1	0	0	0	2	0	0	4	0	0	0	0	0
485	1	0	2	1	3	8	3	4	3	2	1	0	0	2	0
480	0	2	3	1	1	17	7	2	2	0	3	4	1	0	0
475	0	17	15	13	1	4	6	11	0	2	0	0	1	0	0
470	0	31	55	9	39	18	29	41	17	6	2	1	0	0	1
465	0	28	10	7	29	9	38	65	6	6	0	1	4	9	5
460	0	0	2	9	4	21	7	31	12	1	0	3	6	1	3
455	0	0	6	6	6	7	29	4	9	1	0	0	2	0	0
450	0	0	20	16	5	3	5	0	0	0	0	0	0	0	0

X

Table S5: Number of days with $0, \cdots, 6$ and > 6 (7 to 46) simultaneous SE deployments (#sd) in 2003-2005 for the Porto district, and corresponding probability function for the number of daily SE deployments.

	Number of days in			
#sd	2003	2004	2005	2003-05
0	290	294	230	814
1	37	31	34	102
2	16	15	25	56
3	4	8	16	28
4	4	3	8	15
5	4	5	5	14
6	6	2	4	12
> 6	4	8	43	55

	Probability of X			
	2003	2004	2005	2003-05
P(X=0)	0.795	0.803	0.630	0.743
P(X=1)	0.101	0.085	0.093	0.093
P(X=2)	0.044	0.041	0.068	0.051
P(X=3)	0.011	0.022	0.044	0.026
P(X=4)	0.011	0.008	0.022	0.014
P(X=5)	0.011	0.014	0.014	0.013
P(X=6)	0.016	0.005	0.011	0.011
P(X>6)	0.011	0.022	0.118	0.050

Table S6: Number of days with $0, \cdots, 6$ and > 6 (7 to 28) simultaneous SE deployments per SE fire (#sdf) in 2003-2005 for the Porto district, and corresponding probability function for the number of daily SE deployments to a SE fire (a fire in which SE vehicles were utilized).

	Number of days in			
#sdf	2003	2004	2005	2003-05
0	290	294	230	814
1	41	34	41	116
2	17	19	28	64
3	4	3	19	26
4	6	5	8	19
5	3	4	9	16
6	3	4	5	12
> 6	1	3	25	29

	Probability of Y			
	2003	2004	2005	2003-05
P(Y=0)	0.795	0.803	0.630	0.743
P(Y=1)	0.112	0.093	0.112	0.106
P(Y=2)	0.047	0.052	0.077	0.058
P(Y=3)	0.011	0.008	0.052	0.024
P(Y=4)	0.016	0.014	0.022	0.017
P(Y=5)	0.008	0.011	0.025	0.015
P(Y=6)	0.008	0.011	0.014	0.011
P(Y>6)	0.003	0.008	0.068	0.026

Table S7: Daily maximum number of new and simultaneous fires in which SE vehicles were utilized (SE fires), per deployment duration (Porto district, 2003-2005).

Deployment duration	Number of SE fires	SE fires, daily maximum	
		new	simultaneous
< 1h	87	4	4
< 2h	216	5	7
< 3h	290	7	8
< 4h	351	7	8
< 8h	479	10	10
< 12h	544	12	13
< 24h	627	16	19
All durations	689	18	28
≥ 1h	602	16	26
≥ 2h	473	15	25
≥ 3h	399	14	24
≥ 4h	338	11	21
≥ 8h	210	10	19
≥ 12h	145	10	17
≥ 24h	62	5	12

Table S8: Sets of selected depots for each $n \in \{1, \cdots, 16\}$, in the "as-is" scenario.

		Number of FRDs															
	CB name	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1	Sapadores do Porto	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2	V. Aguda	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
3	V. Amarante	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4	V. Areosa	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
5	V. Avintes	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
6	V. Baião	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1
7	V. Baltar	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
8	V. Carvalhos	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1
9	V. Cête	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0
10	V. Coimbrões	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
11	V. Crestuma	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
12	V. Entre-os-Rios	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1
13	V. Ermesinde	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1
14	V. Felgueiras	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
15	V. Freamunde	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
16	V. Gondomar	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
17	V. Leça do Balio	0	1	1	1	1	0	1	1	0	0	0	0	0	1	1	1
18	V. Leixões	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
19	V. Lixa	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	0
20	V. Lordelo	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
21	V. Lousada	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
22	V. Marco de Canaveses	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
23	V. Matosinhos-Leça	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1
24	V. Melres	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1
25	V. Moreira da Maia	0	0	0	0	0	1	0	0	1	1	1	1	1	1	1	1
26	V. Paço de Sousa	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1
27	V. Paços de Ferreira	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0
28	V. Paredes	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1
29	V. Penafiel	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
30	V. Póvoa do Varzim	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1
31	V. Rebordosa	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1
32	V. S. Mamede de Infesta	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
33	V. S. Pedro da Cova	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1
34	V. Santa Marinha do Zêzere	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
35	V. Santo Tirso	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
36	V. Tirsenses	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1
37	V. Trofa	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
38	V. Valadares	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
39	V. Valbom	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
40	V. Valongo	1	0	0	0	0	1	1	1	1	1	1	0	0	0	0	0
41	V. Vila das Aves	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
42	V. Vila do Conde	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
43	V. Vila Meã	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
44	Sapadores de Gaia	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
45	V. Portuenses	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Table S9: Selected set of depots for each $n \in \{1, \cdots, 16\}$, in the "WUI expansion" scenario.

	Number of FRDs															
CB name	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1 Sapadores do Porto	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2 V. Aguda	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
3 V. Amarante	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4 V. Areosa	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
5 V. Avintes	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
6 V. Baião	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1
7 V. Baltar	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
8 V. Carvalhos	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1
9 V. Cête	0	0	1	0	0	0	1	1	1	1	1	1	1	1	1	1
10 V. Coimbrões	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
11 V. Crestuma	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
12 V. Entre-os-Rios	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1
13 V. Ermesinde	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1
14 V. Felgueiras	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
15 V. Freamunde	0	0	0	0	0	0	1	0	0	0	1	1	0	0	0	0
16 V. Gondomar	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
17 V. Leça do Balio	0	1	1	1	1	0	0	0	1	1	1	0	0	0	0	0
18 V. Leixões	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
19 V. Lixa	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
20 V. Lordelo	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
21 V. Lousada	0	0	0	0	0	0	0	0	1	1	0	0	1	1	1	1
22 V. Marco de Canaveses	0	0	1	1	1	1	1	0	0	0	0	0	0	0	0	1
23 V. Matosinhos-Leça	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1
24 V. Melres	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1
25 V. Moreira da Maia	0	0	0	0	0	1	1	1	0	0	0	1	1	1	1	1
26 V. Paço de Sousa	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0	0
27 V. Paços de Ferreira	0	0	0	1	1	1	0	1	0	0	0	0	0	0	0	0
28 V. Paredes	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
29 V. Penafiel	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1
30 V. Póvoa do Varzim	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1
31 V. Rebordosa	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1
32 V. S. Mamede de Infesta	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
33 V. S. Pedro da Cova	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1
34 V. Santa Marinha do Zêzere	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
35 V. Santo Tirso	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
36 V. Tirsenses	0	0	0	0	0	0	0	0	1	1	0	1	1	1	1	1
37 V. Trofa	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
38 V. Valadares	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
39 V. Valbom	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
40 V. Valongo	0	0	0	0	0	1	1	1	1	1	1	1	1	0	0	0
41 V. Vila das Aves	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
42 V. Vila do Conde	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
43 V. Vila Meã	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	0
44 Sapadores de Gaia	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
45 V. Portuenses	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Table S10: Selected set of depots for each $n \in \{1, \cdots, 16\}$, in the "increased surveillance" scenario.

	Number of FRDs															
CB name	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1 Sapadores do Porto	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2 V. Aguda	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
3 V. Amarante	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4 V. Areosa	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
5 V. Avintes	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
6 V. Baião	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1
7 V. Baltar	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0
8 V. Carvalhos	0	0	0	1	0	1	1	1	1	1	1	1	1	1	1	1
9 V. Cête	0	1	0	0	0	0	0	0	0	0	0	0	0	1	1	0
10 V. Coimbrões	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
11 V. Crestuma	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
12 V. Entre-os-Rios	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1
13 V. Ermesinde	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1
14 V. Felgueiras	0	0	0	0	0	0	0	0	0	0	1	1	0	1	0	0
15 V. Freamunde	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
16 V. Gondomar	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
17 V. Leça do Balio	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
18 V. Leixões	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
19 V. Lixa	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	1
20 V. Lordelo	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
21 V. Lousada	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
22 V. Marco de Canaveses	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
23 V. Matosinhos-Leça	0	0	0	0	0	0	0	1	0	1	1	1	1	1	1	1
24 V. Melres	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1
25 V. Moreira da Maia	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1
26 V. Paço de Sousa	0	0	0	0	1	1	1	0	0	1	1	1	1	0	0	1
27 V. Paços de Ferreira	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	1
28 V. Paredes	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
29 V. Penafiel	0	0	0	0	0	0	0	0	1	0	1	1	1	1	1	1
30 V. Póvoa do Varzim	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1
31 V. Rebordosa	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1
32 V. S. Mamede de Infesta	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0
33 V. S. Pedro da Cova	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1
34 V. Santa Marinha do Zêzere	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
35 V. Santo Tirso	0	0	0	0	0	0	0	0	1	0	0	1	0	1	0	1
36 V. Tirsenses	0	0	0	0	0	0	0	0	0	1	1	0	1	0	1	0
37 V. Trofa	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
38 V. Valadares	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
39 V. Valbom	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
40 V. Valongo	1	0	0	0	0	1	1	1	0	0	0	0	0	0	0	0
41 V. Vila das Aves	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
42 V. Vila do Conde	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
43 V. Vila Meã	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
44 Sapadores de Gaia	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
45 V. Portuenses	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Table S11: Selected set of depots for each $n \in \{1, \cdots, 16\}$, in the "law enforcement" scenario.

	Number of FRDs															
CB name	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1 Sapadores do Porto	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2 V. Aguda	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
3 V. Amarante	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4 V. Areosa	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
5 V. Avintes	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
6 V. Baião	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1
7 V. Baltar	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
8 V. Carvalhos	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1
9 V. Cête	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0
10 V. Coimbrões	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
11 V. Crestuma	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
12 V. Entre-os-Rios	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1
13 V. Ermesinde	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1
14 V. Felgueiras	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	1
15 V. Freamunde	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
16 V. Gondomar	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
17 V. Leça do Balio	0	1	1	1	1	0	0	1	1	0	0	0	0	0	0	1
18 V. Leixões	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0
19 V. Lixa	0	0	0	0	0	0	0	0	1	1	0	1	1	1	0	0
20 V. Lordelo	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
21 V. Lousada	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
22 V. Marco de Canaveses	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
23 V. Matosinhos-Leça	0	0	0	0	0	0	0	0	0	1	1	1	1	0	1	1
24 V. Melres	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1
25 V. Moreira da Maia	0	0	0	0	0	1	1	0	0	1	1	1	1	1	1	1
26 V. Paço de Sousa	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1
27 V. Paços de Ferreira	0	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0
28 V. Paredes	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1
29 V. Penafiel	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1
30 V. Póvoa do Varzim	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1
31 V. Rebordosa	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1
32 V. S. Mamede de Infesta	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
33 V. S. Pedro da Cova	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1
34 V. Santa Marinha do Zêzere	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
35 V. Santo Tirso	0	0	0	0	0	0	0	0	0	1	0	1	1	1	0	1
36 V. Tirsenses	0	0	0	0	0	0	0	1	1	0	1	0	0	0	1	0
37 V. Trofa	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
38 V. Valadares	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
39 V. Valbom	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
40 V. Valongo	1	0	0	0	0	1	1	1	1	1	1	0	0	0	0	0
41 V. Vila das Aves	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
42 V. Vila do Conde	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
43 V. Vila Meã	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
44 Sapadores de Gaia	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
45 V. Portuenses	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Table S12: Optimization results: minimum total straight-line distance for $n = 1, \cdots, 16$.

		As-is	WUI expansion	Increased surveillance	Law Enforcement
Number of FRDs	1	12,623.60	17,258.96	10,523.12	10,801.97
	2	8,405.48	12,231.06	7,666.74	7,278.41
	3	7,427.18	10,431.72	6,627.80	6,377.07
	4	6,554.91	9,324.55	5,760.95	5,658.47
	5	5,787.61	8,327.48	5,037.04	4,981.89
	6	5,144.80	7,638.27	4,485.80	4,426.03
	7	4,804.43	7,183.01	4,139.16	4,135.30
	8	4,494.01	6,765.31	3,858.94	3,863.21
	9	4,236.45	6,405.62	3,619.46	3,624.26
	10	3,995.76	6,123.35	3,391.43	3,407.31
	11	3,799.51	5,845.04	3,184.87	3,247.67
	12	3,615.47	5,596.30	3,035.25	3,086.32
	13	3,474.30	5,367.67	2,894.72	2,961.52
	14	3,352.66	5,157.08	2,780.17	2,864.60
	15	3,232.39	4,976.67	2,663.25	2,764.79
	16	3,119.27	4,835.07	2,566.36	2,667.48
Maximum		12,624	17,259	10,523	10,802
Mean		5,254	7,717	4,515	4,509
Median		4,365	6,585	3,739	3,744
Minimum		3,119	4,835	2,566	2,667

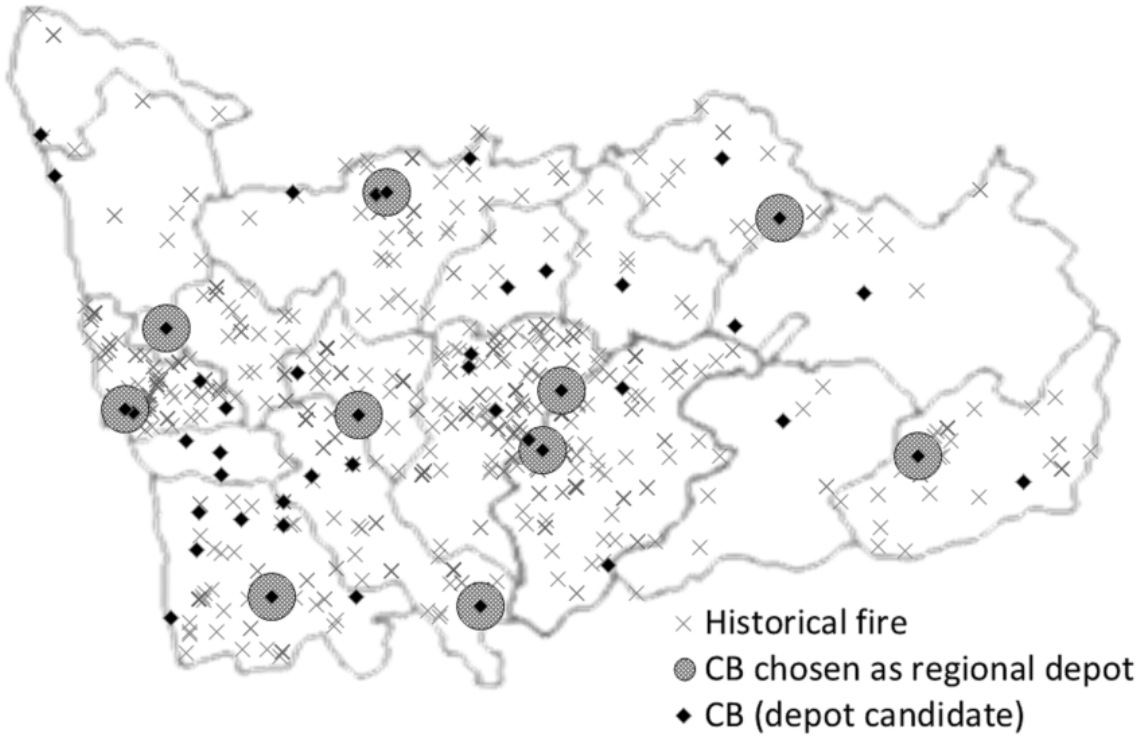


Fig. S1 Optimal set of FRDs, in the "as-is" scenario, for $n = 10$.

Table S13: Gains for the entire country extrapolated (a) proportionally by the number of CBs (criterion A1) and the size of the SE fleet (criterion A2), and (b) directly by the number and corresponding cost of each SE vehicle class (criterion B), from the gains estimated for the Porto district (€4.54 million) achieved with a 45.1% SE fleet (2005) reduction (cost of each SE vehicle class obtained from an expert).

		Criterion A1	Criterion A2	Criterion B
		proportional by		*directly by*
		# CBs	# SE vehicles	number/class value
Porto	number of	45	142	n. a.
	estimated	€ 4.54 million	€ 4.54 million	€ 4.54 million
Portugal	number of	434	1589	n.a.
	extrapolated	€ 43.8 million	€ 50.8 million	€ 52.72 million

Chapter 5

Intra-annual optimization of prevention and suppression investment mix under uncertainty

The most wonderful discovery
made by scientists is science itself.
Jacob Bronowski

6th paper (*submitted*)

Pacheco, Abílio Pereira, and João Claro. 2017. "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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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 for 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

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1 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 Australia, the countries of North America, and the Mediterranean Basin (Fernandes et al. 2016, Fischer et al. 2016, Lee et al. 2012), and raise complex challenges to FFM (Lee et al. 2012, O'Connor, Thompson, and Rodríguez y Silva 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 (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, Thompson, and Rodríguez y Silva 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, González-Cabán, and Englin 2001). The absence of adequate policies – e.g., on WUI expansion (Keiter 2012), or the traditional use of fire in land management (Tedim, Leone, and Xanthopoulos 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, Leone, and Xanthopoulos 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, Thompson, and Rodríguez y Silva 2016), e.g., between 2003-2012, in the US, 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.

1.1 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, Rudi, and Van Mieghem 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, de Neufville, and Geltner 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.

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, Rudi, and Van Mieghem 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.

1.2 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 from 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 tradeoffs 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 (2005), Pacheco (2011), and Chow and Regan (2011), and for the former, Minas, Hearne, and Martell (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 (2005) presented an integer programming model capable of addressing multiple simultaneous ignitions. Pacheco, Claro, and Oliveira (2012) 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, Hearne, and Martell (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 tradeoffs 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, Hearne, and Martell (2015), or Mercer, Haight, and Prestemon (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, Claro, and Oliveira 2014) 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 (i) suppression resources deployed and (ii) 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 tradeoffs 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, Haight, and Prestemon (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, Haight, and Prestemon (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 tradeoff 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, Hearne, and Martell (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 fifth section. All the parameters and results considered not to be essential for the reader are provided in appendices as supplementary material.

2 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 (i) fuel management and (ii) fire suppression preparedness.

Viewing flexibility as the ability to adapt to change (Chod, Rudi, and Van Mieghem 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, Rudi, and Van Mieghem 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:

- Suppression postponement and spatial flexibility to be substitutes. Higher postponement flexibility will decrease the value of spatial flexibility, as decisions made at a later stage will face lower uncertainty, and this reduces the value of spatial flexibility, which is only exercised at the beginning of the fire season.
- Higher postponement flexibility in fuel treatment reduces the value of suppression postponement flexibility. Each type of decision, when occurring at a later stage, can adapt to the earlier decision, and increase its value.
- On the other hand, there is a direct relationship of substitution between fuel treatment postponement flexibility and suppression spatial flexibility, with an argument similar to the relationship between suppression postponement and spatial flexibility.

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.

2.1 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 modelled 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.

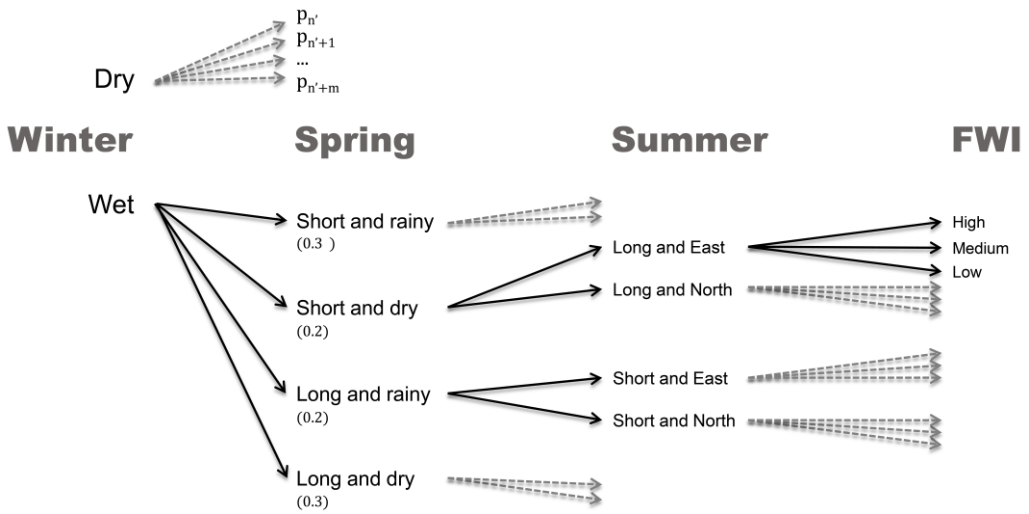


Fig. 1 Scenario tree – part related to intra-annual weather variability. $n', n'+1, \cdots, n'+m$ are $m+1$ nodes that share a same immediate ancestor, each with an assigned probability such that $p_{n'} + p_{n'+1} + \cdots + p_{n'+m} = 1$.

The micro-uncertainty is modelled 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.

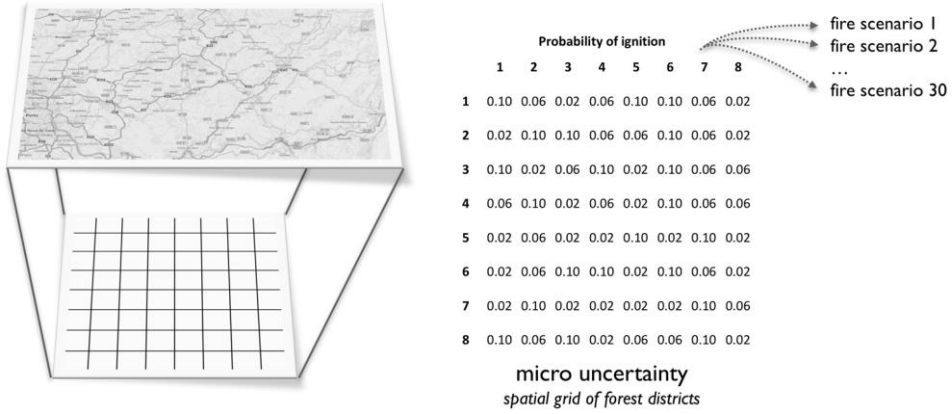


Fig. 2 Scenario tree – part related to the micro-uncertainty in fire occurrence, location, and severity.

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.

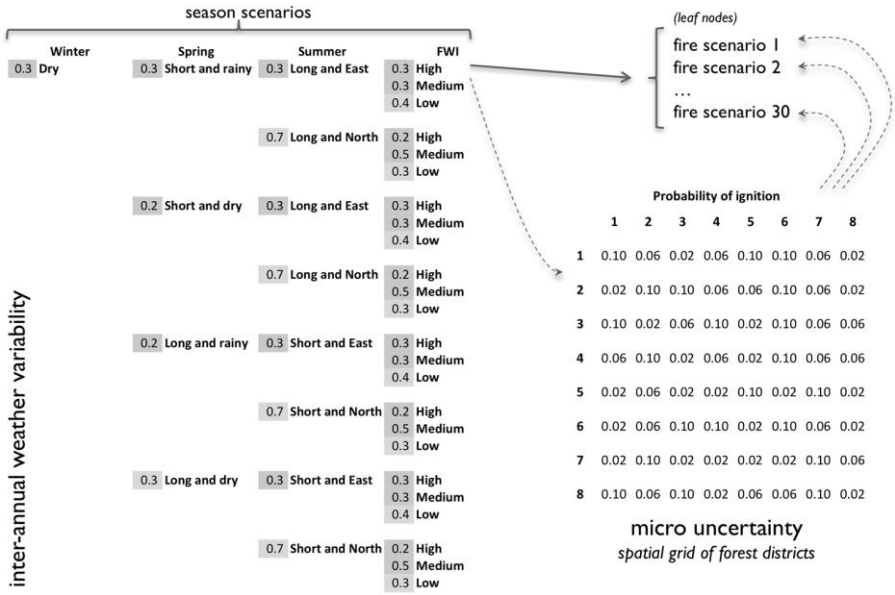


Fig. 3 Model uncertainty overview: scenario tree joining intra-annual weather variability with micro-uncertainty.

2.2 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 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 node n;

s, S index and set of fire season scenarios, i.e., parents (direct ancestors) of the leaf nodes in the scenario tree;

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} 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.

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

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

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

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

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

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

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

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

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

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

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

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 equations (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.

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.

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.

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.

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.

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).

2.3 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 sections 3.1 and 3.2, respectively). The values of the parameters for the test landscape are summarized in Table 1.

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 kilometers 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	$\#\mathrm{N} = 70$ (please see Fig. 4)
Set of fire season scenarios: S	$\#\mathrm{S} = 12$ (please see Fig. 4)
Set of fire scenarios: S′	$\#\mathrm{S}' = 48$ (please see Fig. 4)
Set of season scenarios (decision nodes): A	$\#\mathrm{A} = 10$ (please see Fig. 4)
Cost of contracting one unit of resource type r in node n: $\mathrm{c}^1_{\mathrm{rn}}$	€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: $\mathrm{c}^2_{\mathrm{i}}$	€8,000 (temporary stations) for any location
Extended cost of an escaped fire (containing, lost value and restoration) at location j: $\mathrm{c}^3_{\mathrm{j}}$	Equal in all locations; 4 and 12 million euros (Table 2, 3, 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 sections 3.1 and 3.2
Cost of treating location j in node n: $\mathrm{c}^0_{\mathrm{jn}}$	€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: $\mathrm{f}_{\mathrm{js}'}$	Ignitions location probability decreases from northwest to southeast 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: 5,000 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 ($\mathrm{d}_{\mathrm{r0}} = 0$): 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 ($\mathrm{v}_{\mathrm{qj0s}} = 1$): $\mathrm{v}_{\mathrm{qjks}}$	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: $\mathrm{O}_{\mathrm{rij}}$	Helicopters and ground crews cover the cell where they are located and all cells reachable within 15 minutes of travel time at a speed of 170 and 40 Km/h, respectively – please see Fig. 6

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 modelled using four fire scenarios for each season scenario. Furthermore, we chose not to consider any decisions in the fall season.

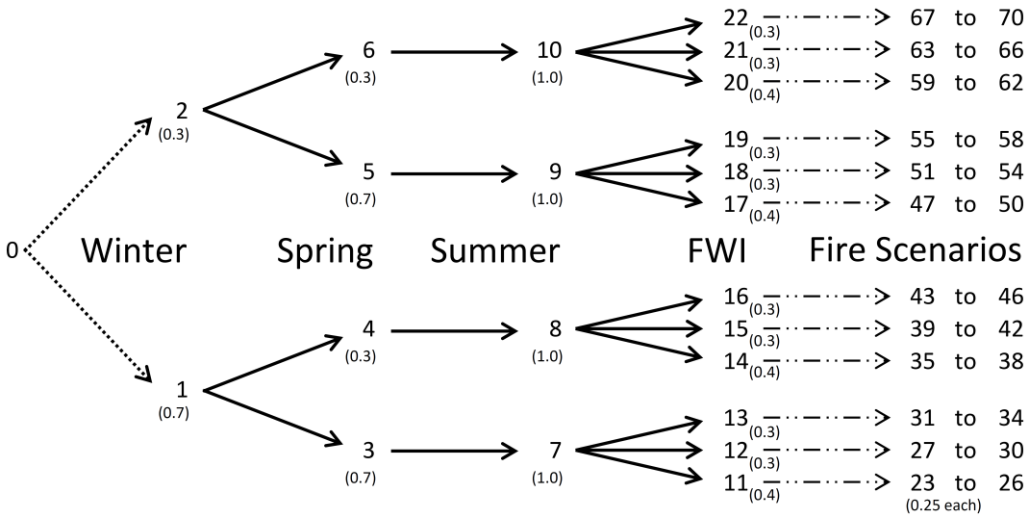


Fig. 4 Scenario tree used in the model proof of concept (please see also supplementary Table A4).

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, Claro, and Oliveira 2014) – 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 to 8 hours (90 minutes, 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 northwest to southeast 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).

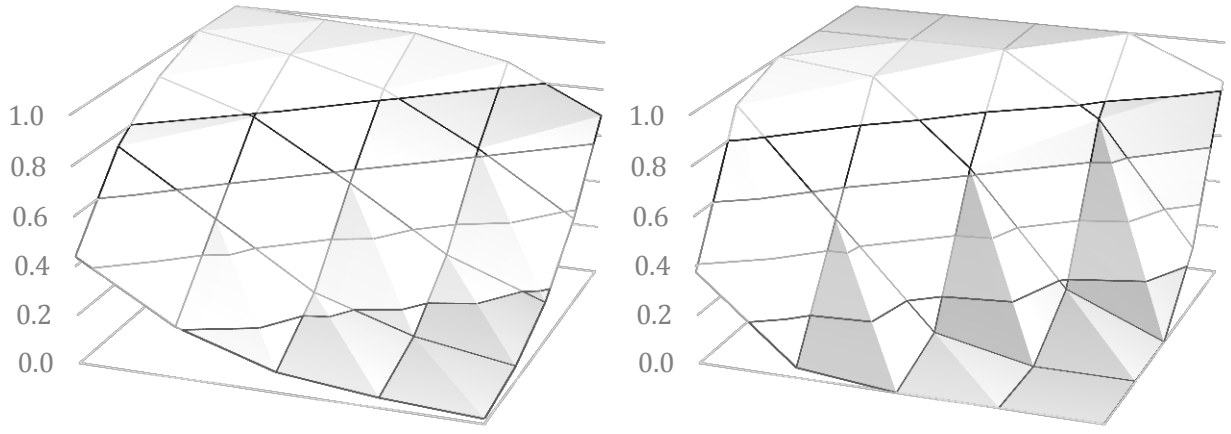


Fig. 5 Representation of the two sample (unconditional) probability distributions used to generate ignition locations (Table A5 and Table A6, respectively), with the same average, but different higher (left) and lower (right) volatilities, for the fire scenario total number of ignitions ($fstni$).

The fire escape probability is influenced by the season scenario, namely by the FWI (in the last stage of the fire season 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 minutes of travel time, considering speeds of 170 and 40 Km/h, respectively. Fig. 6 shows three examples of resource coverage.

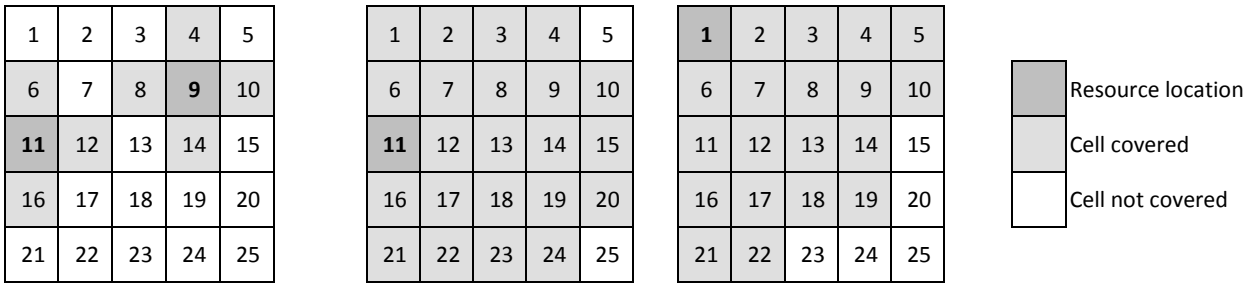


Fig. 6 Suppression resource 15 minute ranges (examples): cells covered by ground crews located in cells 11 and 9 (left) and cells covered by a helicopter located in cells 11 (middle) and 1 (right).

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, Claro, and Oliveira 2014, Pacheco et al. 2014).

Forest fires are a critical problem in Portugal. They account for more than half of the fires in the EU Mediterranean region (San-Miguel-Ayanz, Moreno, and Camia 2013) and over the years, the consequences of forest fires 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 two larger than 310,000 ha – please see the work of Fernandes et al. (2016) on the 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 resulting from forest fires. 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).

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 hours of flight at a cost of €788/h (an average utilization of about 7h 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 pre-existing 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 €2,500 for its preparation, and a maintenance cost of €60 per day, obtaining a rounded total of €8,000. 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 four 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., 1,000 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 €2,000 (€0.2/m^2), the cell value is €20,000,000 and an escaped fire would cause an EFeC of 2,000M/cell (where "thousands of euros" are denoted simply by "M"). Similarly to other costs, we consider the EFeC to be identical in all locations.

3 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_{is} are decided at the last moment (Summer; Fig. 4).

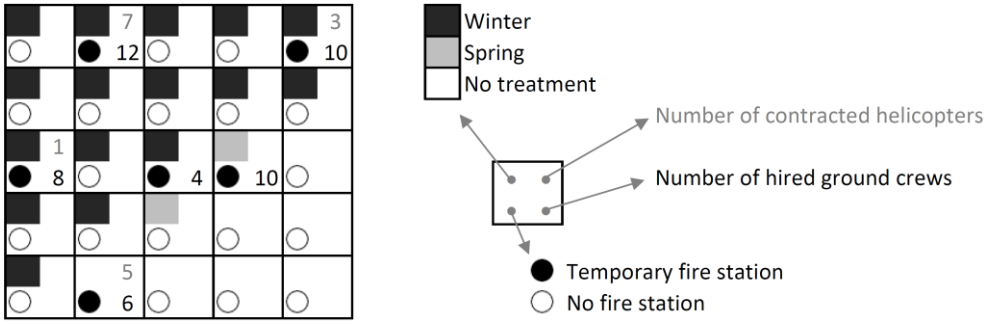


Fig. 7 Spatial view of the solution for branches 1 – 3, for an escaped fire extended cost (EFeC) of 12,000M, with lower volatility in the set of fire scenarios (see Table 3). For the solution with higher volatility, please see supplementary Fig. A1.

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 3.1 we start by analyzing how changes in EFeC and in the volatility of the demand (total number of ignitions in the fire scenarios) influence (i) the postponement of capacity investments along the year, (ii) the total expenditures, and the (iii) investment mix. The observation that the budget increases about proportionally to EFeC, leads us to further exploring this issue later, in section 3.2: 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.

3.1 Investment mix, volatility, $EFeC$, and flexibility

To model the volatility in weather conditions, we maintain the probabilities associated to 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 to the 12 fire season scenarios. As mentioned preciously (in section 2.3), 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 (4,000M and 12,000M, 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_{rn}^{1} 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.

Table 2 Budget allocation (absolute and percentage) for an escaped fire extended cost (EFeC) of 4,000M, 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%		83%	17%	
Suppression (helicopters)	--	--	58.7%	--	--	59.3%
Fire Stations	83%	17%		86%	14%	

Table 3 Budget allocation (absolute and percentage) for an escaped fire extended cost (EFeC) of 12,000M, 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%		89%	11%	
Suppression (helicopters)	87%	13%	87.3%	78%	22%	87.2%
Fire Stations	83%	17%		86%	14%	

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 to 46 (59 to 70) feature less ignitions than fire scenarios 23 to 34 (47 to 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), 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 4,375M (Table 4) to 14,216M (Table 5), and from 5,693M (Table 4) to 17,319M (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 4 Budget allocation decisions in 1 (Winter) and 3 (Spring) for an escaped fire extended cost (EFeC) of 4,000M (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	1,600.00	208.00	1,808.00	1,900.00	416.00	2,316.00
Suppression (ground crews)	2,244.00	274.56	2,518.56	2,772.00	549.12	3,321.12
Suppression (helicopters)	0.00	0.00	0.00	0.00	0.00	0.00
Fire Stations	40.00	8.00	48.00	48.00	8.00	56.00
Suppression total	2,284.00	282.56	2,566.56	2,820.00	557.12	3,377.12
Total (prevention + suppression)	3,884.00	490.56	4,374.56	4,720.00	973.12	5,693.12
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 12,000M (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	1,600.00	208.00	1,808.00	1,800.00	416.00	2,216.00
Suppression (ground crews)	1,012.00	91.52	1,103.52	1,452.00	183.04	1,635.04
Suppression (helicopters)	9,800.00	1,456.00	11,256.00	10,500.00	2,912.00	13,412.00
Fire Stations	40.00	8.00	48.00	48.00	8.00	56.00
Suppression total	10,852.00	1,555.52	12,407.52	12,000.00	3,103.04	15,103.04
Total (prevention + suppression)	12,452.00	1,763.52	14,215.52	13,800.00	3,519.04	17,319.04
Ratio (suppression/prevention)	6.78	7.48	6.86	6.67	7.46	6.82

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 3,439M to 10,832M for the lower volatility, and from 3,821M to 10,551M 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 1, 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.

(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 (744M vs 132M), as it involves the hiring of one helicopter (1x700M) and two ground crews (2x22M) instead of six ground crews (6x22M). 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).

Table 6 Summary of total budget (please see Table 4, Table 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)	
	4,000M		12,000M		C4 to C12		Low to High	
	Low	High	Low	High	Low	High	C4	C12
2-6	2,948	2,848	9,068	7,032	3.1	2.5	1.0	0.8
2-5	3,439	3,821	10,832	10,551	3.2	2.8	1.1	1.0
1-4	3,884	4,720	12,452	13,800	3.2	2.9	1.2	1.1
1-3	4,375	5,693	14,216	17,319	3.2	3.0	1.3	1.2
0-2-5	3,326	3,713	10,484	10,282	3.2	2.8	1.1	1.0
0-1-3	4,262	5,585	13,868	17,050	3.3	3.1	1.3	1.2
0 (fall)	2,836	2,740	8,720	6,763	3.1	2.5	1.0	0.8

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

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 consequence of the shift from no investment to a large investment in helicopters.

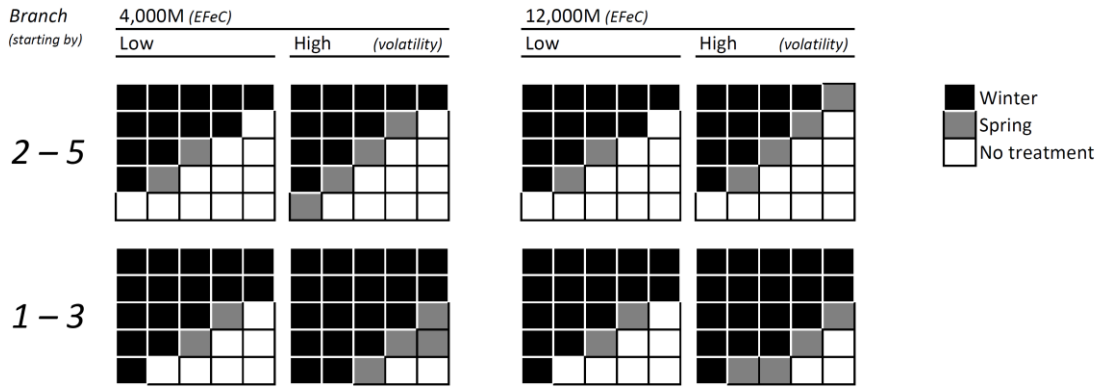


Fig. 8 Spatial view of the cells chosen for the application of fuel treatments in winter and spring, in the two branches of the test landscape, for a low and a high volatility in the set of fire scenarios, with a fire escape extended cost of 4 and 12 thousands euros (see Table A10, for the number of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

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% to 57% reduction) but their weight in the budget (Table 4, Table 5, Table A7, and Table A8) is reduced from 58% to about 1/7 to 1/5 (13% to 21%) of the total budget – a proportion roughly 1/3 lower.

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% to 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% to 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.

3.2 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 (§1), 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 6,490 (€/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 6,490 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 section 2.3 above, are of about €10,804/ha (€1.08/m^2).

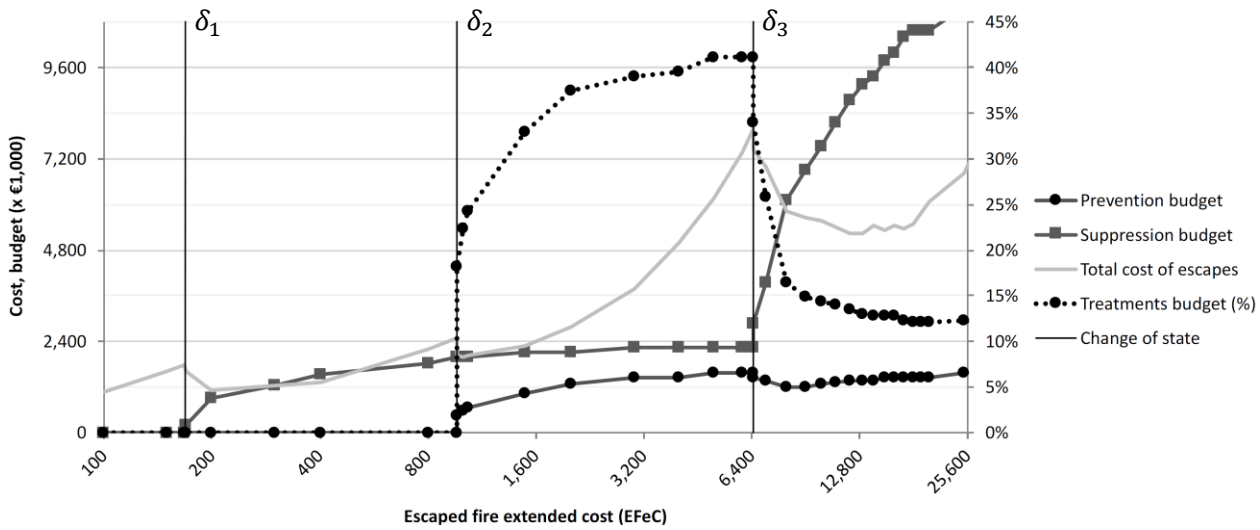


Fig. 9. Global system behavior (high volatility) and stages (*let burn*, *no prevention*, *prevention focus*, and *suppression dominance*) according to the hectare value or escaped forest fire loss (M) – please see supplementary Table A11; horizontal axis with log-transformed values (base 2) – for a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

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 1,600, 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 2, start at (Table 1) 100M, 140M ($6 \times 22\text{M} + 1 \times 8\text{M}$), and 752M ($1 \times 700\text{M} + 2 \times 22\text{M} + 1 \times 8\text{M}$), respectively. As observed previously, the interactions between the options complicate this analysis.

In the lowest system stage (or region), for an EFeC $< \delta_1$, 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 ($[\delta_1, \delta_2[$), 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 ($[\delta_2, \delta_3[$), 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 $\geq \delta_3$, 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: 1,382 and 1,465 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 to the optimal portfolio mix. Unless society is willing to pay a suboptimal price, there will always exist some (positive) expected burnt area.

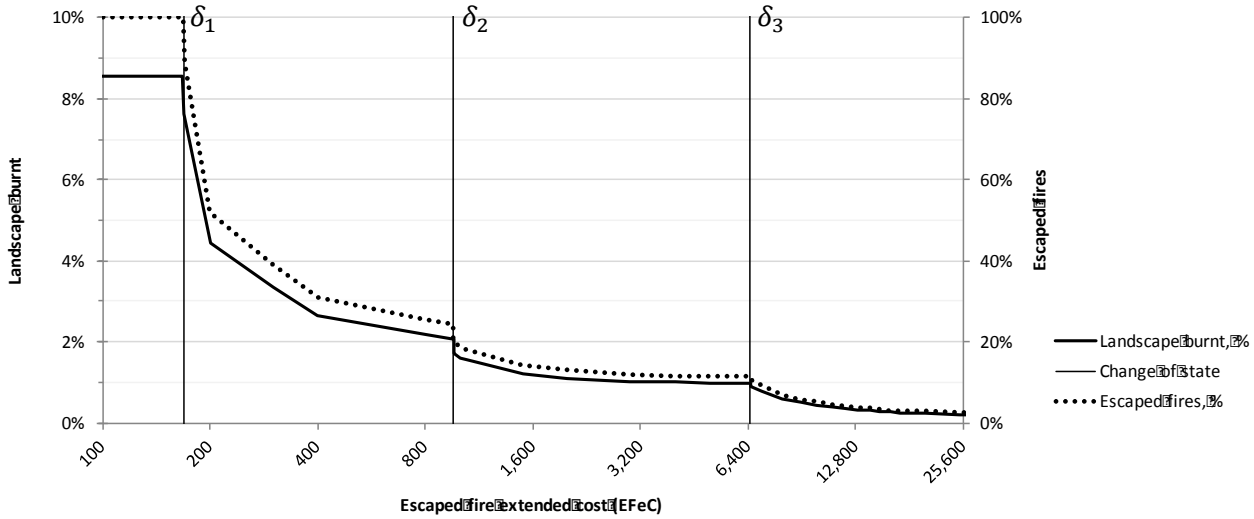


Fig. 10. Socioecological context and changes in the percentage of landscape burnt and escaped fires (high volatility), as EFeC rises (values in supplementary Table A11) – horizontal axis with log-transformed values (base 2).

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 50,000M). 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 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 to 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.

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[1)] %	100	88.9 to 24.2 (22.6)	19.9 (14.6) to 11.5 (10.8)	10.7 (10.2) to 2.36[2)]
Landscape burnt[1)] %	8.6 (9.7)	7.6 to 2.1 (2.2)	1.7 (1.4) to 1.0	0.9 (1.0) to 0.20 (0.23)[2)]
	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. & services Birch logs Sawlogs	Non-market resources[3)] 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)

1) lower volatility values within brackets; 2) at an EFeC of 50,000 (20,000); 3) cultural heritage, ecological values, and others.

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" (€1,435/ha), and ISA (2005) for the "value losses" in "timber products" (€917/stand-ha), "non-timber products" (€1,045/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 signifcantly 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).

4 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 (§3.1), how the optimal investment mix responds to weather volatility and the values at risk (EFeC), through system-endogenous flexibilities, and then (§3.2), how the optimal budget composition changes as the values at risk rise.

We found that (i) 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; (ii) 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 (iii) 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 §3.1, 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 §3.2. 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.

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.

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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Appendix A (Supplementary material)

Table A1 Budget allocation (absolute and percentage) for an escaped fire extended cost (EFeC) of 4,000M, with low and high volatility in the set of fire scenarios, overall and per decision node (Winter and Spring) – branch 2-5 (for branch 1-3, please see Table 2).

Portfolio options	Volatility					
	Low			High		
	Winter [2]	Spring [5]	Total	Winter [2]	Spring [5]	Total
Fuel treatments	12	2	14	11	4	15
Suppression (ground crews)	78	12	90	78	24	102
Suppression (helicopters)	0	0	0	0	0	0
Fire Stations	4	1	5	4	1	5
	Investment balance		*Bdgt Prt*	*Investment balance*		*Bdgt Prt*
Fuel treatments	85%	15%	40.9%	73%	27%	39.7%
Suppression (ground crews)	86%	14%		76%	24%	
Suppression (helicopters)	--	--	59.1%	--	--	60.3%
Fire Stations	80%	20%		80%	20%	

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

Portfolio options	Volatility					
	Low			High		
	Winter [2]	Spring [5]	Total	Winter [2]	Spring [5]	Total
Fuel treatments	12	2	14	10	4	14
Suppression (ground crews)	38	4	42	50	8	58
Suppression (helicopters)	10	2	12	7	4	11
Fire Stations	4	1	5	4	1	5
	Investment balance		*Bdgt Prt*	*Investment balance*		*Bdgt Prt*
Fuel treatments	85%	15%	13.0%	71%	29%	13.4%
Suppression (ground crews)	90%	10%		86%	14%	
Suppression (helicopters)	83%	17%	87.0%	63%	37%	86.6%
Fire Stations	80%	20%		80%	20%	

Table A3 The escape probability is the same in all locations for all scenarios and by definition, always 1 for dispatch class 0; it decreases by a half if a cell is treated and a fifth if class 2 (instead of 1) is dispatched; as the FWI change from “low” to “medium” or “high”, the escape probability grow by a factor of 1.3 or 2, respectively.

Types of treatment	Dispatch class					
	K=1			K=2		
	FWI scenario			FWI scenario		
	High	Medium	Low	High	Medium	Low
without treatment (q=0)	0.3000	0.1950	0.1500	0.0600	0.0390	0.0300
treated (q=1)	0.1500	0.0975	0.0750	0.0300	0.0195	0.0150

Table A4 Fire season, fire, and overall season scenarios probabilities with the individual fire scenario identification ("Id") which is useful for reading Table A5 and Table A6).

	Fire season scenarios probability					Fire scenario	Season
Id	Winter	Spring	Summer	FWI		probability	probability
23	0.3	0.3	1	0.3	(high).	0.25	0.00675
24	0.3	0.3	1	0.3		0.25	0.00675
25	0.3	0.3	1	0.3		0.25	0.00675
26	0.3	0.3	1	0.3		0.25	0.00675
27	0.3	0.3	1	0.3	(medium).	0.25	0.00675
28	0.3	0.3	1	0.3		0.25	0.00675
29	0.3	0.3	1	0.3		0.25	0.00675
30	0.3	0.3	1	0.3		0.25	0.00675
31	0.3	0.3	1	0.4	(low).	0.25	0.009
32	0.3	0.3	1	0.4		0.25	0.009
33	0.3	0.3	1	0.4		0.25	0.009
34	0.3	0.3	1	0.4		0.25	0.009
35	0.3	0.7	1	0.3	(high).	0.25	0.01575
36	0.3	0.7	1	0.3		0.25	0.01575
37	0.3	0.7	1	0.3		0.25	0.01575
38	0.3	0.7	1	0.3		0.25	0.01575
39	0.3	0.7	1	0.3	(medium).	0.25	0.01575
40	0.3	0.7	1	0.3		0.25	0.01575
41	0.3	0.7	1	0.3		0.25	0.01575
42	0.3	0.7	1	0.3		0.25	0.01575
43	0.3	0.7	1	0.4	(low).	0.25	0.021
44	0.3	0.7	1	0.4		0.25	0.021
45	0.3	0.7	1	0.4		0.25	0.021
46	0.3	0.7	1	0.4		0.25	0.021
47	0.7	0.3	1	0.3	(high).	0.25	0.01575
48	0.7	0.3	1	0.3		0.25	0.01575
49	0.7	0.3	1	0.3		0.25	0.01575
50	0.7	0.3	1	0.3		0.25	0.01575
51	0.7	0.3	1	0.3	(medium).	0.25	0.01575
52	0.7	0.3	1	0.3		0.25	0.01575
53	0.7	0.3	1	0.3		0.25	0.01575
54	0.7	0.3	1	0.3		0.25	0.01575
55	0.7	0.3	1	0.4	(low).	0.25	0.021
56	0.7	0.3	1	0.4		0.25	0.021
57	0.7	0.3	1	0.4		0.25	0.021
58	0.7	0.3	1	0.4		0.25	0.021
59	0.7	0.7	1	0.3	(high).	0.25	0.03675
60	0.7	0.7	1	0.3		0.25	0.03675
61	0.7	0.7	1	0.3		0.25	0.03675
62	0.7	0.7	1	0.3		0.25	0.03675
63	0.7	0.7	1	0.3	(medium).	0.25	0.03675
64	0.7	0.7	1	0.3		0.25	0.03675
65	0.7	0.7	1	0.3		0.25	0.03675
66	0.7	0.7	1	0.3		0.25	0.03675
67	0.7	0.7	1	0.4	(low).	0.25	0.049
68	0.7	0.7	1	0.4		0.25	0.049
69	0.7	0.7	1	0.4		0.25	0.049
70	0.7	0.7	1	0.4		0.25	0.049

Table A5 Ignitions location in all fire scenarios for the test landscape with an higher standard deviation (5.71); please see the "Id" meaning in Table A4; "$fstni$" stand for "fire scenario total number of ignitions" – for the test landscape with the same average (13.5) but a lower standard deviation (2.84), please see Table A6.

		Fire locations (j)																									
		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	
Id	FWI	Ignition Yes/No (1/0)																									$fstni$
23	(high).	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	25
24		1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	24
25		1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	23
26		1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	0	0	22
27	(medium).	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	0	0	0	21
28		1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	1	1	0	0	0	20
29		1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	0	0	1	1	0	0	0	19
30		1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	0	0	1	0	0	0	0	18
31	(low).	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	0	0	0	1	0	0	0	0	17
32		1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	1	1	0	0	0	1	0	0	0	0	16
33		1	1	1	1	1	1	1	1	1	0	1	1	1	0	0	1	1	0	0	0	1	0	0	0	0	15
34		1	1	1	1	1	1	1	1	1	0	1	1	1	0	0	1	1	0	0	0	0	0	0	0	0	14
35	(high).	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	0	0	0	21
36		1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	1	1	0	0	0	20
37		1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	0	0	1	1	0	0	0	19
38		1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	0	0	1	0	0	0	0	18
39	(medium).	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	0	0	0	1	0	0	0	0	17
40		1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	1	1	0	0	0	1	0	0	0	0	16
41		1	1	1	1	1	1	1	1	1	0	1	1	1	0	0	1	1	0	0	0	1	0	0	0	0	15
42		1	1	1	1	1	1	1	1	1	0	1	1	1	0	0	1	1	0	0	0	0	0	0	0	0	14
43	(low).	1	1	1	1	1	1	1	1	1	0	1	1	1	0	0	1	0	0	0	0	0	0	0	0	0	13
44		1	1	1	1	1	1	1	1	1	0	1	1	0	0	0	1	0	0	0	0	0	0	0	0	0	12
45		1	1	1	1	1	1	1	1	0	0	1	1	0	0	0	1	0	0	0	0	0	0	0	0	0	11
46		1	1	1	1	0	1	1	1	0	0	1	1	0	0	0	1	0	0	0	0	0	0	0	0	0	10
47	(high).	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	0	0	0	1	0	0	0	0	17
48		1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	1	1	0	0	0	1	0	0	0	0	16
49		1	1	1	1	1	1	1	1	1	0	1	1	1	0	0	1	1	0	0	0	1	0	0	0	0	15
50		1	1	1	1	1	1	1	1	1	0	1	1	1	0	0	1	1	0	0	0	0	0	0	0	0	14
51	(medium).	1	1	1	1	1	1	1	1	1	0	1	1	1	0	0	1	0	0	0	0	0	0	0	0	0	13
52		1	1	1	1	1	1	1	1	1	0	1	1	0	0	0	1	0	0	0	0	0	0	0	0	0	12
53		1	1	1	1	1	1	1	1	0	0	1	1	0	0	0	1	0	0	0	0	0	0	0	0	0	11
54		1	1	1	1	0	1	1	1	0	0	1	1	0	0	0	1	0	0	0	0	0	0	0	0	0	10
55	(low).	1	1	1	1	0	1	1	1	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	9
56		1	1	1	1	0	1	1	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	8
57		1	1	1	1	0	1	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	7
58		1	1	1	0	0	1	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	6
59	(high).	1	1	1	1	1	1	1	1	1	0	1	1	1	0	0	1	0	0	0	0	0	0	0	0	0	13
60		1	1	1	1	1	1	1	1	1	0	1	1	0	0	0	1	0	0	0	0	0	0	0	0	0	12
61		1	1	1	1	1	1	1	1	0	0	1	1	0	0	0	1	0	0	0	0	0	0	0	0	0	11
62		1	1	1	1	0	1	1	1	0	0	1	1	0	0	0	1	0	0	0	0	0	0	0	0	0	10
63	(medium).	1	1	1	1	0	1	1	1	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	9
64		1	1	1	1	0	1	1	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	8
65		1	1	1	1	0	1	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	7
66		1	1	1	0	0	1	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	6
67	(low).	1	1	1	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5
68		1	1	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4
69		1	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3
70		1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2

Table A6 Ignitions location in all fire scenarios for the test landscape with a lower standard deviation (2.84); please see the "Id" meaning in Table A4; "$fstni$" stand for "fire scenario total number of ignitions" – for the test landscape with the same average (13.5) but an higher standard deviation (5.71), please see Table A5.

		Fire locations (j)																									
		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	
Id	FWI	Ignition Yes/No (1/0)																									$fstni$
23		1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	0	0	1	1	0	0	0	19
24		1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	0	0	1	1	0	0	0	19
25	(high).	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	0	0	1	0	0	0	0	18
26		1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	0	0	1	0	0	0	0	18
27		1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	0	0	0	1	0	0	0	0	17
28	(medium).	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	0	0	0	1	0	0	0	0	17
29		1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	1	1	0	0	0	1	0	0	0	0	16
30		1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	1	1	0	0	0	1	0	0	0	0	16
31		1	1	1	1	1	1	1	1	1	0	1	1	1	0	0	1	1	0	0	0	1	0	0	0	0	15
32		1	1	1	1	1	1	1	1	1	0	1	1	1	0	0	1	1	0	0	0	1	0	0	0	0	15
33	(low).	1	1	1	1	1	1	1	1	1	0	1	1	1	0	0	1	1	0	0	0	0	0	0	0	0	14
34		1	1	1	1	1	1	1	1	1	0	1	1	1	0	0	1	1	0	0	0	0	0	0	0	0	14
35		1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	0	0	0	1	0	0	0	0	17
36		1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	0	0	0	1	0	0	0	0	17
37	(high).	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	1	1	0	0	0	1	0	0	0	0	16
38		1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	1	1	0	0	0	1	0	0	0	0	16
39		1	1	1	1	1	1	1	1	1	0	1	1	1	0	0	1	1	0	0	0	1	0	0	0	0	15
40	(medium).	1	1	1	1	1	1	1	1	1	0	1	1	1	0	0	1	1	0	0	0	1	0	0	0	0	15
41		1	1	1	1	1	1	1	1	1	0	1	1	1	0	0	1	1	0	0	0	0	0	0	0	0	14
42		1	1	1	1	1	1	1	1	1	0	1	1	1	0	0	1	1	0	0	0	0	0	0	0	0	14
43		1	1	1	1	1	1	1	1	1	0	1	1	1	0	0	1	0	0	0	0	0	0	0	0	0	13
44		1	1	1	1	1	1	1	1	1	0	1	1	1	0	0	1	0	0	0	0	0	0	0	0	0	13
45	(low).	1	1	1	1	1	1	1	1	1	0	1	1	0	0	0	1	0	0	0	0	0	0	0	0	0	12
46		1	1	1	1	1	1	1	1	1	0	1	1	0	0	0	1	0	0	0	0	0	0	0	0	0	12
47		1	1	1	1	1	1	1	1	1	0	1	1	1	0	0	1	1	0	0	0	1	0	0	0	0	15
48		1	1	1	1	1	1	1	1	1	0	1	1	1	0	0	1	1	0	0	0	1	0	0	0	0	15
49	(high).	1	1	1	1	1	1	1	1	1	0	1	1	1	0	0	1	1	0	0	0	0	0	0	0	0	14
50		1	1	1	1	1	1	1	1	1	0	1	1	1	0	0	1	1	0	0	0	0	0	0	0	0	14
51		1	1	1	1	1	1	1	1	1	0	1	1	1	0	0	1	0	0	0	0	0	0	0	0	0	13
52	(medium).	1	1	1	1	1	1	1	1	1	0	1	1	1	0	0	1	0	0	0	0	0	0	0	0	0	13
53		1	1	1	1	1	1	1	1	1	0	1	1	0	0	0	1	0	0	0	0	0	0	0	0	0	12
54		1	1	1	1	1	1	1	1	1	0	1	1	0	0	0	1	0	0	0	0	0	0	0	0	0	12
55		1	1	1	1	1	1	1	1	0	0	1	1	0	0	0	1	0	0	0	0	0	0	0	0	0	11
56		1	1	1	1	1	1	1	1	0	0	1	1	0	0	0	1	0	0	0	0	0	0	0	0	0	11
57	(low).	1	1	1	1	0	1	1	1	0	0	1	1	0	0	0	1	0	0	0	0	0	0	0	0	0	10
58		1	1	1	1	0	1	1	1	0	0	1	1	0	0	0	1	0	0	0	0	0	0	0	0	0	10
59		1	1	1	1	1	1	1	1	1	0	1	1	1	0	0	1	0	0	0	0	0	0	0	0	0	13
60		1	1	1	1	1	1	1	1	1	0	1	1	1	0	0	1	0	0	0	0	0	0	0	0	0	13
61	(high).	1	1	1	1	1	1	1	1	1	0	1	1	0	0	0	1	0	0	0	0	0	0	0	0	0	12
62		1	1	1	1	1	1	1	1	1	0	1	1	0	0	0	1	0	0	0	0	0	0	0	0	0	12
63		1	1	1	1	1	1	1	1	0	0	1	1	0	0	0	1	0	0	0	0	0	0	0	0	0	11
64	(medium).	1	1	1	1	1	1	1	1	0	0	1	1	0	0	0	1	0	0	0	0	0	0	0	0	0	11
65		1	1	1	1	0	1	1	1	0	0	1	1	0	0	0	1	0	0	0	0	0	0	0	0	0	10
66		1	1	1	1	0	1	1	1	0	0	1	1	0	0	0	1	0	0	0	0	0	0	0	0	0	10
67		1	1	1	1	0	1	1	1	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	9
68		1	1	1	1	0	1	1	1	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	9
69	(low).	1	1	1	1	0	1	1	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	8
70		1	1	1	1	0	1	1	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	8

Table A7 Budget allocation decisions in 2 (Winter) and 5 (Spring) for an escaped fire extended cost (EFeC) of 4,000M (values in thousands of euros, M) – for branches starting with 1-3, please see Table 4.

Portfolio options	Volatility					
	Low			High		
	Winter	Spring	Total	Winter	Spring	Total
Fuel treatments	1,200.00	208.00	1,408.00	1,100.00	416.00	1,516.00
Suppression (ground crews)	1,716.00	274.56	1,990.56	1,716.00	549.12	2,265.12
Suppression (helicopters)	0.00	0.00	0.00	0.00	0.00	0.00
Fire Stations	32.00	8.00	40.00	32.00	8.00	40.00
Suppression total	1,748.00	282.56	2,030.56	1,748.00	557.12	2,305.12
Total (prevention + suppression)	2,948.00	490.56	3,438.56	2,848.00	973.12	3,821.12
Ratio (suppression/prevention)	1.46	1.36	1.44	1.59	1.34	1.52

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

Portfolio options	Volatility					
	Low			High		
	Winter	Spring	Total	Winter	Spring	Total
Fuel treatments	1,200.00	208.00	1,408.00	1,000.00	416.00	1,416.00
Suppression (ground crews)	836.00	91.52	927.52	1,100.00	183.04	1,283.04
Suppression (helicopters)	7,000.00	1,456.00	8,456.00	4,900.00	2,912.00	7,812.00
Fire Stations	32.00	8.00	40.00	32.00	8.00	40.00
Suppression total	7,868.00	1,555.52	9,423.52	6,032.00	3,103.04	9,135.04
Total (prevention + suppression)	9,068.00	1,763.52	10,831.52	7,032.00	3,519.04	10,551.04
Ratio (suppression/prevention)	6.56	7.48	6.69	6.03	7.46	6.45

Table A9 Percentage of budget allocated to temporary fire stations per branch, for an escaped fire extended cost (EFeC) of 4 and 12 thousands euros, with low and high volatility in the set of fire scenarios.

Branch	Fire escape extended cost			
	4,000M		12,000M	
	Volatility		Volatility	
	Low	High	Low	High
1 - 3	1.10%	0.98%	0.34%	0.32%
2 - 5	1.16%	1.05%	0.37%	0.38%

Table A10 Number of fuel treatments and percentage of treated cells of the test landscape, for an escaped fire extended cost (EFeC) of 4 and 12 thousands euros, with low and high volatility in the set of fire scenarios.

Branch	Number of fuel treatments				Percentage of treated cells			
	4,000M (EFeC)		12,000M (EFeC)		4,000M (EFeC)		12,000M (EFeC)	
	Volatility		Volatility		Volatility		Volatility	
	Low	High	Low	High	Low	High	Low	High
1 – 3	18	23	18	22	72%	92%	72%	88%
2 – 5	14	15	14	14	56%	60%	56%	56%

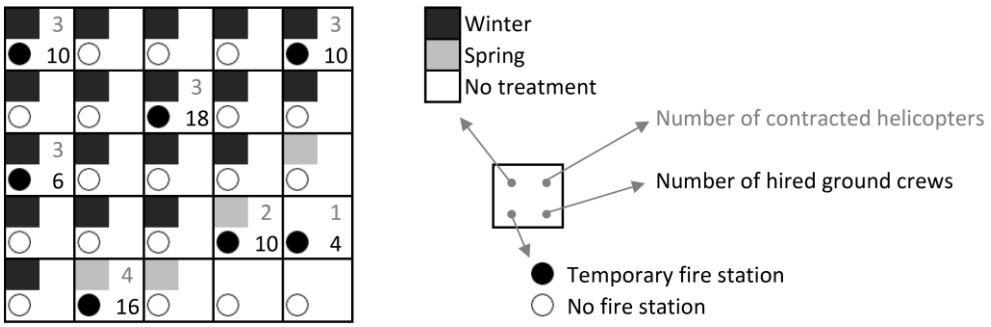


Fig. A1 Spatial view of the solution on the branch 1 – 3 for an escaped fire extended cost (EFeC) of 12,000M, with high volatility in the set of fire scenarios (see Table 3); for the lower volatility, please see Fig. 7.

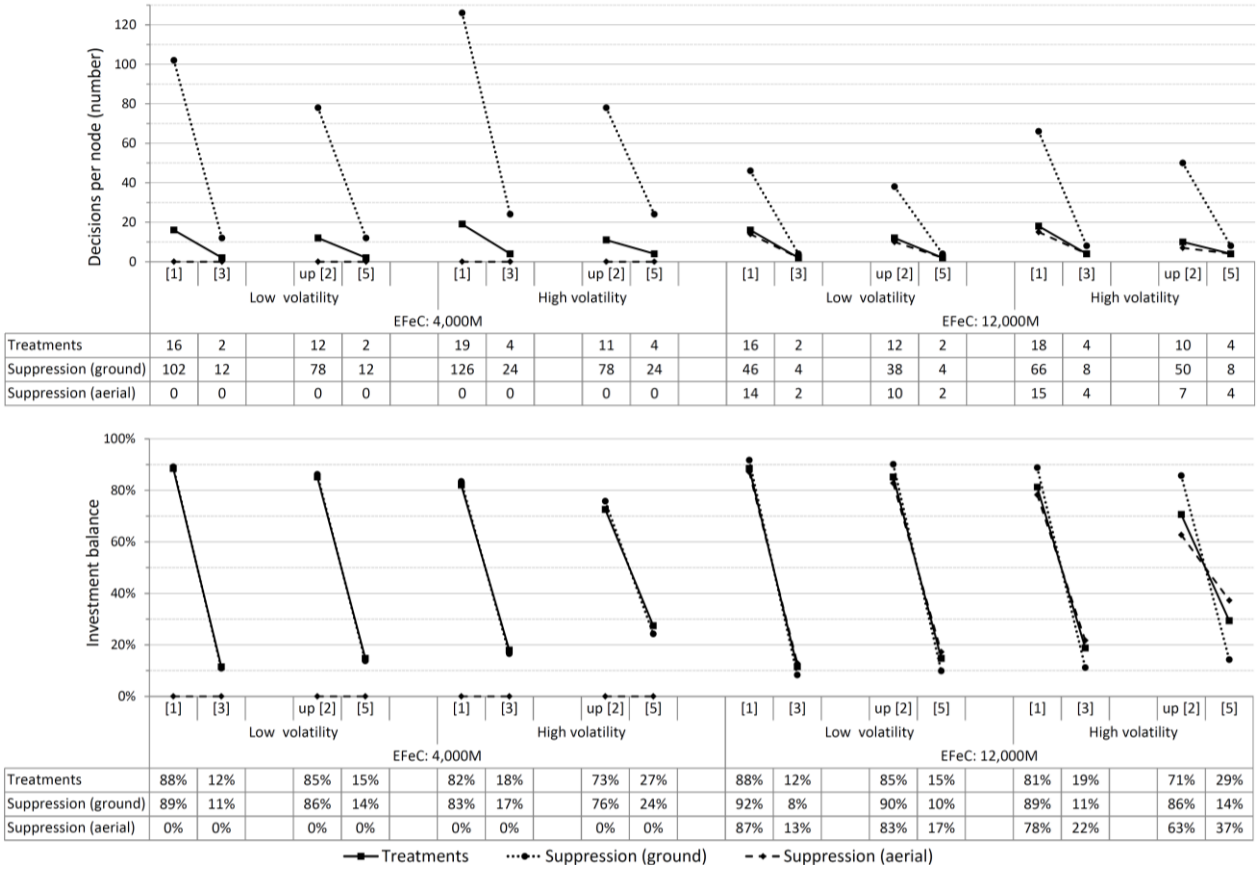


Fig. A2 Decisions of investment in capacity (top) and investment postponement (bottom) per node (instances C4L, C4H, C12L, and C12H) – in treatments, ground crews, and helicopters.

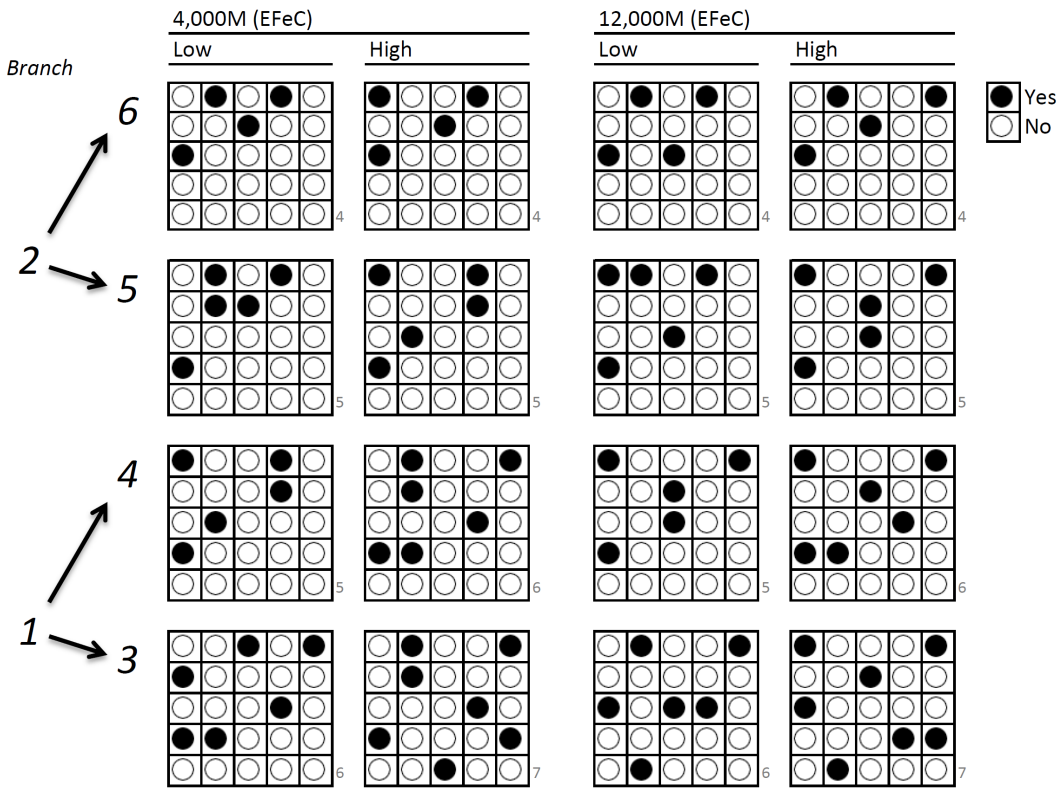


Fig. A3 Number of temporary fire stations and their optimal location (instances C4L, C4H, C12L, and C12H).

Note 1: The location of the temporary fire stations is chosen in the last decision node (Summer; Fig. 4). Thus, it is not directly influenced by postponement. Even so, it is possible to determine the number of temporary fire stations (Table 2, Table 3, supplementary Table A1, and Table A2) implicitly chosen in the previous decision nodes. However, the percentage of the optimal total budgets allocated to temporary fire stations is very small (about 1%, please see Table A9) as well as its value, thus making its impact on the final budget negligible. Despite not having a direct effect on the postponement of capacity investment, volatility and EFeC influence the number and location patterns of temporary fire stations.

Examining the location patterns (Fig. A3, above), there is a clear trend to spread stations out from northwest to southeast, as a result of the decreasing likelihood of the location of ignitions along that direction in all fire scenarios (please see f_{js}, parametrization in Table 1, and Ignitions location in supplementary Table A5 and Table A6). The coverage tends to increase with higher volatility (simple coverage and redundant coverage), and is held or increased with raising EFeC.

Table A11 Results (x€1,000) of the sensitivity analysis of the model, varying one of the parameters, EFeC, between €0 and 20,000M, for the lower and higher volatilities; graphical representation in Fig. 9, Fig. 10, Fig. A4, and Fig. A5.

EFeC	Low volatility			High volatility					
	Prevention budget	Suppression budget	Total cost of escapes	Prevention budget	Suppression budget	Total cost of escapes	Landscape burnt, %	Escaped fires, %	Socioecological context
0	0	0	0	0	0	0	8.56%	100.0%	*"let it burn"*
100	0	0	1,210	0	0	1,070	8.56%	100.0%	
150	0	0	1,815	0	0	1,605	8.56%	100.0%	
168	0	0	2,033	0	0	1,798	8.56%	100.0%	
200	0	1,320	869	0	895	1,112	4.45%	52.0%	*"No*
300	0	1,521	1,050	0	1,228	1,255	3.35%	39.1%	*prevention"*
400	0	1,618	1,280	0	1,524	1,332	2.66%	31.1%	
800	0	1,861	2,184	0	1,834	2,199	2.20%	25.7%	
959	0	1,861	2,618	0	1,972	2,486	2.07%	24.2%	
960	920	1,861	1,700	440	1,972	2,048	1.71%	19.9%	*"Prevention*
1,000	982	1,861	1,708	565	1,972	2,008	1.61%	18.8%	*focus"*
1,040	982	1,861	1,776	634	1,972	2,018	1.55%	18.1%	
1,500	1,182	1,994	2,159	1,034	2,105	2,271	1.21%	14.2%	
2,000	1,282	1,994	2,760	1,265	2,105	2,764	1.11%	12.9%	
3,000	1,382	1,994	4,004	1,434	2,237	3,783	1.01%	11.8%	
4,000	1,382	1,994	5,339	1,465	2,237	5,004	1.00%	11.7%	
5,000	1,482	1,994	6,561	1,565	2,237	6,142	0.98%	11.5%	
6,000	1,482	1,994	7,874	1,565	2,237	7,371	0.98%	11.5%	
6,489	1,482	1,994	8,515	1,565	2,237	7,971	0.98%	11.5%	
6,490	1,382	2,606	8,005	1,465	2,849	7,460	0.92%	10.7%	*"Suppression*
7,000	1,282	3,218	8,113	1,383	3,962	6,970	0.80%	9.3%	*dominance"*
8,000	1,182	8,006	4,163	1,209	6,114	5,804	0.58%	6.8%	
9,000	1,282	8,618	3,933	1,213	6,917	5,663	0.50%	5.9%	
10,000	1,282	8,618	4,371	1,265	7,529	5,584	0.45%	5.2%	
11,000	1,351	9,230	4,085	1,334	8,141	5,420	0.39%	4.6%	
12,000	1,382	9,230	4,424	1,365	8,753	5,238	0.35%	4.1%	
13,000	1,382	9,651	4,358	1,365	9,174	5,240	0.32%	3.8%	
14,000	1,382	9,842	4,493	1,365	9,365	5,443	0.31%	3.6%	
15,000	1,382	9,842	4,814	1,434	9,786	5,321	0.28%	3.3%	
16,000	1,382	9,842	5,135	1,465	9,977	5,443	0.27%	3.2%	
17,000	1,382	10,263	5,028	1,465	10,398	5,355	0.25%	2.9%	
18,000	1,382	10,454	5,129	1,465	10,589	5,475	0.24%	2.8%	
19,000	1,382	10,454	5,414	1,465	10,589	5,780	0.24%	2.8%	
20,000	1,382	10,454	5,699	1,465	10,589	6,084	0.24%	2.8%	

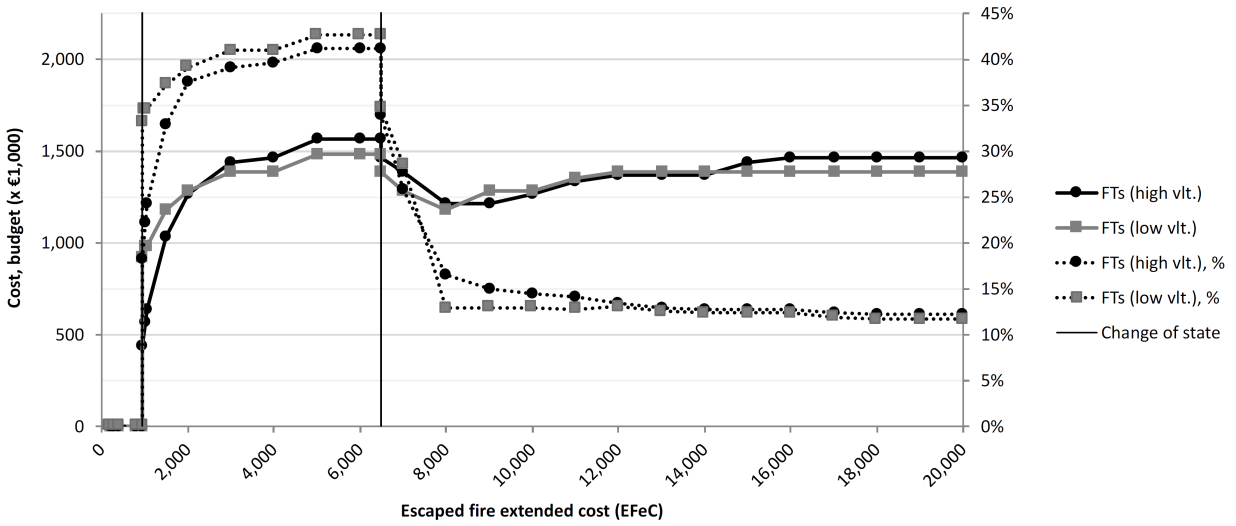


Fig. A4 Global system behavior and changes of stage, with lower and higher volatility (values in Table A11).

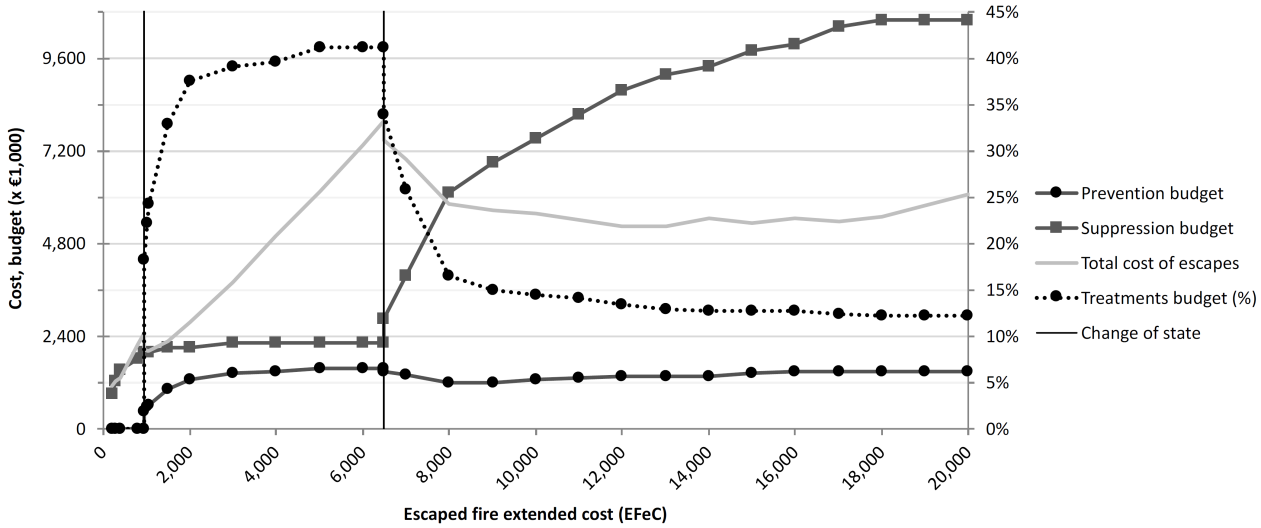


Fig. A5 Global system behavior (high volatility) and stages (*let burn*, *no prevention*, *prevention focus*, and *suppression dominance*) according to the hectare value or escaped forest fire loss (M) – please see supplementary Table A11; for a similar overview but with horizontal axis with log-transformed values (base 2), please see Fig. 9; next Fig. A6 shows a detail: EFeC values between 0 and 1,600 (*let burn*, *no prevention*, and the beginning of the *prevention focus* level).

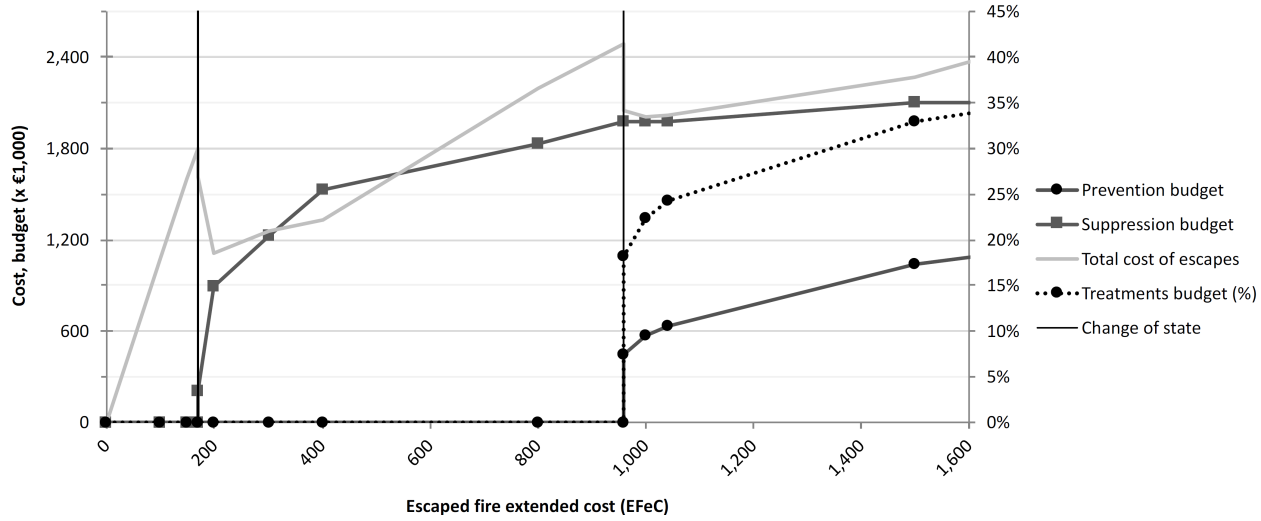


Fig. A6 Detail of the global system behavior (high volatility) and stages (*let burn*, *no prevention*, and the beginning of the *prevention focus* level) according to the hectare value or escaped forest fire loss (M) – please see supplementary Table A11; previous Fig. A5 (Fig. 9, horizontal axis with log-transformed values) shows the system behavior for all EFeC values (*let burn*, *no prevention*, *prevention focus*, and *suppression dominance*).

Chapter 6
Conclusion

Beyond a certain point there is no return.
This point has to be reached.
Franz Kafka

A system can be almost one hundred percent reliable, and even so its narrow margin of ineffectiveness be responsible for catastrophic results (e.g., would someone board a flight knowing that its flight management system does not fail 99% of the time?). The FFM system is one such system – when it fails the consequences can be severe. Indeed, when, e.g., containment during an initial attack or a mop-up fail, the consequence can be a large fire with a tremendous destructive impact on the community and the ecosystem. In the face of this characteristic, there is a critical need for FFM systems and their subsystems (e.g., prevention, suppression) to be carefully scrutinized, looking for ways to improve the effectiveness of the subsystems and the interconnections between them, that can be exploited to improve the system as a whole.

This thesis simultaneously contributes to a better understanding of FFM systems and their contexts, and offers tools to leverage that understanding to improve their behavior and results. It is mostly focused on the suppression subsystem and its interconnection with the prevention subsystem, paying particular attention to the exposure to critical uncertainties and to the complex dynamics that characterize the FFM system – a 'messy' complex system, involving nature, people, and technology. This focus led to the adoption of an ES perspective – jointly considering a broader set of relevant engineering, management, and social sciences concerns, and their intersections in particular, for the design and operation of the system (Larson 2008a, Larson 2008b) – with a heightened attention to aspects of integrated management and flexibility in system design.

We start with the identification and characterization of sources of ineffectiveness in the suppression subsystem in Chapter 2[1]. In Chapter 3 we present a review of the evolution of DSSs for FFM, and its relation with advancements in risk handling. The studies that comprise Chapter 4 expand the analysis of the impact of the sources of ineffectiveness, and propose tools to address them, including the measurement of their impact and the inclusion and explicit consideration of flexibility in the redesign of the subsystem. This is then extended to the integrated design of the suppression and prevention subsystems, in Chapter 5.

In this chapter, we summarize the key contributions from this work to the body of knowledge of FFM, explicitly relating them to the research questions. The chapter proceeds as follows: first, we outline the main empirical findings, followed by the key theoretical contributions; next, we present the implications from our findings to managers and policy makers; and finally, we present the limitations of the research and bridges for future work.

[1] And also, partially, in Chapter 4, where RQ1.2 and RQ1.3 are addressed.

6.1. Empirical findings

Our empirical findings are mostly related to large fires. In addition to the study of extremely large fires (RQ1.4) and the fleet mostly used in the extended attack (RQ1.3), the study of rekindles and false alarms also bears relevance for large fires. In fact, many large fires originate in rekindles, and rekindles together with (unmanaged) false alarms (RQ1.2) contribute to diverting suppression resources from initial attack and mop-up operations, potentially leading to an increase in escaped fires, and to a self-reinforcing loop in rekindles (RQ1.1). These results were obtained by reviewing the literature and by data analysis, and further validated by fieldwork. The studies are exclusively about fires in mainland Portugal, or in some of the country's regions[2], but they contribute with generalizable findings to the body of knowledge about large fires, currently one of the most important issues in FFM (Thompson et al. 2017, Rönnqvist et al. 2015).

We identified the set of physical, natural, technical, and organizational factors that influence the occurrence of rekindles, together with (for the first time) the burden of false alarms in the system, presenting evidence of the impact of these problems in the suppression subsystem.

Our finding of a statistically significant positive relationship between daily fire occurrences and rekindle proportions, for six of the seven districts in Portugal with a relevant number of rekindles, suggests that the pressure to immediately attack starting fires is causing more fires (RQ1.1) due to problems in post-fire management related to the double-duty (attack and mop-up) of firefighters (Beighley and Hyde 2009). The analysis of the relative effort (number of suppression resources and time spent) put into the handling of false alarms (RQ1.2), in comparison with other regions of the world, also suggests they should be managed. These findings support the relevance of evaluating their joint impact (RQ3.1) in the suppression subsystem's point of collapse.

Studying the suppression fleet itself, we focused on the vehicles mostly used in the extended attack (RQ1.3), finding a scattered old fleet with very low utilization – an opportunity for cost improvement, which we then develop, by proposing (RQ3.2) the flexible redesign of the system with a network of regional depots[3].

Finally, we studied the characteristics of extremely large fires (RQ1.4), examining the relative explanatory power of fire weather, vegetation and fuel characteristics, and committed fire-suppression resources, for fire size and average growth rate. Our findings are consistent with the available literature (Finney, Grenfell, and McHugh 2009) and show also for Portugal the opportunistic nature of suppression success, and (the importance of) its interconnection with the prevention subsystem.

Our empirical findings point to opportunities in the suppression subsystem to improve performance (management of false alarms in order to reduce the pressure on firefighters, which in turn can better perform mop-up operations, thus reducing the number of rekindled fires, thus reducing the number of starting fires, thus reducing the number of initial attacks, thus reducing the pressure on firefighters, in a virtuous positive feedback cycle) and costs (redesigning the network of depots used by the extended attack fleet). Most importantly, the opportunistic nature of suppression success suggests the relevance of

[2] In the meantime extended to other regions and years with the collaboration of others (Barros et al. 2014).

[3] Exploring this set of ideas, Stonesifer et al. (2015) applied them to helicopter flexible basing in Sardinia, Italy, which in turn inspired a master's thesis, Torres (2016), presented in the WCNRM2017 conference (Torres et al. 2017), and currently being further developed and prepared for publication.

nurturing such opportunities, mainly through fuel treatments, and thus the relevance of an integrated management of prevention and suppression efforts (RQ4.1).

6.2. Theoretical contributions

The key theoretical contributions from our work relate to the three simulations and/or optimization models presented in Chapter 4 and Chapter 5, which focus on improving the behavior and the results of the FFM system, under uncertainty. The two models in Chapter 4 are concerned with the suppression subsystem, and the third, in Chapter 5, looks at the suppression and prevention subsystems in an integrated manner.

As a result of our work to address RQ2.1 and RQ2.2, analyzing operational and strategic DSSs that include some form of economic evaluation of FFM alternatives under uncertainty, in addition to providing a review of the state of the art, we also identified an important trend in the development of the DSSs, towards an increased risk handling capability. This trend, enabled by a coexisting trajectory of continuous increase in computational power, is relevant and positive, because it reflects methodological progresses in risk handling, as well as the flow of scientific knowledge towards the creation of effective tools for risk assessment, management, and governance.

In the scope of our work on RQ3.1, using DES, we showed how a joint reduction of rekindles[4] and false alarms can lead to a significant improvement in the suppression subsystem's point of collapse (proposed as a new performance measure). The DES model can be easily configured with alternative dispatch policies or probability distributions for the performance of the initial attack response system, as well as easily expanded to address other aspects[5], thus presenting a great potential to be used to improve the behavior, performance, and costs of the subsystem.

To address RQ3.2, we showed how flexible design can be used to improve the FFM system[6], considering uncertainty in the intensity and location of fires, by using two-dimensional fire distributions[7], optimization of network locations, and simulation to evaluate the performance over the years, under several scenarios. This methodological approach[8] can be applied to other spatial location problems under uncertainty.

Finally, in the paper included in Chapter 5, we addressed the integrated management of the prevention and suppression subsystems, showing how to manage a portfolio of FFM options along the fire year, considering the economic conditions, the impact of the different options on each other, and key uncertainties in weather and fire location (RQ4.1). Our results on the evolution of the investment mix along the year, confirm a postponement of the investment

[4] Part of our contribution to a System Dynamics approach to analyse rekindles is *The Consequence of Aggressive Fire Suppression Targets on Future Rekindling of Fires*, a model co-authored with Ross Collins (MIT) and included in Collins (2012), Appendix C, Operational Model Documentation, pp. 149-153.

[5] A first step in this direction has already been given in a master's thesis (da Silva 2016), recently presented in an international conference (Pacheco, da Silva, and Claro 2017), and currently being further developed and prepared for publication.

[6] Flexibility was introduced in the system design through management decision rules.

[7] Two-dimensional (spatial) distributions were used here, to the best of our knowledge, for the first time.

[8] Other contributions, from a practitioner point of view, are: (i) the method to randomly generate a spatially explicit ignitions pattern, according to a two-dimensional distribution obtained from historical data; (ii) the method to dynamically choose the best locations of new regional depots; (iii) the methodology for developing new scenarios; (iv) the developed scenarios themselves (expansion of the WUI, increased surveillance policy, and law enforcement); and finally (v) an implementation fully carried out with near freely available software.

decisions for higher volatilities in weather conditions, and highlight the value of this source of flexibility, together with spatially explicit solutions. Studying the optimal mix of investment in prevention and suppression (RQ4.2) we concluded that the optimal balance changes for different socioecological contexts, a result that, at first sight, could be considered unexpected, challenging, and controversial.

Overall, we contribute a set of models that are useful to identify improvement opportunities in the FFM system, under conditions of uncertainty. These simulation and/or optimization models adopt a broad ES perspective and explicitly consider flexibility, allowing the evaluation of the impact of inefficiencies, suggesting changes to system design, and supporting the extension of the scope of management to neighboring interconnected systems.

6.3. Practical and policy implications

Our empirical findings and theoretical contributions have a number of relevant practical implications for managers and policy makers concerned with FFM. We offer them in the next eleven points, the final three being eventually more far-reaching.

Neglected costs of rekindles and false alarms

By studying their joint impact (rekindles and false alarms) on the suppression subsystem's point of collapse, we showed their importance and overlooked costs.

Rekindles vicious cycle

We identified a suppression ineffectiveness cycle: bad mop-up operations lead to more rekindles, thus more fires, increasing the pressure to attack starting fires, which in turn leads to an increase in bad mop-ups, and so on.

Inverting the vicious cycle with false alarms management

We found that managing false alarms leads to a lower number of incidents in the suppression subsystem, which reduces the pressure on firefighters, releasing resources for fighting real fires and with time to invest in better mop-up operations, thus reducing the number of rekindles, contributing again to reducing the number of incidents, and so on, in a positive feedback loop.

Improving performance and reducing the costs of extended attack

We showed how to replace the existing underused and old firefighting fleet by a more efficient one, with fewer vehicles (less costs) but ensuring safety levels, over time, similar to the current ones.

Large-fire management

Current large-fire management and operations need to be improved in order to take advantage of weather, fuel and topographic changes that create containment opportunities for effective fire control. Landscape-scale fuel treatment projects, integration of such knowledge in the suppression subsystem, and increased community fire self-protection, can foster that improvement.

DSSs and risk handling

To perform economic evaluations of fire management programs, integrate forest fire risk concerns into forest planning processes, or evaluate options in real time during suppression operations, DSSs are vital, jointly with the involvement of multiple stakeholders. They enable risk-based analyses, which are critical for the integration of risk handling and fire management. The confirmation of the lack of utilization of any kind of DSS in Portugal,

almost half a century after they started being employed in other countries, is enigmatic, at least, and reveals an important opportunity for improvement.

Optimal investment mix and values at risk

We found that the balance between prevention and suppression changes qualitatively in the system according to the cost attributed to escaped fires. The optimal investment mix in each of the different system states explains some observed controversial actual behaviors, challenging several FFM myths (e.g., prevention investments are *always* good; the prevention budget proportion *should be one third*; the utilization of helicopters is *always* a waste). Optimal investment mixes depend heavily on the values at risk.

Fuel treatment prevalence

Even if the investment mix (prevention/suppression budget balance) changes qualitatively in the system, fuel treatments are always of value above a certain (low) value at risk threshold. Independently of how the escape costs rise after that threshold, the optimal absolute value of the budget for fuel treatments almost does no change. In other words, after a certain threshold, the investments in fuel treatments are stable and always needed.

Initial attack response system design

As the initial attack response system represents about 90% of suppression activity, our simulation model can be used by managers to improve the effectiveness of the suppression system and, at the same time, reduce its costs.

Flexible design

Introducing flexibility in the design of a system can be of value, significantly improving the performance and reducing the investment costs, while maintaining safety levels. Our approach to the partial centralization of the extended attack fleet can be applied to obtain other improvements.

Flexible management

An integrated intra-annual flexible FFM leads to a cost-effective budget allocation, reducing losses with catastrophic fires.

Besides the above practical implications, our empirical findings and theoretical contributions have a number of relevant policy implications which we summarize next:

- the increasing technical, operational, and managerial complexity of firefighting requires nowadays from firefighting teams a level of expertise that can only be provided by a backbone of professional firefighters;
- the highly dynamic nature of the wildfire management system requires a frequent strategic reassessment of the suppression subsystem resources, e.g., of their adequacy, their distribution throughout the territory, their organizational structure, and their sources of financing;
- the investment in large-fire suppression intelligence and organization can have a great impact in leveraging basic resource availability;
- the integration with fire prevention can also have a great impact in leveraging fire suppression, e.g., by having professionals creating opportunities (through interventions such as fuel treatments) outside the fire season, and then, in the critical period, applying the knowledge of their location and how best to use them;

- the significant variation in structural fire challenges across regional contexts requires a regional specialization of wildfire management policies (e.g., concerning whether and how to utilize aerial resources);
- the high risk exposure and level of interdependence between the actors and subsystems of the wildfire management suggest that socially preferable policies may have to be favored, even if economically sub-optimal, with a participative and careful design of where, when, and how interventions such as market regulation and cross-subsidization should be implemented;
- there is a strong need and ample opportunity for infusing science and technology at all system levels, e.g., through the implementation and routinization of the use of economic DSSs at the strategic level, and DSSs for rapid assessment of values at risk and fire simulation, at the operational level;
- as pointed above, the wildfire management system has a highly dynamic nature, and as such any implementation of these policy suggestions should be reassessed periodically (and action taken accordingly).

6.4. Limitations and future research

The limitations of our research, which are also bridges for future research, are addressed in each of the papers. We highlight them next, together with some objectives that we started working towards and were not able to achieve within the scope of this thesis, but would be worthwhile future research directions.

Bad mop-ups (RQ1.1 and RQ3.1) currently are still a significant issue in Portugal, and as data for more recent fire seasons becomes available, a monitoring of the current situation should be undertaken. Besides operational considerations (RQ1.1), the conditions for a rekindle to happen depend also on the fuel conditions and on the subsoil characteristics. However, the study of which of these factors are preponderant was not done – and with such knowledge, the territories with better environmental conditions for the occurrence of rekindles could be identified a priori (territories where mop-up operations and vigilance should be performed with extra care).

The analysis of the performance of alternative organizational designs of the suppression system (RQ3.1), including specialized teams assigned to different suppression tasks, has already been done[5] elsewhere (da Silva 2016), as well as the application to other districts and years[2] (Barros et al. 2014). Other limitations in the model do not challenge the essence of the analysis, namely (a) the deterministic sequence of the two classes of daily incident frequency, (b) the absence of weekly patterns in occurrences number, and of a differentiated treatment of ELF, (c) no differentiation, in terms of queue priority, between IA and EA, (d) fire durations depending on the resources allocated only indirectly, and (e) the lack of productivity losses in result of overload in consecutive days of higher fire occurrence, or from the relocation of crews to less familiar sites (the latter, also a limitation in the approach proposed to address RQ3.2).

However, overcoming these limitations can add more precision to the model, be useful to analyze alternative dispatch policies, and evolve the model to a simulation of the suppression system over a larger region (a set of districts). Moreover, further exploring the model's ability to compute CO_2 emissions and burnt areas, thus, value losses, will also be of value: suppression resources capacity and dispatch policies could then be tested and optimized, at different levels of rekindles and false alarms.

Regardless of the available resources, an ELF will likely expand as long as fire control capacity is overwhelmed by the combined effects of weather, fuel and terrain – as pointed out, our study (RQ1.4) has some limitations regarding the descriptors used to study the effects of fire-suppression force variation versus the concomitant fire environment conditions, on ELF duration, size and growth rate.

Regarding the concomitant fire environment, we did not consider metrics of topography or landscape fuel connectivity and diversity (effects, to some extent, captured through the considered regional variation) and gradual or abrupt changes in the fire environment. The conditions indicated by the nearest weather station (the only we considered) differ from those observed at the fire ignition location and they also change along the fire lifespan (variations not considered at all in our study). Indeed, changes in fire environment contribute decisively to fire containment and we do not identify the conditions that actually end the active spread.

Regarding the fire-suppression effort, besides aircraft resources being incompletely considered (although more decisive in initial attack containment), equivocal links between suppression resources and tactics explain the failure of our struggle to describe fire-suppression effort through more sophisticated metrics. Indeed, we used data on the available suppression resources, but not on their actual activity and effectiveness.

To address these caveats and further understand the role of fire suppression on fire characteristics, future studies should also include topographic metrics, changes at the fire edge, the putative influences of WUI and other anthropogenic features, and be complemented with an observational study of suppression activity, namely considering fire crew qualification and specialization, quantifying fire-suppression resources distribution among operational strategies and tactics, and assessing the corresponding operational outcomes, and registering fire environment and behavior characteristics in relation to fire control operations and fireline production rates.

Besides the mentioned data refinements, complemented with observational studies, the characterization of the links between fire-suppression force variation and the concomitant fire environment effects would benefit from the replication of our study to large fires, and the study of the conditions which characterize IA failure. Indeed, our general process to estimate time to containment can be applied to analyze the relationship between initial attack efforts versus concomitant fire environment conditions, and the fire escape probability, namely by the designing of a production function model for the wildfire escape probability.

The importance of the integration between risk handling and DSS development, to facilitate and improve the quality of decisions under uncertainty and enable a cohesive fire management in an uncertain environment, is stressed in our review of DSSs in current use (RQ2.1 and RQ2.2). Future work can assess the extension of such integration in the places of the world where these DSS are being used.

We also pointed out the importance of understanding the ecological and institutional constraints, and the need to engage stakeholders also through the usability and flexibility of these systems. In particular, the institutional constraints of management programs within which forest fire mitigation programs develop and the need for stakeholder engagement should be addressed in future studies, considering the trade-offs between model complexity and implementation challenges, adoption willingness, and resistance to change (Chaiken 1978, Lawless 1987), which can undermine desired policy shifts, e.g., the frustrations related with the practical impacts of the Fire Project in New York City (Green and Kolesar 2004), or the

"knowledge fight" about the Fire Program Analysis modeling approach in 2006 (Pacheco et al. 2015).

In the approach proposed to address RQ3.2 (and RQ1.3), future research could explore the current limitations in the structure of the models, and in the data. Limitations in the structure of the models include (a) the inaccurate assumption that the system can only deploy vehicles to areas within its jurisdiction[9], (b) the use of a maximum straight line distance instead of a real distance run by the vehicles, and (c) the absence of a constraint imposing a realistic maximum number of deployments associated to each depot. Overcoming the limitations in the data could benefit from the analysis of longer time series of the number of fires and vehicle deployments, resulting in improved estimates of the deployments spatial distribution, the mean reversion process, and the straight-line to trip distance conversion parameters.

Even so, we believe that our approach can be useful for other problems in which centralization of resources can be translated into efficiency gains. Within the suppression subsystem, our approach can be applied to the allocation of fire-fighting helicopters to heliports[3], storage of fire retardant agents, allocation of suppression crews to fire departments, and the rationalization of initial attack vehicles. More generally, our approach could be useful in the location of all kinds of emergency supplies (e.g., those to deploy for earthquakes, floods and other disasters), contributing to address an important issue in emergency supply-chain management.

Finally, the application of the intra-annual model (RQ4.1 and RQ4.2) to a case study is an important next step, as is also optimizing the timing, sizing, and location of different types of prevention and suppression resources, and other FFM related activities, from an inter-annual perspective, i.e., extending our model of the optimal mix of investment of a limited FFM budget also to an inter-annual perspective (as in RQ3.2).

As a closing reflection, the understanding of the mostly non-linear relationships between interconnected physical, ecological, and cultural systems, which influence the severity of forest fires, is needed to effectively reduce the vulnerability of ecosystems and human societies, through improved and proactive risk governance. With the perspective of more severe fire seasons in the future and because we cannot change the weather, one of the remaining options is to reduce the human impact (Flannigan et al. 2013). The latter can be fostered through changes in the current policies pointed out by our results.

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Even the worst thing hath two good reverse sides.
Friedrich Nietzsche
(Also sprach Zarathustra, LXXIII. THE HIGHER MAN. 19)

It is through science that we prove, but through intuition that we discover.
Jules Henri Poincaré

We are the representatives of the cosmos; we are an example of what hydrogen atoms can do, given 15 billion years of cosmic evolution.
Carl Sagan

You will die but the carbon will not; its career does not end with you. It will return to the soil, and there a plant may take it up again in time, sending it once more on a cycle of plant and animal life.
Jacob Bronowski

I have always imagined that Paradise will be a kind of library.
Jorge Luis Borges

Anyone who keeps the ability to see beauty never grows old.
Franz Kafka

Não vale a pena estar morto.
Carlos César Pacheco
(epitáfio)