IMPROVING OUR UNDERSTANDING OF INDIVIDUAL WILDFIRES BY COMBINING SATELLITE DATA WITH FIRE SPREAD MODELLING

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SCIENTIFIC ADVISOR: Ph.D José Miguel Cardoso Pereira (Full Professor)

THESIS PRESENTED TO OBTAIN THE DOCTOR DEGREE IN

FORESTRY ENGINEERING AND NATURAL RESOURCES

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JÚRI:

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Para a Liandra, Naíma e Maira.

Para todas as familias que faleceram ou perderam entes queridos nos incêndios de 2017.

Contents

Abstract

Wildfires pose real threats to life and property. In Portugal, the recent year of 2017 had the largest burnt area extent and number of casualties. A knowledge gap still exists in wildfire research related with better understanding individual wildfires, which has important implications for fire suppression, management, and policies.

Wildfire spread models have been used to study individual wildfires, however, associated uncertainties and the lack of systematic evaluation methods hamper their capability for accurately predicting their spread. Understanding how fire spread predictions can be improved is a critical research task, as they will only be deemed useful if they can provide accurate and reliable information to fire managers.

The present Thesis proposes to contribute to improve fire spread predictions by:

i) Developing a methodology to systematically evaluate fire spread predictions

ii) Thoroughly characterizing input data uncertainty and its impact on predictions;

iii) Improving predictions using data-driven model calibration.

The spread of large historical wildfires were studied by combining satellite data and models. The major findings of the present Thesis were:

i) Satellite data accurately contributed to provide accurate fire dates and ignition information for large wildfires.

ii) The evaluation metrics were very useful in identifying areas and periods of low/high spatio-temporal agreement, highlighting the strong underprediction bias and poor accuracy of the predictions.

iii) Uncertainties in wind speed and direction, fuel model assignment and typology, location and timing of ignitions, had a major impact on prediction accuracy.

iv) Predictions were improved by ‘learning’ from past wildfires, significantly reducing the impact of data uncertainty on the accuracy of fire spread predictions.

Overall, the work contributed to advance the body of knowledge regarding individual wildfires and identified future research steps towards a reliable operational fire system capable of supporting more effective and safer fire management decisions with the aim of reducing the dramatic impacts of wildfires.

Keywords: fire spread; modelling; satellite thermal data; fire management; uncertainty.

Resumo

Em Portugal, o ano de 2017 teve a maior extensão área ardida e número de fatalidades de que há registo. Existe uma lacuna no conhecimento relacionada com um melhor entendimento de incêndios, o que tem implicações importantes para o seu combate, a gestão e politicas associadas.

Os modelos de propagação do fogo têm sido utilizados para estudar incêndios, no entanto, as incertezas associadas e a carência de métodos de avaliação, dificultam a sua capacidade de corretamente prever o comportamento dos incêndios. Compreender como é que as previsões de propagação podem ser melhoradas é uma tarefa crítica de investigação, pois estas apenas serão úteis se providenciarem aos gestores informação fiável.

A presente Tese pretende contribuir para a melhoria das previsões de propagação do fogo através de:

i) Desenvolvimento de uma metodologia para avaliar sistematicamente as previsões de propagação do fogo.
ii) Caracterizar as incertezas nos dados de entrada (e.g. vento, combustíveis) e o seu impacto nas previsões.
iii) Melhorar as previsões realizando uma calibração orientada por dados.

A progressão de grandes incêndios históricos foi estudada combinando dados de satélite e modelos. As descobertas mais relevantes da Tese foram:

i) Os dados de satélite contribuem para providenciar informação precisa sobre as datas dos incêndios e a respetivas ignições.
ii) As métricas de avaliação identificaram áreas e períodos com baixa/alta concordância espacio-temporal, destacando a forte subestimação do crescimento dos incêndios e a baixa fidelidade das previsões.
iii) As incertezas na direção e velocidade do vento, atribuição e tipologia de modelos de combustível, e a localização e ‘timing’ das ignições, tiveram um importante impacto na fidelidade das previsões.

iv) As previsões foram melhoradas "aprendendo" com incêndios passados, reduzindo significativamente o impacto da incerteza dos dados na fidelidade das previsões.

Este trabalho contribuiu para avançar no conhecimento relacionado com incêndios individuais e identificar passos de investigação necessários à criação de um sistema operacional capaz de suportar decisões mais seguras e eficientes com o objetivo de reduzir os impactos dramáticos dos incêndios.

Palavras-chave: propagação do fogo; modelação; dados térmicos de satélite; gestão do fogo; incerteza.

Extended Abstract

In the last 20 years, Portugal has stood out as the European country with the largest average annual burned area. The years of 2003 and 2005 were particularly severe, with around 400,000 and 300,000 ha burned each year, respectively. However, the recent year of 2017 was unprecedented, with the largest annual burnt area extent (c.a. 500,000ha) and the largest number of casualties (over 100). Climate change is likely to increase the frequency and extent of wildfires due to a higher frequency and intensity of droughts and heat waves.

Each wildfire is a unique event that burns under specific environmental conditions, and ultimately leads to a unique array of impacts. Fuel, weather and topography are key environmental factors that affect the occurrence, the dynamics and the consequences of each wildfire. A knowledge gap still exists related to better understanding individual wildfires, which has important implications for fire suppression, management, and policies. Considering the future climate scenarios, improving our scientific knowledge on individual wildfires is crucial and research needs to be linked with fire-management decisions.

Wildfires can be studied using different sources of information with very different characteristics. Field-acquired fire information is often scarce, expensive, incomplete and with low accuracy. In particular, information on observed fire line location, growth patterns and intensity is often deemed of poor quality. Due to their spatial coverage and synoptic capabilities, satellite data are a cost-effective alternative to systematically monitoring large wildfires, and can be used to complement existing information. Nevertheless, satellite data have many limitations and uncertainties that need to be taken into account, since they only provide snapshots of the spread of large wildfires.

Wildfire spread models have been used to study individual wildfires, since they allow not only to understand the growth and behaviour of past wildfires, but they can also be used to predict the spread of active wildfires and therefore be used to support suppression strategies, evacuation orders and public warnings. This ability is particularly relevant in regions where wildfires pose real threats to life and property,

including Portugal, and of paramount importance for extreme wildfires that escape initial attack, become large and last for multiple days.

Despite, the large potential of these tools, modelling such complex environmental phenomena is fraught with uncertainties. Consequently, the capability for accurately predicting fire spread still is very limited, undermining the utility of such predictions for decision-making. Uncertainties arise mainly from the imperfect scientific knowledge regarding the mechanisms controlling fire spread, input data quality, natural variability, and parametric uncertainty. Although progress has been made, our ability to produce accurate predictions has evolved little, not only due to the complexity of the phenomena, but also due to the lack of systematic methods for model validation. Inaccurate fire spread predictions can have dramatic consequences.

Fire management decisions often miss a strong scientific background compromising their efficiency, therefore, the research community has been questioning which research approaches are needed to improve the fire spread prediction accuracy of operational models. Understanding how fire spread predictions can be improved is a critical research task, as they will only be deemed useful if they can provide reliable information to fire managers. Fire spread predictions can be improved in a number of ways, however these may involve challenging tasks that are too expensive and time consuming, not meeting the demands of fire managers for short-term and inexpensive improvements.

The present Thesis proposes to tackle some of the above mentioned limitations that constrain our understanding of large wildfires, addressing the following questions: What can we learn from past wildfires to mitigate their future impacts? How can fire spread predictions be made sufficiently reliable to support fire management? These questions are addressed by investigating a set of key issues that have been identified as paramount importance to improve fire spread predictions for operational purposes, namely:

i) Develop a methodology to systematically evaluate fire spread predictions over both space and time, using satellite data with a proper uncertainty quantification;

ii) Better understand the nature of uncertainty in the input data, how it propagates through fire spread models and how it affects its predictions;

iii) Improve fire spread predictions using inexpensive and low-time consuming approaches based on data-driven model calibration.

In the present Thesis, satellite data and fire spread modelling were combined in an innovative way, to minimize their individual limitations and maximize their potential. The analyses were performed by studying historical wildfires, and framed considering some of the biggest challenges involved in setting up and using a fire spread modelling system. All these steps precede one major long term goal: to develop an operational system capable of providing relevant information on large wildfires that can support safe and effective fire suppression strategy and tactics.

The major findings of the present Thesis work are:

i) Satellite-derived fire dates had moderate to very good agreement when compared with reported data. The spatio-temporal agreement between reported and satellite-derived ignitions showed temporal lags and distances within 12 h and 2 km, respectively. In sum, results showed that satellite data can contribute to improve information regarding dates and ignitions of large wildfires, which can be a valuable asset to complement and correct inconsistencies in existing fire databases.

ii) Satellite thermal data captured the major spatio-temporal dynamics of the large wildfires studied. The evaluation metrics proved to be very useful in identifying areas and periods of low/high spatio-temporal agreement between simulated and observed fire growth. Overall, this approach highlighted the poor accuracy of the fire spread simulations due to a strong underprediction bias. The methodology developed can be applied to a comprehensive number of large wildfires towards a more systematic and objective evaluation of fire spread simulations.

iii) Uncertainties in input data were very large and had important impacts on fire spread predictions. In particular, uncertainties in wind speed and direction, fuel model assignment and typology, location and timing of ignitions, had a major impact on prediction accuracy. The work developed was a first and necessary step to integrate data uncertainties in future fire spread predictions.

iv) Using a robust iterative algorithm for regional model calibration, fire spread predictions can be continuously improved by 'learning' from past wildfires, and significantly reduce the impact of the input data uncertainty on the accuracy of predictions. This showed that without additional information or significant improvements on the quality of the major input variables, the negative impacts of uncertainty could be reduced leading to more reliable fire spread predictions.

Overall, the work contributed to advance the body of knowledge regarding individual wildfires, using an innovative combination of satellite thermal data and fire spread modelling tools. It showed that it is possible to integrate knowledge from past wildfires to improve our understanding. It contributed to improve the accuracy of fire spread predictions in pursue of the long term goal, i.e. to provide fire spread predictions that are sufficiently reliable to support fire management decisions in the future. Along with these developments, it identified future research steps towards a reliable operational fire spread system that has a solid scientific background, which can support more effective and safer fire management decisions with the aim of reducing the dramatic impacts of wildfires.

Resumo Alargado

Nos últimos 20 anos, Portugal destacou-se como o país Europeu com maior área ardida anual em média. Os anos de 2003 e 2005 foram particularmente severos, com cerca de 400,000 e 300,000 ha ardidos cada ano, respetivamente. No entanto, o ano de 2017 não teve precedente, com a maior extensão de área ardida anual (cerca de 500,000 ha) e o maior número de fatalidades. As alterações climáticas provavelmente aumentarão a frequência e extensão dos incêndios devido a uma maior frequência e intensidade de secas e ondas de calor.

Cada incêndio é um evento único que arde sob condições ambientais específicas, que conduz a conjunto único de impactos. Os combustíveis, a meteorologia e a topografia são fatores ambientais chave que afetam a ocorrência, as dinâmicas e as consequências de cada incêndio. Existe uma lacuna no conhecimento relacionada com um melhor entendimento de incêndios, o que tem implicações importantes para o seu combate, a gestão e politicas associadas.

Os incêndios podem ser estudados utilizando diferentes fontes de informação, com diferentes características. Informação recolhida no campo é frequentemente dispendiosa, incompleta, com baixa precisão e insuficiente. Em particular, informação sobre a localização das linhas do fogo, os padrões de crescimento do incêndio e intensidade são geralmente consideradas de baixa qualidade. Devido à sua cobertura espacial e capacidades sinópticas, os dados adquiridos por satélite são uma alternativa custo-eficiente para monitorizar sistematicamente grandes incêndios, e podem ser usados para complementar informação existente. No entanto, os dados de satélite têm várias limitações e incertezas que precisam ser tidas em conta, uma vez que apenas providenciam “fotografias” da progressão de grandes incêndios.

Os modelos de propagação do fogo têm sido utilizados para estudar incêndios individuais, uma vez que permitem não apenas compreender o crescimento e comportamento de incêndios passados, mas também podem ser utilizados para prever a propagação de incêndios ativos e consequentemente ser utilizados para suportar estratégias de combate, ordens evacuação e avisos às populações. Esta capacidade é particularmente relevante em regiões onde os incêndios criam verdadeiras ameaças à vida e à propriedade, incluindo Portugal, e são de primordial importância para incêndios extremos que escapam ao ataque inicial, tornam-se grandes e duram vários dias.

Apesar do grande potencial destas ferramentas, modelar um fenómeno ambiental tão complexo está carregado de incertezas. Consequentemente, a capacidade para prever corretamente a propagação dos incêndios é ainda bastante limitada, minando a utilidade destas previsões para a tomada de decisão. As incertezas advêm essencialmente do conhecimento imperfeito sobre os mecanismos que controlam o comportamento do fogo, a qualidade dos dados de entrada, a variabilidade natural, e a incerteza paramétrica. Apesar de terem sido feitos progressos, a nossa capacidade de produzir previsões fiáveis evoluiu pouco, não apenas devido à complexidade do fenómeno, mas também devido à falta de métodos sistemáticos de validação dos modelos. Previsões incorretas podem ter consequências dramáticas.

A gestão dos incêndios amiúde carece de um "background" científico sólido comprometendo a sua eficiência, consequentemente, a comunidade científica tem vindo a questionar que abordagens de investigação são necessárias para melhorar a fiabilidade das previsões operacionais. Compreender como as previsões de propagação do fogo podem ser melhoradas é uma tarefa de investigação crítica, pois estas apenas serão consideradas úteis se providenciarem informação fiável aos gestores do fogo. As previsões de propagação do fogo podem ser melhoradas de várias formas, no entanto estas melhorias podem envolver tarefas desafiantes que necessitam de muito tempo e recursos, o que pode não atender à necessidade dos gestores para melhorias de curto-prazo e pouco dispendiosas.

A presente Tese pretende contribuir para reduzir algumas das limitações que restringem a nossa compreensão relacionadas com grandes incêndios, abordando as seguintes questões: O que podemos aprender sobre incêndios passados que possa mitigar os seus impactos futuros? Como é que as previsões de comportamento do fogo podem ser tornadas suficientemente fiáveis para suportar a gestão do fogo? Estas questões são abordadas investigando um conjunto de temas que têm sido identificados como de extrema relevância para melhorar as previsões de propagação do fogo para fins operacionais, nomeadamente:

i) Desenvolver uma metodologia para avaliar sistematicamente as previsões de propagação do fogo no espaço e no tempo, utilizando dados de satélite com uma quantificação apropriada da incerteza.

ii) Compreender melhor a natureza da incerteza nos dados de entrada (e.g. vento, combustíveis), como é propagada através dos modelos e como é que afeta as previsões.

iii) Melhorar as previsões utilizando uma técnica pouco dispendiosa e rápida baseada em calibração orientada por dados.

A progressão de grandes incêndios históricos foi estudada combinando dados de satélite e modelos. As análises foram feitas estudando incêndios passados, e enquadradas considerando os principais desafios envolvendo a configuração e utilização de um sistema de modelação de propagação do fogo. Todos os passos precedem um objetivo fundamental a longo prazo: desenvolver um sistema operacional capaz de fornecer informação relevante sobre grandes incêndios que possa suportar estratégias e táticas de gestão do fogo seguras e eficazes.

As descobertas mais relevantes da Tese foram:

i) A datação dos incêndios utilizando dados de satélite teve concordâncias entre o moderado e o muito bom quando comparadas com dados reportados. A concordância espacio-temporal entre as ignições reportadas e derivadas por satélite mostrou desfasamentos temporais e distâncias abaixo das 12h e 2km, respetivamente. Os resultados mostraram que os dados de satélite podem contribuir com informação sobre as datas e ignições de grandes incêndios, o que pode ser um ativo importante para complementar e corrigir problemas nas bases de dados existentes.

ii) Os dados de satélite capturaram as principais dinâmicas espacio-temporais dos grandes incêndios estudados. As métricas de avaliação foram bastante úteis em identificar áreas e períodos com baixa/alta concordância espacio-temporal entre o crescimento observado e simulado. No geral, esta abordagem destacou a baixa fidelidade das previsões devido a uma forte subestimativa do crescimento dos incêndios. A metodologia desenvolvida pode ser aplicada a um grande número de grandes incêndios em direção a uma avaliação mais sistemática e objetiva das simulações de propagação do fogo.

iii) As incertezas nos dados de entrada foram consideradas bastante significativas e tiveram impactos importantes nas previsões de propagação do fogo. Em particular, as incertezas na direção e velocidade do vento, atribuição de modelos de combustível e respetiva tipologia, e a localização e 'timing' das ignições, tiveram um importante impacto na fidelidade das previsões. O trabalho desenvolvido foi um primeiro passo necessário para integrar as incertezas nos dados em previsões futuras de propagação do fogo.

iv) Utilizando um algoritmo iterativo e robusto para calibração regional do modelo, as previsões de propagação do fogo foram continuamente melhoradas "aprendendo" com os incêndio passados, e reduzindo significativamente o impacto da incerteza nos dados de entrada na precisão das previsões. Isto mostrou que sem informação adicional ou melhorias significativas na qualidade das principais variáveis de entrada, os impactos negativos da incerteza podem ser reduzidos levando a melhorias na precisão das previsões.

No geral, este trabalho contribuiu para avançar no conhecimento relacionado com incêndios individuais utilizando uma combinação inovadora de dados térmicos de satélite com ferramentas de propagação do fogo. Mostrou que é possível integrar conhecimento de incêndios passados para melhorar o nosso conhecimento. Contribuiu também para melhorar a precisão das previsões de propagação do fogo na procura de um objetivo de longo prazo, i.e. providenciar previsões de propagação que são suficientemente fiáveis para suportar decisões relacionadas com a gestão do fogo no futuro. Para além destes desenvolvimentos, identificou os passos de investigação necessários à criação de um sistema operacional capaz de suportar decisões mais seguras e eficientes com o objetivo de reduzir os impactos dramáticos dos incêndios.

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The work developed in the present Thesis has been presented in oral and poster communications in several international conferences.

Introduction

Wildfires that spread under favourable conditions can become large and intense, and lead to severe ecological and environmental degradation, and ultimately and most dramatically, to the loss of life and property. In Europe, most wildfires are concentrated in southern countries bordering the Mediterranean Basin, which have suitable fuel and climate conditions for the occurrence of large wildfires [1]. Here, wildfires are typically larger and more intense during the summer months where dry, hot and windy atmospheric, sometimes exacerbated by drought, are prevalent [2]. In the last 20 years, Portugal has stood out as the European country with the largest average annual burned area in Europe [3]. The years of 2003 and 2005 were particularly severe, with around 400,000 and 300,000 ha burned each year, respectively. However, the recent year of 2017 was unprecedented, with the largest burnt area extent (c.a. 500,000ha) and the largest number of casualties (over 100) [4]. Under the umbrella of climate change the frequency and extent of wildfires are likely to increase due to a higher frequency and intensity of favorable climatic conditions, such as droughts and heat waves [5,6]. Hence, their environmental and socio-economic costs and losses are also expected to increase [7].

Each wildfire is a unique event that burns under specific environmental conditions across the landscape, and ultimately leads to a unique array of impacts [8,9]. Fuel, weather and topography are key environmental factors that affect the occurrence, the dynamics and the consequences of each wildfire. They can partially or totally determine the i) success of a potential ignition in starting a wildfire ; ii) fire rate of spread; iii) fire size and duration; iv) fire perimeter; v) flame length or fire intensity; and vi) fire impacts [10-15]. Additionally, ignition location and timing also strongly influence wildfire characteristics, mostly due to the spatial interaction with fuels and topography, and by setting the start of the ‘temporal window’ that frames the coincident meteorological conditions [11,16,17]. For extreme wildfires, given their size and intensity, the effectiveness of fire suppression decreases, and becomes less relevant in determining the above mentioned characteristics [18]

A knowledge gap still exists in wildfire research related to better understanding individual wildfires, which is relevant to identify the factors controlling fire occurrence [19,20], to estimate fire risk [21], characterize fire regime [22], to understand the complex interactions between fire spread and its main drivers [10], to estimate carbon emissions [14] and assess fire-related impacts [13]. Ultimately, all these aspects can have important implications for fire suppression and management, and for the improvement of prevention policies [19,23]. Considering the future climate scenarios, improving our scientific knowledge on individual wildfires is crucial and research needs to be linked with fire-management decisions. In particular, the accurate prediction and anticipation of the spread and behaviour of active wildfires is an important research area, which can have important benefits supporting safer and more effective fire management decisions [24,25].

Wildfires can be studied using different sources of information, such as field data remotely sensed data (air- and space-borne) [26]. These data sources vary in spatial and temporal resolutions, time span, and accuracy. Acquiring individual fire data in the field is expensive, time consuming and difficult, especially in remote areas [8,27]. Information collected and compiled by land management authorities depends on the resources allocated, which vary in time and space [22,28]. Consequently, field-acquired information is often scarce, incomplete and with low accuracy [20,22,28-32]. In particular regarding wildfire spread, information on observed fire line location, growth patterns and intensity is often deemed of poor quality [33], and is only seldom used in research studies [24,34,35]. Some of the most promising field-data sources (e.g. infrared airborne: http://nirops.fs.fed.us/, UAVs, night observation of firelines) still have very low acquisition frequency and spatial coverage, are expensive and some have jurisdictional\safety issues that limit their application [25].

Another source of information on individual wildfires is satellite data, which have been widely used for fire management and research, particularly due to the size, duration and inaccessibility of many wildfires [8]. Satellites offer clear advantages over other fire data sources, and can be used to complement existing information and overcome some of the traditional limitations [27,32]. However, they have seldom been used to study individual fire events, with some exceptions aimed at mapping/monitoring fire occurrence [36-38], reconstructing fire progression [34,39-41], analysing fire behaviour [42,43], estimating fire-related emissions [42,43] and identify lightning-ignited fires [32]. Regarding the study of wildfire spread, satellite data are a cost-effective alternative to systematically monitoring the spatio-temporal dynamics of large wildfires [34,44-46]. Nevertheless, one should bear in mind that satellite data have many limitations and uncertainties that need to be taken into account [for in-depth discussion see 8,27,32,40]. Most of them are related with satellite detection capabilities, revisit cycle, viewing geometry and pixel size [27,47]. Other factors are related to fire environment such as fire size, duration, intensity, thermal contrast with surrounding areas, vegetation type affected, and persistent cloud clover and/or dense smoke plumes also constrain satellite detection rate [48-50]. Most importantly, satellites can only provide snapshots of the spread of large wildfires [50].

Modelling tools can also be used to study individual wildfires, in conjunction with field and satellite data. Wildfire fire spread models can be divided into two main types: (1) empirical or semi-empirical, and (2) physically-based models [51,52]. Empirical or semi-empirical models provide quick estimates of fire spread that are suitable for operational decision-making process, while physically-based models have been developed for theoretical approaches with the objective of better understanding the processes controlling fire propagation [53]. The current role, capability and suitability of both types is currently under debate in the scientific community [54,55]. Nevertheless, it is obvious that both have strong limitations, being one of the largest the fact that the basic mechanisms of fire spread are still not well understood [56], and are therefore, not incorporated in current models.

Spatially explicit wildfire spread models have been used to assess wildfire risk [21,57], test the effectiveness of fuel treatment options [58-61], assess fire suppression preparedness [62] and to understand the main drivers of fire behaviour [63] and of fire regimes [64]. These modelling tools are of special relevance, since they allow not only to study the growth and behaviour of past wildfires [65-67], but they can also be used to predict the spread of on-going active wildfires and therefore be used to support tactical suppression decisions [68,69]. Models have been used to predict the direction, and rate of spread and intensity of wildfires [15,70-72] supporting fire managers in their suppression strategies, evacuation orders and public warnings [73,74]. This ability is particularly relevant in regions of the world where wildfires pose real threats to life and property [24], including Portugal, and of paramount importance for extreme wildfires that escape initial attack, become large and last for multiple days [25].

Despite, the large potential of these tools to study individual wildfires, modelling such complex environmental phenomena is fraught with uncertainties [75]. Consequently the capability for accurately predicting fire spread still is very limited, undermining the utility of such predictions for decision-making [53]. Considering the relevance of the concept of uncertainty in the present Thesis, it is important to understand its meaning and separate it from other concepts also used throughout the work. Uncertainty can be defined as lack of information, bounded by complete ignorance and perfect information in opposite ends [76]. On the other hand, an 'error' can be defined as a deviation of the estimates when compared with observations (i.e. the 'truth') of the same variable. The definition of a ground truth is also what separates a classical 'validation', i.e. a quantitative comparison between estimations and observations to assess the performance of a model, from an 'evaluation' or 'assessment', where no formal ground truth is defined. In an assessment, two independent sources of data can be compared and their 'agreement' or 'discrepancy' can be analysed and quantified. If both agree, it can be stated as a case of convergence of evidence. In the present Thesis, due to the inherent uncertain nature of the data used to compare with the estimations, only assessments are performed, providing information on model-data agreement or discrepancy.

Uncertainties in fire spread modelling arise mainly from the imperfect scientific knowledge regarding the mechanisms controlling fire spread, model applicability and its inherent limitations, input data quality, natural variability, and parametric uncertainty [15,76-82]. Furthermore, wind and fuel variability, dynamic interactions between fire and its surrounding environment, long-range spotting and simultaneous ignitions [35,77,83] add complexity to the phenomena and increase the difficulty of accurately predicting fire spread.

Improvements in fire behaviour predictions have been pursued mainly through the use of better data, such as fuel characteristics [84,85], and wind speed and direction [86,87], as well as from structural improvements in the models [24]. Under certain conditions, input data reliability can be the dominant source of error in fire spread predictions [77]. Errors associated with wind and fuel data have been considered the most relevant [15]. The temporal and spatial variability of wind, due to the turbulent nature of the atmospheric boundary layer [88], is extremely difficult to capture and can result in large errors [15,89,90]. Errors associated with fuel classification and parameterization [91], along with the large spatial fuel variability and heterogeneity also have profound impacts on predicted fire behaviour [15,92].

Although progress has been made in understanding and modelling the behaviour of wildland fires, our ability to produce accurate predictions has evolved little, not only due to the complexity of the phenomena, but also due to the lack of systematic methods for model validation [53,77,93,94]. The latter is a key step in the application of models, especially in operational contexts [95,96]. Inaccurate fire spread predictions can have dramatic consequences on the environment, human life and property, as well as lead to incorrect preventive fuel management actions [77]. These aspects can significantly jeopardize the utility of such models in aiding fire managers [24].

Recently, the research community has been questioning which research approaches are needed to improve the fire spread prediction accuracy of operational models [24,25]. Understanding how simulations can be improved is a critical research task, as fire spread predictions will only be deemed useful if they can provide reliable information to fire managers, and potentially contribute to mitigate negative downstream consequences. Fire spread predictions can be improved in a number of ways, namely by i) increasing scientific knowledge of the physical processes driving fire behaviour and spread mechanisms; ii) developing more accurate and reliable models; iii) using higher quality input data (e.g. wind, fuels); and iv) through model calibration. Cruz et al. [24] prioritized some of the approaches they believed would allow to improve fire spread modelling, such as the design of field experiments, the reanalysis of existent fire spread data, and the increase of case study documentation. Gollner et al. [25] proposed a data-driven approach and argued that improvements in the input data, on our knowledge regarding physics of fire, remote sensing capabilities, and the current fire databases, are fundamental to provide accurate operational fire spread forecasts in the next decade(s). They also argued that both input data (e.g. wind, fuels) and observed fire data (e.g. fire line location, rate of spread) need to be accompanied by a proper quantification of uncertainty to be deemed as useful. However, it must be noted that improving data, models and scientific knowledge, may involve challenging tasks that are too expensive and time consuming, not meeting the demands of fire managers for short-term and inexpensive improvements of fire spread predictions. Additionally, these key improvement areas encapsulate complex research questions by themselves.

Fire management in Southern Europe rarely, if ever, is supported by information derived from fire behaviour models. Thus, fire management decisions often miss a strong scientific background compromising their efficiency. The present Thesis proposes to tackle some of the above mentioned limitations that constrain our understanding of individual large wildfires, addressing the following generic questions: What can we learn from past wildfires to mitigate their future impacts? How can fire spread predictions be made sufficiently reliable to support fire management? These questions are addressed by investigating a set of key issues that have been identified as paramount importance to improve fire spread predictions for operational purposes, namely:

i) Develop a methodology to systematically evaluate fire spread predictions over both space and time, using satellite data with a proper uncertainty quantification;
ii) Better understand the nature of uncertainty in the input data, how it propagates through fire spread models and how it affects its predictions;
iii) Improve fire spread predictions using inexpensive and low-time consuming approaches based on data-driven model calibration.

In the present Thesis, satellite data and fire spread modelling are combined in an innovative way, to minimize their individual limitations and maximize their potential. The analyses were performed by studying historical wildfires, and framed considering some of the biggest challenges involved in setting up and using a fire spread modelling system. All these steps precede one major long term goal: to develop an operational system capable of providing relevant information on large wildfires, including the forecast of fire spread and behaviour that can support safe and effective fire suppression strategy and tactics in the future.

Outline

The work is divided into four papers published in peer-reviewed journals, all presented in the original journal format. Three of them were published as first author and another as co-author.

Paper I: Benali et al., *Determining Fire Dates and Locating Ignition Points With Satellite Data*, published in Remote Sensing.
http://www.mdpi.com/2072-4292/8/4/326

Paper II: Sá et al., *Evaluating fire growth simulations using satellite active fire data*, published in Remote Sensing of Environment.
https://www.sciencedirect.com/science/article/pii/S0034425716305028.

Paper III: Benali et al., *Deciphering the impact of uncertainty on the accuracy of large wildfire spread simulations*, published in Science of the Total Environment.
https://www.sciencedirect.com/science/article/pii/S0048969716312852

Paper IV: Benali et al., *Fire spread predictions: Sweeping uncertainty under the rug*, published in Science of the Total Environment.
https://www.sciencedirect.com/science/article/pii/S0048969717306186?via%3Dihub

The motivation behind each paper, what was done and how the work is linked with the rest of the doctoral Thesis is described below.

In **Paper I**, the following research question was addressed: *Can satellite data be used to derive relevant information on large wildfires*. Information on where and when a fire started, and its duration is important to improve our understanding on the dynamics of individual wildfires. For example, fire dates determine the weather and fuel conditions under which a wildfire occurs and consequently its behaviour, size [9,10], among other aspects. Ignition location strongly influences fire spread, extent and intensity, due to the interaction with weather, fuels and topography [16]. This information is typically included in fire databases that are known to have multiple errors, limited spatial coverage and/or time span, and often-unknown accuracy and uncertainty [21]. In **Paper I**, it was hypothesized that satellite thermal data can reduce such limitations and provide accurate and systematic information regarding start/end dates and ignition location(s) for large wildfires. The methodology was explored for large wildfires that occurred in five areas of the world and results were compared with field data and accompanied by an uncertainty analysis.

In **Paper II**, the following research question is addressed: *Can we use satellite data to evaluate fire spread simulations?* As mentioned, fire spread predictions seldom are accompanied by proper and systematic model evaluation which is a crucial step to evaluate their reliability [69]. For reasons detailed above, the availability of observed wildfire data is scarce, which hampers comprehensive evaluation [24]. Additionally, many of the most common evaluation metrics [e.g. 91,92] ignore the spatio-temporal patterns of fire spread [32,93-95]. Due to their frequency and synoptic coverage, satellite thermal data are able to systematically monitor the spatial and temporal dynamics of large wildfires [33,44], although very few studies have combined both approaches [45]. In **Paper II**, it is hypothesized that the spatial and temporal patterns of fire growth observed by satellite can be used to assess fire spread simulations. An innovative evaluation scheme was developed that uses satellite thermal data to assess fire spread simulations by explicitly calculating their discrepancies. The work focused on a set of large wildfires that occurred in Portugal between 2003 and 2012. The FARSITE modelling system [96] was used to simulate their fire growth. The satellite-derived fire dates and ignitions estimated in **Paper I** were used as input to the fire spread simulations. **Paper II** was developed in co-authorship that consisted in performing fire spread simulations, comparing them with satellite data and analysing the results.

In **Paper III**, the following research question was addressed: *How do uncertainties in input data affect the accuracy of fire spread predictions?* Uncertainties in input data can have large impacts on fire spread predictions, and in certain conditions, can be the dominant source of error [14,70,83,84]. Consequently, it is important to clarify the nature of uncertainty, how it propagates through fire spread models and how it affects its predictions [74,97]. In **Paper III**, it was hypothesized that the uncertainties in wind and fuel variables have a large impact on the accuracy of fire spread predictions. The work focused on understanding, characterizing and quantifying the impact of data uncertainty on the fire spread predictions, for set of large wildfires that occurred in Portugal between 2003 and 2012. The impact was assessed by analysing the effects on simulated fire growth rate and on the accuracy of the predictions, based on the data and evaluation scheme developed in **Paper II.** The spatial and temporal disagreements between reported and observed fire ignitions, in **Paper I**, were used to characterize their uncertainty. It was also discussed how integrating uncertainty can help to improve fire spread predictions and to provide useful information for researchers and fire managers.

In **Paper IV**, the following research question was addressed: *Can the impact of data uncertainties be reduced?* Apart from the impact of errors in the input data, another approach to improve fire spread predictions is to calibrate the modelling system using a data-driven approach, i.e. to adjust its parameters with the aim improving the agreement between estimated and observed fire spread and behaviour [24,98,99]. In **Paper IV** it was hypothesized that the impact of input data uncertainties can be reduced using a robust regional calibration methodology based on information on prior wildfires. Specifically, it was investigated if the calibration of the empirical ROS adjustment factors of FARSITE can be a simple, fast and inexpensive way of improving the consequent fire spread predictions based on information collected from historical large wildfires. Additionally, it aims at understanding to what extent decreasing parametric uncertainty can counterbalance the impact of input data uncertainty (studied in **Paper III**). Again, fire spread predictions were evaluated based on the data and evaluation scheme developed in **Paper II**.

The papers presented in the following pages, followed by a general discussion and conclusion of the doctoral Thesis.

Besides the papers identified above, during the course of the doctoral Thesis, other parallel work was developed, and although it was not included in the present document, it is worth mentioning it briefly:

1. Bedia et al. *Global patterns in the sensitivity of burned area to fire-weather: Implications for climate change,* published in Agricultural and Forest Meteorology. https://www.sciencedirect.com/science/article/pii/S0168192315007078

2. Nunes et al. A simple water balance model adapted for soil water repellency: application on Portuguese burned and unburned eucalypt stands, published in Hydrological Processes. https://onlinelibrary.wiley.com/doi/abs/10.1002/hyp.10629

3. Benali et al. *Bimodal fire regimes unveil a global-scale anthropogenic fingerprint*, published in Global Ecology and Biogeography. https://onlinelibrary.wiley.com/doi/abs/10.1111/geb.12586

4. Pinto et al. Probabilistic fire spread forecast as a management tool in an operational setting, published in SpringerPlus. https://springerplus.springeropen.com/articles/10.1186/s40064-016-2842-9

Paper I - Determining Fire Dates and Locating Ignition Points With Satellite Data

remote sensing

MDPI

Article

Determining Fire Dates and Locating Ignition Points With Satellite Data

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Abstract: Each wildfire has its own "history", burns under specific conditions and leads to unique environmental impacts. Information on where and when it has started and its duration is important to improve understanding on the dynamics of individual wildfires. This information is typically included in fire databases that are known to have: (i) multiple error sources; (ii) limited spatial coverage and/or time span, and; (iii) often unknown accuracy and uncertainty. Satellite data have a large potential to reduce such limitations. We used active fire data from the MODerate Resolution Imaging Spectroradiometer (MODIS) to estimate fire start/end dates and ignition location(s) for large wildfires that occurred in Alaska, Portugal, Greece, California and southeastern Australia. We assessed the agreement between satellite-derived estimates and data from fire databases, and determined the associated uncertainty. Fire dates and ignition location(s) were estimated for circa 76% of the total burnt area extent for the five study regions. The ability to estimate fire dates and ignitions from satellite data increased with fire size. The agreement between reported and estimated fire dates was very good for start dates (Model efficiency index, MEF = 0.91) and reasonable for end dates (MEF = 0.73). The spatio-temporal agreement between reported and satellite-derived wildfire ignitions showed temporal lags and distances within 12 h and 2 km, respectively. Uncertainties associated with ignition estimates were generally larger than the disagreements with data reported in fire databases. Our results show how satellite data can contribute to improve information regarding dates and ignitions of large wildfires. This contribution can be particularly relevant in regions with scarce fire information, while in well-documented areas it can be used to complement, potentially detect, and correct inconsistencies in existing fire databases. Using data from other existing and/or upcoming satellites should significantly contribute to reduce errors and uncertainties in satellite-derived fire dates and ignitions, as well as improve coverage of small fires.

Keywords: MODIS; fire events; ignition; extinction; Alaska; Portugal; Greece; California; Australia; uncertainty

1. Introduction

Wildfires play a major role in ecosystem dynamics and pose as an important threat to lives, human and natural resources of fire-prone regions. At the global and regional levels, the causes and consequences of wildfires are typically integrated over large areas and long time periods [1]. However, at the landscape level, each wildfire is a distinct event with its own "history", ignited and burning under specific fuel and weather conditions, ultimately leading to unique social and ecological impacts [2,3].

The identification of individual fire events has been acknowledged as necessary to better understand how fire extent and frequency affect global environmental processes [2,4]. Characterizing individual wildfires is relevant to identify associated causes [5,6], to understand the factors controlling fire occurrence [7,8], to estimate fire risk [9], characterize fire regime [10], to understand the complex interactions between fire spread and its main drivers [11], to estimate carbon emissions [12] and assess fire-related impacts [13]. Improving the quality and quantity of the information regarding individual wildfires has important implications for fire suppression and management, and for improvement of prevention policies [5,7].

To study a specific wildfire event, it is crucial to know where and when it started (*i.e.*, ignition location and timing) and how long it lasted (*i.e.*, duration). The fire start and end dates partially determine the weather and fuel conditions under which a wildfire occurs and consequently its behavior, size [11,14,15], severity of effects [13] and consequent pyrogenic emissions [12]. Ignition location strongly influences fire spread [16], extent and intensity, due to the interaction with weather, fuels and topography [14,17].

Fires can be characterized using different sources of information, such as field data collected by various agencies, fire-occurrence records and remotely sensed data (air- and space-borne) [18]. These data sources vary in spatial and temporal resolutions, time period covered, and accuracy. Fire atlases have been widely used and contain information regarding the location and date of each fire event, among other relevant attributes [19]. However, these databases are incomplete and affected by multiple error sources, such as: incorrect database compilation; incorrect location assignment; data acquisition errors; ambiguous recording of events; data loss or misplacement; inadequate documentation; multiple recording of the same fire event [6,8,10,19–22]. As a result, accuracy of the information contained in fire databases varies in space and time and is largely unknown [2,10,18,22].

Acquiring individual fire data in the field is expensive, time consuming and difficult, especially in remote areas [2,23]. Information collected and compiled by land management authorities depends on the resources allocated, which vary in time and space [10,22]. Consequently, the accuracy and extent of total burned area mapped, and of fire ignition location, as well as the timing of ignition and extinction included in fire databases can be lower than is desirable. Thus, it is important to improve the quality and availability of fire event data, including the timing of fire occurrence and ignition location.

Satellite data have clear advantages over other fire data sources that may complement existing information and overcome some of the traditional limitations [6,23], that are dependent on the scale of application [2]. In fact, satellite data have been widely used for fire management and research, particularly due to the size, duration and inaccessibility of many wildfires [2]. Despite this, they have seldom been used to study individual fire events, with some exceptions aimed at mapping/monitoring fire occurrence [24–26], reconstructing fire progression [27–30], analyzing fire behavior [31,32], estimating fire-related emissions [33] and identify lightning-ignited fires [6]. In the United States of America (USA), satellite data have been used by land managers to complement existing fire data and aid management efforts [19]. Nevertheless, one should bear in mind that satellite data have many limitations and uncertainties that need to be taken into account (for in-depth discussions see [2,6,23,29]).

Some authors have used satellite data to study the dynamics of individual wildfires [6,28,29]. Nevertheless, a comprehensive evaluation of the potential use of satellite data to detect wildfire ignitions is still missing, as well as a broad scale analysis of the potential of satellite data to estimate the start/end dates of wildfires. Thus, the aim of the present study is to evaluate the potential of satellite data to provide reliable information regarding the start/end dates of large individual wildfires, as well as, the location of their ignition(s). We discuss associated limitations of satellite data to

(i) complement existing fire databases or (ii) to provide unprecedented information in regions with deficient fire monitoring and mapping. Finally, we quantify and analyze the uncertainty associated with satellite-derived estimates.

2. Materials and Methods

2.1. Study Areas and Fire Databases

We selected five distinct study areas: Portugal, Greece, California, Alaska and Southeastern (SE) Australia (Figure 1). Portugal, Greece and California have a Mediterranean or Mediterranean-like climatic influence with the bulk of fire activity occurring under dry summer conditions, burning mostly shrublands and temperate forests [10,34,35]. Extreme fire seasons occurred in 2003 and 2005 in Portugal [36,37], 2007 in Greece [38], and 2003 and 2007 in California [39,40]. The two remaining study areas, Alaska and SE Australia, have very different climatic conditions, which are naturally reflected on fuel dynamics and fire activity. In Alaska, fire activity occurs mainly during the summer, it is concentrated in the interior of the state and affects mainly boreal forests [22]. Recently, biomass burning emissions have been reported to be increasing due to climate change [41]. Alaska experienced extreme fire seasons in 2004 and 2005 [42]. In SE Australia fires occur every year, mainly during spring and summer seasons, burning mainly grasslands and dry forests [43]. As a consequence of severe droughts, SE Australia experienced extreme fire seasons in 2003 and 2009 [43,44].

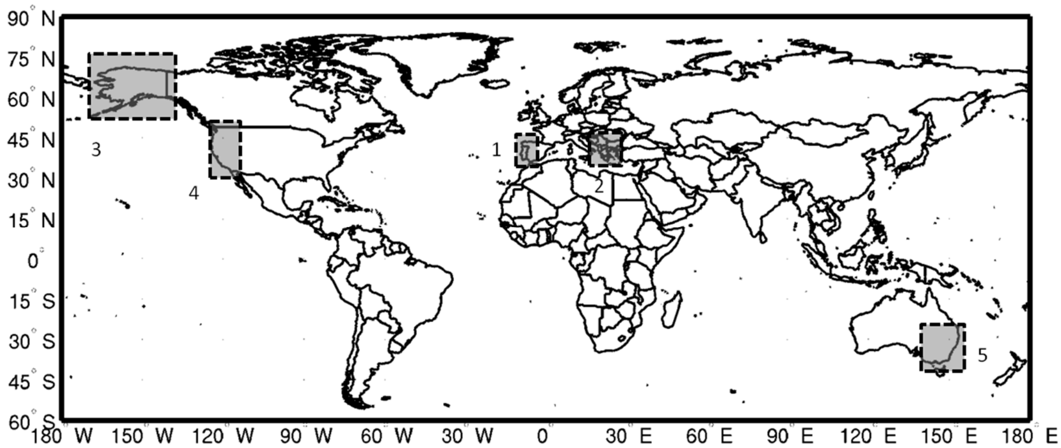

Figure 1. Study areas: (**1**) Portugal; (**2**) Greece; (**3**) Alaska; (**4**) California and (**5**) SE Australia.

The sources and time span of the databases for all the study regions are described in Table 1. The fire database for Portugal, provided by the Instituto de Conservação da Natureza e Florestas (ICNF), contains information regarding the beginning and end of each fire, as well as the location and date of ignitions for wildfires that occurred in Portugal between 2001 and 2009 using ground collected data [45]. Until the beginning of the current study, the Portuguese fire-atlas contained end-of-season annual fire perimeters from 1975 to 2009, derived from high spatial resolution satellite imagery [46].

The Alaska fire database, managed by the Alaska Interagency Coordination Center (AICC), contains a very long record of fires (since 1940) [47] derived from ground and aerial surveys, as well as through the interpretation of aerial photography and satellite data [22]. The California fire perimeters database is provided by the Department of Forestry and Fire Protection [48] and covers the entire state since 1878. Information regarding fire dates and ignitions for Alaska and California were retrieved from a comprehensive database covering the USA between 1992 and 2011 [21].

Table 1. Temporal coverage and sources of the fire perimeters and databases containing information on fire dates and ignitions.

Region	Fire Perimeters	Fire Dates	Ignitions	Sources
Portugal	2000–2009	2001–2009	2001–2009	[45,46]
Alaska	2000–2013	2001–2013	2001–2010	[21,47]
California	2000–2011	2001–2011	2001–2010	[21,48]
Greece	2000–2011	2000–2007	2000–2007	[49,50]
SE Australia	2000–2011	2000–2011	2000–2008	NSW Office of Environment and Heritage (unpublished data)

For SE Australia, we used a fire database from the New South Wales (NSW) Office of Environment and Heritage (unpublished data), containing fire perimeters, dates and ignitions since 1977. The fire perimeters for Greece were derived from high resolution satellite imagery, covering the period of 2000–2011 [49,50], while the fire dates and ignitions database covers the period of 2001–2007 (unpublished data).

The fire perimeters for all study regions were originally in vector format (polygons) and were converted to raster format. The information on fire dates and ignitions were contained within vector (points) and database formats. We performed an exploratory analysis and found suspicious records in almost all study regions, such as: (i) multiple records per burnt area (in some cases with dates separated by several months); and (ii) records located outside any fire perimeter (in some cases off by several kilometers out).We removed data records that had: (i) negative duration; (ii) incorrect or inconsistent date format; (iii) locations outside the study region; (iv) missing information about the ignition hour; or (v) very large duration (over 6 months). Data records that only contained either start or end fire date were kept while ignition records that contained only the location or the date/hour were excluded.

2.2. Satellite Data

The MODerate Resolution Imaging Spectroradiometer (MODIS) is aboard the Terra and Aqua spacecrafts, since early 2000 and mid-2002, respectively. The MODIS active fire product (MCD14ML) provides information about the location of fires burning at the time of satellite overpass based on thermal anomalies [51] and is supplied in text format. Due to the orbit of both satellites, Terra data are acquired during day and nighttime at around 10:30–12:00 a.m./p.m. local time, respectively, and Aqua data at around 1:00–3:00 a.m./p.m, respectively. The pixel size is approximately 1 km^2, but its footprint size increases away from nadir reaching up to about 10 km^2 [52]. An active fire can be detected even if only a small part of the pixel is burning, due to its strong radiance signal and contrast with surrounding areas [40], although only its centroid is recorded in the MCD14ML product. The footprint of each active fire was computed using the formulations of Ichoku and Kaufman [53] that relate the scan angle and Earth's geometry with the pixel dimensions.

Additionally, we used the quality flags of the MODIS Land Surface Temperature (LST) product (MOD11A1 and MYD11A1 [54]; provided in HDF raster format) to determine if the observations were done under clear-sky conditions. The quality flags were used to estimate a proxy of cloud cover (in %) over each fire perimeter. The advantage of using the LST product is that it provides information regarding day and nighttime MODIS acquisitions for both Terra and Aqua sensors.

2.3. Wildfire Dates

To determine the start (ignition) and end (extinction) dates, we assumed that a fire event is constrained in space and time. To handle the spatial dimension of the problem, we overlapped the fire perimeters and the MODIS active fires, in spite of their very different spatial resolutions. All fire perimeters smaller than 200 ha were excluded from analysis, considering MODIS active fire detection capabilities [23]. An active fire was considered to overlap the fire perimeter if at least 5% of its footprint was within the fire perimeter.

To handle the temporal dimension of the problem, we developed a temporally constrained clustering algorithm (Figure 2). For each wildfire, all active fires that overlapped its perimeter were grouped in temporal clusters based on three empirical parameters (*i.e.*, constraints): minimum and maximum gap (*minG* and *maxG*) and minimum density of active fires (*minD*). The term "gap" refers to the time period without active fire detections. The term "density" refers to the fraction of active fires detected within the fire perimeter in a specific year. The main issue when clustering active fire observations was to determine whether they belonged to the same cluster, *i.e.*, if they corresponded to the same fire event. When a time gap occurred, *i.e.*, no active fires were detected after a group of detections, the *minG* parameter controlled the number of days the algorithm searched for subsequent detections and included them in the initial cluster. If no detections were found prior to *minG*, we used the satellite quality flags to determine if later observations were affected by smoke or clouds. The algorithm determined, each day at a time within the *minG* and *maxG* window, whether the entire fire perimeter was clearly observed by the satellite. If active fires were detected within that time window, they were merged with the initial group to form a single cluster. When all clusters were determined, we retained the cluster with the highest density (%) of active fires detected over the fire perimeter. If the density was greater than *minD*, the start and end dates were assigned as the dates of the first and last active fire(s) detected over the fire perimeter, respectively. Lower *minD* values increase the probability of assigning start and end dates to fire perimeters comprising more than one fire event.

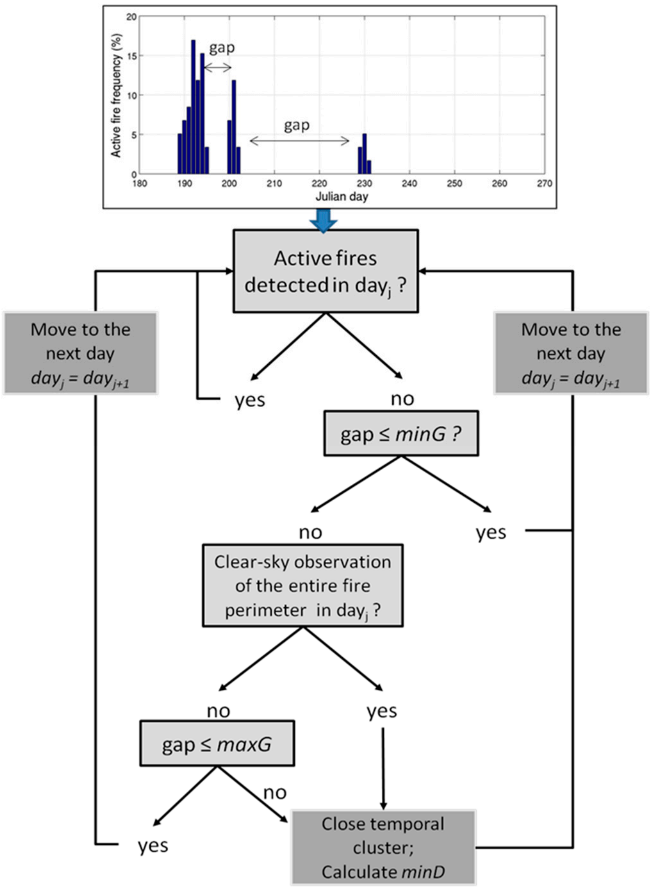

Figure 2. Methodological flow chart of the temporally constrained clustering algorithm used in the estimation of fire start/end dates.

After constraining the data in space and time, we found some ambiguous active fire detections that could belong to more than one fire perimeter. We calculated the time lag between ambiguous and non-ambiguous neighboring active fire detections. An ambiguous active fire detection was assigned to a fire perimeter based on the smallest temporal lag. If the assignment was not possible, we assigned the active fire to the perimeter with highest percentage of footprint overlap. After assigning ambiguous active fires detections, the clustering algorithm was run again.

The *minG* parameter was set to 2 days. The *maxG* and *minD* parameters were estimated using a simple multi-objective optimization procedure. Details are provided in Supplementary Material Section 1. The *maxG* and *minD* parameters were estimated as 9 days and 85% respectively, and were used hereafter.

2.4. Wildfire Ignitions

The first active fire(s) detected in a wildfire event were defined as its ignitions, *i.e.*, the active fire(s) corresponding to the estimated start date (see Section 2.3). Ignitions were represented as areas, rather than points, by retaining only the part of the pixel footprint within the fire perimeter. We discarded the fire perimeters for which estimated fire start and end dates were equal.

Temporal uncertainty associated with satellite-derived ignitions was defined as the time lag between estimated ignition (*i.e.*, start date) and the closest precedent clear-sky observation (in hours), up to a maximum of 72 h. For example, if the ignition time was estimated based on a nighttime Terra acquisition (~22 p.m.) the uncertainty was approximately 7 h if the entire fire perimeter was clearly observed during Aqua daytime acquisition (~3 p.m.). The spatial uncertainty was defined as the fraction of the total burnt area covered by the ignition area (%), *i.e.*, how much the potential ignition area was narrowed down within the entire burnt area perimeter.

2.5. Assessment of Satellite-Derived Wildfire Dates and Ignitions

We calculated the agreement between the satellite-derived fire dates and ignitions and correspondent data reported in the fire databases. The quantitative assessment was performed based on the availability of both fire perimeters and reported data for fire dates and ignitions, independently (see Table 1). Thus, to coincide with the period of MODIS activity, only data post-2000 data were used.

Fire locations records have uncertainties and are generally imprecise [55]. As mentioned, we found several reported records located outside any fire perimeter. The assignment of the location of the closest place name (e.g., 10) is probably one of the most frequent causes of uncertainties. To minimize the impacts of incorrect geolocation that would exclude a large proportion of the data records, an empirical analysis was performed to define the optimal buffer size around a fire perimeter. Details are provided in Supplementary Material Section 2. The optimal buffer was set to 2 km.

We performed an additional screening of the fire databases and removed the records that were not within the burnt area perimeter and its optimal buffer, and the records that overlaid multiple fire perimeters. Since some fires had multiple records within its perimeter e.g., [10], for each fire perimeter we performed the assessment considering only the data record with the date closest to the satellite-derived start date. For the satellite-derived ignitions assessment we narrowed down the initial evaluation sample by excluding records that had a time lag between reported and estimated start dates larger than three days. The size of the assessment dataset varied significantly among regions and for each fire parameter, due to data availability and screening procedures (Figure 3).

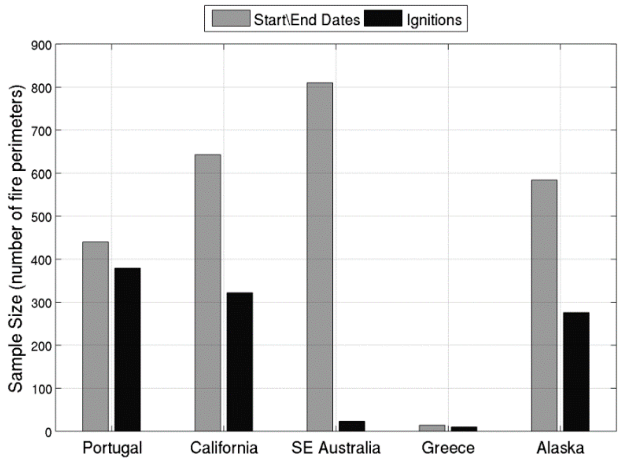

Figure 3. Evaluation sample size for the five study regions, regarding the total number of wildfire perimeters with reported start/end dates (N = 2491) and reported ignitions (N = 1010).

To assess the agreement between satellite-derived and reported fire dates we calculated the Nash–Sutcliffe Model Efficiency index (MEF) as a measure of predictive power [56]:

$$\mathrm{MEF} = 1 - \frac{\sum_{\mathrm{i}=1}^{\mathrm{N}} (\mathrm{P_i} - \mathrm{O_i})^2}{\sum_{\mathrm{i}=1}^{\mathrm{N}} \left(\mathrm{O_i} - \overline{\mathrm{O}}\right)^2} \tag{1}$$

where, $\mathrm{P_i}$ and $\mathrm{O_i}$ denote the predicted and observed values (*i.e.*, fire start or end dates), and $\overline{O}$ is the observed mean. The database records corresponded to the observations in Equation 1.

To assess the agreement between satellite-derived ignitions and data reported in the fire databases we calculated: (i) the temporal lag between reported and estimated ignition dates; and (ii) the minimum Euclidean distance between satellite-derived and reported ignition locations.

2.6. Limitations of Satellite Data to Derive Wildfire Dates and Ignition

The main reasons behind the inability of satellite data to provide fire date information, and consequently on their ignitions, were investigated. A decision tree was built to classify the possible cause behind the absence of satellite-derived fire dates in a step-wise fashion (Supplementary Material Section 3). For each fire perimeter without satellite-derived dates, we determined whether active fires had been detected over the fire perimeter. If not, we used the reported fire dates and identified the following potential causes:

1. *Persistent cloud cover*, if the average cloud cover affecting the fire perimeter between the reported start and end dates was higher than 80%.
2. *Small fire*, if the burnt area was smaller than 500 ha (larger than 200 ha, see Section 2.3).
3. *Short duration*, if the reported fire duration was shorter than 12 h.
4. *Unknown*, if none of the above conditions were verified.

Since the causes were determined in a step-wise fashion, a small and short duration fire was only classified as a small fire. We excluded all fire perimeters that did not have reported fire dates or that had multiple records indicating multiple fire dates.

When there were active fires detected over the fire perimeter, the following reasons may explain the inability of satellite data to provide fire date information:

5. *Insufficient information*, if active fires were detected only for one satellite overpass.
6. *Multiple fire events*, if the minimum frequency of the largest temporal cluster was below minD (see Section 2.3).

3. Results

3.1. The Potential of Satellite Data

Using MODIS active fire data, combined with higher spatial resolution fire perimeters, a total of 3475 (23%) fires were dated, which correspond to about 77% of the total burnt area for the five study regions. The fire ignitions were determined for 2627 (17%) fires, corresponding to about 76% of the total burnt area.

The ability to estimate fire dates from satellite imagery increased with fire size (Figure 4). For most fires smaller than 500 ha it was not possible to estimate the start/end dates. This fraction increased with burnt area. Above 2500 ha, most fire perimeters had satellite-derived dates, corresponding to 75% of the total burnt area analyzed (Table 2). The patterns for satellite-derived fire ignitions were identical, with a lower number of estimations for burnt areas below 500 ha (not shown).

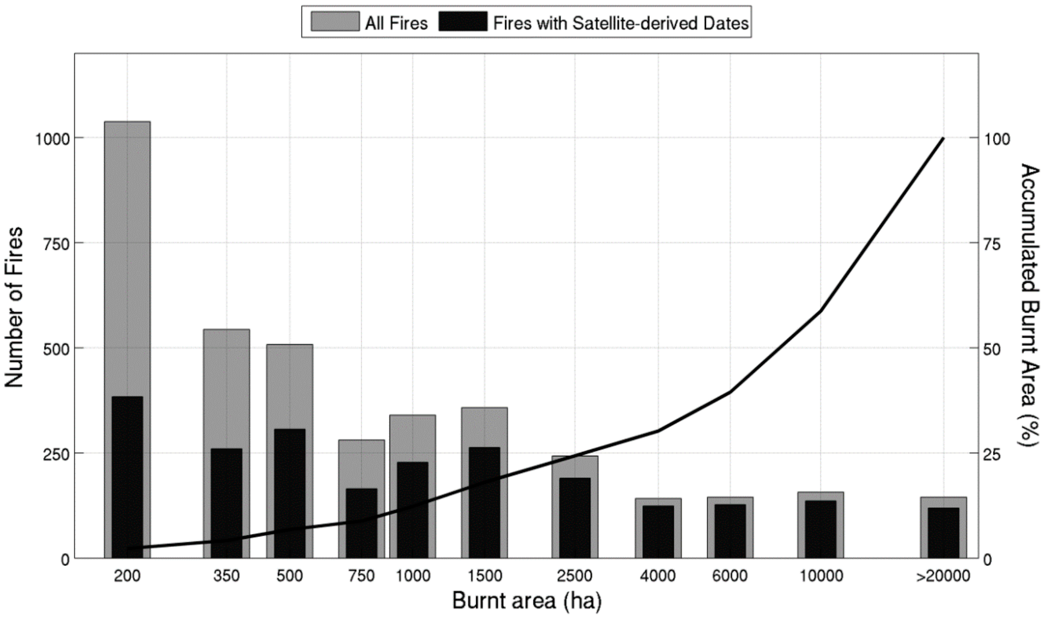

Figure 4. Distribution of the number of fire events larger than 200 ha dated using satellite data according to their burnt area extent. The bars represent burnt area intervals with irregular spacing due to the skewed fire size distribution and the value in the x-axis represents the lower bound of the interval. The black line represents cumulative burnt area (%).

Table 2. Fraction of total burnt area (%) covered with data of wildfires' start/end dates and ignitions (between brackets) for all study regions.

	Satellite-Derived Data Available	Satellite-Derived Data Unavailable
Reported Data Available	74.5 (86.6)	15.4 (6.2)
Reported Data not Available	8.0 (5.0)	2.1 (2.3)

Satellite-derived fire dates complemented existing fire databases in about 9% of total burnt area. For ignitions, satellite-derived data can be used to evaluate and complement existing databases on about 87% and 5% of total burnt area, respectively. For regions with limited fire date information, satellite-derived dating can be very useful (Supplementary Material Section 4). Within Greece, satellite-derived data were the only source of information on fire dates and ignitions for 16% and 14% of total burnt area, respectively. For SE Australia, it provided new information on fire dates and ignitions for 34% and 76% of the total burnt area. This contrasted with well-documented regions where satellite-derived information only filled fire dating gaps for less than 6% of the total burnt area (Supplementary Material Section 4).

3.2. Assessment and Uncertainty Analysis

3.2.1. Fire Dates

The comparison between reported and estimated fire start dates for the five study regions showed a very good agreement, with most of the points close or on the 1:1 line (MEF = 0.91; Figure 5a). For fire end dates, the agreement was considerably lower showing a tendency toward underestimation (MEF = 0.71, Figure 5b).

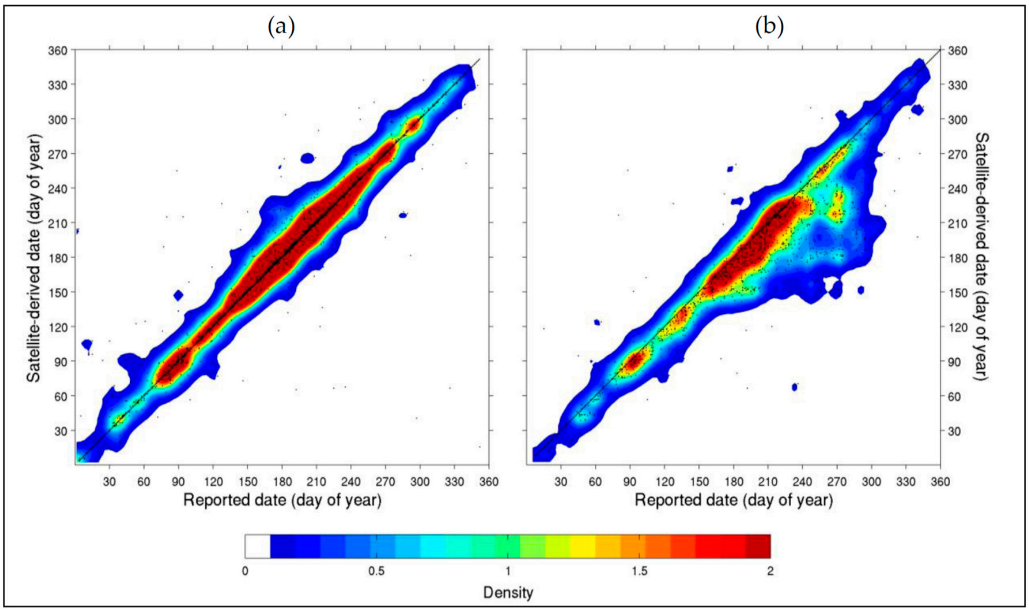

Figure 5. Pairwise comparison between reported and satellite-derived fire (**a**) start dates (N = 2395, MEF = 0.91) and; (**b**) end dates (N = 1397, MEF = 0.73). The colorbar indicates the number of pairs within each satellite-derived/reported date bin. White color indicates null or very low density.

The region-by-region assessment showed that the estimated start date had good agreement when compared with reported data for all regions (Table 3). Optimization of the temporally constrained clustering algorithm shows that the optimal set of parameters were different for each study region (Figure S2). Alaska and Portugal had very low agreement for fire end dates, when compared with reported dates. This led to a lower overall MEF for the satellite-derived end date estimation (Figure 5b). We investigated the fire perimeters causing a significant departure from the 1:1 line in both regions. For Portugal, the cases with large discrepancies between estimated and reported end dates (N = 8) corresponded to suspicious records, all of them with reported dates outside of the fire season and some corresponding to large fires (>2500 ha) with very short durations. For Alaska, we identified a large number of suspicious cases, almost half of the assessment sample size (N = 258). For these cases, the average fire duration was around 60 days while for the remaining was around 30 days. We identified (i) 50 cases that were reported as extinguished after October, some of them in late December; (ii) 17 cases with durations exceeding 4 months; and (iii) 17 cases that burned less than 500 ha each, but lasted for more than one month.

Table 3. Region-by-region Model Efficiency Index (MEF) and sample size (between brackets) for fire start and end dates.

Region	Start Date	End Date
Portugal	0.77 (394)	0.41 (139)
Greece	0.69 (12)	0.85 (11)
Alaska	0.79 (564)	−0.28 (503)
California	0.94 (589)	0.77 (212)
SE Australia	0.88 (766)	0.89 (532)
All Regions	0.91 (2325)	0.73 (1397)

3.2.2. Fire Ignitions

Overall, the spatio-temporal agreement between reported and satellite-derived ignitions was good (Figure 6). Most records had absolute temporal lags under 12 h and Euclidean distances below 2 km (Figure 6 and Supplementary Material Section 5). As expected, the satellite-derived ignition dates were typically delayed when compared with reported data, thus exhibiting a negative time lag. About 50%, 65% and 81% of the assessment sample had absolute temporal lags below 6 h, 12 h and 24 h, respectively (Figure 6 and Supplementary Material Section 5). Regarding the spatial agreement, the bulk of the distribution was concentrated on low distances (*i.e.*, higher agreement). Around 75% of the estimates had spatial discrepancies below 2 km, thus lower than the buffer size used for data records located outside the fire perimeters and in the same order of magnitude as the satellite footprint size for moderate viewing angles [41]. About 10% of the fires analyzed had reported ignition locations outside the fire perimeter and satellite-derived ignitions within the perimeter (not shown). For these cases the average distance between satellite-derived and reported ignitions was on average 800 m, but varied greatly, with the 95% of the data contained in the 90–2200 m interval.

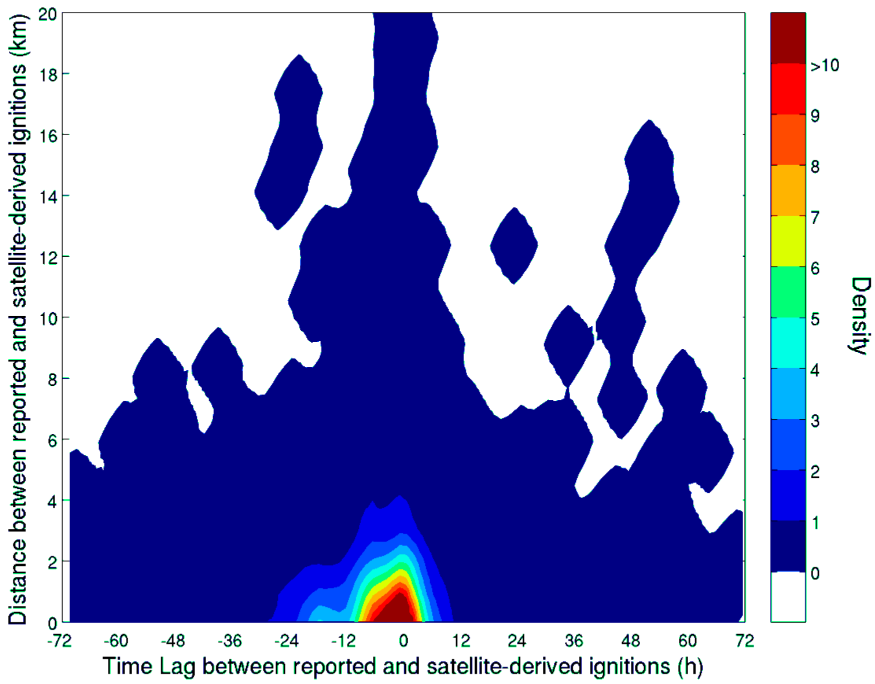

Figure 6. Temporal and spatial discrepancies between reported and satellite-derived ignition data ($N = 1376$). The colorbar indicates the number of pairs within each reported-estimated time lag/distance bin.

The relation between the spatial and temporal uncertainty associated with satellite-derived fire ignitions is shown in Figure 7. Most points were concentrated in an area with spatial and temporal uncertainties lower than 30% and 12 h, respectively. About 60% of the fire perimeters had a spatial uncertainty below 33%, *i.e.*, using satellite data we were able to narrow the ignition area to less than one third of the entire fire perimeter (Supplementary Material Section 5). About 70% of ignitions were estimated with less than 12 h of temporal uncertainty (Supplementary Material Section 5). The distribution of the latter followed the differences between Terra and Aqua overpasses. For example, the time lag between Terra and antecedent Aqua overpasses is generally around 8 to 11 h, while the time lag between Aqua and antecedent Terra overpasses, the temporal lag is around 1 h to 4 h.

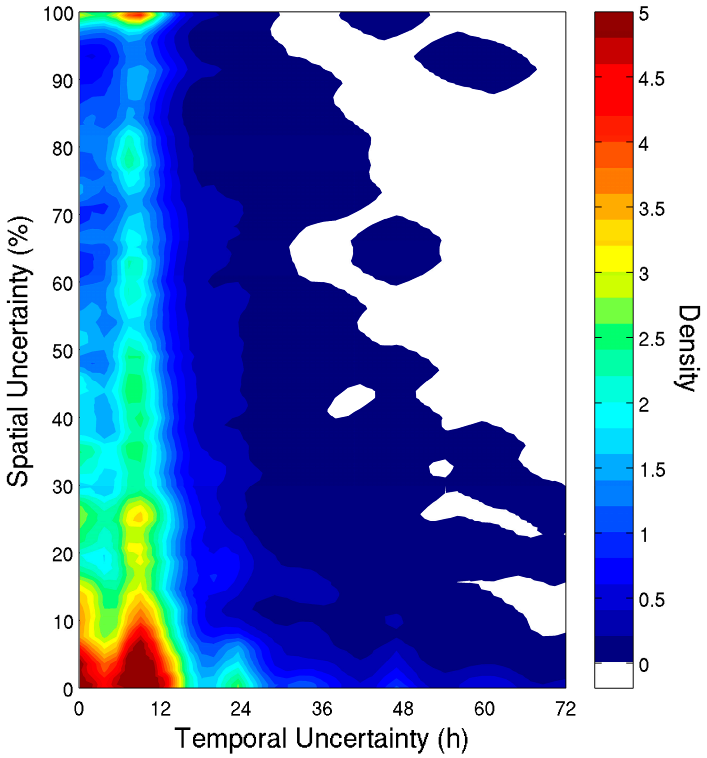

Figure 7. Relation between temporal and spatial uncertainty of satellite-derived ignitions (N = 2379). The colorbar indicates the number of pairs within each temporal/spatial uncertainty bin.

Spatial uncertainty and its variability decreased markedly with increasing fire size (Figure 8). Smaller fires were responsible for the largest spatial uncertainties. Temporal uncertainty increased less markedly with burnt area up to 2×10^5 ha, and increased sharply above this value. The number of fires larger than 2×10^5 ha was very small in our sample. We assumed that the likelihood of having clear sky observations covering the entire fire perimeter is smaller for larger fires.

We compared spatial and temporal uncertainty with the disagreements between reported and satellite-derived ignitions (Figure 9). Most satellite-derived ignitions had larger temporal uncertainties than disagreements with reported data (Figure 9a). Areas of low temporal uncertainty and disagreement coincided. The same pattern was observed for the spatial dimension (Figure 9b). The range of spatial uncertainty was larger than the range of spatial discrepancies.

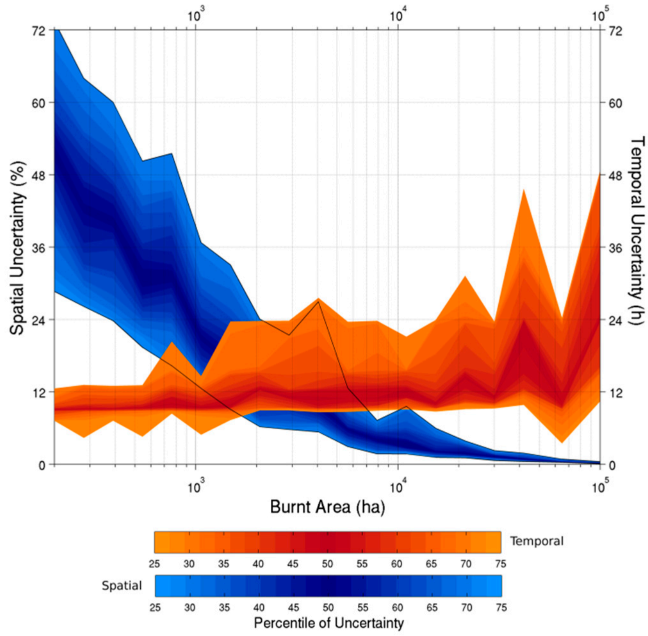

Figure 8. Interquartile distribution of spatial and temporal uncertainty against burnt area extent. The colorbars correspond to the percentiles of temporal uncertainty (orange color bar) and spatial uncertainty (blue color bar).

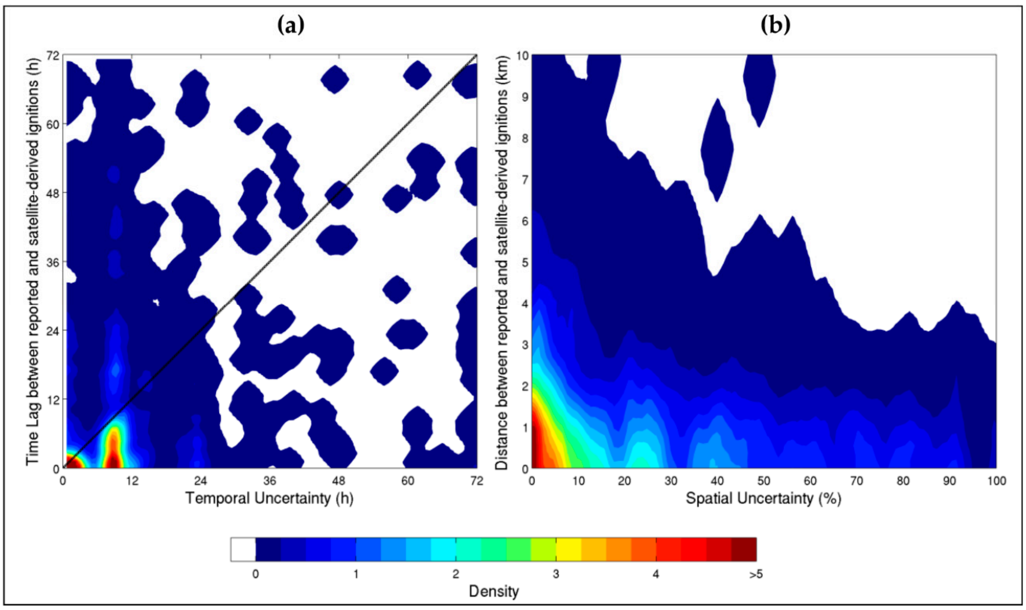

Figure 9. Comparison between (**a**) temporal discrepancy and temporal uncertainty of satellite-derived ignitions (hours); and (**b**) temporal discrepancy and spatial uncertainty of satellite-derived ignitions (hours) (N = 1376). The colorbar indicates the number of pairs within each temporal uncertainty/reported-estimated time lag bin (**a**) and spatial uncertainty/reported-estimated distance bin.

3.3. Limitations of Satellite Data

The main causes behind the inability of satellite data to provide information on fire dates and ignitions for some fire events was investigated. Active fires were detected in about 65% of the fire perimeters, but information was either insufficient because data were acquired during a single overpass

(~25%), or there were multiple fire events within a mapped perimeter (~40%) (Figure 10a). In the latter case, the burnt area extent of the fire perimeters showed large variability and included several very large fires (Figure 10b).

The main cause behind the failure to detect active fires over fire perimeters was their small size (<500 ha) (Figure 10a). In fact, in a broader sense, the failure to detect active fires was mostly associated with fire perimeters smaller than 3000 ha (Figure 10b). The contribution of persistent cloud cover and short-duration fires was marginal (<5%). However, small fires were often associated with short durations. We were unable to identify the causes for the failure to detect active fires in about 10% of the fire perimeters. These had a size distribution slightly larger than the remaining fires. The contribution of fire perimeters without reported fire dates, or with multiple reported fire dates was relevant and led to the exclusion of about 40% of the data from the analysis. When taking these data into account, the fraction of fire perimeters without active fire detections was around 78%.

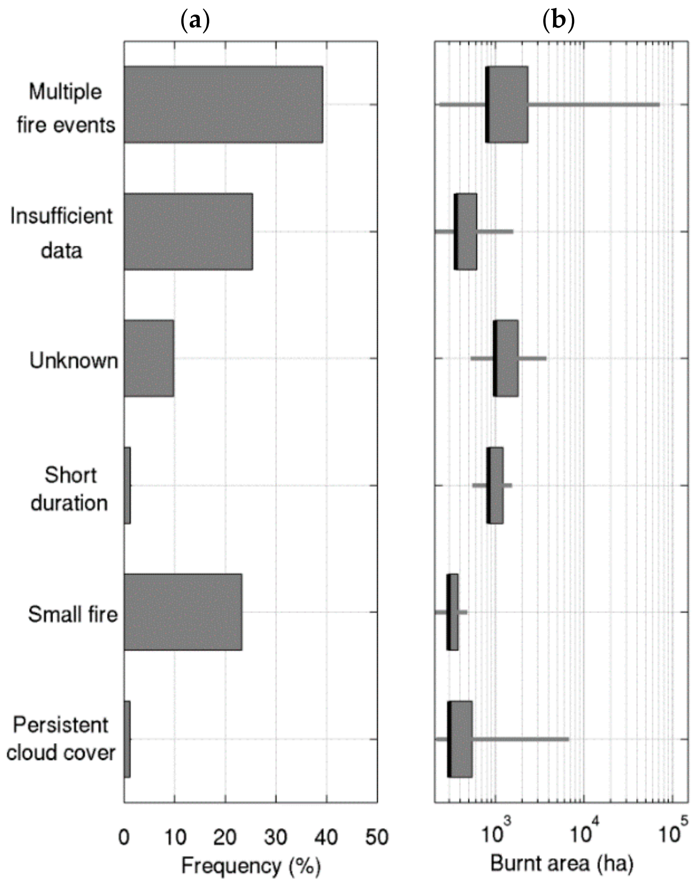

Figure 10. Main causes for the absence of satellite-derived fire dates and ignitions: (**a**) frequency and (**b**) associated fire size distribution (N = 1135). For the fire size distribution, the boxes represent the interquartile range and the horizontal grey lines, the 5th and 95th percentiles. The median is represented in black.

4. Discussion

4.1. Potential and Limitations of Satellite Data

Overall, results showed that satellite active fire data can provide accurate information on fire start and end dates, as well as the timing and location of fire ignitions. Satellite data have more potential to provide information on larger than smaller fires mainly due to detection thresholds, temporal sampling and pixel size [23]. Thus, although only a relatively small fraction of the total number of fires was covered, the corresponding total burnt area percent was high (~77%).

Fire databases are incomplete and have multiple sources of errors [6,8,10,20–22,28]. We have highlighted some clear examples of such inaccuracies (see Sections 2.1 and 2.5). Moreover, the fire databases have been derived using different methods and criteria. Bearing this in mind, we stress that, although the comparison between satellite-derived and reported data was necessary, it should be understood as an assessment and not as a validation. The analysis was performed to evaluate the potential of satellite data to provide useful information on fire dates and ignitions. Thus, when both sources provided similar values, confidence on the accuracy of satellite-derived data was strengthened, but interpretation of divergent values was not as straightforward.

Results showed different agreements between satellite-derived and reported fire dates for each study region, particularly for the estimation of the fire end date. This regional variability was also marked in the optimization of the clustering algorithm (Supplementary Material Section 2). Some fire records in Alaska and Portugal were likely incorrect, as often occurs in fire databases. For example, the reported end dates in Alaska can be the dates when the fire reports and records were closed, and not the actual extinction dates (K. Short, *personal communication*). However, It is also possible that low intensity smoldering fires burned for several months without being detected, and may have burned outside the summer season [41,57]. A regionally-based calibration will surely improve the accuracy of satellite-derived fire information by accounting for specific fire regime characteristics, e.g., increasing *maxG* in regions with smoldering fires or with long cloudy periods during the fire season.

Although the causes for errors and uncertainties in the fire databases are relatively easy to identify, quantifying the errors and their impacts on subsequent studies is very difficult and, to the best of our knowledge, has not been done. Satellite-derived start/end fire dates and ignition locations can be used as additional information to identify and correct suspicious data records present in fire databases. For instance, the existence of multiple or repeated records in the same fire perimeter, some with large spatial and temporal discrepancies can be corrected by using satellite-data to identify the most plausible records. We found a large proportion of data records containing pertinent information that were located outside any fire perimeter. In fact, by using a buffer around the fire perimeters, we duplicated the sample size without introducing significant noise in the analysis. Clearly, satellite-derived data have a large potential to help correct these inaccurate records for large wildfires.

Our results have also shown that satellite data can be useful to complement existing fire databases (see also [58]). The MODIS archive goes back to the year 2000, providing continuous information since then, while the fire databases have gaps. Thus, satellite data may be the only source of information on fire dates and ignitions for some years. Additionally, for regions with mapped fire perimeters but without information on fire dates and ignitions, satellite data can be quite useful. For example, satellite data can be used to complement existing databases in well-documented areas such as USA, Europe and Australia. Moreover, in regions with an increasing trend on fire frequency satellite-derived data can be an important tool for complementary information. For regions of the world without or with scarce fire information, satellite data can be the only data source available. Satellite fire detections can be particularly useful in remote areas such as the boreal region or the tropical savannas of Africa and South America.

The utility of satellite-derived information is greatly enhanced when accompanied with uncertainty estimates. We assessed the temporal and spatial uncertainties associated with fire ignitions estimates using simple methods. Both timing and location estimates reflected the characteristics of the MODIS active fire product, *i.e.*, medium resolution and a relatively high revisiting time (two operating sensors). Acceptable levels of uncertainty will depend on the application and ultimately on user needs. The impact of ignition location uncertainty has been shown to significantly affect simulated fire patterns [16]. Benali, *et al.* [59] used satellite-derived ignitions to model fire growth and found that the uncertainty associated with ignition location had a large impact on the accuracy of simulations, while the impact of the uncertainty associated with ignition date/hour was relatively low.

Some of the methodological options in the current work were empirically-based. The parameters of the temporally constrained algorithm were defined using a simple multi-objective optimization approach. Results show that expanding satellite-derived estimates to cover a larger number of fires and total burnt area could be achieved, by alleviating or removing the criterion based on the agreement with reported databases of unknown accuracy. Assessing our satellite-derived estimates by comparing them with the most contemporaneous records, and no more than three days apart, biased the analysis. Considering all the data records would decrease the satellite *versus* reported agreement, however, this step was necessary to minimize the impact of multiple problems found in the fire databases.

Our results highlighted the major limitations of using MODIS data to estimate fire dates and ignitions. Two prominent features stood out: (i) lack or insufficient number of active fire detections and (ii) the potential occurrence of multiple fire events within a single fire perimeter.

Firstly, insufficient data can arise from asynchronous fire activity and satellite detections, low satellite detection thresholds due to sensor characteristics, limited number of overpasses, landscape heterogeneity, cloud cover and smoke [51,60–62]. Small or short duration or fast moving or low intensity fires are likely to be more affected by satellite omissions [60]. Although simulations indicate that MODIS has a 50% probability of detecting a 0.01 ha flaming fire [51], validation studies using Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) data suggest that this detection threshold could be considerably larger [63–65]. At the global scale, Hantson, *et al.* [66] showed that 36% to 86% of fire perimeters were omitted by MODIS active fire detections, however, omission errors dropped significantly to a maximum of 20% when only fires larger than 500 ha were considered. Hawbaker *et al.* [23] showed that MODIS detected about 82% of the fires and that cloud cover significantly affected detection rates. Our results showed that 65% of the fires above 200 ha were detected, and we did not find a significant role of cloud cover in satellite omissions. However, the data and methods were substantially different and results will likely be highly dependent on the region and corresponding weather conditions during the fire season. Furthermore, since detection rates decrease with fire size and we only analyzed fires larger than 200 ha, large fraction of the total number of fires will be omitted by satellite detections.

Secondly, fire perimeters mapped using late fire season data (e.g., Landsat data) are insensitive to the number of events that can coalesce into a single burnt scar. Under these conditions, distinguishing multiple fire events that lead to a single fire perimeter is very difficult. However, it must be noted that even reported data on fire databases will likely fail to distinguish such events and the associated burnt area extent. We discuss some potential improvements that can tackle these limitations in Section 4.2.

4.2. Future Research Directions

Estimating fire dates and ignitions based on satellite data will surely benefit from multi-sensor approaches that integrate active fire products available from recent and upcoming sensors. The first Visible Infrared Imaging Radiometer Suite (VIIRS) was launched in late 2011 and provides active fire products with global coverage at both 375 m and 750 m twice per day [67]. Although the revisit time is longer than for MODIS, the enhanced spatial resolution and smaller footprint deformation with increasing viewing angles, have the potential to provide higher quality information regarding the location of fire ignitions. Additionally, VIIRS products have higher detection capabilities than MODIS, thus increasing the probability of detecting active fires, especially smaller ones [68]. Integrating VIIRS products will surely improve the capability of satellite data to provide information on small fires, improve the accuracy of ignition location estimates for large fires and reduce spatial uncertainty. Geostationary data from Meteosat (First and Second Generation; MFG and MSG, respectively) and Geostationary Operational Environmental Satellite (GOES) have been used to monitor active fire activity for large areas [69,70]. These sensors have low spatial resolution but a very high frequency (every 15 min). In principle, active products from geostationary satellites can be used for earlier detection of fires, thus helping to improve the estimation of fire dates and reduce temporal uncertainties. Finally, the upcoming Sentinel-3 satellites will provide global coverage of active fires with higher detection capabilities than MODIS [71]. Fusing these several sources of active fire data, minimizing their limitations and maximizing their potential, will contribute to a richer and more complete data archive on fires [72], thus surely improving the satellite-derived estimation of fire start/end dates and ignition locations.

The methodology described in the current work depends on the availability of fine resolution fire perimeters. This methodology has the potential to be applied to any region of the globe to estimate fire dates and ignitions as long as other sources of fire perimeters are available. The MODIS burnt area products can provide such information on a global scale with approximately 500 m of spatial resolution [73–75]. Combining coarse burnt area products with active fire detections can be used to estimate fire dates and ignitions. This would imply not capturing information for small fires and dealing with a larger number of fire perimeters containing multiple fire events. To tackle the latter issue, a method has been proposed to identify individual fires combining MODIS active fire and coarse burnt area products [76], but can also be applied using finer resolution fire perimeters.

One specific issue that was not accounted for in the current work was the existence of multiple independent and separate ignitions that led to a single final fire perimeter. These ignitions could be detected simultaneously or not by the satellite active fire product. This issue can be important in some regions of the world, for instance in the Australian savannas [77]. From visual analysis of satellite active fire data we found evidence of multiple-ignition fires in Portugal and Greece. This issue requires future work.

5. Conclusions

Satellite data can significantly contribute with accurate information on start/end dates and ignition locations for large wildfires in regions with scarce fire information. It can also be used to complement existing fire databases in well-documented areas (e.g., fill missing data) and/or to detect and correct inconsistencies. In the future, the fusion of multi-sensor active fire data will surely contribute to create a richer and more accurate archive of satellite-derived information to be used in the study of individual fires.

Supplementary Materials: The following are available online at www.mdpi.com/2072-4292/8/4/326/s1. Figure S1: The (**a**) total burnt area; (**b**) total number of fires with start and end dates assigned; and (**c**) MEF, for several combinations of the minimum density (*minD*) and maximum gap (*maxG*) parameters. Figure S2: Multi-objective function values (f(x)) for a range of minimum density (*minD*) and maximum gap (*maxG*) parameter combinations for (**a**) Portugal; (**b**) Greece; (**c**) Alaska; (**d**) California; (**e**) SE Australia, and (**f**) all study regions together. Figure S3: Assessment of the optimal buffer size to assign reported data to a given fire perimeter. Figure S4: Flow chart for identifying potential causes behind the inability of satellite data to provide information on fire dates and ignitions. Figure S5: Temporal (**a**) and spatial (**b**) agreement between reported and satellite-derived ignitions (*N* = 1376). Figure S6: Temporal (**a**) and spatial (**b**) uncertainty associated with satellite-derived ignitions (N = 2976). Table S1: Fraction of burnt area (%) covered with data of wildfires' start/end dates and ignitions (between brackets) for Portugal. Table S2: Fraction of burnt area (%) covered with data of wildfires' start/end dates and ignitions (between brackets) for Greece. Table S3: Fraction of burnt area (%) covered with data of wildfires' start/end dates and ignitions (between brackets) for Alaska Table S4: Fraction of burnt area (%) covered with data of wildfires' start/end dates and ignitions (between brackets) for California. Table S5: Fraction of burnt area (%) covered with data of wildfires' start/end dates and ignitions (between brackets) for SE Australia.

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Conflicts of Interest: The authors declare no conflict of interest.

Abbreviations

The following abbreviations are used in this manuscript:

USA	United States of America
SE	Southeastern
ICNF	Instituto de Conservação da Natureza e Florestas
AICC	Alaska Interagency Coordination Center
NSW	New South Wales
MODIS	MODerate Resolution Imaging Spectroradiometer
ASTER	Advanced Spaceborne Thermal Emission and Reflection Radiometer
MEF	Nash–Sutcliffe Model Efficiency index
VIIRS	Visible Infrared Imaging Radiometer Suite
MFG	Meteosat First Generation
MSG	Meteosat Second Generation
GOES	Geostationary Operational Environmental Satellite

References

1. Van der Werf, G.R.; Randerson, J.T.; Giglio, L.; Collatz, G.J.; Mu, M.; Kasibhatla, P.S.; Morton, D.C.; Defries, R.S.; Jin, Y.; van Leeuwen, T.T. Global fire emissions and the contribution of deforestation, savanna, forest, agricultural, and peat fires (1997–2009). *Atmos. Chem. Phys.* **2010**, *10*, 11707–11735. [CrossRef]
2. Lentile, L.B.; Holden, Z.A.; Smith, A.M.S.; Falkowski, M.J.; Hudak, A.T.; Morgan, P.; Lewis, S.A.; Gessler, P.E.; Benson, N.C. Remote sensing techniques to assess active fire characteristics and post-fire effects. *Int. J. Wildland Fire* **2006**, *15*, 319–345. [CrossRef]
3. French, N.H.; de Groot, W.J.; Jenkins, L.K.; Rogers, B.M.; Alvarado, E.; Amiro, B.; De Jong, B.; Goetz, S.; Hoy, E.; Hyer, E.; *et al.* Model comparisons for estimating carbon emissions from North American wildland fire. *J. Geophys. Res.* **2011**, *116*, G00K05. [CrossRef]
4. Giglio, L.; Kendall, J.; Justice, C. Evaluation of global fire detection algorithms using simulated AVHRR infrared data. *Int. J. Remote Sens.* **1999**, *20*, 1947–1985. [CrossRef]
5. Ganteaume, A.; Camia, A.; Jappiot, M.; San-Miguel-Ayanz, J.; Long-Fournel, M.; Lampin, C. A review of the main driving factors of forest fire ignition over Europe. *Environ. Manag.* **2013**, *51*, 651–662. [CrossRef] [PubMed]
6. Bar-Massada, A.; Hawbaker, T.J.; Stewart, S.I.; Radeloff, V.C. Combining satellite-based fire observations and ground-based lightning detections to identify lightning fires across the conterminous USA. *IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens.* **2012**, *5*, 1438–1447. [CrossRef]
7. Moreira, F.; Catry, F.X.; Rego, F.; Bacao, F. Size-dependent pattern of wildfire ignitions in Portugal: When do ignitions turn into big fires? *Landsc. Ecol.* **2010**, *25*, 1405–1417. [CrossRef]
8. Catry, F.X.; Rego, F.C.; Bação, F.L.; Moreira, F. Modeling and mapping wildfire ignition risk in portugal. *Int. J. Wildl. Fire* **2009**, *18*, 921–931. [CrossRef]
9. Salis, M.; Ager, A.A.; Arca, B.; Finney, M.A.; Bacciu, V.; Duce, P.; Spano, D. Assessing exposure of human and ecological values to wildfire in Sardinia, Italy. *Int. J. Wildl. Fire* **2013**, *22*, 549–565. [CrossRef]
10. Pereira, M.G.; Malamud, B.D.; Trigo, R.M.; Alves, P.I. The history and characteristics of the 1980–2005 Portuguese rural fire database. *Nat. Hazards Earth Syst. Sci.* **2011**, *11*, 3343–3358. [CrossRef]
11. Parisien, M.-A.; Parks, S.A.; Miller, C.; Krawchuk, M.A.; Heathcott, M.; Moritz, M.A. Contributions of ignitions, fuels, and weather to the spatial patterns of burn probability of a boreal landscape. *Ecosystems* **2011**, *14*, 1141–1155. [CrossRef]
12. Lavoué, D.; Gong, S.; Stocks, B.J. Modelling emissions from Canadian wildfires: A case study of the 2002 quebec fires. *Int. J. Wildl. Fire* **2008**, *16*, 649–663. [CrossRef]
13. Thompson, J.R.; Spies, T.A. Factors associated with crown damage following recurring mixed-severity wildfires and post-fire management in southwestern Oregon. *Landsc. Ecol.* **2010**, *25*, 775–789. [CrossRef]
14. Cary, G.J.; Flannigan, M.D.; Keane, R.E.; Bradstock, R.A.; Davies, I.D.; Lenihan, J.M.; Li, C.; Logan, K.A.; Parsons, R.A. Relative importance of fuel management, ignition management and weather for area burned: Evidence from five landscape–fire–succession models. *Int. J. Wildl. Fire* **2009**, *18*, 147–156. [CrossRef]

15. Slocum, M.G.; Beckage, B.; Platt, W.J.; Orzell, S.L.; Taylor, W. Effect of climate on wildfire size. *Ecosystems* **2010**, *13*, 828–840. [CrossRef]
16. Bar-Massada, A.; Syphard, A.D.; Hawbaker, T.J.; Stewart, S.I.; Radeloff, V.C. Effects of ignition location models on the burn patterns of simulated wildfires. *Environ. Model. Softw.* **2011**, *26*, 583–592. [CrossRef]
17. LaCroix, J.J.; Ryu, S.-R.; Zheng, D.; Chen, J. Simulating fire spread with landscape management scenarios. *For. Sci.* **2006**, *52*, 522–529.
18. Shapiro-Miller, L.B.; Heyerdahl, E.K.; Morgan, P. Comparison of fire scars, fire atlases, and satellite data in the northwestern United States. *Can. J. For. Res.* **2007**, *37*, 1933–1943. [CrossRef]
19. Morgan, P.; Hardy, C.C.; Swetnam, T.W.; Rollins, M.G.; Long, D.G. Mapping fire regimes across time and space: Understanding coarse and fine-scale fire patterns. *Int. J. Wildl. Fire* **2001**, *10*, 329–342. [CrossRef]
20. Amatulli, G.; Peréz-Cabello, F.; de la Riva, J. Mapping lightning/human-caused wildfires occurrence under ignition point location uncertainty. *Ecol. Model.* **2007**, *200*, 321–333. [CrossRef]
21. Short, K.C. A spatial database of wildfires in the United States, 1992–2011. *Earth Syst. Sci. Data* **2014**, *6*, 1–27. [CrossRef]
22. Kasischke, E.S.; Williams, D.; Barry, D. Analysis of the patterns of large fires in the boreal region of Alaska. *Int. J. Wildl. Fire* **2002**, *11*, 131–144. [CrossRef]
23. Hawbaker, T.J.; Radeloff, V.C.; Syphard, A.D.; Zhu, Z.; Stewart, S.I. Detection rates of the MODIS active fire product in the United States. *Remote Sens. Environ.* **2008**, *112*, 2656–2664. [CrossRef]
24. Holden, Z.; Smith, A.; Morgan, P.; Rollins, M.; Gessler, P. Evaluation of novel thermally enhanced spectral indices for mapping fire perimeters and comparisons with fire atlas data. *Int. J. Remote Sens.* **2005**, *26*, 4801–4808. [CrossRef]
25. Thorsteinsson, T.; Magnusson, B.; Gudjonsson, G. Large wildfire in Iceland in 2006: Size and intensity estimates from satellite data. *Int. J. Remote Sens.* **2011**, *32*, 17–29. [CrossRef]
26. Lee, B.S.; Alexander, M.E.; Hawkes, B.C.; Lynham, T.J.; Stocks, B.J.; Englefield, P. Information systems in support of wildland fire management decision making in Canada. *Comput. Electron. Agric.* **2002**, *37*, 185–198. [CrossRef]
27. Loboda, T.V.; Csiszar, I.A. Reconstruction of fire spread within wildland fire events in Northern Eurasia from the MODIS active fire product. *Glob. Planet. Chang.* **2007**, *56*, 258–273. [CrossRef]
28. Parks, S.A. Mapping day-of-burning with coarse-resolution satellite fire-detection data. *Int. J. Wildl. Fire* **2014**, *23*, 215–223. [CrossRef]
29. Veraverbeke, S.; Sedano, F.; Hook, S.J.; Randerson, J.T.; Jin, Y.; Rogers, B.M. Mapping the daily progression of large wildland fires using MODIS active fire data. *Int. J. Wildl. Fire* **2014**, *23*, 655–667. [CrossRef]
30. Chuvieco, E.; Martin, M. A simple method for area growth mapping using AVHRR channel 3 data. *Int. J. Remote Sens.* **1994**, *15*, 3141–3146. [CrossRef]
31. Smith, A.M.S.; Wooster, M.J. Remote classification of head and backfire types from MODIS fire radiative power and smoke plume observations. *Int. J. Wildl. Fire* **2005**, *14*, 249–254. [CrossRef]
32. Dennison, P.E.; Charoensiri, K.; Roberts, D.A.; Peterson, S.H.; Green, R.O. Wildfire temperature and land cover modeling using hyperspectral data. *Remote Sens. Environ.* **2006**, *100*, 212–222. [CrossRef]
33. Wooster, M.; Zhukov, B.; Oertel, D. Fire radiative energy for quantitative study of biomass burning: Derivation from the bird experimental satellite and comparison to MODIS fire products. *Remote Sens. Environ.* **2003**, *86*, 83–107. [CrossRef]
34. Keeley, J.E.; Fotheringham, C.J. Historic fire regime in southern california shrublands. *Conserv. Biol.* **2001**, *15*, 1536–1548. [CrossRef]
35. Dimitrakopoulos, A.P.; Vlahou, M.; Anagnostopoulou, C.G.; Mitsopoulos, I. Impact of drought on wildland fires in greece: Implications of climatic change? *Clim. Change* **2011**, *109*, 331–347. [CrossRef]
36. Trigo, R.M.; Pereira, J.M.C.; Pereira, M.G.; Mota, B.; Calado, T.J.; da Camara, C.C.; Santo, F.E. Atmospheric conditions associated with the exceptional fire season of 2003 in portugal. *Int. J. Climatol.* **2006**, *26*, 1741–1757. [CrossRef]
37. Trigo, R.M.; Sousa, P.M.; Pereira, M.G.; Rasilla, D.; Gouveia, C.M. Modelling wildfire activity in iberia with different atmospheric circulation weather types. *Int. J. Climatol.* **2013**. [CrossRef]
38. Boschetti, L.; Roy, D.; Barbosa, P.; Boca, R.; Justice, C. A modis assessment of the summer 2007 extent burned in greece. *Int. J. Remote Sens.* **2008**, *29*, 2433–2436. [CrossRef]

39. Keeley, J.E.; Safford, H.; Fotheringham, C.; Franklin, J.; Moritz, M. The 2007 southern california wildfires: Lessons in complexity. *J. Forest.* **2009**, *107*, 287–296.
40. Keeley, J.E.; Fotheringham, C.; Moritz, M.A. Lessons from the october 2003. Wildfires in Southern California. *J. Forest.* **2004**, *102*, 26–31.
41. Turetsky, M.R.; Kane, E.S.; Harden, J.W.; Ottmar, R.D.; Manies, K.L.; Hoy, E.; Kasischke, E.S. Recent acceleration of biomass burning and carbon losses in alaskan forests and peatlands. *Nat. Geosci.* **2011**, *4*, 27–31. [CrossRef]
42. Loboda, T.V.; Hoy, E.E.; Giglio, L.; Kasischke, E.S. Mapping burned area in alaska using modis data: A data limitations-driven modification to the regional burned area algorithm. *Int. J. Wildl. Fire* **2011**, *20*, 487–496. [CrossRef]
43. Sullivan, A.L.; McCaw, W.L.; Cruz, M.G.; Matthews, S.; Ellis, P.F. Fuel, fire weather and fire behaviour in australian ecosystems. In *Flammable Australia: Fire Regimes, Biodiversity and Ecosystems in a Changing World*; CSIRO Publishing: Melbourne, Australia, 2012; pp. 51–79.
44. Cruz, M.G.; Sullivan, A.L.; Gould, J.S.; Sims, N.C.; Bannister, A.J.; Hollis, J.J.; Hurley, R.J. Anatomy of a catastrophic wildfire: The black saturday kilmore east fire in victoria, australia. *For. Ecol. Manag.* **2012**, *284*, 269–285. [CrossRef]
45. INCF. Available online: http://www.icnf.pt/portal/florestas/dfci/inc/estat-sgif (accessed on 10 February 2016).
46. Oliveira, S.L.J.; Pereira, J.M.C.; Carreiras, J.M.B. Fire frequency analysis in Portugal (1975–2005), using Landsat-based burnt area maps. *Int. J. Wildl. Fire* **2012**, *21*, 48–60. [CrossRef]
47. AICC. Available online: http://fire.ak.blm.gov/ (accessed on 10 February 2016).
48. CALFIRE. Available online: http://frap.cdf.ca.gov/data/ (accessed on 10 February 2016).
49. Koutsias, N.; Pleniou, M.; Mallinis, G.; Nioti, F.; Sifakis, N.I. A rule-based semi-automatic method to map burned areas: Exploring the usgs historical Landsat archives to reconstruct recent fire history. *Int. J. Remote Sens.* **2013**, *34*, 7049–7068. [CrossRef]
50. Pleniou, M.; Xystrakis, F.; Dimopoulos, P.; Koutsias, N. Maps of fire occurrence—Spatially explicit reconstruction of recent fire history using satellite remote sensing. *J. Maps* **2013**, *8*, 499–506. [CrossRef]
51. Giglio, L.; Descloitres, J.; Justice, C.O.; Kaufman, Y.J. An enhanced contextual fire detection algorithm for MODIS. *Remote Sens. Environ.* **2003**, *87*, 273–282. [CrossRef]
52. Wolfe, R.E.; Roy, D.P.; Vermote, E. MODIS land data storage, gridding, and compositing methodology: Level 2 grid. *IEEE Trans. Geosci. Remote Sens.* **1998**, *36*, 1324–1338. [CrossRef]
53. Ichoku, C.; Kaufman, Y.J. A method to derive smoke emission rates from MODIS fire radiative energy measurements. *IEEE Trans. Geosci. Remote Sens.* **2005**, *43*, 2636–2649. [CrossRef]
54. Wan, Z. MODIS Land-Surface Temperature. Algorithm Theoretical Basis Document. Available online: http://modis.gsfc.nasa.gov/data/atbd/atbd_mod11.pdf (accessed on 1 August 2015).
55. Schmidt, K.M.; Menakis, J.P.; Hardy, C.C.; Hann, W.J.; Bunnell, D.L. *Development of Coarse-Scale Spatial Data for Wildland Fire and Fuel Management*; General Technical Report; USDA Forest Service, Rocky Mountain Research Station: Fort Collins, CO, USA, 2002; p. 41.
56. Nash, J.E.; Sutcliffe, J.V. River flow forecasting through conceptual models part I—A discussion of principles. *J. Hydrol.* **1970**, *10*, 282–290. [CrossRef]
57. Turquety, S.; Logan, J.A.; Jacob, D.J.; Hudman, R.C.; Leung, F.Y.; Heald, C.L.; Yantosca, R.M.; Wu, S.; Emmons, L.K.; Edwards, D.P.; *et al.* Inventory of boreal fire emissions for north america in 2004: Importance of peat burning and pyroconvective injection. *J. Geophys. Res. Atmos.* **2007**, *112*, D12S03. [CrossRef]
58. De Klerk, H. A pragmatic assessment of the usefulness of the MODIS (Terra and Aqua) 1-km active fire (MOD14A2 and MYD14A2) products for mapping fires in the fynbos biome. *Int. J. Wildl. Fire* **2008**, *17*, 166–178. [CrossRef]
59. Benali, A.; Ervilha, A.R.; Sá, A.C.L.; Fernandes, P.M.; Pinto, R.M.S.; Trigo, R.M.; Pereira, J.M.C. Deciphering the impact of uncertainty on the accuracy of large wildfire spread simulations. Unpublished data. 2016.
60. Giglio, L. MODIS Collection 5 Active Fire Product User's Guide Version 2.4. 2010. Available online: http://www.fao.org/fileadmin/templates/gfims/docs/MODIS_Fire_Users_Guide_2.4.pdf (accessed on 12 April 2016).
61. Giglio, L. Characterization of the tropical diurnal fire cycle using VIRS and MODIS observations. *Remote Sens. Environ.* **2007**, *108*, 407–421. [CrossRef]

62. Schroeder, W.; Morisette, J.T.; Csiszar, I.; Giglio, L.; Morton, D.; Justice, C.O. Characterizing vegetation fire dynamics in brazil through multisatellite data: Common trends and practical issues. *Earth Interact.* **2005**, *9*, 1–26. [CrossRef]
63. Morisette, J.; Giglio, L.; Csiszar, I.; Justice, C. Validation of the MODIS active fire product over southern Africa with ASTER data. *Int. J. Remote Sens.* **2005**, *26*, 4239–4264. [CrossRef]
64. Morisette, J.T.; Giglio, L.; Csiszar, I.; Setzer, A.; Shroeder, W.; Morton, D.; Justice, C.O. Validation of MODIS active fire detection products derived from two algorithms. *Earth Interact.* **2005**, *9*, 1–25. [CrossRef]
65. Csiszar, I.A.; Morisette, J.T.; Giglio, L. Validation of active fire detection from moderate-resolution satellite sensors: The MODIS example in northern Eurasia. *IEEE Trans. Geosci. Remote Sens.* **2006**, *44*, 1757–1764. [CrossRef]
66. Hantson, S.; Padilla, M.; Corti, D.; Chuvieco, E. Strengths and weaknesses of MODIS hotspots to characterize global fire occurrence. *Remote Sens. Environ.* **2013**, *131*, 152–159. [CrossRef]
67. Schroeder, W.; Oliva, P.; Giglio, L.; Csiszar, I.A. The new VIIRS 375m active fire detection data product: Algorithm description and initial assessment. *Remote Sens. Environ.* **2014**, *143*, 85–96. [CrossRef]
68. Oliva, P.; Schroeder, W. Assessment of VIIRS 375m active fire detection product for direct burned area mapping. *Remote Sens. Environ.* **2015**, *160*, 144–155. [CrossRef]
69. Amraoui, M.; Liberato, M.L.R.; Calado, T.J.; da Camara, C.C.; Coelho, L.P.; Trigo, R.M.; Gouveia, C.M. Fire activity over Mediterranean Europe based on information from Meteosat-8. *For. Ecol. Manag.* **2013**, *294*, 62–75. [CrossRef]
70. Schroeder, W.; Csiszar, I.; Giglio, L.; Schmidt, C.C. On the use of fire radiative power, area, and temperature estimates to characterize biomass burning via moderate to coarse spatial resolution remote sensing data in Brazilian Amazon. *J. Geophys. Res.* **2010**, *115*, D21121. [CrossRef]
71. Wooster, M.J.; Xu, W.; Nightingale, T. Sentinel-3 SLSTR active fire detection and FRP product: Pre-launch algorithm development and performance evaluation using MODIS and ASTER datasets. *Remote Sens. Environ.* **2012**, *120*, 236–254. [CrossRef]
72. Freeborn, P.H.; Wooster, M.J.; Roberts, G.; Malamud, B.D.; Xu, W. Development of a virtual active fire product for Africa through a synthesis of geostationary and polar orbiting satellite data. *Remote Sens. Environ.* **2009**, *113*, 1700–1711. [CrossRef]
73. Giglio, L.; Loboda, T.; Roy, D.P.; Quayle, B.; Justice, C.O. An active-fire based burned area mapping algorithm for the MODIS sensor. *Remote Sens. Environ.* **2009**, *113*, 408–420. [CrossRef]
74. Roy, D.P.; Boschetti, L.; Justice, C.O.; Ju, J. The collection 5 MODIS burned area product—Global evaluation by comparison with the MODIS active fire product. *Remote Sens. Environ.* **2008**, *112*, 3690–3707. [CrossRef]
75. Justice, C.O.; Giglio, L.; Korontzi, S.; Owens, J.; Morisette, J.T.; Roy, D.; Descloitres, J.; Alleaume, S.; Petitcolin, F.; Kaufman, Y. The MODIS fire products. *Remote Sens. Environ.* **2002**, *83*, 244–262. [CrossRef]
76. Archibald, S.; Roy, D.P. Identifying individual fires from satellite-derived burned area data. In Proceedings of the 2009 IEEE International Geoscience and Remote Sensing Symposium (IGARSS 2009), Cape Town, South Africa, 12–17 July 2009.
77. Price, O.F. Potential role of ignition management in reducing unplanned burning in Arnhem land, Australia. *Austral Ecol.* **2015**, *40*, 857–868. [CrossRef]

Paper II - Evaluating fire growth simulations using satellite active fire data

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Evaluating fire growth simulations using satellite active fire data

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ABSTRACT

The recognized shortcomings of fire spread modeling systems and the widespread use of their outcomes in fire management decisions render the evaluation of fire simulation results crucial for model calibration and improvement. Additionally, new methods are essential to avoid model misapplication in fuel and fire management decision processes.

This study proposes an exploratory evaluation framework of fire growth simulations using satellite active fire data. It uses nine very large fires that occurred in Portugal between 2003 and 2012. Their fire growth was simulated using the Fire Area Simulator (FARSITE) and compared with active fire data from the MODerate-resolution Imaging Spectroradiometer (MODIS). The evaluation is based on two spatial measures that quantify the absolute (*SpD*) and relative (*NRSpD*) spatial discrepancies between fire growth simulations and satellite active fires. Both measures account for the uncertain location of the fire front(s) inside the active fire footprint.

Results highlight the contribution of the spatial discrepancy measures to locate areas of low/high spatio-temporal agreement between simulated fire growth and MODIS active fires, thereby aiding the assessment of potential sources of simulation error. Results also show that despite the coarse spatial resolution of MODIS active fires, these data are able to capture the spatial dynamics of fire growth. Limitations on the spatial measures were identified, particularly the lack of independence of evaluations using the *NRSpD*.

In spite of being exploratory, this study represents a novel contribution to the evaluation of fire growth simulations because: 1) it uses satellite active fire data and is independent of the collection of reference burnt area perimeters; 2) it proposes two simple quantitative spatial discrepancy measures; and 3) it can be applied to a large number of wildfires, regardless of their geographical location. This innovative approach represents a potential cost effective evaluation scheme, that can be used systematically whenever evaluation of a large number of large wildfires is required and reference burned area perimeters are not available.

1. Introduction

On average, more than half a million hectares of forests, shrublands, and croplands burn every year in Europe with fires in southern countries contributing the most to the total annual burned area (Schmuck et al., 2015). Wildfires in the Mediterranean Basin, including Portugal, Spain and Greece, are infrequent but have large environmental and socio-economic impacts (San-Miguel-Ayanz et al., 2013). Wildfire intensity is usually greatest during summer months under dry, hot and windy atmospheric conditions and can be amplified by drought (Trigo et al., 2013b). Projections of future climate point to an increase in frequency and severity of summer heat waves (Pachauri et al., 2014), such that an increase in the number and extent of wildfires is likely (Sousa et al., 2015). Hence, wildfire impacts and resources required to manage them are also likely to increase in the future (Arca et al., 2010; Kalabokidis et al., 2015; Turco et al., 2014).

Those scenarios highlight the importance of studying wildfires to improve landscape and fire management decisions, aiming at anticipating and minimizing their impacts. Spatially explicit wildfire spread models are often used to understand the intertwined relationships between fire, topography, fuel, and weather (Sullivan, 2009). They are

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commonly used to simulate wildfire behavior and growth (Arca et al., 2007; Stratton, 2006), to assess wildfire risk (Alcasena et al., 2015; Salis et al., 2013), to test the effectiveness of fuel treatment options (Ager et al., 2010; Loureiro et al., 2006; Salis et al., 2016), and to support tactical decisions in fire-fighting operations (Calkin et al., 2011; Kochanski et al., 2013).

More often than not, fire spread modeling systems are used to support fuel and fire management decisions without a proper evaluation of their outputs (Alexander and Cruz, 2013; Scott and Reinhardt, 2001). Consequently, lack of systematic information on the quality of fire spread predictions can have a considerable impact on those decisions. Nonetheless, little research has been done to assess those predictions (Cui and Perera, 2010) in spite of the general understanding that fire spread models are simplifications of reality and that their reliability is particularly dependent on model assumptions, calibration and quality of input data (Albini, 1976; Arca et al., 2007; Cruz and Alexander, 2013).

Information on actual wildfire spread, intensity and growth patterns is of poor quality (Duff et al., 2013), and it is typically collected post-fire using ground data, and space or airborne imagery. Evaluation of fire growth simulations based on simple indices and statistics, as the Sørensen similarity index (Sørensen, 1948) and the Kappa coefficient (Cohen, 1960), are commonly derived from superimposing observed and simulated final burnt perimeters. However, an evaluation based on these type of metrics provides little information on the causes of discrepancy between fire perimeters, ignores the spatio-temporal patterns of fire spread, therefore contributing little to characterize error sources and to improve model performance (Cui and Perera, 2010; Duff et al., 2013; Filippi et al., 2014b; Fujioka, 2002).

Recognizing the importance of evaluating model dynamics, new methods and indices have been developed to evaluate fire spread simulations by quantifying spread errors in terms of magnitude, spatial and temporal variability. Filippi et al. (2014b) reviewed a set of evaluation methods and proposed two new metrics, *arrival time agreement* and *shape agreement*, based on fire simulation dynamics between time steps of fire duration. Fire spread vectors have been used to compare simulated and observed fire perimeters at common azimuth points starting from the ignition point (Cui and Perera, 2010; Fujioka, 2002), or by assigning pseudo-landmarks on the perimeters being compared (Duff et al., 2012), from which indices encompassing size, orientation and shape perimeter differences are derived. Duff et al. (2013) presented an alternative method based on travel path vectors where distances represent the actual fire spread on the ground between two fire duration time steps. All the previous dynamic evaluation approaches rely on the collection of reference perimeters and field-based measures of fire locations, which can be difficult to implement for large wildfires, given their stochastic nature in space and time, and expensive to obtain for a large number of case studies. Also, in the previous studies, model bias evaluation was performed using a single fire, which may lead to a lack of robustness (Duff et al., 2013; Filippi et al., 2014a). This is not the case of the study of Filippi et al. (2014a) that simulates 80 wildfires and uses different error scoring methods to compare the performance of four different fire spread models.

Satellite active fire data are a cost-effective alternative to systematically provide information on the spatial dynamics of large wildfires. This data source can be especially important to characterize fires occurring in remote areas, and where existing fire databases have scarce information and/or large inconsistencies (Benali et al., 2016; Hawbaker et al., 2008; Schroeder et al., 2014). Some authors have explored the potential of satellite thermal data to monitor wildfire growth. Jin et al. (2015) used active fire data from the MODerate-resolution Imaging Spectroradiometer (MODIS) to characterize fire spread rate, direction and duration of large wildfires. Parks (2014) and Veraverbeke et al. (2014) also used MODIS active fires to produce continuous fire progression maps for large wildfires. Nonetheless, active fire satellite observations have not yet been used to evaluate fire spread model estimates, in spite of their widespread use in other fire research fields. This has been limited in part by the absence of a methodology to systematically evaluate simulation results over both space and time.

There are potential limitations when using satellite active fire data to monitor the progression of individual fires, mostly related with satellite detection capabilities: revisit cycle, viewing geometry and pixel size (Hawbaker et al., 2008; Oliva and Schroeder, 2015). Other factors related with fire environment such as fire size, duration, intensity, thermal contrast with surrounding areas, vegetation type affected, and persistent cloud clover and/or dense smoke plumes also constrain satellite detection rate (Csiszar et al., 2006; Giglio et al., 2003; Hantson et al., 2013). Fire commission is significantly lower for large and intense fires (Hawbaker et al., 2008; Oliva and Schroeder, 2015).

The potential of satellite active fire data can be applied in the evaluation of fire growth simulations although this requires an approach that: i) can be objectively applied to a comprehensive number of large wildfires; ii) uses metrics capable of evaluating simulation dynamics; and iii) does not rely on the collection of reference burnt area perimeters. Based on these needs, the current study proposes an exploratory approach for quantifying the spatial and temporal discrepancies between simulated fire growth and time series of satellite active fire observations. We acknowledge that the evaluation is not intended to be a quantification of model error nor an assessment of model performance because the first requires ground reference data and the second reliable model input data. Specific goals are: 1) to propose a spatial discrepancy distance metric; 2) to assess the impact that satellite pixel size has on the evaluation measure; and 3) to discuss evaluation sheme limitations and identify future research needs. To achieve these objectives the method is applied to nine large wildfires that occurred in Portugal between 2003 and 2012. Analysis is limited to the evaluation framework using available input and satellite fire data. We describe the fire model and the configuration used although a discussion of its merits falls outside the scope of this study.

2. Data and methods

2.1. Fire case studies

Portugal is one of the Southern European countries most affected by wildfires (Schmuck et al., 2015; Tedim et al., 2013). Burned area exceeded 400,000 ha and 350,000 ha in 2003 and 2005, respectively (Oliveira et al., 2012; Tedim et al., 2013). Based on a 39-year record (1975–2013) of annual fire perimeters mainly derived from Landsat satellite image classification (Oliveira et al., 2012), nine large fires (>10,000 ha, above the 99th percentile of the fire size distribution) that occurred in central-southern Portugal were selected for this analysis (Fig. 1). Five of the nine events occurred in 2003, two in 2005, one in 2004 and one in 2012 (Table 1).

Portugal experienced an exceptional heat wave in 2003, which was characterized by record high minimum and maximum temperatures, extremely low relative humidity and relatively high wind speed (Tedim et al., 2013; Trigo et al., 2006). Similarly, the 2005 and 2012 fire seasons coincided with two of the most severe droughts on record (Pereira et al., 2005; Trigo et al., 2013a).

2.2. Fire spread simulations

The FARSITE (Fire Area Simulator, Finney (2004)), one of the most widely used fire propagation simulation systems, predicts fire behavior in spatially heterogeneous terrain and fuels landscapes, under variable weather conditions (Papadopoulos and Pavlidou, 2011; Sullivan, 2009). FARSITE is based on a semi-empirical fire spread model (Rothermel, 1972) that relies on Rothermel-based fuel models (Rothermel, 1972; Scott and Burgan, 2005), and integrates models for surface and crown fire spread (Rothermel, 1972, 1991; Wagner, 1977), dead fuel moisture (Nelson, 2000) and spotting from torching trees (Albini, 1979). Surface fire growth is simulated as an elliptical

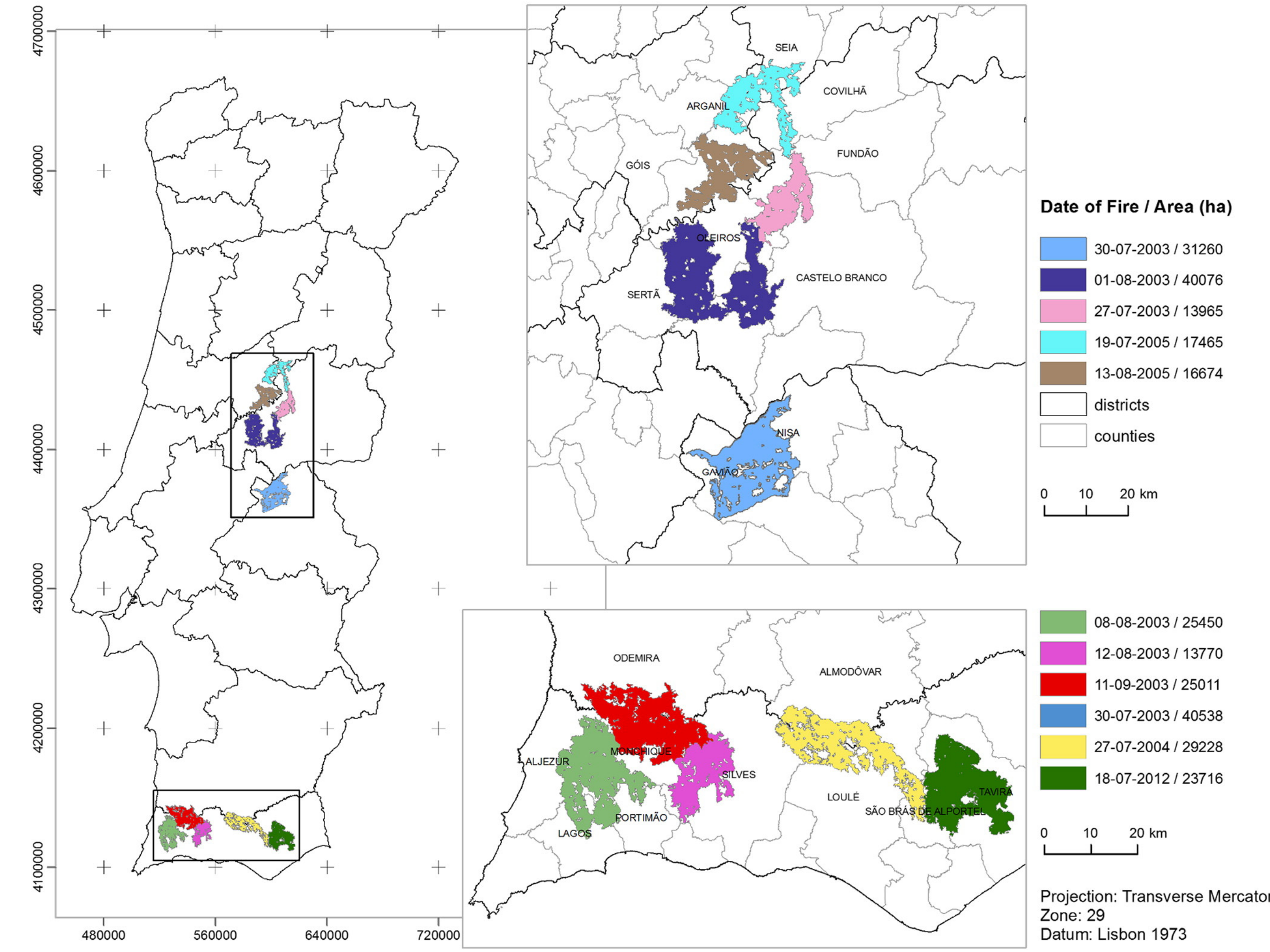

Fig. 1. Location of nine large fires (>10,000 ha) that occurred in Portugal between 2003 and 2012. Fires are coded as: CasteloBranco1 (CBR1); CasteloBranco2 (CBR2); Covilhã1 (COV1); Covilhã2 (COV2); Monchique1 (MCQ1); Monchique2 (MCQ2); Monchique3 (MCQ3); Loulé (LL); and Tavira (TAV).

wave propagation based on the Huygens' principle (Finney, 2004) to model the expansion of a polygonal fire front through time (Richards, 1990).

FARSITE incorporates raster layers of topography and fuels, as well as weather data (temperature, precipitation, relative humidity, wind and cloud cover). Digital elevation data were acquired from the NASA Shuttle Radar Topography Mission (SRTM) at 90 m spatial resolution (Farr et al., 2007). Slope and aspect variables were derived from the elevation dataset.

Table 1
Fire name, code, area, start date and duration (see Section 2.3 for the calculation of the fire event duration).

Name (fire code)	Area (ha)	Start date (day/month/year)	Duration (days)
CasteloBranco1 (CBR1)	40,076	01/08/2003	4
CasteloBranco2 (CBR2)	13,965	27/07/2003	8
Covilhã1 (COV1)	17,465	19/07/2005	5
Covilhã2 (COV2)	16,674	13/08/2005	8
Monchique1 (MCQ1)	25,450	08/08/2003	7
Monchique2 (MCQ2)	13,770	12/08/2003	3
Monchique3 (MCQ3)	25,011	11/09/2003	5
Loulé (LL)	29,228	27/07/2004	5
Tavira (TAV)	23,716	18/07/2012	5

The fuel complex was described by the Northern Forest Fire Laboratory (NFFL) stylized set of 13 fuel models (Anderson, 1982). Most of the NFFL fuel maps were provided by the Portuguese municipalities affected by the fire events analyzed, at 25 ha spatial resolution. Where this information was not available, the Corine Land Cover (CLC) dataset (Bossard et al., 2000; Caetano et al., 2009) was used to guide the assignment of NFFL fuel models to Portuguese vegetation types, a procedure adopted by Portuguese fire management agencies (Fernandes, 2005). The conversion table from CLC classes to NFFL fuel models is shown in the supplementary material (Supplementary Table 1) . Areas burned by fires that occurred earlier in the same year were classified as non-burnable. Recent 1 and 2-year-old burns were assigned to the CLC shrubland class (324). This class assignment procedure based on expert knowledge has been also used for converting Sardinian land use maps into fuel class maps (Salis et al., 2014). Canopy cover (%) was obtained from the MODIS Vegetation Continuous Fields Yearly L3 Global 250 m (MOD44B) product (DiMiceli et al., 2011).

Hourly-simulated weather data (temperature, precipitation, insolation, relative humidity and wind speed and direction) were retrieved from a regional climate simulation performed with the Pennsylvania State University/National Center for Atmospheric Research (PSU/NCAR) mesoscale MM5 model (Grell et al., 1994) that spans the period 1959–2007. This simulation was run at 10 km hourly spatial and temporal resolutions, driven by the European Re-Analysis data (ERA-40, Uppala et al. (2005)) at the domain boundaries. Details of it can be found in Jerez et al. (2013) and Lorente-Plazas et al. (2014). Nonetheless, one of the case studies was outside the time span of the referred climate simulation. Thus, for the 2012 Tavira wildfire we used weather data produced with the Weather and Research Forecasting (WRF) model (Skamarock et al., 2005), that roots on the MM5 model. The WRF weather simulation corresponds to a dynamic downscaling of the ERA-Interim re-analysis (Dee et al., 2011) for Iberia at 9 km spatial and hourly temporal resolutions (Soares et al., 2012). To account for the effect of the interaction between topography and local winds, the above mentioned gridded wind data were further modeled with WindNinja vers. 2.1.3 (Forthofer, 2007).

The daily weather data were used to calculate dead fuel moisture content values (FMC) during the simulation period. Initial FMC values for dead and live fuels were obtained from the literature (Scott and Burgan, 2005). Initial herbaceous and woody live fuel moisture contents were set to 60 and 90%, respectively. Moisture content values for 1-h, 10-h and 100-h time-lag dead fuels classes were set to 6%, 7% and 8%, respectively. A 3-day fuel-conditioning period was specified to adjust these initialization values over the landscape, prior to the start of the simulations.

Based on the spatial resolution of the input variables, and on the computing resources required to run the simulations, we used a 1-hour time step and 100 m spatial resolution, which provided an acceptable level of detail for heterogeneous landscapes (Clark et al., 2008). We did not simulate spotting fires due to their stochastic nature nor fire suppression operations because of the absence of detailed and consistent operational data on the processes driving fire spread for all the cases studied.

2.3. Satellite active fire data

Satellite active fire data were used to i) determine the fire start and end dates, thus fire event duration; ii) determine ignition location(s); and iii) evaluate temporal and spatial discrepancies between active fire's observations and simulated fire growth. The first and last active fires detected over the post-fire reference fire perimeter were used to determine the start and end dates, respectively (Benali et al., 2016). Additionally, we removed active fires close to the end date that were likely flare-ups and did not exhibit relevant fire spread. The locations of the first active-fires detected were set as the ignition points. Fire spread simulations were run from the start date until the end date.

We used active fire data from the MODIS Global Monthly Fire Location Product (MCD14ML, collection 5), which combines the middle-infrared and the thermal bands to detect fires that are burning at the time of overpass, providing information about the location, date, and time of the detected active fires (Giglio, 2010). The MODIS instruments onboard the Terra and Aqua satellites supply daytime and nighttime observations at four nominal acquisition times (Terra: 10:30 am and 10:30 pm; and Aqua: 2:00 pm and 2:00 am, local time). MODIS active fire data can provide valuable and detailed information on wildfire occurrence and spread, especially where ground or airborne fire reference data do not exist or are of poor quality (Parks, 2014; Veraverbeke et al., 2014).

The spatial resolution at nadir is approximately 1 km but the pixel footprint can greatly increase with view angle (Wolfe et al., 1998) reaching up to 10 km^2 at the scene's edge (Ichoku and Kaufman, 2005). A pixel does not have to be fully occupied by smoldering/flaming fires in order to be detected; typically fractional fire areas as small as 0.01% with an average temperature of 900 K will show >50% probability of detection by the MODIS fire product (Giglio et al., 2003). The location of the fire front within a 1-km^2 MODIS active fire pixel is uncertain, and the magnitude of this uncertainty depends on size of the pixel footprint and the number of fire fronts within it (Campagnolo and Montano, 2014; Veraverbeke et al., 2014). The active pixel footprints were calculated using the scan and track fields from the MCD14ML data set, with formulations that relate the scan angle and Earth's geometry with the pixel dimensions (Ichoku and Kaufman, 2005).

2.4. Fire growth evaluation measures

Quantification of the spatio-temporal discrepancies of fire growth simulations was based on two novel measures: the Spatial Discrepancy (*SpD*) and the Normalized Relative Spatial Discrepancy (*NRSpD*). The *SpD* provides information on how distant the simulated fire growth is from the active fire(s) detected at a given satellite overpass, and can be integrated for the full individual fire length. The *NRSpD* is a relative measure useful for: 1) comparing simulations of fires of different sizes and durations; and ii) comparing time intervals of the same fire. Information on the relative position of the simulated burned area (accelerated or delayed) when compared with satellite observed fire position was also included in this metric.

Conceptually, definition of the discrepancy measures relies on: i) the closest distance between an active fire and the corresponding position in the simulated fire perimeter, assuming that this position has the highest likelihood of being a point from the fire front represented by that active fire; and ii) given the uncertain location of the fire front in the sub-pixel active fire, the minimum distance within it is considered, based on the fact that the spatial discrepancy will always be greater than or equal to this distance. Spatial discrepancy measures are calculated for each active fire from each satellite overpass selected for comparison with the fire growth simulation. Fig. 2 illustrates the calculation of the *SpD* measure for a single active fire from the TAV case study. As an example, consider three consecutive satellite overpasses (Sat_{t0} - first detected active fires after ignition, Sat_{t1} - an intermediate satellite overpass during the fire propagation, and Sat_{t2} - the overpass from which we selected active fire *j* for calculating the *SpD* measure) and the corresponding simulated fire perimeters for each satellite overpasses after the first satellite detection (Sim_{t1} and Sim_{t2}). For satellite overpass Sat_{t2} and active fire *j*, it is calculated as the minimum Euclidean distance between each sub-pixel element *k* (i.e. within the satellite active fire footprint that is divided into cells of 100 m) and all the simulated burned pixels (*n*) from Sim_{t2} (Fig. 2, $SpD_{j,k}$ term). SpD_j between each satellite active fire *j* and the corresponding simulation is calculated first over *n* and then over *k*, as the minimum value of all active fire sub-pixel $SpD_{j,k}$ values Eq. (1):

$$SpD_j = min_k\left(SpD_{j,k}\right) = min_k\left(min_n\left(dist\left(Sat_{j,k,t}; Sim_{t,n}\right)\right)\right) \quad (1)$$

where *k* is the sub-pixel element centroid in the satellite active fire footprint *j* of satellite overpass *t*, and *n* a simulated burned area pixel. For later analysis (Section 3.3.2) the SpD_j can assume the SpD_{min} or the SpD_{ctr} abbreviation depending if the minimum or the centroid distance of the active fire footprint is used in its calculation, respectively.

The *SpD* absolute distance cannot be used to compare fires of different sizes and/or between different time intervals of the same fire, thus to address these limitations we propose the Normalized Relative Spatial Discrepancy (*NRSpD*) measure Eq. (2):

$$NRSpD_j = \alpha\left(1 - \frac{minD_j - SpD_j}{minD_j + SpD_j}\right) = \alpha\left(\frac{2SpD_j}{minD_j + SpD_j}\right) \quad (2)$$

where SpD_j is the spatial discrepancy Eq. (1) and $minD_j$ is the distance between an active fire *j* and the closest observed ignition (Fig. 2). This ignition can be from satellite or other source of data. The parameter α identifies under- and over-prediction based on the rational that if an active fire is detected after ignition time and is contained within the simulated fire perimeter from that time, α is 1 (overprediction). Otherwise, α is −1 (underprediction). *NRSpD* varies between −1 and converges to 2, depending on the values of *minD* and *SpD* (Fig. 3).

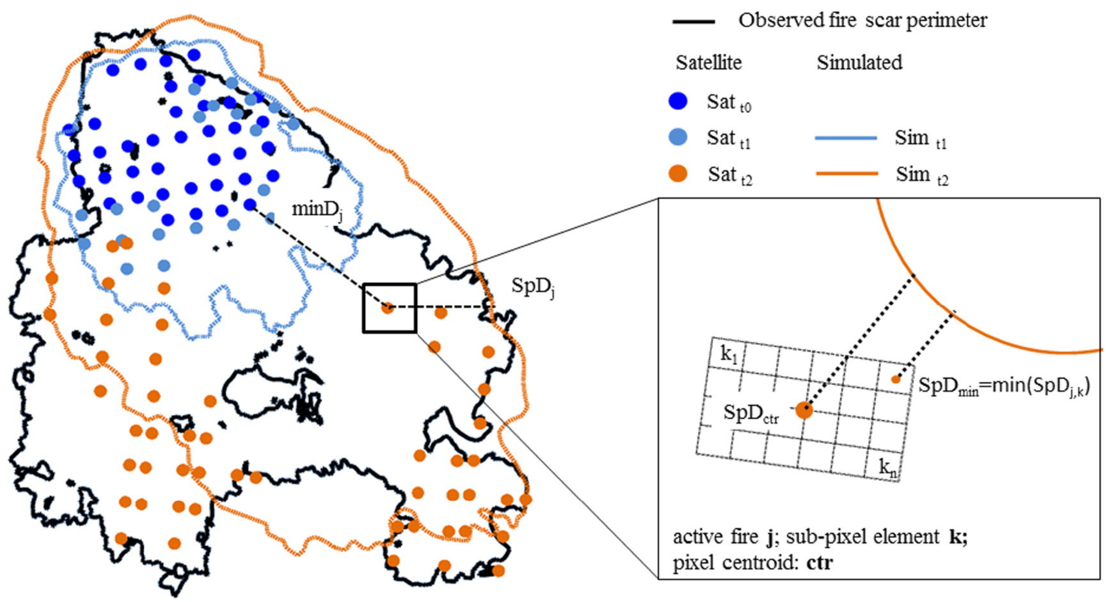

Fig. 2. Spatial discrepancy (*SpD*) between satellite active fire data (Sat) and simulated fire growth (Sim) for the TAV case study. For a given satellite overpass *t*, and for each sub-pixel *k* element from an active fire *j*, $SpD_{j,k}$ is calculated and then the minimum spatial discrepancy value (SpD_j) for that active fire is determined Eq. (1). *minD* is the minimum distance between the closest ignition and active fire *j* (see text for the details).

NRSpD is equal to −1 when the simulated fire does not spread and consequently *minD* equals *SpD* and α is −1 (strong underprediction of fire growth). The *NRSpD* is greater or equal to 1 and converges to 2 when *SpD* is greater or equal to *minD* (overprediction of fire growth). When *SpD* is less than *minD*, the *NRSpD* ranges between −1 and 1 and the sign depends on the value of α. Finally, the *NRSpD* is 0 when the agreement is perfect, i.e. *SpD* equals to 0. The *NRSpD* measure can be used to compare different fire growth simulations. Since it's a normalized ratio it takes as reference the distance between ignition and active fires from a given satellite overpass, thus it is unaffected by fire size, duration and time of satellite overpass.

The median and the interquartile range were computed for each measure of discrepancy and for each case study. The analyses considers each fire duration and number of detected active fires (total and between time steps). To minimize the bias arising from heterogeneous sample sizes the time intervals were defined to yield a similar sample size, i.e. number of active fires for which the discrepancy measures were calculated.

2.5. Impact of MODIS active fire limitations on the evaluation scheme

We analyzed how some of the recognized limitations of MODIS active fire data can potentially affect the proposed satellite-derived fire growth discrepancy measures by focusing on two main issues: i) underestimation of fire activity; and ii) spatial resolution.

Fires burning under persistent cloud cover and dense smoke plumes are hard to detect (Hawbaker et al., 2008; Schroeder et al., 2008). Still, detection may be possible if the cloud or smoke layer is thin (Hawbaker et al., 2008). The CBR1 wildfire occurred under exceptionally hot and dry thunderstorm conditions (Ramos et al., 2011), which led to a period of time with dense cloud cover and limited thermal detections by MODIS. Also, this fire was driven by multiple ignitions, with

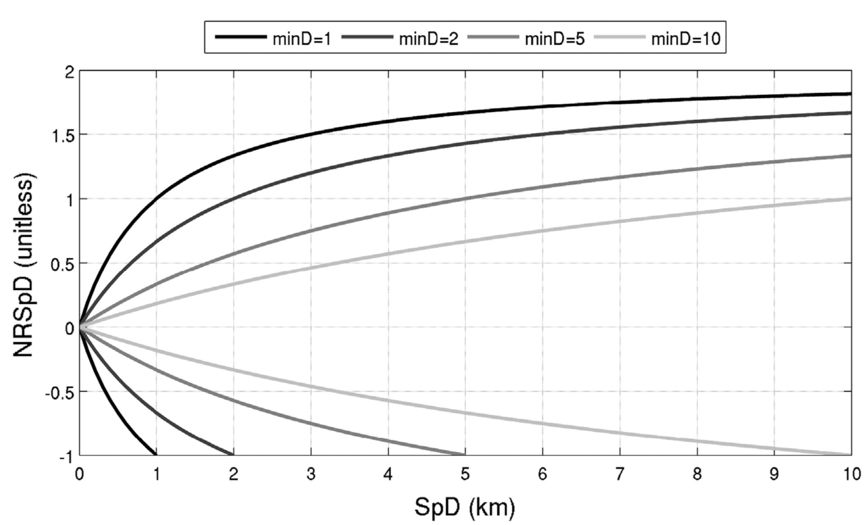

Fig. 3. Relationship between *Normalized Ratio Spatial Discrepancy* (*NRSpD*) and *Spatial Discrepancy* (*SpD*) for different values of the distance between a given active fire and the nearest ignition (*minD* in km).

large burning areas that caused extensive smoke coverage. To illustrate the potential impact of cloud cover and smoke plumes on MODIS detections, we visually explored the CBR1 fire growth by overlaying MODIS active fires on the MODIS Land Surface Reflectance images (MOD09GA/MYD09GA, Vermote et al. (2011)) and on the MODIS Land Surface Temperature and Emissivity (LST) nighttime quality control data set (MOD11A1/MYD11A1, (Wan, 2013)). We used a RGB-7,2,1 band combination of the MODIS land surface reflectance product (LSR) for daytime monitoring of fire affected areas. Additionally, reported ignitions from the Portuguese Rural Fire Database (PRFD, Pereira et al. (2011)) were overlaid.

The effect of pixel size on the proposed discrepancy measures and evaluation scheme was investigated by: i) explicitly taking into account the uncertainty in sub-pixel location; and ii) using a higher spatial resolution active fire data set. The spatial discrepancy calculated using the minimum distance location (SpD_{min}) was compared with the same measure but calculated using the active fire centroid (SpD_{ctr}). The former approach integrates the sub-pixel uncertainty and the effect of pixel size, while the last does not. This analysis proposes to assess under which circumstances is use of $SpDmin$ within the pixel footprint preferable over using SpD_{ctr}.

The impact of MODIS pixel size on the evaluation scheme was further explored by comparing the spatial discrepancy results with those obtained using active fire data from the improved spatial resolution 375 m Visible Infrared Imaging Radiometer Suite (VIIRS) sensor. On-board the Suomi National Polar-orbiting Partnership (S-NPP), the S-NPP/VIIRS was launched in October 2011, has an equator crossing time of 1:30 pm and 1:30 am, and acquires simultaneous co-registered 375 m and 750 m spatial resolution data (Schroeder et al., 2014). We selected the TAV case study (the only one dated after 2011) for comparing

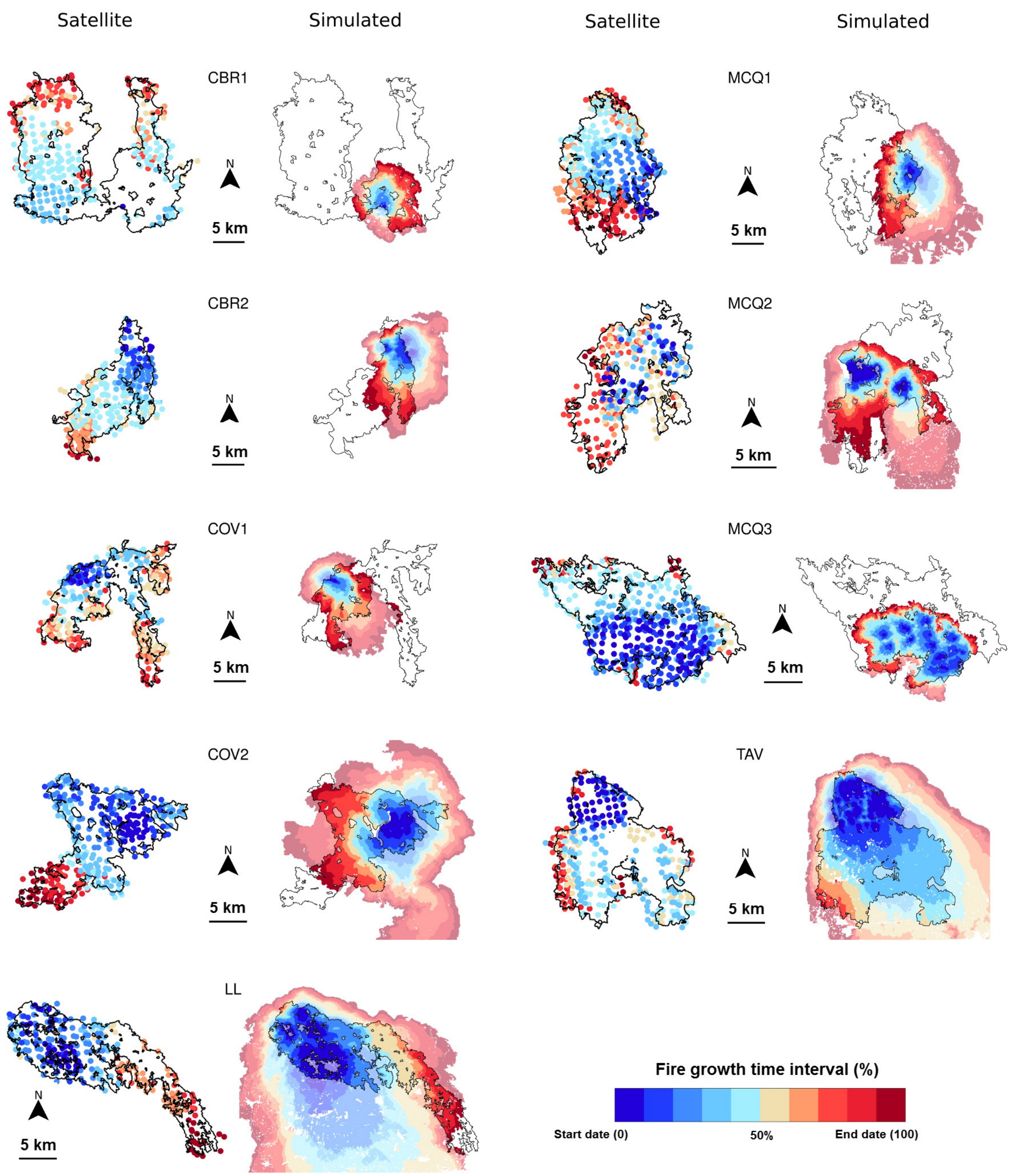

Fig. 4. For each case study, detected MODIS active fires (left) and fire growth simulations (right) are shown in the same temporal scale. Fire growth is represented by 10% elapsed time increments from the start to the end date of the event. Mapped burnt scar perimeters are also shown for each case study.

the spatial discrepancy measures calculated using active fire data from both sensors. Given their temporal resolution difference, time intervals for comparison needed to be adjusted.

3. Results

3.1. Active fires and fire growth simulations

Fire growth simulations were run and its estimates were compared with the satellite active fires position for the same time periods (Fig. 4). Three case studies (COV2, TAV and LL) showed reasonable spatial and temporal correspondence between the observed active fires and the corresponding fire growth simulations. The COV2 simulation covered nearly the entire fire perimeter, while trailing slightly behind compared with the satellite active fire positions. Similarly, for the TAV and LL case studies, fire growth simulations surpassed active fire progression denoting slight model overestimation. Nevertheless, most case studies (six out of nine) underpredicted fire growth. For example, the active fire spatio-temporal distribution of CBR1 shows that this was an extremely fast fire with two northbound propagating fire fronts, and with most of the area burned during the first half of the event's duration. This fast growth pattern and the large total burned area extent were not reproduced by the simulation. The same fire growth underestimation was observed for MCQ3 with most of its extent consumed in less than half of its duration, as shown by the small number of active fires with orange to red tones. A similar pattern of active fire progression was observed in the CBR2 case study. The MCQ1 wildfire displayed a complex spatio-temporal distribution of active fires, pointing to multiple event ignitions as shown by the reddish points in the north, west and south boundaries of the fire perimeter, with a fire growth pattern that would be hardly reproduced by a single run simulation.

3.2. Fire growth discrepancies

While Fig. 4 maps the temporal distribution of active fires and simulated fire growth along each interval of elapsed time, quantification of the spatial discrepancy between both sources of data for each active fire position is mapped on Fig. 5. There are mainly two classes

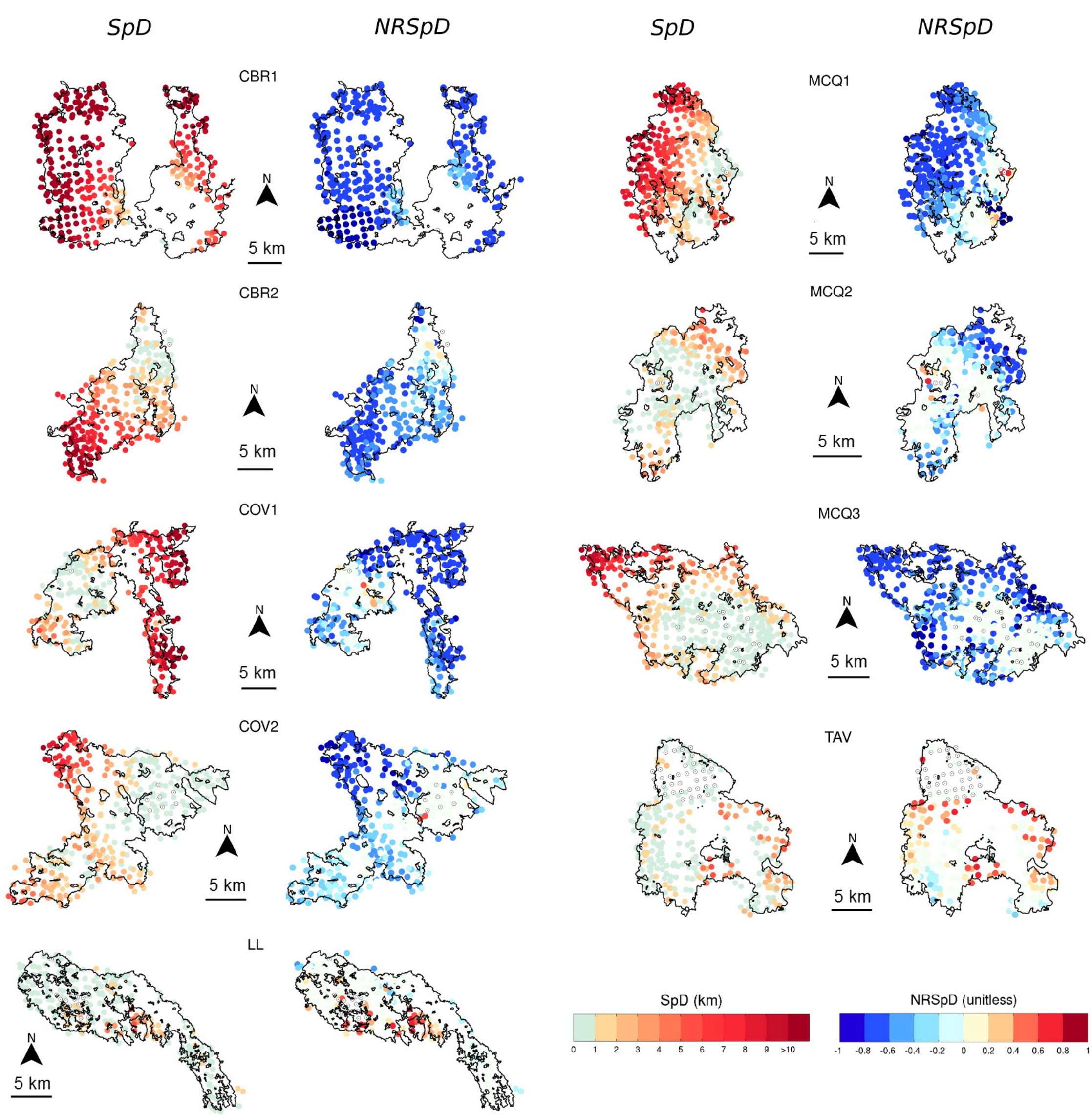

Fig. 5. Spatial Discrepancy (*SpD*, on the left) and Normalized Ratio Spatial Discrepancy (*NRSpD*, on the right) measures mapped for each case study. Burnt scar perimeters are also overlaid (black lines).

of spatial discrepancy values depicted in Fig. 5: observations with *SpD* lower than 1 km and *NRSpD* values between −0.2 and 0.2 (those with the best spatial agreement); and those observations with *SpD* >1–2 km, which correspond to those observations with a strong delay of the fire growth simulation (*NRSpD* values lower than −0.4). The combined information from Figs. 4 and 5 shows a general pattern of increasing discrepancies with time elapsed since ignition. In the southwest region of the COV2 case study, there are some differences between the timing of satellite detection and of simulated fire front (Fig. 4). However, the spatial discrepancy for most of the active fires is below 1 km, which denotes a good spatial agreement between simulation and active fire data. The largest *SpD* and lowest *NRSpD* values are found in areas where the simulations were not able to reproduce the fire growth pattern given the slow rate of simulated fire growth (observations where the spatial discrepancy is >2–3 km) (Fig. 5). Excluding these areas, most of the discrepancies are below ~2 km, leading to slightly negative *NRSpD* values (light blue tones in Fig. 5).

In general, the variability of both measures, aggregated for the full case study, is very large, with most of the median *SpD* values below ~4 km, and with five out of nine median *NRSpD* values below −0.5 (Fig. 6). Fire growth estimates for the LL case study show the lowest spatial discrepancies with active fire data, with perfect agreement for 50% of the comparisons. For the TAV case study, 25% of the comparisons show perfect agreement (*NRSpD* = 0) while 25% have *NRSpD* values below 0.25, which represents a good spatial agreement between simulated and satellite fire growth.

The worst simulations are from the CBR1, CBR2, COV1, and MCQ1 case studies, with the largest top four median *SpD* values. The strong delay of the CBR1 simulated fire growth is depicted by large values of median *SpD* and low *NRSpD* values for the entire duration, denoting a strong fire growth underprediction (Figs. 5 and 6). Despite MCQ3 having a relatively low median *SpD* value, it shows a strong underprediction, with >50% of the *NRSpD* below −0.5 (Fig. 6).

The temporal evolution of the spatial discrepancies for each fire event is shown in Fig. 7. The CBR2, MCQ1 and MCQ3 case studies show increasing *SpD* values during the initial 60–70% of their total duration, decreasing afterwards. In general, the *NRSpD* values increase towards 0 near the end of the fire's duration.

Grouping all the case studies, the evolution of *NRSpD* values along elapsed time since ignition is shown in Fig. 8. Overall, simulated fire growth is consistently underpredicted (*NRSpD* < 0) when compared with satellite active fire data. The non-monotonic evolution of the median *NRSpD* value indicates that discrepancy decreases after ca. 60% of time elapsed. Periods of agreement and overprediction (*NRSpD* ≥ 0) between the simulations and the active fire data also occur, as shown by the upper percentile of the *NRSpD* and illustrated in the TAV and LL fire growth simulations (Figs. 5, 6 and 7).

3.3. Impact of MODIS active fire limitations on the evaluation scheme

3.3.1. Underestimation of fire activity

During the CBR1 fire growth, the thunderstorm conditions led to almost two days of limited thermal detections due to cloud cover (Fig. 9b, c and d). Still, some fire detections occurred, probably under a layer of thin clouds (Fig. 9c and d). Even considering this period of fire detections absence, it was possible to use approximately 300 active fire pixels to evaluate the simulation. This fire was driven by large burning areas along with well-developed smoke plumes (Fig. 9e and f). However, the smoke plumes did not appear to preclude the active fire detections. Multiple fire ignitions were recorded in the PRFD (Fig. 9b and c), although some of them were not detected by MODIS due to the thick cloud cover (Fig. 9b).

3.3.2. Spatial resolution

Analysis of the impact of the MODIS pixel size on the spatial discrepancy measures was based on a total number of 3136 active fires, with active fire footprint area ranging from the nominal value of 1 km^2 to 10 km^2, and an overall median of 1.86 km^2 (Supplementary Fig. 1). Approximately 40% of the active fires (light grey data in Fig. 10a) have $SpD_{min} < SpD_{ctr} - SpD_{min}$ and $SpD_{min} < 2$ km, which corresponds to those active fires spatially close to the simulated fire perimeter. Of these pixels, approximately 40% have the lowest footprint areas (100–200 ha, Fig. 10b). For increasing values of the MODIS footprint size ($SpD_{ctr} - SpD_{min}$ distance increases), using the active fire minimum distance position decreases the uncertainty for large pixel footprint size and thus the SpD_{min} favors the simulation's accuracy.

For the remaining active fires (ca. 60% of the active fires, dark grey data in Fig. 10a), SpD_{min} is always greater or equal than the $SpD_{ctr} - SpD_{min}$ distance, thus even considering the minimum distance active fire location, evaluation measures show a large discrepancy (under or over-estimation) between fire growth simulations and active fire data. Approximately 60% of these observations corresponds to active fires with footprint areas between 100 and 200 ha (Fig. 10b). In spite of being the smallest active fires, thus with the lowest uncertainty, the large values of SpD_{min} turns irrelevant to use the minimum or the centroid distance because simulation results inevitably show a poor agreement with active fires.

For the more recent (2012) TAV case study, MODIS and the improved spatial resolution VIIRS data show similar fire growth patterns (Fig. 11). For this case study, MODIS active fire data have a

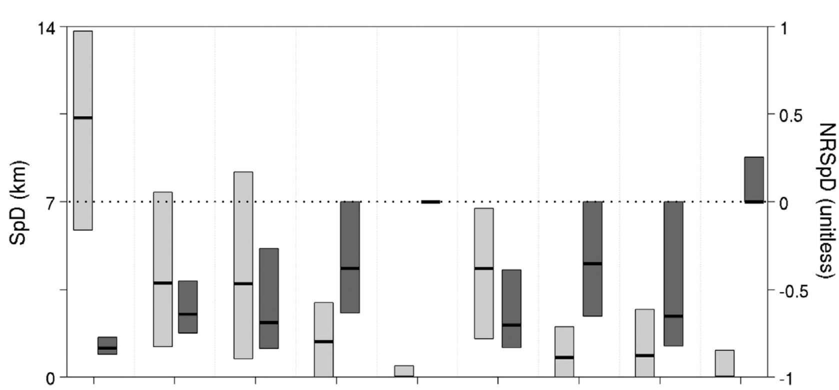

Fig. 6. Interquartile range values of the *SpD* (light grey boxes) and *NRSpD* (dark grey boxes) measures for each case study. The zero *NRSpD* dashed line represents the perfect agreement between fire growth simulations and active fire data observations.

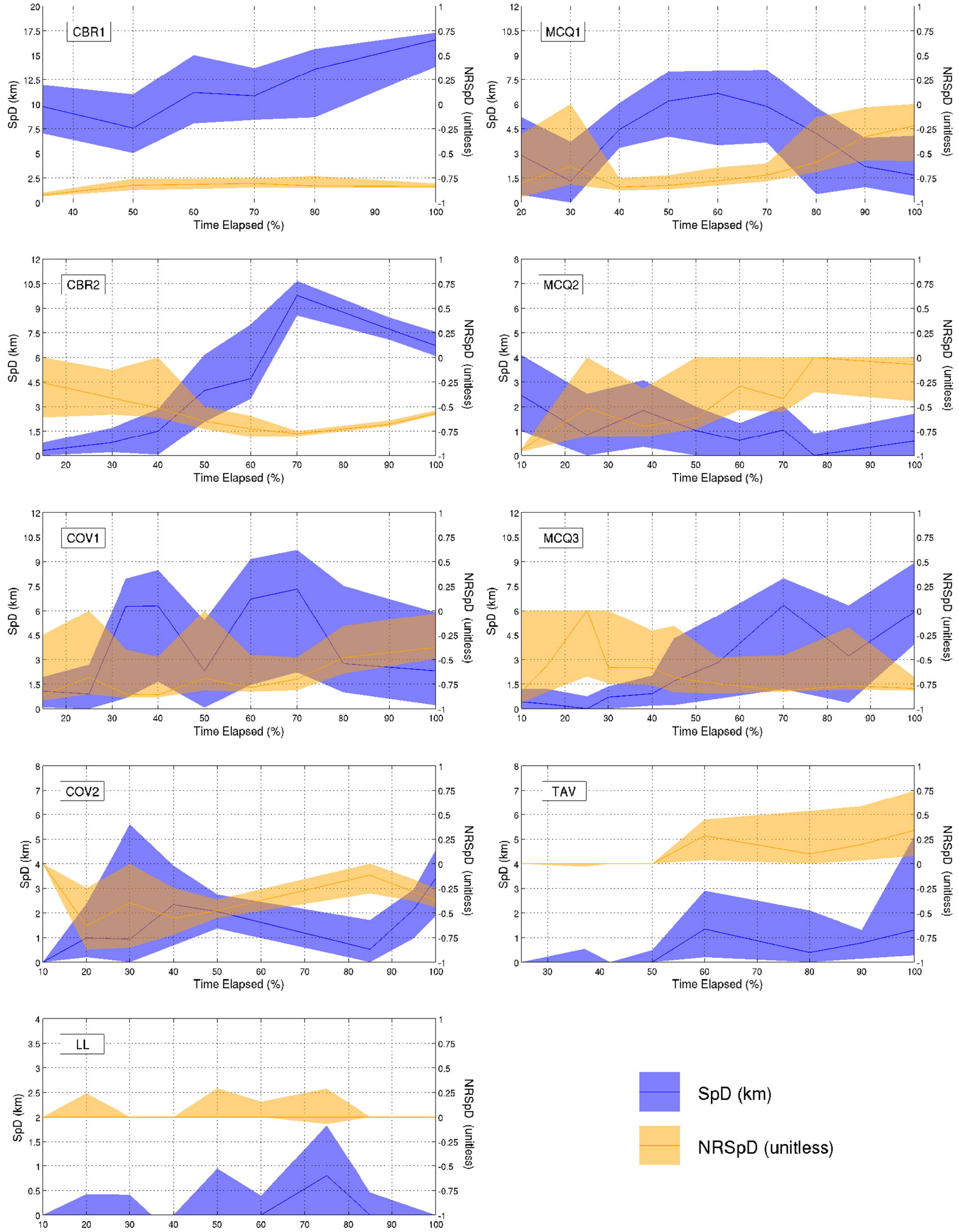

Fig. 7. Median and corresponding interquartile ranges of *SpD* (km) and *NRSpD* (unitless) measures along time elapsed (%) since first detection, for each case study. Simulated-satellite fire growth discrepancies show a dynamic pattern along fire length.

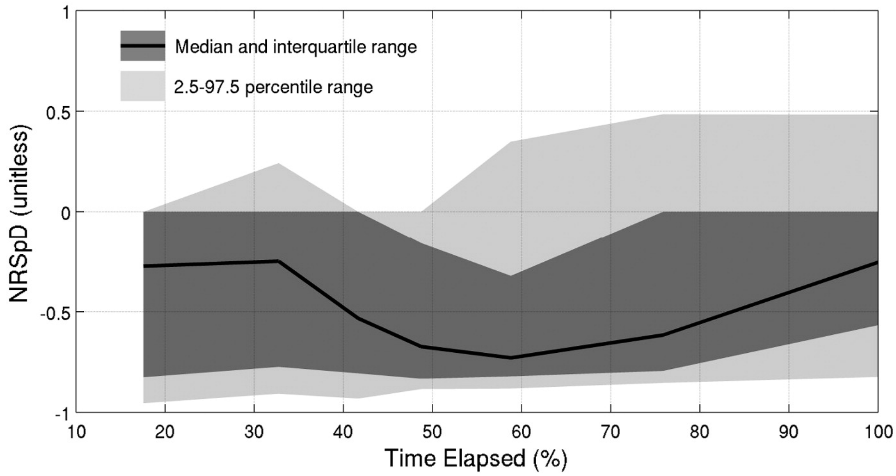

Fig. 8. *NRSpD* median and interquartile range evolution along time elapsed (%) since ignition, encompassing all case studies. Spatial discrepancy decreases after ca. 60% of time elapsed.

median footprint value of 200 ha (Appendix B) while the median VIIRS footprint size is approximately 20 ha (boxplot not presented). Despite the large difference between median footprint sizes, the evolution of the spatial discrepancy measures across elapsed time since ignition and the spatio-temporal distribution of active fires of both sensors are similar (Fig. 11b and c). As expected, the calculated *SpD* values using VIIRS active fire data have a larger variability and are 2× larger than those using MODIS active fires, with a maximum median value of 3 km at 65% of elapsed time since ignition (Fig. 11a), when the fire stopped spreading south and had started expanding from the flanks given a sudden change on wind direction (Viegas et al., 2012). This corresponds to the period when the fire was most active. Fire growth simulation is overpredicted, which is in agreement with the small positive values of the *NRSpD* from both sensors in the last half of the fire length (Fig. 11b and e). Except for the fire flanks, simulated fire growth reproduced the active fire positions during most of the event duration, with median *NRSpD* values near 0 in the second half of the event denoting good simulation-satellite agreement (Fig. 11b). It is also possible to observe the number of each satellite overpasses per time elapsed interval, with significant difference for example in the 25–55% interval where there is only a single acquisition of VIIRS active fire data.

4. Discussion

4.1. Evaluation of fire growth discrepancies

For most of the case studies, fire growth occurred during the initial 50–70% of fire length time, a pattern not followed by the simulations, except for the LL and TAV case studies. Fire growth simulations were delayed for most of the case studies when compared with satellite active fire positions (Fig. 4). The discrepancies observed between the fire spread simulations and active detections could have been caused by a number of factors, namely: 1) the fire spread model itself; 2) fuel model assignment and classification; 3) spatial resolution of weather data, particularly of wind data; 4) geometric representation of satellite fire ignitions; and 5) absence of spotting and fire suppression simulation. Exploring the detailed implications of these limitations on the simulation results is beyond the scope of the present study.

Overall, the *SpD* values are large and the *NRSpD* values close to −1, meaning that simulations underestimated fire growth with large spatial discrepancies (>1–2 km). Quantifying and mapping the spatial discrepancy measures enable the selection of different spatial discrepancy thresholds, for example to select those observations with values >1 km to explore potentially related sources of error. It is also possible to explore what are the landscape/weather properties that lead a simulation to a condition of extreme under or over prediction of fire growth. Thus, it is important not only to identify the regions of under or over fire growth prediction but also the magnitude of their spatial discrepancy. By integrating the spatial discrepancy values over the length time of each case study (Fig. 6), allows exploring their variability and to identify those simulations with problems (low accuracy).

There is also a large variability in the spatial discrepancy measures along time elapsed since ignition (Fig. 7). The median values for both measures show non-monotonic profiles throughout the duration of the fires. In general, *SpD* increases with elapsed time, which agrees with the statement that fire growth prediction errors compound with each time step (Bachmann and Allgöwer, 2002). However, those discrepancies do not increase linearly along elapsed simulation time and vary with case study, sometimes decreasing at the final stages of the fire (Figs. 7 and 8). Identifying the time intervals of significant under or over fire growth prediction also allows exploring the potential sources of simulation errors, supporting model calibration, and thus improving model estimates. In an operational context, information on the *SpD* is crucial to help fire managers to decide whether they use or not the simulation results to support their decisions. The confidence in the information given by the absolute discrepancies will depend on the values and human lives at risk.

The median *NRSpD* encompassing all the case studies shows consistent underprediction of fire growth, decreasing until ~60% of time elapsed and increasing afterwards (Fig. 8). The observed increase in the *NRSpD* in the last half-time of the fire event can be due to an improvement in fire growth simulations and/or a combined effect of weather and fire-control operations. Under the typical severe weather conditions driving the very fast wildfire spread conditions, firefighting effectiveness is limited. Once weather conditions moderate, there is an opportunity window for more effective fire suppression (Finney et al., 2009). Therefore, towards the end of the fire event, active fire progression slows (as shown in Fig. 4) and thus the spatial discrepancy between simulated fire growth and satellite active fire observations decrease. The *NRSpD* measure highlights the dynamic pattern of the evaluation of fire spread simulations that was never explored before but which requires information on the processes driving fire propagation to validate the raised hypothesis. This

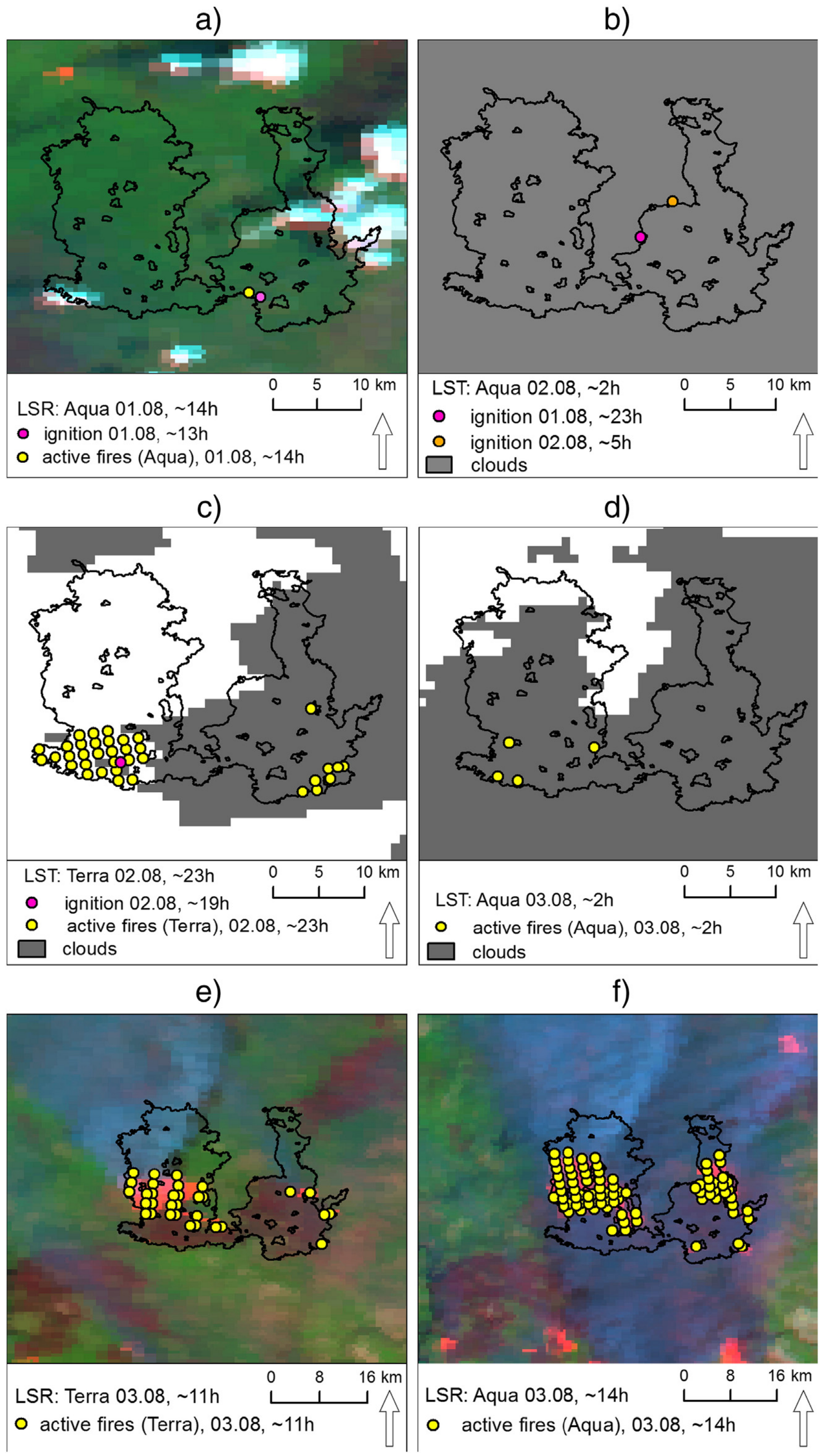

Fig. 9. CBR1 wildfire growth. Satellite active fires (yellow dots) are shown overlaying the diurnal MODIS LSR (a, e, f) and nighttime MODIS LST (b, c, d) images. Multiple ignition points are also shown (PRFD, pink and orange dots). LSR stands for Land Surface Reflectance and is a RGB-7,2,1 band color composition. RST stands for Land Surface Temperature. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

suggested different pattern of simulation performance is masked when only a post-fire assessment approach is used to evaluate fire spread simulations.

Despite exploratory, evaluation results highlight the ability of the proposed evaluation metrics to depict different spatial dynamics of simulated fire growth. However, further research is needed to improve the proposed spatial measures, particularly to overcome some limitations of the *NRSpD*. A relative spatial discrepancy measure is required to compare fires that have different sizes and/or durations. However, if the first detected active fires are also used as ignitions in the simulations (as they were in this study), this creates a dependency between fire growth simulations and the *NRSpD* values. This is not a problem when

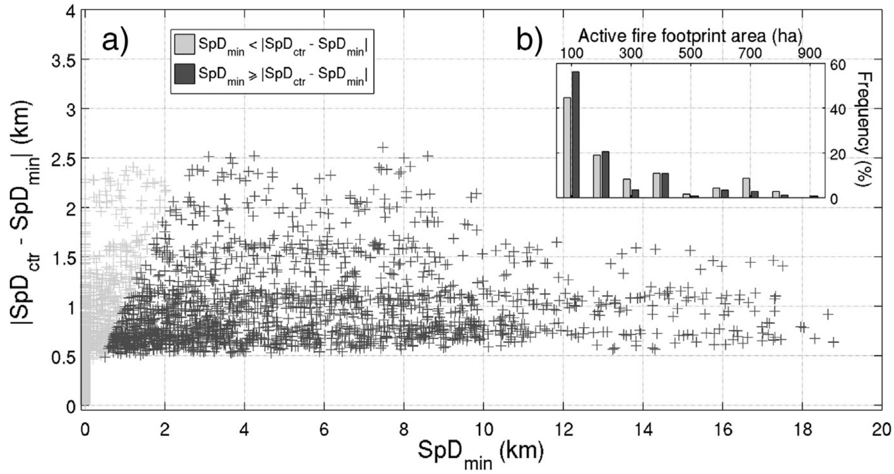

Fig. 10. Comparison between the spatial discrepancy calculated using the minimum distance (SpD_{min}) and using the centroid position (SpD_{ctr}) for each active fire from all the case studies (a); frequency of active fires for active fire footprint area classes (b). Most of the cases evaluation results are not affected by the fire front sub-pixel location given the large spatial discrepancies of fire growth simulations.

ignition is obtained from fire databases. This measure, due to its definition, has a scale range that is not intuitive ($-1, +\infty$). A deeper analysis on the distribution properties of *NRSpD* is required, and to explore if it is more sensitive to the shape (given the comparison with the active fires position) than to the size of the simulated fire. It is worthy to note that the under/over-prediction parameter (alpha) in the *NRSpD* formula can

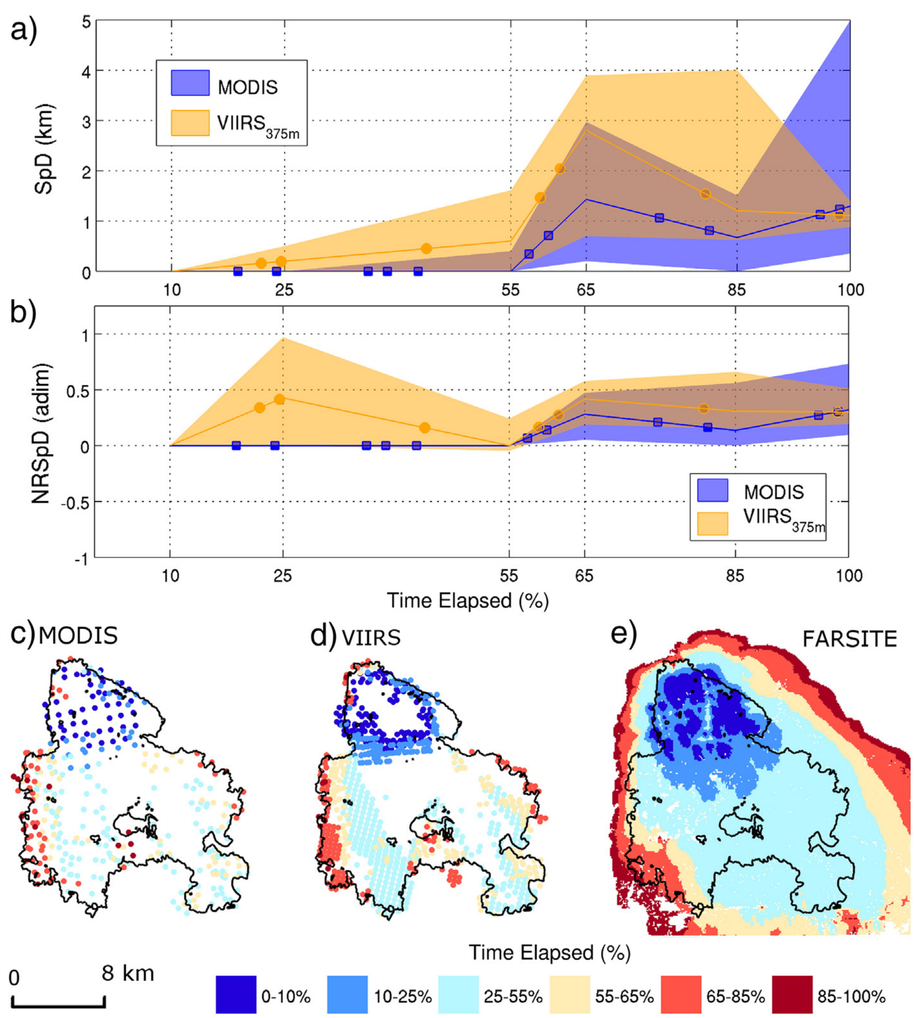

Fig. 11. Comparison between MODIS and VIIRS 375 m active fire data and fire growth simulations along time elapsed (%) for the TAV wildfire case study. Median and interquartile range values of *SpD* (a) and *NRSpD* (b); MODIS active fires (c); VIIRS 375 m active fires (d); and FARSITE fire growth simulation (e). Satellite squares and dots in a) and b) represent MODIS and VIIRS satellite overpasses, respectively. Spatial discrepancy measures calculated using MODIS and VIIRS active fires show a similar temporal pattern for the TAV case study fire.

be linked to the *SpD* measure instead, increasing the richness of its information.

4.2. Impact of MODIS active fire limitations on the evaluation scheme

4.2.1. Underestimation of fire activity

Potential underestimation of fire activity due to cloud cover and smoke plumes is a problem that affects thermal detections from all sensors, not only MODIS. The CBR1 example shows that due to cloud cover, during a considerable time length of fire growth there were no thermal detections. Therefore, during this period we were not able to evaluate the quality of fire growth simulations. However, thin clouds and smoke plumes did not totally prevent MODIS active fire detections (Fig. 9c, f). Even with these restrictions it was possible to use ca. 300 active fires (Appendix B) in the evaluation of the spatial discrepancies for the whole fire event. In Portugal, large summer wildfires typically occur under extreme hot and dry meteorological conditions (Trigo et al., 2006), thus cloud cover is unlikely to occur during these fire events.

Besides, the CBR1 example also illustrates the potential of active fire data to provide information on the location of new fire ignitions and fire front burning areas. This information can be used to re-initialize the simulation system as implemented in the study of Coen and Schroeder (2013).

4.2.2. Spatial resolution

Based on our case study's samples, MODIS pixel footprints range between 1 and 10 km^2, although most of them are below 2 km^2. Small active fire's footprint sizes increases the accuracy of the calculated spatial discrepancy measures. Therefore, a conservative evaluation approach may be adopted by selecting only those active fires that meet a given footprint threshold, based on its relationship with sensor scanning angles (Fig. 12). For example, selecting only pixels with up to 2 km^2 (for scanning angles below 35°) increases confidence in the evaluation measures but the sample will only have half of the MODIS active fires.

Analysis of the impact of fire front location uncertainty within satellite active fire pixel on *SpD* (Fig. 10) showed that for more than half of the comparisons MODIS pixel size does not affect our evaluation approach. Disregarding the quality of input data used in the simulations, these observations have large SpD_{min} values. Therefore, fire growth simulations agree poorly with satellite observations and consequently it's irrelevant to consider the centroid or the minimum distance to calculate *SpD*. However, for the remaining active fires (ca. 40%), considering SpD_{min} favors the simulations, while opting for SpD_{ctr} measure increases satellite versus simulated spatial discrepancy. Therefore, for large, long lasting fires it is important to recognize the tradeoff between the number of active fires selected for the evaluation and their pixel footprint size, considering its variation with scan angle. Thermal detections based on low zenithal scan angles, thus with smaller footprint sizes, produce higher confidence spatial discrepancy measures, which may be calculated using the active fire centroid position. For larger active fire footprints, a conservative evaluation approach may be adopted by using the minimum distance, thus benefitting the simulations given the higher uncertainty of those satellite observations.

Further assessment of the impact that MODIS pixel size has on the proposed evaluation scheme was performed by comparing the spatial discrepancy measures using MODIS and VIIRS 375 m active fires (Fig. 11). The overall spatial and temporal patterns of detected active fires from both satellites are analogous (Fig. 11c, d). Similarly, the corresponding evaluation measures show comparable profiles across the fire event time length. As expected, the median spatial discrepancy values calculated using the VIIRS are larger than the ones calculated using the MODIS data. However, for the last half time duration of the TAV fire event, both *NRSpD* values are similar pointing to overprediction of the simulated fire growth (Fig. 11b, e). Therefore, results suggest that despite the coarse spatial resolution and pixel deformation with increasing scanning angles of MODIS active fire data, this study fire growth evaluation approach is not affected. Moreover, MODIS high revisit cycle provides additional active fire detections between VIIRS passages. This allows more detailed temporal monitoring of fire growth as well as a larger sample of active fires between satellite overpasses. For example, in the 25–55% elapsed time interval there was a single VIIRS overpass and three MODIS overpasses (Fig. 11a, b), thus enabling an improved description of the fire growth temporal patterns. These results are based on a single fire event analysis and differences may occur for other fire events. However, the comparison with VIIRS data showed that MODIS active fire data can provide valuable information for evaluating fire growth simulations despite its relative coarse spatial resolution pixel. These findings open way to a large number of fire growth simulations of global large fires that occurred since 2001.

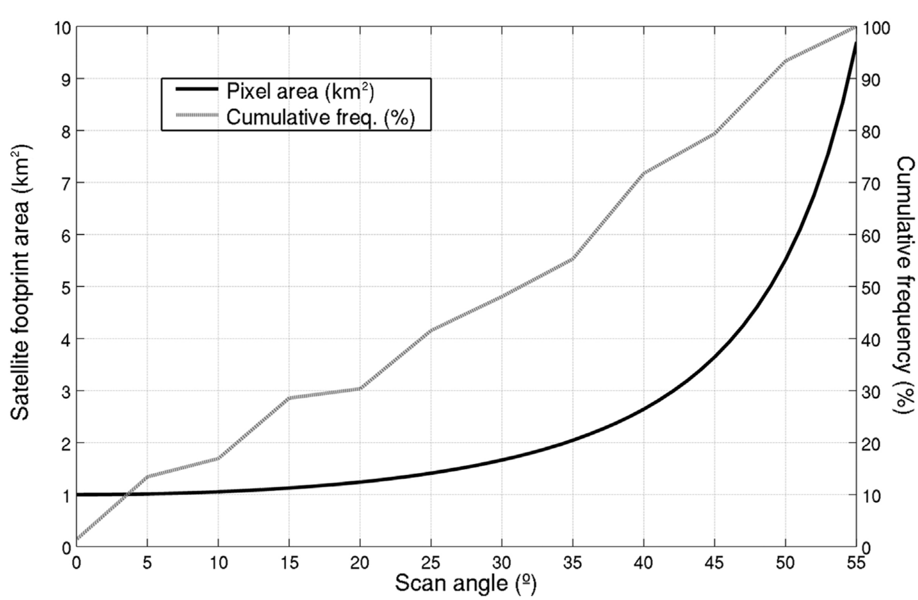

Fig. 12. Relationship between sensor scan angle and satellite footprint size (left y-axis); cumulative frequency of active fires and corresponding footprint area (right y-axis).

4.3. Future research directions

The current systematic model evaluation approach requires a future statistical analysis framework to describe the distribution properties of the proposed spatial discrepancy measures. Additionally, it is relevant for fire modelers and managers to develop a test to the null hypothesis that fire growth simulations are consistent with active fire data in order to accept or reject a fire growth simulation at a given confidence level. To accomplish this, more wildfire growth simulations with improved input data quality is required, and the collection of burnt area perimeters during the fire event propagation (for example using Unmanned Aerial Vehicles, UAV's) is also important to assess the degree of adherence of the approach.

Concerning the remote sensing component of this study, the proposed satellite-based evaluation measures would certainly benefit from using only the active fires located in the fire front(s), instead of using all the active fires from a given satellite overpass. Although some authors have studied this topic (Ononye et al. (2007); Wooster et al. (2003); Smith and Wooster (2005)), further research is needed to improve calculation of spatial discrepancy measures.

The proposed satellite-based evaluation scheme is applicable to any other satellite or airborne thermal dataset. The fusion of existent active fire data sets from existing and/or upcoming sensors, with improved spatial and temporal resolutions (e.g. Freeborn et al. (2009)) will enhance the applicability of satellite active fire data to evaluate fire growth simulations. In this context, VIIRS active fire data have remarkable potential given their higher spatial resolution, smaller footprint deformation and higher detection rates, when compared with MODIS data, particularly for small and low-intensity fires (Schroeder et al., 2014). This potential has been demonstrated for large and long-lasting fires with low-to-moderate spread rates (Oliva and Schroeder, 2015; Schroeder et al., 2014). The Bi-spectral InfraRed Detection (BIRD) satellite can also provide valuable medium spatial resolution active fire data and its capabilities to identify individual fire fronts have been shown previously (Wooster et al., 2003). The upcoming Sentinel-3 satellites will provide additional information on active fires at the global scale with higher detection capabilities than MODIS (Wooster et al., 2012). Finally, the potential of using UAV's for real-time data gathering to support scientific data collection (for example, fire growth perimeters) is truly enticing and their ability to monitor disasters, including wildfires, have been previously demonstrated (Ambrosia et al., 2003; Watts et al., 2012).

5. Conclusions

This study proposes a new exploratory evaluation approach of fire spread simulations based on the assessment of simulated fire growth discrepancies using satellite active fire data. This evaluation approach represents a contribution to fire spread modeling evaluation since it: 1) explores two simple quantitative evaluation measures; 2) does not require the collection of reference burnt area perimeters; and 3) is a cost effective, consistent, and adaptable to any satellite active fire data or fire spread simulation system.

The *SpD* and *NRSpD* measures enable the location of areas of low/high spatio-temporal agreement between simulated fire growth and satellite active fires, aiding to the identification of potential sources of simulation error. Integration of *NRSpD* for all the case studies shows a non-monotonic pattern, with relative spatial discrepancy decreasing after 60% of time elapsed since ignition. We showed that the evaluation scheme is simple, the proposed measures can capture the spatio-temporal patterns of simulated fire growth but further research is needed to address some of the existent limitations, specifically with the *NRSpD* metric. Furthermore, the proposed measures integrate in their calculation fire front location uncertainty. We concluded that as active fire footprint size increases, it is more relevant to consider the location of the minimum discrepancy distance, instead the classic centroid position. Comparison with VIIRS data for a single case study showed that the proposed evaluation scheme is not affected by MODIS pixel size and that this sensor revisit cycle represents an advantage to better describe fire growth dynamics. Overall, this study proposes a systematic evaluation approach and is a first attempt to show the potential of using MODIS active fire data to evaluate fire spread simulations. Furthermore, the approach can also be extended to evaluate other spreading processes such as for example flooding, vegetation mortality and oil spills.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at http://dx.doi.org/10.1016/j.rse.2016.12.023.

References

Ager, A.A., Vaillant, N.M., Finney, M.A., 2010. A comparison of landscape fuel treatment strategies to mitigate wildland fire risk in the urban interface and preserve old forest structure. For. Ecol. Manag. 259, 1556–1570.
Albini, F.A., 1976. Estimating wildfire behavior and effects. Gen. Tech. Rep. INT-30. Department of Agriculture, Forest Service, Intermountain Forest and Range Experiment Station (92 p).
Albini, F.A., 1979. Spot fire distance from burning trees: a predictive model. Gen. Tech. Rep. INT-56. Department of Agriculture, Forest Service, Intermountain Forest and Range Experiment Station (73 p).
Alcasena, F.J., Salis, M., Ager, A.A., Arca, B., Molina, D., Spano, D., 2015. Assessing landscape scale wildfire exposure for highly valued resources in a Mediterranean area. Environ. Manag. 55, 1200–1216.
Alexander, M.E., Cruz, M.G., 2013. Are the applications of wildland fire behaviour models getting ahead of their evaluation again? Environ. Model. Softw. 41, 65–71.
Ambrosia, V.G., Wegener, S.S., Sullivan, D.V., Buechel, S.W., Dunagan, S.E., Brass, J.A., Stoneburner, J., Schoenung, S.M., 2003. Demonstrating UAV-acquired real-time thermal data over fires. Photogramm. Eng. Remote. Sens. 69, 391–402.
Anderson, H.E., 1982. Aids to determining fuel models for estimating fire behavior. The Bark Beetles, Fuels, and Fire Bibliography. 143.
Arca, B., Duce, P., Laconi, M., Pellizzaro, G., Salis, M., Spano, D., 2007. Evaluation of FARSITE simulator in Mediterranean maquis. Int. J. Wildland Fire 16, 563.
Arca, B., Salis, M., Pellizzaro, G., Bacciu, V., Spano, D., Duce, P., Ager, A., Finney, M., 2010. Climate change impact on fire probability and severity in Mediterranean areas. In: Viegas, D.X. (Ed.), VI International Conference on Forest Fire Research. Coimbra, Portugal, University of Coimbra, Portugal, pp. 5–18.
Bachmann, A., Allgöwer, B., 2002. Uncertainty propagation in wildland fire behaviour modelling. Int. J. Geogr. Inf. Sci. 16, 115–127.
Benali, A., Russo, A., Sá, A.C.L., Pinto, R.M.S., Price, O., Koutsias, N., Pereira, J.M.C., 2016. Determining fire dates and locating ignition points with satellite data. Remote Sens. 8, 1–20.
Bossard, M., Feranec, J., Otahel, J., 2000. CORINE land cover technical guide: Addendum 2000. European Environment Agency Copenhagen Technical Report No. 40 (Copenhagen, Denmark).
Caetano, M., Nunes, V., Nunes, A., 2009. CORINE land cover 2006 for Continental Portugal. Technical Report. Instituto Geográfico Português (IGP), Lisbon, Portugal.
Calkin, D.E., Thompson, M.P., Finney, M.A., Hyde, K.D., 2011. A real-time risk assessment tool supporting wildland fire decision making. J. For. 274–280.
Campagnolo, M.L., Montano, E.L., 2014. Estimation of effective resolution for daily MODIS gridded surface reflectance products. IEEE Trans. Geosci. Remote Sens. 52, 5622–5632.
Clark, R.E., Hope, A.S., Tarantola, S., Gatelli, D., Dennison, P.E., Moritz, M.A., 2008. Sensitivity analysis of a fire spread model in a chaparral landscape. Fire Ecology. 4.
Coen, J.L., Schroeder, W., 2013. Use of spatially refined satellite remote sensing fire detection data to initialize and evaluate coupled weather-wildfire growth model simulations. Geophys. Res. Lett. 40, 5536–5541.
Cohen, J., 1960. A coefficient of agreement for nominal scales. Educ. Psychol. Meas. 20, 37–46.

Cruz, M.G., Alexander, M.E., 2013. Uncertainty associated with model predictions of surface and crown fire rates of spread. Environ. Model. Softw. 47, 16–28.

Csiszar, I.A., Morisette, J.T., Giglio, L., 2006. Validation of active fire detection from moderate-resolution satellite sensors: The MODIS example in northern Eurasia. IEEE Trans. Geosci. Remote Sens. 44, 1757–1764.

Cui, W., Perera, A., 2010. Quantifying spatio-temporal errors in forest fire spread modelling explicitly. J. Environ. Inform. 16, 19–26.

Dee, D., Uppala, S., Simmons, A., Berrisford, P., Poli, P., Kobayashi, S., Andrae, U., Balmaseda, M., Balsamo, G., Bauer, P., 2011. The ERA-interim reanalysis: configuration and performance of the data assimilation system. Q. J. R. Meteorol. Soc. 137, 553–597.

DiMiceli, C., Carroll, M., Sohlberg, R., Huang, C., Hansen, M., Townshend, J., 2011. Annual Global Automated MODIS Vegetation Continuous Fields (MOD44B) at 250 m Spatial Resolution for Data Years Beginning Day 65, 2000–2010, Collection 5 Percent Tree Cover. University of Maryland, College Park.

Duff, T.J., Chong, D.M., Taylor, P., Tolhurst, K.G., 2012. Procrustes based metrics for spatial validation and calibration of two-dimensional perimeter spread models: a case study considering fire. Agric. For. Meteorol. 160, 110–117.

Duff, T.J., Chong, D.M., Tolhurst, K.G., 2013. Quantifying spatio-temporal differences between fire shapes: estimating fire travel paths for the improvement of dynamic spread models. Environ. Model. Softw. 46, 33–43.

Farr, T.G., Rosen, P.A., Caro, E., Crippen, R., Duren, R., Hensley, S., Kobrick, M., Paller, M., Rodriguez, E., Roth, L., 2007. The shuttle radar topography mission. Rev. Geophys. 45.

Fernandes, P., 2005. Equivalência genérica entre os modelos de combustível do USDA Forest Service (Anderson, 1982) e as formações florestais portuguesas. Guia metodológico para elaboração do Plano. Municipal/Intermunicipal de Defesa da Floresta Contra Incêndios. Direção Geral dos Recursos Florestais, Lisbon, Portugal.

Filippi, J.-B., Mallet, V., Nader, B., 2014a. Evaluation of forest fire models on a large observation database. Nat. Hazards Earth Syst. Sci. 14, 3077–3091.

Filippi, J.-B., Mallet, V., Nader, B., 2014b. Representation and evaluation of wildfire propagation simulations. Int. J. Wildland Fire 23, 46–57.

Finney, M.A., 2004. FARSITE, fire area simulator–model development and evaluation. Research Paper RMRS-RP-4 Revised. Ogden, UT: U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station (47 p).

Finney, M., Grenfell, I.C., McHugh, C.W., 2009. Modeling containment of large wildfires using generalized linear mixed-model analysis. For. Sci. 55, 249–255.

Forthofer, J.M., 2007. Modeling Wind in Complex Terrain for Use in Fire Spread Prediction. Colorado State University.

Freeborn, P.H., Wooster, M.J., Roberts, G., Malamud, B.D., Xu, W., 2009. Development of a virtual active fire product for Africa through a synthesis of geostationary and polar orbiting satellite data. Remote Sens. Environ. 113, 1700–1711.

Fujioka, F.M., 2002. A new method for the analysis of fire spread modeling errors. Int. J. Wildland Fire 11, 193–203.

Giglio, L., 2010. MODIS Collection 5 Active Fire Product User's Guide Version 2.4. Science Systems and Applications, Inc.

Giglio, L., Descloitres, J., Justice, C.O., Kaufman, Y.J., 2003. An enhanced contextual fire detection algorithm for MODIS. Remote Sens. Environ. 87, 273–282.

Grell, G.A., Dudhia, J., Stauffer, D.R., 1994. A description of the fifth-generation Penn State/NCAR mesoscale model (MM5). NCAR Tech. Note NCAR/TN-398 + STR (117 p).

Hantson, S., Padilla, M., Corti, D., Chuvieco, E., 2013. Strengths and weaknesses of MODIS hotspots to characterize global fire occurrence. Remote Sens. Environ. 131, 152–159.

Hawbaker, T.J., Radeloff, V.C., Syphard, A.D., Zhu, Z., Stewart, Z.I., 2008. Detection rates of the MODIS active fire product in the United States. Remote Sens. Environ. 112, 2656–2664.

Ichoku, C., Kaufman, Y.J., 2005. A method to derive smoke emission rates from MODIS fire radiative energy measurements. IEEE Trans. Geosci. Remote Sens. 43, 2636–2649.

Jerez, S., Trigo, R., Vicente-Serrano, S.M., Pozo-Vázquez, D., Lorente-Plazas, R., Lorenzo-Lacruz, J., Santos-Alamillos, F., Montávez, J., 2013. The impact of the North Atlantic oscillation on renewable energy resources in southwestern Europe. J. Appl. Meteorol. Climatol. 52, 2204–2225.

Jin, Y., Goulden, M.L., Faivre, N., Veraverbeke, S., Sun, F., Hall, A., Hand, M.S., Hook, S., Randerson, J.T., 2015. Identification of two distinct fire regimes in Southern California: implications for economic impact and future change. Environ. Res. Lett. 10, 094005.

Kalabokidis, K., Palaiologou, P., Gerasopoulos, E., Giannakopoulos, C., Kostopoulou, E., Zerefos, C., 2015. Effect of climate change projections on forest fire behavior and values-at-risk in southwestern Greece. Forests 6, 2214–2240.

Kochanski, A.K., Jenkins, M.A., Mandel, J., Beezley, J., Krueger, S., 2013. Real time simulation of 2007 Santa Ana fires. For. Ecol. Manag. 294, 136–149.

Lorente-Plazas, R., Montávez, J., Jerez, S., Gómez-Navarro, J., Jiménez-Guerrero, P., Jiménez, P., 2014. A 49 year hindcast of surface winds over the Iberian peninsula. Int. J. Climatol. 35, 3007–3023.

Loureiro, C., Fernandes, P., Botelho, H., Mateus, P., 2006. A simulation-based test of a landscape fuel management project in the Marão range of northern Portugal. For. Ecol. Manag. 234, S245.

Nelson Jr., R.M., 2000. Prediction of diurnal change in 10-h fuel stick moisture content. Can. J. For. Res. 30, 1071–1087.

Oliva, P., Schroeder, W., 2015. Assessment of VIIRS 375 m active fire detection product for direct burned area mapping. Remote Sens. Environ. 160, 144–155.

Oliveira, S.L., Pereira, J.M., Carreiras, J.M., 2012. Fire frequency analysis in Portugal (1975–2005), using Landsat-based burnt area maps. Int. J. Wildland Fire 21, 48–60.

Ononye, A.E., Vodacek, A., Saber, E., 2007. Automated extraction of fire line parameters from multispectral infrared images. Remote Sens. Environ. 108, 179–188.

Pachauri, R.K., Allen, M., Barros, V., Broome, J., Cramer, W., Christ, R., Church, J., Clarke, L., Dahe, Q., Dasgupta, P., 2014. Climate change 2014: synthesis report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change.

Papadopoulos, G.D., Pavlidou, F.-N., 2011. A comparative review on wildfire simulators. IEEE Syst. J. 5, 233–243.

Parks, S.A., 2014. Mapping day-of-burning with coarse-resolution satellite fire-detection data. Int. J. Wildland Fire 23, 215–223.

Pereira, M.G., Trigo, R.M., da Camara, C.C., Pereira, J.M., Leite, S.M., 2005. Synoptic patterns associated with large summer forest fires in Portugal. Agric. For. Meteorol. 129, 11–25.

Pereira, M., Malamud, B., Trigo, R., Alves, P., 2011. The history and characteristics of the 1980–2005 Portuguese rural fire database. Nat. Hazards Earth Syst. Sci. 11, 3343–3358.

Ramos, A.M., Ramos, R., Sousa, P., Trigo, R.M., Janeira, M., Prior, V., 2011. Cloud to ground lightning activity over Portugal and its association with circulation weather types. Atmos. Res. 101, 84–101.

Richards, G.D., 1990. An elliptical growth model of forest fire fronts and its numerical solution. Int. J. Numer. Methods Eng. 30, 1163–1179.

Rothermel, R.C., 1972. A mathematical model for predicting fire spread in wildland fuels. Res. Pap. INT-115. U.S. Department of Agriculture, Forest Service, Intermountain Forest and Range Experiment Station, Ogden, UT (40 p).

Rothermel, R.C., 1991. Predicting behavior and size of crown fires in the Northern Rocky Mountains. Res. Pap. INT-438. U.S. Department of Agriculture, Forest Service, Intermountain Forest and Range Experiment Station, Ogden, UT (46 p).

Salis, M., Ager, A.A., Arca, B., Finney, M.A., Bacciu, V., Duce, P., Spano, D., 2013. Assessing exposure of human and ecological values to wildfire in Sardinia, Italy. Int. J. Wildland Fire 22, 549.

Salis, M., Ager, A.A., Finney, M.A., Arca, B., Spano, D., 2014. Analyzing spatiotemporal changes in wildfire regime and exposure across a Mediterranean fire-prone area. Nat. Hazards 71, 1389–1418.

Salis, M., Laconi, M., Ager, A.A., Alcasena, F.J., Arca, B., Lozano, O., de Oliveira, A.F., Spano, D., 2016. Evaluating alternative fuel treatment strategies to reduce wildfire losses in a Mediterranean area. For. Ecol. Manag. 368, 207–221.

San-Miguel-Ayanz, J., Schulte, E., Schmuck, G., Camia, A., 2013. The European Forest fire information system in the context of environmental policies of the European Union. Forest Policy Econ. 29, 19–25.

Schmuck, G., San-Miguel-Ayanz, J., Camia, A., Durrant, T.H., Boca, R., Libertá, G., Petroliagkis, T., Di Leo, M., Rodriguez-Aseretto, D., Boccacci, F., 2015. Forest Fires in Europe, Middle East and North Africa 2014. Publications Office of the European Union.

Schroeder, W., Prins, E., Giglio, L., Csiszar, I., Schmidt, C., Morisette, J., Morton, D., 2008. Validation of GOES and MODIS active fire detection products using ASTER and ETM+ data. Remote Sens. Environ. 112, 2711–2726.

Schroeder, W., Oliva, P., Giglio, L., Csiszar, I.A., 2014. The new VIIRS 375 m active fire detection data product: algorithm description and initial assessment. Remote Sens. Environ. 143, 85–96.

Scott, J.H., Burgan, R.E., 2005. Standard fire behavior fuel models: a comprehensive set for use with Rothermel's surface fire spread model. The Bark Beetles, Fuels, and Fire Bibliography. 66.

Scott, J.H., Reinhardt, E.D., 2001. Assessing crown fire potential by linking models of surface and crown fire behavior. USDA Forest Service Research Paper, RMRS-29. U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station, Fort Collins, CO (59 p).

Skamarock, W., Klemp, J., Dudhia, J., Gill, D., Barker, D., 2005. A description of the advanced research WRF version 2. NCAR Technical Note NCAR/TN-468 + STR (113 p).

Smith, A.M., Wooster, M.J., 2005. Remote classification of head and backfire types from MODIS fire radiative power and smoke plume observations. Int. J. Wildland Fire 14, 249–254.

Soares, P.M.M., Cardoso, R.M., Miranda, P.M.A., de Medeiros, J., Belo-Pereira, M., Espirito-Santo, F., 2012. WRF high resolution dynamical downscaling of ERA-interim for Portugal. Clim. Dyn. 39, 2497–2522.

Sørensen, T., 1948. A method of establishing groups of equal amplitude in plant sociology based on similarity of species and its application to analyses of the vegetation on Danish commons. Biol. skr. 5, 1–34.

Sousa, P.M., Trigo, R.M., Pereira, M.G., Bedia, J., Gutiérrez, J.M., 2015. Different approaches to model future burnt area in the Iberian peninsula. Agric. For. Meteorol. 202, 11–25.

Stratton, R.D., 2006. Guidance on spatial wildland fire analysis: models, tools, and techniques. Tech. Rep. RMRS-GTR-183. U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station, Fort Collins, USA (2006).

Sullivan, A.L., 2009. Wildland surface fire spread modelling, 1990–2007. 3: simulation and mathematical analogue models. Int. J. Wildland Fire 18, 387–403.

Tedim, F., Remelgado, R., Borges, C., Carvalho, S., Martins, J., 2013. Exploring the occurrence of mega-fires in Portugal. For. Ecol. Manag. 294, 86–96.

Trigo, R.M., Pereira, J.M.C., Pereira, M.G., Mota, B., Calado, T.J., da Camara, C.C., Santo, F.E., 2006. Atmospheric conditions associated with the exceptional fire season of 2003 in Portugal. Int. J. Climatol. 26, 1741–1757.

Trigo, R.M., Añel, J., Barriopedro, D., García-Herrera, R., Gimeno, L., Nieto, R., Castillo, R., Allen, M.R., Massey, N., 2013a. The record winter drought of 2011–12 in the Iberian peninsula [in "explaining extreme events of 2012 from a climate perspective"]. Bull. Am. Meteorol. Soc. 94, S41–S45.

Trigo, R.M., Sousa, P.M., Pereira, M.G., Rasilla, D., Gouveia, C.M., 2013b. Modelling wildfire activity in Iberia with different atmospheric circulation weather types. Int. J. Climatol.

Turco, M., Llasat, M.-C., von Hardenberg, J., Provenzale, A., 2014. Climate change impacts on wildfires in a Mediterranean environment. Clim. Chang. 125, 369–380.

Uppala, S.M., Kållberg, P., Simmons, A., Andrae, U., Bechtold, V., Fiorino, M., Gibson, J., Haseler, J., Hernandez, A., Kelly, G., 2005. The ERA-40 re-analysis. Q. J. R. Meteorol. Soc. 131, 2961–3012.

Veraverbeke, S., Sedano, F., Hook, S.J., Randerson, J.T., Jin, Y., Rogers, B.M., 2014. Mapping the daily progression of large wildland fires using MODIS active fire data. Int. J. Wildland Fire 23, 655–667.
Vermote, E., Kotchenova, S., Ray, J., 2011. MODIS surface reflectance user's guide. MODIS Land Surface Reflectance Science Computing Facility, Version, 1.
Viegas, D.X., Ribeiro, L.M., Gabbert, W., Viegas, M.T., Figueiredo, A.R., Oliveira, R., Reva, V., Raposo, J.R., Almeida, M.A., 2012. Tavira/São Brás de Alportel Forest Fire Report 18 to 22 July 2012. ADAI/LAETA, University of Coimbra, Coimbra, Portugal.
Wagner, C.V., 1977. Conditions for the start and spread of crown fire. Can. J. For. Res. 7, 23–34.
Wan, Z., 2013. Collection-5 MODIS Land Surface Temperature Products Users'Guide. (http://www.icess.ucsb.edu/modis/LstUsrGuide/usrguide.html).
Watts, A.C., Ambrosia, V.G., Hinkley, E.A., 2012. Unmanned aircraft systems in remote sensing and scientific research: classification and considerations of use. Remote Sens. 4, 1671–1692.
Wolfe, R.E., Roy, D.P., Vermote, E., 1998. MODIS land data storage, gridding, and compositing methodology: level 2 grid. IEEE Trans. Geosci. Remote Sens. 36.
Wooster, M., Zhukov, B., Oertel, D., 2003. Fire radiative energy for quantitative study of biomass burning: derivation from the BIRD experimental satellite and comparison to MODIS fire products. Remote Sens. Environ. 86, 83–107.
Wooster, M.J., Xu, W., Nightingale, T., 2012. Sentinel-3 SLSTR active fire detection and FRP product: pre-launch algorithm development and performance evaluation using MODIS and ASTER datasets. Remote Sens. Environ. 120, 236–254.

Paper III - Deciphering the impact of uncertainty on the accuracy of large wildfire spread simulations

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Deciphering the impact of uncertainty on the accuracy of large wildfire spread simulations

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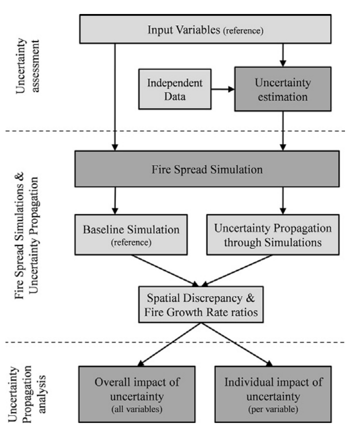
HIGHLIGHTS

- Fire spread predictions have large uncertainties that can undermine their utility.
- Uncertainties in input variables were propagated in a fire spread model.
- Prediction accuracy was quantified using satellite active fire data.
- Uncertainty in wind, fuels and ignitions have large impacts on prediction accuracy.
- Uncertainty ought to be integrated in future fire spread predictions.

GRAPHICAL ABSTRACT



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ABSTRACT

Predicting wildfire spread is a challenging task fraught with uncertainties. 'Perfect' predictions are unfeasible since uncertainties will always be present. Improving fire spread predictions is important to reduce its negative environmental impacts. Here, we propose to understand, characterize, and quantify the impact of uncertainty in the accuracy of fire spread predictions for very large wildfires. We frame this work from the perspective of the major problems commonly faced by fire model users, namely the necessity of accounting for uncertainty in input data to produce reliable and useful fire spread predictions. Uncertainty in input variables was propagated throughout the modeling framework and its impact was evaluated by estimating the spatial discrepancy between simulated and satellite-observed fire progression data, for eight very large wildfires in Portugal. Results showed that uncertainties in wind speed and direction, fuel model assignment and typology, location and timing of ignitions, had a major impact on prediction accuracy. We argue that uncertainties in these variables should be integrated in future fire spread simulation approaches, and provide the necessary data for any fire model user to do so.

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1. Introduction

Wildfires have important impacts on air and water quality, ecosystem dynamics, soil properties, and are important threats to humans. Fire spread is a complex phenomenon, determined by chemical and physical processes that occur over multiple spatial and temporal scales. Interactions between fire, fuels, weather and topography, broadly determine fire spread, rate of energy release and the shape of its perimeter (Albini, 1976; Rothermel, 1972). Fire spread models have been widely used to predict the spatio-temporal patterns of fire behavior (Finney, 2004), to study the effects of fuel treatments (e.g. Cochrane et al., 2012), perform risk assessments (e.g. Salis et al., 2013), predict short-term fire behavior (e.g. Kochanski et al., 2013), and to understand the main drivers of fire behavior (e.g. Cruz et al., 2012) and of fire regimes (e.g. Fernandes et al., 2014).

Accurate fire behavior prediction remains a difficult and challenging objective to achieve, despite numerous modeling efforts. This is due to a wide range of factors such as wind and fuel variability, dynamic interactions between fire and its surrounding environment, long-range spotting and simultaneous ignitions (Alexander and Cruz, 2013b; Cruz and Alexander, 2013; Hilton et al., 2015). Additionally, computational constraints and poorly understood small-scale processes (Beven, 2002) increase the difficulty of accurately predicting fire spread. Although much progress has been made in understanding and modeling the behavior of wildland fires, our ability to produce accurate predictions has evolved very little, mainly due to the spatial and temporal variability of the phenomenon, but also due to the lack of systematic methods for model validation (Alexander and Cruz, 2013a; Alexander and Cruz, 2013b; Salvador et al., 2001).

Modeling complex environmental phenomena is fraught with uncertainties (Beven and Binley, 1992) and fire behavior is no exception. Uncertainty is intrinsically associated with lack of information. Knowledge uncertainty is driven by imperfect state-of-the-art scientific knowledge and results from the way natural processes are conceptualized, how processes are modeled, and data quality (see Refsgaard et al., 2007; Thompson and Calkin, 2011 for in-depth reviews).

Modeling fire behavior is intrinsically uncertain due to: i) model applicability, scope and inherent limitations; ii) limitations of current scientific knowledge; iii) inherent accuracy of model structure; iv) parametric uncertainty; v) natural variability; vi) input data reliability; and vii) skill and knowledge of the user (Albini, 1976; Alexander and Cruz, 2013b; Bachmann and Allgöwer, 2002; Beven and Binley, 1992; Cruz, 2010; Liu et al., 2015; Thompson and Calkin, 2011). Under certain conditions, input data reliability can be the dominant source of error in fire spread predictions (Alexander and Cruz, 2013b). Errors associated with wind and fuel data have been considered the most relevant (e.g. Albini, 1976). The temporal and spatial variability of wind, due to the turbulent nature of the atmospheric boundary layer (Cruz, 2010), is extremely difficult to capture and can result in large errors (Albini, 1976; Anderson et al., 2007; Bachmann and Allgöwer, 2002). Errors associated with fuel classification and parameterization (Keane and Reeves, 2012), along with the large spatial fuel variability and heterogeneity have profound impacts on predicted fire behavior (Albini, 1976; Salazar, 1985).

Cruz and Alexander (2013) noted that "the only certainty about wildland fire behavior predictions is that it is extremely unlikely that a prediction will exactly match the observed fire behavior". Consequently, it is important to better understand the nature of uncertainty, how it propagates through fire spread models and how it affects its predictions (Sullivan, 2009; Thompson and Calkin, 2011). Through realistic estimation of predictive uncertainty one can improve the accuracy of fire spread simulations and promote a better understanding of model capabilities (Beven, 2002), as well as provide information on the variability and reliability of fire behavior predictions that can be used to improve risk management and decision-making (Bachmann and Allgöwer, 2002; Thompson and Calkin, 2011). However, to the best of our knowledge, this topic has merited little research (Bachmann and Allgöwer, 2002; Clark et al., 2008; Salazar, 1985; Salvador et al., 2001), despite the wide use of fire spread models in recent years.

Fire behavior modeling will be truly useful when its predictions are accurate. Therefore, we frame this work considering some of the biggest challenges involved in setting up and using a fire spread modeling system. Our main objective is to understand, characterize and quantify the impact of data uncertainty on the accuracy of fire spread predictions for large wildfires. We investigate i) the overall impact of uncertainty on simulation accuracy, and ii) the response of simulation accuracy to the range of uncertainty values of each input variable. For this purpose, the accuracy of fire spread predictions is estimated by comparison with satellite active fire data for eight large wildfires in Portugal. The quantification uncertainty of was focused on the environmental input variables, leaving out the uncertainty regarding fire spread model parameters, i.e. the empirical values constant throughout the simulations (e.g. adjustment factors). Uncertainties resulting from knowledge limitations and model structure were also not considered. Finally, we discuss how integrating uncertainty can help to improve fire spread predictions and to provide useful information for researchers and fire managers.

2. Data and methods

2.1. Case studies

Over 3.4 Mha burned in Portugal between 1980 and 2010 (JRC, 2011), corresponding to ca. 38% of the total area of the country. This period includes very severe fire seasons, such as those of 2003 and 2005, during each of which area burned exceeded 350,000 ha (Oliveira et al., 2012). The summer of 2003 was characterized by an exceptional heatwave in western Iberia (Trigo et al., 2006) and 2005 coincided with one of the most severe droughts recorded in the entire Iberian Peninsula during the last century (Trigo et al., 2013).

We used the Portuguese fire atlas, which contains over 30 years of annual burnt area perimeters (1975–2013) derived from high resolution satellite imagery (Oliveira et al., 2012). Focusing on very large wildfires, we selected eight events that between 2003 and 2005 in the Center and Southern Portugal and burned over 13,000 ha each (Fig. 1). According to the Corine Land Cover 2000 (CLC) (Bossard et al., 2000), forests and shrublands prevailed in the burned areas, respectively coniferous forests and shrublands in central Portugal, and broadleaf evergreen woodlands, shrublands and croplands mixed with natural vegetation in the southern region of the country.

2.2. Reference input data

Spatially explicit fire spread models require data on weather, ignitions and landscape-related variables. Topographic data were acquired from the NASA Shuttle Radar Topography Mission (SRTM) at 90 m spatial resolution (Farr et al., 2007), from which slope and aspect variables were derived.

Fuel maps were created based on expert knowledge by translating CLC land cover classes into fire behavior fuel models as per the Northern Forest Fire Laboratory (NFFL; Anderson, 1982) and the Portuguese custom Fuel Models (PTFM; Fernandes, 2005) typologies (Table 1). Fuel moisture contents (FMC) for dead and live fuels were obtained from Scott and Burgan (2005). Initial dead fuel moisture contents (DFMC) were set to 6%, 7% and 8%, for 1-h, 10-h and 100-h time-lag classes respectively. Live fuel moisture contents (LFMC) were set to 60% and 90%, for herbaceous and woody components, respectively, for all the case studies. Canopy cover density was extracted from the 250 m MODIS Vegetation Continuous Fields product (MOD44B) (DiMiceli et al., 2011).

Weather variables, including temperature, precipitation, relative humidity, wind speed and direction, were simulated at 10 km-hourly resolution using the PSU/NCAR mesoscale model (MM5, Grell et al., 1994),

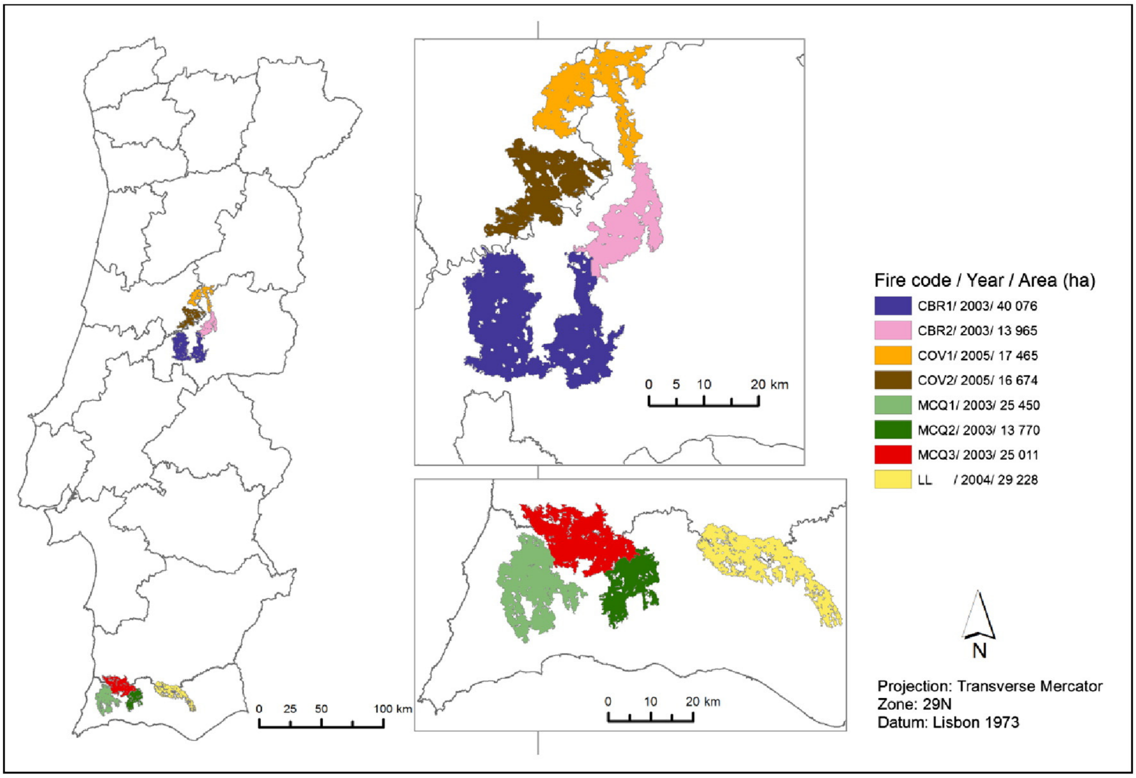


Fig. 1. Fire location, year of burning and burnt area extent of the selected case studies.

driven by ERA40 reanalysis data (Uppala et al., 2005) at the domain boundaries. Simulated weather data were available for the period 1977–2007 with proven capabilities to reproduce the most relevant regional climatic and circulation patterns (e.g. Jerez et al., 2013).

Table 1
Reference CLC land cover class to fuel model assignment, for NFFL and PTFM typologies and correspondent LFMC (%) ranges.

Corine Land Cover (CLC) class		NFFL		PTFM	
		Fuel model	Woody LFMC	Fuel model	Woody LFMC
211	Non-irrigated arable land	1	[b]	224	60–120
221[a]	Vineyards	1	[b]	224	60–120
222	Fruit trees and berry plantations	1	[b]	224	60–120
223[a]	Olive groves	1	[b]	224	60–120
231	Pastures	1	[b]	232	[b]
241	Annual crops associated with permanent crops	1	[b]	224	60–120
242	Complex cultivation patterns	1	[b]	232	[b]
243	Land principally occupied by agriculture, with significant areas of natural vegetation	5	60–100	237	60–100
244	Agro-forestry areas	1	[b]	232	[b]
311	Broad-leaved forest	9	[b]	221	90–150
312	Coniferous forest	6	[b]	227	60–100
313	Mixed forest	6	[b]	227	60–100
321[a]	Natural grasslands	1	[b]	232	[b]
322	Moors and heathland	6	[b]	234	70–120
323	Sclerophyllous vegetation	6	[b]	237	60–100
324	Transitional woodland-shrub	5	60–100	234	70–120
333	Sparsely vegetated areas	8	[b]	235	80–140
334	Burnt areas	8	[b]	235	80–140

[a] CLC class not represented in the case studies.
[b] LFMC range not applicable.

2.3. Satellite active fire data

The Moderate Resolution Imaging Spectroradiometer (MODIS) active fire product (MCD14ML) provides information about the location of fires burning at the time of overpass, based on thermal data (Giglio et al., 2003). MODIS active fires are acquired on average four times per day, with a nominal spatial resolution of 1 km^2. MODIS can detect fires burning about 1–10% of the pixel area, however, the detection capabilities depend on fire size, temperature of the fire and surrounding areas, viewing geometry and atmospheric contamination (Giglio, 2010). MODIS has limited capabilities in detecting small fires, especially for large scan angles, due to the low amount of energy that reaches the sensor, but it consistently detects larger fires (Hantson et al., 2013; Hawbaker et al., 2008) and has been used successfully to study their progression (Anderson et al., 2009; Parks, 2014; Veraverbeke et al., 2014).

We used MODIS active fire data for multiple purposes. The start/end dates of each fire event were determined by performing a temporally constrained clustering of all MODIS active fires that overlapped the mapped fire perimeter in the corresponding year of burning (Benali et al., 2016). For each fire, the first active fires detected within the temporal cluster were defined as the ignition points and the centroid coordinates were used to represent location.

Some authors have demonstrated that satellite active fire data can be a reliable and accurate data source to monitor the progression of large wildfires (Parks, 2014; Veraverbeke et al., 2014). Here, we assumed MODIS active fires as the reference fire spread data and estimated the discrepancy between the satellite-derived patterns and the simulated fire growth (Sá et al., under review). The "discrepancy" between both sources of data should be understood as the difference between two measures that ought to be similar, even if both are inaccurate representations of reality. We assumed the spatial discrepancy is representative of fire spread simulation accuracy, where lower discrepancy was interpreted as a closer match between the simulated and satellite-observed fire growth and consequently a higher prediction accuracy.

The spatial discrepancy (hereafter, SpD) was defined as the minimum Euclidean distance between a MODIS active fire pixel and the nearest simulated cell burning at the time of satellite overpass. Each MODIS active fire pixel has an associated area and the sub-pixel location of the fire front is unknown. Therefore, we calculated the minimum Euclidean distance between all the possible sub-pixel locations within the MODIS active fire pixel and the closest simulated pixel. Finally, for each case study, we calculated the median of the spatial discrepancies computed for each active fire. Details of this methodology are presented in Sá et al. (under review).

2.4. Reference fire spread simulations

To simulate fire spread over the selected case studies, we used the FARSITE fire modeling system (Finney, 2004), due to its recognized capability for providing acceptable fire growth and behavior predictions of historical fires (Cochrane et al., 2012; Papadopoulos and Pavlidou, 2011; Sullivan, 2009), including in Mediterranean areas (e.g. Arca et al., 2007). FARSITE is based on Rothermel's semi-empirical fire spread model, using separate models for surface fire spread (Rothermel, 1972), crown fire transition (van Wagner, 1977), and crown fire spread (Rothermel, 1991).

Temperature and relative humidity were provided as streams of minimum and maximum daily data, while wind direction and speed were supplied as gridded hourly data streams. Ignitions were defined using satellite active fire data. Topographic variables and fuels were provided as gridded data.

Given the large number of simulations, we used FARSITE 4 command line version with a landscape cell-size of 100 m and an hourly time step. We enabled crown fire and no-wind no-slope ROS for the spread rate of back fires. The ROS adjustment factors were set to one (i.e. no adjustment). A 3-day conditioning period was used to re-calculate the DFMC prior to the start of the simulations to represent local weather conditions. Spotting and fire suppression were not simulated due to their stochastic nature and unavailability of information, respectively.

The input variables described in Section 2.2, along with the model settings described in this section, were used to perform deterministic simulations for the eight case studies without integrating uncertainty, and are hereafter referred to as *reference*.

2.5. Uncertainty assessment

Depending on the aim and nature of the modeling process, as well as the type of variables used, uncertainty can be quantified using a wide range of methods (e.g. Refsgaard et al., 2007). A key point in uncertainty assessment is the availability of reliable independent data, i.e. alternative data sets representing the target variable(s).

We followed a data-based uncertainty approach for the variables for which reliable independent data sets were available (e.g. relative humidity and temperature). For the remaining variables we performed multi-model simulations, either using the uncertainty information already provided in the data sets (e.g. tree cover), or by comparing them with independent simulations (e.g. wind speed and direction). When no independent data were available, we estimated uncertainty based on used expert knowledge and literature (e.g. DFMC and LFMC).

For each variable, we calculated the frequency of values falling under each uncertainty bin. The frequencies were normalized, representing the probability of a given uncertainty value being sampled. Therefore, the histograms were the basis for the sampling procedures used in the propagation of uncertainty throughout the fire spread model (see Section 2.6).

2.5.1. Weather

We collected minimum and maximum daily temperature and relative humidity data measured at over 100 meteorological stations from the Sistema Nacional de Informação de Recursos Hídricos (SNIRH, 2015) and defined uncertainty as the difference between measured and simulated data. Positive uncertainty values mean that measured values were higher than simulated ones. The meteorological stations were located over the entire Portuguese mainland and the analysis was constrained to the summer periods (July–September) of 2003, 2004 and 2005.

Wind variables are also commonly measured at meteorological stations. However, they are often considered less reliable than other standard meteorological variables, being highly conditioned by the location of the station and often reflecting fine-scale patterns (Azorin-Molina et al., 2014). Alternatively, we defined wind speed and direction uncertainty using a multi-model ensemble approach (Palmer et al., 2005; Refsgaard et al., 2007) based on independent wind simulations from the Weather Research and Forecasting (WRF) model (Skamarock et al., 2005) with 5 km-3 h spatial and temporal resolution, respectively (Ferreira et al., 2012), and covering Portugal for the 2000–2005 period. When compared with *reference* wind simulations, both had different time spans, and different spatial and temporal resolutions. We limited the comparison between both data sets to the summer periods of 2003, 2004 and 2005. The WRF data set was upscaled to a 10 km spatial resolution by calculating the circular mean of the corresponding pixels within the coarser MM5 pixel, while the MM5 simulations were converted from hourly to 3 h temporal resolution by calculating the circular mean. Uncertainty was estimated by calculating the circular distance for wind direction, and for wind speed, the difference between both data sets at a common 10 km-3 h resolution.

2.5.2. Ignitions

We divided the uncertainty in wildfire ignitions into two distinct and uncorrelated components: location (spatial) and timing (temporal). Both estimates were based on Benali et al. (2016) regarding a database of large wildfires (>1000) that occurred in Portugal between 2001 and 2009. Uncertainty was estimated by calculating the Euclidean distance and the time lag between the location and date of satellite-derived and field-reported ignitions, respectively. A large number of reported ignitions were located outside the fire perimeters, thus we constrained the comparison to ignitions located within 2 km of the fire perimeter.

2.5.3. Vegetation

We focused on the uncertainty associated with fuel models, fuel moisture contents and tree cover. A fire behavior fuel model is a numerical description of the structure and composition of the surface layer (up to 2 m height) of a burnable vegetation type, comprising all organic matter capable of flaming combustion (Albini, 1976). For large areas, where detailed and reliable fuel maps are not available, often the solution is to use vegetation type maps and assign fuel models, assuming spatial homogeneity (e.g. Arca et al., 2007; Fisher, 1982; Salis et al., 2013). Uncertainty arising from this conversion process has not been quantified, although Salazar (1985) investigated the impact of fuel model variations on fire behavior simulations using the two-fuel-model concept. We analyzed the uncertainty resulting from: i) choice of the fuel model typology and, ii) land cover class to fuel model conversion.

To analyze the impact of the uncertainty associated with fuel typology, each land cover class was converted to the PTFM fuel scheme and compared with *reference* simulations (see Table 1). The Instituto da Conservação da Natureza e Florestas (ICNF) recently released a fuel map for Portugal (ICNF, 2014), created by converting a detailed 100 m national land use map for 2007 (COS2007) to the NFFL and PTFM fuel typologies. We calculated the percentage of ICNF 2007 fuel classes corresponding to each CLC 2006 class (EEA, 2007). This percentage reflects the probability of assigning a given NFFL (or PTFM) fuel model to a specific CLC class, hereafter referred to as *confusion matrix* (Table 2). In order to keep only the most representative fuel models, for each CLC class we removed all ICNF fuel models with frequencies below 2.5%, keeping at least 95% of the data (total coverage). Additionally, we performed a similar analysis using the PTFM fuel scheme (see S1 Table 1), to assess the extent to which results depend on fuel typology.

The fuel moisture content (%) is the weight of water in dead or live fuel particles divided by the sample oven dry weight (e.g. Matthews, 2014). Uncertainty in DFMC was defined according to the different moisture scenarios presented by Scott and Burgan (2005), considering ranges of 3–12%, 4–13% and 5–14% for 1-h, 10-h and 100-h time-lag classes, respectively. We defined plausible LFMC ranges for each fuel model based on expert knowledge, both for NFFL and PTFM fuel typologies (Table 1). For example, negative uncertainty corresponded to vegetation drier than the *reference*. Additionally, we investigated the impact of DFMC uncertainty on simulation accuracy for several conditioning period lengths.

The MODIS tree cover product provides a measure of uncertainty defined as the standard deviation of the 30 models used to generate a given canopy cover density value (DiMiceli et al., 2011). Assuming a normal distribution, characterized by the mean (i.e. the tree cover pixel value) and its standard deviation, we generated multiple tree cover values for each pixel. For example, a positive uncertainty represented tree cover values higher than the mean (i.e. *reference*).

2.6. Uncertainty propagation through simulations

Uncertainties in the input variables were i) independently estimated a priori, ii) propagated through the fire spread modeling system, and iii) their impact was assessed downstream by analyzing simulation outputs (details in next section). When one variable was perturbed, all other variables were kept constant, allowing us to focus on the individual impact of its uncertainty in fire spread simulations.

For maximum and minimum daily temperature and relative humidity, wind direction and speed, as well as tree cover, we sampled 100 values from the uncertainty histogram of each variable (see Section 2.5.1). Fire spread simulations were performed independently, i.e. varying one variable at a time, setting a new variable value by adding uncertainty to the *reference* value.

Regarding the spatial and temporal ignition uncertainties, we sampled 100 values from the uncertainty histogram of each variable (see Section 2.5.2). For the spatial uncertainty, we generated random ignition points within the fire perimeter (Amatulli et al., 2007), with a distance to the *reference* location equal to the sampled uncertainty value. For the temporal uncertainty, the sampled value was used to start the simulation before or after the *reference* ignition time and simulations were run until the end date regardless of the uncertainty signal.

For fuel model assignment uncertainty we converted each land cover class to a NFFL fuel model based on the *confusion matrix* (see Table 2). The number of times a land cover class was translated to a given fuel model was determined by the frequency in the *confusion matrix*. Uncertainty was propagated in two distinct ways: i) conversion was performed class by class to separate the impact of assignment uncertainty at land cover class level, and ii) conversion was performed for all land cover classes simultaneously to evaluate the overall impact of fuel model assignment uncertainty. For the latter case, a total of 100 combinations of land cover-fuel model assignments were defined.

Similarly, for the fuel typology uncertainty we investigated the overall impact at the impact at the land cover class level. For the first analysis, we replaced the conversion of each land cover class to a NFFL fuel model by a PTFM fuel model, one class at a time (see Section 2.5.3 and Table 1). For the second analysis, for each case study we performed 100 fire spread simulations by converting all land cover classes to the PTFM fuel typology simultaneously, based on the *confusion matrix*.

All fuel-related uncertainty propagation simulations that predicted a burnt area that overlaid <5% of the area of the targeted fuel model were excluded from the analysis, because the impact of uncertainty could not be assessed. For instance, this occurred when a fuel model was present in the landscape but the simulation never or barely reached it.

For DFMC and LFMC, we sampled 20 equidistant values within the uncertainty ranges of each fuel model, assuming Uniform distributions. Live fuels are an important component of Mediterranean wildlands, both in shrublands (Anderson et al., 2015) and in the forest understory (Fernandes, 2009). Since only two NFFL fuel models have live components, we also analyzed the impact of LFMC uncertainty using the PTFM fuel typology to understand if responses were affected by the fuel scheme.

2.7. Uncertainty propagation analysis

Uncertainty propagation analysis can be done by estimating the impact of input data variability with respect to fixed *reference* values (Bachmann and Allgöwer, 2002; Refsgaard et al., 2007). We assessed the impact of uncertainty of each variable by analyzing variations in the resulting spatial discrepancy and fire growth ratios. To estimate the relative impact of uncertainty on the satellite-simulation spatial discrepancy, we calculated the spatial discrepancy ratio (SpD_{ratio}):

$$SpD_{ratio_{i,j}}(\%) = \frac{SpD_{i,j} - SpD_{REF_j}}{SpD_{REF_j}} \times 100 \quad (1)$$

where $SpD_{i,j}$ is the spatial discrepancy for the i-th uncertainty propagation simulation for the j-th case study and SpD_{REF} is the spatial discrepancy for the *reference* simulation. A positive ratio means that propagating uncertainty through the model leads to a larger satellite-simulated discrepancy, i.e. a lower satellite-simulated agreement and a decrease in the SpD_{ratio}, when compared with the *reference* simulation. Analogously we calculated the fire growth rate ratio (FGR_{ratio}) defined as the simulated burnt area extent divide by the actual duration of the fire spread simulation.

The SpD_{ratio} and FGR_{ratio} were calculated for all uncertainty propagation simulations, for all case studies. We analyzed the overall and individual impact of uncertainty in each variable. For the overall analysis, we explored how the model output variability changed with uncertainty of input variables. For the individual analysis, we evaluated the range of responses of model outputs to different values of uncertainty. In general, the distribution of predictive uncertainty does not follow a Normal

Table 2
Confusion matrix of CLC to NFFL fuel models assignment.

CLC class	NFFL fuel model								
	1	2	4	5	6	7	8	9	Total coverage[a]
211	59.6	31.0		5.5					96.1
221[b]	39.6	17.0	9.0	19.3		12.2		2.6	99.7
222	24.1	15.4	7.8	41.2		7.0		4.4	99.9
223[b]	28.1	28.3	7.8	25.8		7.7			97.7
231	47.1	25.5	3.9	18.2		3.0			97.7
241	50.4	13.3	4.0	17.7		11.0		3.6	99.9
242	48.7	18.5	5.4	15.2		9.3		2.9	99.9
243	19.3	16.9	11.5	32.5		16.5		3.1	99.7
244	11.5	69.3		16.8					97.6
311		25.9		40.4		27.5		2.3	96.1
312			4.7	8.7		78.1		4.8	96.3
313		5.5	4.7	19.8		61.1		6.3	97.4
321[b]	4.2	16.7	36.0	36.8		4.9			98.6
322	2.9	9.3	40.0	37.1		8.2			97.4
323		13.3	12.6	66.6		3.7			96.2
324	2.6	7.6	19.6	32.3		34.9			97.1
333		11.1	32.9	46.1		7.0			97.0
334	5.8	12.4	20.8	35.7		23.6			98.2

Each data entry of the table corresponds to the frequency that a NFFL fuel model is assigned to a given CLC class.
[a] Sum of fuel model frequencies.
[b] Not represented in the case studies.

distribution when models have nonlinear equations (Beven and Binley, 1992). We used the 2.5th and 97.5th percentiles of the SpD_{ratio} and FGR_{ratio} as the 95% predictive uncertainty boundaries. Statistical measures were calculated per variable individually and inter-compared for an overall assessment. A flow chart of the most relevant methodological steps is shown in Fig. 2.

3. Results

3.1. Overall impact of uncertainty on fire spread predictions

The uncertainty associated with wind and fuel-related input variables had the largest impact on the variability of satellite-simulated spatial discrepancy (Fig. 3). The uncertainty associated with the land cover-fuel model assignment led to a 95% SpD_{ratio} predictive interval limits ranging from −100% to 102%, i.e. ranging from perfect satellite-simulated agreement, to a two-fold discrepancy increase. Comparatively, fuel model typology uncertainty had a slightly lower impact on simulation accuracy, with the SpD_{ratio} ranging from −50% to 25%. Both fuel-related variables were skewed towards negative values.

Wind speed had high impact on simulation accuracy, with the 95% of predicted SpD_{ratio} limits ranging from −43% to 99% (Fig. 3). Wind direction was also among the most important variables, with the SpD_{ratio} ranging from −29% to 97%. Additionally, results showed that a Normal distribution cannot be fitted to the SpD_{ratio} data (see S2 Table 1 and S2 Fig. 1), supporting the use of percentiles to assess the impact of uncertainty (see Section 2.6).

Uncertainty in ignition location and timing had a significant impact on simulation accuracy, with the SpD_{ratio} varying between −59% and 43%, and between −42% and 49% for spatial and temporal ignition uncertainty, respectively. Uncertainty in the LFMC had a similar impact on the SpD_{ratio} for the different fuel typologies, with the 95% of the SpD_{ratio} limits ranging between −66% and 18%, for the NFFL models.

Uncertainty in relative humidity and tree cover variables had significantly lower impact on prediction accuracy, with the SpD_{ratio} 95% interval limits varying roughly around 40–50%. Both temperature and DFMC had low impact on predictive accuracy, with an absolute SpD_{ratio} range of ca. 5%.

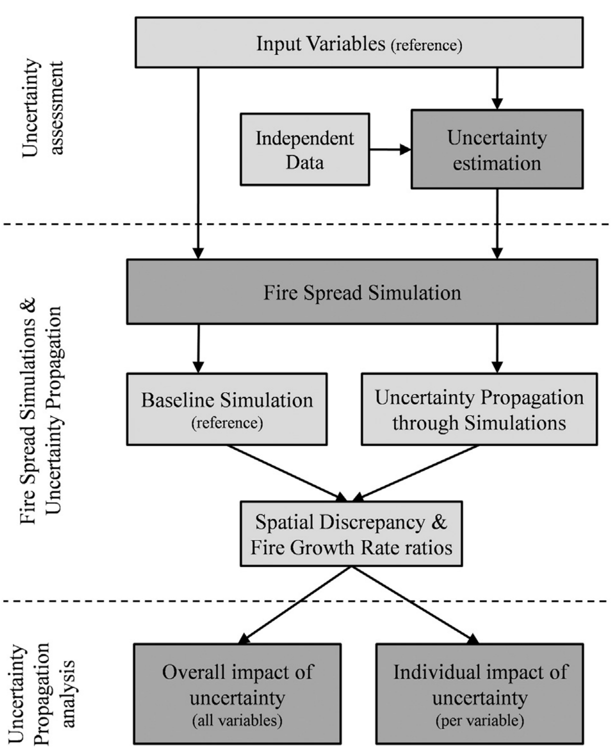


Fig. 2. Flowchart of the methodology followed. Light grey boxes represent inputs and outputs, dark grey boxes represent methodological steps.

In a parallel study, Sá et al. (under review) reported an important fire growth underprediction for the same case studies used here. To compensate such underprediction, the SpD_{ratio} followed an opposite trend when compared to the FGR_{ratio}. Uncertainties in fuel model assignment and typology, wind speed and ignition location, had very large impacts on the FGR_{ratio}. Some variables showed SpD_{ratio} distributions skewed towards negative values with a wide model response range, for instance fuel model assignment and typology, ignition location and LFMC (Fig. 3 and S2 Fig. 1). In these cases, propagating the uncertainty through the model led to an improvement in the satellite-simulation agreement. In some cases, such as wind speed and direction, although the variability of the SpD_{ratio} was large for both variables, their distribution was not skewed but centered. Implications of the resulting SpD_{ratio} are addressed in the Discussion.

3.2. Impact of individual variable uncertainty on fire spread simulations

3.2.1. Weather

The uncertainty histogram for minimum and maximum daily relative humidity followed a bell-shaped distribution centered on 0% (Fig. 4a,b) with varying asymmetry around the peak and different uncertainty ranges. For both variables, the SpD_{ratio} decreased with negative uncertainty (i.e. drier conditions) and increased with positive uncertainty (i.e. wetter conditions), followed by an opposite response of the FGR_{ratio}. At the lower and upper uncertainty sampling ranges, the SpD_{ratio} decreased and increased about 10–20% and 20–30%, respectively, for both variables. Variability of the SpD_{ratio} was relatively small throughout the uncertainty range, except for extreme positive uncertainty values (40–50%) driven by steeper responses in three case studies (*COV2*, *LL* and *MCQ1*; see S2 Fig. 2a,b).

The distribution of the uncertainty histogram for wind direction was centered at 0°, slightly skewed towards positive values (Fig. 4c). More than 80% of the sampled uncertainty values were within the −45° to 45° angle range. The response of the SpD_{ratio} to wind direction uncertainty was highly variable between case studies, being more abrupt in fires with elongated perimeters (e.g. *CBR2* and *LL*; see S2 Fig. 2c). For the remaining case studies, the SpD_{ratio} increased from 5% to 40% at the boundaries of the 95% limits, almost symmetrically. Increased uncertainty in both directions led to higher SpD_{ratio} and lower simulated FGR_{ratio}, particularly evident over 45° of absolute uncertainty. These results reinforce the view that simulated wind direction data were accurate and that uncertainty only had a profound impact on accuracy above an absolute value of 45°. However, the response to wind direction uncertainty varied per case study and both *LL* and *COV2* had maximal SpD_{ratio} decreases around −40° and +70°, respectively.

The wind speed uncertainty histogram was centered at −2 km/h and skewed towards negative values, i.e. *reference* wind speed was slightly higher than the alternative data (Fig. 4d). For the 95% predictive limits, the SpD_{ratio} increased by 20% to 60% at the lower uncertainty sampling boundary, and decreased by 20 to 35% at the upper boundary. Positive wind speed uncertainty resulted in higher prediction accuracy due to larger simulated fire growth rates, counterbalancing the general underprediction in the *reference* simulations. Variability the SpD_{ratio} increased with uncertainty in both directions, and was particularly high for negative uncertainty. Variability of the SpD_{ratio} and FGR_{ratio} exhibited opposite response patterns. Increased uncertainty led to a smaller and higher range of SpD_{ratio} and FGR_{ratio}, respectively; while decreased uncertainty led to higher and lower range of SpD_{ratio} and FGR_{ratio}, respectively. The response of the SpD_{ratio} to wind speed uncertainty was highly variable for each case study, ranging from highly insensitive, for the *MCQ2* and *CBR1* case studies, to highly sensitive, for the *LL* and *COV2* case studies (see S2 Fig. 2d). For all case studies, variability was much larger for negative than positive uncertainty.

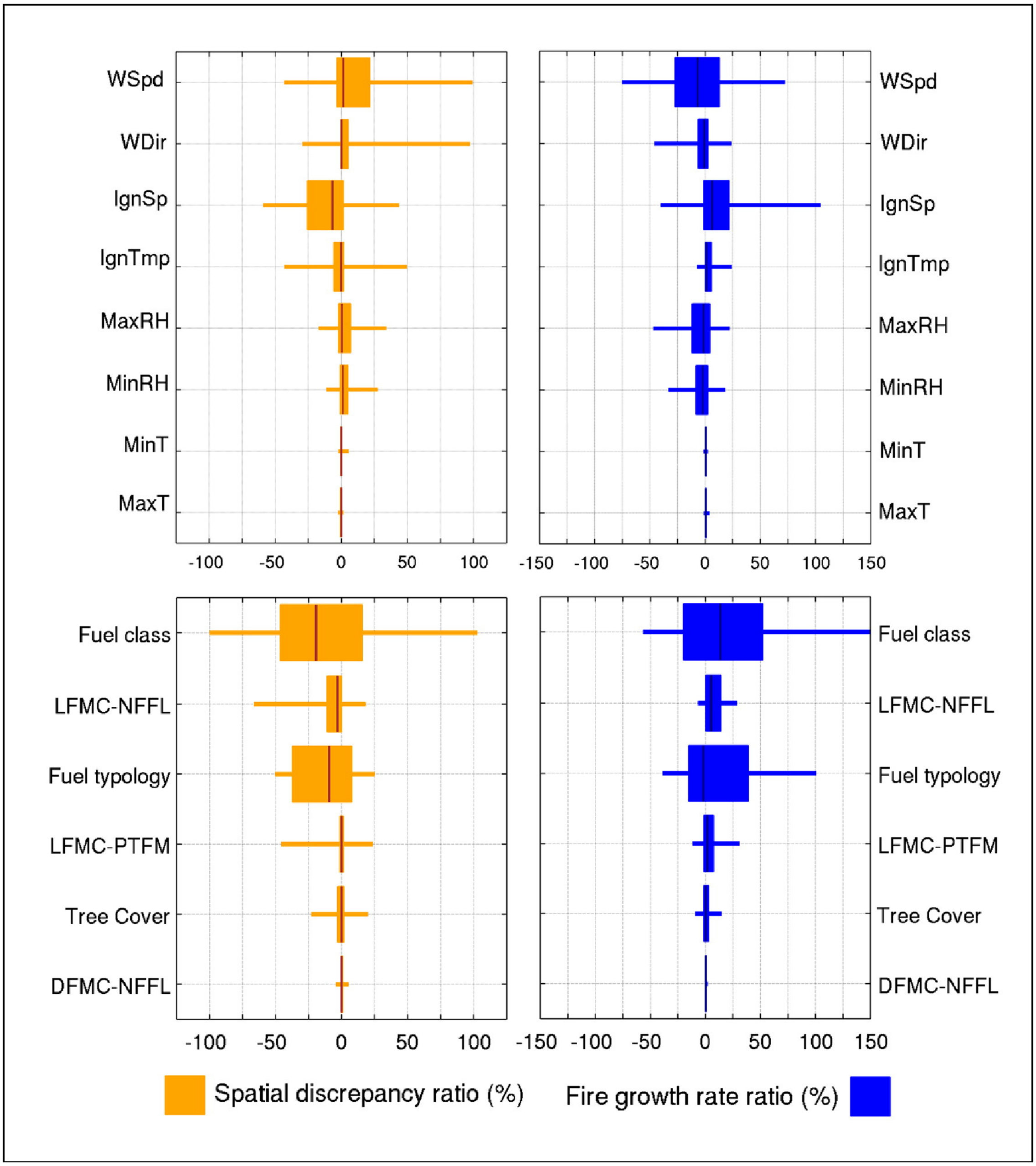
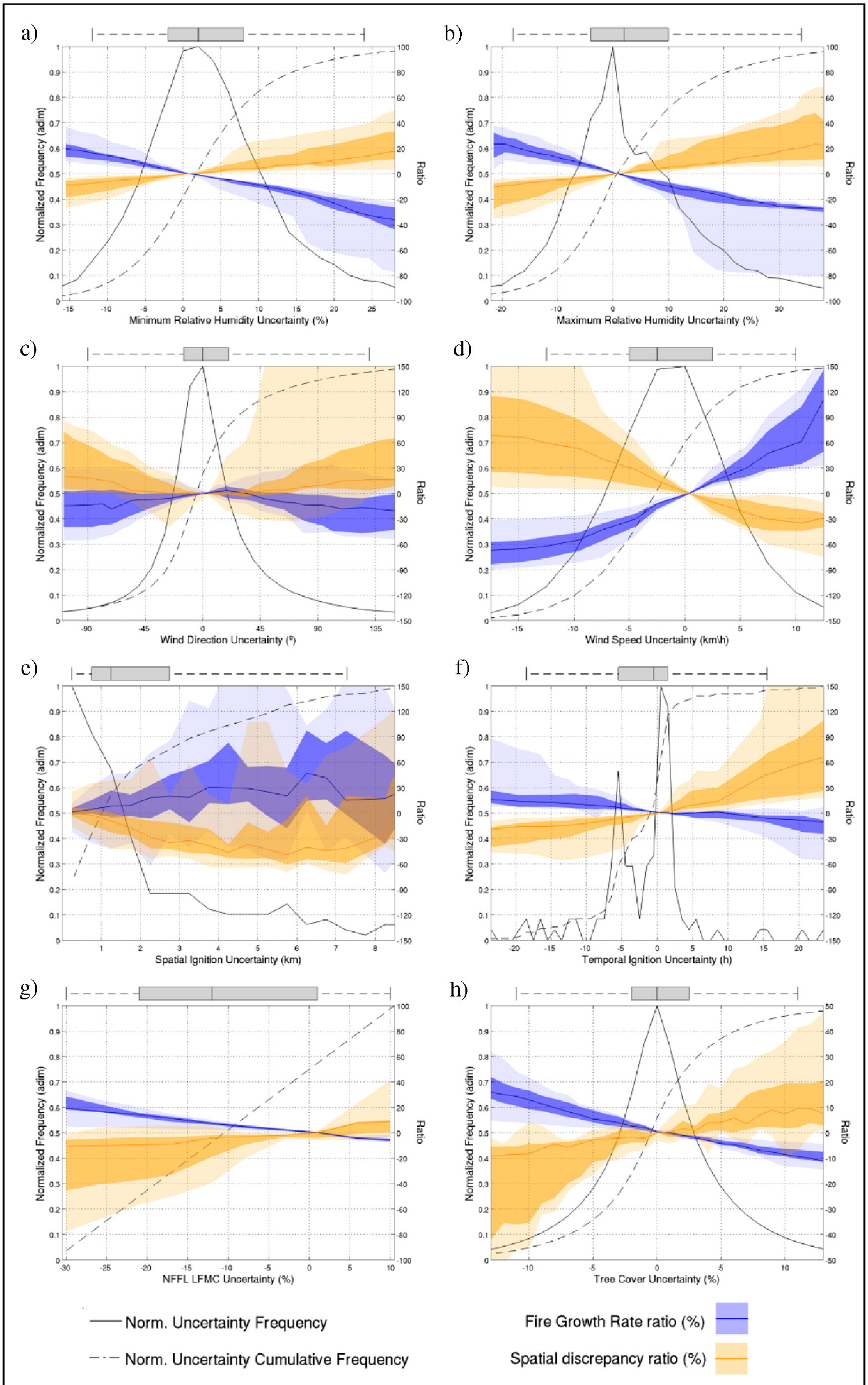


Fig. 3. Overall impact of uncertainty in SpD_{ratio} (left) and FGR_{ratio} (right) variability for the studied variables. The top panel displays the weather, wind and ignition variables and the bottom one shows the fuel-related variables. The dark orange line represents the median of the SpD_{ratio}; orange boxes and horizontal lines represent the interquartile range and the 95% predicted uncertainty limits, respectively; the same description is applicable to the fire growth rate but for blue colors. Variables were abbreviated as follows: WSpd: wind speed; WDir: wind direction; IgnSp: ignition location; IgnTmp: ignition timing; MaxRH: maximum relative humidity; MinRH: minimum relative humidity; MinT: minimum temperature; MaxT: maximum temperature; LFMC: live fuel moisture content; DFMC: dead fuel moisture content. NFFL and PTFM stand for Northern Forest Fire Laboratory and Portuguese custom Fuel Models, respectively. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

3.2.2. Ignitions

For ignition location, a lower number of uncertainty values was sampled with increased uncertainty, with 80% of the values sampled below 3500 m (Fig. 4e). In general, the SpD_{ratio} decreased with increased spatial ignition uncertainty up to 6000 m, increasing above that value, while the FGR_{ratio} had opposite response. Given the large variability observed, a distinct trend was not clear (see Section 2.6). However, ignition spatial uncertainty had a large impact on simulation accuracy, with the SpD_{ratio} ranging from −60% to over 80% in some case studies (Fig. 4e and S2 Fig. 2e).

Temporal ignition uncertainty had a distinct bimodal histogram, with peaks around 1 h and −6 h (Fig. 4f), corresponding to the average time lag between early afternoon and early nighttime MODIS acquisitions. In general, negative temporal ignition uncertainty (i.e. fire starting before *reference* ignition date) led to higher prediction accuracy, shown by the consistent decrease in the spatial discrepancy ratio. Since fire growth was generally underpredicted, starting simulations earlier led to a larger satellite-simulated agreement. The response to uncertainty was highly asymmetrical: for the 95% limits, the SpD_{ratio} decreased by 5% to 45% at the lower uncertainty sampling boundary, but increased by 20% to >150% at the upper boundary. This asymmetric trend was observed in all case studies, but was particularly pronounced in the *LL* case study (see S2 Fig. 2f), a fast moving wildfire for which the ignition points were late and scattered MODIS detections (Sá et al., under review).


a)
Normalized Frequency (adim)
Ratio
Minimum Relative Humidity Uncertainty (%)
b)
Normalized Frequency (adim)
Ratio
Maximum Relative Humidity Uncertainty (%)
c)
Normalized Frequency (adim)
Ratio
Wind Direction Uncertainty (º)
d)
Normalized Frequency (adim)
Ratio
Wind Speed Uncertainty (km\h)
e)
Normalized Frequency (adim)
Ratio
Spatial Ignition Uncertainty (km)
f)
Normalized Frequency (adim)
Ratio
Temporal Ignition Uncertainty (h)
g)
Normalized Frequency (adim)
Ratio
NFFL LFMC Uncertainty (%)
h)
Normalized Frequency (adim)
Ratio
Tree Cover Uncertainty (%)
Norm. Uncertainty Frequency
Norm. Uncertainty Cumulative Frequency
Fire Growth Rate ratio (%)
Spatial discrepancy ratio (%)

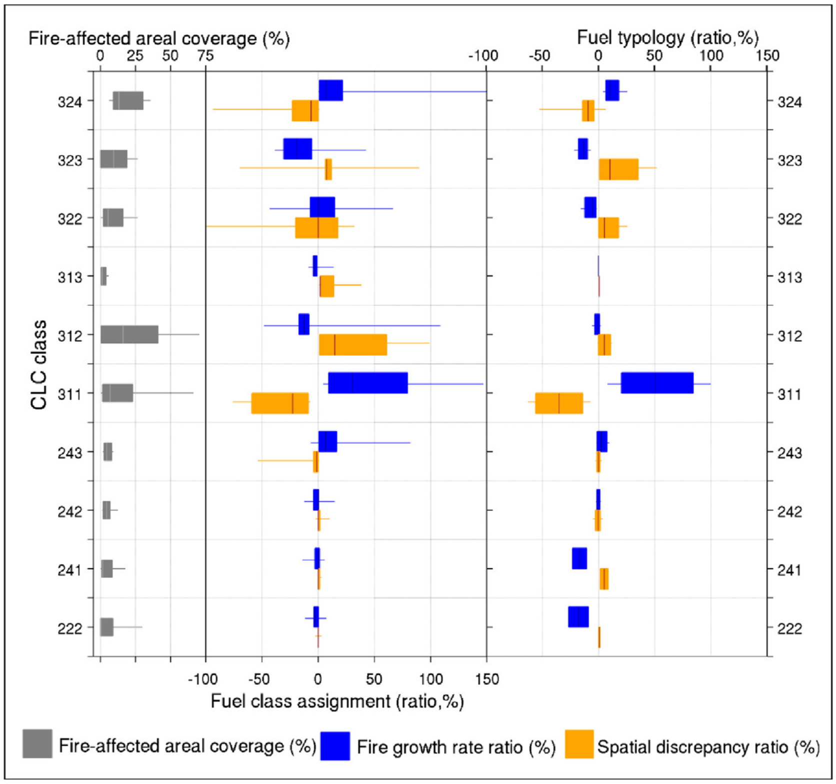


Fig. 5. The impact of NFFL fuel model assignment and typology uncertainty on the SpD_{ratio} and FGR_{ratio}, per land cover class.

3.2.3. Vegetation

The uncertainty in fuel model assignment showed larger SpD_{ratio} variability in the most fire-affected land cover classes, namely for broadleaved and coniferous forests (CLC 311 and 312) and shrublands (CLC 322–324) (Fig. 5). Forests have large spatial variability of the understory fuel layer. Interestingly, the two major forest types had opposite responses to uncertainty. Changing the fuel model assigned to coniferous forests (CLC 312) increased the SpD_{ratio} from 1% to around 100%, while for broadleaf forests (CLC 311) decreased the SpD_{ratio} by 10% to 75%. Uncertainty in fuel model assignment for shrubland classes also caused a large impact on simulations, with the SpD_{ratio} varying from −100% to 85%, skewed towards lower values. The distribution of the fuel models assigned in the current work and by the ICNF showed large discrepancies (S3 Fig. 1). The results for the alternative PTFM fuel typology were very similar (S3 Fig. 2).

Overall, the impact of the uncertainty arising from fuel model typology was lower than that generated by the fuel model assignment. For broadleaf forests, the SpD_{ratio} varied from −60% to −10%, showing a relevant accuracy improvement. Conversely, the impact of uncertainty in coniferous forests was very low. Shrubland classes exhibited different patterns. The SpD_{ratio} increased by changing fuel typology for sclerophyllous vegetation (CLC 323), ranging from 0% to 50%, while for transitional woodland-shrub (CLC 324) the SpD_{ratio} decreased by the same magnitude.

Similarly to fuel model assignment, the impact of using a different fuel model typology was dependent on the coverage of each land cover class. The impact was generically higher in shrublands (CLC 323, 324) and broadleaf forests (CLC 311). For agricultural classes (CLC 222, 241, 242, 243) and mixed forest (CLC 313) the impact of uncertainty was low since they were under-represented in the case studies. The opposite FGR_{ratio}-SpD_{ratio} response was also evident for fuel uncertainty, due to the already mentioned overall fire growth underprediction.

Uncertainty in fuel model assignment had a relevant impact on the SpD_{ratio} for most case studies, with a maximum range of −100% to 180% for *COV2* (Fig. 6). In five out of eight case studies, the satellite-simulation discrepancy consistently decreased when integrating uncertainty in fuel model assignment. Consistent with the previous analysis (see Fig. 5), case studies with larger coverage of shrublands and broadleaf forests showed higher SpD_{ratio} variability. When compared with fuel model assignment, the uncertainty in fuel typology had lower impact at the case study level.

Negative LFMC uncertainty resulted in higher prediction accuracy due to higher simulated FGR_{ratio}. The SpD_{ratio} increased up to about 10–40% at the upper boundary, and decreased down to −80% at the lower boundary (Fig. 4g). Results showed low inter-case study variability (see S2 Fig. 2g). The LFMC for PTFM fuel models had lower uncertainty range but similar SpD_{ratio} and FGR_{ratio} responses to uncertainty (see S3 Fig. 3). For both measures, variability increased with uncertainty. The impact of DFMC uncertainty on the variability of SpD_{ratio} was only noticeable when disabling the conditioning period, and ranged from −15% to 0% and 0% to 30% in the lower and upper distribution ranges, respectively (S3 Fig. 4).

The tree cover uncertainty histogram shows a distribution centered at 0%. For the 95% uncertainty limits, the SpD_{ratio} decreased and increased up to 50% at lower and upper sampling boundaries, respectively (Fig. 4h). Positive tree cover uncertainty resulted in lower prediction accuracy, shown by the consistent increase in the SpD_{ratio}. Analyzing the impact per fire showed that tree cover had a very small impact for

Fig. 4. Impact of uncertainty in weather, wind, ignitions, LFMC and tree cover, on the SpD_{ratio} and FGR_{ratio}. Minimum and maximum daily relative humidity are shown in a) and b); Wind direction and speed in c) and d); Ignition location and timing in e) and f); LFMC of NFFL fuel models in g) and tree cover in h). The dark orange line represents the median of the SpD_{ratio}, the orange and light orange areas represent the interquartile range and the 95% predicted uncertainty limits, respectively; the dark blue line represents the median of the FGR_{ratio}, the blue and light blue areas represent the interquartile range and the 95% predicted uncertainty limits, respectively. The grey box and whiskers delimit the interquartile range and 95% limits of the sampled uncertainty, respectively. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

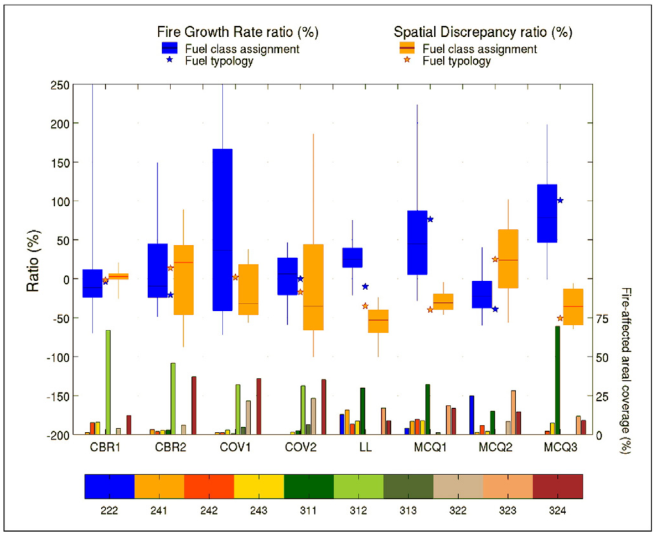


Fig. 6. Impact of fuel model assignment and typology uncertainty on the SpD_{ratio} and FGR_{ratio}, per case study.

most case studies, except for the *LL*, *COV2* and *CBR2* case studies (see S2 Fig. 2h).

4. Discussion

4.1. Understanding uncertainty

Uncertainty in input variables had a relevant impact on the accuracy of fire spread predictions, defined here as the discrepancy between satellite and simulated fire growth patterns. The response of SpD_{ratio} and FGR_{ratio} to uncertainty differed widely among variables and exhibited large response ranges for some of them. Uncertainty in wind and fuel data had the largest impacts on the accuracy of fire spread predictions (see Fig. 3), as expected (Bachmann and Allgöwer, 2002; Clark et al., 2008; Salvador et al., 2001).

The assessment of uncertainty in fire spread predictions should be performed at the beginning of the modeling process, rather than at the end as is often the case, providing to the fire model user detailed information regarding the response of fire spread predictions to data errors (Refsgaard et al., 2007). It also assists in the prioritization of efforts to reduce uncertainty and improve fire spread predictions. As an example, uncertainty analysis suggested that to improve the fire spread predictions for our specific case studies, it would be more efficient to target efforts towards refining fuel model selection and ignition location accuracy, rather than wind speed and direction (see Fig. 3 and S2 Fig. 1). This was evidenced by the large variability and skewed distribution towards negative SpD_{ratio} values when propagating uncertainty in fuel models and ignition location.

Some authors have studied the impact of uncertainty on fire spread simulations. However, to the best of our knowledge, a comprehensive characterization of the uncertainty associated with the major input variables along with a detailed assessment of their impact on the accuracy of simulated fire spread patterns, has not been performed. A key reason behind this is the lack of appropriate independent large scale fire spread evaluation data (Alexander and Cruz, 2013a). Here, we used satellite active fire data as an indicative accuracy measure. We acknowledge that satellite active fires are an "imperfect" data source with associated limitations (Giglio et al., 2003; Hawbaker et al., 2008). However, it has been shown that it provides accurate independent information on the major spatio-temporal patterns of fire progression for large wildfires and can be very useful for evaluation and assessment purposes (Anderson et al., 2009; Hantson et al., 2013; Parks, 2014; Veraverbeke et al., 2014). These data can contribute to the demand of a concerted effort for long-term systematic monitoring of the spread of large wildfires (Alexander and Cruz, 2013a; Alexander and Cruz, 2013b). A detailed discussion regarding the error sources and limitations of satellite data to monitor fire progression, as well as the limitations of the satellite-simulation discrepancy measures, can be found in Sá et al. (under review) and references therein. Information derived from other sources (e.g. ground, airborne) can be potentially used as an alternative (e.g. http://nirops.fs.fed.us/); however, issues related with data availability, coverage, cost and accuracy can significantly undermine their applicability.

Correlation and co-variation between input variables can have relevant impacts on uncertainty analysis (Refsgaard et al., 2007), however, full independence rarely is attained (Salvador et al., 2001). Maximum and minimum daily temperature ($r = 0.78$) and maximum and minimum daily relative humidity ($r = 0.69$) were the only linearly correlated variables. Studying these interactions was beyond the scope of the current work, but we acknowledge that results concerning these variables should be addressed with caution. Future work will be dedicated to further address this issue.

Uncertainties resulting from knowledge limitations, parametric uncertainty and model inaccuracy, were not addressed, neither were those arising from the spatial resolution of the input data. Beven (2002) highlighted the importance of uncertainty stemming from non-linear sub-grid processes that were often ignored. However, Clark et al. (2008) showed that spatial resolution had little impact on fire spread predictions. Furthermore, we did not simulate spotting processes which can have a large impact on fire behavior, particularly in large wildfires (Alexander and Cruz, 2013b), neither accounted for fire suppression operations.

Extrapolation to other case studies must be done with caution. The impact of uncertainty will be dependent on the range of input values due to the nonlinear nature of fire spread models (Albini, 1976). Focusing on a small set of large wildfires burning under extreme conditions is certainly a biased sample (Finney et al., 2011b). For example, uncertainty can have significantly different impacts on the accuracy of fire spread simulations under different environmental scenarios (Salvador et al., 2001).

In the following sub-sections we disentangle the impact of uncertainty for the major groups of variables: weather, ignitions, and vegetation.

4.1.1. Weather

The assumption of wind homogeneity over a coarse grid cell and the intra-hourly fluctuations of average wind speed are important sources of uncertainty (Anderson et al., 2007; Hilton et al., 2015; Sanjuan et al., 2014) that were not addressed in the current work. Instead, we focused on the knowledge uncertainty resulting from discrepancies in wind predictions caused by uncertainties in the initial conditions and the computational representation of the equations of motion (Palmer et al., 2005). The relevance of uncertainties in wind direction and speed (see Fig. 3) is consistent with previous studies (Anderson et al., 2007; Bachmann and Allgöwer, 2002; Clark et al., 2008; Salvador et al., 2001).

For wind speed, the SpD_{ratio} variability showed an asymmetric response to uncertainty, with a two-fold spatial discrepancy range and median for negative uncertainty, when compared with positive uncertainty (see Fig. 4d). These results can be partially due to the unique characteristics of the case studies, such as canopy cover, vegetation height and the structure of vegetation fuels, which affect midflame wind speed (Finney, 2004). Wind speed uncertainty will have significantly larger impact on fires burning in landscapes with low canopy cover, higher proportion of vertical fuels and lower wind direction variability. Regarding wind direction, Clark et al. (2008) stated that it was not an influential variable, while Hilton et al. (2015) showed that it significantly influenced the expansion of fire flanks. Our results demonstrate a very relevant impact of wind direction uncertainty on the accuracy of fire spread predictions and that, in general, simulated wind direction was accurate, since uncertainty propagation led to lower prediction accuracy (see Fig. 4c).

Uncertainty concerning relative humidity had a lower than expected impact on fire spread predictions, when compared with the results presented by Anderson et al. (2007). However, larger impact should be expected for wildfires burning under less extreme conditions (Clark et al., 2008). Surprisingly, maximum relative humidity had a larger impact than minimum relative humidity (see Fig. 3). Simulated daily maximum relative humidity was higher than expected for summer conditions and exhibited larger variability than minimum relative humidity (S4 Fig. 1). Our case studies lasted for several days, so it is likely that nighttime conditions played an important role, that, along with the wider range of the uncertainty histogram (Fig. 4a,b), may explain the higher impact of maximum than minimum relative humidity uncertainty in prediction accuracy.

4.1.2. Ignitions

There are multiple sources of uncertainty regarding wildfire ignitions reported in fire databases (Amatulli et al., 2007; Pereira et al., 2011). As an alternative, we used MODIS active fire data to determine the location and timing of ignitions, which in turn also have multiple sources of uncertainty (Bar-Massada et al., 2012; Giglio et al., 2003; Hawbaker et al., 2008). Nevertheless, satellite-derived ignitions are a valuable data source that can be used alone or as a complement of reported data (Benali et al., 2016).

Uncertainty in ignition location led to significantly higher variability of the SpD_{ratio} and FGR_{ratio}, when compared with timing uncertainty. The response of simulation accuracy to spatial uncertainty was highly variable and showed the least distinctive patterns of all variables studied (Fig. 4e). Ignition uncertainty affects predictions due to the complex interactions with weather conditions, fuels and topography (Parisien et al., 2010). It also strongly influences simulated fire patterns (Bar Massada et al., 2011, and references therein), which is consistent with the results shown here, and significantly different from the results of Clark et al. (2008).

A distinct SpD_{ratio} response to uncertainty was not clear probably due to the random sampling approach used to define potential ignition locations. However, the choice of constraining 'new' ignition locations within the final fire perimeter was an optimistic approach, considering the errors in the Portuguese fire database (Benali et al., 2016; Pereira et al., 2011). It is expected that, in the absence of final fire perimeters (e.g. under operational conditions) and under milder weather conditions, the impact of ignition uncertainty on the accuracy of fire spread predictions will be even larger (Bar Massada et al., 2011). Consequently, impacts should vary greatly from region to region, consistent with the observed large inter-case study response variability.

4.1.3. Vegetation

Uncertainty in fuel model assignment and parameterization had large impacts on the accuracy of fire spread predictions. Several authors have stated that small changes in fuel structure can lead to large changes in simulated or observed fire spread (Anderson, 1982; Fernandes et al., 2004; Salazar, 1985). Mapping fuels is a labor-intensive and expensive task, due to their high temporal and spatial variability, large heterogeneity across multiple scales, limitations of remote sensing techniques to map surface fuels, difficulty of establishing a robust mapping protocol and classification subjectivity (Keane and Reeves, 2012). Moreover, uncertainties in moisture content arise from variations in vegetation structure and type, fuel bed depth, canopy cover, soil moisture, topography and weather (see Matthews, 2014 for in-depth discussion). Finally, the assumption of fuel homogeneity in a coarse 100 m grid cells (Hilton et al., 2015) and scale effects (Salvador et al., 2001) introduce important uncertainties that were not accounted for in this study.

Fuel model assignment uncertainty had a large impact in forest classes, with opposite response patterns (see Fig. 5). In Portugal, pine trees dominate the composition of coniferous forests. We assigned NFFL model 6 to coniferous forests, while the ICNF assigned mostly (over 78% of the times) NFFL model 7 (see Table 1 and Table 2) and never assigned NFFL model 6. The main broadleaf forest types in Portugal are deciduous oaks, the evergreens cork oak and holm oak, and blue gum eucalypt, generating large spatial variability in understory composition and structure, which may explain the high impact of uncertainty. We assigned NFFL model 9 to broadleaf forest (CLC class 311), while the ICNF assigned models 2, 5 and 7. For shrubland areas, we assigned model 6 to CLC classes 322–323 and model 5 to CLC class 324, while the ICNF assigned models 4, 5 and 7 (see Table 2 and S3 Fig. 1). The fuel models assigned to each case study showed remarkable discrepancies, highlighting the differences resulting from inherent subjectivity in model assignment, but also from significant differences in the spatial detail level of the base vegetation maps.

Results showed that changing the parameterization of fuels models in forests and shrublands had an important impact on the accuracy of fire spread predictions, and led to a decrease in satellite-simulation discrepancies for most case studies (see Fig. 5). These results showed the importance of integrating expert knowledge when mapping and parameterizing local fuel models (Keane and Reeves, 2012; Reeves et al., 2009). Results also showed the benefits of using custom fuel models in the reduction of uncertainty and satellite-simulation discrepancy (Salazar, 1985). Comparatively, fuel model uncertainty had a larger relative impact (e.g. when compared with wind speed) on fire spread simulations than shown by Clark et al. (2008), probably in part due to the over simplistic uniform uncertainty distribution they assumed.

The same authors showed that DFMC accounted for more model output variation than fuel model uncertainty, while our results showed a marginal impact of DFMC on fire spread simulations, regardless of the conditioning period length. DFMC ranges were representative of summer conditions in Portugal (Lopes et al., 2006). The FMC are calculated by FARSITE throughout the simulation from environmental conditions and the influence of initial FMC vanishes rapidly (Finney, 2004), thus fire spread is barely dependent on the initial DFMC values.

The importance of LFMC on wildfires is complex and subject to debate (Yebra et al., 2013). Our results showed that LFMC uncertainty has a moderate impact on the accuracy of fire spread predictions, regardless of fuel typology (see Fig. 4g). Furthermore, we studied large wildfires that occurred under extreme conditions, and the response of the SpD_{ratio} to LFMC uncertainty suggests that LFMC was likely overestimated in the *reference* simulations. FMC will likely have a larger influence on fires occurring in less extreme conditions (Clark et al., 2008).

Tree cover affects the calculation of fuel moisture and surface wind speed (Finney, 2004), as a consequence, negative uncertainty will render drier fuels, due to decreased shading, and higher midflame wind speed. Although uncertainty in tree cover had relatively low impact on the accuracy of fire spread simulations, it must be noted that the uncertainty ranges were small and estimated by the MODIS algorithm (Fig. 4h; DiMiceli et al., 2011). Consequently, higher impacts on the accuracy of fire spread predictions might be expected, particularly under significant year-to-year land cover changes. A comprehensive validation of the MODIS tree cover product is needed for further assessments.

4.2. Integrating uncertainty

Integrating uncertainty to produce reliable fire spread predictions is still relatively new and difficult because fire behavior is highly variable (Finney, 2005). Traditional deterministic predictions based on the best available data fail to provide information regarding the uncertainty that pervades model predictions. Alternatively, probabilistic approaches allow the quantification of predictive uncertainty, identification of prediction limits, and improved understanding of the probability of occurrence of possible fire behavior outcomes (Finney et al., 2011b; Gill, 2001).

Fire managers are used to handle multiple sources of uncertainty when managing wildfires. Integrating uncertainty into fire spread predictions will certainly improve risk assessment and the decision-making processes (Anderson et al., 2007; Thompson and Calkin, 2011), especially in an operational context where uncertainty is high and will likely result in large errors (Cruz and Alexander, 2013). However, realistically accounting for uncertainty can only be accomplished if users demand it and acknowledge that even if explanatory power is not improved, useful complementary information can be provided, such as error bounds and probabilistic outcomes (Cruz, 2010).

Previous studies have focused on integrating the uncertainty in meteorological variables to produce probabilistic fire spread predictions (Anderson et al., 2007; Cruz, 2010; Finney et al., 2011a). Our results show that other sources of uncertainty also need to be accounted for, such as ignition location and fuels, as they are important sources of prediction errors.

Our results show that considering normally distributed uncertainty around a mean value of zero can be a considerable over-simplification for meteorological variables (Anderson et al., 2007; Bachmann and Allgöwer, 2002; Cruz, 2010). We recognize the need for better understanding the uncertainties present in meteorological variables, such as wind-terrain interaction, the downscaling of meteorological information from coarse grid cells, the temporal variability of wind speed, and the necessity of integrating them into future ensemble predictions. Additionally, we stress the need for weather forecasts to provide explicit representations of model uncertainty.

Uncertainty in wildfire ignitions is large, especially regarding its location, and should be taken into account in future studies. For satellite-derived ignitions, the use of additional sensors ought to increase the number of clear-sky overpasses and the spatial resolution of active fires (e.g. Schroeder et al., 2014), thus increasing the probability of accurately detecting the location and timing of ignitions in any part of the globe. It is crucial that uncertainty in ignition location and timing are integrated (e.g. Amatulli et al., 2007).

Our results for vegetation-related variables show the importance of integrating their uncertainty in future fire spread predictions. When detailed comprehensive information is available for fuel mapping purposes (e.g. LANDFIRE, see Reeves et al., 2009) and while a new paradigm for fuel mapping is not established, we argue that the most efficient procedure would be to explicitly define the uncertainties in fuel model assignment and parameterizations and integrate them in fire behavior simulations. For instance, Reeves et al. (2009) described how expert knowledge was used to classify fuel models based on a majority vote. This is a good example where uncertainty could be integrated by using the multiple fuel classifications done by experts. Alternatively, when fuels are mapped by converting a generic vegetation map, uncertainties in fuel model classifications could be integrated by using the knowledge from multiple fire experts under the assumption that it is likely the best information available (Thompson and Calkin, 2011).

We focused our analysis on the impact of uncertainty that each individual input variable has on the accuracy of fire spread simulations. In reality, several variables will be correlated to some extent (e.g. weather variables; Salvador et al. (2001)) and therefore, their uncertainties will not be completely independent. Future work should focus on the study of such interactions, improving our knowledge on how to integrate the data uncertainty, for instance, in the simulation of 'real' wildfires in an operational context. Under such context, it is expectable that for some variables the uncertainties will decrease (e.g. ignition location) while for others it will increase (e.g. weather forecasts) when compared with the research context presented here.

5. Conclusions

The impact of uncertainty in the most relevant variables on fire spread prediction accuracy has not been quantified before. We have shown how uncertainties in input variables of a fire spread modeling framework can influence the quality of the downstream predictions. Results showed that uncertainties in wind speed and direction, fuel model assignment and typology, location and timing of ignitions had important impacts on prediction accuracy.

Uncertainty assessment should be performed at the beginning of the fire modeling process, to enable for: i) the characterization of the most important uncertainties; ii) the identification of target variables where predictions will be likely improved by reducing uncertainty, and iii) an improved characterization of errors associated with fire spread predictions.

Since uncertainties will always be present and our knowledge on fire behavior will continue to be imperfect, understanding and quantifying the impact of uncertainties in model accuracy is essential to help fire managers make better management decisions and, ultimately, to extend our current knowledge. By integrating uncertainty in fire spread predictions one can expect to improve the anticipation of fire behavior estimates and minimize both their negative environment impacts and risk to human life and health.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at http://dx.doi.org/10.1016/j.scitotenv.2016.06.112.

References

Albini, F.A., 1976. Estimating wildfire behavior and effects. USDA For. Serv., Intermt. For. Range Exp. Stn., Ogden, UT. Gen. Tech. Rep. (INT-30. 92 p).

Alexander, M.E., Cruz, M.G., 2013a. Are the applications of wildland fire behaviour models getting ahead of their evaluation again? Environ. Model. Softw. 41, 65–71.

Alexander, M.E., Cruz, M.G., 2013b. Limitations on the accuracy of model predictions of wildland fire behaviour: a state-of-the-knowledge overview. For. Chron. 89, 372–383.

Amatulli, G., Peréz-Cabello, F., de la Riva, J., 2007. Mapping lightning/human-caused wildfires occurrence under ignition point location uncertainty. Ecol. Model. 200, 321–333.

Anderson, H.E., 1982. Aids to determining fuel models for estimating fire behavior. The Bark Beetles, Fuels, and Fire Bibliography. 143.

Anderson, K., Reuter, G., Flannigan, M.D., 2007. Fire-growth modelling using meteorological data with random and systematic perturbations. Int. J. Wildland Fire 16, 174.

Anderson, K.R., Englefield, P., Little, J.M., Reuter, G., 2009. An approach to operational forest fire growth predictions for Canada. Int. J. Wildland Fire 18, 893.

Anderson, W.R., Cruz, M.G., Fernandes, P.M., McCaw, L., Vega, J.A., Bradstock, R.A., Fogarty, L., Gould, J., McCarthy, G., Marsden-Smedley, J.B., 2015. A generic, empirical-based model for predicting rate of fire spread in shrublands. Int. J. Wildland Fire 24, 443–460.

Arca, B., Duce, P., Laconi, M., Pellizzaro, G., Salis, M., Spano, D., 2007. Evaluation of FARSITE simulator in Mediterranean maquis. Int. J. Wildland Fire 16, 563.

Azorin-Molina, C., Vicente-Serrano, S.M., McVicar, T.R., Jerez, S., Sanchez-Lorenzo, A., López-Moreno, J.-I., Revuelto, J., Trigo, R.M., Lopez-Bustins, J.A., Espírito-Santo, F., 2014. Homogenization and assessment of observed near-surface wind speed trends over Spain and Portugal, 1961–2011*. J. Clim. 27, 3692–3712.

Bachmann, A., Allgöwer, B., 2002. Uncertainty propagation in wildland fire behaviour modelling. Int. J. Geogr. Inf. Sci. 16, 115–127.

Bar Massada, A., Syphard, A.D., Hawbaker, T.J., Stewart, S.I., Radeloff, V.C., 2011. Effects of ignition location models on the burn patterns of simulated wildfires. Environ. Model. Softw. 26, 583–592.

Bar-Massada, A., Hawbaker, T.J., Stewart, S.I., Radeloff, V.C., 2012. Combining satellite-based fire observations and ground-based lightning detections to identify lightning fires across the conterminous USA. IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens. 5, 1438–1447.

Benali, A., Russo, A., Sá, A.C., Pinto, R., Price, O., Koutsias, N., Pereira, J., 2016. Determining fire dates and locating ignition points with satellite data. Remote Sens. 8, 326.
Beven, K., 2002. Towards a coherent philosophy for modelling the environment. Proc. R. Soc. A : Math., Phys. Eng. Sci. 458, 2465–2484.
Beven, K., Binley, A., 1992. The future of distributed models: model calibration and uncertainty prediction. Hydrol. Process. 6, 279–298.
Bossard, M., Feranec, J., Otahel, J., 2000. CORINE land cover technical guide: Addendum 2000 (European Environment Agency Copenhagen).
Clark, R.E., Hope, A.S., Tarantola, S., Gatelli, D., Dennison, P.E., Moritz, M.A., 2008. Sensitivity analysis of a fire spread model in a chaparral landscape. Fire Ecol. 4.
Cochrane, M., Moran, C., Wimberly, M., Baer, A., Finney, M., Beckendorf, K., Eidenshink, J., Zhu, Z., 2012. Estimation of wildfire size and risk changes due to fuels treatments. Int. J. Wildland Fire 21, 357–367.
Cruz, M.G., 2010. Monte Carlo-based ensemble method for prediction of grassland fire spread. Int. J. Wildland Fire 19, 521.
Cruz, M.G., Alexander, M.E., 2013. Uncertainty associated with model predictions of surface and crown fire rates of spread. Environ. Model. Softw. 47, 16–28.
Cruz, M.G., Sullivan, A.L., Gould, J.S., Sims, N.C., Bannister, A.J., Hollis, J.J., Hurley, R.J., 2012. Anatomy of a catastrophic wildfire: the black Saturday Kilmore east fire in Victoria, Australia. For. Ecol. Manag. 284, 269–285.
DiMiceli, C., Carroll, M., Sohlberg, R., Huang, C., Hansen, M., Townshend, J., 2011. Annual Global Automated MODIS Vegetation Continuous Fields (MOD44B) at 250 m Spatial Resolution for Data Years Beginning Day 65, 2000–2010, Collection 5 Percent Tree Cover. University of Maryland, College Park.
EEA, 2007. European Environment Agency: CLC2006 Technical Guidelines, Copenhagen.
Farr, T.G., Rosen, P.A., Caro, E., Crippen, R., Duren, R., Hensley, S., Kobrick, M., Paller, M., Rodriguez, E., Roth, L., 2007. The shuttle radar topography mission. Rev. Geophys. 45.
Fernandes, P., 2005. Equivalência genérica entre os modelos de combustível do USDA Forest Service (Anderson, 1982) e as formações florestais portuguesas. Guia metodológico para elaboração do Plano Municipal/Intermunicipal de Defesa da Floresta Contra Incêndios Direção Geral dos Recursos Florestais.
Fernandes, P., 2009. Combining forest structure data and fuel modelling to classify fire hazard in Portugal. Ann. For. Sci. 66, 1–9.
Fernandes, P., Loureiro, C.A., Botelho, H.S., 2004. Fire behaviour and severity in a maritime pine stand under differing fuel conditions. Ann. For. Sci. 61, 537–544.
Fernandes, P.M., Loureiro, C., Guiomar, N., Pezzatti, G.B., Manso, F.T., Lopes, L., 2014. The dynamics and drivers of fuel and fire in the Portuguese public forest. J. Environ. Manag. 146, 373–382.
Ferreira, J., Rocha, A., Castanheira, J.M., Carvalho, A.C., 2012. Dynamical downscaling intercomparison for high resolution climate reconstruction. EGU General Assembly, Vienna, Austria, pp. 22–27 (April 2012).
Finney, M.A., 2004. FARSITE: Fire Area Simulator—Model Development and Evaluation. USDA Research Paper RMRS-RP-4.
Finney, M.A., 2005. The challenge of quantitative risk analysis for wildland fire. For. Ecol. Manag. 211, 97–108.
Finney, M.A., Grenfell, I.C., McHugh, C.W., Seli, R.C., Trethewey, D., Stratton, R.D., Brittain, S., 2011a. A method for ensemble Wildland fire simulation. Environ. Model. Assess. 16, 153–167.
Finney, M.A., McHugh, C.W., Grenfell, I.C., Riley, K.L., Short, K.C., 2011b. A simulation of probabilistic wildfire risk components for the continental United States. Stoch. Env. Res. Risk A. 25, 973–1000.
Fisher, W.C., 1982. Photo guide for appraising downed woody fuels in Montana forests: Grand Fir-Lach-Douglas-Fir, Western Hemlock, Western Hemlock-Western Redcedar, and Western Redcedar cover types. General Technical Report INT-96, Intermountain Forest and Range Experiment Station. 133.
Giglio, L., 2010. MODIS Collection 5 Active Fire Product User's Guide Version 2.4.
Giglio, L., Descloitres, J., Justice, C.O., Kaufman, Y.J., 2003. An enhanced contextual fire detection algorithm for MODIS. Remote Sens. Environ. 87, 273–282.
Gill, A., 2001. A Transdisciplinary View of Fire Occurrence and Behaviour, Bushfire. pp. 1–12.
Grell, G.A., Dudhia, J., Stauffer, D.R., 1994. A description of the fifth-generation Penn State/NCAR mesoscale model (MM5). NCAR Technical Note NCAR/TN-398 + STR, doi: 10.5065/D60Z716B.
Hantson, S., Padilla, M., Corti, D., Chuvieco, E., 2013. Strengths and weaknesses of MODIS hotspots to characterize global fire occurrence. Remote Sens. Environ. 131, 152–159.
Hawbaker, T.J., Radeloff, V.C., Syphard, A.D., Zhu, Z., Stewart, S.I., 2008. Detection rates of the MODIS active fire product in the United States. Remote Sens. Environ. 112, 2656–2664.
Hilton, J.E., Miller, C., Sullivan, A.L., Rucinski, C., 2015. Effects of spatial and temporal variation in environmental conditions on simulation of wildfire spread. Environ. Model. Softw. 67, 118–127.
Jerez, S., Trigo, R., Vicente-Serrano, S.M., Pozo-Vázquez, D., Lorente-Plazas, R., Lorenzo-Lacruz, J., Santos-Alamillos, F., Montávez, J., 2013. The impact of the North Atlantic oscillation on renewable energy resources in southwestern Europe. J. Appl. Meteorol. Climatol. 52, 2204–2225.
JRC, 2011. Forest Fires in Europe 2010. JRC Scientific and Technical Reports, p. 98.
Keane, R.E., Reeves, M., 2012. Use of expert knowledge to develop fuel maps for Wildland fire management. In: Perera, A.H., Drew, C.A., Johnson, C.J. (Eds.), Expert Knowledge and Its Application in Landscape Ecology. Springer Science and Business Media, LLC, New York, USA, pp. 211–228.
Kochanski, A.K., Jenkins, M.A., Mandel, J., Beezley, J.D., Krueger, S.K., 2013. Real time simulation of 2007 Santa Ana fires. For. Ecol. Manag. 294, 136–149.
Liu, Y., Jimenez, E., Hussaini, M.Y., Okten, G., Goodrick, S., 2015. Parametric uncertainty quantification in the Rothermel model with randomised quasi-Monte Carlo methods. Int. J. Wildland Fire 24, 307.
Lopes, S.M.G., Viegas, D.X., Viegas, M.T., de Lemos, L.T., 2006. Moisture content of fine forest fuels in the Central Portugal (Lousa) for the period 1996–2004. For. Ecol. Manag. 234, S71.
Matthews, S., 2014. Dead fuel moisture research: 1991–2012. Int. J. Wildland Fire 23, 78–92.
Oliveira, S.L.J., Pereira, J.M.C., Carreiras, J.M.B., 2012. Fire frequency analysis in Portugal (1975–2005), using Landsat-based burnt area maps. Int. J. Wildland Fire 21, 48.
Palmer, T.N., Shutts, G.J., Hagedorn, R., Doblas-Reyes, F.J., Jung, T., Leutbecher, M., 2005. Representing model uncertainty in weather and climate prediction. Annu. Rev. Earth Planet. Sci. 33, 163–193.
Papadopoulos, G.D., Pavlidou, F.-N., 2011. A comparative review on wildfire simulators. IEEE Syst. J. 5, 233–243.
Parisien, M.-A., Miller, C., Ager, A.A., Finney, M.A., 2010. Use of artificial landscapes to isolate controls on burn probability. Landsc. Ecol. 25, 79–93.
Parks, S.A., 2014. Mapping day-of-burning with coarse-resolution satellite fire-detection data. Int. J. Wildland Fire 23, 215.
Pereira, M.G., Malamud, B.D., Trigo, R.M., Alves, P.I., 2011. The history and characteristics of the 1980-2005 Portuguese rural fire database. Nat. Hazards Earth Syst. Sci. 11, 3343–3358.
Reeves, M.C., Ryan, K.C., Rollins, M.G., Thompson, T.G., 2009. Spatial fuel data products of the LANDFIRE project. Int. J. Wildland Fire 18, 250.
Refsgaard, J.C., van der Sluijs, J.P., Højberg, A.L., Vanrolleghem, P.A., 2007. Uncertainty in the environmental modelling process — a framework and guidance. Environ. Model. Softw. 22, 1543–1556.
Rothermel, R.C., 1972. A mathematical model for predicting fire spread in wildland fuels. USDA For. Serv. Res. Pap. INT-115.
Rothermel, R.C., 1991. Predicting behavior and size of crown fires in the northern Rocky Mountains. USDA For. Serv. Res. Pap. INT-438.
Sá, A.C.L., Benali, A., Fernandes, P.M., Pinto, R.M.S., Trigo, R.M., Salis, M., Russo, A., Jerez, S., Soares, P.M., Schroeder, W., Pereira, J.M.C., 2016. Evaluating Fire Growth Simulations Using Satellite Active Fire Data. Submitted to Remote Sensing of Environment (under review).
Salazar, L.A., 1985. Sensitivity of fire behavior simulations to fuel model variations. In: Berkeley, C.A. (Ed.), Res. Paper PSW-178 11. Pacific Southwest Forest and Range Experiment Station, Forest Service, U.S. Department of Agriculture.
Salis, M., Ager, A.A., Arca, B., Finney, M.A., Bacciu, V., Duce, P., Spano, D., 2013. Assessing exposure of human and ecological values to wildfire in Sardinia, Italy. Int. J. Wildland Fire 22, 549.
Salvador, R., Pinol, J., Tarantola, S., Pla, E., 2001. Global sensitivity analysis and scale effects of a fire propagation model used over Mediterranean shrublands. Ecol. Model. 136, 175–189.
Sanjuan, G., Brun, C., Margalef, T., Cortés, A., 2014. Wind field uncertainty in Forest fire propagation prediction. Procedia Comput. Sci. 29, 1535–1545.
Schroeder, W., Oliva, P., Giglio, L., Csiszar, I.A., 2014. The new VIIRS 375m active fire detection data product: algorithm description and initial assessment. Remote Sens. Environ. 143, 85–96.
Scott, J.H., Burgan, R.E., 2005. Standard fire behavior fuel models: a comprehensive set for use with Rothermel's surface fire spread model. The Bark Beetles, Fuels, and Fire Bibliography. 66.
Skamarock, W., Klemp, J., Dudhia, J., Gill, D., Barker, D., 2005. NCAR Technical Note NCAR/TN-468 + STR. A description of the Advanced Research WRF Version 2 (113 p).
Sullivan, A.L., 2009. Wildland surface fire spread modelling, 1990–2007. 3: simulation and mathematical analogue models. Int. J. Wildland Fire 18, 387–403.
Thompson, M.P., Calkin, D.E., 2011. Uncertainty and risk in wildland fire management: a review. J. Environ. Manag. 92, 1895–1909.
Trigo, R.M., Pereira, J.M.C., Pereira, M.G., Mota, B., Calado, T.J., da Camara, C.C., Santo, F.E., 2006. Atmospheric conditions associated with the exceptional fire season of 2003 in Portugal. Int. J. Climatol. 26, 1741–1757.
Trigo, R.M., Sousa, P.M., Pereira, M.G., Rasilla, D., Gouveia, C.M., 2013. Modelling wildfire activity in Iberia with different atmospheric circulation weather types (International Journal of Climatology). (in press).
Uppala, S.M., Kållberg, P., Simmons, A., Andrae, U., Bechtold, V., Fiorino, M., Gibson, J., Haseler, J., Hernandez, A., Kelly, G., 2005. The ERA-40 re-analysis. Q. J. R. Meteorol. Soc. 131, 2961–3012.
van Wagner, C.E., 1977. Conditions for the start and spread of crownfire. Can. J. For. Res. 7, 23–24.
Veraverbeke, S., Sedano, F., Hook, S.J., Randerson, J.T., Jin, Y., Rogers, B.M., 2014. Mapping the daily progression of large wildland fires using MODIS active fire data. Int. J. Wildland Fire 23, 655–667.
Yebra, M., Dennison, P.E., Chuvieco, E., Riaño, D., Zylstra, P., Hunt, E.R., Danson, F.M., Qi, Y., Jurdao, S., 2013. A global review of remote sensing of live fuel moisture content for fire danger assessment: moving towards operational products. Remote Sens. Environ. 136, 455–468.

Web references

SNIRH, http://snirh.apambiente.pt/, accessed at 5 of January 2015.
ICNF, http://www.icnf.pt/portal/florestas/dfci/cartografia-dfci, accessed at 5 of May 2015.

Paper IV - Fire spread predictions: Sweeping uncertainty under the rug

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Fire spread predictions: Sweeping uncertainty under the rug

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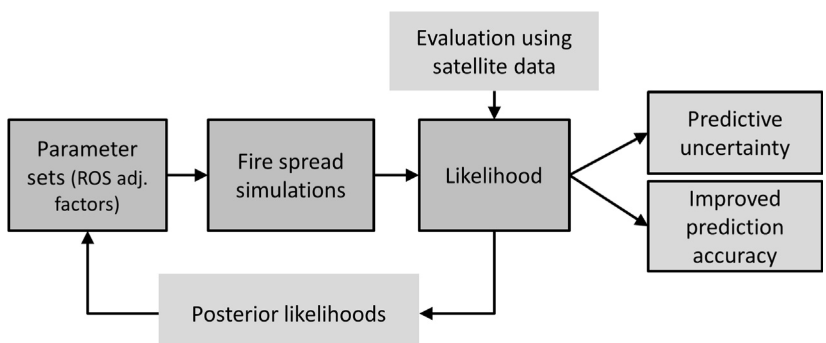
HIGHLIGHTS

- Uncertainties undermine the utility of fire spread predictions.
- Model parameter calibration was made using the GLUE methodology.
- Prediction accuracy was estimated using satellite active fire data.
- The impact of uncertainty was reduced, improving prediction accuracy.
- Large potential to improve future fire spread predictions.

GRAPHICAL ABSTRACT



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ABSTRACT

Predicting fire spread and behavior correctly is crucial to minimize the dramatic consequences of wildfires. However, our capability of accurately predicting fire spread is still very limited, undermining the utility of such simulations to support decision-making. Improving fire spread predictions for fire management purposes, by using higher quality input data or enhanced models, can be expensive, unfeasible or even impossible. Fire managers would benefit from fast and inexpensive ways of improving their decision-making. In the present work, we focus on i) understanding if fire spread predictions can be improved through model parameter calibration based on information collected from a set of large historical wildfires in Portugal; and ii) understanding to what extent decreasing parametric uncertainty can counterbalance the impact of input data uncertainty. Our results obtained with the Fire Area Simulator (FARSITE) modeling system show that fire spread predictions can be continuously improved by 'learning' from past wildfires. The uncertainty contained in the major input variables (wind speed and direction, ignition location and fuel models) can be 'swept under the rug' through the use of more appropriate parameter sets. The proposed framework has a large potential to improve future fire spread predictions, increasing their reliability and usefulness to support fire management and decision making processes, thus potentially reducing the negative impacts of wildfires.

1. Introduction

Wildfires are a disruptive phenomenon with important environment and socio-economic impacts. Accurately predicting and anticipating fire spread and behavior is crucial to minimize dramatic consequences. For this purpose, fire spread models have been widely used to support fire

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management decisions, such as in real-time fire behavior prediction (Kochanski et al., 2013), anticipated fire risk assessment (Calkin et al., 2011), fire suppression preparedness (Sneeuwjagt and Peet, 1985) and fire and fuel hazard mitigation resulting from planned fuel treatments (Ager et al., 2010).

The capability of accurately predicting fire spread is still very limited, and associated uncertainties strongly undermine the utility of such predictions for decision-making (Alexander and Cruz, 2013a). Modeling fire behavior is uncertain mainly due to imperfect scientific knowledge regarding the mechanisms driving fire spread, model applicability and its inherent limitations, input data quality, natural variability, and parametric uncertainty (Albini, 1976; Alexander and Cruz, 2013b; Ervilha et al., 2017; Liu et al., 2015; Refsgaard et al., 2007; Thompson and Calkin, 2011). In a general sense, the lack of knowledge (epistemic uncertainty), rather than simple random variability, can be responsible for important prediction errors (Beven and Binley, 2014). For instance, it has been shown that errors in input data can lead to large prediction errors (Albini, 1976; Anderson et al., 2007; Bachmann and Allgöwer, 2002; Benali et al., 2016a).

There is a certain inability of the current fire-research modeling community to completely take into account the strong limitations imposed by the pervasive levels of uncertainties. This is of paramount relevance, as fire spread simulations will only be deemed useful if they can provide reliable information to fire managers. Understanding how simulations can be improved is, therefore, a critical research task that can contribute to mitigate negative downstream consequences. For example, in an operational context, anticipating correctly where and when a location will burn, and the corresponding level of confidence, is important to define suppression strategies (Pinto et al., 2016). On the other hand, in a pre-operational context, improving fire spread predictions can, for example, render more reliable assessments of fire risk and improve fuel management decisions (Ager et al., 2010; Salis et al., 2013).

Currently, there are many fire spread models available that range from empirical to physically-based (Sullivan, 2009a, b, c). Each option has advantages and disadvantages that depend on several aspects, such as computational and data demand, costs, accuracy, complexity, among others (Papadopoulos and Pavlidou, 2011). Among these, the Fire Area Simulator (FARSITE) modeling system (Finney, 2004) has been widely used to simulate the spread and behavior of individual fires. Its accuracy, easiness to use, along with its moderate complexity, data size demands and computation times, have been recognized by many authors (Arca et al., 2007; Papadopoulos and Pavlidou, 2011; Salis et al., 2016; Sullivan, 2009c). FARSITE, along with several other fire modeling systems, uses the Rothermel semi-empirical fire spread model (Rothermel, 1972) to predict rate of spread (ROS) at any given spread direction of a surface fire. It is based on topographic, weather and vegetation information. The latter is based on fuel models that consist of a numerical description of the structure and composition of surface organic matter capable of flaming combustion (Anderson, 1982). Fuel models are composed by several parameters describing the fuel complex, with different impacts on the expected fire behavior (Ervilha et al., 2017; Liu et al., 2015).

Fire spread predictions can be improved in a number of ways, namely by i) increasing scientific knowledge driving fire behavior and spread mechanisms; ii) developing more accurate and reliable models; iii) using higher quality input data; and iv) model calibration. However, we have different levels to improve these "four horses of apocalypse" that hamper fire-spread model results. Improving data, models and scientific knowledge, may involve challenging tasks that are too expensive and time consuming. Additionally, the complexity of models can significantly undermine their application by fire managers. Consequently, the characteristics of these options rarely coincide with the demands and requirements of fire managers for short-term and inexpensive improvements of fire spread predictions.

Within this context, model calibration can be a relatively inexpensive, fast and simple way of improving fire spread predictions, and consequently, decision-making. Several fire modeling systems have enclosed in their model structure parameters (i.e. the empirical values constant throughout the simulations) that can be adjusted with the objective of improving the agreement between estimated and observed fire spread and behavior (Cruz and Alexander, 2010; Finney, 2004; Mandel et al., 2014). Among these, the calibration of fuel model parameters has been often done with significant improvements to fire spread prediction accuracy (Ascoli et al., 2015; Cai et al., 2014; Cruz and Fernandes, 2008; Rothermel and Rinehart, 1983; Salis et al., 2016). Nevertheless, the large uncertainties associated with the lack of detailed and accurate information required for fuel mapping at large spatial scales (Keane and Reeves, 2012), as well as the spatial variability within each mapping unit (Hilton et al., 2015), can significantly jeopardize the utility of fuel model calibration for prediction improvement.

Alternatively, Duguy et al. (2007) used FARSITE to reproduce the fire spread patterns of an historical event by tuning the ROS adjustment factors, scalars that multiplied by the estimated ROS and that do not affect other fire behavior outputs. Contrary to several parameters that are not easily accessible to the average fire model user for model calibration, these empirical factors are used to rapidly adjust the fire spread rate based on the expected or observed fire behavior for each individual fuel model (Finney, 2004; Rothermel and Rinehart, 1983). Despite this effort, the potential improvement of fire spread predictions that result from tuning such empirical parameters remains largely unknown. In particular, it is still unknown if this simple calibration approach can be applied to other wildfires to effectively reduce prediction errors, or if they are mostly case-specific and have little effectiveness in improving predictions of subsequent wildfires.

We explore whether the calibration of the empirical ROS adjustment factors of FARSITE can be a simple, fast and inexpensive way of improving the consequent fire spread predictions. We do not consider the uncertainties associated with fuel model parameters that have been studied elsewhere (Ascoli et al., 2015; Bachmann and Allgöwer, 2002; Ervilha et al., 2017; Liu et al., 2015). The impact of data uncertainty is taken into account based on preceding work (see Benali et al., 2016a). Investigating other sources of uncertainty is outside the scope of the work, however, the readers are referred to Thompson and Calkin (2011) and Webley et al. (2016) for further information. Here, we propose to i) quantify how fire spread predictions can be improved through model parameter calibration based on information collected from historical large wildfires; and ii) understand to what extent decreasing parametric uncertainty can counterbalance the impact of input data uncertainty. For this purpose, the fire spread predictions are evaluated using satellite active fire data for seven large historical wildfires in Portugal that occurred between 2003 and 2005. Understanding and quantifying the sources of prediction error, or producing the best possible predictions, is beyond the scope of the work, as we focus on the relative improvements made by calibrating the fire modeling system.

2. Data and methods

2.1. Fire spread simulations

We selected seven very large wildfires that occurred in Portugal between 2003 and 2005. Each wildfire burned between ~13,700 ha and 40,000 ha and lasted for several days. These historical case studies were above the 99th percentile of fire size distribution considering all the wildfires that occurred between 1975 and 2013 in mainland Portugal (Sá et al., 2017). The location, burned area perimeter, fire name and respective acronym are displayed in S1 Fig. 1, along with their characteristics shown in S1 Table 1. The burned area perimeters of all case studies were extracted from the Landsat-derived Portuguese fire atlas (Oliveira et al., 2012). The ignition locations, start and end date of the case studies were defined using satellite active fire data (Benali et al., 2016b).

We used FARSITE to simulate the fire spread patterns of the case studies. FARSITE uses distinct models for surface fire spread (Rothermel, 1972), crown fire transition (van Wagner, 1977), and crown fire spread (Rothermel, 1991). We used FARSITE 4 command line version to simulate surface fire, with a landscape cell-size of 100 m and an hourly time step. Spotting, crown fires and fire suppression were not simulated due to their stochastic nature and the lack of information, respectively.

FARSITE requires a comprehensive set of landscape and weather variables. Slope and aspect were derived from the digital elevation data acquired from the NASA Shuttle Radar Topography Mission (SRTM) (Farr et al., 2007). Fuel maps were produced by reclassifying the Corine Land Cover (Bossard et al., 2000) classes into fire behavior fuel models as per the Northern Forest Fire Laboratory (NFFL; Anderson, 1982). The reclassification key and the correspondent fuel maps are shown in S2. Initial dead fuel moisture contents were set to 6%, 7% and 8%, for 1-hr, 10-hr and 100-hr time-lag classes, respectively, based on Scott and Burgan (2005). Live fuel moisture contents were set to 60% and 90%, for herbaceous and woody components, respectively. Canopy cover density was extracted from the Moderate Resolution Imaging Spectroradiometer (MODIS) Vegetation Continuous Fields (VCF) product (DiMiceli et al., 2011). Weather variables were derived from a high-resolution dataset based on PSU/NCAR mesoscale model (MM5) simulations (Lorente-Plazas et al., 2015) and used as hourly data at 10 km resolution. A comprehensive list of the required input variables to model fire spread using FARSITE is provided in S3 Table 1.

Using the set of input variables described above and setting the adjustment factors to one (i.e. no adjustment) we performed the *reference* fire spread simulations for the seven historic case studies. In Sections 2.3 and 2.4 we describe how the uncertainty in the ROS adjustment factors and input variables was integrated in the fire spread simulations.

2.2. Evaluation of fire spread simulations

Evaluating fire spread simulations against static burned area perimeters ignores the spatio-temporal patterns of fire spread, not effectively contributing to improve predictions (Cui and Perera, 2010; Duff et al., 2013; Filippi et al., 2014). Alternatively, the MODIS active fire product (MCD14ML) uses thermal data to identify the location of fires burning at the time of overpass with a nominal spatial resolution of 1 km^2 (Giglio et al., 2003). MODIS is aboard two satellites, resulting in four distinct acquisition periods per day on average: Terra data are acquired during day and nighttime at around 10:30–12:00 a.m./p.m. local time, respectively, and Aqua data at around 1:00–3:00 a.m./p.m., respectively. MODIS active fire data are specially suited to monitor large and long-lasting wildfires (Anderson et al., 2009; Hawbaker et al., 2008; Parks, 2014; Veraverbeke et al., 2014).

Recently, Sá et al. (2017) proposed evaluating the accuracy of fire spread simulations using satellite active fire data. The evaluation scheme is based on quantifying the spatial discrepancy (hereafter, *SpD*) between fire spread simulations and fire growth observed by satellite thermal acquisitions. The *SpD* is defined by the authors as the minimum Euclidean distance (in km) between a satellite active fire pixel and the nearest simulated cell burning at the time of satellite overpass. Due to the uncertainty in the sub-pixel location of the fire front, the minimum Euclidean distance between all the possible sub-pixel locations within the MODIS active fire pixel and the closest simulated burned pixel was calculated. We made some modifications to the evaluation scheme proposed by Sá et al. (2017) to use only the most outward satellite active fires in the *SpD* calculation. Details are provided in S2. The spatial discrepancy was assumed to be an indicator of prediction accuracy, such that a low discrepancy was interpreted as a close match between satellite-observed and simulated fire growth.

2.3. Uncertainty quantification

In this section we describe the quantification of the uncertainty associated with fire spread modeling inputs, specifically with variables and parameters. The uncertainty associated with the most relevant input variables has been estimated by Benali et al. (2016a). Here, we provide only a brief overview of the latter work (Section 2.3.1). Quantification of the uncertainty associated with model parameters was focused in the ROS adjustment factors and is described in Section 2.3.2. Here after, model parameters refer to the ROS adjustment factors unless stated otherwise. Finally, we describe how the impact of the uncertainty associated with input variables and parameters on the output fire spread predictions was assessed (Section 2.3.3).

2.3.1. Model variables

The uncertainty associated with the input variables was estimated previously, using different methods and independent data sources, along with its impact on fire spread predictions (Benali et al., 2016a). Here, based on the previous study results, we focused on the variables for which the uncertainty had a larger impact on the prediction accuracy: wind speed and direction, ignition location, and fuel model assignment.

We sampled 100 values from the uncertainty histograms of wind speed and direction, and ignition location variables (see Fig. 4c–e in Benali et al., 2016a). For the wind-related variables, uncertainty was propagated by adding the sampled uncertainty value to the reference value, and generating the correspondent fire spread simulation. For the ignition location, we generated random ignition points within the burned area perimeter with a distance to the reference location equal to the sampled uncertainty value. The uncertainty associated with the assignment of NFFL fuel models based on CLC land cover classes was calculated using a confusion matrix (see Table 2 in Benali et al., 2016a). A total of 100 combinations of land cover-fuel model assignments were defined and a simulation was performed for each combination. The uncertainties were propagated through the fire model for each case study independently, one variable at a time.

2.3.2. Model parameters: the ROS adjustment factors

To the best of our knowledge, there is no data available regarding the 'true' distribution of the ROS adjustment factors. We estimated their probability distribution through inverse modeling following the Generalized Likelihood Uncertainty Estimation (GLUE) methodology (Beven and Binley, 1992). The underlying rationale is that models are fraught with uncertainties, hence a "true" parameter set that provides an "optimal" fit to the observed data does not exist. Instead, different parameter sets can produce equivalent and equally acceptable predictions, leading to *equifinality*. The likelihood of a parameter set being an adequate system simulator was assessed and used to provide an estimate of the associated uncertainty. The estimation of the uncertainty associated with the ROS adjustment factors using GLUE required the following steps:

i) A large number of fire spread simulations with randomly assigned parameter sets;
ii) The estimation of the likelihood of each parameter set;
iii) The use of the likelihood as weights to estimate uncertainty;
iv) The update of the likelihood weights using new data.

Steps i), ii) and iii) are described in the current section, while step iv) is described in Section 2.4.

The GLUE methodology requires an appropriate definition of the prior parameter distributions. In the current work, a *parameter set* is a vector with ROS adjustment factor values for each NFFL fuel model. Considering the lack of a priori information regarding the distributions of the ROS adjustment factors, a wide parameter range was defined (0.33 to 3) and Uniform distributions were used. The parameter range corresponds to a 3 fold decrease and increase in the estimated ROS, respectively. For each case study, only the fuel models with at least 2.5% of areal coverage and summing up at least 95% of the total simulation area were considered as representative. We randomly assigned parameter values to the most representative fuel models and then performed one fire spread simulation per parameter set, for a total of 500 simulations. Parameter sets were exactly the same for all case studies.

GLUE requires that an appropriate likelihood measure is defined and calculated for each parameter set. The term *likelihood* is used in a general sense, as the possibility that a given parameter set leads to an agreement between model predictions and satellite active fires. The likelihood was formally defined as:

$$L_{i,j} = \left(\frac{1}{SpD_{i,j}}\right)^2 \quad (1)$$

where $L_{i,j}$ is the likelihood and the $SpD_{i,j}$ is the simulation-satellite spatial discrepancy of the *i-th* parameter set for the *j-th* case study (see Section 2.2). A large spatial discrepancy means that a given parameter set has a low (or even null) likelihood of being a system simulator. The inverse relationship. All $SpD_{i,j}$ below 0.5 km were truncated to avoid numerical problems (i.e. division by zero) and pronounced extremes in the likelihood function.

The likelihoods were rescaled for each case study so that the sum of all values equaled 1, yielding the probability density function of the parameter sets. The uncertainty associated with the ROS adjustment factors was estimated by using the previously calculated likelihood values to weight the correspondent simulation. A higher likelihood was translated into a larger weight of a given parameter set and its correspondent simulation, and vice versa. The weights were used to quantify the impact of uncertainty in the model outputs, i.e. predictive uncertainty, explained in detail in Section 2.3.3.

2.3.3. Predictive uncertainty

The impact of the uncertainty associated with input variables and parameters on the fire spread predictions was assessed by calculating the spatial discrepancy ratio and the burn probability. The former provides information regarding the impact of uncertainty on simulation accuracy and the latter on the estimated fire growth spatial patterns. The spatial discrepancy ratio was defined as (Benali et al., 2016a):

$$SpD_{ratio_{i,j}}(\%) = \frac{SpD_{i,j} - SpD_{REF_j}}{SpD_{REF_j}} \times 100 \quad (2)$$

where $SpD_{ratioi,j}$ is the spatial discrepancy ratio of the *i-th* parameter set for the *j-th* case study and SpD_{REFj} is the spatial discrepancy for the *reference* simulation for the *j-th* case study. A positive ratio means that propagating uncertainty leads to a larger satellite-simulated discrepancy when compared with the *reference* simulation, thus to less accurate fire spread predictions. The likelihoods ($L_{i,j}$) were used to weight each $SpD_{ratioi,j}$, yielding a distribution of values for each *j-th* case study.

Some authors have proposed to integrate uncertainty into fire spread predictions using probabilistic approaches (Cruz, 2010; Finney et al., 2011; Pinto et al., 2016). Instead of a deterministic estimation of fire spread, the probability of a given pixel burning (hereafter, *burn probability*) was estimated by performing multiple simulations integrating uncertainty. We estimated the burn probability by using the likelihoods ($L_{i,j}$) to weight the corresponding fire growth simulation. The latter was reclassified to 1 and 0, i.e. burned and unburned, for the corresponding simulation period. Burn probability maps were reclassified into six discrete probability classes based on Pollack (2005; see S5 Table 1). Additionally, we estimated the burn probability resulting from each main input variable uncertainty and compared with that resulting from the integration of the ROS adjustment factors uncertainty, by calculating the absolute burn probability difference between both. For the input variable uncertainty, each simulation had the same weight.

2.4. The impact of new data on predictive uncertainty and accuracy

We investigated how integrating new data regarding the likelihood of the parameter sets influenced the predictive uncertainty and the accuracy of fire spread predictions. Using the GLUE methodology and Bayes' theorem, the likelihood of the parameter sets can be updated (i.e posterior likelihood) combining prior with new likelihood estimates (Beven and Binley, 1992):

$$L_p(\Theta|y) = L_y(\Theta|y)L_o(\Theta) \quad (3)$$

where $L_o(\Theta)$ is the prior likelihood distribution, $L_p(\Theta|y)$ is the posterior likelihood distribution, and $L_y(\Theta|y)$ is the calculated likelihood distribution of the parameter sets given the set of new observations (y). For example, if the $L_o(\Theta)$ and $L_y(\Theta|y)$were the likelihood distributions of the previous and posterior wildfire events, respectively, the $L_p(\Theta|y)$ would be the likelihood distribution obtained from updating the previous likelihood with the information gathered for the posterior wildfire. We used two distinct approaches that mainly differed on the composition of the 'new data' used to update the prior likelihood values.

For the first approach, the posterior likelihoods of a given case study were estimated by combining the likelihoods of all the remaining case studies. This allowed us to evaluate the level of applicability of the parameter sets calibrated for a specific case study when applied to other case studies, hereafter referred to as the *leave-one-out likelihood* approach. In the second approach, the posterior likelihoods were estimated by considering the information obtained from wildfires that had occurred previously. The case studies were ordered based on their occurrence date and the posterior likelihoods of the parameter sets for a given case study were estimated by combining the likelihoods of all past case studies, hereafter referred to as the *iterative likelihood* approach.

To evaluate the degree of improvement in the predictions and the uncertainty reduction caused by integrating additional data, we analyzed the *SpD* temporal distribution of: i) the *reference* simulation; ii) the simulations using the *iterative likelihood* considering all the previous case studies; and iii) only the first case study (hereafter *initial likelihood*). This analysis was only performed for the most recent case study (COV).

We also compared the impact of the uncertainty arising from the major input variables and the ROS adjustment factors on the prediction accuracy. This was done by comparing the SpD_{ratio} distribution derived from propagating uncertainty in the major input variables and the ROS adjustment factors, for each case study independently. For the ROS adjustment factors we used the *leave-one-out likelihood* approach. The analysis was done for all the case studies.

3. Results

3.1. Impact of ROS adjustment factor uncertainty on prediction accuracy

Applying the ROS adjustment factors using the weights given by the *leave-one-out likelihood* approach leads to a general improvement in prediction accuracy (Fig. 1). This is shown by the consistent decrease in SpD_{ratio}, i.e. a decrease in spatial discrepancy when compared with the reference simulations that had no adjustment. The median SpD_{ratio} is below −25% for all case studies, with some fires presenting substantial declines (e.g. CBR2 and LL). Additionally, the interquartile range remains below 0%, showing a consistent decrease in the satellite-simulation discrepancy. This consistent improvement in prediction accuracy is minor for some case studies, such as CBR1, MCQ1 and MCQ3, where the SpD_{ratio} does not drop below −50%, but is substantial in other case studies, such as CBR2 and LL (also seen in Fig. 1).

The update of the posterior likelihoods based on the information collected for past wildfires (i.e. the *iterative likelihood* approach) leads to an overall improvement of prediction accuracy (Fig. 2). Once again, the median SpD_{ratio} is below −25% for all case studies and the interquartile range was always below 0%. The consistent decrease in the satellite-simulation discrepancy is minor in some case studies, such as CBR1, MCQ1 and MCQ3, but is substantial for others, such as the more recent case studies, LL and COV, which burned in 2004 and 2005, respectively.

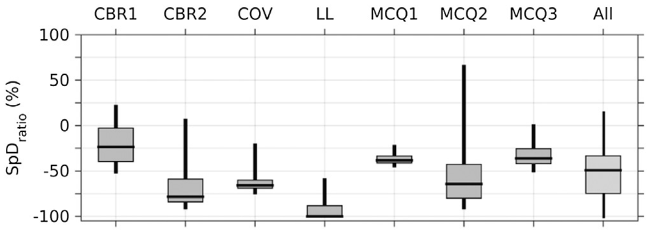

Fig. 1. Distribution of SpD_{ratio} for the case studies using the ROS adjustment factors tuned for all the remaining case studies (box and whisker plots). For each case study, the gray box represents the interquartile range, the thick horizontal line the median, and the vertical thick lines the 5th and 95th percentiles of the $SpD_{ratio.}$ Each distribution comprises the median SpD_{ratio} weighted by the leave-one-out posterior likelihoods 'All' encompasses all case studies.

The distribution of the *SpD* along elapsed time for the most recent case study (COV) shows a pronounced decrease in the *SpD* from the *reference* simulation to the *initial likelihood* simulations, but a hardly noticeable decrease from the latter to the *posterior likelihood* simulations (Fig. 3). The median *SpD* is ca. 1 km up to about 35 h of elapsed time for all simulations, and afterwards the median *SpD* increases pronouncedly for the *reference* simulation (over 6 km) accompanied by a minor increase in the *initial* and *posterior likelihood* simulations (ca. 2.5 km). The variability of the *SpD* (represented by the 90% interval) decreases when using data from new case studies, i.e. from *initial* to *posterior* likelihood simulations, suggesting that prediction uncertainty decreases with additional data.

3.2. Relation with the major input variables

The uncertainty in the major input variables and in the ROS adjustment factors has widely variable and heterogeneous impacts on prediction accuracy depending on the case study (Fig. 4). The most obvious distinction is related with the magnitude of the impact of uncertainty on prediction accuracy, represented by the variability of the SpD_{ratio} 90% interval. The impact is very small for CBR1, MCQ1 and MCQ3, contrasting with the remaining case studies. These three case studies are discussed separately below. For the remaining, CBR2 and LL correspond to elongated-shape wildfires, for which the uncertainty in wind speed and direction has a large impact on the SpD_{ratio}, often increasing the value of SpD_{ratio} although with large variability among all runs. The COV and MCQ2 wildfires have complex burned area perimeters and uncertainty in fuel model assignment leads to a widely variable SpD_{ratio} response, with significant prediction accuracy improvement and decrease, respectively. Considering the latter four case studies, the uncertainty in ignition location has a relevant impact on SpD_{ratio} for the case studies with multiple (and distinct) ignition areas, such as LL and MCQ2 (see Sá et al., 2017 for details).

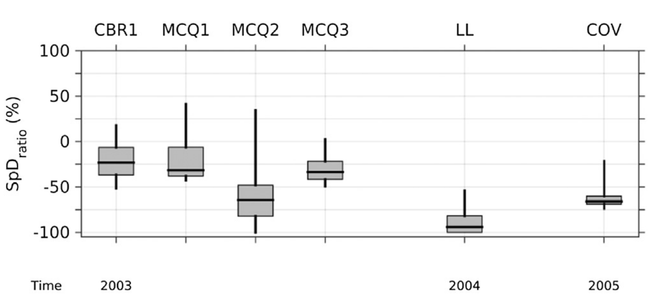

Fig. 2. Distribution of the SpD_{ratio} for the case studies using the ROS adjustment factors tuned for the case studies that occurred previously. For each case study, the gray box represents the interquartile range, the thick horizontal line the median, and the vertical thick lines the 5th and 95th percentiles of the SpD_{ratio}. Each distribution comprises the median SpD_{ratio} weighted by the iterative posterior likelihoods.

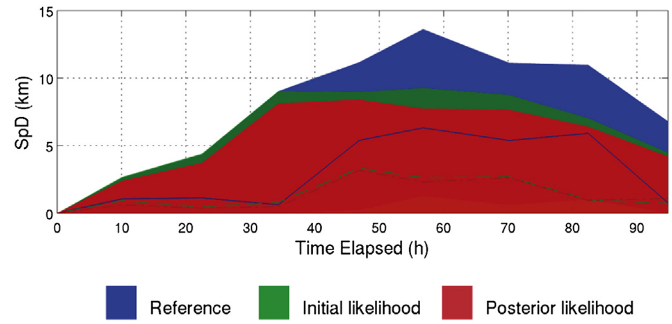

Fig. 3. Temporal distribution of the *SpD* for the COV case study, considering the reference simulation (blue), the initial (green) and the posterior likelihood (red) simulations. The areas show the 90% uncertainty limits and the lines refer to the median values over elapsed simulation time. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Despite all the above mentioned patterns, reducing the uncertainty in the ROS adjustment factors leads to an overall decrease in the SpD_{ratio} that is consistently larger than the one resulting from propagating the uncertainty in any of the major input variables.

3.3. Implications for fire management

The *reference* simulations show a consistent underestimation of fire spread when compared with the final mapped burned area perimeter (Fig. 5), as stated by Benali et al. (2016a) and Sá et al. (2017). Applying the *leave-one-out likelihoods* to calculate the burn probability maps leads to a decrease in fire spread underestimation. The area deemed as "probable" is always larger than the reference simulation, and the one deemed as "very probable" is still larger, except for the CBR1 case study. The CBR1, MCQ1 and MCQ3 have considerable parts of their burned areas with "null probability" class of fire spread. For the remaining four case studies, the burned areas are entirely or almost entirely covered with "medium probability" to "very probable" classes (Fig. 5).

Integrating the ROS adjustment factor uncertainty consistently increases the probability of burning inside the burned area perimeter, when compared with the integration of both fuel model assignment and wind speed uncertainty (Fig. 6). However, it also largely increases the simulated burn probability outside the mapped fire perimeter. For some case studies, the median increase in non-burned areas is larger than the median increase in burned areas (e.g. COV; CBR2), while for other case studies it is not (e.g. MCQ1).

4. Discussion

4.1. Understanding the role of the ROS adjustment factors

Our results show that the accuracy of fire spread predictions can be improved by integrating information from past large wildfires. Furthermore, the most likely parameter sets are applicable to multiple case studies and improve the corresponding fire spread predictions. Improving the accuracy of fire spread simulations can significantly increase their reliability, potentially contributing to support critical fire management decisions. This is particularly relevant, and can be a cost-effective alternative in a resource-limited context, where improving the quality of the input variables and/or modeling systems can be unfeasible in the short-term.

The impact of uncertainty of input variables on the prediction accuracy varies markedly between case studies. For example, counter intuitively, for most case studies integrating uncertainty in wind data barely contributes towards improving simulation results. For some case studies, the impact of data uncertainty on improving prediction accuracy is small, suggesting that improvements on input data quality would not

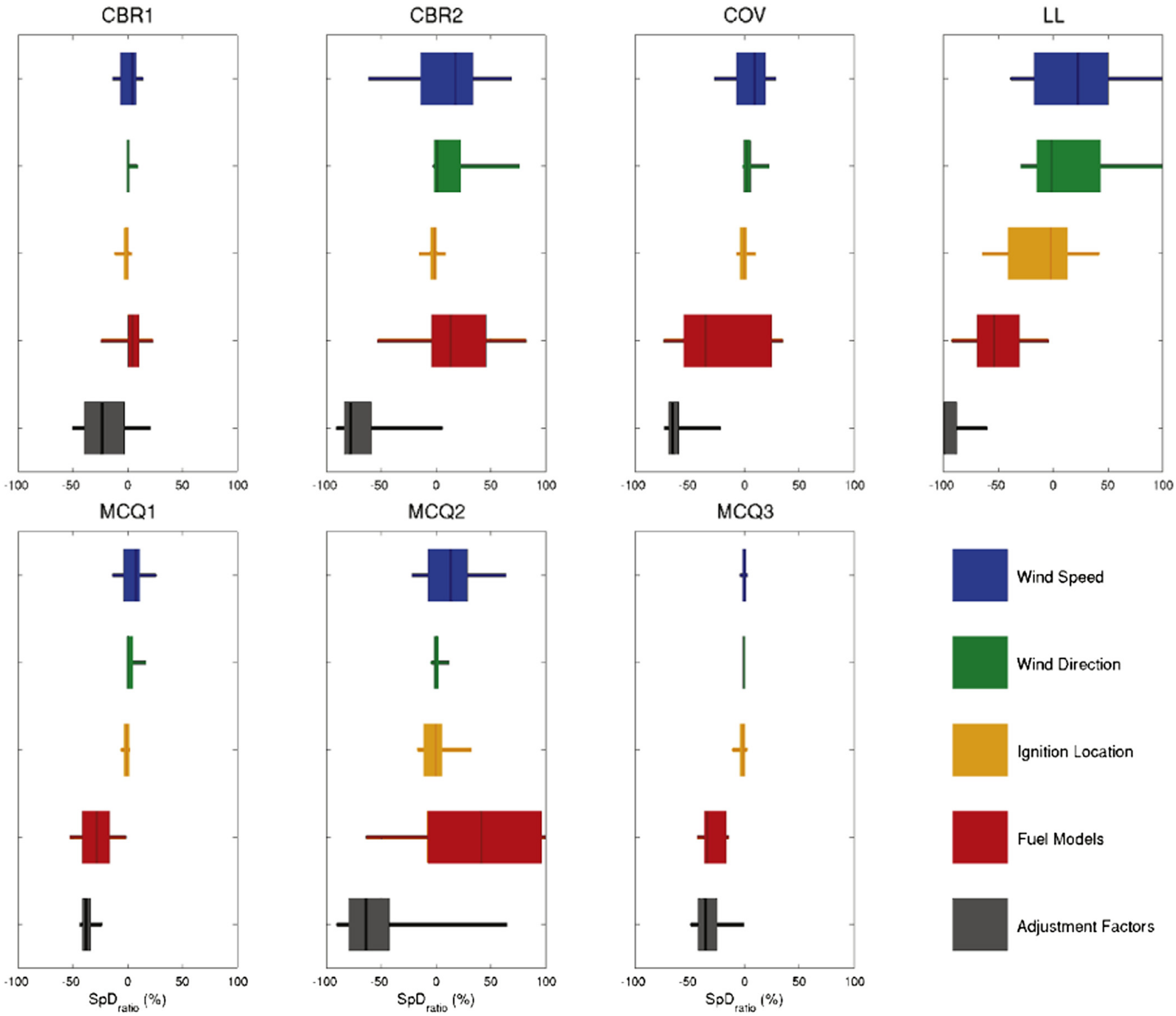

Fig. 4. The impact of the uncertainty in the major input variables and the ROS adjustment factors on the SpD_{ratio}, for each case study individually.

be effective (e.g. MCQ1, 2 and 3). Regardless, the ROS adjustment factors uncertainty strongly counterbalances the negative impacts of input variable uncertainty on prediction accuracy. This clearly shows that, without additional information or significant improvements on the quality of the major input variables, the negative impacts of data uncertainty can be compensated and 'swept under the rug', leading to more reliable fire spread predictions.

Although the ROS adjustment factors are used only to tune the estimated ROS for each individual fuel model, these parameters can affect the simulated fire patterns considerably. Tuning such parameters compensates for prediction errors, not only associated with the incorrect parameterization and/or assignment of fuel models, but also with the remaining input variables. In practice, these parameters also counterbalance, at least partially, the uncertainties resulting for example from model applicability, knowledge limitations, model structure and natural variability (Albini, 1976; Alexander and Cruz, 2013b; Cruz, 2010). Unfortunately, in this context, the most likely parameter sets cannot be used to identify fuel models needing improvement. In fact, the large variability and strong compensation between the most likely parameters are strong indicators of the existence of multiple acceptable system simulators, i.e. equifinality.

The use of likelihood weights to describe the uncertainty in the ROS adjustment factors increased the estimated burn probability for all case studies. To compensate for the underestimation of fire spread in the *reference* simulations (Benali et al., 2016a; Sá et al., 2017), the most likely parameter sets increased the estimated ROS (i.e. adjustment factors above one, not shown). Other studies have documented the underprediction of fire spread rates (Cruz and Alexander, 2013) and specifically using FARSITE (Arca et al., 2007). As a consequence, the estimated burn probability increased both for burned and non-burned areas, and for some cases, it was larger in the latter. While we acknowledge that increasing the probability of non-burned areas can be considered a downside of the methodology and can have important implications for fire management, it must be considered that these results were obtained without simulating fire suppression efforts. Moreover, because of its potential consequences, it is fire spread underestimation that represents a larger concern in an operational context (Cheney, 1981).

For the CBR1, MCQ1 and MCQ3 case studies, the uncertainty in both input variables and ROS adjustment factors had a smaller impact on prediction accuracy when compared with the remaining cases. These case studies had considerable parts of their burned areas covered by "null

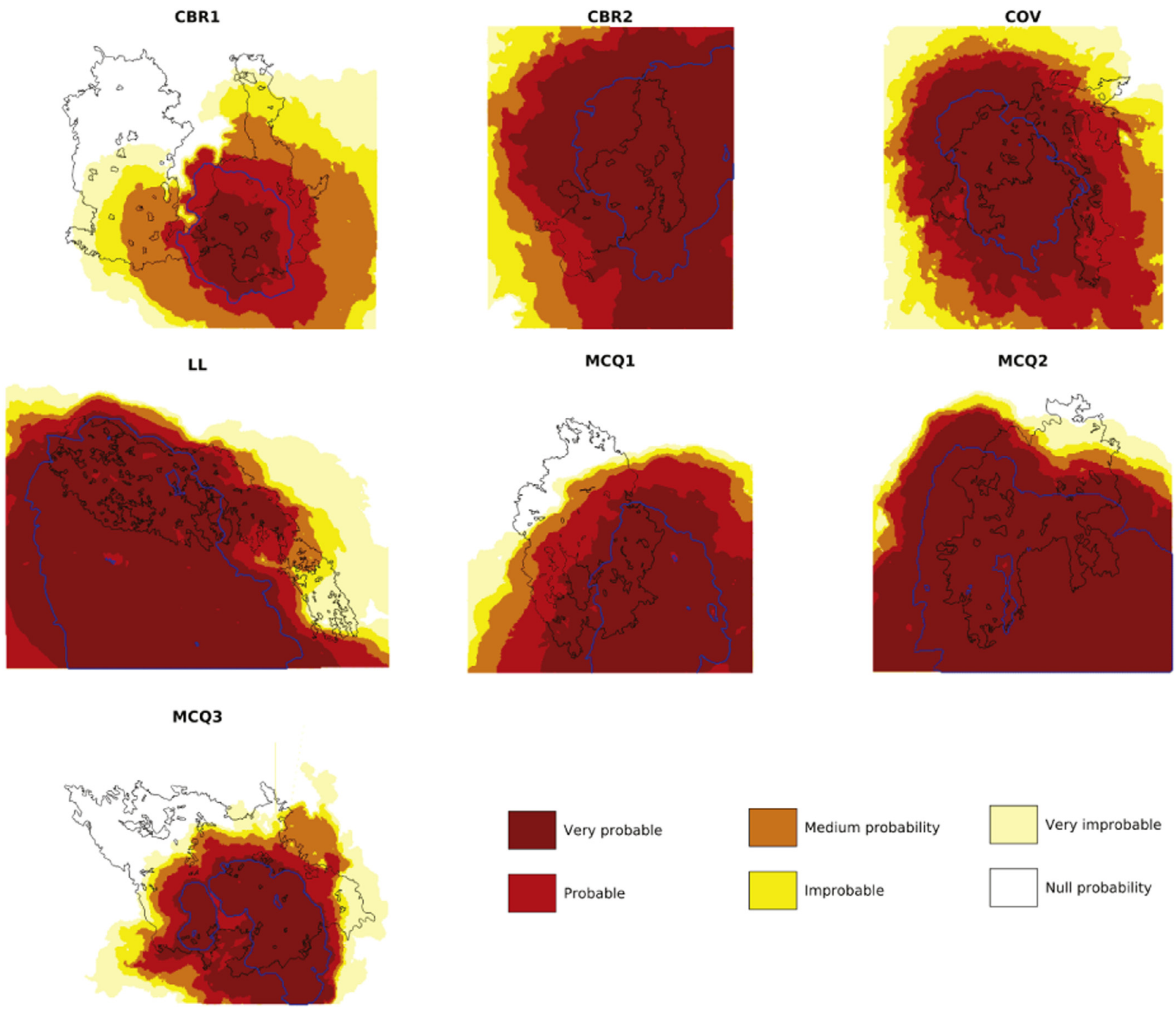

Fig. 5. Burn probability maps based on leave-one-out likelihood. The observed burned area perimeter is mapped in black line and the burned area perimeter resulting from the reference simulation (i.e. no adjustment) is mapped in blue line. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

probability" estimates, shown both by the burned area perimeter and satellite active fire data. These results suggest model structural errors and/or epistemic errors, superimposing the uncertainty in input variables and ROS adjustment factors. For instance, spotting was not simulated and most likely occurred in some of the above mentioned case studies, since it is a common feature in Portuguese large wildfires (http://www.fire.uni-freiburg.de/iffn/iffn_34/03-IFFN-34-Portugal-Country-Report-2.pdf). According to the Portuguese Rural Fire Database, the CBR1 wildfire had multiple ignitions dispersed over space and time, which were not simulated (http://www.icnf.pt/portal/florestas/dfci/inc/estat-sgif). The MCQ1 wildfire had a strong shift in the prevailing winds, from Southeast to North, which transformed the southern flank into a large burning fire front. After careful inspection, these complex patterns were not correctly reproduced by the input wind data, possibly due to epistemic errors. Although the estimated likelihoods integrate several sources of error and a great deal of uncertainty is encompassed in the ROS adjustment factors, it should not be expected to compensate strong limitations of the modeling system. Whether the low impact on the variability of prediction accuracy is indicative of strong model structural errors requires further investigation. Nevertheless, identifying and understanding why models fail are crucial steps towards their improvement (Beven and Binley, 2014).

4.2. Limitations

A thorough investigation of the factors behind the inability to accurately predict the fire spread of the historical case studies is beyond the scope of the work. The impact of input data uncertainties on the accuracy of fire spread predictions has been addressed in a preceding work (Benali et al., 2016a). As mentioned, the fact that spotting fires were not simulated may be one of the major causes behind the fact that some case studies had considerable parts of their burned area without any estimated fire spread. Nevertheless, although we recognize that data quality and model settings need to be improved, the results clearly show a relative improvement in the prediction accuracy by calibrating the ROS adjustment factors. On the other hand, it cannot be expected that parametric uncertainty can encompass all the uncertainties resulting from inadequate or an incomplete model structure, as clearly mentioned by Beven and Binley (1992).

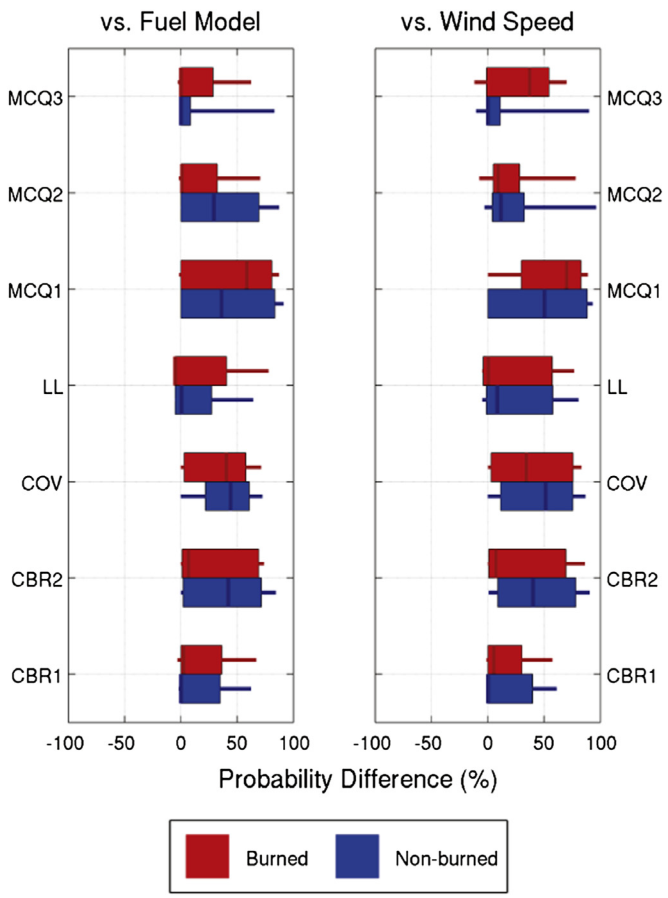

Fig. 6. Difference between the burn probability accounting for the uncertainty in ROS adjustment factors versus the burn probability accounting for the fuel model assignment (left) and the wind speed uncertainty (right). The distribution of the differences is calculated inside (red) and outside (blue) the burned area perimeter. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

We acknowledge that satellite active fire data also have errors and only provide a snapshot of the observed fire spread. Previous studies thoroughly discussed the role and limitations of satellite data to monitor fire progression and evaluate fire spread simulations (Coen and Schroeder, 2013; Hawbaker et al., 2008; Sá et al., 2017). Nevertheless, we would like to reinforce that satellite active fire data have a large potential to provide important insights on the fire growth patterns of large and long-lasting wildfires, thus providing a robust data source for evaluating and consequently improving fire spread simulations.

Other limitations were related with the calibration of the ROS adjustment factors. The spatial variability and the accuracy of the fuel maps inevitably influence the estimated likelihoods for each parameters set. The methodology has limited applicability for wildfires that had a significant contribution of crown and/or spot fires, since the ROS adjustment factors refer only to surface rate of spread. However, the GLUE methodology can be extended to other parameters that control the behavior of spotting and/or crown fires.

Finally, we acknowledge that the formal definition of an appropriate likelihood function, which is essential to estimate predictive uncertainty under the GLUE methodology, is inherently subjective as stressed by Beven and Binley (1992). The initial parameter distribution is also subjective, although the Uniform distribution has been recognized as the most appropriate in situations with lack of a priori knowledge about the parameter distributions and, the priors become increasingly less important with the addition of new data (Beven and Binley, 2014). The definition of the likelihood function should be carefully evaluated by the modeler, by assessing intermediate results, to assess the suitability of the measure for the desired purpose. We have addressed these issues, but acknowledge that other likelihood function could be equally or even more adequate than the one proposed.

4.3. Future applications

Using information from previous wildfires and updating the correspondent likelihoods improved prediction accuracy and reduced *SpD* variability for the posterior wildfires. This important result suggests that integrating additional fire data can reduce predictive uncertainty, as stated by Beven and Binley (1992), making the information provided to fire managers more reliable. It is expected that with additional case studies the posterior likelihoods greater than zero will become increasingly well constrained. This issue requires further analysis by integrating additional wildfires and using more sophisticated measures to assess the impact on predictive uncertainty (Beven and Binley, 2014).

The modifications to compute the *SpD* index improved its suitability to evaluate the quality of fire spread predictions, focusing on the description of the broad spatio-temporal patterns of fire spread and on the flaming front. The errors and limitations associated with satellite active fire data have been thoroughly described in previous studies (Benali et al., 2016a, b; Hawbaker et al., 2008). We acknowledge that the satellite active fire data are imperfect, and it should not be expected fire spread predictions to be better than the former. These epistemic errors will be difficult to separate but should be, at least partially, contained in the estimation prediction bounds. Future improvements in *SpD* calculation, including the use of other satellite or airborne thermal data, will certainly improve the determination of the most likely parameter sets. In this context, the Visible Infrared Imaging Radiometer Suite (VIIRS), with improved spatial resolution, has a large potential to provide relevant high quality information regarding the spread patterns of wildfires (Schroeder et al., 2014).

The application of other fire spread evaluation measures (e.g. Cui and Perera, 2010; Duff et al., 2013; Filippi et al., 2014; Fujioka, 2002) should be feasible as long as they i) provide a measure of goodness-of-fit in a general sense, ii) are monotonic and continuous, and iii) the likelihood function is carefully adapted (Beven and Binley, 1992). A complete discussion regarding the GLUE methodology and the importance of correctly defining the likelihood function is provided by Beven and Binley (2014).

The posterior likelihood distribution calculated for previous case studies (*iterative likelihood* approach) can be used to project the predictive uncertainty for new wildfires and has great potential to be applied to future wildfires under an operational context. Additionally, the approach presented can provide complementary information that can be useful for fire management, such as error bounds and probabilistic outcomes (Cruz, 2010). The GLUE methodology has the flexibility to be applied to new wildfires using different sets of input variables and/or model settings. These different settings should be mirrored in the posterior likelihoods. Nevertheless, further work is still needed by applying the methodology to a larger number of case studies that cover a wide range of wildfire characteristics regarding, among others: i) size, including smaller, more frequent and lower intensity wildfires; ii) growth rate, including slow and fast burning wildfires; and iii) type, including surface and crown fires. Additionally, further work should integrate multiple model structures towards a more complete definition of fire spread uncertainty.

5. Conclusions

Improving fire spread predictions for management purposes, by using higher quality input data or enhanced models, can be expensive, unfeasible and even impossible under the current scientific paradigm. Within this context, we showed that fire spread predictions can be improved by appropriately defining the distribution of the 'tunable' parameters contained in the fire spread modeling system. Of special importance, we showed that fire spread predictions can be continuously improved by 'learning' from past wildfires. The uncertainty contained in the major input variables (wind speed and direction, ignition location and fuel models) can be 'swept under the rug' to a certain extent, and their negative impacts can be counterbalanced through the use of more appropriate parameter sets.

The framework proposed can be applied to future wildfires and the posterior likelihoods can be continuously updated by including new observations. Arguably, it has a large potential to improve future fire spread predictions, improving their reliability and usefulness to support fire management and decision making processes, thus potentially reducing the negative impacts of wildfires.

Acknowledgements

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Appendix A. Supplementary data

Supplementary data to this article can be found online at http://dx.doi.org/10.1016/j.scitotenv.2017.03.106.

References

Ager, A.A., Vaillant, N.M., Finney, M.A., 2010. A comparison of landscape fuel treatment strategies to mitigate wildland fire risk in the urban interface and preserve old forest structure. For. Ecol. Manag. 259, 1556–1570.
Albini, F.A., 1976. Estimating wildfire behavior and effects. USDA For. Serv., Intermt. For. Range Exp. Stn. (Ogden, UT. Gen. Tech. Rep. INT-30. 92 p).
Alexander, M.E., Cruz, M.G., 2013a. Are the applications of wildland fire behaviour models getting ahead of their evaluation again? Environ. Model. Softw. 41, 65–71.
Alexander, M.E., Cruz, M.G., 2013b. Limitations on the accuracy of model predictions of wildland fire behaviour: a state-of-the-knowledge overview. For. Chron. 89, 372–383.
Anderson, H.E., 1982. Aids to determining fuel models for estimating fire behavior. The Bark Beetles, Fuels, and Fire Bibliography. 143.
Anderson, K., Reuter, G., Flannigan, M.D., 2007. Fire-growth modelling using meteorological data with random and systematic perturbations. Int. J. Wildland Fire 16, 174.
Anderson, K.R., Englefield, P., Little, J.M., Reuter, G., 2009. An approach to operational forest fire growth predictions for Canada. Int. J. Wildland Fire 18, 893.
Arca, B., Duce, P., Laconi, M., Pellizzaro, G., Salis, M., Spano, D., 2007. Evaluation of FARSITE simulator in Mediterranean maquis. Int. J. Wildland Fire 16, 563.
Ascoli, D., Vacchiano, G., Motta, R., Bovio, G., 2015. Building Rothermel fire behaviour fuel models by genetic algorithm optimisation. Int. J. Wildland Fire 24, 317–328.
Bachmann, A., Allgöwer, B., 2002. Uncertainty propagation in wildland fire behaviour modelling. Int. J. Geogr. Inf. Sci. 16, 115–127.
Benali, A., Ervilha, A.R., Sá, A.C.L., Fernandes, P.M., Pinto, R.M.S., Trigo, R.M., Pereira, J.M.C., 2016a. Deciphering the impact of uncertainty on the accuracy of large wildfire spread simulations. Sci. Total Environ. 569, 73–85.
Benali, A., Russo, A., Sá, A.C., Pinto, R., Price, O., Koutsias, N., Pereira, J., 2016b. Determining fire dates and locating ignition points with satellite data. Remote Sens. 8, 326.
Beven, K., Binley, A., 1992. The future of distributed models: model calibration and uncertainty prediction. Hydrol. Process. 6, 279–298.
Beven, K., Binley, A., 2014. GLUE: 20 years on. Hydrol. Process. 28, 5897–5918.
Bossard, M., Feranec, J., Otahel, J., 2000. CORINE land cover technical guide: Addendum 2000. European Environment Agency Copenhagen.
Cai, L., He, H.S., Wu, Z., Lewis, B.L., Liang, Y., 2014. Development of standard fuel models in boreal forests of northeast China through calibration and validation. PLoS One 9, e94043.
Calkin, D.E., Thompson, M.P., Finney, M.A., Hyde, K.D., 2011. A real-time risk assessment tool supporting wildland fire decisionmaking. J. For. 274–280.
Cheney, N., 1981. Fire behaviour. Fire and the Australian biota 151–175.
Coen, J.L., Schroeder, W., 2013. Use of spatially refined satellite remote sensing fire detection data to initialize and evaluate coupled weather-wildfire growth model simulations. Geophys. Res. Lett. 40, 5536–5541.
Cruz, M.G., 2010. Monte Carlo-based ensemble method for prediction of grassland fire spread. Int. J. Wildland Fire 19, 521.
Cruz, M.G., Alexander, M.E., 2010. Assessing crown fire potential in coniferous forests of western North America: a critique of current approaches and recent simulation studies. Int. J. Wildland Fire 19, 377.
Cruz, M.G., Alexander, M.E., 2013. Uncertainty associated with model predictions of surface and crown fire rates of spread. Environ. Model. Softw. 47, 16–28.
Cruz, M.G., Fernandes, P.M., 2008. Development of fuel models for fire behaviour prediction in maritime pine (*Pinus pinaster* Ait.) stands. Int. J. Wildland Fire 17, 194–204.
Cui, W., Perera, A., 2010. Quantifying spatio-temporal errors in forest fire spread modelling explicitly. J. Environ. Inform. 16, 19–26.
DiMiceli, C., Carroll, M., Sohlberg, R., Huang, C., Hansen, M., Townshend, J., 2011. Annual Global Automated MODIS Vegetation Continuous Fields (MOD44B) at 250 m Spatial Resolution for Data Years Beginning Day 65, 2000–2010, Collection 5 Percent Tree Cover. University of Maryland, College Park.
Duff, T.J., Chong, D.M., Tolhurst, K.G., 2013. Quantifying spatio-temporal differences between fire shapes: estimating fire travel paths for the improvement of dynamic spread models. Environ. Model. Softw. 46, 33–43.
Duguy, B., Alloza, J.A., Röder, A., Vallejo, R., Pastor, F., 2007. Modelling the effects of landscape fuel treatments on fire growth and behaviour in a Mediterranean landscape (eastern Spain). Int. J. Wildland Fire 16, 619.
Ervilha, A., Pereira, J., Pereira, J., 2017. On the parametric uncertainty quantification of the Rothermel's rate of spread model. Appl. Math. Model. 41, 37–53.
Farr, T.G., Rosen, P.A., Caro, E., Crippen, R., Duren, R., Hensley, S., Kobrick, M., Paller, M., Rodriguez, E., Roth, L., 2007. The shuttle radar topography mission. Rev. Geophys. 45.
Filippi, J.-B., Mallet, V., Nader, B., 2014. Representation and evaluation of wildfire propagation simulations. Int. J. Wildland Fire 23, 46–57.
Finney, M.A., 2004. FARSITE: Fire Area Simulator—Model Development and Evaluation. USDA Research Paper RMRS-RP-4.
Finney, M.A., Grenfell, I.C., McHugh, C.W., Seli, R.C., Trethewey, D., Stratton, R.D., Brittain, S., 2011. A method for ensemble wildland fire simulation. Environ. Model. Assess. 16, 153–167.
Fujioka, F.M., 2002. A new method for the analysis of fire spread modeling errors. Int. J. Wildland Fire 11, 193–203.
Giglio, L., Descloitres, J., Justice, C.O., Kaufman, Y.J., 2003. An enhanced contextual fire detection algorithm for MODIS. Remote Sens. Environ. 87, 273–282.
Hawbaker, T.J., Radeloff, V.C., Syphard, A.D., Zhu, Z., Stewart, Z.I., 2008. Detection rates of the MODIS active fire product in the United States. Remote Sens. Environ. 112, 2656–2664.
Hilton, J.E., Miller, C., Sullivan, A.L., Rucinski, C., 2015. Effects of spatial and temporal variation in environmental conditions on simulation of wildfire spread. Environ. Model. Softw. 67, 118–127.
Keane, R.E., Reeves, M., 2012. Use of expert knowledge to develop fuel maps for wildland fire management. In: Perera, C.A.D.A.H., Johnson, C.J. (Eds.), Expert Knowledge and its Application in Landscape Ecology. Springer Science and Business Media, LLC, New York, USA, pp. 211–228.
Kochanski, A.K., Jenkins, M.A., Mandel, J., Beezley, J.D., Krueger, S.K., 2013. Real time simulation of 2007 Santa Ana fires. For. Ecol. Manag. 294, 136–149.
Liu, Y., Jimenez, E., Hussaini, M.Y., Okten, G., Goodrick, S., 2015. Parametric uncertainty quantification in the Rothermel model with randomised quasi-Monte Carlo methods. Int. J. Wildland Fire 24, 307.
Lorente-Plazas, R., Montávez, J., Jerez, S., Gómez-Navarro, J., Jiménez-Guerrero, P., Jiménez, P., 2015. A 49 year hindcast of surface winds over the Iberian Peninsula. Int. J. Climatol. 35, 3007–3023.
Mandel, J., Kochanski, A.K., Vejmelka, M., Beezley, J.D., 2014. Data Assimilation of Satellite Fire Detection in Coupled Atmosphere-Fire Simulation by WRF-SFIRE (arXiv preprint arXiv:1410.6948).
Oliveira, S.L.J., Pereira, J.M.C., Carreiras, J.M.B., 2012. Fire frequency analysis in Portugal (1975–2005), using Landsat-based burnt area maps. Int. J. Wildland Fire 21, 48.
Papadopoulos, G.D., Pavlidou, F.-N., 2011. A comparative review on wildfire simulators. IEEE Syst. J. 5, 233–243.
Parks, S.A., 2014. Mapping day-of-burning with coarse-resolution satellite fire-detection data. Int. J. Wildland Fire 23, 215.
Pinto, R.M., Benali, A., Sá, A.C., Fernandes, P.M., Soares, P.M., Cardoso, R.M., Trigo, R.M., Pereira, J.M., 2016. Probabilistic fire spread forecast as a management tool in an operational setting. SpringerPlus 5, 1205.
Pollack, H.N., 2005. Uncertain Science… Uncertain World. Cambridge University Press.
Refsgaard, J.C., van der Sluijs, J.P., Højberg, A.L., Vanrolleghem, P.A., 2007. Uncertainty in the environmental modelling process – a framework and guidance. Environ. Model. Softw. 22, 1543–1556.
Rothermel, R.C., 1972. A mathematical model for predicting fire spread in wildland fuels. USDA For. Serv. Res. Pap. (INT-115).
Rothermel, R.C., 1991. Predicting behavior and size of crown fires in the northern Rocky Mountains. USDA For. Serv. Res. Pap. (INT-438).
Rothermel, R.C., Rinehart, G.C., 1983. Field Procedures for Verification and Adjustment of Fire Behavior Predictions. US Department of Agriculture, Forest Service, Intermountain Forest and Range Experiment Station.
Sá, A.C.L., Benali, A., Fernandes, P.M., Pinto, R.M.S., Trigo, R.M., Salis, M., Russo, A., Jerez, S., Soares, P.M., Schroeder, W., Pereira, J.M.C., 2017. Evaluating fire growth simulations using satellite active fire data. Remote Sens. Environ. 190, 302–317.
Salis, M., Ager, A.A., Arca, B., Finney, M.A., Bacciu, V., Duce, P., Spano, D., 2013. Assessing exposure of human and ecological values to wildfire in Sardinia, Italy. Int. J. Wildland Fire 22, 549.
Salis, M., Arca, B., Alcasena, F., Arianoutsou, M., Bacciu, V., Duce, P., Duguy, B., Koutsias, N., Mallinis, G., Mitsopoulos, I., 2016. Predicting wildfire spread and behaviour in Mediterranean landscapes. Int. J. Wildland Fire 25, 1015–1032.
Schroeder, W., Oliva, P., Giglio, L., Csiszar, I.A., 2014. The new VIIRS 375m active fire detection data product: algorithm description and initial assessment. Remote Sens. Environ. 143, 85–96.

Scott, J.H., Burgan, R.E., 2005. Standard fire behavior fuel models: a comprehensive set for use with Rothermel's surface fire spread model. USDA For. Serv. Gen. Tech. Rep. (RMRS-GTR-153, Rocky Mountain Research Station, Fort Collins, CO., 66).
Sneeuwjagt, R.J., Peet, G.B., 1985. Forest Fire Behaviour Tables for Western Australia. WA Department Conservation & Land Management.
Sullivan, A.L., 2009a. Wildland surface fire spread modelling, 1990–2007. 1: physical and quasi-physical models. Int. J. Wildland Fire 18, 349–368.
Sullivan, A.L., 2009b. Wildland surface fire spread modelling, 1990–2007. 2: empirical and quasi-empirical models. Int. J. Wildland Fire 18, 369–386.
Sullivan, A.L., 2009c. Wildland surface fire spread modelling, 1990–2007. 3: simulation and mathematical analogue models. Int. J. Wildland Fire 18, 387–403.
Thompson, M.P., Calkin, D.E., 2011. Uncertainty and risk in wildland fire management: a review. J. Environ. Manag. 92, 1895–1909.
van Wagner, C.E., 1977. Conditions for the start and spread of crownfire. Can. J. For. Res. 7, 23–24.
Veraverbeke, S., Sedano, F., Hook, S.J., Randerson, J.T., Jin, Y., Rogers, B.M., 2014. Mapping the daily progression of large wildland fires using MODIS active fire data. Int. J. Wildland Fire 23, 655–667.
Webley, P., Riley, K., Thompson, M., Patra, A., Bursik, M., 2016. Natural Hazard Uncertainty Assessment: Modeling and Decision Support. John Wiley & Sons.

Discussion

The major findings of the present Thesis are:

v) Satellite-derived fire dates had moderate to very good agreement when compared with reported data. The spatio-temporal agreement between reported and satellite-derived ignitions showed temporal lags and distances within 12 h and 2 km, respectively. Uncertainties were generally larger than disagreements. In sum, results showed that satellite data can contribute to improve information regarding dates and ignitions of large wildfires, which can be a valuable asset to complement and correct inconsistencies in existing fire databases.

vi) Satellite thermal data captured the major spatio-temporal dynamics of the large wildfires studied. The evaluation metrics proved to be very useful in identifying areas and periods of low/high spatio-temporal agreement between simulated and observed fire growth. Overall, this approach highlighted the poor accuracy of the fire spread simulations due to a strong underprediction bias. The methodology developed can be applied to a comprehensive number of large wildfires towards a more systematic and objective evaluation of fire spread simulations.

vii) Uncertainties in input data were very large and had important impacts on fire spread predictions. In particular, uncertainties in wind speed and direction, fuel model assignment and typology, location and timing of ignitions, had a major impact on prediction accuracy. The work developed was a first and necessary step to integrate the uncertainties in these variables in future fire spread predictions, adding useful information to fire managers.

viii) Using a robust iterative algorithm for regional model calibration, fire spread predictions can be continuously improved by 'learning' from past wildfires. In fact, this parameter calibration can counterbalance the impact of the uncertainty contained in the major input variables on the accuracy of fire spread predictions. This showed that without additional information or significant improvements on the quality of the major input variables, the negative impacts of data uncertainty could be reduced leading to more reliable fire spread predictions. The proposed framework has a large potential to improve future fire spread predictions.

Overall, the work developed contributed to advance the body of knowledge regarding individual wildfires, using an innovative combination of satellite thermal data and fire spread modelling tools. It showed that it is possible to integrate knowledge from past wildfires to improve our understanding. It contributed to improve the accuracy of fire spread predictions in pursue of the long term goal, i.e. to provide fire spread predictions that are sufficiently reliable to support fire management decisions in the future. These developments contribute to provide a more solid scientific background in decision-making with the aim of reducing the dramatic impacts of wildfires.

Nevertheless, the work has several limitations. Here, the major ones are discussed and accompanied by proposals of future research needed to overcome them. Most, if not all of the issues discussed below have been included in a scientific proposal written and approved during the period of this thesis, namely the FIRE-MODSAT-II project. Therefore, these issues will be tackled and subject of investigation, at least, in the next three years.

i) Limitations of the modelling system: The poor ability of the fire spread modelling system to predict the fire spread of the historical case studies was evident. Although a thorough investigation of the factors behind this inability was beyond the scope of the work, future research will focus on better understanding them. Improving the quality of the input data will surely increase the reliability of predictions. The work developed regarding the impact of input data uncertainty shed light on where to prioritize efforts to attain such improvements. Furthermore, spotting was not simulated and most likely occurred in some of the historical case studies, since it is a common feature in large wildfires [77]. Future work will include this fire spread component. Overall, the evaluation methodology presented here will allow for better understanding and identifying why fire spread modelling tools are failing, a crucial step towards their improvement [97].

ii) Satellite-based evaluation framework: Satellite thermal data have relevant limitations. Data on fire location with a higher temporal frequency would be desirable, however, in the next few years it is not likely to be available [25]. Data with higher spatial resolution is also necessary to overcome the large limitations of coarse satellite thermal data. The Visible Infrared Imaging Radiometer Suite (VIIRS) active fire product [98], with improved spatial resolution (~375m), has a large potential to tackle some of these limitations [46] and should be used in the future to evaluate fire spread predictions. Improvements to the evaluation framework are also necessary in order to better represent the location of active fire lines, penalize overestimation of fire spread, and extend the evaluation to stochastic fire spread simulations.

iii) Historical case studies: The small set of large wildfires burning under extreme conditions is certainly a biased sample [99]. The calibration and evaluation of the fire modelling system needs to be extended to a larger set of wildfires and ensure the analysis is representative of large wildfires that occur(ed) in Portugal. These should cover a wide range of characteristics regarding: size, including smaller, more frequent and lower intensity wildfires; growth rate, including slow and fast burning wildfires; type, including surface and crown fires. It should be noted that the methods presented are easily applicable to new wildfires using different sets of input variables and/or model settings.

iv) A better understanding of fundamental mechanisms driving wildfires: The data-driven approach presented in this work can meet at least part of the needs of fire managers for more accurate fire spread predictions. However, it is very limited in providing insights on the fundamental mechanisms driving fire propagation [81,82]. This parallel line of research is crucial to improve the accuracy of predictions in the long term.

Coen and Schroeder [46] used satellite thermal data to reinitialize fire spread simulations at different time steps showing that it improved the accuracy of the predictions. Considering the obvious context, a similar analysis was also performed during the current thesis [100], however, future work is still needed to ensure that model re-initialization improves the spread predictions of large wildfires in Portugal. The use of higher resolution data from VIIRS, as well as a more correct definition of the active fire lines (mentioned previously), will certainly contribute for a more accurate data-driven model re-initialization.

Additionally, the current Thesis does not address two important components. First, it lacks a detailed analysis of the potential of satellite data to reproduce the spread patterns of large wildfires in Portugal. This should include the derivation of relevant fire spread indicators (e.g. rate of spread, fire intensity, fire growth rate, spread direction) and compare them, if possible, with other data sources. Second, it lacks the integration of both the satellite-derived evaluation component and the uncertainty quantification, to build stochastic wildfire spread simulations for specific case studies. This was partially accomplished in a parallel work for the Tavira wildfire of 2012 [101]. However, this was the result of a preliminary and exploratory approach that did not include, the final evaluation framework, the detailed uncertainty quantification, nor the regional model calibration. Nevertheless, it showed how fire spread simulations can be used to anticipate the fire location in the next hours, and provide the support for more effective fire suppression decisions. Both components highlighted here surely deserve more research in the future.

Conclusion

The current Thesis contributed to the advance of the body of knowledge regarding individual large wildfires. It combined satellite thermal data and modelling tools to: i) derive relevant information regarding individual wildfires; ii) evaluate the accuracy of fire spread simulations; iii) characterize and quantify the uncertainties in input data and their impact on fire spread predictions, and iv) improve predictions through regional model calibration. Most importantly, it identified future research steps towards a reliable operational fire spread system, which can support more effective and safer fire management decisions.

References

1. San-Miguel-Ayanz, J.; Schulte, E.; Schmuck, G.; Camia, A. The european forest fire information system in the context of environmental policies of the european union. *Forest Policy and Economics* **2013**, *29*, 19-25.
2. Trigo, R.M.; Sousa, P.M.; Pereira, M.G.; Rasilla, D.; Gouveia, C.M. Modelling wildfire activity in iberia with different atmospheric circulation weather types. *International Journal of Climatology* **2013**, *in press*.
3. San-Miguel-Ayanz, J.; Moreno, J.M.; Camia, A. Analysis of large fires in european mediterranean landscapes: Lessons learned and perspectives. *Forest Ecology and Management* **2013**, *294*, 11-22.
4. Instituto da Conservação da Natureza e das Florestas. Acessed online on August 2018: http://www2.icnf.pt/portal/florestas/dfci/inc/mapas
5. Pachauri, R.K.; Allen, M.R.; Barros, V.R.; Broome, J.; Cramer, W.; Christ, R.; Church, J.A.; Clarke, L.; Dahe, Q.; Dasgupta, P. *Climate change 2014: Synthesis report. Contribution of working groups i, ii and iii to the fifth assessment report of the intergovernmental panel on climate change*. IPCC: 2014.
6. Sousa, P.M.; Trigo, R.M.; Pereira, M.G.; Bedia, J.; Gutiérrez, J.M.J.A.; Meteorology, F. Different approaches to model future burnt area in the iberian peninsula. **2015**, *202*, 11-25.
7. Turco, M.; Llasat, M.-C.; von Hardenberg, J.; Provenzale, A. Climate change impacts on wildfires in a mediterranean environment. *Climatic Change* **2014**, *125*, 369-380.
8. Lentile, L.B.; Holden, Z.A.; Smith, A.M.S.; Falkowski, M.J.; Hudak, A.T.; Morgan, P.; Lewis, S.A.; Gessler, P.E.; Benson, N.C. Remote sensing techniques to assess active fire characteristics and post-fire effects. *International Journal of Wildland Fire* **2006**, *15*, 319.
9. French, N.H.; de Groot, W.J.; Jenkins, L.K.; Rogers, B.M.; Alvarado, E.; Amiro, B.; De Jong, B.; Goetz, S.; Hoy, E.; Hyer, E. Model comparisons for estimating carbon emissions from north american wildland fire. *Journal of Geophysical Research: Biogeosciences (2005–2012)* **2011**, *116*.
10. Parisien, M.-A.; Parks, S.A.; Miller, C.; Krawchuk, M.A.; Heathcott, M.; Moritz, M.A. Contributions of ignitions, fuels, and weather to the spatial patterns of burn probability of a boreal landscape. **2011**, *14*, 1141-1155.
11. Cary, G.J.; Flannigan, M.D.; Keane, R.E.; Bradstock, R.A.; Davies, I.D.; Lenihan, J.M.; Li, C.; Logan, K.A.; Parsons, R.A. Relative importance of fuel management, ignition management and weather for area burned: Evidence from five landscape–fire–succession models. *International Journal of Wildland Fire* **2009**, *18*, 147-156.
12. Slocum, M.G.; Beckage, B.; Platt, W.J.; Orzell, S.L.; Taylor, W. Effect of climate on wildfire size. *Ecosystems* **2010**, *13*, 828-840.
13. Thompson, J.R.; Spies, T.A. Factors associated with crown damage following recurring mixed-severity wildfires and post-fire management in southwestern oregon. *Landscape Ecology* **2010**, *25*, 775-789.
14. Lavoué, D.; Gong, S.; Stocks, B.J. Modelling emissions from canadian wildfires: A case study of the 2002 quebec fires. *International Journal of Wildland Fire* **2008**, *16*, 649-663.
15. Albini, F.A. Estimating wildfire behavior and effects. *USDA For. Serv., Intermt. For. Range Exp. Stn., Ogden, UT. Gen. Tech. Rep. INT-30. 92 p.* **1976**.
16. LaCroix, J.J.; Ryu, S.-R.; Zheng, D.; Chen, J. Simulating fire spread with landscape management scenarios. *Forest Science* **2006**, *52*, 522-529.
17. Bar Massada, A.; Syphard, A.D.; Hawbaker, T.J.; Stewart, S.I.; Radeloff, V.C. Effects of ignition location models on the burn patterns of simulated wildfires. *Environmental Modelling & Software* **2011**, *26*, 583-592.

18. Fernandes, P.M.; Pacheco, A.P.; Almeida, R.; Claro, J.J.E.J.o.F.R. The role of fire-suppression force in limiting the spread of extremely large forest fires in portugal. **2016**, *135*, 253-262.
19. Moreira, F.; Catry, F.X.; Rego, F.; Bacao, F. Size-dependent pattern of wildfire ignitions in portugal: When do ignitions turn into big fires? *Landscape Ecology* **2010**, *25*, 1405-1417.
20. Catry, F.X.; Rego, F.C.; Bação, F.L.; Moreira, F. Modeling and mapping wildfire ignition risk in portugal. *International Journal of Wildland Fire* **2009**, *18*, 921.
21. Salis, M.; Ager, A.A.; Arca, B.; Finney, M.A.; Bacciu, V.; Duce, P.; Spano, D. Assessing exposure of human and ecological values to wildfire in sardinia, italy. *International Journal of Wildland Fire* **2013**, *22*, 549.
22. Pereira, M.G.; Malamud, B.D.; Trigo, R.M.; Alves, P.I. The history and characteristics of the 1980-2005 portuguese rural fire database. *Natural Hazards and Earth System Science* **2011**, *11*, 3343-3358.
23. Ganteaume, A.; Camia, A.; Jappiot, M.; San-Miguel-Ayanz, J.; Long-Fournel, M.; Lampin, C. A review of the main driving factors of forest fire ignition over europe. *Environmental management* **2013**, *51*, 651-662.
24. Cruz, M.G.; Alexander, M.E.; Sullivan, A.L.; Gould, J.S.; Kilinc, M. Assessing improvements in models used to operationally predict wildland fire rate of spread. *Environmental Modelling & Software* **2018**, *105*, 54-63.
25. Gollner, M.; Trouve, A.; Altintas, I.; Block, J.; de Callafon, R.; Clements, C.; Cortes, A.; Ellicott, E.; Filippi, J.B.; Finney, M. *Towards data-driven operational wildfire spread modeling: A report of the nsf-funded wifire workshop*; 2015.
26. Shapiro-Miller, L.B.; Heyerdahl, E.K.; Morgan, P. Comparison of fire scars, fire atlases, and satellite data in the northwestern united states. *Canadian Journal of Forest Research* **2007**, *37*, 1933-1943.
27. Hawbaker, T.J.; Radeloff, V.C.; Syphard, A.D.; Zhu, Z.; Stewart, S.I. Detection rates of the modis active fire product in the united states. *Remote Sensing of Environment* **2008**, *112*, 2656-2664.
28. Kasischke, E.S.; Williams, D.; Barry, D. Analysis of the patterns of large fires in the boreal region of alaska. *International Journal of Wildland Fire* **2002**, *11*, 131-144.
29. Amatulli, G.; Peréz-Cabello, F.; de la Riva, J. Mapping lightning/human-caused wildfires occurrence under ignition point location uncertainty. *Ecological Modelling* **2007**, *200*, 321-333.
30. Short, K.C. A spatial database of wildfires in the united states, 1992-2011. *Earth System Science Data* **2014**, *6*, 1-27.
31. Morgan, P.; Hardy, C.C.; Swetnam, T.W.; Rollins, M.G.; Long, D.G. Mapping fire regimes across time and space: Understanding coarse and fine-scale fire patterns. *International Journal of Wildland Fire* **2001**, *10*, 329-342.
32. Bar-Massada, A.; Hawbaker, T.J.; Stewart, S.I.; Radeloff, V.C. Combining satellite-based fire observations and ground-based lightning detections to identify lightning fires across the conterminous USA. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing* **2012**, *5*, 1438-1447.
33. Duff, T.J.; Chong, D.M.; Tolhurst, K.G. Quantifying spatio-temporal differences between fire shapes: Estimating fire travel paths for the improvement of dynamic spread models. *Environmental Modelling & Software* **2013**, *46*, 33-43.
34. Parks, S.A. Mapping day-of-burning with coarse-resolution satellite fire-detection data. *International Journal of Wildland Fire* **2014**, *23*, 215.
35. Cruz, M.G.; Alexander, M.E. Uncertainty associated with model predictions of surface and crown fire rates of spread. *Environmental Modelling & Software* **2013**, *47*, 16-28.

36. Holden, Z.; Smith, A.; Morgan, P.; Rollins, M.; Gessler, P. Evaluation of novel thermally enhanced spectral indices for mapping fire perimeters and comparisons with fire atlas data. *International Journal of Remote Sensing* **2005**, *26*, 4801-4808.
37. Thorsteinsson, T.; Magnusson, B.; Gudjonsson, G. Large wildfire in iceland in 2006: Size and intensity estimates from satellite data. *International journal of remote sensing* **2011**, *32*, 17-29.
38. Lee, B.S.; Alexander, M.E.; Hawkes, B.C.; Lynham, T.J.; Stocks, B.J.; Englefield, P. Information systems in support of wildland fire management decision making in canada. *Computers and Electronics in Agriculture* **2002**, *37*, 185-198.
39. Loboda, T.V.; Csiszar, I.A. Reconstruction of fire spread within wildland fire events in northern eurasia from the modis active fire product. *Global and Planetary Change* **2007**, *56*, 258-273.
40. Veraverbeke, S.; Sedano, F.; Hook, S.J.; Randerson, J.T.; Jin, Y.; Rogers, B.M. Mapping the daily progression of large wildland fires using modis active fire data. *International Journal of Wildland Fire* **2014**.
41. Chuvieco, E.; Martin, M. A simple method for area growth mapping using avhrr channel 3 data. *International Journal of Remote Sensing* **1994**, *15*, 3141-3146.
42. Smith, A.M.S.; Wooster, M.J. Remote classification of head and backfire types from modis fire radiative power and smoke plume observations. *International Journal of Wildland Fire* **2005**, *14*, 249-254.
43. Dennison, P.E.; Charoensiri, K.; Roberts, D.A.; Peterson, S.H.; Green, R.O. Wildfire temperature and land cover modeling using hyperspectral data. *Remote Sensing of Environment* **2006**, *100*, 212-222.
44. Jin, Y.; Goulden, M.L.; Faivre, N.; Veraverbeke, S.; Sun, F.; Hall, A.; Hand, M.S.; Hook, S.; Randerson, J.T.J.E.R.L. Identification of two distinct fire regimes in southern california: Implications for economic impact and future change. **2015**, *10*, 094005.
45. Veraverbeke, S.; Sedano, F.; Hook, S.J.; Randerson, J.T.; Jin, Y.; Rogers, B.M. Mapping the daily progression of large wildland fires using modis active fire data. *International Journal of Wildland Fire* **2014**, *23*, 655-667.
46. Coen, J.L.; Schroeder, W. Use of spatially refined satellite remote sensing fire detection data to initialize and evaluate coupled weather-wildfire growth model simulations. *Geophysical Research Letters* **2013**, *40*, 5536-5541.
47. Oliva, P.; Schroeder, W. Assessment of viirs 375m active fire detection product for direct burned area mapping. *Remote Sensing of Environment* **2015**, *160*, 144-155.
48. Csiszar, I.A.; Morisette, J.T.; Giglio, L. Validation of active fire detection from moderate-resolution satellite sensors: The modis example in northern eurasia. *IEEE Transactions on Geoscience and Remote Sensing* **2006**, *44*, 1757-1764.
49. Giglio, L.; Descloitres, J.; Justice, C.O.; Kaufman, Y.J. An enhanced contextual fire detection algorithm for modis. *Remote Sensing of Environment* **2003**, *87*, 273-282.
50. Hantson, S.; Padilla, M.; Corti, D.; Chuvieco, E. Strengths and weaknesses of modis hotspots to characterize global fire occurrence. *Remote Sensing of Environment* **2013**, *131*, 152-159.
51. Sullivan, A.L. Wildland surface fire spread modelling, 1990–2007. 2: Empirical and quasi-empirical models. *International Journal of Wildland Fire* **2009**, *18*, 369-386.
52. Sullivan, A.L. Wildland surface fire spread modelling, 1990–2007. 1: Physical and quasi-physical models. *International Journal of Wildland Fire* **2009**, *18*, 349-368.
53. Alexander, M.E.; Cruz, M.G. Are the applications of wildland fire behaviour models getting ahead of their evaluation again? *Environmental Modelling & Software* **2013**, *41*, 65-71.

54. Mell, W.; Simeoni, A.; Morvan, D.; Hiers, J.K.; Skowronski, N.; Hadden, R.M. Clarifying the meaning of mantras in wildland fire behaviour modelling: Reply to cruz et al.(2017). *International Journal of Wildland Fire* **2018**.
55. Cruz, M.G., Alexander, M., Sullivan, A.L. Mantras of wildland fire behaviour modelling: facts or fallacies? *International Journal of Wildland Fire* **2018**.
56. Finney, M.A. Cohen, J.D., Forthofer, J.M., McAllister, S.S., Gollner, M.J., Gorhamb, D.J., Saito, K., Akafuah, N.K., Adam, B.A., English, J.D., Role of buoyant flame dynamics in wildfire spread. PNAS, **2018**, 112, 32
57. Alcasena, F.J.; Salis, M.; Ager, A.A.; Arca, B.; Molina, D.; Spano, D.J.E.M. Assessing landscape scale wildfire exposure for highly valued resources in a mediterranean area. **2015**, *55*, 1200-1216.
58. Ager, A.A.; Vaillant, N.M.; Finney, M.A.J.F.E.; Management. A comparison of landscape fuel treatment strategies to mitigate wildland fire risk in the urban interface and preserve old forest structure. **2010**, *259*, 1556-1570.
59. Salis, M.; Laconi, M.; Ager, A.A.; Alcasena, F.J.; Arca, B.; Lozano, O.; de Oliveira, A.F.; Spano, D.J.F.E.; Management. Evaluating alternative fuel treatment strategies to reduce wildfire losses in a mediterranean area. **2016**, *368*, 207-221.
60. Loureiro, C.; Fernandes, P.; Botelho, H.; Mateus, P.J.F.E.; Management. A simulation-based test of a landscape fuel management project in the marão range of northern portugal. **2006**, S245.
61. Cochrane, M.; Moran, C.; Wimberly, M.; Baer, A.; Finney, M.; Beckendorf, K.; Eidenshink, J.; Zhu, Z. Estimation of wildfire size and risk changes due to fuels treatments. *International Journal of Wildland Fire* **2012**, *21*, 357-367.
62. Sneeuwjagt, R.; Peet, G.; Beggs, B. *Forest fire behaviour tables for western australia*. Forests Department, Western Australia: 1979.
63. Cruz, M.G.; Sullivan, A.L.; Gould, J.S.; Sims, N.C.; Bannister, A.J.; Hollis, J.J.; Hurley, R.J. Anatomy of a catastrophic wildfire: The black saturday kilmore east fire in victoria, australia. *Forest Ecology and Management* **2012**, *284*, 269-285.
64. Fernandes, P.M.; Loureiro, C.; Guiomar, N.; Pezzatti, G.B.; Manso, F.T.; Lopes, L. The dynamics and drivers of fuel and fire in the portuguese public forest. *Journal of Environmental Management* **2014**, *146*, 373-382.
65. Arca, B.; Duce, P.; Laconi, M.; Pellizzaro, G.; Salis, M.; Spano, D. Evaluation of farsite simulator in mediterranean maquis. *International Journal of Wildland Fire* **2007**, *16*, 563.
66. Stratton, R.D.J.G.T.R.R.-G.-F.C., CO: US Department of Agriculture, Forest Service, Rocky Mountain Research Station. 15 p. Guidance on spatial wildland fire analysis: Models, tools, and techniques. **2006**, *183*.
67. Salis, M.; Arca, B.; Alcasena, F.; Arianoutsou, M.; Bacciu, V.; Duce, P.; Duguy, B.; Koutsias, N.; Mallinis, G.; Mitsopoulos, I.J.I.J.o.W.F. Predicting wildfire spread and behaviour in mediterranean landscapes. **2016**, *25*, 1015-1032.
68. Calkin, D.E.; Thompson, M.P.; Finney, M.A.; Hyde, K.D. A real-time risk assessment tool supporting wildland fire decisionmaking. *Journal of Forestry* **2011**, 274-280.
69. Kochanski, A.K.; Jenkins, M.A.; Mandel, J.; Beezley, J.D.; Krueger, S.K. Real time simulation of 2007 santa ana fires. *Forest Ecology and Management* **2013**, *294*, 136-149.
70. Rothermel, R.C. Predicting behavior and size of crown fires in the northern rocky mountains. *USDA For. Serv. Res. Pap. INT-438.* **1991**.
71. Cheney, N.P.; Gould, J.S.; McCaw, W.L.; Anderson, W.R.J.F.E.; Management. Predicting fire behaviour in dry eucalypt forest in southern australia. **2012**, *280*, 120-131.

72. Anderson, W.R.; Cruz, M.G.; Fernandes, P.M.; McCaw, L.; Vega, J.A.; Bradstock, R.A.; Fogarty, L.; Gould, J.; McCarthy, G.; Marsden-Smedley, J.B. A generic, empirical-based model for predicting rate of fire spread in shrublands. *International Journal of Wildland Fire* **2015**, *24*, 443-460.
73. Scott, A.C.; Bowman, D.M.; Bond, W.J.; Pyne, S.J.; Alexander, M.E. *Fire on earth: An introduction*. John Wiley & Sons: 2013.
74. Cruz, M.G.; Gould, J.S.; Alexander, M.E.; Sullivan, A.L.; McCaw, W.L.; Matthews, S. *A guide to rate of fire spread models for australian vegetation*. Australasian Fire and Emergency Service Authorities Council Limited and Commonwealth Scientific and Industrial Research Organisation: 2015.
75. Beven, K.; Binley, A. The future of distributed models: Model calibration and uncertainty prediction. *Hydrological processes* **1992**, *6*, 279-298.
76. Thompson, M.P.; Calkin, D.E. Uncertainty and risk in wildland fire management: A review. *Journal of Environmental Management* **2011**, *92*, 1895-1909.
77. Alexander, M.E.; Cruz, M.G. Limitations on the accuracy of model predictions of wildland fire behaviour: A state-of-the-knowledge overview. *The Forestry Chronicle* **2013**, *89*, 372-383.
78. Ervilha, A.; Pereira, J.; Pereira, J.J.A.M.M. On the parametric uncertainty quantification of the rothermel's rate of spread model. **2017**, *41*, 37-53.
79. Liu, Y.; Jimenez, E.; Hussaini, M.Y.; Okten, G.; Goodrick, S. Parametric uncertainty quantification in the rothermel model with randomised quasi-monte carlo methods. *International Journal of Wildland Fire* **2015**, *24*, 307.
80. Refsgaard, J.C.; van der Sluijs, J.P.; Højberg, A.L.; Vanrolleghem, P.A. Uncertainty in the environmental modelling process – a framework and guidance. *Environmental Modelling & Software* **2007**, *22*, 1543-1556.
81. Finney, M.A.; Cohen, J.D.; McAllister, S.S.; Jolly, W.M.J.I.j.o.w.f. On the need for a theory of wildland fire spread. **2013**, *22*, 25-36.
82. Finney, M.A.; Cohen, J.D.; Forthofer, J.M.; McAllister, S.S.; Gollner, M.J.; Gorham, D.J.; Saito, K.; Akafuah, N.K.; Adam, B.A.; English, J.D.J.P.o.t.N.A.o.S. Role of buoyant flame dynamics in wildfire spread. **2015**, *112*, 9833-9838.
83. Hilton, J.E.; Miller, C.; Sullivan, A.L.; Rucinski, C. Effects of spatial and temporal variation in environmental conditions on simulation of wildfire spread. *Environmental Modelling & Software* **2015**, *67*, 118-127.
84. Keane, R.E. *Wildland fuel fundamentals and applications*. Springer: 2015.
85. Sullivan, A.; Matthews, S.J.E.M.; Software. Determining landscape fine fuel moisture content of the kilmore east 'black saturday'wildfire using spatially-extended point-based models. **2013**, *40*, 98-108.
86. Forthofer, J.M.; Butler, B.W.; McHugh, C.W.; Finney, M.A.; Bradshaw, L.S.; Stratton, R.D.; Shannon, K.S.; Wagenbrenner, N.S.J.I.J.o.W.F. A comparison of three approaches for simulating fine-scale surface winds in support of wildland fire management. Part ii. An exploratory study of the effect of simulated winds on fire growth simulations. **2014**, *23*, 982-994.
87. Lopes, A.; Ribeiro, L.; Viegas, D.; Raposo, J.J.I.j.o.w.f. Effect of two-way coupling on the calculation of forest fire spread: Model development. **2017**, *26*, 829-843.
88. Cruz, M.G. Monte carlo-based ensemble method for prediction of grassland fire spread. *International Journal of Wildland Fire* **2010**, *19*, 521.
89. Anderson, K.; Reuter, G.; Flannigan, M.D. Fire-growth modelling using meteorological data with random and systematic perturbations. *International Journal of Wildland Fire* **2007**, *16*, 174.

90. Bachmann, A.; Allgöwer, B. Uncertainty propagation in wildland fire behaviour modelling. *International Journal of Geographical Information Science* **2002**, *16*, 115-127.
91. Keane, R.E.; Reeves, M. Use of expert knowledge to develop fuel maps for wildland fire management. In *Expert knowledge and its application in landscape ecology.* , A.H. Perera, C.A.D., and C.J. Johnson, Ed. Springer Science and Business Media, LLC: New York, USA, 2012; p 211−228.
92. Salazar, L.A. Sensitivity to fire behavior simulations to fuel model variations. *Research Paper PSW-178, Berkeley CA, Pacific Southwest Forest and Range Experiment Station, Forest Service, U.S. Department of Agriculture* **1985**, 11.
93. Salvador, R.; Pinol, J.; Tarantola, S.; Pla, E. Global sensitivity analysis and scale effects of a fire propagation model used over mediterranean shrublands. *Ecological Modelling* **2001**, *136*, 175-189.
94. Scott, J.H.; Reinhardt, E.D.J.R.P.R.-R.-F.C., CO: US Department of Agriculture, Forest Service, Rocky Mountain Research Station. 59 p. Assessing crown fire potential by linking models of surface and crown fire behavior. **2001**, *29*.
95. Jakeman, A.J.; Letcher, R.A.; Norton, J.P. Ten iterative steps in development and evaluation of environmental models. *Environmental Modelling & Software* **2006**, *21*, 602-614.
96. Alexandrov, G.; Ames, D.; Bellocchi, G.; Bruen, M.; Crout, N.; Erechtchoukova, M.; Hildebrandt, A.; Hoffman, F.; Jackisch, C.; Khaiter, P.J.E.M.*, et al.* Technical assessment and evaluation of environmental models and software: Letter to the editor. **2011**, *26*, 328-336.
97. Sørensen, T. Aa method of establishing groups of equal amplitude in plant sociology based on similarity of species and its application to analyses of the vegetation on danish commons. *Biol. Skr.* **1948**, *5*, 1-34.
98. Cohen, J. A coefficient of agreement for nominal scales. Educational and psychosocial measurement, 20, 37-46. 1960.
99. Cui, W.; Perera, A. Quantifying spatio-temporal errors in forest fire spread modelling explicitly. *Journal of Environmental Informatics* **2010**, *16*, 19-26.
100. Filippi, J.-B.; Mallet, V.; Nader, B. Representation and evaluation of wildfire propagation simulations. *International journal of wildland fire* **2014**, *23*, 46-57.
101. Fujioka, F.M. A new method for the analysis of fire spread modeling errors. *International Journal of Wildland Fire* **2002**, *11*, 193-203.
102. Finney, M.A. Farsite: Fire area simulator—model development and evaluation. *USDA Research Paper RMRS-RP-4* **2004**.
103. Sullivan, A.L. Wildland surface fire spread modelling, 1990–2007. 3: Simulation and mathematical analogue models. *International Journal of Wildland Fire* **2009**, *18*, 387-403.
104. Cruz, M.G.; Alexander, M.E. Assessing crown fire potential in coniferous forests of western north america: A critique of current approaches and recent simulation studies. *International Journal of Wildland Fire* **2010**, *19*, 377.
105. Mandel, J.; Kochanski, A.K.; Vejmelka, M.; Beezley, J.D. Data assimilation of satellite fire detection in coupled atmosphere-fire simulation by wrf-sfire. *arXiv preprint arXiv:1410.6948* **2014**.
106. Beven, K.; Binley, A.J.H.p. Glue: 20 years on. **2014**, *28*, 5897-5918.
107. Schroeder, W.; Oliva, P.; Giglio, L.; Csiszar, I.A. The new viirs 375m active fire detection data product: Algorithm description and initial assessment. *Remote Sensing of Environment* **2014**, *143*, 85-96.

108. Finney, M.A.; McHugh, C.W.; Grenfell, I.C.; Riley, K.L.; Short, K.C. A simulation of probabilistic wildfire risk components for the continental united states. *Stochastic Environmental Research and Risk Assessment* **2011**, *25*, 973-1000.
109. Sá, A., Benali, A., Pinto, R.M.S., Fernandes, P., Russo, A., Santos, F., Trigo, R., Pereira, J.M.C., Jerez, S., Da-Camara, C. Improving wildfire spread simulations using modis active fires: The fire-modsat project. In *VII International Conference on Forest Fire Research*, D. X. Viegas, E., Ed. Coimbra, Portugal, 2014.
110. Pinto, R.M.; Benali, A.; Sá, A.C.; Fernandes, P.M.; Soares, P.M.; Cardoso, R.M.; Trigo, R.M.; Pereira, J.M.J.S. Probabilistic fire spread forecast as a management tool in an operational setting. **2016**, *5*, 1205.