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# Fire spread predictions: Sweeping uncertainty under the rug

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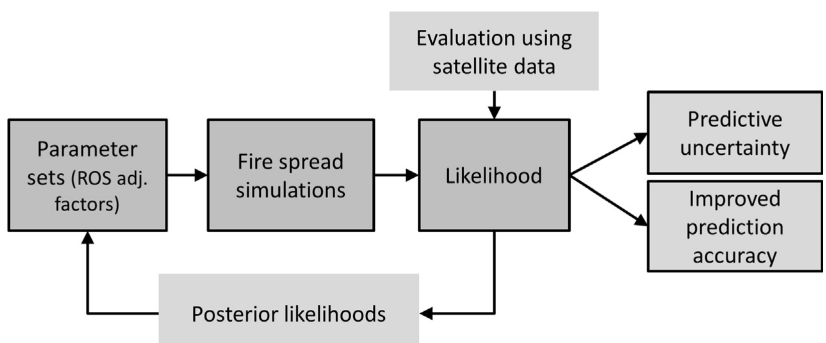
## HIGHLIGHTS

- 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,