ADVANCES IN FOREST FIRE RESEARCH

2022

Edited by
DOMINGOS XAVIER VIEGAS
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Validation of operational fire spread models in California

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Keywords

Fire modelling, Wildfire Analyst,

Abstract

The use of wildfire simulators allows estimating fire spread and behaviour in diverse and complex fire environments, supporting fire planning and analysis of incidents in operational environments. However, uncertainty derived from the spatio-temporal estimation of input variables and model's inherent inaccuracies related to its limitations and assumptions may undermine the utility of such predictions. Here, we assessed the performance of well-known operational surface and crown fire spread models used in California through the analysis of the rate of spread (ROS) of 1,853 wildfires occurring in the State from 2019 to 2021. For each detected wildfire, we retrieved the observed fire progression using the FireGuard (FG) database which provides the fire progression through geo-spatial polygons every 15 minutes approximately. Based on this data, we developed an algorithm that characterises the ROS for each FG polygon and the average ROS in the first 8 hours of the fire. Also, we ran a fire simulation for each wildfire with Wildfire Analyst Enterprise using high-resolution fuel and weather data to estimate the rate of spread. Then, we assessed 1) the accuracy of the fire simulations by comparing the real and simulated ROS based on the Mean Absolute Error (MAE), Mean Bias Error (MBE) and Mean Absolute Percentage Error (MAPE); 2) the most important factors influencing the accuracy of fire simulations, including the wind speed, and fuel types. Although the models clearly underestimated ROS in timber fuels, especially when no crown fire behaviour was predicted, most of the fire simulations had an acceptable error to be used in operational environments given the new techniques to adjust and calibrate the fires with field data. Finally, we used this analysis to present new approaches to optimise the fire predictions, including the optimisation of new custom fuels through genetic algorithms and enhancement of crown fire spread models.

1. Introduction

Wildfires are a natural disturbance of many ecosystems (Pausas and Keeley 2009) although they suppose a growing threat to the environment, economical assets and population (Molina-Terrén *et al.* 2019). Important amounts of financial resources have been invested in fire management aiming to reduce the substantial damage of wildfires and ensure safety for the population (Liang *et al.* 2008; Cardil and Molina 2015; Stocks and Martell 2016). In this sense, the estimation of the wildfire rate of spread (ROS) across complex landscapes is essential for effective planning and fire suppression, including the release of timely and operative public warnings for disaster management and evacuation orders (Cruz *et al.* 2018; Monedero *et al.* 2019; Ramirez *et al.* 2019).

Several mathematical approaches have been developed in the last decades aimed at predicting fire behaviour. The capability of accurately predicting the fire spread is directly linked to the model's inherent inaccuracy derived from its limitations and assumptions (Albini 1976; Ascoli *et al.* 2015; Vacchiano and Ascoli 2015) and input data, factors that may undermine the utility of such predictions for decision-making (Cruz and Alexander 2013; Benali *et al.* 2017; Ramirez *et al.* 2019). Cruz and Alexander (2013) quantified errors and biases of several wildfire ROS models after conducting a comprehensive survey of studies gathering a database comprising 1,278 paired predicted vs observed ROS values. Other studies assessed model's performance in several fire-prone areas and analysed how new improvements in fire spread models may enhance the performance to their previous ones (Cruz *et al.* 2018).

This work assesses the predictive accuracy of fire spread models currently used in California in operational settings under different environmental conditions using 1,853 fires from 2019 to 2021. The analysis identifies in what conditions the models may over or under-estimate the ROS and, subsequently, the burned area and associated fire impacts on buildings or other assets. The analysis is based on well-known error metrics and statistical approaches (Cruz *et al.* 2018) aiming to compare the predicted with observed ROS values. Finally, we propose several improvements in the current fire spread models to enhance their performance.

2. Methodology

2.1. Study area

This study was developed in California, a region dominated by Mediterranean climatic conditions, known to foster recurrent large wildfires (Pyne *et al.* 1998). Fire-prone weather situations such as long and dry summers with thunderstorms episodes, low relative humidity and strong dry winds are typical of this region (Sugihara and Barbour 2006).

2.2. Fire progression data (FireGuard)

The National Fireguard Detections product (FG) provides wildfire detection and monitoring across the USA at all times. It allows the detection of new wildfires as well as areas of significant fire growth which is especially useful in remote regions and during the first 24 - 48 hours when this information is usually scarce. Updates on the fire progression are often provided every 15 minutes.

We retrieved all FG polygons in California from October 2019 to November 2021 and removed prescribed fires. Then, we clustered FG polygons based on distance and fire arrival time to aggregate them to real incidents and create progression maps of individual fires (Figure 1). For each cluster, we selected the first FG polygon later used as ignition source. As a result, the progression of 1,853 wildfires was obtained for further analysis. We used the first burning period (8 hours from the fire start) to compare the simulated ROS with the real ROS obtained through FG. We developed an algorithm to analyse the ROS for each FG polygon (see ROS vectors for some fires in Figure 1) to finally estimate the average ROS during the first burning period. Also, for each fire we retrieved a set of environmental variables for identifying in what conditions the models may over or under-estimate the ROS and, subsequently, the burned area and associated fire impacts on buildings or other assets. This set of variables includes surface fuel types, canopy characteristics, weather conditions (forecast and stations), dead and live fuel moisture content.

2.3. Fire modelling with Wildfire Analyst Enterprise (WFA-e)

Fire modelling was carried out using Wildfire Analyst Enterprise (WFA-e) that provides real-time analysis of wildfire behaviour and simulates the spread of wildfires to directly support multi-agency wildfire incident management. Currently, many public and private entities, such as natural resource agencies, electrical investor-owned utilities, insurance and forestry companies strongly rely on WFA-e which facilitates optimal decision-making. We simulated 1,853 fires using the first FG polygon as an ignition source based on well-known semi-empirical fire spread models currently used in California including the Rothermel's (1972) surface fire spread model, van Wagner's (1977) crown fire initiation model, Rothermel's (1991) crown fire spread model, Albini's (1979) spotting model, and Andrews' (2012) conversion factor and wind profile and Minimum Travel Time time evolution algorithm (Finney 2002). We calculated the average hourly ROS and average simulated ROS during the real fire duration based on the FG fire progression up to 8 hours after the fire start (first burning period).

Improved high-resolution surface fuel types (Scott and Burgan 2005) and canopy characteristics maps (canopy cover, canopy height, canopy base height and canopy bulk density) were collected to perform the fire simulations. These maps were modelled by Technosylva Inc based on an Object-based Image Analysis by grouping homogeneous vegetation areas into vector objects later classified with machine learning algorithms and ground truth data with an accuracy of 90%. We used high-resolution weather data at 2 km using the Weather Research and Forecasting model, a mesoscale numerical weather prediction system designed for operational forecasting applications. Nelson's 2000 model was used to estimate dead fuel moisture content and live fuel moisture content was retrieved from the US National Fuel Moisture Database (WFAS; https://www.wfas.net/index.php/national-fuel-moisture-database-moisture-drought-103).

2.4. Statistical analysis

We compared the ROS predicted by WFA-e and observed through FG based on four different metrics (Cruz *et al.* 2018): 1) *ROS residual* representing the difference between the predicted and observed ROS. Therefore, a positive residual indicates an over-prediction; 2) *Mean Absolute Error (MAE)*, representing an average of the absolute error (eq. 1); 3) *Mean Bias Error (MBE)*, representing an average bias between the predicted and observed values (eq. 2); 4) *Mean Absolute Percentage Error (MAPE)*, a measure of prediction accuracy of a forecasting method in statistics. It expresses the accuracy as a ratio (eq. 3).

$$\mathrm{MAE} = \frac{\sum_{i=1}^{n} |WFA_i - FG_i|}{n} \qquad \text{(equation 1)}$$

$$\mathrm{MBE} = \frac{\sum_{i=1}^{n} (WFA_i - FG_i)}{n} \qquad \text{(equation 2)}$$

$$\mathrm{MAPE} = \frac{100}{n} \sum_{i=1}^{n} \left| \frac{FG_i - WFA_i}{FG_i} \right| \qquad \text{(equation 3)}$$

where *FGi* represents the ROS measures through FG, *WFAi* is the estimated ROS by WFA-e and *n* the number of wildfires.

We analysed the simulation accuracy based on these metrics considering input data for fire simulations and enhancements in our models through the use of simulated local wind fields (Windninja (Wagenbrenner *et al.* 2016)) and improved crown fire spread models.

3. Results and discussion

Rothermel (1972) model is the most widely evaluated fire spread model on Earth based on prescribed fires and some wildfires (Cruz and Alexander 2013). However, the amount, nature and quality of data provided in this work allows a better understanding of the model's performance under different environmental conditions in California. The observed (FG) and predicted (WFA-e) fire progression were compared analytically based on the methods described in section 2.4. However, as an example, we showed four fires in figure 1 to illustrate the ROS vectors calculated automatically from the FG data and the fire simulation for each fire. Although this visual assessment is useful to clarify how we compared the predicted and observed ROS, a statistical analysis was carried out to assess the performance of models for all the fires retrieved from FG in the study period considering the different combinations of environmental conditions influencing fire behaviour (fuels, weather, topography, etc).

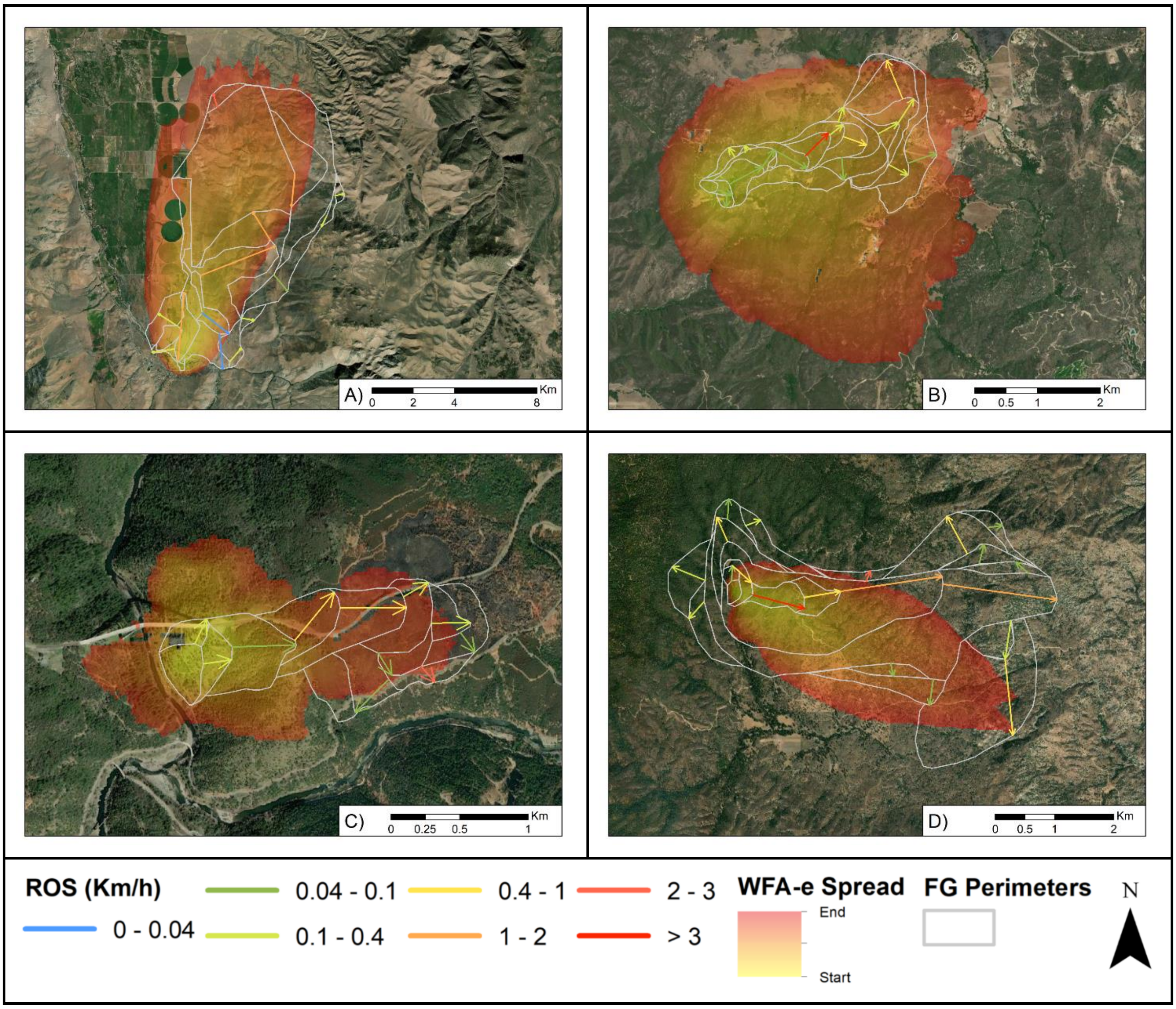

Figure 1. Fire progression and simulation of four wildfires in California. A) Mountain View fire (lat = 38.515; lon = -119.465; 2020/11/17); B) Chaparral fire (lat = 33.485; lon = -117.399; 2021/08/28); C) Bridge fire (lat = 38.921; lon = -121.037; 2021/09/05); D) French fire (lat = 35.687; lon = -118.55; 2021/08/18); Note that the FG polygons and WFA-e simulated fire progression have the same time duration.

Overall, the model produced the best predictions for Grass (GR), Grass-Shrub (GS) and Shrub (SH) Scott and Burgan (2005) fuel types with MAPE values of approximately 60% (Fig. 2) similarly to other studies (Cruz *et al.* 2018). The lowest MAE (0.31 km/h), MBE (0.016 km/h) and MAPE (59 %) values were found for the SH fuel types, followed by GS and GR fuel types. Thus, we found the highest error and bias in timber fuel types (Fig 2) with a MAPE value of 80%, also in line with other studies assessing the performance of Rothermel's model (Cruz *et al.* 2018). The histogram of ROS residuals showed a normal distribution for GR, GS and SH Scott and Burgan (2005) fuel types (Fig. 2A) with low bias in the predictions (MBE; Fig 2C). However, the models had a preponderant ROS under-prediction bias in most timber fires as shown by the histogram of ROS residuals, MAE and MBE metrics (Fig 2), an error type leading to potentially negative consequences in operational decision-making (Cheney and Gould 1995). This analysis suggests that new enhancements are needed to decrease the error and bias of fire spread models in line with other studies developed in other regions such as Australia (Cruz *et al.* 2018). Previous studies found the lowest MAE values in timber and logging slash fuel types but also the largest MAPE (76 %) values. This was derived from the range of observed ROS values in these fuel types that were substantially lower than in grasslands and shrublands fuel types (Cruz *et al.* 2018). However, in our study, we also found the highest MAE and MBE values in timber fuel types since the database contained fires with high ROS. The simulated ROS tended to be under-predicted in extremely fast fires (average observed ROS > 1.5 km/h) in all fuel types and specially in timber fuel types. This may be related to convective fire behaviour leading to local winds in the fire front not considered by the weather models.

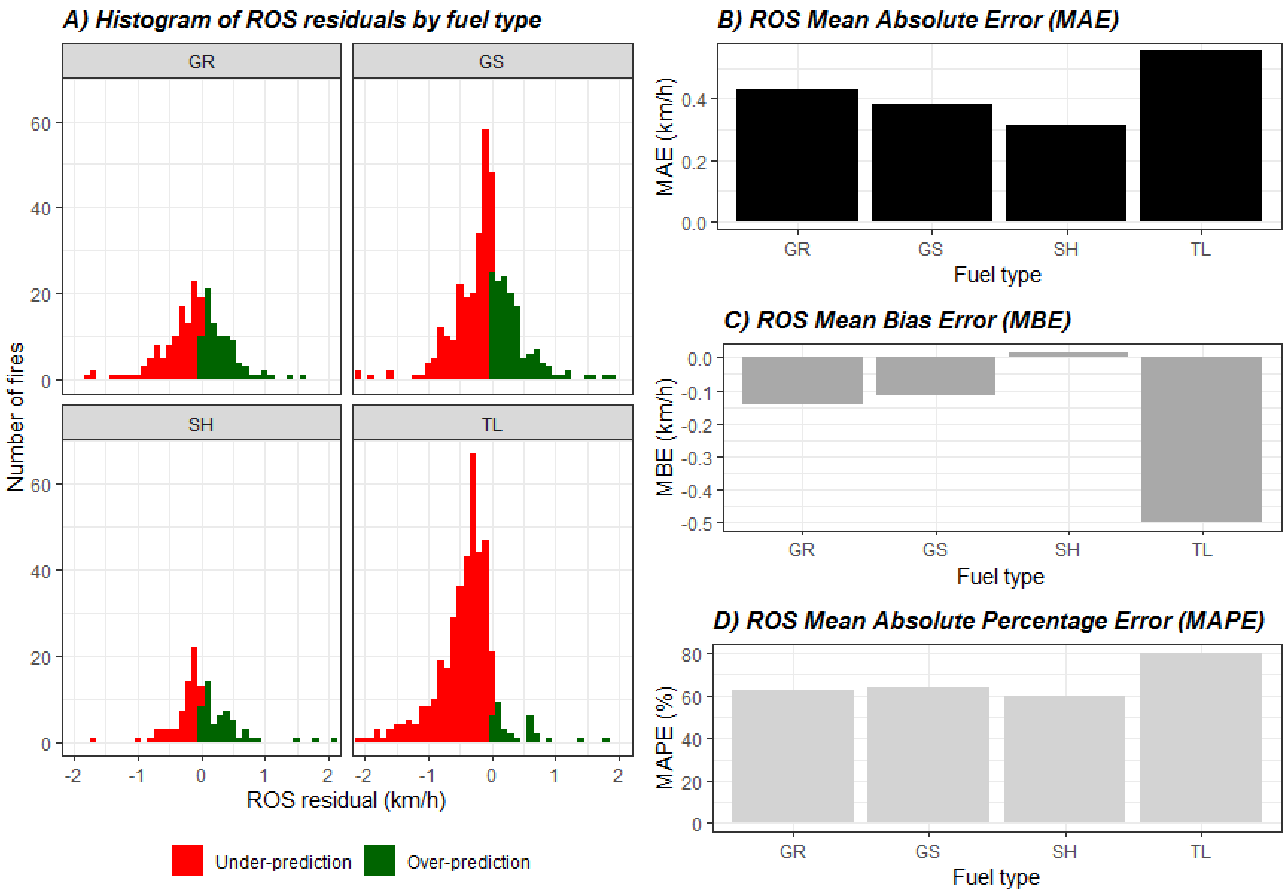

Figure 2. Fire spread model's performance analysis for 1,853 wildfires occurred in California in the 2019-2021 period. A) Histogram of ROS residuals by fuel type based on Scott and Burgan (2005); B) ROS mean absolute error (MAE); C) ROS mean bias error (MBE); D) ROS mean absolute percent error (MAPE). GR: Grass Fuel Types 101 to 109; GS: Grass-Shrub Fuel Types 121 to 124; SH: Shrub Fuel Types 141 to 149; TL: Timber-Litter-Understory Fuel Types 161 to 189.

Fire spread model's accuracy was also influenced by other environmental variables beyond fuel types (fuel moisture content, wind speed, etc), a fact not deeply studied in previous research studies. In general, high wind speeds led to ROS overprediction and low wind speed to underprediction, especially in GS and TL fires. This effect may be amplified in TL fuel types given that the crown fire spread models often require high wind speeds to forecast crown fire activity. Also, these models often behave binarily given a specific set of environmental conditions dramatically influencing the predicted ROS. We tried to address this issue in this work decreasing the MAPE up to 60% by smoothing the active crown ratio as follows:

$$ROS = surfaceROS * (1-\alpha) + \alpha * crownROS \quad \text{(Equation 4)}$$

where surfaceROS is the surface ROS fire spread by Rothermel 1972, crownROS represents the crown ROS by crown fire behaviour models and $\alpha = activeRatio^{1/factor}$ is the active crown ratio that is modulated by a factor defined by the fire analyst.

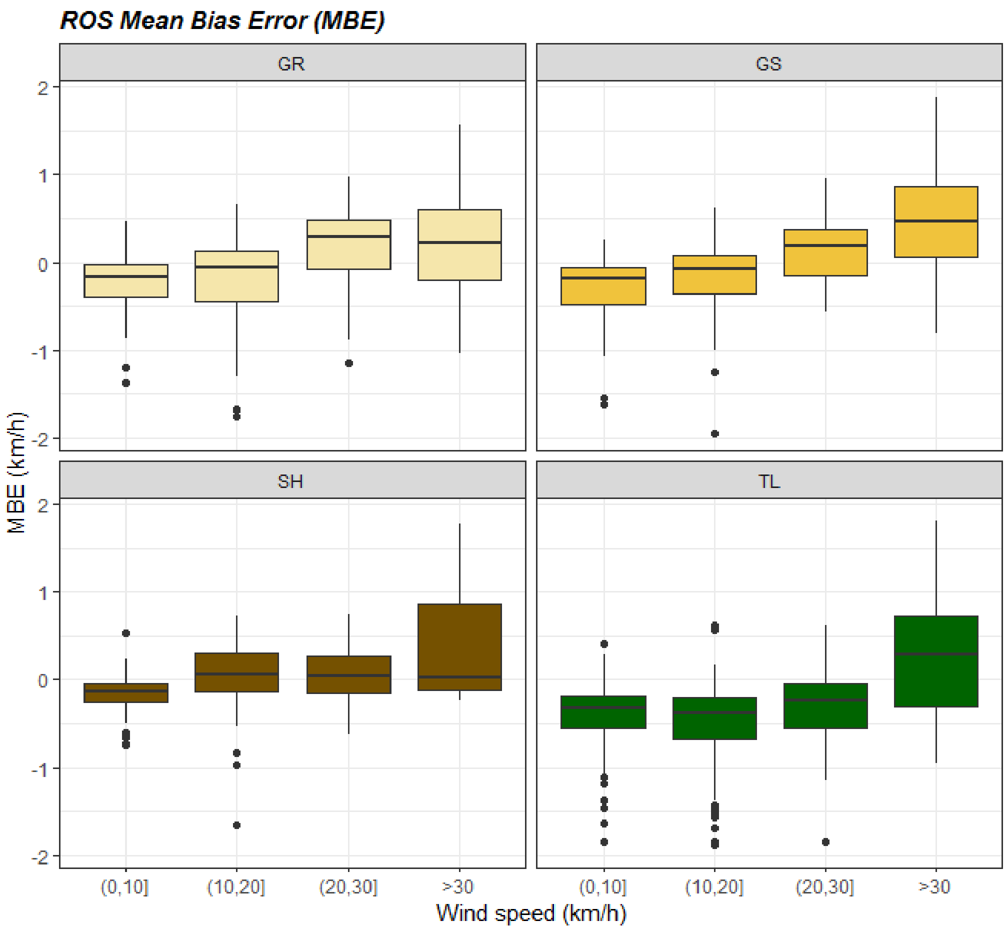

Figure 3. Boxplot of the ROS bias error (MBE) by fire and fuel type based on Scott and Burgan (2005) for 1,853 wildfires occurred in California in the 2019-2021 period. GR: Grass Fuel Types 101 to 109; GS: Grass-Shrub Fuel Types 121 to 124; SH: Shrub Fuel Types 141 to 149; TL: Timber-Litter-Understory Fuel Types 161 to 189.

4. Conclusions and further research

This work concludes that the fire spread model's performance for California is in line with previous studies developed in other regions and the accuracy of fire behaviour outputs are modulated by environmental conditions, especially wind speed. Therefore, the models are accurate enough to be used in real-time operations, especially with the use of adjustment modes that allow the calibration of predictions using field data (Artès *et al.* 2015; Cardil *et al.* 2019). However, we also recognize that there are challenges regarding the effect of pyroconvection on local wind fields and the estimation of ROS in timber areas. The results of this evaluation suggest that the accuracy of fire simulations may be improved with newer models aiming to address the modelling of crown fire behaviour.

The FG data and the algorithms developed in this research work to calculate ROS vectors represent a crucial enhancement to better analyse the fire spread model's performance and calibrate and provide new models and fuel families. Our approach addresses issues arising from the use of long fire runs, encompassing at times variations in fuel types, the estimation of fuel characteristics across the landscape, and the averaging of wind speed over broad spatial and temporal scales.

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