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.

Keywords: Wildfires, Portugal, Agreement, fire spread simulations, discrepancy, hotspots, active fires, FARSITE, MODIS, VIIRS

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 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 fire 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 wide-spread 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 cover 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 scheme 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 heatwave in 2003, which was characterized by record high minimum and maximum temperatures, extremely low relative humidity and relatively high wind

97 speed (Tedim et al. 2013; Trigo et al. 2006). Similarly, the 2005 and 2012 fire seasons coincided with
 98 two of the most severe droughts on record (Pereira et al. 2005; Trigo et al. 2013a).

99
 100 **Fig. 1.** Location of nine large fires (>10,000ha) that occurred in Portugal between 2003 and 2012. Fires are
 101 coded as: Castelo Branco1 (CBR1); Castelo Branco2 (CBR2); Covilhã1 (COV1); Covilhã2 (COV2);
 102 Monchique1 (MCQ1); Monchique2 (MCQ2); Monchique3 (MCQ3); Loulé (LL); and Tavira (TAV).
 103

104
 105 **Table 1.** Fire name, code, area, start date and duration (see section 2.3 for the calculation of the fire event
 106 duration).

Name (fire code)	Area (ha)	Start date (day/month/year)	Duration (days)
Castelo Branco1 (CBR1)	40,076	01/08/2003	4
Castelo Branco2 (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

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 Jr 2000) and spotting from torching trees (Albini 1979). Surface fire growth is simulated as an elliptical 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 90m spatial resolution (Farr et al. 2007). Slope and aspect variables were derived from the elevation dataset.

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 Appendix A. 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 10km 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 WRFweather 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 WindNinjavers. 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 fuelmoisture contents were set to 60 and 90%, respectively. Moisture content valuesfor 1-hr, 10-hr and 100-hr 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 a1-hour time step and 100m 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 norfire suppression operationsbecause of the absence of detailed and consistentoperational 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 spatialdiscrepancies 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-upsand 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 MODISGlobal Monthly Fire Location Product (MCD14ML, collection 5), whichcombines 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 1km but the pixel footprint can greatly increase with view angle (Wolfe et al. 1998) reaching up to 10 km² 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 900K will show greater than 50% probability of detection by the MODIS fire product (Giglio et al. 2003). The location of the fire front within a 1-km² 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_{t_0} - first detected active fires after ignition, Sat_{t_1} - an intermediate satellite overpass during the fire propagation, and Sat_{t_2} - 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):

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

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.

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).

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):

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

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. 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).

$NRSpD$ 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 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 SpD_{min} 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. Onboard 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 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.

284 **3 Results**

285 **3.1 Active fires and fire growth simulations**

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

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.

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 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 greater than 1-2 km,

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

324
 325 **Fig. 5.** Spatial Discrepancy (*SpD*, on the left) and Normalized Ratio Spatial Discrepancy (*NRSpD*, on the right)
 326 measures mapped for each case study. Burnt scar perimeters are also overlaid (black lines).
 327

328 In general, the variability of both measures, aggregated for the full case study, is very large, with
 329 most of the median SpD values below ~ 4 km, and with five out of nine median $NRSpD$ values below
 330 -0.5 (Fig. 6). Fire growth estimates for the LL case study show the lowest spatial discrepancies with
 331 active fire data, with perfect agreement for 50% of the comparisons. For the TAV case study, 25% of
 332 the comparisons show perfect agreement ($NRSpD = 0$) while 25% have $NRSpD$ values below 0.25 ,
 333 which represents a good spatial agreement between simulated and satellite fire growth.

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

339 **Fig. 6.** Interquartile range values of the SpD (light grey boxes) and $NRSpD$ (dark grey boxes) measures for
 340 each case study. The zero $NRSpD$ dashed line represents the perfect agreement between fire growth
 341 simulations and active fire data observations.
 342
 343

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

348 Grouping all the case studies, the evolution of $NRSpD$ values along elapsed time since ignition is
 349 shown in Fig. 8. Overall, simulated fire growth is consistently underpredicted ($NRSpD < 0$) when
 350 compared with satellite active fire data. The non-monotonic evolution of the median $NRSpD$ value
 351 indicates that discrepancy decreases after ca. 60% of time elapsed. Periods of agreement and
 352 overprediction ($NRSpD \geq 0$) 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).

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.

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 (Figs. 9b, 9c and 9d). Still, some fire detections occurred, probably under a layer of thin clouds (Figs. 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 (Figs. 9e and 9f). However, the smoke plumes did not appear to preclude the active fire detections. Multiple fire ignitions were recorded in the PRFD (Fig 9b and 9c), although some of them were not detected by MODIS due to the thick cloud cover (Fig 9b).

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.

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 3,136 active fires, with active fire footprint area ranging from the nominal value of 1km^2 to 10km^2 , and an overall median of 1.86km^2 (Appendix B). Approximately 40% of the active

384 fires (light grey data in Fig. 10a) have $SpD_{min} < SpD_{ctr} - SpD_{min}$ and $SpD_{min} < 2$ km, which corresponds to
 385 those active fires spatially close to the simulated fire perimeter. Of these pixels, approximately 40%
 386 have the lowest footprint areas (100 - 200 ha, Fig. 10b). For increasing values of the MODIS footprint
 387 size ($SpD_{ctr} - SpD_{min}$ distance increases), using the active fire minimum distance position decreases the
 388 uncertainty for large pixel footprint size and thus the SpD_{min} favors the simulation's accuracy.

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

397
 398 **Fig. 10.** Comparison between the spatial discrepancy calculated using the minimum distance (SpD_{min}) and
 399 using the centroid position (SpD_{ctr}) for each active fire from all the case studies (a); frequency of active fires
 400 for active fire footprint area classes (b). Most of the cases evaluation results are not affected by the fire front
 401 sub-pixel location given the large spatial discrepancies of fire growth simulations.
 402

403 For the more recent (2012) TAV case study, MODIS and the improved spatial resolution VIIRS
 404 data show similar fire growth patterns (Fig. 11). For this case study, MODIS active fire data have a
 405 median footprint value of 200 ha (Appendix B) while the median VIIRS footprint size is
 406 approximately 20 ha (boxplot not presented). Despite the large difference between median footprint
 407 sizes, the evolution of the spatial discrepancy measures across elapsed time since ignition and the
 408 spatio-temporal distribution of active fires of both sensors are similar (Figs. 11b and 11c). As

409 expected, the calculated SpD values using VIIRS active fire data have a larger variability and are 2x
 410 larger than those using MODIS active fires, with a maximum median value of 3 km at 65% of elapsed
 411 time since ignition (Fig. 11a), when the fire stopped spreading south and had started expanding from
 412 the flanks given a sudden change on wind direction (Viegas et al. 2012). This corresponds to the
 413 period when the fire was most active. Fire growth simulation is overpredicted, which is in agreement
 414 with the small positive values of the $NRSpD$ from both sensors in the last half of the fire length (Figs.
 415 11b and 11e). Except for the fire flanks, simulated fire growth reproduced the active fire positions
 416 during most of the event duration, with median $NRSpD$ values near 0 in the second half of the event
 417 denoting good simulation-satellite agreement (Fig. 11b). It is also possible to observe the number of
 418 each satellite overpasses per time elapsed interval, with significant difference for example in the 25-
 419 55 % interval where there is only a single acquisition of VIIRS active fire data.

Fig. 11. Comparison between MODIS and VIIRS 375m 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 375m 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.

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 (greater than 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 greater than 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 timestep (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, fire-fighting 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 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 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 (α) in the *NRSpD* formula can 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 km², although most of them are below 2 km². Small active fire's footprint sizes increase 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 km² (for scanning angles below 35°) increases confidence in the evaluation measures but the sample will only have half of the MODIS active fires.

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).

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 375m 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.

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

595 fire data to evaluate fire spread simulations. Furthermore, the approach can also be extended to
596 evaluate other spreading processes such as for example flooding, vegetation mortality and oil spills.

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