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Quantifying spatio-temporal differences between fire shapes: Estimating fire travel paths for the improvement of dynamic spread models

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A B S T R A C T

Dynamic fire spread models are a recent development in landscape management that provide for the simulation of the spread of fires through time under complex weather conditions. These allow risks to be assessed and resources to be strategically managed. The need for reliable and accurate fire models is of particular importance in the face of recent catastrophic wildfires in Australia, Europe and the United States. However, while fire spread models are developed using physical knowledge and empirical observations, there are few techniques which can be used to objectively assess the 'goodness of fit' of spatial predictions of fire spread. We propose a new method to allow the comparison of fire perimeters, providing for the discrimination of sources of simulation error and assisting in the collection of empirical spread data from observed fires. Differences between fire perimeters are quantified using linear vectors aligned with the direction of spread of the perimeter being sampled. These can provide an indication of difference in terms of the fire spread distance on the ground. The location, direction and length of these vectors can be used to assess spread rates to assist with model calibration. We demonstrated the utility of this method using a case study which assessed differences between the observed and simulated progression of an Australian wildfire. The new indices were found to be effective descriptors of differences in fire shape and hold potential for the spatial evaluation of fire spread models. The indices can be used to compare similar fire shapes; however they are unsuited for cases where there are large differences between perimeters.

1. Introduction

In recent years dynamic fire spread models have become an important tool in the management of fire in mediterranean-type landscapes (Perry, 1998; Sullivan, 2009b). Such models have been adopted by agencies for aiding suppression planning and assisting with strategic risk management. These include FARSITE in the United States (Finney, 2004), PHOENIX Rapidfire in Australia (Tolhurst et al., 2008), and Prometheus in Canada (Tymstra et al., 2007). Dynamic fire spread models provide the opportunity to assess hypothetical scenarios (Finney et al., 2002; Ntaimo et al., 2008), enable the identification of areas of high risk (Atkinson et al., 2010) and allow for the provision of real-time feedback to fire control agencies as wildfires occur (Chi et al., 2003; Han et al., 2010). With recent occurrences of catastrophic fires in Australia, Europe and Northern America (Cameron et al., 2009; Keeley et al., 2009; Pyne, 2008) and projected further increases in incidence of large wildfires as a result of climate change (Hughes, 2003; Podur and Wotton, 2010), there is an escalating focus on the development of accurate tools to aid the prediction of fire behaviour (Alexander and Cruz, 2013; Sullivan, 2009a).

Fire spread models are typically developed or calibrated using observations of small experimental fires (Sneeuwajgt and Frandsen, 1977; Sullivan, 2009c) and so need to be conditionally verified at larger scales if they are to be used outside test conditions (Alexander and Cruz, 2013; He et al., 2011; Jakeman et al., 2006; Perry, 1998). This is of particular importance if they are intended to be used for the prediction of intense wildfires. Fire spread models are predominantly developed as single dimensional relationships (Andrews, 2007; Noble et al., 1980), which are then adapted to

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simulate fire progression spatially (Perry, 1998). When translating a one dimensional spread model to a form which enables spatio-temporal predictions, there are a range of additional factors that need to be accounted for. Fires in complex landscapes experience variation in spread rates due to size (McAlpine and Wakimoto, 1991), atmospheric dynamics (Chatto, 1999), interactions between winds and topography (Sharples, 2008) and changing fuel and weather conditions (Anderson et al., 2007; Catchpole et al., 2001). Spatially explicit dynamic spread models must parameterise these relationships and consequently require methods to verify resultant predictions under real world conditions (Alexander and Cruz, 2013). As wildfires occur in a stochastic manner in space and time (Dayananda, 1977), progress rapidly and are a threat to human safety (Podur and Wotton, 2010), the potential to collect data as they occur is limited. Hence information for verification is typically collected post-fire where the affected (burnt) area is evident, but information on actual spread rates, intensities, pre-fire fuel levels, progression patterns and fire weather is generally of poor quality.

Dynamic fire models simulate the process of a spreading combustion reaction through heterogeneous fuels on varying topography under changing weather conditions (Pastor et al., 2003). These models must incorporate the effect of a variety of factors, including weather (Caballero, 2006; Long, 2006), vegetation based fuels (Bradstock et al., 2010; Cheney et al., 1998; Dennison and Moritz, 2009) and topography (Viegas, 2002). Many of these inputs are inherently chaotic, exhibiting small scale variation through space and time. Consequently they are impossible to determine with certainty (Bachmann and Allgower, 2002; Palmer, 2000). In addition, assumptions about model structure may be an additional source of uncertainty (Peltier et al., 2010). As a result, determining causality between observed fire behaviour and model input parameters is a complex process.

Poor performances of dynamic spread models may be due to inaccurate inputs, poor calibration, user error or errors in model assumptions (Peltier et al., 2010). As dynamic spread models predict spread through time, such errors are likely to compound with each time-step (Bachmann and Allgower, 2002). Effective methods for determining model 'goodness of fit' and for partitioning sources of error are essential for improving the accuracy of spread models by aiding calibration processes and targeting data collection (Cui and Perera, 2008). As dynamic spread models are often intended to be used as decision support tools for managers, there are tangible benefits to correctly identifying risk and optimising management responses to fires.

While fire spread can be evaluated by estimating rates using linear vectors (Johnston et al., 2008; Rothermel and Rinehart, 1983), the result of a dynamic spread model is inherently spatial. As burnt area is the most easily evaluated property of a wildfire, the assessment of dynamic spread models typically involves the comparison of an observed perimeter of fire affected area with a modelled perimeter. As fire perimeters are discrete spatial features consisting of a binary condition (burnt or unburnt), different parts of the same perimeter cannot be considered to be spatially independent (Claude, 2008). For example, the probability of a specific point in the landscape being affected will be increased if neighbouring points are within the fire perimeter. As a result, assumptions of stationarity are not met and so typical methods available for the calibration of spatially autocorrelated regression models are not valid (Dormann et al., 2007).

Relative to the focus on the development of spread models, methods for quantifying error in fire spread predictions have had limited attention (Cui and Perera, 2008, 2010; Feunekes, 1991; Fujioka, 2002; Green et al., 1983). Few techniques are used consistently and there are no standard indices being used. Consequently, the dominant method of reviewing model performance is subjective expert opinion (Berjak and Hearne, 2002; de Vasconcelos et al., 2002; Johnston et al., 2008; Stratton, 2006). Some basic numerical indices such as area, area overlap and shape deviation index may be calculated. However, while these values provide an indication of overall model performance, there is little information to assist with the objective partitioning of sources of error for model calibration (Berjak and Hearne, 2002; Cui and Perera, 2010; de Vasconcelos et al., 2002).

Recent efforts to quantify spread errors in greater detail have focused on differences between two fire boundaries along evenly spaced radii from the fire origin (Cui and Perera, 2010; Fujioka, 2002). These methods effectively describe differences between two shapes, but differences are measured from a 'line-of-sight' perspective from the fire origin, and do not represent the differences in the distance that the fire has travelled (Fig. 1A). We propose an alternative approach where differences are assessed in terms of the actual spread distances on the ground by the fire (Fig. 1B). Fire spread paths can be emulated based on the assumption that fires spread in a direction perpendicular to the fire edge when all other conditions are constant. By estimating differences between fire shapes at each point on the perimeter of a fire shape, spatially specific objective estimates of prediction performance can be generated. These can be used to link model bias to particular conditions such as fuel or topographic position.

This paper introduces a new method for objectively quantifying differences in closely aligned fire perimeters by assessing differences between two fire shapes in terms of probable fire travel path. This is demonstrated using a case study comparing the progression of a fire which occurred in South Eastern Australia with outputs generated from a dynamic fire spread model. This technique is intended to be used on similarly shaped fires as it will be uninformative where gross shape differences are present.

2. Method

To demonstrate the travel path method, observations of an actual wildfire at two different points in time were compared to an equivalent simulation. A dynamic fire spread model was used to simulate the fire spread for the duration of time between the two observations, using the state of the fire at the time of the first observation as a starting point. The simulated fire perimeter was then compared to the second observed fire perimeter.

2.1. Actual fire shapes

A large wildfire occurred in western Victoria, Australia near Stawell (36.98°S, 142.66°E) on the 31st of December 2005 and burned though open woodlands and grasslands. The fire perimeter was surveyed during its progression using an aircraft based multispectral scanner (Sourced Department of Sustainability and Environment, Victoria, 2009) at 2030 h, 2300 and 0200 h on the 1st January, 2006. The isochrones at 2030 h and 2300 h were selected for method evaluation. These were recorded at a resolution of 50 m and stored as a series of boundary coordinates.

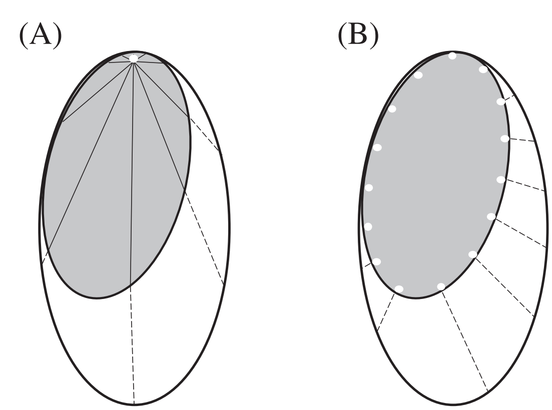

Fig. 1. Schema of perimeter illustrating (A) origin based radial sampling and (B) perimeter spread sampling.