

Modelling suppression difficulty: current and future applications

*Francisco Rodríguez y Silva, Christopher D. O'Connor,
 Matthew P. Thompson, Juan Ramón Molina Martínez and David E. Calkin*

International Journal of Wildland Fire **29** <https://doi.org/10.1071/WF19042>

The authors wish to advise of errors in Equations 2 and 5b in the above paper.

The correct Equation 2 should be:

$$I_{ce} = \left[\sum \left(\frac{2 \times FL_i \times HUA_i}{FL_i + HUA_i} \right) \times \left(\frac{A_i}{A_t} \right) \right]$$

The correct Equation 5b should be:

$$I_{ice} = \left[\sum \left(\frac{2 \times FL_i \times HUA_i}{FL_i + HUA_i} \right) \times \left(\frac{A_i}{A_t} \right) \right] + \left[\sum \left(\frac{2 \times FL_j \times HUA_j}{FL_j + HUA_j} \right) \times \left(\frac{A_j}{A_t} \right) \right] + \left[\sum \left(\frac{2 \times FL_k \times HUA_k}{FL_k + HUA_k} \right) \times \left(\frac{L_k}{L_t} \right) \right]$$

Modelling suppression difficulty: current and future applications

Francisco Rodríguez y Silva^{A,D}, Christopher D. O'Connor^B,
Matthew P. Thompson^C, Juan Ramón Molina Martínez^A and David E. Calkin^B

^ADepartment of Forest Engineering, Forest Fire Laboratory, University of Córdoba,
Edificio Leonardo da Vinci, Campus de Rabanales, E-14071 Córdoba, Spain.

^BUS Department of Agriculture Forest Service, Rocky Mountain Research Station,
800 East Beckwith Avenue, Missoula, MT 59801, USA.

^CUS Department of Agriculture Forest Service, Rocky Mountain Research Station,
240 West Prospect Road, Fort Collins, CO 80526, USA.

^DCorresponding author. Email: ir1rosif@uco.es

Abstract. Improving decision processes and the informational basis upon which decisions are made in pursuit of safer and more effective fire response have become key priorities of the fire research community. One area of emphasis is bridging the gap between fire researchers and managers through development of application-focused, operationally relevant decision support tools. In this paper we focus on a family of such tools designed to characterise the difficulty of suppression operations by weighing suppression challenges against suppression opportunities. These tools integrate potential fire behaviour, vegetation cover types, topography, road and trail networks, existing fuel breaks and fireline production potential to map the operational effort necessary for fire suppression. We include case studies from two large fires in the USA and Spain to demonstrate model updates and improvements intended to better capture extreme fire behaviour and present results demonstrating successful fire containment where suppression difficulty index (SDI) values were low and containment only after a moderation of fire weather where SDI values were high. A basic aim of this work is reducing the uncertainty and increasing the efficiency of suppression operations through assessment of landscape conditions and incorporation of expert knowledge into planning.

Additional keywords: fire responder safety, maps, modelling, risk management, spatial analysis, suppression operations, wildland fire planning and response.

Received 27 March 2019, accepted 4 April 2020, published online 5 May 2020

Introduction

Management of wildland fire events is a complex endeavour, wherein decision makers face considerable uncertainty and are often forced to balance competing socioecological objectives (Thompson *et al.* 2013; Thompson 2014). Primary among fire management objectives is protection of human life and safety, which can be particularly challenging for fire responders given the myriad hazards to which they can be exposed (e.g. falling trees, entrapments; National Wildfire Coordinating Group (NWCG) 2017). In such decision environments it becomes essential to prepare for response through pre-fire assessment and planning, in order to dampen time pressures, reduce uncertainties and expand options (Meyer *et al.* 2015; O'Connor *et al.* 2016; Thompson *et al.* 2016a; Thompson *et al.* 2016b). In the USA, for example, federal wildland fire guidance and direction imposes a responsibility on managers to ‘predetermine’ a range of response strategies that balance land and resource objectives with responder exposure (National Interagency Fire Center 2017). Improving decision processes and the information upon

which decisions are made, in pursuit of a safer and more effective fire response, have therefore become key priorities of the fire research community (Dunn *et al.* 2017a; Dunn *et al.* 2017b; Thompson *et al.* 2017a). Correspondingly, a rich array of tools have been developed to support risk-informed response planning and decision making, varying from conceptual to applied in nature (Calkin *et al.* 2011b; Thompson *et al.* 2011; Belval *et al.* 2015; Duff and Tolhurst 2015; Martell 2015; Minas *et al.* 2015; Pacheco *et al.* 2015; Belval *et al.* 2016; Kalabokidis *et al.* 2016; Thompson *et al.* 2016a).

Similarly, researchers have developed frameworks to characterise responder exposure and suppression effectiveness (Calkin *et al.* 2011a; Penman *et al.* 2013; Stonesifer *et al.* 2014; Katuwal *et al.* 2016; Rodríguez y Silva and González-Cabán 2016; Stonesifer *et al.* 2016; Thompson *et al.* 2016b; Katuwal *et al.* 2017; Wei *et al.* 2018). Recent advances in mapping fire danger ratings (Jolly and Freeborn 2017), escape routes (Campbell *et al.* 2017a; Campbell *et al.* 2019), safety zones (Campbell *et al.* 2017b; Page and Butler 2017) and

potential fire control locations (O'Connor *et al.* 2017) can together help fire managers target more effective suppression actions and thereby reduce unnecessary responder exposure.

We begin by performing a comparative review of relevant literature, ultimately narrowing our focus to a recently developed framework, known as the suppression difficulty index (SDI), that combines variables related to fire behaviour and variables related to suppression operations into a spatially explicit multicriteria evaluation tool (Rodríguez y Silva *et al.* 2014; O'Connor *et al.* 2016). In the methods and results sections, we describe examples from the USA and Spain, beginning with a real-world application of the SDI for large fire decision support in the USA that illustrates the operational relevance of the SDI as a decision support tool. We then offer a brief review of recent updates to the framework intended to better capture extreme fire behaviour and present a test case from a large fire in Spain as a validation exercise of this next-generation SDI. Changes to SDI calculations stemmed from the compilation and evaluation of manager feedback, observations and concerns. Lastly, we offer ideas and suggestions for future directions in modelling suppression difficulty and integrating results into fire management decision processes.

For our purposes here, we can generally identify three classes of suppression difficulty models. The first, and simplest, class of models considers the fire environment alone. Many approaches are effectively variants of what is often called the 'hauling chart' (Andrews *et al.* 2011), which can be linked back to a fire suppression interpretation chart provided by Andrews and Rothermel (1982). Although more sophisticated approaches to quantifying fuel loads and simulating fire behaviour have since been developed, the basic idea of linking suppression difficulty back to fire intensity thresholds remains common. Mitsopoulos *et al.* (2016), for example, used this approach to quantify suppression difficulty for three different ecosystems in Europe. Wotton *et al.* (2017) similarly applied operational fire intensity thresholds to explore how climate change effects on fire activity in Canada may increase the proportion of days in which suppression capabilities could be overwhelmed. Dillon *et al.* (2015) arithmetically combined weighted fire intensity metrics to create a composite index of suppression difficulty for the continental USA.

The second class of models consider the fire environment and its effect on active suppression operations. Some of these approaches focus on estimating production rates, whereas others incorporate production rates into models of fire containment. Examples of the former include Hirsch *et al.* (2004), who quantified initial attack crew productivity using an expert-judgement elicitation study, and Broyles (2011), who used field data to update fireline production rates used in the USA. In an earlier review, Hirsch and Martell (1996) illustrated how fireline production rates vary with environmental and fire behaviour conditions. Almost 20 years later, Duff and Tolhurst (2015) reached a similar set of conclusions and identified a need for improved realism in suppression modelling, including better estimating of fireline production rates and accounting for a wider variety of strategies and tactics, topics we will return to later in this paper. Combining econometric analyses with operational data, Holmes and Calkin (2013) assessed alignment between published and measured fireline production rates,

leading to additional studies estimating patterns of resource use and productivity (e.g. Hand *et al.* 2017) and quantifying effectiveness of suppression resources (Katuwal *et al.* 2016).

The third, and arguably most complex, class of models incorporates additional factors related to suppression operations. Page *et al.* (2013) presented a useful conceptual model identifying three primary factors (fire behaviour, firefighter safety and suppression operations) as determinants of resistance to control. More recent tools that similarly focus on safety, but in a geospatial context, provide standardised methods to map travel impedance, escape routes and safety zones (Dennison *et al.* 2014; Campbell *et al.* 2017a, 2017b). Though not exhaustive, the model most relevant to spatial response planning, in terms of suppression resource deployments and control actions, may be the SDI, developed in Spain by Rodríguez y Silva *et al.* (2014). The SDI weighs potential fire hazards, represented by fire behaviour metrics, against a series of proxies for control opportunities, including road and fuel break density, responder mobility, fireline production rate and aerial resource cycle time. Although both the fire hazard and control opportunities summarised in the SDI account for components of the fire operating environment, the SDI does not explicitly address fire responder safety. Initial development of SDI inputs came from case studies in Spain, Israel and Chile (Rodríguez y Silva *et al.* 2014). These inputs were adapted for use in the western United States as the terrestrial SDI (tSDI) because of a lack of aerial cycling time data (O'Connor *et al.* 2016).

Throughout this paper we refer to different versions and updates of the SDI models. The original SDI refers to the equations published by Rodríguez y Silva *et al.* (2014), the original tSDI refers to modifications to the original SDI by O'Connor *et al.* (2016) and references to the updated SDI and tSDI models are detailed in the methods section.

SDI models have been used to assess the effects of fuel breaks and other landscape treatments on the future operating environment and as an aid for identifying safer control opportunities. The tSDI has proven particularly valuable for a related fire planning concept known as potential wildland fire operational delineations (PODs), which are essentially fire management units whose boundaries are relevant to fire control operations (e.g. roads), within which fire risks, response objectives and other information can be summarised (Thompson *et al.* 2016a). PODs have proven useful to guide actual response operations and can serve as a planning unit for optimising preventative fuel treatment and suppression response strategies (Thompson *et al.* 2017b; Thompson *et al.* 2018a; Wei *et al.* 2018; O'Connor and Calkin 2019). SDI maps have been used in geospatial analyses to identify potential control locations that can serve as the basis for POD boundaries (O'Connor *et al.* 2017).

During an incident response, the tSDI is run under current and forecasted weather conditions to quickly size up suppression challenges, orient new incident management teams to a landscape and to prioritise fire responder safety during the incident response (RMAT 2019). Four years of beta testing in Spain and the USA have resulted in a series of improvements to the SDI calculations framework to more accurately capture surface, crown and canyon fire behaviour, incorporate the advantages and limitations of mechanised fireline construction, streamline calculations and update formulae for better spatial

standardisation of potential fire behaviour, more realistic weighting of slope and aspect effects on accessibility, and to account for non-fire hazards to fire responders.

Our intention with this work is not to identify a single best way to characterise suppression difficulty, but instead to demonstrate how a flexible framework that incorporates consistent concepts relevant to fire responder safety and suppression effort can be applied to fire management systems incorporating a variety of spatial scales, data types and potential applications. Tools developed from this framework can be used to assess prevention and preparedness needs, to forecast likely suppression resource demands and accompanying suppression expenditures, to develop strategic courses of action and plans for mobilisation of resources and to inform tactical deployment decisions of where to send suppression resources or conversely where to avoid sending them.

Methods

The SDI equation is calculated as potential fire behaviour, represented as the surface fire energy behaviour sub-index (I_{ce}), divided by suppression opportunity index (S_{oi}), calculated as the sum of sub-indices for accessibility (I_a , road density), mobility (I_m , fuel break density), penetrability (I_p , foot travel difficulty), aerial resources (I_{ar} , cycle time) and fireline construction rate (I_c) (Eqn 1). The SDI is a multicriteria evaluation tool developed by a former incident commander with more than 25 years of wildfire experience that relies on expert judgement to rescale all sub-index values from 1 to 10 and combines them into an overall dimensionless index where higher values indicate higher suppression difficulty. Sub-index scaling thresholds were determined through a Delphi process involving incident command structure officers from the Andalucía Regional Government in Spain (Plan INFOCA) and reviewed by fire managers on the Tonto National Forest in the USA.

$$SDI = \left[\frac{\sum (I_{ce})}{\sum (S_{oi})} \right] = \left[\frac{\sum (I_{ce})}{\sum (I_a + I_m + I_p + I_{ar} + I_c)} \right] \quad (1)$$

For a given level of potential fire behaviour, greater control opportunities reduce the overall suppression difficulty. This provides a simple yet useful summary index that can be mapped across landscapes and its sub-indices can be deconstructed and mapped individually. The energy behaviour sub-index (Eqn 2) combines values for flame length (FL_i) and heat per unit area (HUA_i) proportionally weighted by the relative abundance of pixel-scaled fuel type within a unit of analysis. A_i is the area of each surface fuel model i and A_t is the size of the landscape cell or pixel being analysed. This formulation allows for aggregation of I_{ce} and SDI values into larger pixels; where the unit of analysis is equal to the resolution of the surface fuel model layer, $A_i = A_t$. Fire behaviour calculations were originally developed using BEHAVE (Andrews 1986), but to incorporate canopy fire behaviour (Scott and Reinhardt 2001) and downscaled, topographically adjusted winds (WindNinja v2.0, Forthofer *et al.* 2009), calculations are now run in FlamMap (Finney 2006). Heat per unit area outputs from FlamMap are converted from kJ m^{-2} to kcal m^{-2} .

$$I_{ce} = \left[\sum \left(\frac{2 \times FL_i \times HUA_i}{FL_i \times HUA_i} \right) \times \left(\frac{A_i}{A_t} \right) \right] \quad (2)$$

tSDI modifications for incident support in the USA

A primary consideration for rapid production of consistent and interpretable decision support tools is the need for broad-scale, accessible spatial data that can be customised for application on individual wildfires. Most of the basic inputs necessary for generation of the SDI (i.e. modelled flame lengths, heat per unit area, road and trail networks, digital elevation models and fireline production rates) are available for the whole of the United States or can be generated from primary national data products. However, because of a lack of available data, the calculation of tSDI does not include aviation cycling time (I_{ar}), existing fire breaks (I_m) or the soil harness component (sh_i) of the penetrability sub-index. The calculation of original tSDI is presented in Eqn 3.

$$tSDI = \left[\frac{\sum (I_{ce})}{\sum (tS_{oi})} \right] = \left[\frac{\sum (I_{ce})}{\sum (I_a + I_p + I_c)} \right] \quad (3)$$

tSDI improvements

In the accessibility sub-index (I_a), we substitute a road distance decay function (see Table S2.4 in Supplementary Material online) for road density per unit area to account for relative accessibility by vehicle. This change produces a smoother tSDI transition in areas with low road density. The revised calculation of the penetrability sub-index (I_p ; accessibility on foot) (Eqn 4) includes summing instead of multiplying sub-index values in the numerator, double weighting and moving pre-existing trails (pt_i) to the numerator and dividing the summed numerator by one more than the total number of inputs, due to double weighting of trails. This series of changes standardises the scaling and emphasises the value of trails for access on foot. Note that in the USA, soil hardness (sh_i) was not available as a national input so the denominator was one less than that used in Spain. The symbol (si) is the weight assigned to the percentage slope of the fuel model area i , (di) is the weight assigned to the difficulty in cutting new line in fuel model i and (ei) is the weight assigned to the fuel model i aspect (accounting for increased sun exposure). Changes to the lookup tables for individual sub-indices are detailed in Tables S2.4, S2.5, S2.6 and S2.7 (in Supplementary Material online).

$$I_p = \left[\sum \left(\frac{si + di + sh_i + ei + 2pt_i}{6} \right) \times \left(\frac{A_i}{A_t} \right) \right] \quad (4)$$

Lastly, a slope hazard function was applied to tSDI outputs in non-burnable locations to account for terrain-specific hazards to fire responders (Table S2.8 in Supplementary Material online).

SDI improvements developed from observations of extreme fire behaviour

We developed a series of additional equations to account for observations of extreme fire behaviour on several large fires in Spain (Table S2.9 in Supplementary Material online). Building

on the first-generation SDI that considered only surface fire behaviour, we introduced sub-indices for crown fire propagation and canyon fire behaviour. This update more accurately captures factors influencing suppression difficulty, including resistance to control and compromised safety, together with prospects for higher suppression resource demands and associated costs.

The updated total energy behaviour sub-index (I_{ice}) is a summation of the surface fire energy behaviour sub-index (I_{ces}) with the crown fire energy behaviour sub-index (I_{cec}) and the canyon fire energy behaviour sub-index (I_{cecy}), as described in Eqns 5a and 5b. The surface fire energy behaviour sub-index (I_{ces}) is calculated as above, with new nomenclature defining it as surface fire only. Indices for crown fire and canyon fire energy behaviour are calculated with identical functional forms, but with different modelling approaches and spatial aggregation methods. Now A_j corresponds to areas of comparable crown fire potential, L_k to the length of each canyon identified in the landscape analysis unit and L_t is the total sum of canyon lengths in the landscape analysis unit.

$$I_{ice} = I_{ces} + I_{cec} + I_{cecy} \quad (5a)$$

$$I_{ice} = \left[\sum \left(\frac{2 \times FL_i \times HUA_i}{FL_i \times HUA_i} \right) \times \left(\frac{A_i}{A_t} \right) \right] + \left[\sum \left(\frac{2 \times FL_j \times HUA_j}{FL_j \times HUA_j} \right) \times \left(\frac{A_j}{A_t} \right) \right] + \left[\sum \left(\frac{2 \times FL_k \times HUA_k}{FL_k \times HUA_k} \right) \times \left(\frac{L_k}{L_t} \right) \right] \quad (5b)$$

Crown fire flame length and heat per unit area metrics are calculated with the Scott and Reinhardt (2001) canopy transition model. Fire behaviour metrics for canyon fire are adapted from Viegas (2005). The variables presented in Eqn 6 include rate of fire spread in m min^{-1} (R), wind speed in m s^{-1} (U), the angle of both sides of the canyon (α), the angle of the slope of the canyon (β) and coefficients relating to different fuel types (Table 1). For each of the fuel groups indicated in Table 1, we developed an equation to calculate the rate of spread in the canyon (see section S1 in Supplementary Material online). Following the calculation of canyon fire spread rates, the flame length and heat per unit area are determined through an equation from Byram (1959). Lastly, weight assignments for flame length and heat per unit area for the crown fire and canyon fire energy behaviour sub-indices are derived and integrated into Eqn 6 (Table 2). The intervals for crown and canyon propagation are based on fire behaviour and capacity of control (Tedim *et al.* 2018) and thematic cartography and geovisualisation (Howard *et al.* 2008; Tyner 2014). Weights for surface fire remain as originally presented in Rodríguez y Silva *et al.* (2014).

$$R = 60 \times [(\beta + \alpha)/\alpha] \times \left[\left(c(1 + aU^{b1})^{b2} \right) / (9, 3/\alpha) \right]^{(0.0009 \times \beta / (1 + 0.0009 \times \beta))} \quad (6)$$

In addition to the changes to the total energy behaviour sub-index, we incorporate all changes to other sub-index calculations detailed in the tSDI improvements section above.

Table 1. Assigned values for each fuel group and coefficients

Coefficients	Grass	Timber litter	Shrub	Slash
a	1.4	1.0	0.8	0.6
c	0.3	0.5	0.5	0.5
b1	2.3	2.2	2.0	1.1
b2	1.5	1.2	1.1	0.8

Table 2. Assigned values for crown fires and canyon fires

Heat per unit area (kcal m^{-2})	Flame length (m)	Assigned value
<8499	<10	1
8500–9060	10–15	2
9061–9620	15–20	3
9621–10 180	20–25	4
10 181–10 740	25–30	5
10 741–11 300	30–35	6
11 301–11 860	35–40	7
11 861–12 420	40–45	8
12 421–12 980	45–50	9
>12 981	>50	10

Classification of SDI and tSDI

SDI classes ‘very-low’, ‘low’, ‘medium’ and ‘high’ (with aviation resources) and ‘very-low’, ‘low’, and ‘medium’ (tSDI) indicate conditions where fire responders are regularly deployed, although the effort necessary to complete suppression operations is increasingly difficult. SDI classes ‘very-high’ and ‘extreme’ (with aviation resources) and ‘high’, ‘very-high’ and ‘extreme’ (tSDI) indicate ‘watch-out’ situations where one or more factors significantly increase the suppression effort necessary to engage a fire and responder safety is of heightened concern. In the Supplementary Material (section S2) we provide more detail on categorisation schemas, detailed input parameters and statistical assessment of case study applications (section S3) and additional equations for updating I_{ce} calculations to account for unprecedented fire weather conditions (section S4).

tSDI application to wildfire incident support (USA)

The Jolly Mountain fire detailed below is a typical example of incident-level decision support provided by risk management assistance teams (RMAT) over the 2017–19 fire seasons in the western United States (RMAT 2019). For these engagements, researchers worked directly with incident management teams (IMT) and local fire staff to produce tSDI from customised fuelscapes and weather inputs for a 3–5-day planning environment during an ongoing incident. The spatial and temporal scales of wildfire management in the western USA are significantly larger than for Spain, thus a 3–5-day forecast is appropriate for short-term decision making on a fire likely to last several weeks with a typical size of thousands to tens of thousands of hectares. The tSDI product was supplied within 24 h from the time of engagement with fire staff and in this case was not updated for subsequent changes in fire weather conditions.

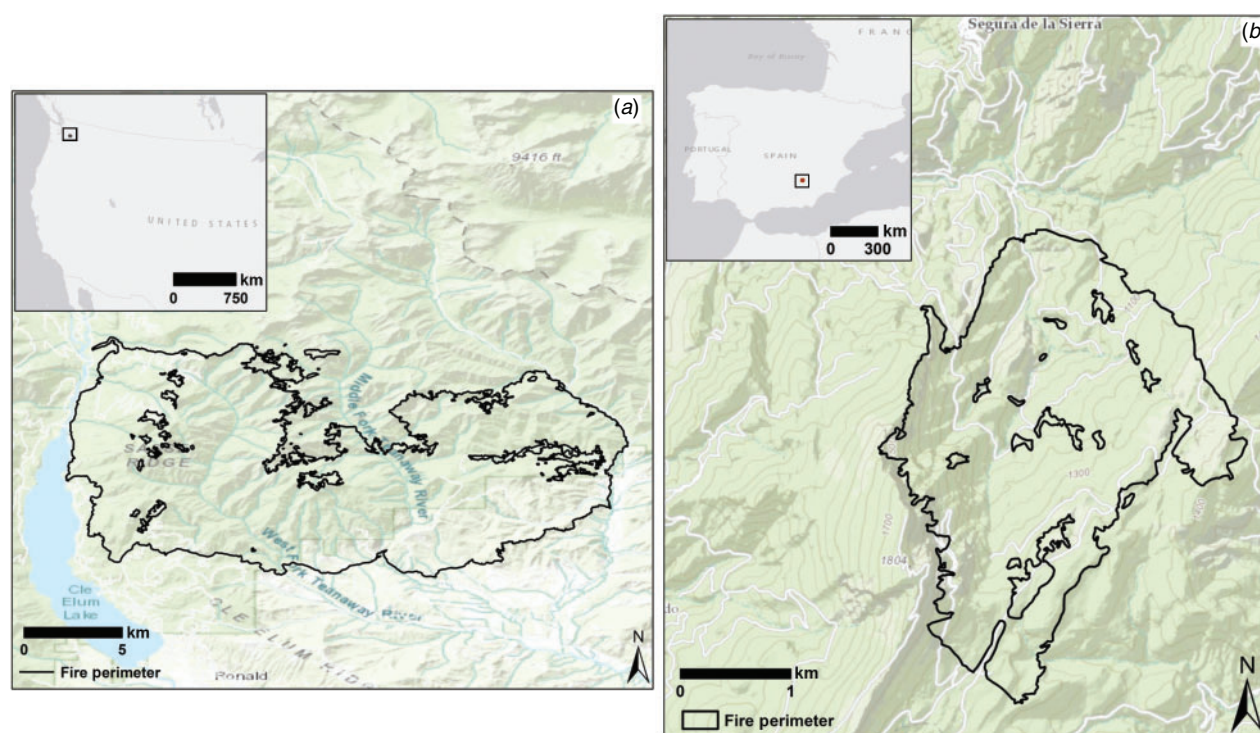


Fig. 1. Study locations of (a) the Jolly Mountain fire in Washington State, USA and (b) Segura fire in Jaén province (Andalucía Region), Spain.

Updates are generally produced at the request of incident managers. Products were supplied with the disclaimer that they were an experimental means of summarising the difficulty of ground-based suppression operations and could be useful for initial assessment of response strategies. Feedback was requested from operations staff for potential future improvements and changes. Although IMT and analysts were generally receptive to tSDI and liked the relative ease of interpretation, there was no evidence that IMT changed strategies based on the tSDI product; instead they used the product to reinforce and communicate strategies that had been assessed and scouted in the field. Mapped outputs were supplied to IMT and agency administrators in PDF and Google Earth (.kmz) (Fig. S3 in Supplementary Material online) formats to facilitate field validation, interpretation and communication.

Incident support case study locations

The Jolly Mountain fire was started by a lightning strike and discovered on 11 August 2017 in the Cascade Mountains of the Okanogan–Wenatchee National Forest of Washington State, USA ($47^{\circ}22'36.40''\text{N}$, $121^{\circ}1'7.00''\text{W}$, 1646 m.a.s.l.) (Fig. 1a). An RMAT analyst group was ordered to support the fire on 27 August 2017, when the fire had grown to a size of 1342 ha (3316 acres) and was burning in mature conifer forest, with dense understory at lower and mid elevations and lighter litter fuels on the southern aspects and near ridgelines. Although the management strategy was full suppression, the steep terrain, limited access, consolidated values at risk and severe fire weather outlook meant that the fire was unlikely to be contained until a season-ending weather event. Protection objectives were centred

on a community to the south and private inholdings along the lakefront to the west of the fire perimeter. Values at risk to the north and east were lower priority public infrastructure (campsites and outbuildings) and the steep terrain limited reasonable control opportunities. Hand and dozer line construction was concentrated along the fire's southern edge and a network of roads was used for containment of the western and eastern flanks. The original tSDI products were delivered on 29 August 2017, using forecasted 97th percentile fire weather and fuel moisture conditions (WFDSS 2017), average winds of 16 kph (10 mph) from the north-west and fuel models updated from LANDFIRE (2017). Detailed inputs used for FlamMap runs are included in Table S3.1 (in Supplementary Material online). A cold front moved through the area on 2nd September, resulting in rapid growth to the south and west that was checked by burnout operations from roads and the dozer line once conditions moderated. A second wind event on 10 September grew the fire to the north and east, nearly doubling the total fire size before a change to cool, wet conditions halted fire progression on 12 September at a final size of 14 896 ha (36 808 acres) (Fig. 2).

Extreme fire behaviour case study location (Spain)

The Segura fire started on 3 August 2017 in the Cazorla, Segura y las Villas Natural Park in the province of Jaén in the Andalucía region of southern Spain ($42^{\circ}37'103.98''\text{N}$, $53^{\circ}11'30.19''\text{W}$, 945 m.a.s.l.) (Fig. 1b). Vegetation was primarily forest with a dense shrub understory located on steeply bisected terrain with large deep canyons and low forest road density. We interviewed members of the incident command team to document the evolution of the Segura fire and suppression actions taken.

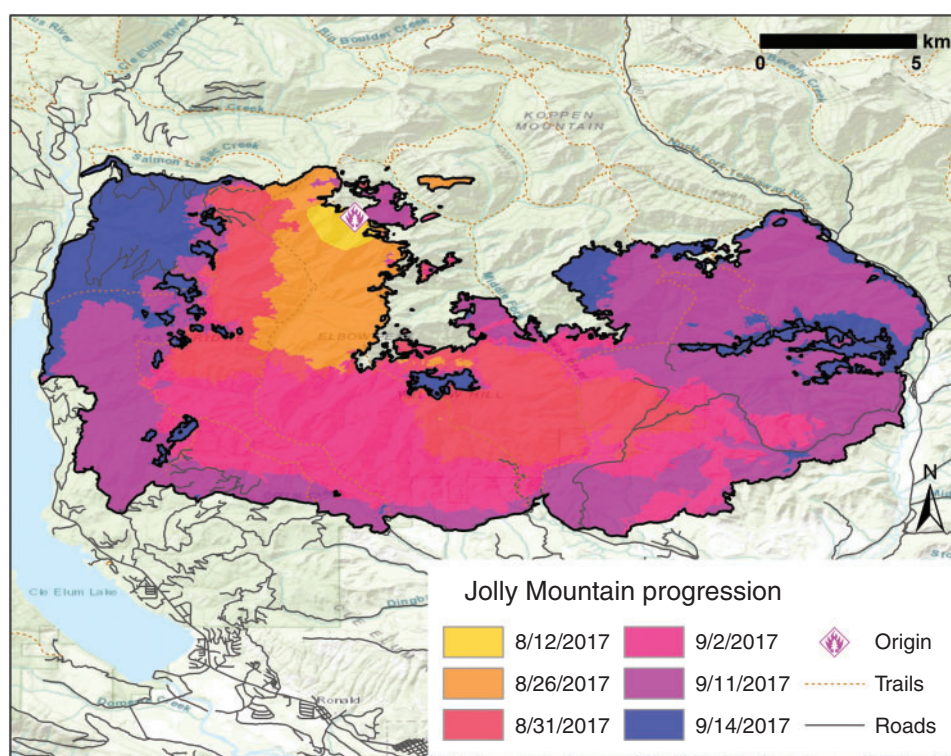


Fig. 2. Jolly Mountain fire progression from fire discovery on 11 August 2017 to final fire perimeter on 14 September 2017.

Over 2 days the Segura fire burned 687 ha (1573 acres). Observed fire behaviour included crown fire spread rates up to $45 \pm 10.56 \text{ m min}^{-1}$ and flame lengths of $18.25 \pm 6.25 \text{ m}$; in canyons, spread rates were $85 \pm 13.06 \text{ m min}^{-1}$ and flame lengths up to $38.25 \pm 8.25 \text{ m}$. Fire behaviour calculations used the national fuels map of Spain (Junta de Andalucía 2017) and weather conditions measured at the incident command post. Extreme heat along sections of the fire perimeter affected suppression operations by constraining resource movement and fireline construction. The landscape in the affected area was conducive to rapid fire spread with limited opportunities for suppression.

Assessment of tSDI and SDI in relation to suppression actions

To assess how suppression actions mapped onto suppression difficulty, results are summarised by tSDI and SDI class (very-low–extreme) for the final fire area as well as for a 30-m buffer around the built fireline (hand line, dozer line and reinforced roads as line) and uncontrolled fire perimeter (Figs 3, 4). For the Segura fire, where additional information on suppression actions was available, we include maps of the updated energy release component (I_{ice}) (Fig. 5a), the S_{ois} representing suppression opportunities (Fig. 5b), and fire progression (Fig. 6). To test the hypothesis that SDI values were significantly lower where active fire suppression actions were concentrated, we used Mood's median test (Brown and Mood 1951) to compare SDI values where a fireline was constructed to values where the fire perimeter was uncontrolled by suppression actions. We sampled raster values along constructed fireline and uncontrolled perimeter with a minimum sample spacing of 60 m (Jolly

Mountain) and 150 m (Segura fire) to reduce the influence of spatial autocorrelation and to account for differences in the pixel resolution used for SDI calculations on each fire. Additionally, we used a non-parametric McNemar test of paired nominal data (McNemar 1947) to assess the statistical significance of differences in classified SDI values between the original and updated algorithms.

Results

2017 Jolly Mountain Fire: tSDI application during an active incident

Mean tSDI values along the uncontrolled fireline were comparable to those calculated for the total fire footprint, while mean values along the constructed fireline were substantially lower (Table 3). The majority of the uncontrolled perimeter and total fire area was classified as medium and high tSDI, with lesser components of low and very-low tSDI, with the exception of uncontrolled perimeter under the original tSDI equation that over-represented very-low tSDI values in steep non-burnable fuel types (Table 3; Fig. 3). In contrast, tSDI classes along the constructed fireline were dominated by very-low and low classes with only minor components of medium and high tSDI (Table 3; Fig. 3c, d).

2017 Segura Fire: mapping SDI in relation to suppression operations

The original and updated SDI algorithms yielded very different results for the total fire area and perimeter of the Segura fire. In the original SDI, the majority of the fire area was medium and

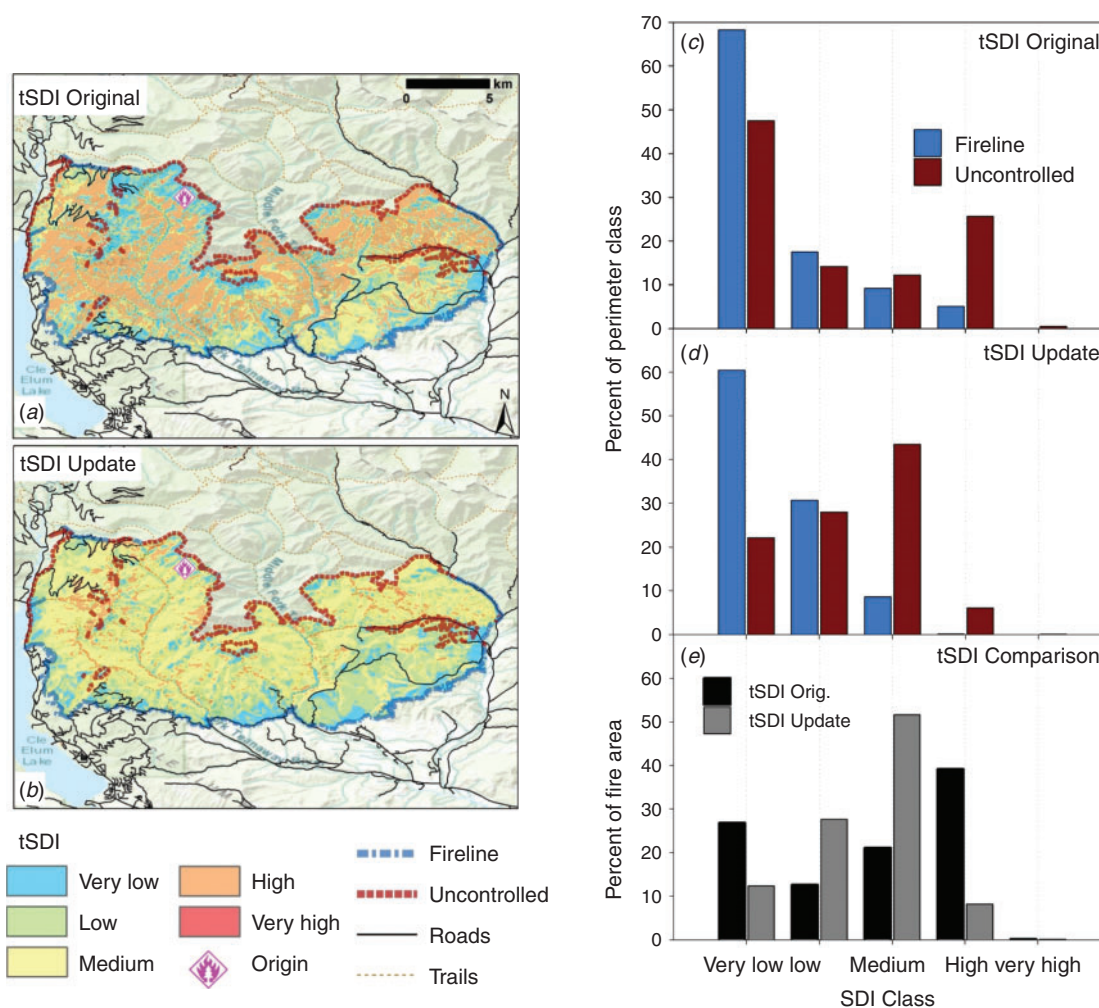


Fig. 3. Comparison of the (a) original and (b) updated tSDI maps of the Jolly Mountain fire, USA. Histograms display the distribution of tSDI values associated with constructed fireline and uncontrolled fire perimeter for the original and updated tSDI outputs (c, d) as well as the distribution of tSDI classes for the total fire area (e). tSDI, terrestrial suppression difficulty index.

high suppression difficulty, with smaller components of low and very-high SDI classes (Table 3; Fig. 4a, e). In contrast, the updated SDI accounting for canopy fire and canyon fire activity classified the Segura fire area as primarily very-high suppression difficulty with sequentially smaller areas classified with each reduction in SDI class (Table 3; Fig. 4b, e). Depending on the version of SDI, 60–90% of pixels along the uncontrolled fire perimeter of the Segura fire were classified as either high or very-high suppression difficulty. Along the constructed fireline, this relationship was inverted, where 51–93% of pixel values were classified as either low or medium SDI (Table 3, Fig. 4c, d).

We use the updated SDI map to demonstrate locations where suppression actions were and were not attempted given the fire conditions (Fig. 6). Initial fire spread (white arrows) occurred in a zone of high suppression difficulty. In this area [1], crown fires and canyon fires were the principal sources of spreading fire, rendering both direct and indirect attack unsuitable. Instead, suppression efforts focused on slowing fire spread with aviation resources. The western boundary of the fire perimeter was a long

ridge with rocks and limited to no fuel cover. A second phase of fire propagation, driven by wind, moved the fire to the south-east where SDI values were generally lower (blue arrows). In this area [2], increased accessibility and fireline production capacity, represented as suppression opportunity that allowed for direct and indirect attack (back fires) (Fig. 5b).

Updated SDI calculations for the Segura fire generally confirmed the results from the Jolly Mountain fire example, where pixels with low and medium SDI values corresponded to locations with the best opportunities to control fire perimeter growth. The incident command team described intense heat and crown fire activity in zone [1] (Fig. 6a), which made ground-based operations unsafe. The energy release component I_{ice} in zone [1] was extreme (ranging from 25 to 30, Fig. 5a, Table S2.2 in Supplementary Material online). By contrast, in zone [2] the energy release component was lower (< 22) (Fig. 4a) and suppression opportunity values were higher (S_{oi} up to 23) (Fig. 5b). Indirect attack with aerial resources was applied along the western edge (300–900 min) and direct attack with

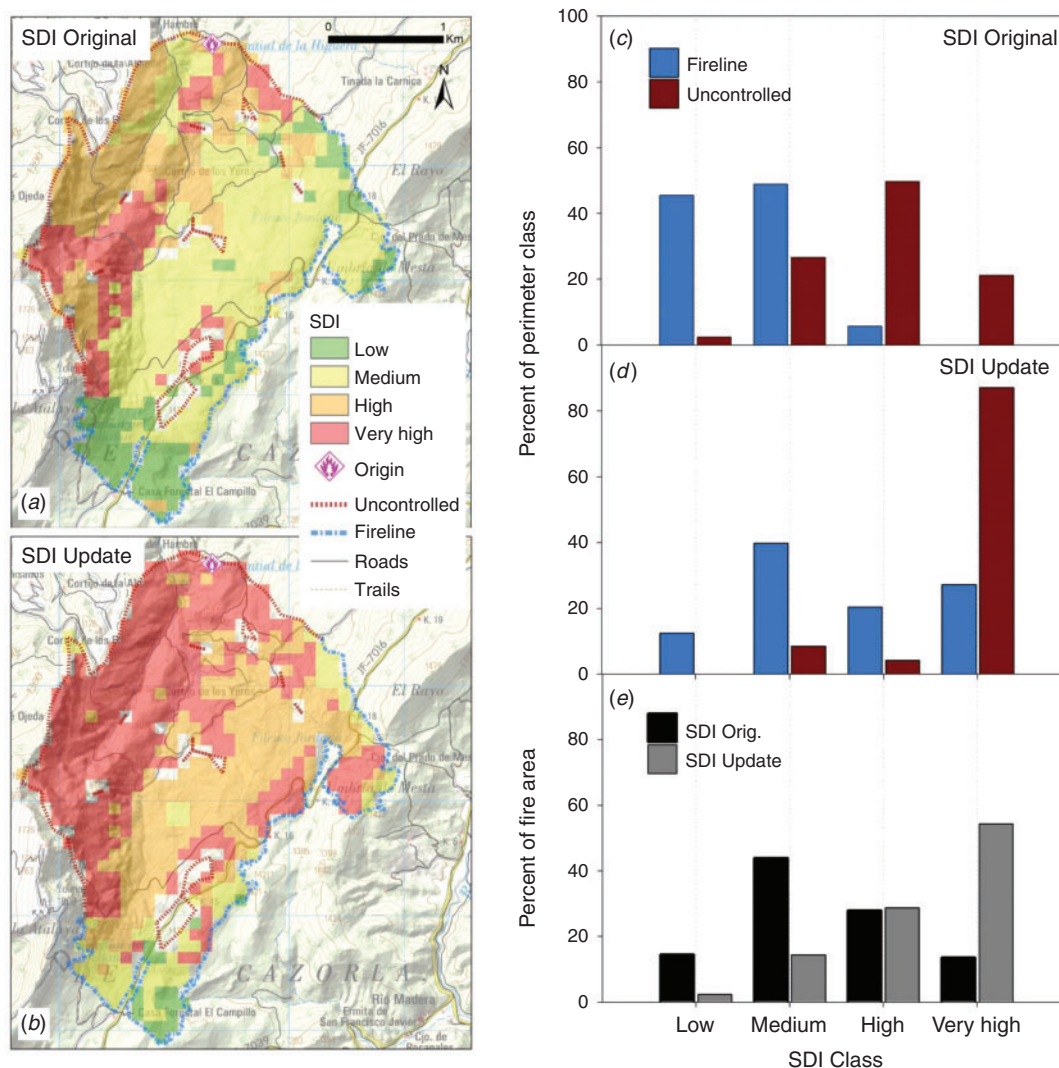


Fig. 4. Comparison of the (a) original and (b) updated SDI results for the Segura fire, Spain. Histograms display the distribution of SDI values associated with constructed fireline and uncontrolled fire perimeter for the original and updated SDI outputs (c, d) as well as the distribution of SDI classes for the total fire area (e). SDI, suppression difficulty index.

helicopter water drops and foam was used along the eastern edge (900–2000 min) (Fig. 6).

Median SDI values along successful firelines were significantly lower ($P < 0.0001$) than median values along the uncontrolled fire perimeter (Table 4). Results were significant for both the original and updated SDI formulations in both case study locations (Table 4).

Results from the McNemar test for differences in the proportion of tSDI classes between original and updated values yielded highly significant differences ($P < 0.001$) for all class categories of fireline on the Jolly Mountain fire and all but one class of the uncontrolled fire perimeter ('very high' class for the uncontrolled perimeter $P = 0.774$) (Table S3.2 in Supplementary Material online). For the Segura fire, all classes of fireline and uncontrolled perimeter in the updated SDI were significantly different ($P < 0.001$) from the original SDI values, with the exception of the 'low' SDI category where the difference was

significant but to a lesser degree (fireline $P = 0.016$ and uncontrolled perimeter $P = 0.022$) (Table S3.3 in Supplementary Material online).

Although the outputs from both models supported the hypothesis that successful ground-based fire containment operations tend to occur in areas with low suppression difficulty, updates to the original tSDI and SDI equations demonstrated stronger differentiation between locations where fire was successfully contained with lines and where the fire perimeter was uncontrolled (Table 4; Fig. 3d, Fig. 4d).

Discussion

Two basic aims of the SDI framework are to reduce the uncertainty and increase the efficiency of suppression operations, through assessment of landscape conditions and incorporation of expert knowledge into planning and decision support. Fire managers must negotiate an array of dynamic information to

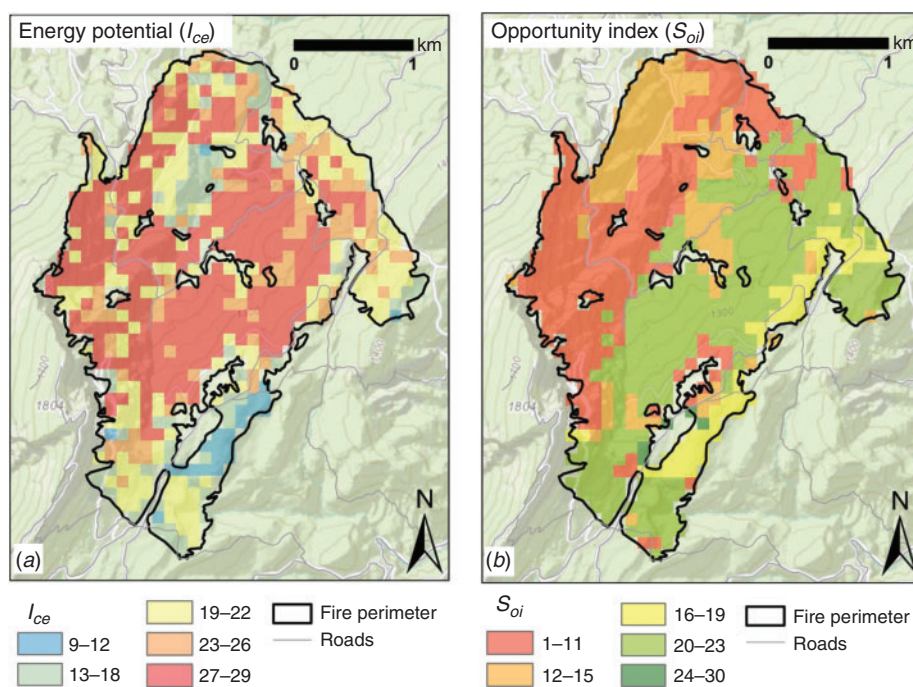


Fig. 5. Maps of (a) updated energy release (I_{ce}) and (b) suppression opportunity index (S_{oi}) of the Segura fire, Spain.

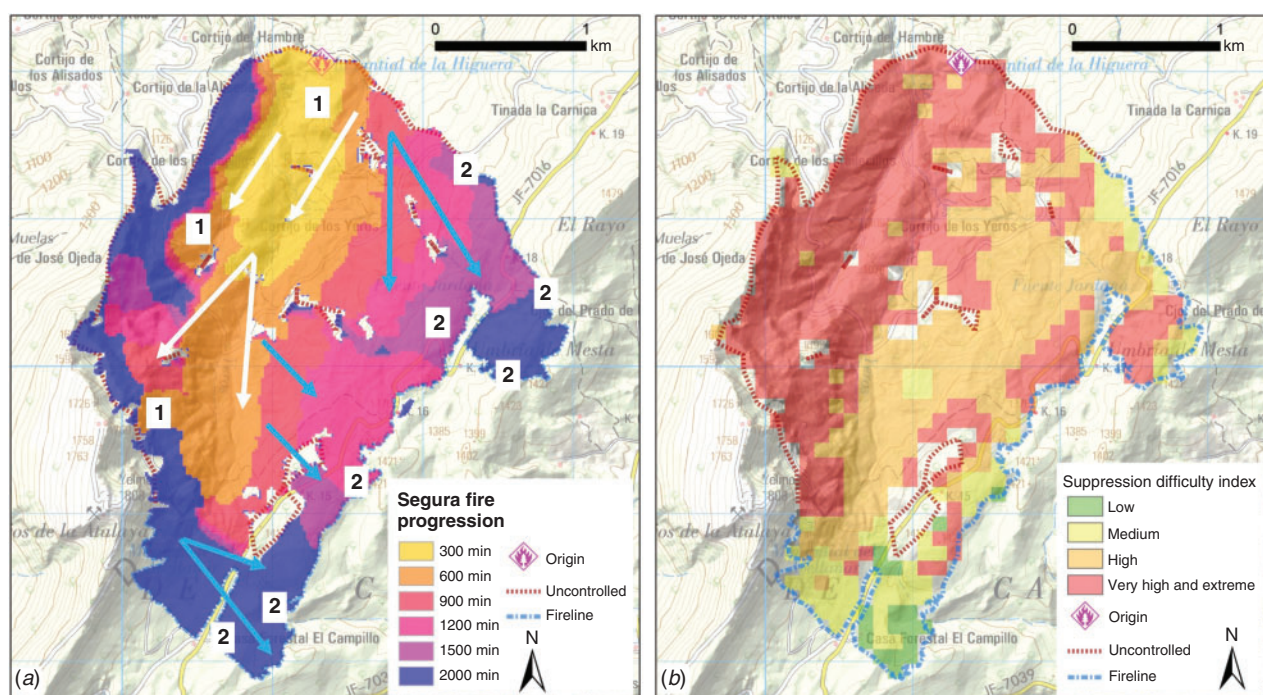


Fig. 6. (a) Fire progression and (b) suppression difficulty with operations zones of the Segura fire, Spain. Progression maps depict progression from 300 min to final containment at 2000 min. White arrows represent initial fire spread, blue arrows represent a second phase of spread and their associated higher [1] and lower [2] suppression difficulty index values.

Table 3. tSDI and SDI statistics for whole fire area, uncontrolled fire perimeter (UFP) and fireline for the Jolly Mountain and Segura fires
SDI, suppression difficulty index; tSDI, terrestrial SDI

Jolly Mountain, USA						
	Fire area		UFP		Fireline	
Average Class (%)	tSDI Orig 0.76	tSDI Update 0.68	tSDI Orig 0.54	tSDI Update 0.60	tSDI Orig 0.28	tSDI Update 0.29
Very low	26.9	12.4	47.5	22.2	68.3	60.4
Low	12.6	27.7	14.2	28	17.5	30.7
Medium	21.1	51.6	12.2	43.5	9.2	8.6
High	39.2	8.2	25.7	6.1	5	1
Segura, Spain						
	Fire area		UFP		Fireline	
Average Class (%)	SDI Orig 0.76	SDI Update 0.68	SDI Orig 0.54	SDI Update 0.60	SDI Orig 0.28	SDI Update 0.29
Low	14.5	2.4	2.4	0	45.5	12.5
Medium	44.0	14.4	26.7	8.6	48.9	39.8
High	27.9	28.8	49.7	4.3	5.7	20.5
Very high	13.6	54.4	21.2	87.1	0	27.3

Table 4. Results from Mood's median test for significant difference between SDI values for fireline and UFP
SDI, suppression difficulty index; UFP, uncontrolled fire perimeter

	Median value			
	Fireline	UFP	Chi-squared	<i>P</i>
Jolly Mountain Fire, USA				
tSDI Original	0.23	0.51	254.46	<0.0001
tSDI Update	0.25	0.57	279.90	<0.0001
<i>n</i>	515	2245		
Segura Fire, Spain				
SDI Original	0.5	1.3	65.84	<0.0001
SDI Update	0.95	2.9	16.77	0.0004
<i>n</i>	68	101		

determine where and when to position resources while considering fire responder exposure, values at risk, probability of success and resource constraints. Maps of the SDI provide operationally relevant information that can help fire managers integrate these concerns.

Over time, an iterative process of application, critique and refinement will ideally expand the relevance and usability of the SDI modelling framework. The modifications presented here represent several cycles of iteration based on manager feedback, fire observations and modelling and algorithmic updates. Revised assessment results for the Jolly Mountain and Segura fire scenarios suggested discernible improvements, although continued research and development are warranted. One near-term approach to better calibrate our understanding of suppression effectiveness in relation to the SDI could be reliance on counterfactual fire modelling, in order to compare the observed

fire perimeter with a hypothetical free-burning perimeter simulated over the same duration and under the same weather conditions (e.g. Rodríguez y Silva and González-Cabán 2010; Cochrane *et al.* 2012; Rodríguez y Silva and González-Cabán 2016; Thompson *et al.* 2016b).

A clear need is more comprehensive collection and analysis of fire behaviour and suppression operations data to improve our understanding of suppression effectiveness (Filkov *et al.* 2018; Plucinski 2019). High-resolution incident-scale data are essential for interpretation and validation of SDI results, as demonstrated with the Segura fire example. Further, rigorous statistical analysis of relationships between SDI values and suppression is premised on sufficient analytical frameworks to define and demonstrate suppression effectiveness, which are incomplete at present (Thompson *et al.* 2017b; Thompson *et al.* 2018a). Eventually, better data streams may pave the way for advanced analytics, such as machine learning, to discover complex relationships and dampen reliance on expert judgement (e.g. O'Connor *et al.* 2017; Liu *et al.* 2018; Thompson *et al.* 2019).

Several pathways forward for enhanced decision support are evident. Running SDI algorithms under a range of potential weather conditions could be a useful application both during active fire management and for pre-positioning information before a fire ignition. One such scenario-based example for extreme fire weather is currently available for the western United States (O'Connor *et al.* 2018); however, this type of information has not yet been integrated into formal wildfire planning or decision making. Summarising SDI values at the POD-level would provide information that can help determine management priorities and opportunities (Thompson *et al.* 2018b), and could support optimisation processes recommending areas to efficiently perform suppression operations not only along POD boundaries (i.e. predefined control locations) but

also within a POD with suitably low SDI values. It would be also possible to update SDI maps to account for past disturbances that may afford control opportunities (Parks *et al.* 2015; Beverly 2017), contrasted against post-disturbance snag dynamics that may increase hazard or reduce mobility (Page *et al.* 2013; Dunn *et al.* 2019). This suggests a stronger integration of the SDI with maps of operational hazards, safety zones, egress routes, etc. that could allow joint safety–difficulty maps to more directly inform on-the-ground operations and tactics. SDI analyses could also be integrated with econometric modelling and development of production functions capable of incorporating variables that affect the efficiency of suppression operations (e.g. Holmes and Calkin 2013; Rodríguez y Silva and González-Cabán 2016; Rodríguez y Silva 2017; Rodríguez y Silva and Hand 2018). Lastly, other applications could focus on evaluating and prioritising fuel breaks and other vegetation treatments designed to enhance suppression on the basis of the SDI.

There are limitations to be aware of when using the SDI. During incident support, fuel model classifications are often calibrated to fire spread rates. However, in the SDI calculations, there is no spread rate component, only heat per unit area and potential flame lengths (flame lengths include indirect information about fire intensity and this variable has a proportional relationship to the rate of spread). This was a significant concern for relying on the tSDI to predict suppression difficulty in the field. For example, in another fire in the USA where the tSDI was provided as part of the RMAT decision support (2017 North Umpqua Complex), stringers of beetle-killed timber had very fast spread rates that were not captured by the HUA/FL components of the model. Fuel models calibrated to spread rates could not account for the heavy fuel loading, resulting in a mismatch between observed spread rates and appropriately modelled heat intensity and flame lengths.

This concern exists despite the established relationships between flame lengths, fire intensity and rate of spread. Advice from the field was to find a way to incorporate spread rate into the SDI, which could be pursued in future iterations of SDI development. In the interim, updating SDI calculations using specified local weather conditions (either directly in the fire behaviour modelling or through the energy behaviour update factor described in section S4) will ideally help alleviate such concerns. It also may be the case that fuel models themselves could be updated to account for such conditions or even that such information could be provided auxiliary to the SDI model itself, recognising that no single model will provide every piece of information that fire managers may want.

Conclusions

In this paper we focused on a family of decision support tools designed to characterise the difficulty of suppression operations. We presented model updates, real-time use cases and post-hoc test cases that we believe demonstrate the viability of the SDI. The SDI framework can be used to assess prevention and preparedness needs, to forecast likely suppression resource demands and accompanying suppression expenditures, to develop strategic courses of action and plans for mobilisation of resources and to inform tactical deployment decisions of where to send suppression resources or conversely where to avoid

sending them. It is our hope that this paper spurs further interest from the fire science and fire management communities in assessing and planning to support a safe and effective response.

Conflicts of interest

The authors declare no conflicts of interest.

Acknowledgements

We thank the GEPRIF project (RTA2014-00011-C06-03) and VIS4FIRE project (RTA2017-00042-C05-04) (funded by the National Institute of Agrarian Research (INIA in Spanish), for their support of this work. We are also appreciative of the support of the USDA Forest Service Rocky Mountain Research Station and the University of Córdoba through a Memorandum of Understanding. Finally, we express our gratitude to three anonymous reviewers for their help in improving the presentation of the material and providing valuable suggestions to clarify this manuscript.

References

- Andrews PL (1986) BEHAVE: fire behavior prediction and fuel modeling system-BURN Subsystem, part 1. General Technical Report INT-194. US Department of Agriculture, Forest Service, Intermountain Research Station. 130 pp. (Ogden, UT, USA)
- Andrews PL, Rothermel RC (1982) Charts for interpreting wildland fire behavior characteristics. US Department of Agriculture, Forest Service, Intermountain Forest and Range Experiment Station, General Technical Report INT-131, 21 pp. (Ogden, UT, USA)
- Andrews P, Heinsch F, Schelvan L (2011) How to generate and interpret fire characteristics charts for surface and crown fire behavior. USDA Forest Service, Rocky Mountain Research Station. General Technical Report RMRS-GTR-253. (Fort Collins, CO, USA)
- Belval EJ, Wei Y, Bevers M (2015) A mixed integer program to model spatial wildfire behavior and suppression placement decisions. *Canadian Journal of Forest Research* **45**, 384–393. doi:10.1139/CJFR-2014-0252
- Belval EJ, Wei Y, Bevers M (2016) A stochastic mixed integer program to model spatial wildfire behavior and suppression placement decisions with uncertain weather. *Canadian Journal of Forest Research* **46**, 234–248. doi:10.1139/CJFR-2015-0289
- Beverly JL (2017) Time since prior wildfire affects subsequent fire containment in black spruce. *International Journal of Wildland Fire* **26**, 919–929. doi:10.1071/WF17051
- Brown GW, Mood AM (1951) 'On median tests for linear hypotheses'. Proceedings of the Second Berkeley Symposium on Mathematical Statistics and Probability. University of California Press, Berkeley, CA. Available at <https://projecteuclid.org/euclid.bsm/1200500226>
- Broyles G (2011) Fireline production rates. Fire Management Report 1151–1805 SDTDC. USDA Forest Service, San Dimas, CA.
- Byram GM 1959. Combustion of forest fuels. In 'Forest fire: control and use'. (Ed. KP Davis) pp. 61–89. McGraw-Hill, New York.
- Calkin D, Phipps J, Holmes T, Rieck J, Thompson M (2011a) The exposure index: developing firefighter safety performance measures. *Fire Management Today* **71**, 24–27.
- Calkin DE, Thompson MP, Finney MA, Hyde KD (2011b) A real-time risk assessment tool supporting wildland fire decisionmaking. *Journal of Forestry* **109**, 274–280.
- Campbell MJ, Dennison PE, Butler BW (2017a) A LiDAR-based analysis of the effects of slope, vegetation density, and ground surface roughness on travel rates for wildland firefighter escape route mapping. *International Journal of Wildland Fire* **26**, 884–895. doi:10.1071/WF17031
- Campbell MJ, Dennison PE, Butler BW (2017b) Safe separation distance score: a new metric for evaluating wildland firefighter safety zones using lidar. *International Journal of Geographical Information Science* **31**, 1448–1466. doi:10.1080/13658816.2016.1270453

- Campbell MJ, Page WG, Dennison PE, Butler BW (2019) Escape route index: a spatially-explicit measure of wildland firefighter egress capacity. *Fire* **2**, 40. doi:10.3390/FIRE2030040
- Cochrane M, Moran C, Wimberly M, Baer A, Finney MA, Beckendorf K, Eidenshink J, Zhu Z (2012) Estimation of wildfire size and risk changes due to fuels treatments. *International Journal of Wildland Fire* **21**, 357–367. doi:10.1071/WF11079
- Dennison PE, Fryer GK, Cova TJ (2014) Identification of firefighter safety zones using lidar. *Environmental Modelling & Software* **59**, 91–97. doi:10.1016/J.ENVSOF.2014.05.017
- Dillon GK, Menakis J, Fay F (2015) Wildland fire potential: a tool for assessing wildfire risk and fuels management needs. In Proceedings of the Large Wildland Fires Conference; May 19–23, 2014, Missoula, MT. (Eds RE Keane, M Jolly, R Parsons, K Riley). USDA, Forest Service, Rocky Mountain Research Station, pp. 60–76. Proceedings RMRS-P-73. (Fort Collins, CO, USA)
- Duff TJ, Tolhurst KG (2015) Operational wildfire suppression modelling: a review evaluating development, state of the art and future directions. *International Journal of Wildland Fire* **24**, 735–748. doi:10.1071/WF15018
- Dunn CJ, Calkin DE, Thompson MP (2017a) Towards enhanced risk management: planning, decision making and monitoring of US wildfire response. *International Journal of Wildland Fire* **26**, 551–556. doi:10.1071/WF17089
- Dunn CJ, Thompson MP, Calkin DE (2017b) A framework for developing safe and effective large-fire response in a new fire management paradigm. *Forest Ecology and Management* **404**, 184–196. doi:10.1016/J.FORECO.2017.08.039
- Dunn CJ, O'Connor CD, Reilly MJ, Calkin DE, Thompson MP (2019) Spatial and temporal assessment of responder exposure to snag hazards in post-fire environments. *Forest Ecology and Management* **441**, 202–214. doi:10.1016/J.FORECO.2019.03.035
- Filkov AI, Duff TJ, Penman TD (2018) Improving fire behaviour data obtained from wildfires. *Forests* **9**, 81. doi:10.3390/F9020081
- Finney MA (2006) 'An overview of FlamMap fire modeling capabilities'. In 'Fuels management: how to measure success', 28–30 March 2006, Portland, OR. (Eds PL Andrews, BW Butler) USDA Forest Service, Rocky Mountain Research Station, Proceedings RMRS-P-41. pp. 213–220. (Fort Collins, CO, USA).
- Forthofer J, Shannon K, Butler B (2009) Simulating diurnally driven slope winds with WindNinja. In 'Proceedings of 8th Symposium on Fire and Forest Meteorological Society', 13–15 October 2009, 13 pp. (KalisPELL, MT, USA)
- Hand M, Katuwal H, Calkin DE, Thompson MP (2017) The influence of incident management teams on the deployment of wildfire suppression resources. *International Journal of Wildland Fire* **26**, 615–629. doi:10.1071/WF16126
- Hirsch KG, Martell DL (1996) A review of initial attack fire crew productivity and effectiveness. *International Journal of Wildland Fire* **6**, 199–215. doi:10.1071/WF9960199
- Hirsch KG, Podur JJ, Janser RF, McAlpine RS, Martell DL (2004) Productivity of Ontario initial-attack fire crews: results of an expert-judgement elicitation study. *Canadian Journal of Forest Research* **34**, 705–715. doi:10.1139/X03-237
- Holmes TP, Calkin DE (2013) Econometric analysis of fire suppression production functions for large wildland fires. *International Journal of Wildland Fire* **22**, 246–255. doi:10.1071/WF11098
- Howard HH, McMaster RB, Slocum TA, Kessler FC (2008) 'Thematic cartography and geovisualization'. (Pearson Prentice Hall: Upper Saddle River, NJ)
- Jolly WM, Freeborn PH (2017) Towards improving wildland firefighter situational awareness through daily fire behaviour risk assessments in the US Northern Rockies and Northern Great Basin. *International Journal of Wildland Fire* **26**, 574–586. doi:10.1071/WF16153
- Junta de Andalucía (2017) Fire information database of Andalucía Spain. Available at: http://www.juntadeandalucia.es/medioambiente/site/rediam/menuitem.04dc44281e5d53cf8ca78ca731525ea0/?vgnextoid=708c621ab7abe410VgnVCM2000000624e50aRCRD&vgnnextchannel=f9b128bbc0761510VgnVCM1000001325e50aRCRD&vgnnextfmt=rediam&lr=lang_en [Verified 14 November 2019]
- Kalabokidis K, Ager A, Finney M, Athanasis N, Palaiologou P, Vasilakos C (2016) AEGIS: a wildfire prevention and management information system. *Natural Hazards and Earth System Sciences* **16**, 643–661. doi:10.5194/NHESS-16-643-2016
- Katuwal H, Calkin DE, Hand MS (2016) Production and efficiency of large wildland fire suppression effort: a stochastic frontier analysis. *Journal of Environmental Management* **166**, 227–236. doi:10.1016/J.JENVMAN.2015.10.030
- Katuwal H, Dunn CJ, Calkin DE (2017) Characterising resource use and potential inefficiencies during large-fire suppression in the western US. *International Journal of Wildland Fire* **26**, 604–614. doi:10.1071/WF17054
- LANDFIRE (2017) LANDFIRE 1.4.0: Surface and canopy fuel models. Available at: <https://www.landfire.gov/fuel.php>. [Verified 12 March 2018]
- Liu Z, Peng C, Work T, Candau J-N, DesRochers A, Kneeshaw D (2018) Application of machine-learning methods in forest ecology: recent progress and future challenges. *Environmental Reviews* **26**, 339–350. doi:10.1139/ER-2018-0034
- Martell DL (2015) A review of recent forest and wildland fire management decision support systems research. *Current Forestry Reports* **1**, 128–137. doi:10.1007/S40725-015-0011-Y
- McNemar Q (1947) Note on the sampling error of the difference between correlated proportions or percentages. *Psychometrika* **12**, 153–157. doi:10.1007/BF02295996
- Meyer MD, Roberts SL, Wills R, Brooks M, Winford EM (2015) Principles of effective USA federal fire management plans. *Fire Ecology* **11**, 59–83. doi:10.4996/FIREECOLOGY.1102059
- Minas J, Hearne J, Martell D (2015) An integrated optimization model for fuel management and fire suppression preparedness planning. *Annals of Operations Research* **232**, 201–215.
- Mitsopoulos I, Mallinis G, Zibtsev S, Yavuz M, Saglam B, Kucuk O, Bogomolov V, Borsuk A, Zaimis G (2016) An integrated approach for mapping fire suppression difficulty in three different ecosystems of Eastern Europe. *Journal of Spatial Science* **62**, 1–17. doi:10.1080/14498596.2016.1169952
- National Interagency Fire Center (2017) Red Book 2017: Interagency Standards for Fire and Fire Aviation Operations. Available at https://www.nifc.gov/policies/pol_ref_redbook.html [Verified 10 April 2018]
- National Wildfire Coordinating Group (NWC) (2017) Report on wildland firefighter fatalities in the United States: 2007–2016, PMS 841.
- O'Connor CD, Calkin DE (2019) Engaging the fire before it starts: a case study from the 2017 Pinal Fire (Arizona). *Wildfire* **28**, 14–18.
- O'Connor CD, Thompson MP, Rodríguez y Silva F (2016) Getting ahead of the wildfire problem: quantifying and mapping management challenges and opportunities. *Geosciences* **6**, 35. doi:10.3390/GEOSCIENCES6030035
- O'Connor CD, Calkin DE, Thompson MP (2017) An empirical machine learning approach for predicting future fire control points from historical fire perimeters. *International Journal of Wildland Fire* **26**, 587–597. doi:10.1071/WF16135
- O'Connor CD, Rodríguez y Silva F, Thompson MP, Gilbertson-Day J, Scott JH (2018) 'Terrestrial suppression difficulty map of the western United States.' Available at: <https://enterprisecontentnew-usfs.hub.arcgis.com/datasets/3d4a174dd1634e8e948880340f5c4548> [Verified 21 April 2020]
- Pacheco AP, Claro J, Fernandes PM, de Neufville R, Oliveira TM, Borges JG, Rodrigues JC (2015) Cohesive fire management within an uncertain

- environment: a review of risk handling and decision support systems. *Forest Ecology and Management* **347**, 1–17. doi:10.1016/J.FORECO.2015.02.033
- Page WG, Butler BW (2017) An empirically based approach to defining wildland firefighter safety and survival zone separation distances. *International Journal of Wildland Fire* **26**, 655–667. doi:10.1071/WF16213
- Page WG, Alexander ME, Jenkins MJ (2013) Wildfire's resistance to control in mountain pine beetle-attacked lodgepole pine forests. *Forestry Chronicle* **89**, 783–794. doi:10.5558/TFC2013-141
- Parks SA, Holsinger LM, Miller C, Nelson CR (2015) Wildland fire as a self-regulating mechanism: the role of previous burns and weather in limiting fire progression. *Ecological Applications* **25**, 1478–1492. doi:10.1890/14-1430.1
- Penman T, Collins L, Price O, Bradstock R, Metcalf S, Chong D (2013) Examining the relative effects of fire weather, suppression and fuel treatment on fire behaviour: a simulation study. *Journal of Environmental Management* **131**, 325–333. doi:10.1016/J.JENVMAN.2013.10.007
- Plucinski MP (2019) Contain and control: wildfire suppression effectiveness at incidents and across landscapes. *Current Forestry Reports* **5**, 20–40. doi:10.1007/S40725-019-00085-4
- RMAT (2019) 'Risk Management Assistance Teams.' Available at <https://wfmra.nwcg.gov/RMA.html#> [Verified 22 July 2019]
- Rodríguez y Silva F (2017) Aproximación metodológica para modelización econométrica de la productividad en la extinción de incendios forestales. 7º Congreso Forestal Español. Available at: <http://7cfe.congresoforestal.es/content/aproximacion-metodologica-para-modelizacion-econometrica-de-la-productividad-en-la-extincion> [Verified 19 July 2019]
- Rodríguez y Silva F, González-Cabán A (2010) 'SINAMI': a tool for the economic evaluation of forest fire management programs in Mediterranean ecosystems. *International Journal of Wildland Fire* **19**, 927–936. doi:10.1071/WF09015
- Rodríguez y Silva F, González-Cabán A (2016) Contribution of suppression difficulty and lessons learned in forecasting fire suppression operations productivity: a methodological approach. *Journal of Forest Economics* **25**, 149–159. doi:10.1016/J.JFE.2016.10.002
- Rodríguez y Silva F, Hand M (2018) Modeling the productivity of forest fire suppression operations using production functions: a methodological approach. In 'Advances in forest fire research' (Ed. DX Viegas), Chapter 6, pp. 1146–1154.
- Rodríguez y Silva F, Martínez JRM, González-Cabán A (2014) A methodology for determining operational priorities for prevention and suppression of wildland fires. *International Journal of Wildland Fire* **23**, 544–554. doi:10.1071/WF13063
- Scott J, Reinhardt E (2001) Assessing crown fire potential by linking models of surface and crown fire potential. USDA Forest Service, Rocky Mountain Research Station, Research Paper RMRS-29. (Fort Collins, CO)
- Stonesifer CS, Calkin DE, Thompson MP, Kaiden JD (2014) Developing an aviation exposure index to inform risk-based fire management decisions. *Journal of Forestry* **112**, 581–590.
- Stonesifer CS, Calkin DE, Thompson MP, Stockmann KD (2016) Fighting fire in the heat of the day: an analysis of operational and environmental conditions of use for large airtankers in United States fire suppression. *International Journal of Wildland Fire* **25**, 520–533. doi:10.1071/WF15149
- Tedim F, Leone V, Amraoui M, Bouillon C, Coughlan MR, Delogu GM, Fernandes PM, Ferreira C, McCaffrey S, McGee TK (2018) Defining extreme wildfire events: difficulties, challenges, and impacts. *Fire* **1**, 9. doi:10.3390/FIRE1010009
- Thompson MP (2014) Social, institutional, and psychological factors affecting wildfire incident decision making. *Society & Natural Resources* **27**, 636–644. doi:10.1080/08941920.2014.901460
- Thompson MP, Calkin DE, Finney MA, Ager AA, Gilbertson-Day JW (2011) Integrated national-scale assessment of wildfire risk to human and ecological values. *Stochastic Environmental Research and Risk Assessment* **25**, 761–780. doi:10.1007/S00477-011-0461-0
- Thompson MP, Calkin DE, Finney MA, Gebert KM, Hand MS (2013) A risk-based approach to wildland fire budgetary planning. *Forest Science* **59**, 63–77. doi:10.5849/FORSCI.09-124
- Thompson MP, Bowden P, Brough A, Scott JH, Gilbertson-Day J, Taylor A, Anderson J, Haas JR (2016a) Application of wildfire risk assessment results to wildfire response planning in the southern Sierra Nevada, California, USA. *Forests* **7**, 64. doi:10.3390/F7030064
- Thompson MP, Freeborn P, Rieck JD, Calkin DE, Gilbertson-Day JW, Cochrane MA, Hand MS (2016b) Quantifying the influence of previously burned areas on suppression effectiveness and avoided exposure: a case study of the Las Conchas Fire. *International Journal of Wildland Fire* **25**, 167–181. doi:10.1071/WF14216
- Thompson MP, Dunn CJ, Calkin DE (2017a) Systems thinking and wildland fire management. In 'Proceedings of the 60th Annual Meeting of the ISSS-2016, Boulder, CO, USA. (Rocky Mountain Research Station, Fort Collins, CO, USA)
- Thompson MP, Silva FR, Calkin DE, Hand MS (2017b) A review of challenges to determining and demonstrating efficiency of large fire management. *International Journal of Wildland Fire* **26**, 562–573. doi:10.1071/WF16137
- Thompson MP, Liu Z, Wei Y, Caggiano MD (2018a) Analyzing wildfire suppression difficulty in relation to protection demand. In 'Environmental risks'. (Ed. F-L Mihai) pp. 45–64. (IntechOpen: London)
- Thompson MP, MacGregor DG, Dunn CJ, Calkin DE, Phipps J (2018b) Rethinking the wildland fire management system. *Journal of Forestry* **116**, 382–390. doi:10.1093/JOFOR/FVY020
- Thompson MP, Wei Y, Calkin DE, O'Connor CD, Dunn CJ, Anderson NM, Hogland JS (2019) Risk management and analytics in wildfire response. *Current Forestry Reports* **5**, 226–239. doi:10.1007/S40725-019-00101-7
- Tyner JA (2014) 'Principles of map design', p. 167. The Guilford Press: New York, NY.
- Viegas DX (2005) A mathematical model for forest fires blowup. *Combustion Science and Technology* **177**, 27–51.
- Wei Y, Thompson MP, Haas JR, Dillon GK, O'Connor CD (2018) Spatial optimization of operationally relevant large fire confine and point protection strategies: model development and test cases. *Canadian Journal of Forest Research* **48**, 480–493. doi:10.1139/CJFR-2017-0271
- WFDSS (2017) Wildland Fire Decision Support System. United States Geological Survey web portal. Available at: <https://wfdss.usgs.gov/> [Verified 26 July 2019]
- Wotton B, Flannigan M, Marshall G (2017) Potential climate change impacts on fire intensity and key wildfire suppression thresholds in Canada. *Environmental Research Letters* **12**, 095003. doi:10.1088/1748-9326/AA7E6E