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A cellular automata model to link surface fires to firebrand lift-off and dispersal

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Abstract. In spite of considerable effort to predict wildland fire behaviour, the effects of firebrand lift-off, the ignition of resulting spot fires and their effects on fire spread, remain poorly understood. We developed a cellular automata model integrating key mathematical models governing current fire spread models with a recently developed model that estimates firebrand landing patterns. Using our model we simulated a wildfire in an idealised *Pinus ponderosa* ecosystem. Varying values of wind speed, surface fuel loading, surface fuel moisture content and canopy base height, we investigated two scenarios: (i) the probability of a spot fire igniting beyond fuelbreaks of various widths and (ii) how spot fires directly affect the overall surface fire's rate of spread. Results were averages across 2500 stochastic simulations. In both scenarios, canopy base height and surface fuel loading had a greater influence than wind speed and surface fuel moisture content. The expected rate of spread with spot fires occurring approached a constant value over time, which ranged between 6 and 931% higher than the predicted surface fire rate of spread. Incorporation of the role of spot fires in wildland fire spread should be an important thrust of future decision-support technologies.

Additional keywords: firebrands, fire-behaviour modelling, fuelbreaks, spot fires.

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Introduction

Most current fire-behaviour models focus on surface and canopy fire propagation. Another equally important aspect of wildland fire spread that lacks substantial research is the phenomenon of fires igniting ahead of the flaming front by firebrands propelled from the wildfire (Brown and Davis 1973; Potter 2011; Albini *et al.* 2012), an event known as spotting. Spot fires that ignite near the main front may have little effect on surface fire propagation because the front can overcome the spot fire before it contributes to the spread rate (Rothermel 1972). However, spotting can occur kilometres ahead of the main front (Albini 1979; Sardoy *et al.* 2007). These long-distance spot fires have the ability to ignite and propagate before converging with the main fire, promoting fire spread. The spatial patterns of spot fire ignition are difficult to predict, creating substantial difficulties for fire suppression (Albini 1979; Potter 2011).

Fuelbreaks are a fuels management strategy that focuses on reducing fuel in linear or patterned strips to hinder fireline propagation (Agee *et al.* 2000; Finney 2001). Shaded fuelbreaks focus efforts on both increasing crown bases and reducing canopy bulk density to prevent torching and spread while retaining shade to retard fuelbed recovery (Agee and Skinner 2005). If conditions permit, the main fire may loft firebrands that could allow spot fires to ignite and propagate beyond (i.e. jump) the fuelbreak. If fire fighters fail to extinguish these spots then, despite the effort of constructing and maintaining fuelbreaks, the fire will continue to propagate throughout the terrain. Although shaded fuelbreaks can be used to impede spotting, current guidelines to determine fuelbreak placement or size are ambiguous or lack empirical validation (Agee *et al.* 2000; Finney 2001; Agee and Skinner 2005). Models that predict spot fire ignition and spread could therefore inform land managers in developing effective fuelbreaks.

Improving fire-behaviour decision-support programs is of great importance because they are considered one of the most important tools implemented by fire managers (Cruz *et al.* 2002; Butler *et al.* 2004). Two software programs commonly utilised to predict fire behaviour are BehavePlus and FARSITE (Andrews *et al.* 2008; Sullivan 2009). BehavePlus (Andrews *et al.* 2008) is a fire modelling system whereas FARSITE (Finney 2004) is a fire-growth simulator. These fire-behaviour programs are useful for many land management applications, but both lack important aspects concerning firebrand dispersal, spot fire ignition and the effects propagation may have on wildland fire spread. Although BehavePlus and FARSITE are based on many of the same mathematical models (Andrews and Bevins 2003), their routines for spot fires are different. BehavePlus calculates the maximum distances spot fires may ignite using work by Albini (1979, 1981, 1983*a*, 1983*b*) and Chase (1981, 1984). FARSITE simulates spot fire ignition and propagation using the same collection of Albini models as well as the work done by Albini and Baughman (1979). BehavePlus calculates the probability of spot fire ignition by lofted firebrands based on work by Schroeder (1969), whereas FARSITE has a user-defined probability of spot fire ignition. For these programs, and those that neglect incorporating spot fires, a method that incorporates recent work concerning firebrand behaviour (e.g. Sardoy *et al.* 2008) can advance attempts to better quantify wildfire spread.

Sardoy *et al.* (2008) determined spatial landing distributions of lofted disc-shaped firebrands using numerical solutions of a fluid dynamical model proposed by Sardoy *et al.* (2007). This model is composed of (1) an extension of the model from Mercer and Weber (1994) to describe the behaviour of a buoyant plume from a line fire, (2) a thermal degradation and combustion model of firebrands that determines landing characteristics and (3) an extension of the numerical model of Sardoy *et al.* (2007) describing the transport of burning disc-shaped firebrands lofted by a three-dimensional steady-state buoyant plume from a crown fire. After Sardoy *et al.* (2008) ran their model under various conditions they found that firebrands have unimodal or bimodal landing distances depending on firebrand char content. When referring to the bimodal landing distances they labelled the two regimes as 'short-distance' and 'long-distance' firebrands. Sardoy *et al.* (2008) concluded that short-distance firebrands present the greater fire danger because more of them are glowing upon landing and they have a greater unburned mass remaining, so they used a lognormal function to describe the short-distance firebrand landing distribution.

Other models have been developed to attempt to better understand the influence of spot fires on the main fire. The earliest is a broad-scale probabilistic model called EMBYR developed by Hargrove *et al.* (2000). They found that the inclusion of spot fires dramatically altered simulated fire dynamics in that both rate of fire spread and the total area burned increased. Porterie *et al.* (2007) developed a cellular automata model with spot fire ignition and propagation using a weighting procedure on the cells based on the characteristic times, thermal degradation and combustion of the flammable site. They stated that their model could be used to answer questions about fuelbreak design and efficiency, but further studies would focus on scaling effects and critical exponents. Alexandridis *et al.* (2008) presented an enhanced methodology for predicting fire spread based on a cellular automata framework. Alexandridis *et al.* claimed that the model has potential to be developed into an effective fire risk-management tool for land managers, although it appears this has not yet been accomplished. Unfortunately these authors did not have access to a model of firebrand landing distributions, so they either assumed their own distribution or used a routine similar to BEHAVE.

To link these attempts and better understand spot fire behaviour, we developed a cellular automata model of a propagating wildland fire that incorporates spot fire ignition and propagation. Our model integrates the statistical model developed by Sardoy *et al.* (2008) with key mathematical models by Rothermel (1972), Van Wagner (1977), Byram (1959), Albini (1979), Albini and Baughman (1979) and Schroeder (1969), which govern current fire-behaviour programs FARSITE and BehavePlus. Using our constructed model, we conducted a sensitivity study where we investigated (1) the probability of a spot fire igniting beyond a fuelbreak and (2) how spot fires directly affect the expected average rate of spread of the main fire under varying conditions of wind speed, surface fuel moisture content, surface fuel load and canopy base height. The utility of this model is to demonstrate the effect spot fires can have on wildfire propagation and clarify the research needs for including spotting in fire-behaviour models.

Model

Our cellular automata model of a propagating wildfire with spot fire ignition and propagation simulates a wildfire in a grid with n rows and m columns. Each cell in the grid has a length and width of Δx m. The temporal progression of the model occurs in discrete portions called time steps Δt. At any time each cell can be in one of the following three states: (i) unburned – the cell is capable of igniting but has yet to, (ii) burned – the cell is currently burning or has burned or (iii) torched – the cell transitioned to a burned state and torched, allowing firebrand lift-off. A cell's state is controlled by the four sub-models: Surface Spread, Tree Torching, Firebrand Dispersal and Spot Ignition. Cells in an unburned state can transition to a burned state if conditions in the Surface Spread sub-model are met. Cells in a burned state can transition to torched if the conditions in the Tree Torch sub-model are met. Upon a cell torching, the model disperses firebrands downwind of that cell using the Firebrand Dispersal sub-model. These firebrands have the potential to have unburned cells away from the main fire transition to a burned state (i.e. ignite spot fires) if conditions in the Spot Ignition sub-model are met. Using cellular automata is the simplest way to capture the stochastic nature of the fire propagation and spot ignition.

Surface spread

To determine the likelihood of an unburned cell adjacent to a burned cell igniting, we used the model of Rothermel (1972). Naturally occurring wildfires do not travel at a constant speed. Changes in the fuelbed alter the fire's progress, so we used Rothermel's model to compute a probability of fire propagation from one cell to the next:

$$P(ROS) = ROS\left(\frac{\Delta t}{\Delta x}\right) f_{dim} \qquad (1)$$

where $P(ROS)$ is the probability of propagation (cells timestep^{-1}), ROS is the surface fire's rate of spread as computed by Rothermel's model (m s^{-1}), Δt is the time step (s timestep^{-1}), Δx is the cell width (m cell^{-1}) and f_{dim} is a dimensionality factor (dimensionless). In order to use Eqn 1 as a probability, Δt must be initialised so that $P(ROS)$ is between 0 and 1.

The dimensionality factor equalises the modelled fire's average rate of spread with no spotting to *ROS*. Without the dimensionality factor the modelled fire propagates twice as fast as the rate predicted by Rothermel's model. This is because we are using Eqn 1 in two-dimensional space, which allows for multiple paths of spread from one cell to the next, and it would be more appropriate in a single dimension where there is only one path for spread. This approach assumes fire spreads diffusely and ignores radiation effects between burned cells and distant unburned cells.

Tree torching

We utilised the tree torching condition of Van Wagner (1977) to determine if a burned cell torches. This condition is not probabilistic, so to add a stochastic element to this sub-model we used a logistic function (Stauffer 2008) of surface fire intensity to determine the probability that a tree torches, $P(torch)$:

$$P(torch) = \frac{\exp(-\sigma_t(I_0 - I))}{1 + \exp(-\sigma_t(I_0 - I))} \tag{2}$$

where σ_t is the shape parameter (m kW^{-1}), I_0 is the critical surface fire intensity needed to ignite the crown computed by the condition of Van Wagner (1977) (kW m^{-1}) and I is the surface fireline intensity computed by the model of Byram (1959) (kW m^{-1}). In our model $P(torch)$ is 0.5 when $I = I_0$. The probability of torching approaches 1 for values of $I > I_0$ and approaches 0 for values of $I < I_0$ (Fig. 1). The parameter σ_t determines the rate of increase of $P(torch)$ as I increases. We assumed torches to be instantaneous, so cells transition from burned to torched in a single time step. To account for the change in wind speed through the forest stand, we used the wind-adjustment factor presented by Albini and Baughman (1979).

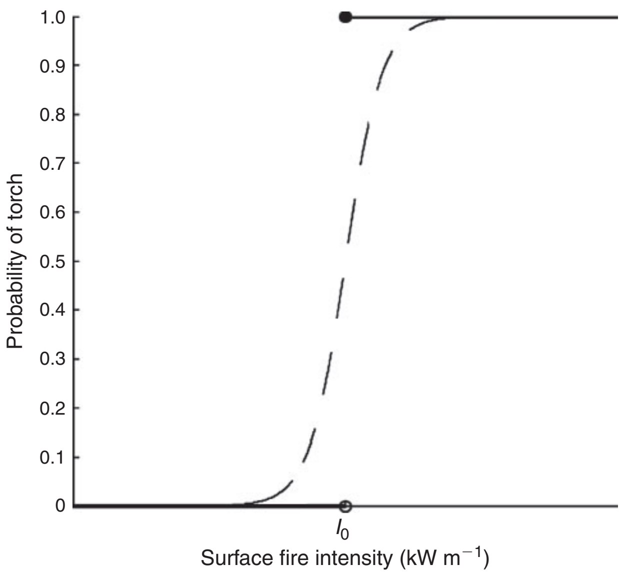

Fig. 1. In this figure, the black step graph displays Van Wagner's (1977) torching condition whereas the dashed curve displays the cell-torch probability function (Eqn 2). The horizontal axis represents the surface fire intensity I (kW m^{-1}) and the y-axis is the probability of torching $P(torch)$. The point of inflection on the curve is the critical surface fire intensity as computed by Van Wagner's torching condition I_0 (kW m^{-1}).

Firebrand dispersal

When a cell transitions to a torched state firebrands are dispersed downwind from that cell. We used the model of Sardoy *et al.* (2008) to determine where these firebrands land parallel to the wind. Sardoy *et al.* (2008) found that the short-distance firebrand distribution can be approximated by a lognormal function of the landing distance:

$$p(d) = \frac{1}{(\sqrt{2\pi}\sigma_{FB} d)} \exp\left(\frac{-(\ln(d) - \mu_{FB})^2)}{(2\sigma_{FB}^2)}\right) \tag{3}$$

where $p(d)$ is the probability firebrands land d metres away from the fireline, σ_{FB} is the standard deviation and μ_{FB} is the mean. To calculate the mean and standard deviation, the Froude number must be computed to determine if the plume is buoyancy driven or wind driven. Sardoy *et al.* (2008) used the following formula to calculate the Froude number:

$$Fr = \frac{U_H}{\sqrt{g\left(\frac{I_F}{(\rho_\infty c_{cg} T_\infty g^{1/2})}\right)^{2/3}}} \tag{4}$$

where U_H is the wind speed at a defined height (m s^{-1}), g is the acceleration due to gravity (~9.8 m s^{-1}), I_F is the fire intensity incorporating the intensity produced by torching trees (kW m^{-1}), ρ_∞ is ambient gas density (~1.1 kg m^{-3}), c_{pg} is the specific heat of gas (kJ kg^{-1} K^{-1}) and T_∞ is ambient temperature (K). Buoyancy-driven regimes have a Froude number less than or equal to 1 whereas wind-driven regimes have a Froude number greater than 1. For buoyancy-driven plumes the mean and standard deviation for Eqn 3 are calculated by:

$$\begin{aligned} \sigma_{FB} &= 0.86(I_F^{-0.21} U_H^{0.44}) + 0.19 \\ \mu_{FB} &= 1.47(I_F^{0.54} U_H^{-0.55)}) + 1.14 \end{aligned} \tag{5}$$

and the mean and standard deviation for wind-driven plumes are calculated by:

$$\begin{aligned} \sigma_{FB} &= 4.95(I_F^{-0.01} U_H^{-0.02}) - 3.48 \\ \mu_{FB} &= 1.32(I_F^{0.26} U_H^{0.11}) - 0.02 \end{aligned} \tag{6}$$

Like Himoto and Tanaka (2005), we used a normal distribution to model the distances firebrands travel perpendicular to the wind. We assumed a mean of 0 and standard deviation of σ_y. Our model tracks how many firebrands from a single torch land in any given cell as well as the distance from the torched cell. A counter tracks the number of firebrands that land outside of the grid, but these firebrands do not contribute to fire spread in our model. We assumed each torch produced 50 firebrands that could potentially ignite a spot fire because there is no known research to aid in determining this value. We only consider firebrands lofted by torches because Sardoy *et al.* (2007, 2008) developed their model with this assumption, but firebrands can be generated by other sources. Models should seek to incorporate firebrands that originate from surface fuels (cones, dead surface fuels) as these are often overlooked, but important sources of spot fires (Clements 1977). This has been investigated by Albini (1981, 1983*a*, 1983*b*), who developed a series of models to determine the maximum spotting distance of firebrands produced by isolated sources and wind-driven surface fires.

Spot ignition

A spot fire will not result from every firebrand. To calculate the probability of spot ignition we used Schroeder's (1969) model. However, we assumed that (1) the probability of ignition would decrease the farther away a firebrand lands from the torch and (2) the probability of ignition would increase based on the number of firebrands that land in the cell. The former supports the importance of the burnout time of lofted firebrands, as proposed by Albini (1979), whereas the latter highlights that as more firebrands land in a cell there is a greater chance of spot ignition. Therefore, we first scaled Schroeder's probability of spot fire ignition based on an exponentially decreasing factor, which is determined by the firebrand's landing distance away from the torch:

$$P(I)_d = P(I)\exp(-\lambda_s d) \quad (7)$$

where $P(I)$ is the probability of spot fire ignition calculated by Schroeder's (1969) model, λ_s is a positive number representing the decay constant, d is the firebrand's landing distance away from the torch (cells) and $P(I)_d$ is the probability of spot ignition considering assumption (1). To handle assumption (2) and determine our model's probability of spot fire ignition $P(I)_d^{FB}$, we exploited the compliment of $P(I)_d$ (Stauffer 2008):

$$P(I)_d^{FB} = 1 - (1 - P(I)_d)^b \quad (8)$$

where b is the number of firebrands that land in the cell. A firebrand will cause an unburned cell to transition to a burned state if the cell receives at least one firebrand and the cell's probability of ignition as computed by Eqn 8 is greater than a randomly generated uniform number.

Before the model ignites a spot fire an appropriate amount of time must pass. We assumed that the amount of time to pass before spot fire ignition t_i, is the sum of three time intervals: the amount of time required for the firebrand to reach its maximum vertical height t_v; the amount of time required for the firebrand to descend from the maximum vertical height to the forest floor t_g; and the amount of time required for a spot fire to ignite and build up to the steady-state t_I. The time it takes a spot fire to build up to the steady state is included because our model assumes that once spot fires ignite they have the same intensity as the main fire. Thus, once spot fires ignite they can torch cells and potentially start more spot fires. There is much research concerning firebrand trajectories (Potter 2011) but we wanted to minimise the complexity of our model while conservatively estimating the effect of firebrands on spread (i.e. overestimating the duration of firebrand transport). Thus, we used formulae given by the model of Albini (1979) to estimate t_v. In addition, we assumed that t_g and t_v were equivalent, and used the estimate stated by McAlpine and Wakimoto (1991) that it takes 20 min for a spot fire to reach the steady-state rate. Our model determines t_i for each spot fire that will eventually ignite and converts the units to time steps. Then, when the appropriate number of time steps passes, the associated spot fire ignites.

Implementation

We constructed our model using the MATLAB programming environment. A schematic of our model's logical procedure of the major processes being modelled is shown in Fig. 2, and images displaying the propagation of a modelled wildfire are shown in Fig. 3. During the initialisation, variables and parameters that remain constant throughout the simulation are set. For each time step, our model examines every cell in the modelling grid. First, the model determines if the cell will torch based on Eqn 2. If the cell torches, the landing locations for each firebrand are determined based on Eqn 3 and the normal probability distribution described above. Then, the model determines which firebrands will start spot fires using Eqn 8. For each spot fire that will eventually ignite, time until ignition is determined based on the assumptions stated above as well as a set of equations defined by Albini (1979). Next, the model determines if a spot fire ignites in the cell. For cells that eventually spot, if the time until ignition has reached 0 the cell is ignited. Otherwise, the time until ignition is decremented. After each cell is checked, the model propagates wildfire. If at least one of the four von Neumann neighbours of an unburned cell is in a burned state, then Eqn 1 is used to determine if the unburned cell transitions to a burned state (i.e. spreads fire). Finally, the model moves to the next time step and repeats the entire process of examining each cell. This continues until the time step has reached the maximum time.

We parameterised the model to simulate a wildfire propagating through an idealised *Pinus ponderosa* (ponderosa pine) ecosystem with flat terrain. Considering crown diameter of mature ponderosa pine trees we let $\Delta x = 7$ m, thus each cell has one tree. This implies that there is one tree crown in a torch. The parameter $\Delta t = 30$ s. To initiate the fire the first column of cells (the western edge of the grid) is set to the burning state. This column is referred to as the source of ignition. We assumed westerly winds so that the fire propagates towards the eastern edge of the grid. When we incorporate the fuelbreak, the length of the grid in the east–west direction is equal to the fuelbreak width plus twice the maximum spotting distance (m). Thus, if a torch occurs when the fire front reaches the fuelbreak the grid is likely to catch most of the firebrands that may ignite a spot fire on the opposite side of the fuelbreak. The fuelbreak's width is initially Δx m and is varied from 25–500 m with increments of 25 m. In the model, we rounded when calculating the number of columns that make up the fuelbreak. Our model allows the wildfire to propagate for 16 h. When determining the average rate of spread with spotting, the modelling grid has an east–west length that is 16 times the maximum spotting distance. This allows the modelled fire to propagate for the full 16 h before contacting the eastern edge. The length of the grid in the north–south direction is 301 m for all simulations.

For our investigation we varied values for surface fuel moisture content m_f, canopy base height z, oven-dry surface fuel loading w_o and wind speed 6 m above the treetop U_{zo+6}. These variables were varied because they encourage extreme

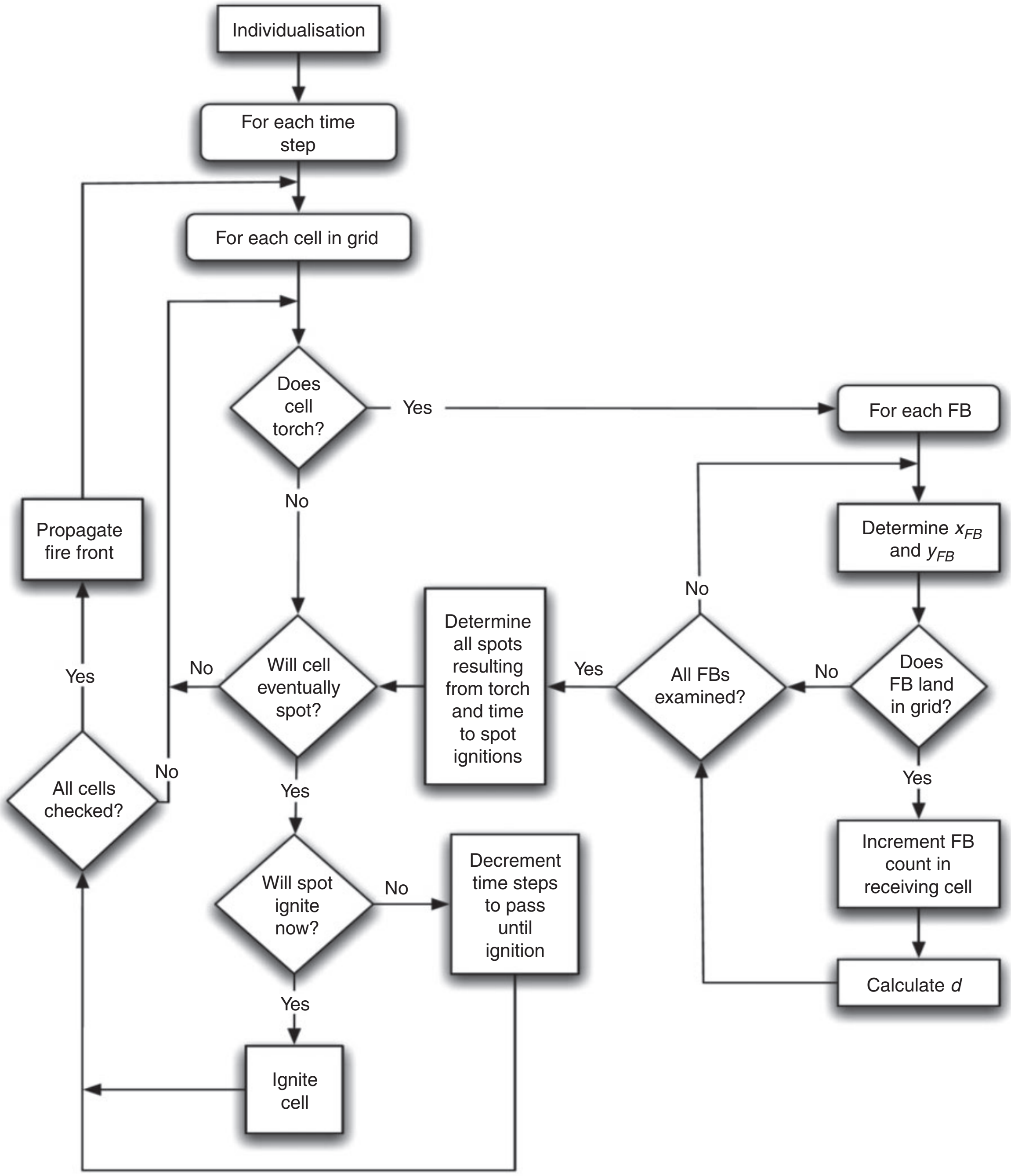

Fig. 2. This figure displays the model's logical process. The model begins in the Initialisation stage and will continue to run until the time step exceeds a set maximum time. Variables x_{FB} and y_{FB} are the distances (cells) firebrands travel from the torch parallel and perpendicular to the wind as described in the text. The variable d is the distance (m) between where the firebrand lands and the cell that torched, and 'FB' represents firebrand.

fire behaviour (i.e. torching, spotting) when fuel moisture content is low, canopy base height is low, oven-dry surface fuel loading is high or wind speed 6 m above the treetop is high. Values were conservatively assigned to fuels (canopy base height, fuel moisture content and surface fuel loading) and wind (Table 1) to represent typical western USA ponderosa pine fire season situations. The system is at ambient conditions when the above variables are set to their medium values. Although one variable was varied the others are set to the medium value. To define constants not varied we used fuel model TL8 described by Scott and Burgan (2005), values used by Sardoy *et al.* (2008), data from Susott (1982) and personal estimation (Table 2). The parameters σ_t (Eqn 2), λ_s (Eqn 7), σ_v and the number of firebrands that land glowing were estimated by fitting preliminary model

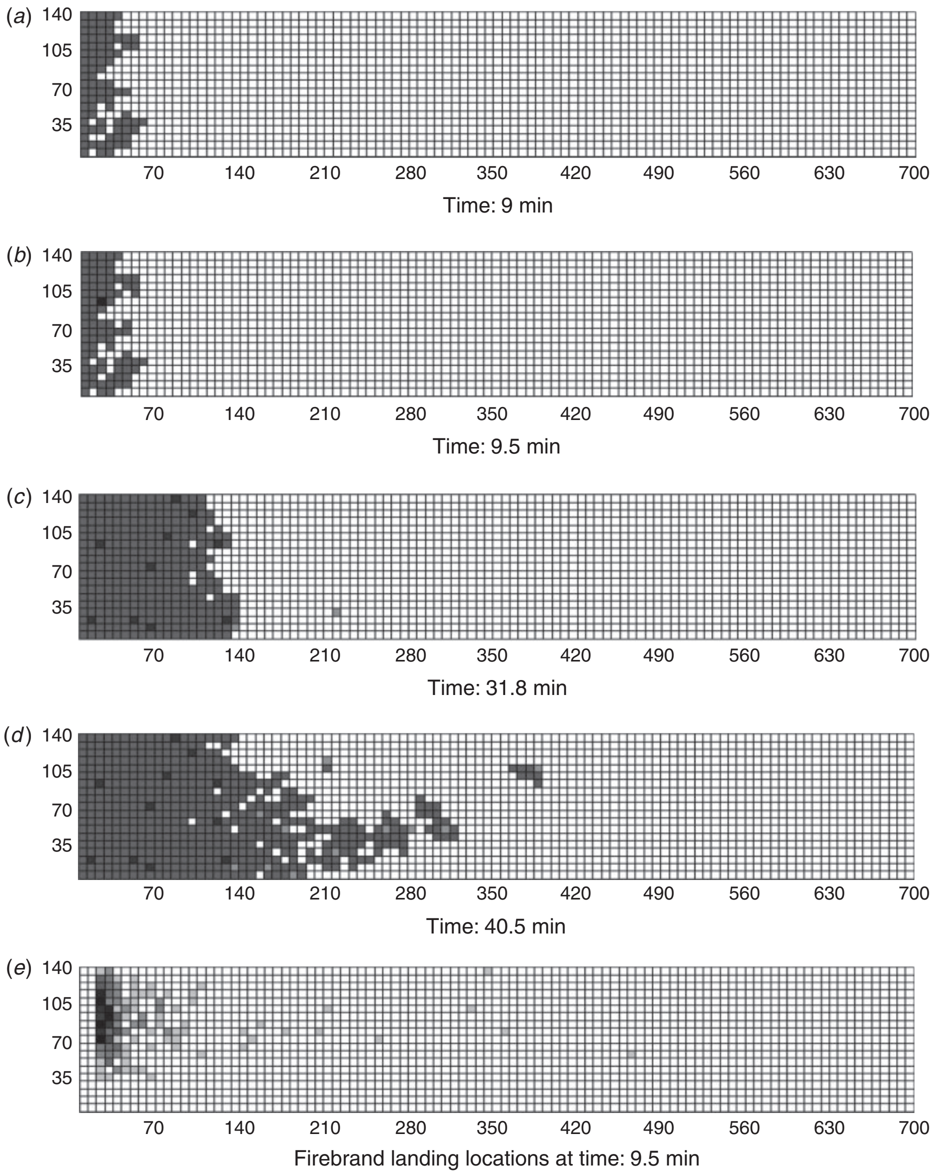

Fig. 3. Panels (*a–d*) display a temporal series of burn states for the various spatial locations of our fire propagation model. For these images, dark grey cells are burned, white cells are unburned, black cells are torched and light grey cells represent the ignition of a spot fire. Panel (*e*) displays the landing locations of firebrands distributed from the torch occurring in panel (*b*). In this image, cell colour corresponds to the number of firebrands that land there. The colours range from black to white; white indicating no firebrands landed in that cell whereas black indicates the most firebrands landed in that cell. For all panels the grid length is 700 m and the width is 140 m.

simulations so that a physically reasonable number of spot fires were generated under ambient conditions (on average 8 spot fires in a 10-h period).The value for f_{dim} was chosen so that the rate of spread with no spotting determined by our model (with varied parameters set to their intermediate values) would be equivalent to the rate of spread determined by Rothermel's model.

The use of Rothermel's model typically includes calculating surface fuel bulk density ρ_b based on a defined surface fuel depth δ and oven-dry surface fuel loading w_o. Without varying δ along with w_o, unnaturally 'airy' fuel beds result. To solve this, we determined a constant value for ρ_b based on the varied variables set to their medium values (Table 2), and adjusted Rothermel's formula for ρ_b to solve for δ. Thus, in our model depth varies appropriately with various oven-dry surface fuel loading values.

Using our model we addressed two scenarios: (1) the probability of spot fires jumping fuelbreaks of various widths and (2) how spot fires directly influence the main fire front's expected rate of spread. For the former, we incorporated a fuelbreak into the centre of the modelling grid. The modelled surface fire will cease propagating once it reaches the fuelbreak, but spot fires

Table 1. Values for the environmental variables varied throughout model simulations

Environmental variables were assigned three different values: low, medium and high. Medium values represent ambient conditions. Values were conservatively assigned based on typical western US *Pinus ponderosa* fire season situations

Variable	Values		
	Low	Medium	High
Canopy base height z (m)	10	15	20
Surface fuel moisture content m_f (kg moisture kg^{-1} oven-dry wood)	0.063	0.094	0.124
Oven-dry surface fuel loading w_o (kg m^{-2})	1.121	2.243	3.364
Wind speed 6 m above tree top height U_{zo+6} (m s^{-1})	4.470	8.941	13.411

Table 2. Model constants and associated data sources

Fuel model TL8 described by Scott and Burgan (2005) was used to define several variables. Susott (1982) provided a value for the heat of combustion H, and the remaining constants were estimated

Constant	Value	Source
Fuel particle effective mineral content S_e (kg silica-free minerals kg^{-1} oven-dry wood)	0.010	TL8
Fuel particle heat content h (kJ kg^{-1})	18 608.003	TL8
Fuel particle surface-area-to-volume ratio σ (m^{-1})	5807.016	TL8
Fuel particle total mineral content S_T (kg minerals/kg^{-1} oven-dry wood)	0.056	TL8
Moisture content of extinction m_x (kg moisture kg^{-1} oven-dry wood)	0.35	TL8
Oven-dry particle density ρ_p (kg m^{-3})	512.591	TL8
Heat of combustion H (kJ kg^{-1})	22 000	Susott (1982)
Ambient gas density T_∞ (K)	300	Sardoy *et al.* (2008)
Specific heat of gas c_{pg} (kJ kg^{-1} K^{-1})	1121	Sardoy *et al.* (2008)
Canopy cover C (%)	40	Estimated
Fire intensity incorporating tree torching intensity T_F (kW m^{-1})	$I + 0.015$	Estimated
Moisture content of canopy m_c (kg moisture kg^{-1} oven-dry wood)	0.80	Estimated
Number of ignited firebrands landing on ground	50	Estimated
Surface fuel bulk density ρ_b (kg m^{-3})	24.520	Estimated
Tree diameter t_d (cm)	50.8	Estimated
Tree height z_o (m)	30	Estimated
$P(ROS)$ dimensionality factor f_{dim}	0.519	Estimated
d_{per} constant σ_v	$(\Delta x)/2$	Estimated
$P(I)_d$ constant λ_s	0.005	Estimated
$P(torch)$ constant σ_t	0.001	Estimated

can ignite and propagate beyond the fuelbreak. The probability of a spot fire jumping a fuelbreak was determined by averaging across 2500 simulations. For the latter, we compared the average rate of spread without spot fires ROS (m s^{-1}), as calculated by Rothermel's formula, to the average rate of spread with spot fires ROS_{spots} (m s^{-1}), which is calculated by our model. It can be argued that using average rate of spread is improper when discussing fire spread by spotting due to the discontinuous spread. However, because we are focussing on the direct effect on the main fire front we believe using an average rate of spread is appropriate.

To calculate ROS_{spots}, first, we determined the distance of the modelled fire front from the initial source of ignition for each row of cells. This is the distance from the source of ignition to the first unburned cell. Thus, spot fires do not aid wildfire propagation until the spot fire and main fire merge. Averaging the front distances for all the rows in the grid at every time step gives the average distance the front has travelled throughout the simulation. We computed ROS_{spots} by averaging across 2500 simulations. Because both ROS and ROS_{spots} are averages, neither rate attempts to describe the accurate rate of spread for a single fire event. This is important given the stochastic nature of wildfires. For both scenarios, averaging across 2500 simulations was ideal because any less decreased the precision of the results and any more had little improvement on precision and increased the models run time. Because our model neglects spot fires backing towards the head fire as well as fire–atmosphere interactions, the models estimates for the rates of spread are likely skewed.

Results

Our model predicts that changes in surface fuel moisture content m_f, canopy base height z, oven-dry surface fuel loading w_o and wind speed 6 m above the treetop U_{zo+6} affect the ability of spot fires to accelerate wildfire propagation. The probability of a spot fire jumping a fuelbreak $P(jump)$ decreased as fuelbreak width (m) increased for all variations, but conditions that support extreme fire behaviour increased the probability of jumping (Fig. 4). Low canopy base height had the largest influence in that it exhibited an increase in *P*(*jump*) by at least 295% from moderate conditions throughout all fuelbreak width variations (Fig. 4*a*). High oven-dry surface fuel loading increased *P*(*jump*) at least 60% from moderate conditions (Fig. 4*b*), high wind speed increased *P*(*jump*) at least 69% from moderate conditions (Fig. 4*d*) and low surface fuel moisture content increased *P*(*jump*) at least 62% from moderate conditions (Fig. 4*c*).

Certain variable variations produced lower *P*(*jump*) values than did moderate conditions. High canopy base height produced a *P*(*jump*) line that was nearly 0 for all fuelbreak widths (Fig. 4*a*). A low wind speed decreased *P*(*jump*) between 55% and 90% (Fig. 4*d*), a low surface fuel loading decreased *P*(*jump*) between 31% and 40% (Fig. 4*b*) and a high surface fuel moisture content decreased *P*(*jump*) between 30% and 59% (Fig. 4*c*).

During individual simulations wildfires without spotting moved at a constant rate of spread (Fig. 5*a*), but wildfires with spot fire ignition and propagation exhibited random jumps in the front distance away from source (Fig. 5*b*). These jumps indicate instances when a spot fire front merged with the main fire front. Averaging the front distance from source over 2500 simulations shows that wildfires without spotting had little variation in the average front distance from source (Fig. 6*a*), but spotting wildfires varied drastically from the average front distance from source (Fig. 6*b*). It is also apparent that on average spotting wildfires had greater front distances from source than did wildfires not spotting (Fig. 6*a*–*b*). After 2 h of propagation, wildfires not spotting exhibited a reasonably constant average rate of spread over time approximately equal to the value produced by Rothermel's model, but spotting wildfires exhibited an increase in the average rate of spread over time (Fig. 6*c*). All variable variations produced similar patterns that highlighted individual values for the average rate of spread when spotting occurred (Table 3). The time that passed before a spotting fire equalised to its average rate of spread varied.

Conditions that encourage extreme fire behaviour (i.e. low fuel moisture content, low canopy base height, high oven-dry surface fuel loading or high wind speed 6 m above the treetop) produced values for the average rate of spread with spotting ROS_{spots} much higher than did the average rate of spread predicted by Rothermel's model *ROS*. Variable variations that deter extreme fire behaviour (i.e. high fuel moisture content,

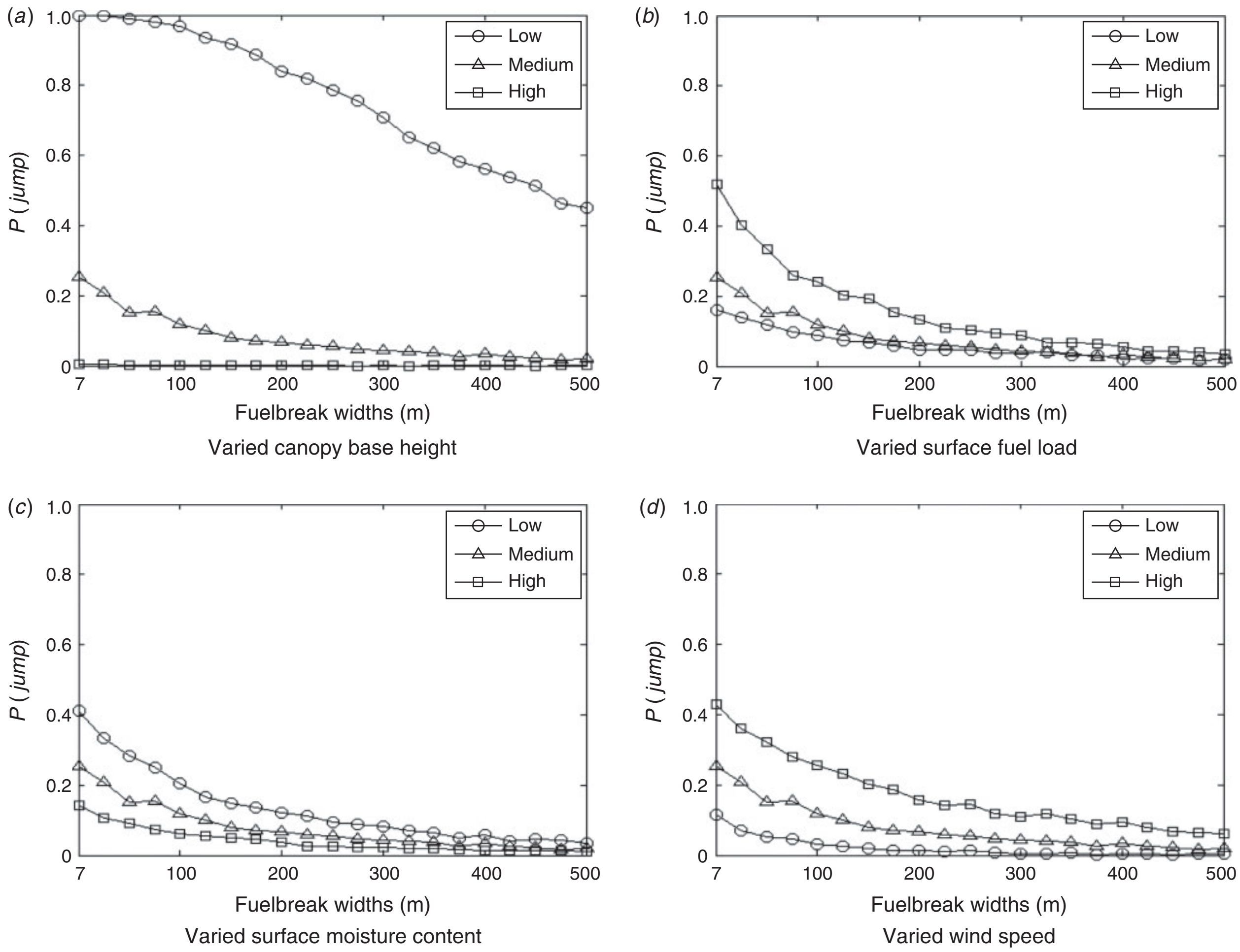

Fig. 4. The above displays the probability of a spot fire igniting beyond a fuelbreak *P*(*jump*) *v*. the fuelbreak width (m). Lines with circles, triangles and squares indicate the stated variable is set to the low, medium and high value. All four panels have the same curve when the stated variable is set to the medium value because the other varied variables are set to the medium values as well.

high canopy base height, low oven-dry surface fuel loading or low wind speed 6 m above the treetop) had a minimal difference between *ROS* and ROS_{spots} (Table 3). A low canopy base height produced a ROS_{spots} 1025% greater than *ROS*, a high surface fuel loading produced a ROS_{spots} 117% higher than *ROS*, a low surface fuel moisture content produced a ROS_{spots} 116% higher than *ROS* and a high wind speed 6 m above treetop produced a ROS_{spots} 117% higher than *ROS*. The increase from *ROS* to ROS_{spots} is minimal with a high canopy base height (6%) but slightly larger with a low surface fuel loading (38%), a high moisture content (38%) and a low wind speed (22%).

Discussion

The developed surface-spot fire cellular automata model provides insights into factors that allow spot fires to aid in the propagation of wildfires. It is a compilation of key mathematical models governing the most utilised fire-behaviour software today along with a model estimating firebrand dispersal (Sardoy *et al.* 2007, 2008). Our results show that not only does the average rate of spread increase when spotting occurs, but after a period of time spotting wildfires appear to approach a constant average rate of spread ROS_{spots}. In addition, our results highlight some potential connections between surface fires, torching trees, dispersed firebrands and the resulting spot fires, which could aid fuelbreak design.

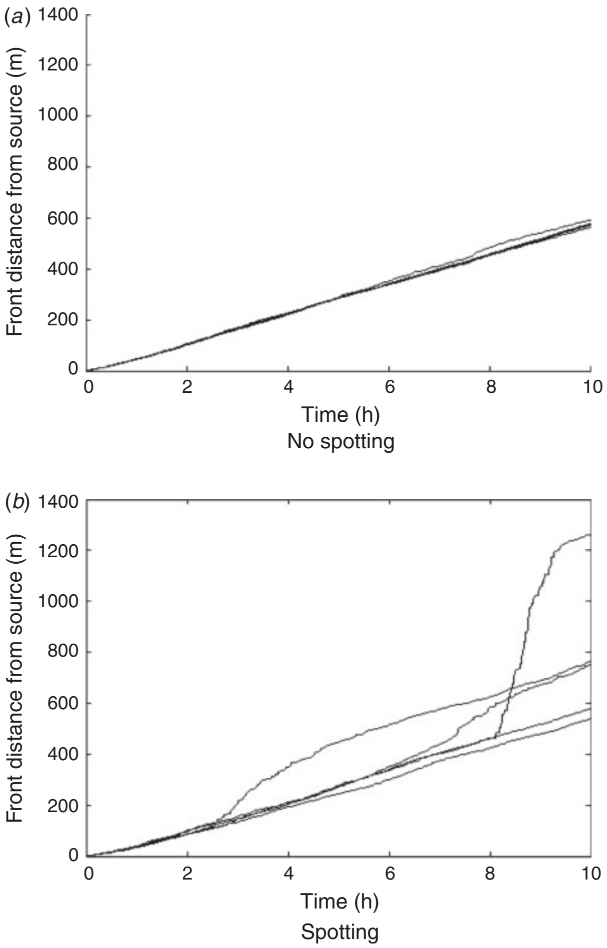

Fig. 5. In the above, panel (*a*) displays the average front distance from the source for five individual simulations when no spotting occurs, whereas panel (*b*) displays the average front distance from the source for five individual simulations with spotting occurring. In panel (*a*) simulations produce a front which moves fairly constant with moments of random, minor peaks. In panel (*b*) there are simulations that appear analogous to panel (*a*), but there are also simulations that produce dramatic spikes in the average front distance. This displays instances when the main fire front merges with a spot fire front.

Of the four variables we analysed, canopy base height may be the most influential variable on spot fires, followed by surface fuel loading, wind speed 6 m above the treetop and surface fuel moisture content (Fig. 4; Table 3). Considering that both canopy base height and surface fuel loading are manageable, these results highlight the important role forest managers have in reducing spot fire ignition, propagation, and therefore overall fire spread. Because canopy base height had the most influence, our results support the contention that canopy base height is one of the most important components of fuels management (Agee *et al.* 2000; Keyes and O'Hara 2002; Agee and Skinner 2005). Thus, to reduce the influence of spot fires constructing fuelbreaks that raise canopy base heights is paramount, followed by reducing surface fuel loading.

An improved comprehension of the role fuelbreaks play in fire suppression will aid managers in the design of effective fuelbreaks (Finney 2001). Our model can investigate fuelbreak development by determining appropriate values for key variables (i.e. canopy base height, surface fuel loading and fuelbreak width). For example, it is obvious that a wider fuelbreak is more effective at preventing firebrands from jumping, but there are economic and environmental tradeoffs. Our model suggests that as fuelbreak width increases the probability of a spot fire ignition beyond a fuelbreak decreases exponentially. Thus, for different fuel beds, fuelbreak width might be prescribed at the inflection point (the point at which the probability of jumping is 50%), or a value that balances ecosystem-specific economic and environmental costs. Our model considers a single, linear fuelbreak but can be re-programmed to consider different fuelbreak patterns.

Although our model currently has somewhat limited direct applicability for fire managers, it summarises the existing knowledge of spot fire ignition and propagation, and highlights research needs. In developing this model, the limited research concerning firebrand and spot fire behaviour became clear and resulted in several assumptions about such important behaviour. These assumptions limit the quantitative accuracy of our results. Having a quantitatively accurate model of wildfire spread may be impossible considering the highly stochastic nature of wildfires, but this does not hinder the need for additional research. Gaining a better understanding of mechanisms that drive spot fire behaviour is necessary in order to improve estimations of the spotting fire front's rate of spread (Potter 2011). Of the three primary mechanisms governing spot fire behaviour (i.e. generation, transport and ignition) firebrand generation and spot fire ignition remain most poorly understood and require more research (Koo *et al.* 2010; Potter 2011). In addition, field research documenting actual wildfire incidence and spread is essential to aid in model calibration as well as model validation and evaluation. Despite these issues, simulations have shown

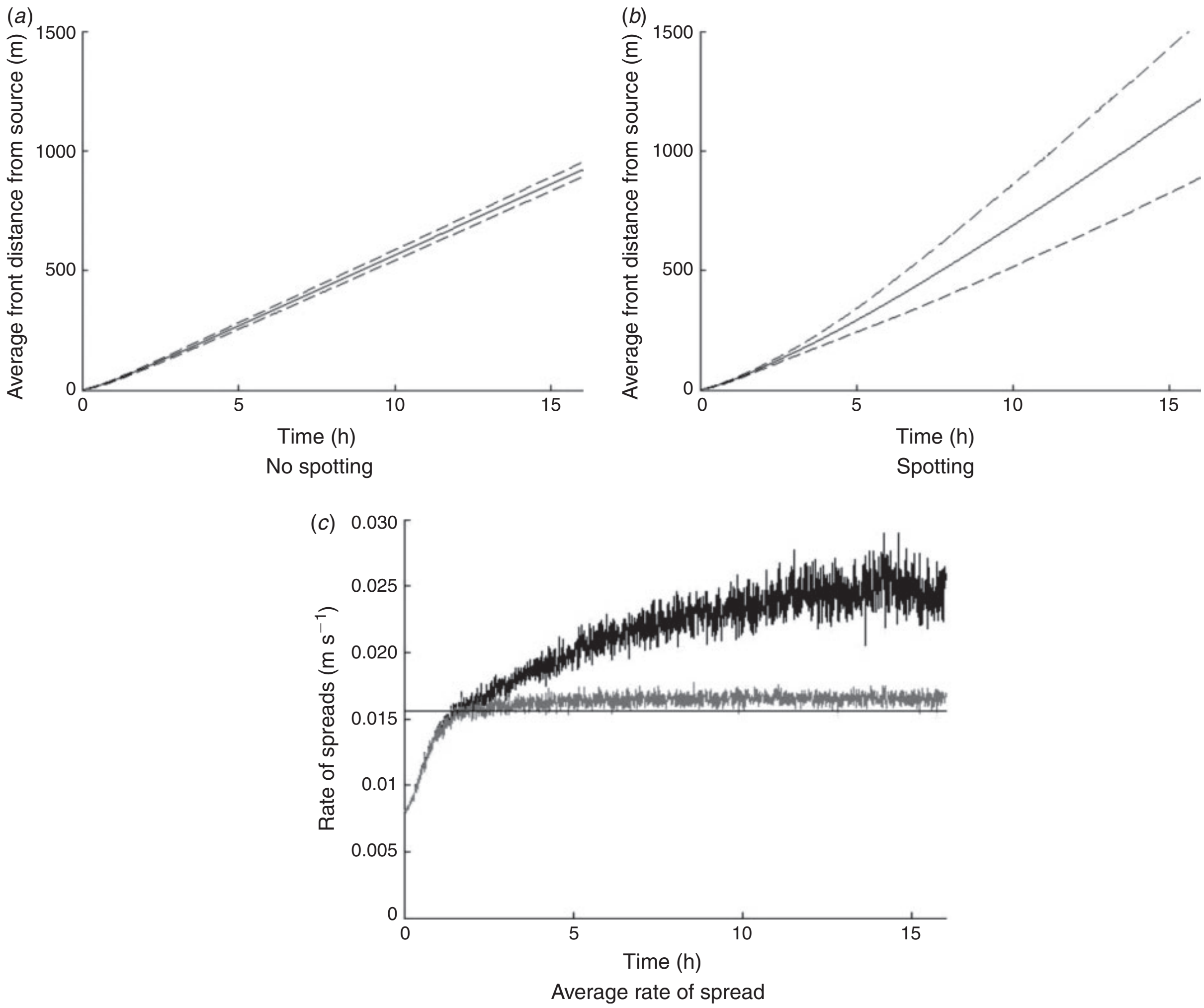

Fig. 6. Panel (*a*) displays the average distance from the source with no spot fires whereas panel (*b*) displays the average distance from the source with spotting. In both panels (*a*) and (*b*), the solid line represents the average front distance from source and the dashed lines represent the standard deviation. Panel (*c*) compares the average rate of spread for panels (*a*) and (*b*), where the average rate of spread without spotting is represented by the grey curve and the average rate of spread with spotting is represented by the black curve. The straight, black line indicates the rate of spread calculated by Rothermel's model. All panels were created by averaging across 2500 wildfire simulations with all varied variables set to medium values.

Table 3. Model results for average rate of spread with and without spotting

For each environmental variable value we collected (i) the average rate of spread without spotting (calculated by Rothermel's 1972 model), (ii) the average rate of spread with spot fire ignition and propagation (determined by averaging across 2500 simulations of our model) and (iii) the time to equalise to the average rate of spread with spotting

Variable	Value	Average rate of spread without spotting ($m\,s^{-1}$)	Average rate of spread with spotting ($m\,s^{-1}$)	Time to equalise (h)
All variables	Medium	0.016	0.025	11
Canopy base height	High	0.016	0.017	5
	Low	0.016	0.180	11
Fuel load	High	0.023	0.050	11
	Low	0.008	0.011	15
Moisture content	High	0.013	0.018	11
	Low	0.019	0.041	11
Wind speed	High	0.024	0.052	10
	Low	0.009	0.011	8

that the qualitative aspects of our results are consistent. More specifically, altering values for various fuel and weather parameters failed to change the order of importance of the variables (i.e. canopy base height > surface fuel loading > wind speed > surface fuel moisture content). By keeping our model simple we have been able to illuminate these basic trends.

Fire-behaviour models enable managers to forecast how to balance the ecological and economic costs of wildfire control and prevention. Having fire prediction software include firebrand and spot fire behaviour would not only improve prediction accuracy, it would also aid fire managers in answering a variety of unanswered questions related to how spot fires influence wildfires as well as fuels management effectiveness. Updating current fire-behaviour prediction programs with new mathematical models is possible, but it may be more worthwhile to develop a new generation of programs that link the models that describe the main aspects of wildfire behaviour to recent advances. Our model, linking key models governing current fire-behaviour programs to a model progressing our knowledge on firebrand distributions, could become a valuable tool to (i) aid in predicting behaviour and average rate of spread of actively spotting wildfires as well as the resulting spot fires, (ii) aid in developing economical yet effective fuelbreaks and (iii) estimate the potential for firefighter entrapment due to spot fires. Existing science can be incorporated into our model to aid its development (e.g. a firebrand-trajectory model and a spot fire backing model). However, lack of research concerning firebrand and spot fire behaviour limit the construction of such a model. More research in these areas, especially firebrand generation and spot fire ignition, would improve our understanding of spot fire behaviour and overall wildfire propagation, which would improve the prediction models utilised by fire managers.

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