

An empirical-based model for predicting the forward spread rate of wildfires in eucalypt forests

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Abstract. Reliable and accurate models of the speed of a wildfire front as it moves across the landscape are essential for the timely prediction of its propagation, to devise suitable suppression strategies and enable effective public warnings. We used data from outdoor experimental fires and wildfires to derive an empirical model for the rate of fire spread in eucalypt forests applicable to a broad range of wildfire behaviour. The modelling analysis used logistic and non-linear regression analysis coupled with assumed functional forms for the effect of different environmental variables. The developed model incorporates the effect of wind speed, fine dead fuel moisture, understorey fuel structure, long-term landscape dryness and slope steepness. Model evaluation against the data used for its development yield mean absolute percentage errors between 35 and 46%. Evaluation against an independent wildfire dataset found mean percentage errors of 81 and 84% for two landscape dryness conditions. For these wildfires, the mean error was found to decrease with increasing rates of spread, with this error dropping below 30% when observed rates of spread were greater than 2 km h⁻¹. The modular structure of the modelling analysis enables subsequent improvement of some of its components, such as the dead fuel moisture content or long-term dryness effects, without compromising its consistency or function.

Keywords: bushfires, eucalypt forests, fire behaviour, fire prediction, fire simulation, fire spread, forward spread rate, spotting, wildfires, wildland urban interface.

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Introduction

Models describing the forward spread rate of wildfires are an integral component of operational prediction tools aimed at forecasting their propagation over the landscape to support the release of timely and effective public warnings. Since the major events of 2003 and 2009 in Australia (McLeod 2003; Doogan, 2006; Teague *et al.* 2010), when fast-spreading wildfires impacted wildland urban interface (WUI) areas without specific, detailed public warnings of impact location being issued, fire spread prediction tools (Tolhurst *et al.* 2008, Miller *et al.* 2015; Plucinski *et al.* 2017) and protocols (Slijepcevic *et al.* 2008; Gibos *et al.* 2015; Neale and May 2018) have been widely adopted in day-to-day operations of fire agencies to support decision making related to fire suppression and public safety warnings (Gibos *et al.* 2015; Neale and May 2020; Whittaker *et al.* 2020).

The widespread application of fire behaviour models has resulted in an increased awareness of their strengths and weaknesses, limiting assumptions and application bounds. For fires in

eucalypt forests, fire behaviour analysts (*sensu* Slijepcevic *et al.* 2008) in eastern Australia rely on three basic fire spread rate models for predicting wildfire propagation over the full range of burning condition: McArthur (1962), (1967) and Cheney *et al.* (2012). However, there is limited guidance on which model should be used in a particular situation, the models yield quite different outputs for identical inputs, and each has distinct under- and over-prediction biases (Burrows and Sneeuwjagt 1991; McCaw *et al.* 2008; Cruz *et al.* 2020). The operational acceptance of these three distinct fire spread models is likely associated with the stepwise escalation in fire spread rate and energy release as burning conditions worsen and distinct fuel layers become involved in the combustion process (Luke and McArthur 1978). This escalation in fire behaviour has been documented in low- to high-intensity fire experiments in eucalypt forests (Gould *et al.* 2007a). A comparable phenomenon occurs with fire behaviour in conifer forests, where notable increases in fire spread rates are observed as a surface fire transitions into a crown fire (Van Wagner 1968; Burrows *et al.*

1988). This nonlinear dynamics in fire spread rate and intensity (e.g. large increase in rate of spread from small changes in wind speed) suggests the existence of different states of propagation where the effect of certain influential variables, such as a fuel characteristic or wind speed, vary along the rate of fire spread spectrum. Overall, these factors add substantial uncertainty to operational fire behaviour predictions.

The objective of the present study was to develop a model describing the forward rate of fire spread in eucalypt forests over a broad range of burning conditions and resultant fire intensities for use in the operational prediction of fire behaviour. The modelling approach was based on the use of existent experimental and wildfire data combined with an understanding of strengths and limitations of previous models, and recent insights into high-intensity fire behaviour gained from consideration of recent wildfire events. We aimed to evaluate the model against independent experimental fire and wildfire data to quantify its limitations and identify areas for future potential improvement. Symbols used in equations and tables are identified in the text and summarised in Table 1.

Methods

Data

Fire spread rate and related fire behaviour data for eucalypt forests were compiled from several studies comprising experimental and wildfire data. The available data were divided into model development and model evaluation datasets.

Model development data

Data used for model development comprised experimental fire data from Project Vesta (Gould *et al.* 2007a) and wildfire data published in Cheney *et al.* (2012). The Project Vesta dataset comprises 116 experimental fires conducted in dry eucalypt forests under summer conditions (Gould *et al.* 2007a). The experiments, each one consisting of a fire originating from a line ignition source and freely spreading at pseudo-steady-state in a 200 × 200 m plot, were conducted at two sites in the south-west of Western Australia with distinct understorey vegetation structures which, coupled with the range in fuel age (given as time since last fire), between 2 and 21 years, gave the dataset a broad array of understorey fuel structures. Detailed data on fuel characteristics, experimental methods and observed fire behaviour can be found in Gould *et al.* (2007a, 2011) and McCaw *et al.* (2012). The wildfire data were compiled by Cheney *et al.* (2012) from agency reports and formal publications describing wildfires in southern Australia spanning a period of 47 years (i.e. 1962–2009). This dataset is characterised by high-intensity fire behaviour, with several fires burning under extreme fire danger conditions. Aiming to characterise the fidelity, or representativeness of the estimated fire environment characteristics, fuel, weather, and fire behaviour data were assessed for their reliability and accordingly given a rating (Cheney *et al.* 2012).

Model evaluation data

An experimental fire and a wildfire dataset were used for model evaluation. The experimental fire dataset arose from

Table 1. List of symbols, quantities and units used in equations and text

Symbol	Description	Units
C	Fuel cover	Fraction
DF	Drought factor	Dimensionless
F	Fuel effect	
FA	Fuel availability	Fraction
MAE	Mean absolute error	km h ⁻¹
$MAPE$	Mean absolute percentage error	%
MC	Fuel moisture content	%
P	Probability	0–1
R	Forward rate of fire spread	km h ⁻¹
RH	Relative humidity	%
$RMSE$	Root mean square error	
T	Air temperature	°C
U_2	Understorey wind speed, estimated at 2-m above ground or eye level	km h ⁻¹
U_{10}	10-m open wind speed	km h ⁻¹
W	Fuel load	kg m ⁻²
h	Fuel height	m
WRF	Wind reduction factor	Dimensionless
β	Regression coefficients	
Φ	Function	
θ	Slope angle	Degrees
Subscripts		
Ad	Adjusted	
el	Elevated	
ns	Near-surface	
s	Surface	
u	Understorey	
L	Linear	
Ob	Observed	
P	Polynomial	
S	Sigmoidal	

Project Aquarius, which included fires conducted during the summers of 1982/1983 and 1984/1985 in south-western Australia and Victoria (Gould *et al.* 1996). Information on the methods used in this study was provided in Hollis *et al.* (2010). Fuel, weather and fire behaviour data are given in Cheney *et al.* (2012). The wildfire data came from the Southern Australian wildfire dataset initially collated by Harris *et al.* (2011) and further refined in Kilinc *et al.* (2012). Fire propagation data were derived from published and unpublished case studies, reports and raw data (e.g. aerial imagery) from wildfires occurring in native eucalypt forests in the states of New South Wales, Victoria and Western Australia. This dataset comprises a broad range of eucalypt forest types, from open dry sclerophyll forests to the denser, multi strata forests typical of wetter, more productive environments. Wildfires in this dataset that were also present in Cheney *et al.* (2012) were not used in the model evaluation. Data on weather, fuel and rate of fire spread were also rated for its reliability using the Cheney *et al.* (2012) classification.

Fuel moisture content estimation

Fine dead fuel moisture content (MC) was directly measured in experimental fires, but not in the wildfires. For the wildfire data, MC was estimated from air temperature (T , °C), relative

humidity ($RH, \%$), time of the day, and season, using equations derived from a process-based dead fuel moisture content model (Matthews 2006; Matthews *et al.* 2010) parameterised for the fine dead fuels on top of a eucalypt forest litter layer (Gould *et al.* 2007b; Cruz *et al.* 2015).

The effect of fine dead fuel moisture content

The Project Vesta experimental fires were conducted in a narrow MC range (McCaw *et al.* 2012), making it necessary to use a pre-defined fuel moisture effect function. In the current fire spread modelling context, a fuel moisture effect function is a mathematical description of the relationship between fuel moisture and rate of fire spread (Sullivan 2009). Cheney *et al.* (2012) used the equation developed by Burrows (1999) in developing their model. This function works well in the mid-range of MC but results in a steep effect under low dead fuel moisture conditions and asymptotes to a value around 0.1 for increasingly high fuel moisture contents (Fig. 1). Evidence from the analysis of various wildfire datasets by Cruz *et al.* (2020) suggest the effect of MC on rate of fire spread (R) flattens below a MC value of $\sim 5\%$ (i.e. decreasing fuel moisture below this level did not increase the R of wind-driven fires. In contrast, in the upper range of fuel moisture contents there exists a ‘moisture of extinction’ threshold (Rothermel 1972; Cheney 1981), above which the likelihood of fire spread decreases. Data from Gould (1994) and Cawson and Duff (2019) suggest that sustained fire propagation in eucalypt forests occurs at MC up to 20–25%.

We tested three MC effect functions (Fig. 1). As a benchmark, we used the Burrows (1999) function (ΦMd_B) as per Cheney *et al.* (2012):

$$\Phi Md_B = \frac{MC^{-1.495}}{0.0545} \quad (1)$$

A second approach was to consider the effect of fuel moisture on rate of fire spread to be linear, as found in controlled experiments (e.g. Anderson 1964). The linear MC effect function (ΦMd_L) was constrained to a value of 1.0 when $MC \leq 5\%$ and zero when $MC > 23.5\%$:

$$\Phi Md_L = \begin{cases} 1, & \text{if } MC \leq 5.0\% \\ 1.20 - 0.05MC, & \text{if } 5.0\% < MC \leq 23.5\% \\ 0, & \text{if } MC > 23.5\% \end{cases} \quad (2)$$

A third approach considered a polynomial equation form as per Rothermel (1972). The polynomial function (ΦMd_P) was made to fit the Burrows (1999) function in the mid-range of MC , flattening to a value of 1.0 when $MC \leq 5\%$, and yielding a value of 0 when $MC > 23.5\%$:

$$\Phi Md_P = \begin{cases} 1, & \text{if } MC \leq 4.1\% \\ 0.9082 + 0.1206MC - 0.03106MC^2 + 0.001853MC^3 - 0.00003467MC^4, & \text{if } 4.1\% < MC \leq 24.0\% \\ 0, & \text{if } MC > 24.0\% \end{cases} \quad (3)$$

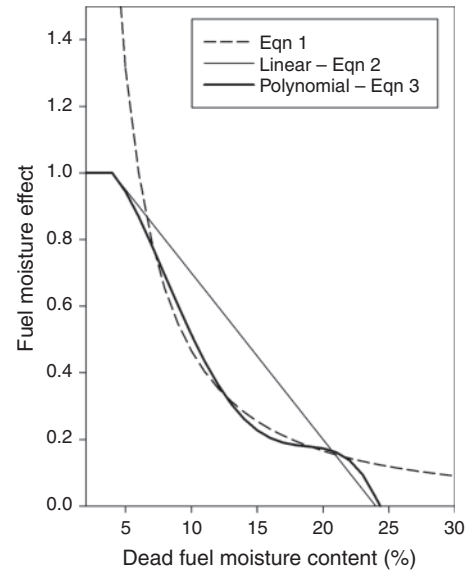


Fig. 1. Relationship between dead fuel fine moisture content and the fuel moisture effect for the functions tested in the analysis.

Effect of seasonal dryness – fuel availability

The moisture content of live and dead fuels with long time-lag responses were not measured comprehensively in the experimental fires or at all in the wildfires used in the present analysis. Although the direct linkages between the moisture content of these fuels and the spread rate of fires have not been clearly established, it is generally recognised that as these moisture contents decrease as a result of seasonal dryness, more fuels become available for combustion (Hollis *et al.* 2011), and in turn, fireline intensity and spread rate increases (Luke and McArthur 1978; Van Wagner 1998). We used McArthur (1967) drought factor (DF) as an approximation of the effect of fuel availability (FA) on the rate of fire spread, testing two equation forms. The first one follows McArthur (1967) linear relationship between DF and FA :

$$\Phi FA_L = 0.1DF \quad (4)$$

where ΦFA is the fuel availability function that varies between 0 and 1. This function implies that all fuel is available for combustion as the DF reaches its maximum value of 10. We also tested an alternative functional form that considers a sigmoid curve, as per the effect of curing in rate of fire spread in grasslands (Cheney *et al.* 1998). The sigmoid equation was fitted by forcing the curve through a FA of 0.5 and 1.0 at DF values of 5.0 and 10 respectively:

$$\Phi FA_S = \frac{1.008}{1 + 104.9 \exp(-0.9306 DF)} \quad (5)$$

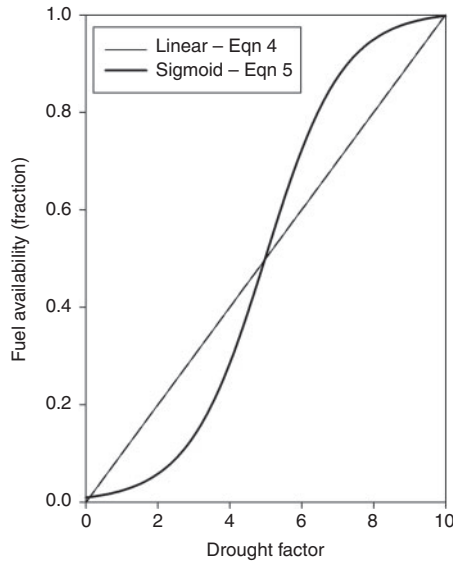


Fig. 2. Relationship between the [McArthur \(1967\)](#) Drought factor and fuel availability for the two functions tested in the analysis.

Figure 2 illustrates the differences between the two ΦFA functions, with the sigmoid function resulting in higher FA outputs when the DF is above 5.0.

The effect of fine dead fuel moisture, as expressed in [Eqns 1–3](#), and long-term fuel dryness as expressed in [Eqns 4–5](#), were integrated into an overall fuel moisture effect function (ΦM):

$$\Phi M = \Phi Md \Phi FA \quad (6)$$

Fire behaviour modelling

Based on the assumption that the rate of fire spread in eucalypt forests over its full range of occurrence cannot be adequately modelled using a single continuous equation, we postulate for practical purposes that there are three distinct phases of fire propagation: (1) a low-intensity state (henceforth called Phase I) associated with short flames consuming mostly surface and near surface fuels; (2) a moderate to high-intensity state (Phase II) involving all understorey fuels plus a proportion of bark fuels; and (3) a third, higher-intensity state (Phase III) associated with fires involving the full fuel complex and short- to medium-range spotting dynamics strongly influencing fire spread. The simplicity of empirically derived analytical equations for rate of fire spread requires that each phase be modelled separately, with each phase being described by one rate of fire spread equation.

We modelled the rate of fire spread using non-linear regression analysis. Models were of the form:

$$R = aU^b \cdot \Phi M \cdot F_1^{c_1} \dots F_k^{c_k} \quad (7)$$

where R is rate of fire spread (km h^{-1}), U is either the 10-m open wind speed or the within-stand wind speed measured at 2-m height above ground (U_{10} or U_2 , km h^{-1}), ΦM is the fuel moisture effect function, F_i are fuel structure predictor variables and the lower case letters (a, b, c) are regression constants. Models were fitted using the `nls` function in R ([R Core Team 2019](#)).

To determine in which phase a fire is spreading (i.e. Phase I, II or III), we classified each data point according to a particular

state or phase on the basis of its rate of fire spread, and used multiple logistic regression analyses to quantify the likelihood a fire is spreading in a given phase. The probability (P) that a fire is spreading in a certain state (i.e. Phase II or III) is given by:

$$P(Y = 1) = \frac{1}{1 + \exp(-g(x))} \quad (8)$$

With the logit $g(x)$ given by the equation:

$$g(x) = \beta_1 + \beta_2 x_2 + \beta_3 x_3 + \dots + \beta_i x_i \quad (9)$$

with x_i being the independent variables and β_i the coefficients estimated through the maximum likelihood method. Model building using the `glm` function in R ([R Core Team 2019](#)) relied on stepwise procedures using the likelihood ratio Chi squared test and Wald test to assess the significance of the coefficients. Model selection took into account the reduction in residual deviance from the null hypothesis as a measure of goodness-of-fit. This was supplemented by calculating Akaike's Information Criterion (AIC) ([Akaike 1974](#)) and McFadden pseudo R^2 statistic ([McFadden 1974](#)).

Model evaluation

The performance of a given rate of fire spread model was first assessed using the residual standard error (RSE), the significance of individual model parameters, the analysis of model behaviour outside the model development data range compared with expectations. Subsequently, promising models were evaluated through the calculation of the mean absolute error (MAE), the mean bias error (MBE), the mean absolute percentage error (MAPE) and the root mean squared error (RMSE) ([Willmott 1982](#)). Detailed evaluation was supplemented by the analysis of residual plots: residuals against fitted values, normal quantile plots of the residuals and residuals versus other variables.

Results

Study results are presented as follows: summary of characteristics of datasets used for model development; modelling the transitions between each fire spread phase; modelling the fire spread rate within each phase; linking of model components; and evaluation of the combined operational model.

Dataset characteristics

The assembled model development datasets for fire spread modelling, comprising data from Project Vesta experimental fires and the wildfires compiled by [Cheney *et al.* \(2012\)](#), were first constrained to reduce the uncertainty introduced into the analysis by variables such as slope angle, θ , and DF . We removed from the model development dataset fires that were characterised by a $\theta > |5^\circ|$ and a $DF < 9.0$. A total of 87 experimental fires and 17 wildfires was then available for the modelling analysis ([Table 2](#)). The U_{10} , MC and R variables in the experimental dataset varied between 7 and 23 km h^{-1} , 5.6 and 9.4%, and 0.028 and 1.16 km h^{-1} respectively. For the wildfire dataset these same quantities varied between 10 and 72 km h^{-1} , 2.8 and 8.6% (estimated MC), and 0.6 and 10.5 km h^{-1} respectively. U_2 was measured in the experimental fires, and estimated from established wind reduction factors for the wildfire data.

Table 2. Basic descriptive statistics, mean (standard deviation) [range], associated with the variables used in the development and evaluation of the models

Dataset	U_{10} (km h ⁻¹)	MC (%)	W_s (kg m ⁻²)	h_u (m)	R (km h ⁻¹)	Fireline intensity (kW m ⁻¹)
Model development						
Vesta ($n = 87$)	13.3 (3.16) [7.3, 23.3]	7.1 (1.0) [5.6, 9.4]	2.1 (0.65) [1.2, 3.9]	0.38 (0.23) [0.06, 0.97]	0.372 (0.236) [0.028, 1.160]	2337 (1902) [112, 8321]
Cheney <i>et al.</i> wildfires ($n = 17$)	38.9 (19.6) [10, 72]	4.4 (1.5) [2.8, 8.6]	2.2 (0.26) [1.57, 2.61]	0.49 (0.08) [0.32, 0.64]	3.7 (3.1) [0.6, 10.5]	44 254 (39 922) [7241, 135 529]
Model evaluation						
Aquarius ($n = 14$)	13.8 (3.7) [8, 19]	6.9 (1.8) [4.6, 9.7]	2.1 (0.002) [2.07, 2.08]	0.42 (0.06) [0.34, 0.47]	0.47 (0.22) [0.2, 0.96]	2240 (1023) [945, 4442]
Southern Australia ($DF > 9$) ($n = 71$)	35.7 (14.0) [12.0, 100.0]	5.4 (2.8) [1.8, 13.3]	1.31 (0.4) [0.4, 2.0]	0.50 (0.10) [0.33, 0.64]	2.37 (1.88) [0.05, 7.98]	25 850 (23 104) [144, 98 452]
Southern Australia ($DF < 9$) ($n = 19$)	33.8 (18.3) [12.0, 95.0]	6.3 (2.2) [2.5, 10.7]	1.49 (0.4) [0.73, 2.0]	0.54 (0.20) [0.31, 1.21]	2.16 (2.03) [0.4, 7.33]	24 387 (21 430) [383, 89 045]

The dry mass, or load (oven-dry weight basis), of surface fuels *sensu* McArthur and Luke (1963), comprising litter and near-surface fuels, constitute the bulk of understorey fine fuels in eucalypt forests (Luke and McArthur 1978; Gould *et al.* 2011). This is a common fuel metric used in Australia to describe fuel condition in eucalypt forests. This quantity varied between 0.66 and 2.18 kg m⁻². On average, litter accounted for 72% of this fuel load metric. Near-surface fuel height varied between 0.05 and 0.5 m. Understorey fuel height (h_u , m), defined as the average height (h_i) of near-surface (lower shrubs and vertically oriented dead fuels) and elevated (taller shrubs) fuels weighted by their cover (C_i), was calculated as follows:

$$h_u = h_{ns}C_{ns} + h_{el}C_{el} \quad (10)$$

This fuel descriptor varied between 0.06 and 0.97 m in the experimental fire dataset and between 0.32 and 0.64 m in the wildfire dataset.

For model evaluation, the experimental fire data from the Project Aquarius ($n = 14$) had U_{10} , MC and R variables varying between 8 and 19 km h⁻¹, 4.6 and 9.7%, and 0.02 and 0.96 km h⁻¹ respectively. Surface fuel load and understorey height averaged 2.1 kg m⁻² and 0.42 m respectively. Of the 183 wildfire-spread observation periods (or ‘fire runs’) in the Southern Australia wildfire dataset, 90 were used in the analysis after removing runs of less than 1.0 h duration. Fire runs where propagation occurred immediately after the passage of a weather front over the fire area, a process that converts the pre-passage fire’s flank into a broad head fire, were also not considered in the evaluation (see Discussion). Of these 90 fire runs, 71 had a $DF \geq 9.0$ (characteristic of dry summer conditions and reflecting a uniformly dry landscape) and 19 were characterised with a $DF < 9.0$. Wind speed and estimated fine dead fuel moisture content were comparable within the two subsets, varying between 12 and 100 km h⁻¹ and 1.8 and 13.3% respectively (Table 2). Rates of forward spread were somewhat faster in the higher DF subset, averaging 2.37 km h⁻¹, compared with 2.16 km h⁻¹ for the lower DF subset. Surface fuel loads averaged 1.31 and 1.49 kg m⁻² for the high and low DF subsets respectively.

Table 3. Rate of fire spread (R) thresholds and range of data used in modelling the three spread phases considered

Phase	Onset of phase threshold	Range of rate of fire spread used in R modelling
I (low R)		0–0.21 km h ⁻¹ ($n = 22$)
II (medium to high R)	$R = 0.12$ km h ⁻¹ (0, $n = 13$; 1, $n = 96$)	0.10–1.5 km h ⁻¹ ($n = 74$)
III (very high R)	$R = 1.5$ km h ⁻¹ (0, $n = 94$; 1, $n = 15$)	>1.0 km h ⁻¹ ($n = 17$)

Modelling the transition between phases

Exploratory analysis of the relationship between fire spread rates and intensity and wind speed in the model development dataset was used to define the range of each fire spread phase and the threshold values defining the transition between phases (Table 3). R was found to be a better discriminator to quantify the transition between phases than fireline intensity (Byram 1959). This was possibly due to the added uncertainty of what constitutes the available fuel load for the calculation of fireline intensity and the fact that R varies over a much wider range than fuel load (Alexander 1982).

The best-fitting model for the transition of Phase I into Phase II had a threshold R of 0.12 km h⁻¹ (Table 3), with U_2 , ΦM and W_s as significant variables (Table 4):

$$g(x) = \beta_1 + \beta_2 U_2 + \beta_3 \Phi M + \beta_4 W_s \quad (11)$$

This model yielded a McFadden pseudo R^2 of 0.62. The use of ΦM (p -value = 0.06) instead of the observed MC resulted in a better fit. Considering fuel structure variables, the use of other fuel variables in the model, such as litter fuel load, understorey fuel load or height, or fuel hazard scores, resulted in comparable coefficient significance and model fit. The use of a higher R threshold value for discriminating Phase I from Phase II, such as 0.18 or 0.24 km h⁻¹, resulted in models with higher AICs and non-significant coefficients for the moisture content effect. The datasets available do not allow exploration of the impact of

Table 4. Coefficient values and model fit statistics for the model describing the transition between Phase I and II (Eqn 11) and Phase II and III (Eqn 13)

Parameters	Coef. (Sig.)	
	Eqn 11	Eqn 13
β_1	-23.9315 (0.003)	-32.3074 (0.01)
β_2	1.7033 (0.006)	0.2951 (0.01)
β_3	12.0822 (0.06)	26.8734 (0.04)
β_4	9.5236 (0.006)	
Fit statistics		
AIC	38.4	23.7
McFadden pseudo R^2	0.62	0.80
Area under the curve	97%	99%

marginal fuel loads (e.g. $< 0.1 \text{ kg m}^{-2}$) on fire propagation. To ensure model outputs are consistent with expectations when fire is spreading where fuel quantity and structure limits the energy available to cause vertical fire transitions, the following condition is imposed:

$$P(\text{II}) = \begin{cases} 0 & \text{if } W_s < 0.1 \text{ kg m}^{-2} \\ 1/(1 + \exp(-g(x))) & \text{if } W_s \geq 0.1 \text{ kg m}^{-2} \end{cases} \quad (12)$$

where $P(\text{II})$ is the probability of Phase II occurring and $g(x)$ is the logit in Eqn 11.

The best-fitting models for the transition between Phase II and III were based on a threshold R of 1.5 km h^{-1} . This threshold was largely dictated by the distribution of the rate of spread data, with all the Phase III data originating from wildfire case studies. The model for the onset of Phase III had wind speed, incorporated as U_{10} , and ΦM , as significant variables (Table 4):

$$g(x) = \beta_1 + \beta_1 U_{10} + \beta_2 \Phi M \quad (13)$$

None of the available fuel variables was significant when further added to the model. This model resulted in a McFadden pseudo R^2 of 0.80. As with Phase II transition, there are no data available to investigate the effect of the understorey fuel structure on the transition into Phase III when the fuel structure state limits this transition, as it would occur in the immediate years after an effective fuel reduction burn. To ensure the model does not identify Phase III fire propagation if understorey fire activity does not generate enough energy to generate the transition into this phase, the following constraint was applied:

$$P(\text{III}) = \begin{cases} 0 & \text{if } R(\text{II}) < 0.3 \text{ km h}^{-1} \\ 1/(1 + \exp(-g(x))) & \text{if } R(\text{II}) \geq 0.3 \text{ km h}^{-1} \end{cases} \quad (14)$$

where $P(\text{III})$ is the probability of Phase III occurring and $g(x)$ is the logit from Eqn 13.

Modelling fire spread rate within each phase

The observed rate of fire spread from the model development data was normalised to an equivalent θ and MC rate of fire spread (R_{Ad} , km h^{-1}), as per Cheney *et al.* (2012):

Table 5. Coefficient values and model fit statistics for the models for R_{Ad}

MAE, mean absolute error (km h^{-1}); MAPE, mean absolute percentage error (%); RMSE, root-mean-squared error (km h^{-1})

Parameters	Coef. (Sig.)		
	Eqn 17 $R(\text{I})_{Ad}$	Eqn 18 $R(\text{II})_{Ad}$	Eqn 19 $R(\text{III})_{Ad}$
a	0.05024 (0.08)	0.19591 (0.0004)	0.05235 (0.38)
b	0.92628 (0.046)	0.82569 (< 0.0001)	1.19128 (0.0008)
c	0.79928 (0.03)	0.46722 (0.006)	
d		0.49500 (< 0.0001)	
Fit statistics			
MAE	0.051	0.129	1.211
MAPE	57	31	28
RMSE	0.059	0.168	1.551

$$R_{Ad} = \frac{R_{Ob}}{\Phi M \Phi \theta} \quad (15)$$

where R_{Ob} is the observed rate of fire spread and R_{Ad} is the adjusted rate of fire spread used as the dependent variable in the regression analysis. ΦM is given by Eqn 6 and $\Phi \theta$ is the effect of slope angle (θ) on fire spread rate as heuristically described by McArthur (1962, 1967) and parameterised by Noble *et al.* (1980):

$$\Phi \theta = \exp(0.069\theta) \quad (16)$$

Modelling R_{Ad} tested the adequacy of the three different $\Phi M d$ functions as given in Eqns (1–3). In the following analysis we focus on the results of the models based on the $\Phi M d_p$ function, as represented by Eqn 3, because this was found to produce the best results. Model parameterisations and fit for the models based on the other two $\Phi M d$ functions are given in the Supplementary Material (Tables S1–S5).

The model for R in Phase I ($R(\text{I})_{Ad}$) was fitted using data with R up to 0.21 km h^{-1} (Table 3). The best model had the form:

$$R(\text{I})_{Ad} - R_t = a(U_2 - U_t)^b W_s^c \quad (17)$$

where R_t is a threshold rate of spread, estimated to be 0.03 , added to the equation to account for the addition of a threshold understorey wind speed, U_t , to the equation. The equation was fitted with U_t of 1 km h^{-1} . U_2 is the understorey wind speed (km h^{-1}) measured at a 2-m height in the forest, and W_s the load of surface and near surface fine fuels (kg m^{-2}). Both parameters were significant at the 0.05α level (Table 5). In this model, U_2 was a better predictor of $R(\text{I})_{Ad}$ than U_{10} . The model produced an MAE of 0.051 km h^{-1} and a MAPE of 57% against the adjusted rate of fire spread. The b exponent in the equation with U_2 had higher statistical significance than was found if U_{10} was used. The use or addition of other fuel parameters, such as understorey fuel height, shrub height and load, or bulk density, did not result in an improved model fit. The use of visual fuel hazard scores (FHS), such as the surface FHS or near-surface FHS (Gould *et al.* 2011), as explanatory variables in the model instead of W_s , resulted in a slight, but not significant, improvement in model fit. Equation 17 is applicable for $U_2 > 2 \text{ km h}^{-1}$. When $U_2 < 2.0 \text{ km h}^{-1}$, $R(\text{I})_{Ad}$ is assumed to be 0.03 km h^{-1} .

The model for rate of fire spread within Phase II was developed with experimental fire data within an R range between 0.10 and 1.5 km h⁻¹. Following the form of Eqn 7, the best model for $R(II)_{Ad}$ had U_2 , and two fuel structure variables, W_s and understorey height (h_u):

$$R(II)_{Ad} = a(U_2)^b W_s^c h_u^d \quad (18)$$

with h_u defined as per Eqn 10. All parameters were statistically significant (Table 5). The effect of U_2 and W_s in this model were not as strong as for the Phase I model, even if h_u was not in the model. The MAE for $R(II)_{Ad}$ was 0.13 km h⁻¹ with an associated MAPE of 31%, a reduction over the percentage error obtained for $R(I)_{Ad}$.

Model fit for the Phase III R was based on a subset of the data with $R > 1.0$ km h⁻¹. The best model form was:

$$R(III)_{Ad} = a(U_{10})^b \quad (19)$$

with the U_{10} exponent being 1.19 (Table 5), a value higher than the exponents found for the Phase I and II models. No physical fuel structure parameters were found to be significant in this model. The use of fuel age as a surrogate for fuel condition was also found not to be significant. These results are consistent with the findings that fuel structure effects on fire spread decrease as fire weather become more severe (Tolhurst and McCarthy 2016; Cruz *et al.* 2020). U_{10} was chosen over U_2 in this model because: (1) there were no accurate understorey wind measurements in most of the high-intensity wildfire data within this subset; and (2) the available wind reduction factors for the wildfire data were only estimated based on broad stand structure assumptions. It is also expected that fires spreading in Phase III involving the full fuel complex will be driven by the open wind rather than understorey winds. The MAE and MAPE for this model were 1.21 km h⁻¹ and 28% respectively.

The application of models in Eqns 17–18 to predict R requires the addition of the effects of MC , FA and θ . The R of Phase i (I, ..., III) is given by:

$$R(i) = R(i)_{Ad} \Phi M \Phi \theta \quad (20)$$

Model linkages

The prediction of R requires linking the transition likelihood models with the fire spread rate models developed for the three phases. The likelihood models define the weight each rate of fire spread model has on the rate of fire spread calculation for a given set of weather and fuel conditions. To avoid the abrupt changes in R that would occur if a fixed likelihood threshold was used to indicate a change from a lower to a higher state (e.g. using $P(II) \geq 0.5$ to shift from $R(I)$ to $R(II)$), or the inverse, the overall rate of fire spread output is a result of the value predicted by the $R(i)$ models (Eqn 20) weighted by the likelihood of the fire is in that state. R is then given as:

The application of Eqn 21 requires assumptions about the vertical wind profile. Considering U_{10} as the benchmark in a given wildfire prediction situation, U_2 can be estimated from the appropriate wind reduction factor (WRF):

$$U_2 = U_{10} WRF \quad (22)$$

Appendix 1 provides guidance on the estimation of WRF for the range of forest cover and heights typical of Australian native eucalypt forests (Sneeuwjagt and Peet 1998; Moon *et al.* 2019).

Figure 3a illustrates how R varies with U_{10} in Eqn 21 and contrasts with predictions for each spread phase as represented by Eqn 20. Figure 3b illustrates the effect of U_{10} and MC in the model outputs, from a low value of 5% as characteristic of extreme fire potential days to a relatively high value of 11%, typical of a mild burning day. Figure 3c shows the model response to changes in fuel structure by considering the effect of wind speed for four fuel ages (e.g. 1, 4, 8 and 16 years since a fuel reduction burn) on a dry eucalypt forest. For the very young fuels, the low available fuel load and the incipient understorey vegetation limit the energy release and the spread in Phase I and II, which then constrain the transition into Phase III, even under high wind speeds and low fuel moisture contents ($MC = 7\%$ in simulated example).

Model evaluation

Model fit against model development data

Table 6 provides goodness-of-fit metrics for Eqn 21 with the data used in the model development (Fig. 4). For the Project Vesta dataset, where the average R was 0.37 km h⁻¹, the MAE was 0.106 km h⁻¹. Mean bias was negligible, as expected from the application of the least square method, and MAPE was 46%. MAE for the wildfire dataset was one order of magnitude higher, at 1.15 km h⁻¹ with a MAPE of 35%, a value lower than that obtained for the experimental fire dataset. The MBE for the wildfire subset was -0.216 km h⁻¹, an under-prediction of less than 6% of the average R of 3.7 km h⁻¹. Figure 4b shows the two fastest wildfire runs used in the model development, with $R > 9.0$ km h⁻¹, were under predicted by the model. These two wildfires had documented spotting distances longer than 10 km observed during these fire runs. The fit statistics for the models developed with the two other MC effect functions, represented by Eqns 1 and 2, are to be found in the Supplementary Material (Tables S6, S7). As products of the same dataset, the fit statistics for the various model forms did not show notable differences.

Model fit against independent data

Model evaluation against the Project Aquarius dataset (average $R = 0.47$ km h⁻¹) yielded an MAE, MAPE and MBE of 0.129 km h⁻¹, 39% and 0.034 km h⁻¹ respectively (Table 7). Ten of the 14 predictions were within the $\pm 35\%$ error margin (Fig. 5) as ascribed by Cruz and Alexander (2013).

The partition of the Southern Australia wildfire dataset into two DF classes allowed for the separate evaluation of the fire

$$R = \begin{cases} R(I)(1 - P(II)) + R(II)P(II) & \text{if } P(II) < 0.5 \\ (R(I)(1 - P(II)) + R(II)P(II))(1 - P(III)) + R(III)(P(III)) & \text{if } P(II) \geq 0.5 \end{cases} \quad (21)$$

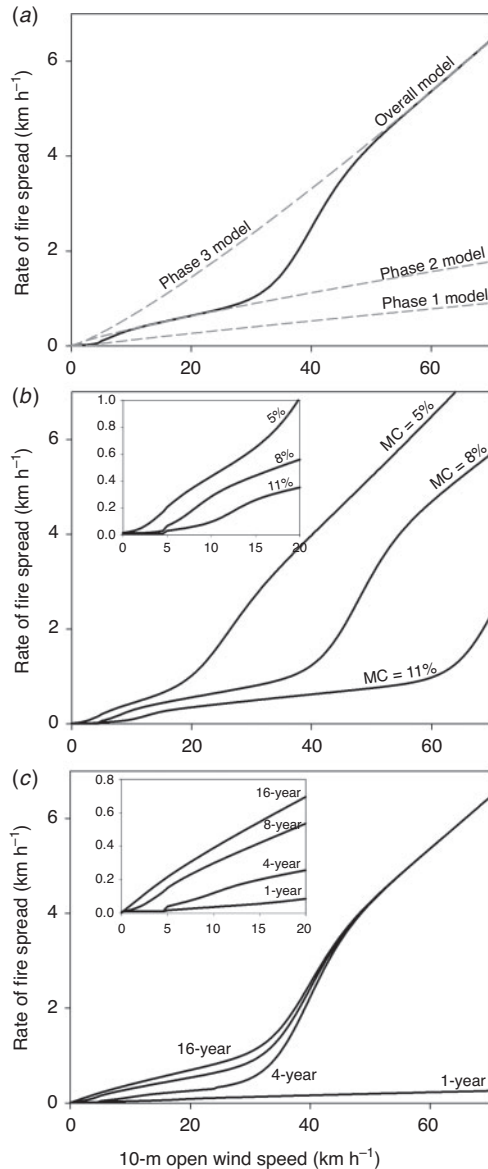


Fig. 3. Modelled rate of fire spread in eucalypt forests as a function of wind speed (a) as described by the three Phase functions and the integrated system (Eqn 21); (b) the effect of dead fuel moisture content; and (c) the effect of fuel age (time since fire). Unless otherwise noted, graphics are based on $MC = 7\%$; $W_s = 1.1 \text{ kg m}^{-2}$; $h_u = 0.5 \text{ m}$. $\theta = 0$, $WRF = 0.4$; $DF = 10$. Fuel characteristics for fuel age simulation in (c) are: 1-year old fuels – $W_s = 0.2 \text{ kg m}^{-2}$; $h_u = 0.05 \text{ m}$; 4-year old fuels – $W_s = 0.8 \text{ kg m}^{-2}$; $h_u = 0.11 \text{ m}$; 8-year old fuels – $W_s = 1.35 \text{ kg m}^{-2}$; $h_u = 0.29 \text{ m}$; 16-year old fuels – $W_s = 1.6 \text{ kg m}^{-2}$; $h_u = 0.45 \text{ m}$.

spread model system for fuel conditions typical of a dry summer (i.e. high DF) and for conditions when the fuel availability is lower and the landscape is not homogeneously dry (i.e. lower DF). For the high DF subset, the model yielded an MAE, MAPE and MBE of 1.26 km h^{-1} , 83% , and 0.266 km h^{-1} respectively. This MBE value corresponds to $\sim 10\%$ of the average R of the subset (i.e. 2.54 km h^{-1}). This low bias is indicative of an overall unbiased prediction of the independent dataset (Table 7).

Table 6. Model fit statistics obtained by the rate of fire spread model in Eqn 21 against the data used in model development

MAE, mean absolute error (km h^{-1}); MAPE, mean absolute percentage error (%); MBE, mean bias error (km h^{-1}); RMSE, root-mean-squared error (km h^{-1})

Statistics	
Vesta experimental data ($n = 87$)	
MAE	0.106
MAPE	46
MBE	−0.001
RMSE	0.141
Cheney <i>et al.</i> (2012) wildfires ($n = 17$)	
MAE	1.150
MAPE	35
MBE	−0.216
RMSE	1.480

The evaluation against the low DF dataset allows one to understand how the implemented ΦFA reduces error relative to a situation where no FA function was implemented. The results showed the application of the ΦFA_S to reduce the error relative to a scenario where no FA correction is applied (Table 7). Without the FA correction, the model produced an MAE of 1.339 km h^{-1} , a MAPE of 114% and an over prediction bias of 0.345 km h^{-1} . With the ΦFA_S , the MAE was reduced to 1.022 km h^{-1} and the MAPE was 84% . The magnitude of the MBE was reduced to -0.155 km h^{-1} (Table 7). This MBE represented $\sim 7\%$ of the average R for the lower DF dataset, and 15% of the MAE. This evaluation of the ΦFA_S is restricted to DF values above 6.2, the lower limit of the DF in the dataset. The use of ΦFA_S produced better results than the application of a linear FA correction ΦFA_L as per Eqn 4.

Figure 6a presents the observed versus predicted rates of fire spread for the independent model evaluation using the Southern Australia wildfire dataset (Kilinc *et al.* 2012). The figure shows a good number of observations were satisfactorily predicted within the $\pm 35\%$ error band. The figure also shows several observations, 9 out of 90 or $\sim 10\%$ of the dataset, where the model either strongly over- or under-predicted the observed rates of fire spread. Given the inherent uncertainties in the wildfire data (Alexander and Cruz 2006), it is unclear if these notable errors are the result of a lack of representativeness in the measured weather conditions for the fire area, the uncertainty in the interpretation of fire perimeter location with time, model error, or the occurrence of other phenomena such as long-range spotting or fire–atmosphere interactions. We interpret these errors as ‘noise’ in the data due to these uncertainties.

Figure 6b, c provides an overview of the distribution of residuals and percentage error associated with the model predictions. Residuals were calculated as predicted minus observed, with negative residuals indicating an under-prediction. The predictions for fires with an observed rate of fire spread $< 4 \text{ km h}^{-1}$ indicate, on average, an over-prediction trend. Fires having an $R > 4 \text{ km h}^{-1}$ were, on average, under-predicted. Of the 20 observations within this condition, 14 (70%) were within the $\pm 35\%$ error band. Error as a percentage of observed rate of fire spread was highest for the slowest spread rate class (i.e. $< 0.5 \text{ km h}^{-1}$, an average over-prediction of

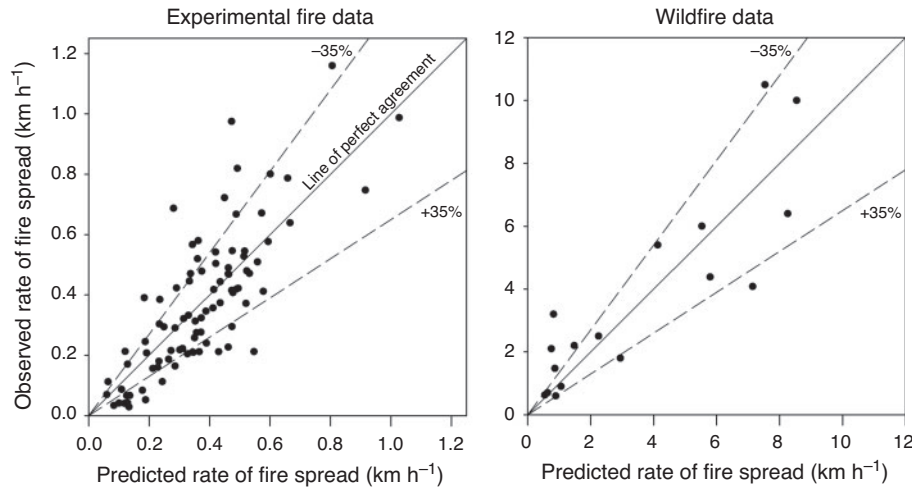


Fig. 4. Plot of observed versus predicted rates of fire spread for (a) the experimental fires and (b) the wildfires used in the model development process. The dashed lines around the solid line of perfect agreement indicate the $\pm 35\%$ error interval.

Table 7. Model fit statistics obtained by the rate of fire spread model systems with distinct fuel moisture functions basis against independent experimental and wildfire data

MAE, mean absolute error (km h^{-1}); MAPE, mean absolute percentage error (%); MBE, mean bias error (km h^{-1}); RMSE, root-mean-squared error (km h^{-1})

Statistics	
Aquarius experimental fires ($n = 14$)	
MAE	0.129
MAPE	39
MBE	0.034
RMSE	0.180
Kilinc <i>et al.</i> (2012) wildfires ($n = 71$; $DF > 9.0$)	
MAE	1.260
MAPE	83
MBE	0.266
RMSE	1.694
Kilinc <i>et al.</i> (2012) wildfires ($n = 19$; $DF < 9.0$). No FA correction	
MAE	1.339
MAPE	114
MBE	0.345
RMSE	2.114
With ΦFA_S – Eqn 11	
MAE	1.022
MAPE	84
MBE	–0.155
RMSE	1.757

126%). Percentage error decreased with increased rate of fire spread, with an average percentage error of 68% for wildfires spreading with R between $0.5\text{--}2.0 \text{ km h}^{-1}$, and 20% for wildfires with R varying between 2.0 and 4.0 km h^{-1} . For fires spreading with an R between $4.0\text{--}6.0$ and $6.0\text{--}8.0 \text{ km h}^{-1}$, the percentage error was -24% and -21% respectively.

Three of the four largest under-predictions (Fig. 6a) were characterised by open wind speeds above 40 km h^{-1} and relative humidity above 25%, a high value for severe fire behaviour in

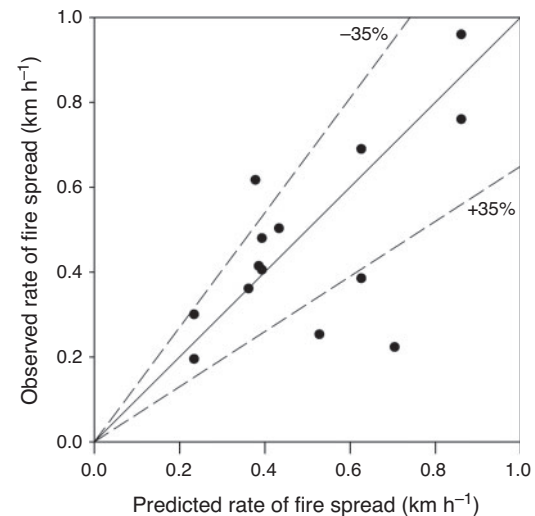


Fig. 5. Plot of observed versus predicted rates of fire spread for the Aquarius experimental data (Cheney *et al.* 2012) used in the model evaluation process. The dashed lines indicate the $\pm 35\%$ error interval.

eucalypt forest. It is unclear if the high relative humidity was representative of the fire area or specific only to the immediate site of the measurement, but it was this variable and its effect on the moisture content of dead fuels that mostly contributed to the large under-prediction. Most of the larger over-predictions observed in the lower range of the observed rate of fire spread (Fig. 6a) were associated with morning or overnight fire runs under high wind speeds (i.e. $U_{10} > 40 \text{ km h}^{-1}$).

Discussion

Wind speed effect

The effect of wind speed is typically incorporated into models for the rate of fire spread through a power function, with the exponent varying around a value of 1.0 (Cheney *et al.* 1998;

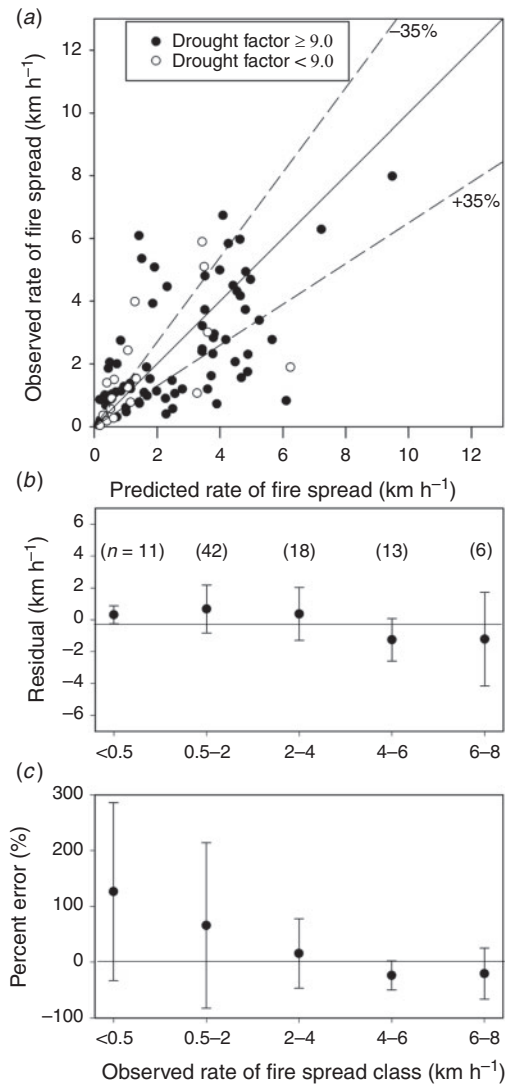


Fig. 6. Plots of (a) observed versus predicted rates of fire spread for Kilinc *et al.* (2012) wildfire data used in the model evaluation process; (b) mean and standard deviation of residuals as a function of observed rate of fire spread; and (c) mean and standard deviation of percentage error per observed rate of fire spread class. The dashed lines indicate the $\pm 35\%$ error interval.

2012; Anderson *et al.* 2015). The exponent is likely a function of not only the effect of wind on the heat transfer from the flame front into unburned fuels, but also the drag effect of overstorey and understorey vegetation on flame level wind flow and the distribution of the fire spread and wind data. In our analysis the wind exponent varied between 0.82 for the low-intensity Phase I and 1.19 for the high-intensity Phase III. The higher exponent found for the Phase III *R* model likely arises from the open nature of the U_{10} input and the effect of firebrand transport and spot fire ignition in driving headfire propagation in high-intensity wildfires in eucalypt forests. The 1.19 exponent makes the outputs of this model under high wind speeds and low fuel moisture contents up to 10% higher than the expectation of *R* being 10% of wind speed under extreme fire spread potential (Cruz and Alexander 2019).

The use of the fire spread model system described here requires knowledge of the wind speed at both the 10-m exposure standard (typically from a weather forecast) and in the understorey (assumed to be 2-m or eye-level height). Conversion between the U_{10} and U_2 requires assumptions about the vertical wind profile under the canopy – a function of several factors, namely forest structure and canopy architecture, understorey development, atmosphere stability and wind speed itself (Moon *et al.* 2019). For an expedited model application, we provide a table of wind reduction factors allowing the direct conversion between U_{10} and U_2 (Appendix 1). This table is a simplified first approximation. Customised wind profiles can be derived from large eddy simulation of wind flow within forest stands as per Pimont *et al.* (2009) and Mueller *et al.* (2014), for example.

Fuel moisture content effect

The effect of fuel moisture on the spread of fires is often portrayed as a well understood and well quantified process. However, this is far from the truth, likely due to the difficulty in controlling for fuel moisture over a relevant range and the fuel moisture gradients present in outdoor fires (Stocks 1970). Only a few studies have established relationships between fuel moisture controlled in a laboratory setting and rate of fire spread (Anderson 1964; Rothermel 1972). Results from field experiments by Burrows (1994) suggest this effect to be indeed linear for a range of fuel moisture contents, but a significant increase in rate of fire spread was observed in the lower fuel moisture levels. It is unclear if this escalation was due to fuel moisture itself or due to the involvement of additional fuel layers in the flame front as fireline intensity increased with the reduction of the fuel moisture content effect on fire spread rate. This bulk effect of fuel moisture content is frequently captured in fire spread models with a function that approximates an exponential decay (Fernandes *et al.* 2009; Sullivan 2009; Anderson *et al.* 2015) or with a polynomial function as done by Rothermel (1972). We tested different functions and found the polynomial form to work best. This effect is nonetheless still a simplification. Anderson and Rothermel (1965) and Burrows (1999) found the effect of fuel moisture to vary with wind speed, a detail we were unable to incorporate in our model due to the lack of data describing this behaviour. Similarly, we assume a nominal dead fuel moisture of extinction of 24% in the current model, but it is accepted that this value will vary with fuel structure, namely fuel bed porosity, and wind speed (Wilson 1985; Awad *et al.* 2020). With model fitting based on data in the lower range of the fuel moisture spectrum (i.e. <10%), changes to the fuel moisture function in the mid- to upper-range of the spectrum (if found necessary from future research work) will not affect the model formulation.

Similarly, advances in the understanding of the influence of the moisture content of live and dead fuels with longer time-lag response on fuel availability and fire behaviour in eucalypt forests can be incorporated in the ΦM without affecting the model presented here.

Estimating fine fuel moisture content and fuel availability

The fire spread model parameterisation was based on mid-afternoon experimental fires and fast-spreading wildfires burning within a homogeneously dry litter and duff layer profile.

The simplified parameterisation of the Matthews (2006) process-based model used in the estimation of fine dead fuel moisture under wildfire conditions is known to give an unbiased prediction for dry, mid-afternoon conditions (Gould *et al.* 2007a). However, using this model with input data from a forecast or open weather station observations might not capture well the forest micro-climate environment during the mid-morning and early afternoon, after fuels have absorbed a significant amount of moisture overnight and before significant boundary layer mixing occurs. In these situations, the fuel moisture model will likely under-predict fuel moisture content (Slijepcevic *et al.* 2015). This might explain why the fire spread model showed an over-prediction trend for the wildfires spreading during the earlier part of the day. For those situations the application of a more detailed moisture estimation using Matthews (2006) model instead of a simplified derivation (as given in Gould *et al.* 2007b), taking into account fuel type specific parameterisations (Slijepcevic *et al.* 2013) and fuel level micro-meteorology inputs, will be required in order to obtain an unbiased input for the fire spread model.

The use of a fuel availability function based on the *DF*, an index calculated daily in Australia, is a pragmatic approach that enables an approximation of the effect of long-term dryness in determining fuel availability to be implemented for operational predictive purposes. Its implementation here led to a 30% reduction in average error for wildfires burning under low *DF* levels relative to predictions without the fuel availability function. Other, more comprehensive fuel availability functions exist that warrant future exploration, namely the Available Fuel Factor in the Western Australia Forest Fire Behaviour Tables (Beck 1995; Sneeuwjagt and Peet 1998). This factor requires knowledge of the moisture content of deep litter and duff fuel layers. These variables are not easily estimated and are typically not tracked or estimated on a daily basis in forest types in eastern Australia. The application of such fuel availability function would limit the use of the system for operational wildfire prediction until systematic and easily implemented models that represent the moisture dynamics of deep forest floor fuel layers are developed.

Fuel structure effect

The effect of fuel quantity and other fuel parameters on the spread rate of fires in eucalypt forests has been a contentious issue within the Australian fire behaviour modelling community. A directly proportional effect of fuel load on the speed a fire travels, with a doubling in fuel load leading to a doubling in rate of fire spread, was first suggested by McArthur (1962), based on data from low-intensity experimental fires. This direct effect has been at the foundation of fire spread modelling in Australia for many decades (McArthur 1967; Sneeuwjagt and Peet 1998). Nonetheless, this assumption has not held true in field studies of fires spreading with moderate to high intensities. Burrows (1994, 1999) did not find a significant relationship between fuel load and rate of fire spread in an experimental fire database with *R* values up to 0.6–0.7 km h⁻¹, and reasoned that the direct relationship as proposed by McArthur (1962) is likely to be only valid for fires spreading under low wind speeds and without developing a definite headfire region. Gould *et al.* (2007a) found a variable effect of fuel load on rate of fire spread, with the

effect being significant for low wind speeds, but non-significant as wind speed and rate of fire spread increased.

Our phased modelling analysis produced similar results, with the load of the surface and near-surface fuels having an almost direct effect on the spread rate of Phase I fires. For Phase II, the main fuel effect was described by the understorey fuel height, although the fuel load still had an effect, albeit lower than for Phase I. Although fuel structure was not found to contribute or influence the rate of fire spread for the faster-spreading fires in Phase III ($R > 1.5$ km h⁻¹), spread in this phase is dependent on the presence of an understorey fuel layer or ladder fuels (e.g. fibrous bark) sufficient to produce flames that allow for the vertical transition of fire into the crowns (i.e. no fuel, no fire). A typical eucalypt forest will not support a Phase III fire when understorey fuels have been removed by prescribed burning. Fuels in eucalypt forests do recover quickly after a burn as a function of site productivity, stand structure and fire intensity (Peet 1971; Walker 1981). For example, in Western Australian forests, bulk density of near-surface fuels will typically reach 80% of the equilibrium level within 4 years (Gould *et al.* 2007a). Consistent with the findings for the rate of fire spread equations, fuel load is an influential variable for the logistic equation predicting the likelihood a fire will spread in Phase II, but not for the transition to Phase III.

The quantity of surface and near-surface fuels is a commonly assessed variable in fuel inventory studies in Australia, and a wealth of information exists on its characterisation, relationships with vegetation or fuel types, and modelling (Walker 1981; Watson *et al.* 2012). However, the fuel that determines how fast a fire spreads is the fuel that is consumed by the flames at the leading edge of the head fire. As the fire increases in intensity it integrates the fuel consumed over an increasingly large volume. Only an unknown fraction of the total fuel consumed is involved in the flaming combustion processes that drive heat transfer into unburned fuels (Gould *et al.* 2007a). So although we can describe the fuel consumed in the overall combustion process, we cannot accurately define or measure the fuel contributing to the flame front. Our findings suggest that the best fuel descriptor from the point of view of the operational prediction of fire spread is the height of the understorey fuels. This variable is defined as the average height of both the near-surface and elevated fuels weighted by their cover on a per area basis. This metric quantifies the volume of fuels per unit area. It can be derived from simple estimates of height and cover, or through remote sensing of fuels using LIDAR (Skowronski *et al.* 2014; Price and Gordon 2016; Hillman *et al.* 2021). Work is under way to provide guidance to its estimation and derive landscape maps from knowledge of other commonly accessed fuel characteristics, such as fuel hazard ratings.

The use of visual hazard scores, such as those used in Cheney *et al.* (2012), resulted in a small improvement in the fit of fire spread rate models for Phase I and II. Nonetheless, this improvement did not warrant its use in the models due to the subjectivity inherent to their estimation (Duff *et al.* 2017).

Spotting

Spotting, or the process of transport of firebrands and the ignition of new fires outside the active fire perimeter, is a complex,

poorly understood and quantified phenomenon that can have an important influence on wildfire propagation. It is an inherent feature of wildfire propagation in eucalypt forests (Cheney and Bary 1969; Luke and McArthur 1978; Ellis 2013). Spotting, either short- (up to 0.75 km by Australian standards) or medium-range (up to 5 km), was present in the model development data and is thus implicit in the model system described herein. Longer spotting distances (i.e. >5 km) occur under severe fire weather conditions in Australian eucalypt forests (McArthur 1969; Rawson *et al.* 1983; Storey *et al.* 2020a). The influence of these longer spotting distances on a wildfire's overall propagation rate is unclear. For a newly ignited spot fire occurring ahead of a wildfire to spread independently and result in an increased *R* relative to the model expectation, it will need to land in an area where wind flow is not influenced by the convection column. Often, spot fires initiating downwind of a fire within the plume wake region (Forthofer and Goodrick 2016) spread without a general direction (see fig. 4 in Storey *et al.* 2020b). These spot fires will be overrun by the main fire without resulting in an increase in the overall speed a wildfire propagates. It is unclear what is the extent and width of this plume wake region for a given combination of fire size and energy release, environmental conditions, and associated fire-atmosphere interactions. It is also unclear, therefore, what the necessary maximum spotting distance is for a long-range spot fire to grow and increase the overall propagation speed of the wildfire beyond the model expectation. The occurrence of such spot fires can result in a model under-prediction.

Model fit and operational considerations

The models developed here are intended for use in the operational prediction of wildfire propagation in eucalypt forests over a broad range of fireline intensities. They assume a pseudo-steady-state has been achieved and aim to predict fire spread over time scales of one or more hours, based on observed or forecasted weather conditions. Their application to fire spread periods of less than 30 min is likely not to accurately capture the finer-scale variability in observed fire behaviour. The models do not capture fire spread dynamics associated with the passage of a cold front or wind change over the fire area, a process that converts a fire's flank into a broad head fire (Luke and McArthur 1978; Cheney *et al.* 2001). This is a poorly understood process, with the post change area growth typically unrelated to the prevailing wind strength and the air mass high relative humidity (McArthur 1967).

Average model error against independent evaluation data varied between 39% for experimental fire data (where accurate estimates of input conditions are known) and 84% for wildfires with larger uncertainty in model inputs. This level of error is consistent, although lower, than the results obtained with other empirically based fire spread models evaluated against wildfire data (Cheney *et al.* 2012; Cruz and Alexander 2013). An important result from the present work is that the percentage error decreased with an increase in observed rate of fire spread, suggesting that the model works best for the conditions in which it will be most needed.

It is believed that in an operational fire prediction scenario, trained fire behaviour analysts will be able to produce more accurate predictions than reported here. Fire behaviour

prediction is both an art and a science, combining the use of models with tailored spot fire weather forecasts and the shared experience of a cadre of qualified users with knowledge of landscape factors and fire processes that are not explicit in the models (Neale and May 2020).

The unquantified effects of the occurrence of long-range spotting and fire-atmosphere interactions (Cheney *et al.* 2012; Fromm *et al.* 2012; McRae *et al.* 2015; Sharples *et al.* 2016) on the precision of model predictions is unclear. Detailed evaluation against several fires known to have exhibited these kind of fire phenomena is required in order to further understand model adequacy/limitations in these situations. Similarly, the evaluation of the models for the marginal- to low-intensity spread conditions characteristic of prescribed burns and overnight fire activity under mild burning conditions is also required.

Concluding remarks

We developed a fire spread model aimed at the operational prediction of the steady-state propagation of wildfires in eucalypt forests. The model blends empirical data covering a broad spectrum of rates of fire spread with assumptions of fire behaviour from published studies. The model was shown to provide adequate predictions when contrasted with independent wildfire data, with the percentage error decreasing with increasing observed rate of fire spread. Evaluation highlighted areas where further submodelling, for example dealing with overnight recovery of dead fuel moisture content, could potentially lead to an improvement in the overall application of the model.

With the model being based on a broad range of rates of fire spread, comprising experimental fires and wildfires, we see its predictions as an expectation of fire spread rates associated with the prevailing environmental conditions. There is natural uncertainty associated with the model, derived from the uncertainty in the experimental fire and wildfire data and the simplicity and coarseness of how the model incorporates the effect of various environmental effects. When the model is used in an operational wildfire prediction setting, the uncertainty inherent in the model will be increased due to the uncertainty in the forecasted (e.g. wind speed and direction, dead fuel moisture content) and modelled (e.g. fuel structure from time since fire) inputs. Uncertainty and errors in model outputs can be reduced from the benchmark results obtained here when predictions are made by qualified and experienced fire behaviour analysts.

Data availability

The data that support this study will be shared upon reasonable request to the corresponding author.

Conflicts of interest

Lachlan McCaw and Andrew Sullivan are Associate Editors of *International Journal of Wildland Fire*, but were blinded from the peer-review process for this paper.

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Appendix 1. Wind reduction factors (*WRF*) to convert 10-m open into 2-m within-stand wind for eucalypt forests of different height and canopy cover

As reference, a *WRF* of 0.8 is suggested for open grassland fuel types (Cheney *et al.* 1993)

Stand canopy cover (%)	Stand height (m)		
	5–10	10–30	>30
10–30	0.40	0.36	0.33
30–60	0.36	0.33	0.25
		(0.29 in fuel types with tall shrubs present)	(0.22 in fuel types with tall shrubs present)
>60	0.25	0.22	0.20
			(0.16 in multi-strata stands with dense mid-storey)

