



# Moisture thresholds for ignition vary between types of eucalypt forests across an aridity gradient

Jane G. Cawson · Jamie E. Burton ·  
Bianca J. Pickering · Trent D. Penman

Received: 6 November 2023 / Accepted: 27 January 2024 / Published online: 11 March 2024  
© The Author(s) 2024

## Abstract

**Context** Quantifying spatial and temporal variations in landscape flammability is important for implementing ecologically desirable prescribed burns and gauging the level of fire risk across a landscape. Yet there is a paucity of models that provide adequate spatial detail about landscape flammability for these purposes.

**Objectives** Our aim was to quantify spatial and temporal variations in ignitability across a forested landscape. We asked: (1) How do fuel moisture and meteorological variables interact to affect ignitability? (2) Do fuel moisture thresholds for ignition vary across a gradient of forest types? (3) How does the spatial connectivity of ignitable fuel vary over time? (4) How could an ignitability model be used to inform fire management decision-making?

**Methods** We conducted field-based ignition tests with flaming firebrands over three fire seasons. Ignitions were attempted across a range of moisture and meteorological conditions at 15 sites in eucalypt forest in south-eastern Australia. Structural equation modelling and generalized linear models were used to quantify relationships between ignitability, aridity, fuel moisture and weather.

**Results** The strongest predictors of ignitability were the moisture content of dead near surface fine fuel and in-forest vapour pressure deficit. Ignition thresholds for both varied across an aridity gradient. Dense forests (i.e., wet and damp eucalypt forests) needed drier fuel and drier in-forest atmospheric conditions to ignite than sparser forests (i.e., shrubby foothill forest).

**Conclusion** Our modelling of ignitability could inform fire planning in south-eastern Australia and the methodology could be applied elsewhere to develop similar models for other regions. Days with consistently high ignitability across the landscape are more conducive to the development of large wildfires whereas days when ignitability is spatially variable are more suitable for prescribed burning.

**Keywords** Firebrand · Flammability · Fuel · Microclimate · Moisture · Vapour pressure deficit · Wildfire

## Introduction

Flammability – the ability of vegetation to burn – often varies spatially across landscapes, reflecting differences in topography, vegetation, and moisture (Ryan 2002; Keane et al. 2008; Burton et al. 2023a). This produces mixed severity fires containing unburnt patches within a broader fire footprint (Hessburg et al. 2005; Penman et al. 2007; Collins et al. 2007;

---

J. G. Cawson (✉) · J. E. Burton · B. J. Pickering ·  
T. D. Penman  
School of Agriculture, Food and Ecosystem Sciences,  
University of Melbourne, 500 Yarra Boulevard, Burnley,  
VIC 3121, Australia  
e-mail: Jane.Cawson@unimelb.edu.au

Bradstock et al. 2010; Oliveira et al. 2015). Fire patchiness is desirable ecologically and thus is a common objective for prescribed burning (Penman et al. 2011). Unburnt patches provide refugia for fire-sensitive flora and fauna, enabling fire-sensitive species to persist in fire-prone landscapes (Sitters et al. 2015; Bain et al. 2016; Burrows and Middleton 2016). Flammability also varies temporally in response to weather. During periods of drying the spatial connectivity of flammable fuel is high, allowing wildfires to burn intensely across whole landscapes (Cruz et al. 2012; Collins et al. 2019). These fires pose the greatest risk to human life, property and the environment, are difficult to suppress and contain few refugia for fire-sensitive species (Filkov et al. 2020b; Collins et al. 2021).

Understanding temporal variations in the spatial connectivity of flammable fuel is important for gauging fire risk across the landscape and implementing ecologically desirable prescribed burns. Quantifying when a forest will ignite (its 'ignitability') is the first step towards predicting its flammability (Pausas et al. 2017). At laboratory scales ignitability is typically a measure of the time required for vegetation to begin an exothermic reaction after exposure to a heat source whereas at field-scales the probability of ignition is a more common measure. A fire front is likely to burn rapidly through vegetation that ignites easily while vegetation that is less ignitable may slow the spread of a fire (Gill and Zylstra 2005). The risk of a large wildfire peaks when ignitability is consistently high across a landscape (Gill and Allan 2008; Caccamo et al. 2012). In contrast, when ignitability is more spatially variable, discontinuities between flammable fuel can inhibit the spread of fire (Bradstock et al. 2010). Accurate quantification of these temporal and spatial fluctuations in ignitability enables windows for prescribed burning to be more easily identified (Slijepcevic et al. 2015; Duff et al. 2018a) and ignition strategies to be designed to achieve desired burn outcomes (McCaw and Burrows 2020).

Dead fine fuel moisture content (FFMC) is the strongest determinant of ignitability in dense forests where there is ample fuel to sustain the ignition (Bradstock 2010; Cawson and Duff 2019). It influences the amount of heat required to dry fuel and raise it to ignition temperature (Keane 2015; Sullivan 2017), with low moistures resulting in faster ignition. Moisture dynamics vary between

fuel elements (Slijepcevic et al. 2013). Dead leaves, fine twigs and bark suspended in standing vegetation close to the ground (i.e., in the near surface fuel stratum (Hines et al. 2010) are most exposed to atmospheric conditions, causing their FFMC to respond rapidly to changes in atmospheric moisture. Vapour pressure deficit (VPD) is one such meteorological variable strongly associated with dead near surface FFMC (Resco de Dios et al. 2015). The FFMC of surface fine fuel at the top of the litter bed is also highly responsive to atmospheric conditions but may also be influenced by soil moisture (Matthews 2014). Soil moisture is most important to the FFMC of subsurface (aka profile) litter in contact with the soil, particularly when the litter bed is deep and the soil moisture is high (Zhao et al. 2021). Despite wide recognition of the importance of dead FFMC to fire activity (Sullivan 2017), it is still unclear which fuel elements (e.g., surface versus subsurface litter) best predict different components of fire behaviour (e.g., ignitability).

Dead FFMC, hence ignitability, varies at fine spatial scales (e.g., metres) within forested landscapes. This variability is caused by spatial variations in canopy density, hillslope shading and elevation (Cawson et al. 2017; Nyman et al. 2018). Gridded meteorological products used to infer fuel moisture typically operate at relatively coarse spatial resolutions (1 to 5 km). These coarse resolution products are useful for gauging wildfire risk across the broader landscape (Nolan et al. 2016a; Sungmin et al. 2020; Clarke et al. 2022), but not for providing the subpixel information needed for evaluating fire risk at local scales and implementing prescribed burns. Burton et al. (2023a) predicted subpixel variability in litter bed ignitability using a fine-scale aridity index that integrates the effect of both broad-scale climate and finer-scale topography on forest productivity and structure (Nyman et al. 2014). However, their ignitability model was only developed for eucalypt forests with little near surface vegetation (i.e., herbs, grass and low shrubs) (Burton et al. 2023a). Near surface vegetation is known to influence fire ignition and spread in forest types where it occurs abundantly (Cheney et al. 2012; Burton et al. 2023b), therefore ignitability should be tested in fuel beds with intact near surface vegetation for these forest types (i.e., in situ ignition testing is required).

Our aim was to quantify spatial and temporal variations in ignitability across a landscape in south-eastern Australia encompassing a spectrum of native eucalypt forest types. Specifically, we asked:

- How do fuel moisture and meteorological variables interact to affect forest ignitability?
- Do fuel moisture thresholds for ignition vary across a gradient of forest types?
- How does the spatial connectivity of ignitable fuel vary over time?
- How could an ignitability model be used to inform fire management decision making?

## Methods

We used field experimentation to test ignitability in native eucalypt forests spanning an aridity gradient in south-eastern Australia. A range of eucalypt forests dominates the mountainous landscape of the region, contributing to its notoriously high wildfire risk. Spot fires ignited from flaming firebrands are a common mechanism of fire spread in eucalypt forests, with the fibrous and ribbon bark from eucalypts providing an important source of firebrands (Cruz et al. 2012; Filkov et al. 2020a). Therefore, our study focused on quantifying the ignition potential from flaming firebrands.

### Study sites

There were 15 study sites in Victoria, south-eastern Australia (Fig. 1; Table 1). Ten sites were in the Yarra State Forest, approximately 70 km east of Melbourne where the rainfall averages 1464 mm yr<sup>-1</sup> and maximum temperatures range from 11.8°C in July to 25.4°C in January for Powelltown, the closest long-term weather station (Bureau of Meteorology station number 086094; 37.87°S, 145.75°E; elevation 189 m) (Bureau of Meteorology 2022). The remaining five sites were in the Wombat State Forest, approximately 50 km west of Melbourne where the rainfall averages 540 mm yr<sup>-1</sup> and maximum temperatures range from 13.2°C in July to 26.6°C in January for Melbourne airport, the closest long-term weather station (Bureau of Meteorology station number 086282; 37.67°S, 144.83°E; elevation 113 m) (Bureau of Meteorology 2022). Data from six sites in the Yarra State Forest

were from an earlier published study (Cawson et al. 2022).

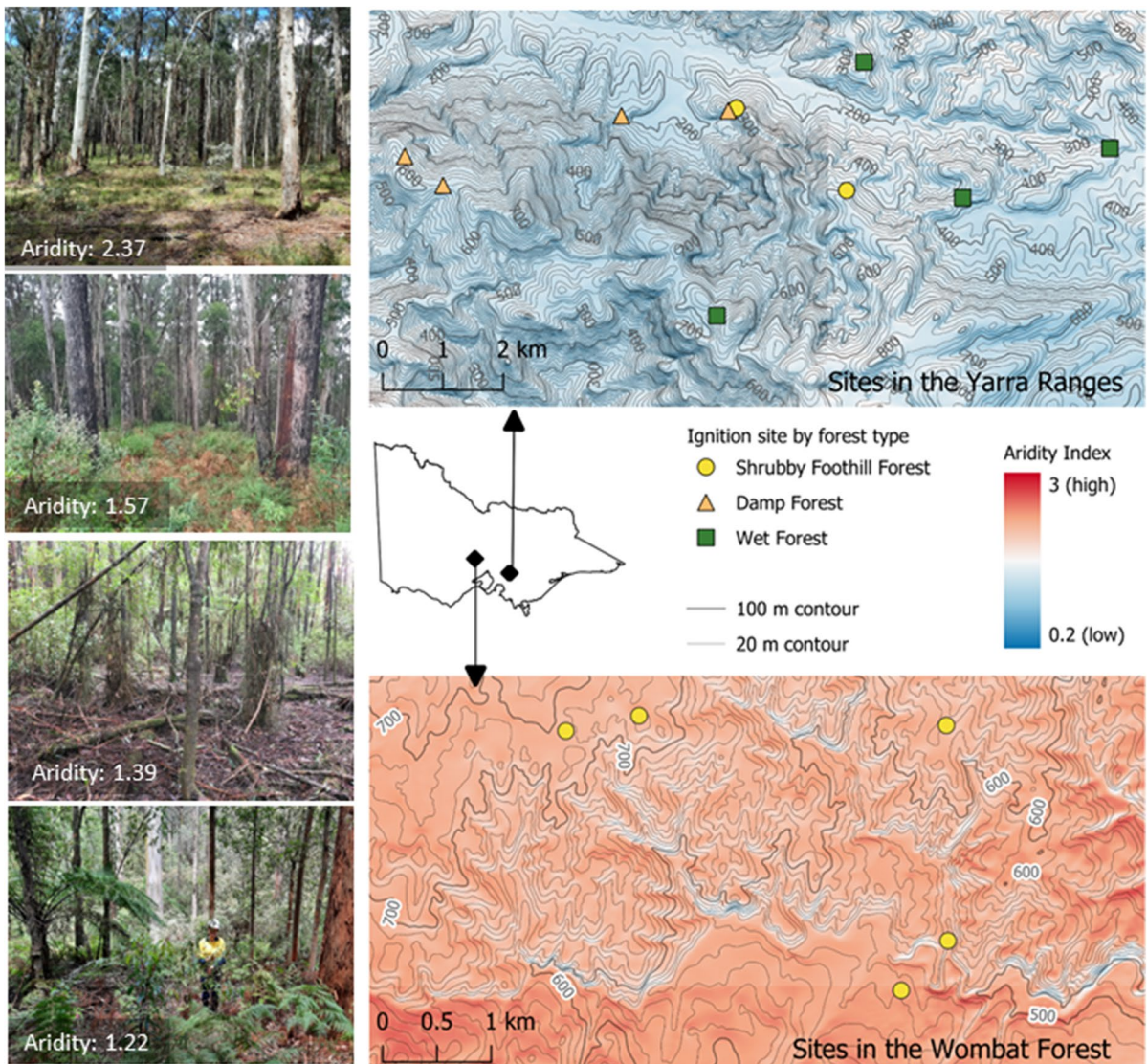
Site selection was governed by a set of criteria that fulfilled both the research requirements of the study and safety considerations associated with conducting unbounded fire experiments in natural forest. All sites were within 20 m of a track to provide ease of access for fire crews. Slopes were as shallow as possible (mostly less than 15°) to reduce the effect of slope and ensure ignitions could be easily suppressed. There were no steep uphill runs above the sites to aid fire suppression in the unlikely event of an ignition escaping containment. All sites were either within scheduled prescribed burn units or comprised unburnt patches within recently burnt units for logistic simplicity.

All sites were comprised of mature eucalypt forest and had not been impacted by wildfire for at least 20 years. They exhibited a range of vegetation structures with varying canopy and understorey densities. Four sites were classified as Wet forest (Ecological Vegetation Class (EVC) no. 30 (Department of Environment Land Water and Planning 2016), with a *Eucalyptus regnans* (Mountain Ash) dominated overstorey. Four sites were Damp forest (EVC no. 29) with an overstorey of *E. cypellocarpa* (Mountain Grey Gum), *E. regnans*, and *E. obliqua* (Messmate Stringybark). Two sites were Shrubby Foothill Forest (EVC no. 45) in the Yarra Ranges with an overstorey of *E. sieberi* (Silvertop Ash), *E. dives* (Broad-leaved Peppermint), and *E. obliqua*. Five sites were Shrubby Foothill Forest in the Wombat Forest with an overstorey of *E. obliqua*, *E. radiata* (Narrow-leaved Peppermint) and *E. rubida* (Candlebark). Forest structure and composition varied as a function of the long-term water balance of the site i.e., its aridity index (Nyman et al. 2014), with the denser forests in the less arid parts of the landscape and the sparser forests associated within higher landscape aridity.

### Field-based ignitability tests

We used a modified version of a method developed in a prior study to test in situ ignitability with flaming firebrands (Cawson et al. 2022). At each site there were a series of adjacent plots (4 m wide x 15 m long) with the number of plots used varying with the number of suitable weather opportunities to ignite each site. Plot perimeters were marked with stakes





**Fig. 1** Map depicting location of study sites as a function of Ecological Vegetation Class and aridity index. Photos illustrate the vegetation structures and compositions captured within the

sites. Photos in order are: Finger post south (Shrubby foothill forest), Learmonth (Shrubby Foothill Forest), Worleys Upper (Wet forest) and Torbet Gilderoy (Damp Forest)

and flagging tape. Within each plot, there were up to 30 ignition points, spaced 1 m apart in a grid. The number of ignition points per plot depended on the success of prior ignitions in that plot (further details below).

Ignitability was tested using flaming firebrands. Our firebrand comprised a solid cotton cylinder, that was proven to be a useful surrogate for flaming stringybark (Burton et al. 2023b), the largest contributor of firebrands in eucalypt forests. The solid

cotton cylinder was ignited using a butane lighter and once flaming it was dropped from 0.3 m onto the litter bed or near surface fuel (where present). An ignition attempt was considered successful if flames propagated 0.5 m from the point of ignition; otherwise, the ignition was considered unsuccessful. After each successful ignition the flame was extinguished using hand tools. If there were three successful ignitions, we ceased igniting the plot and declared the plot ‘ignitable’. Otherwise, we continued with the

**Table 1** Study site details. All values are averages for the plots within each site

Forest region	Site name	Latitude, Longitude	No. plots tested for ignitability	Slope, °	Aspect, °	Aridity index	Forest type	Canopy cover, %	Tree height, m	Litter depth, mm	Litter cover, %	Near surface cover, %	Dominant near surface species
Yarra	Beenak	-37.8721, 145.6714	9	7	50	1.51	Damp	71	39	36	95	40	<i>Cyathea australis</i> ; <i>Goodenia ovata</i> ; <i>Lepidosperma elatius</i>
	Bertha	-37.8577, 145.758	9	14	145	1.38	Wet	66	40	62	100	20	<i>Blechnum</i> spp; <i>Lepidosperma elatius</i>
	Big Creek	-37.8702, 145.8044	8	3	232	1.49	Wet	66	50	27	90	30	<i>Correa lawrenceana</i> ; <i>C. australis</i> ; <i>Polystichum proliferum</i> ; <i>Tetrarrhena juncea</i>
	Fifth Dam	-37.8765, 145.6788	9	3	355	1.46	Damp	65	47	42	95	40	<i>C. lawrenceana</i> ; <i>L. elatius</i>
	Learmonth	-37.8768, 145.7550	2	12	27	1.57	Shrubby foothill	55	26	47	100	66	<i>T. juncea</i> ; <i>Platylobium obtusangulum</i> ; <i>Pteridium esculentum</i> ; <i>Spyridium parviflora</i>
	Torbet-Gilderoy	-37.8660, 145.7122	2	8	161	1.22	Damp	63	33	18	89	27	<i>C. australis</i> ; <i>Zieria arborescens</i> ; <i>Blechnum cartilagineum</i> ; <i>Calochlaena dubia</i>
	Turners	-37.8777, 145.7767	9	5	296	1.43	Wet	62	43	33	90	70	<i>C. australis</i> ; <i>L. elatius</i> ; <i>T. juncea</i>
	Worileys North	-37.8648, 145.7338	2	6	48	1.49	Shrubby foothill	47	28	38	100	83	<i>S. parvifolium</i> ; <i>P. obtusangulum</i> ; <i>T. juncea</i> ; <i>P. esculentum</i>
	Worileys Upper	-37.8950, 145.7288	9	4	220	1.39	Wet	67	48	30	95	28	<i>C. lawrenceana</i> ; <i>C. australis</i> ; <i>Prostanthera melissifolia</i> ; <i>T. juncea</i>
	Worileys South	-37.8653, 145.7324	3	15	189	1.03	Damp	64	28	33	91	34	<i>C. australis</i> ; <i>Goodenia ovata</i> ; <i>T. juncea</i> ; <i>Blechnum cartilagineum</i>

Table 1 (continued)

Forest region	Site name	Latitude, Longitude	No. plots tested for ignitability	Slope, °	Aspect, °	Aridity index	Forest type	Canopy cover, %	Tree height, m	Litter depth, mm	Litter cover, %	Near surface cover, %	Dominant near surface species
Wombat	Burnt mill east	-37.4483, 144.4505	6	3	315	2.22	Shrubby foothill	60	19	23	98	15	<i>P. esculentum</i> ; <i>Pultenaea gunnii</i> ; <i>Pultenaea muelleri</i> <i>var reflexifolia</i>
	Burnt mill west	-37.4495, 144.4428	6	2	288	2.21	Shrubby foothill	58	20	26	96	21	<i>L. elatius</i> ; <i>Acacia verticillata</i> ; <i>P. esculentum</i> ; <i>Poa tenera</i>
	Fingerpost gully	-37.4669, 144.4826	3	12	106	1.99	Shrubby foothill	58	20	19	66	60	<i>P. esculentum</i> ; <i>Viola hederacea</i> ; <i>Lomandra longifolia</i>
	Fingerpost north	-37.4491, 144.4825	6	2	180	2.19	Shrubby foothill	55	20	20	93	42	<i>Pultenaea gunnii</i> ; <i>Acacia mucronata</i> ; <i>T. juncea</i> ; <i>L. longifolia</i> ; <i>P. tenera</i>
	Fingerpost south	-37.4710, 144.4777	6	2	341	2.37	Shrubby foothill	46	20	30	94	68	<i>A. mucronata</i> ; <i>P. tenera</i> ; <i>Acacia mearnsii</i> ; <i>Dillwynia sp.</i> ; <i>Dianella revoluta</i> ; <i>Pultenaea gunnii</i>

ignitions until there had been 30 attempts. If less than three attempts ( $<3/30$ ) resulted in a successful ignition, we declared the plot ‘not-ignitable.’

To capture a range of fuel moisture conditions we repeated the process on different days in adjacent plots within each site. Wind speeds were less than  $20 \text{ km h}^{-1}$  in the open to reduce the risk of fire escape, meaning there was almost no wind beneath the forest canopy at the sites. Ignitions occurred during a six-hour window from 11 am to 5 pm, when fuels were assumed to be driest and most ignitable. Ignitions occurred from November to April during the 2022/2023 fire season, and data were combined with ignitions from an earlier study (Cawson et al. 2022) that occurred from November to March in the 2019/20 and 2020/21 fire seasons.

In addition to the field-based ignitions, we undertook ignition tests in the laboratory for four sites in the Wombat State Forest on a dry day when there were insufficient fire-fighting resources to support the field ignition tests. To test ignitability in the laboratory we followed the procedure developed by Burton et al. (2023b), which found laboratory experiments to be an adequate substitution for field experiments when using the field method of the current study. This involved collecting all dead surface leaf litter from the forest floor within a 125 mm radius sampling ring. The surface (top 1 cm of litter) and subsurface (remaining litter) were collected separately to preserve the moisture differential between surface and subsurface litter. We collected 10 surface fuel samples per site. Samples were stored in airtight containers and a cooler box to ensure they retained their *in-situ* moisture content and transferred to the laboratory within three hours of collection. In the laboratory, samples were carefully reconstructed and ignited using the cotton cylinder flaming firebrand. An ignition was deemed successful if the litter ignited and burnt from the centre to the edge of the sample ring. All 10 samples ignited successfully for each site, so the sites were classified as ‘ignitable’ for the fuel and weather conditions on that day.

#### Moisture variables

A range of fuel moisture and microclimate variables were collected so they could be tested as potential predictors of ignitability. Fine fuel ( $<6 \text{ mm}$  thick) moisture content (FFMC) was determined in the field

immediately prior to ignition for: surface dead fine fuel, subsurface dead fine fuel and near surface dead fine fuel (Table 2). Surface fine fuel constituted dead leaves, twigs and bark in the upper part of the litter bed exposed to the atmosphere (top 1 cm) whereas subsurface fine fuel was the litter at the base of the litter bed in contact with the soil (bottom 1 cm). Near surface dead fine fuel constituted dead leaves, twigs and bark suspended within the live vegetation up to 0.5 m above the litter bed. The dead fine fuel samples were collected from five separate locations within the plot and bulked into the same airtight tin for moisture analysis. All samples were weighed, oven-dried at  $105 \text{ }^\circ\text{C}$  for at least 24 h until they were completely dry (determined by weighing a subset of samples twice several hours apart to ensure there was no further mass loss), then reweighed to determine the mass of moisture in the sample as a fraction of oven dry mass.

Weather stations (Decagon Em50 or ATMOS 41) at each site recorded screen height (1.2 m) air temperature, relative humidity, wind speed, wind direction and solar radiation at 10-minute intervals. These data were used to calculate the vapour pressure deficit (VPD) (as per the equation in Burton et al. 2023a). We then obtained the maximum in-forest VPD at the time of ignition and daily total solar radiation.

A range of landscape moisture metrics were also extracted for the date of ignition. Each metric is fully described in Table 2. We considered rootzone soil moisture (Frost et al. 2018) and standardized precipitation evapotranspiration index (SPEI) (Vicente-Serrano et al. 2010) as indicators of drought. Rootzone soil moisture reflects both individual precipitation events and longer-term trends because it captures the average moisture conditions across the upper (0–10 cm) and rootzone (10–100 cm) soil profile. SPEI was calculated for the three months preceding the month of ignition, so it captures drying trends over this seasonal timeframe. Fuel moisture (Vesta FFMC) was calculated from temperature and relative humidity using the afternoon (12 noon to 5 pm) equation from within the Vesta fire spread model, which is used operationally for fire spread prediction in Australian dry eucalypt forests (Cruz et al. 2015, 2022).

#### Analysis

We used piecewise structural equation modelling (SEM) to quantify the relative contribution

**Table 2** Descriptions of the moisture and climatic variables used for modelling ignitability. Footnotes indicate which variables were used for each component of the analysis

Variable	Description	Units	Spatial resolution	Min, Max
Surface FFMCA <sup>B</sup>	Mass of water per unit mass of dead fine fuel (<6 mm thick) within the upper 1 cm of the litter bed.	%	Direct measure	9, 257
Near surface FFMCA <sup>B</sup>	Mass of water per unit mass of fine fuel (<6 mm thick) for dead leaves, twigs and bark suspended in the near surface strata (up to a height of 0.5 m)	%	Direct measure	11, 99
Subsurface FFMCA <sup>B</sup>	Mass of water per unit mass of dead fine fuel (<6 mm thick) for litter at the base of the litter bed in contact with the soil.	%	Direct measure	15, 237
Aridity <sup>ABC</sup>	Non-dimensional measure of the long-term balance between rainfall and net radiation (Nyman et al. 2014)	NA	20 m	1.03, 2.37
In-forest solar radiation <sup>A</sup>	Total amount of solar radiation measured in the forest over a day using the in-forest weather stations	MJ/day	Direct measure	0, 9.4
Open solar radiation <sup>C</sup>	Total amount of solar radiation over a day. Data obtained from SILO database of Australian climate data (Jeffrey et al. 2001)	MJ/day	5 km	10.3–32.1
In-forest VPD <sup>AC</sup>	Deficit between the amount of moisture in the air and amount that can be held when saturated (Monteith and Unsworth 2013). Calculated from in-forest weather station data for the time ignition.	kPa	Direct measure or 30 m	0.05, 4.1
Daily upper soil moisture <sup>A</sup>	Water in the upper (0–10 cm) soil layer expressed as a percentage of available water content. Daily value from the Australian Landscape Water Balance model (Frost et al. 2018)	%	5 km	0.5, 14.3
Daily rootzone soil moisture <sup>A</sup>	Sum of water in the upper (0–10 cm) and lower (10–100 cm) soil layers expressed as a percentage of available water content. Daily value from the Australian Landscape Water Balance model (Frost et al. 2018)	%	5 km	14.4, 85.3
Monthly rootzone soil moisture <sup>C</sup>	Sum of water in the upper (0–10 cm) and lower (10–100 cm) soil layers expressed as a percentage of available water content. Monthly value from Australian Landscape Water Balance model (Frost et al. 2018)	%	5 km	16.8, 83.7
SPEI <sup>AC</sup>	Standardised Precipitation Evapotranspiration Index measures drought from the difference in precipitation and potential evapotranspiration over a defined temporal window (Vicente-Serrano et al. 2010). Calculated for the three-months preceding the month of ignition, using data from the SILO database of Australian climate data (Jeffrey et al. 2001)	NA	5 km	-1.2, 1.7
Vesta FFMCA <sup>C</sup>	Predicted mass of water per unit mass of fine fuel (<6 mm thick) for dead leaves, twigs and bark within the litter bed. The equation from Cruz et al. (2015): $FFMC = 2.76 + 0.124 * RH - 0.0187 * Temp$ was calculated using daily maximum temperature and minimum relative humidity from the SILO database of Australian climate data (Jeffrey et al. 2001)	%	5 km	4.1, 10.8

<sup>A</sup> Structural equation model (SEM)

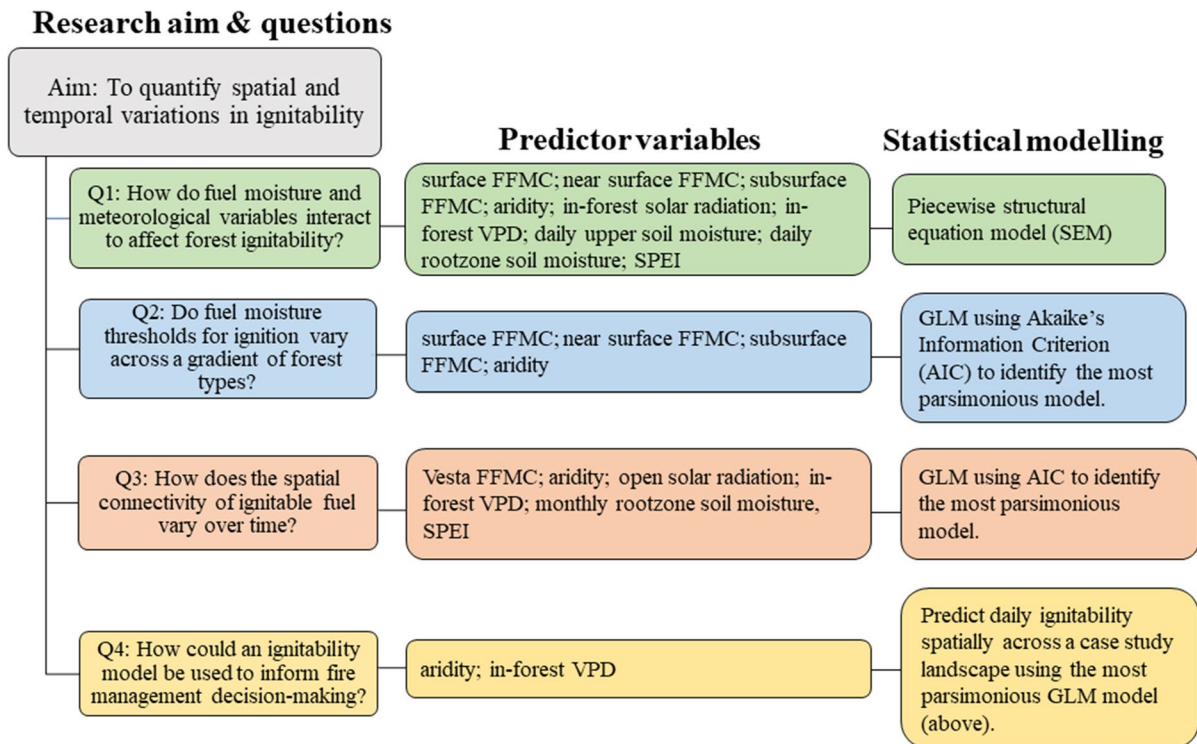
<sup>B</sup> Generalised Linear Model (GLM) for identifying fuel moisture thresholds for ignition

<sup>C</sup> GLM for predicting ignitability across the landscape

of a range of variables to forest ignitability (i.e., to address research question 1) (Lefcheck 2016)

(Fig. 2). SEMs quantify direct and indirect causal relationships between multiple variables in a single





**Fig. 2** Flow chart to illustrate the key analysis steps and how they relate to the research questions

network. Our SEM tested the hypothesis that dead fine fuel moisture (surface, near surface and/or subsurface FFMC) directly affects the probability of ignition, while microclimatic variables (VPD, solar radiation), soil moisture (rootzone and upper soil moisture) and drought (SPEI) directly affect fuel moisture, and therefore indirectly affect ignitability. A fine-scale (20 m) topographically varying aridity index was used as an indicator of the long-term effects of water availability on vegetation cover between and within forest types, i.e., a proxy for rainfall-induced differences in vegetation cover (Nyman et al. 2014). A direct link between solar radiation and ignitability was also included as solar radiation has been known to influence ignitability by heating the fuel surface (Kreye et al. 2020). Previous studies indicate a strong link between fine-scale aridity and forest type (Burton et al. 2023a).

Linear models (LM) were used to predict fuel moisture (surface, near surface and subsurface dead FFMC) and a generalized linear model (GLM) with a binomial distribution was used to predict ignitability within the SEM. All variables were checked for

normality and those with skewed distributions were transformed (using a log transformation for near surface FFMC, surface FFMC and in-forest VPD and a square root transformation for subsurface FFMC and daily upper soil moisture). First, we fit the saturated model with all variables and pathways included. Then we fit a reduced model showing only the variables that had a significant (or close to significant  $P$ -value  $< 0.10$ ) direct or indirect effect on ignitability. For both models we report the standardized path coefficient for each path, which indicates the relative strength of the different predictors on the response variable, and the  $p$ -values for each path. The  $R^2$  is reported for each response variable; Nagelkerke's  $R^2$  for the GLM and adjusted- $R^2$  for the LMs. We evaluated the fit of the entire SEM using the Fisher's  $C$  test, with small Fisher's  $C$  and  $p > 0.05$  indicating good model fit.

We fit GLMs with a binomial distribution using the three fuel moisture metrics (surface, near surface and subsurface dead FFMC) and aridity as a proxy for forest productivity to test whether moisture thresholds for ignition vary across a gradient of

forest types (research question 2). First, we checked for multicollinearity by examining the variable inflation factor (VIF) for each variable within the global model. VIF measures how much the standard error of the estimated coefficient for a variable is inflated due to multicollinearity, with values less than three indicating minimal multicollinearity. No values exceeded three, so all were retained in the model. Models were fit with all combinations of predictor variables and the level of support for the models was assessed using Akaike's information criterion (AICc) and Akaike weight, which is the probability that the model is the most parsimonious model in the set (Burnham and Anderson 2004). The highest-ranked models (within two AIC units of the best model) were presented in the results as the preferred set. Goodness of fit was measured by McFadden  $R^2$  (likelihood ratio index) and  $-2 \log$  (Likelihood). Marginal effects plots were created for the simplest model (with the fewest terms) within the preferred set to visualize the effect of each predictor variable on the probability of ignition.

We built a model to predict ignitability across the landscape to understand how the spatial connectivity of ignitable fuels varies over time (research question 3). To do this we used the same information theoretic approach outlined above, but rather than use the field-based fuel moisture measurements as predictors, we used variables that are available as spatially-derived and forecastable products. The forecasting criteria allows the model to be used for fire management decision-making in the future. The fuel moisture measurements were replaced with a fuel moisture model for surface fine fuel (Cruz et al. 2015) derived from 5 km gridded maximum temperature and minimum relative humidity (Vesta FFM). In-forest VPD was retained because it can be modelled spatially (Burton et al. under review) and forecast. In-forest solar radiation was replaced with open solar radiation because in-forest solar radiation cannot yet be spatially modelled. Daily upper and rootzone soil moisture were also excluded because they cannot be forecast. These were replaced with monthly rootzone soil moisture, a forecastable product. SPEI was retained because it is derived using data from the preceding three months, rather than data from the day of ignition. Aridity was retained as it is a long-term average value and therefore does not vary over the temporal frame within which the model is likely to be used.

The simplest model in the preferred set was used to make spatial predictions of ignitability for two case studies to demonstrate the potential utility of the model for fire management decision making (research question 4). The first case study involved predicting spatial and temporal trends in maximum daily ignitability for the Yarra Ranges over a two-week period during the 2019–2020 Black Summer fire season (Filkov et al. 2020b). During this period two whole of Victoria total fire bans were declared on 20th and 30th December 2019 and the Black Summer fires in the east of Victoria were burning intensely with major runs coinciding with dry conditions on the 20th and 30th December (Salkin 2022). Boxplots were used to show the distribution of ignition probabilities within the landscape on each day. The second case study involved predicting ignitability across a prescribed burn for the five days leading up to the burn. The burn outcome (burnt polygons) are overlaid on the ignitability prediction to visually assess the level of agreement between modelled ignitability and final outcome of the burn. In both examples, maximum daily in-forest VPD was calculated using a downscaling function by Burton et al. (under review), which derives in-forest VPD from gridded temperature and relative humidity (5 km) from the SILO database (<https://www.longpaddock.qld.gov.au/silo/>) and 30 m resolution topographic variables.

All analyses were done using the R-programming language version 4.2.2 (Core Team 2022). SEM models were fit using *piecewiseSEM* (Lefcheck 2016), LMs and GLMs were fit using *glmulti* package (Calcagno 2013), the *visreg* package was used to plot predictions (Breheny and Burchett 2017). Raster data were manipulated using the *sf* (Pebesma 2018) and *raster* packages (Hijmans 2022). Maps were created in QGIS version 3.14 (Development Team 2020).

## Results

Ignitions were attempted in 89 plots, with 46% of the plots classified as ignitable. Ten of 35 plots (29%) were ignitable in wet forest, 13 of 25 plots (52%) in damp forest and 18 of 29 plots (62%) in shrubby foothill forest. Ignitions were attempted for a range of fuel moisture conditions, but particularly when the fuel was likely to be transitioning from a non-ignitable to ignitable state (i.e., when surface FFM)

ranged from 10 to 25%). The moisture content of near surface dead fine fuel (i.e., dead leaves and bark suspended less than 0.5 m above the litter bed) ranged from 12 to 99% in wet forest, 13–54% in damp forest and 11–32% in shrubby foothill forest.

#### Direct and indirect effects of moisture variables on ignitability

Near surface FFMFC had a larger direct effect on the probability of ignition than the other fuel moisture variables (Fig. 3). The influence of surface FFMFC in the saturated SEM (Fig. 3a) was non-significant, so it was omitted from the reduced SEM (Fig. 3b). Subsurface FFMFC was retained in the reduced SEM, but its path coefficient (-0.23) was less than half that of near surface FFMFC (-0.59). SPEI also had negligible influence in the saturated SEM and was omitted from the reduced SEM. Near surface FFMFC was significantly influenced by in-forest VPD, in-forest solar radiation and upper soil moisture, with in-forest VPD having the largest influence (path coefficient of -0.64 in the reduced SEM). Subsurface FFMFC was significantly influenced by upper and rootzone soil moisture and in-forest VPD, with upper soil moisture having the largest influence (path coefficient of 0.44 in the reduced SEM). In-forest solar radiation also had a direct effect on the probability of ignition (path coefficient of 0.28 in the reduced model). However, in-forest VPD was the most influential of the climatic variables overall (combined path coefficient of 0.47). The direct effect of aridity was marginally non-statistically significant ( $p=0.06$ ). The reduced structural equation model was a good fit to the data (Fisher's  $C=13.758$ ,  $P$ -value=0.62,  $df=16$ ) (Fig. 3b).

#### Fuel moisture thresholds for ignition

Aridity and near surface FFMFC were significant predictors in all three highest ranked fuel moisture-based models of ignitability (Table 3). In contrast, surface and subsurface FFMFC were less important, only appearing in one model and with non-significant effects. The near surface FFMFC threshold for ignition increased within increasing aridity, meaning mesic forests needed drier fuel to ignite (Fig. 4). For an aridity index of 1.4 (average for the wet forest sites), the fuel moisture threshold needed for a 50% probability of ignition was about 17%, whereas a fuel moisture

threshold of approximately 20% was required for an aridity index of 2.0 (average for the shrubby foothill forest sites) (Fig. 4d).

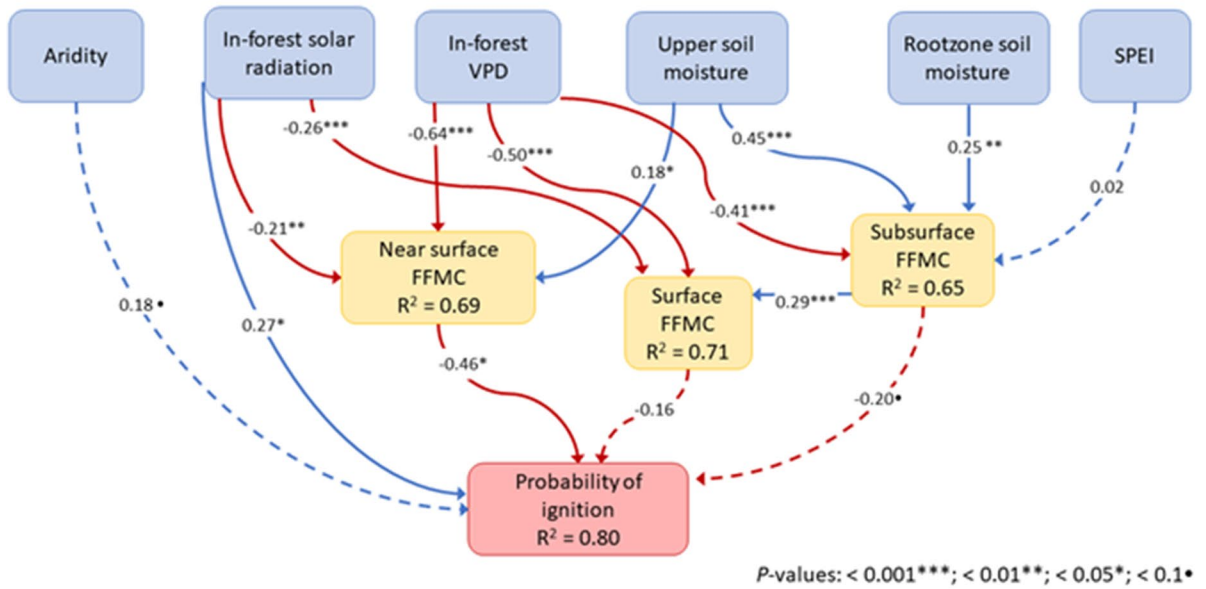
#### Modelling the spatial connectivity of ignitable fuel over time

Aridity and in-forest VPD were the strongest spatially-derived predictors of ignitability and were significant predictors in the three highest ranked models of ignitability (Table 4). In contrast, the effects of SPEI and solar radiation within the highest ranked models were non-significant and Vesta FFMFC was not selected in any of the highest ranked models. Monthly rootzone soil moisture was omitted from the model selection process as it had a variable inflation factor exceeding three. The effect of VPD on ignitability varied with aridity (Fig. 5) with more arid sites having a lower VPD threshold for ignition. This means more arid sites would ignite under moister atmospheric conditions. For an aridity index of 1.4 (average for the wet forest sites), the VPD threshold needed for a 50% probability of ignition was about 1.7 kPa, whereas the VPD threshold decreased to approximately 1.0 kPa for sites with an aridity of 2.0 (average for the shrubby foothill forest sites) (Fig. 5d).

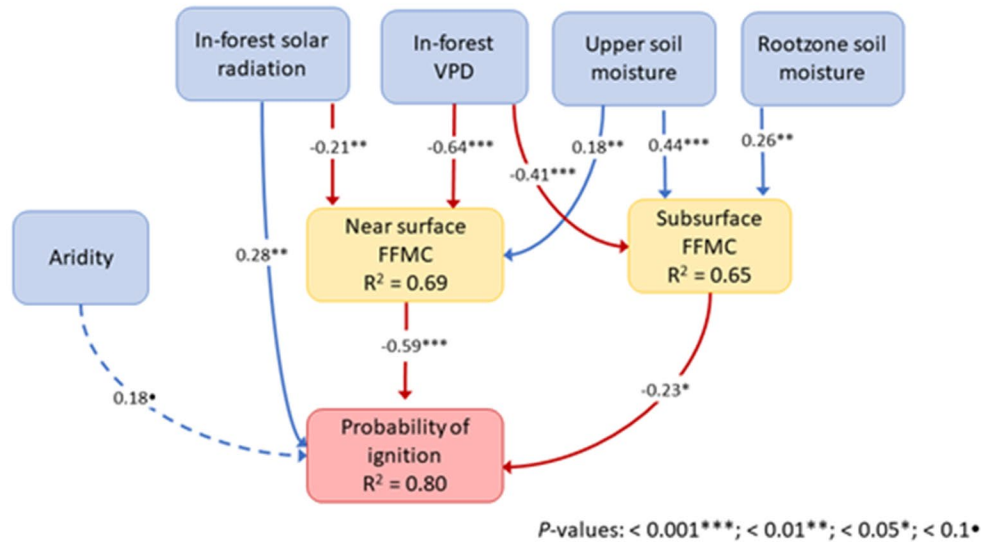
#### Potential utility of ignitability model to inform fire management decision-making

The ignitability model can gauge the level of wildfire risk across the landscape by illustrating the spatial connectivity of ignitable fuel (Fig. 6). The median probability of ignition each day gives an indication of the overall level of ignitability (high median means increased likelihood of sustained ignitions), whereas the interquartile range indicates spatial continuity (small interquartile range means increased spatial connectivity) (Fig. 7). Days of highest wildfire risk (e.g. 20th and 30th December 2019) exhibit high median ignitability across the landscape coupled with a small interquartile range, meaning most of the landscape has a high probability of ignition and there are few barriers to the spread of wildfire. In contrast, days with relatively high median ignitability coupled with a larger interquartile range (e.g. 25th December 2019) pose less wildfire risk because there are areas of low ignitability interspersed across the landscape that could act as a barrier to the spread of wildfire.

(a) Saturated Model



(b) Reduced Model

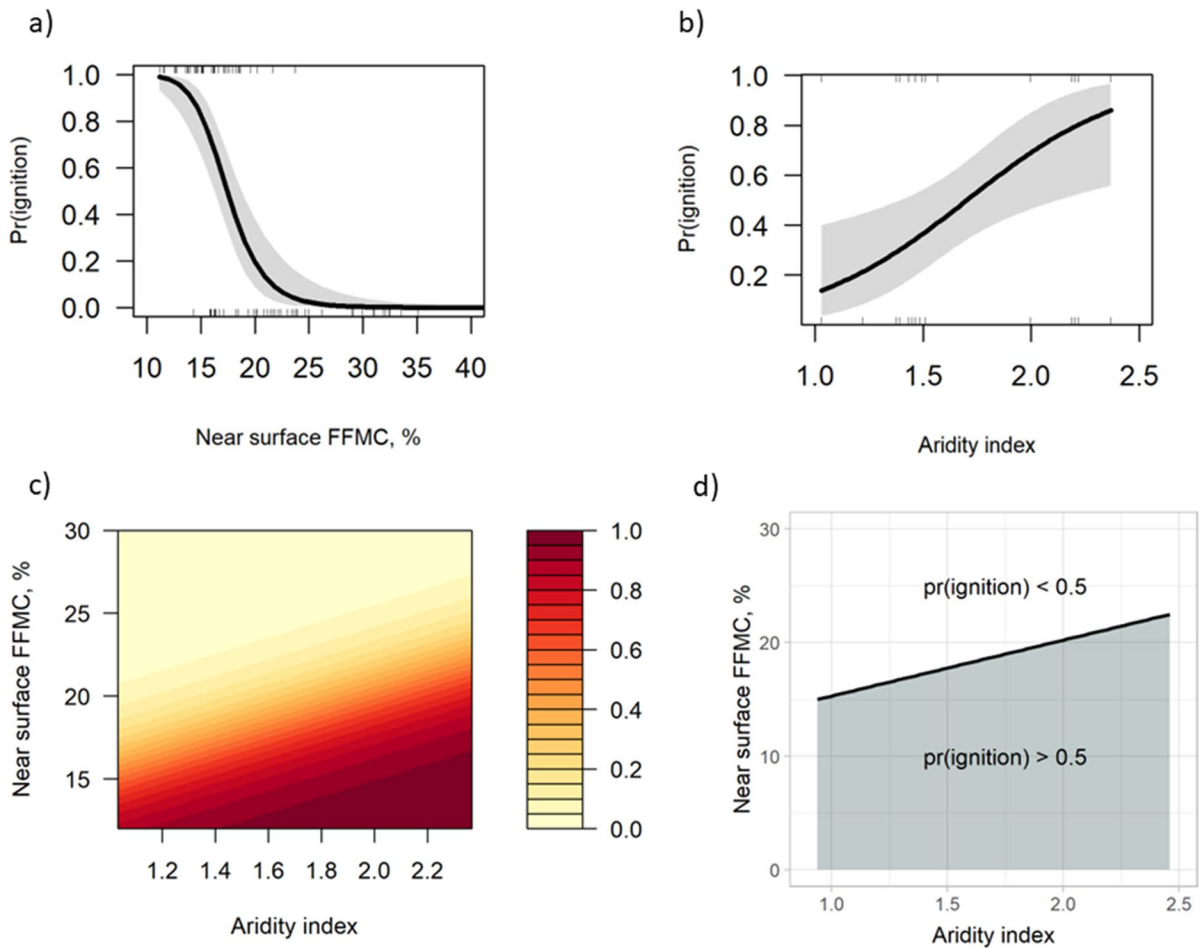


**Fig. 3** Structural equation models for testing the direct and indirect effects of different moisture variables on the probability of ignition. **a** Saturated model with all variables and model pathways included. **b** Reduced model showing only variables that have a significant direct or indirect effect on ignitability. Solid arrows indicate significant relationships between vari-

ables and numbers on these arrows show the standardised path coefficients: red for a negative coefficient and blue for a positive coefficient. Dashed arrows indicate non-significant pathways. R<sup>2</sup> for each individual model are shown in the box of the response variables. Saturated model: Fisher's C = 102.47, P-value = 0, df = 30

The ignitability model could also be used as a tool to assist with prescribed burning. As a test

case, we used the ignitability model to predict spatial variations in fuel ignitability across an



**Fig. 4** Plots depicting the influence of aridity and near surface FFMC on the probability of ignition. Plots were derived using the second ranked model in Table 3. Marginal effect plots show the individual effects of **a** near surface FFMC and **b** aridity index on the probability of ignition with the other variable held constant at its mean. **c** Shows the interactive effect (addi-

tive) of near surface FFMC and aridity index on the probability of ignition. The colour gradient represents the probability of ignition from 0 (pale yellow) to 1 (deep red). **d** Shows the moisture threshold for a 50% probability of ignition as a function of aridity

operational prescribed burn (Fig. 8). The model predicted increasing average ignitability across the landscape in the days leading up to the burn (increasing median; Fig. 9). However, highly ignitable fuel was interspersed by fuel with lower ignitability (wide interquartile range of ignitability values; Fig. 9). The operational burn was ignited with aerial incendiaries along ridgetops and handheld drip torches along the perimeters by fire agency personnel. Burnt areas mostly overlapped with areas predicted to have the highest ignitability on the day of the burn (Fig. 8) whereas areas with the lowest predicted ignitability generally did not burn. The

most notable disagreement between the ignition predictions and burn outcome were in the southern section of the burn where aerial incendiaries were dropped early in the day before ignitability had reached its peak for the day.

**Discussion**

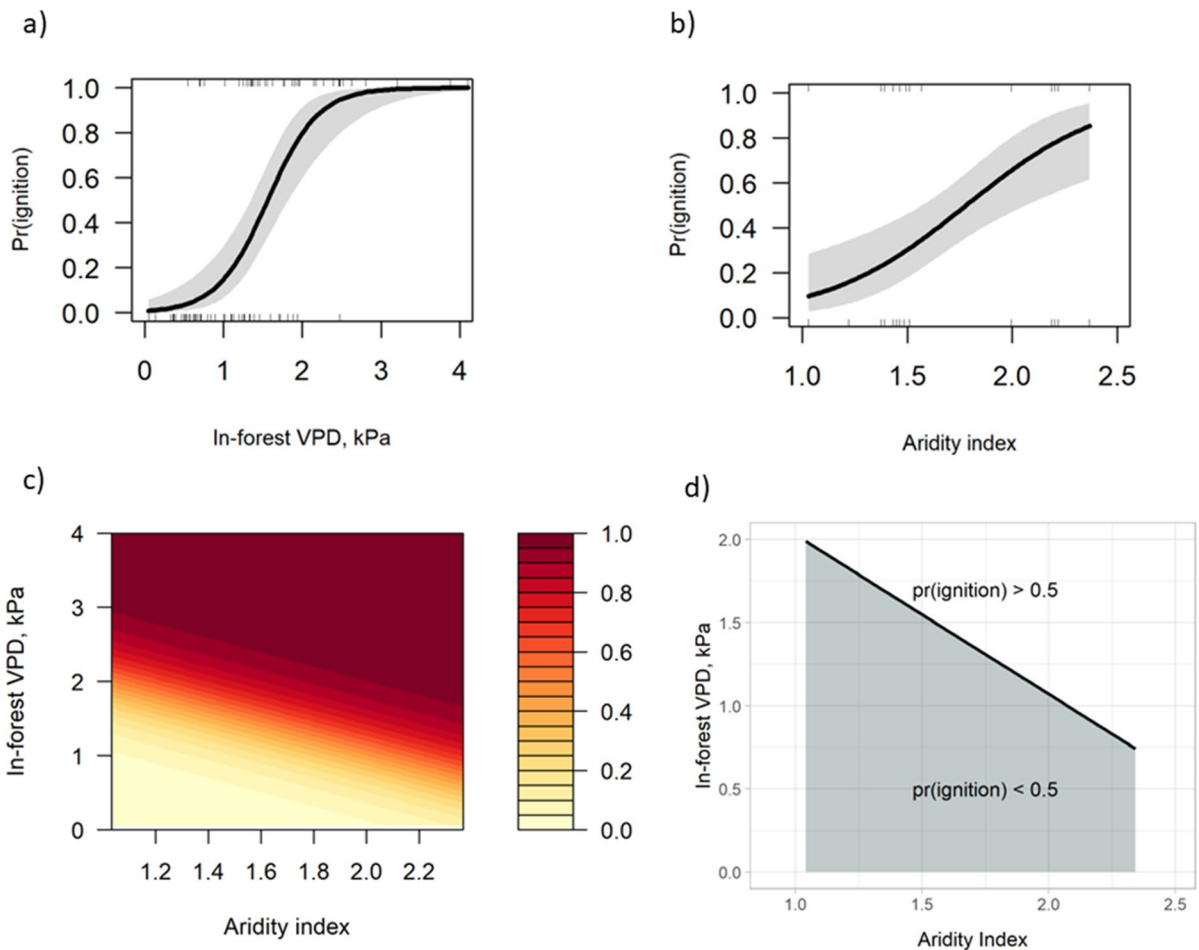
Moisture thresholds for ignition varied by forest type. Dense forests in less arid parts of the landscape needed drier fuel and a drier microclimate to ignite than sparser forests in more arid areas. We modelled



**Table 3** Estimated coefficients for the highest ranked GLMs (within 2 AICc units of the highest ranked model) to predict the probability of ignition. The preferred model from this sub-

set (model 2) is highlighted because it is within 2 AIC units of the highest ranked model but has fewer terms

Rank	Variables	Coefficient	s.e.	P-value	df	LogLik	ΔAICc	Akaike weight	R <sup>2</sup>	AUC
1	Intercept	6.599	2.198	0.003 **	4	−28.75	0	0.41	0.53	0.93
	Aridity	2.835	1.120	0.019 *						
	Near surface FFMC	−0.535	0.125	<0.001 ***						
	Subsurface FFMC	−0.011	0.007	0.108						
2	Intercept	5.800	2.024	0.004 **	3	−30.08	0.47	0.32	0.51	0.93
	Aridity	2.756	1.048	0.009 **						
	Near surface FFMC	−0.560	0.124	<0.001 ***						
3	Intercept	5.431	2.067	0.009 **	4	−29.16	0.83	0.27	0.53	0.93
	Aridity	2.627	1.064	0.013 *						
	Near surface FFMC	−0.434	0.152	0.004 **						
	Surface FFMC	−0.080	0.070	0.255						



**Fig. 5** Plots depicting the influence of in-forest VPD and aridity on the probability of ignition. Plots were derived using the second ranked model in Table 4. Marginal effect plots show the individual effects of **a** in-forest VPD and **b** aridity index on the probability of ignition with the other variable held constant

at its mean. **c** Shows the interactive effect (additive) of in-forest VPD and aridity index on the probability of ignition. The colour gradient represents the probability of ignition from 0 (pale yellow) to 1 (deep red). **d** Shows the VPD for a 50% probability of ignition as a function of aridity

**Table 4** Estimated coefficients for the highest ranked GLMs (within 2 AICc units of the highest ranked model) to predict the probability of ignition. The preferred model from this sub-

set (Model 2) is highlighted in grey because it is within 2 AIC units of the highest ranked model but has fewer terms

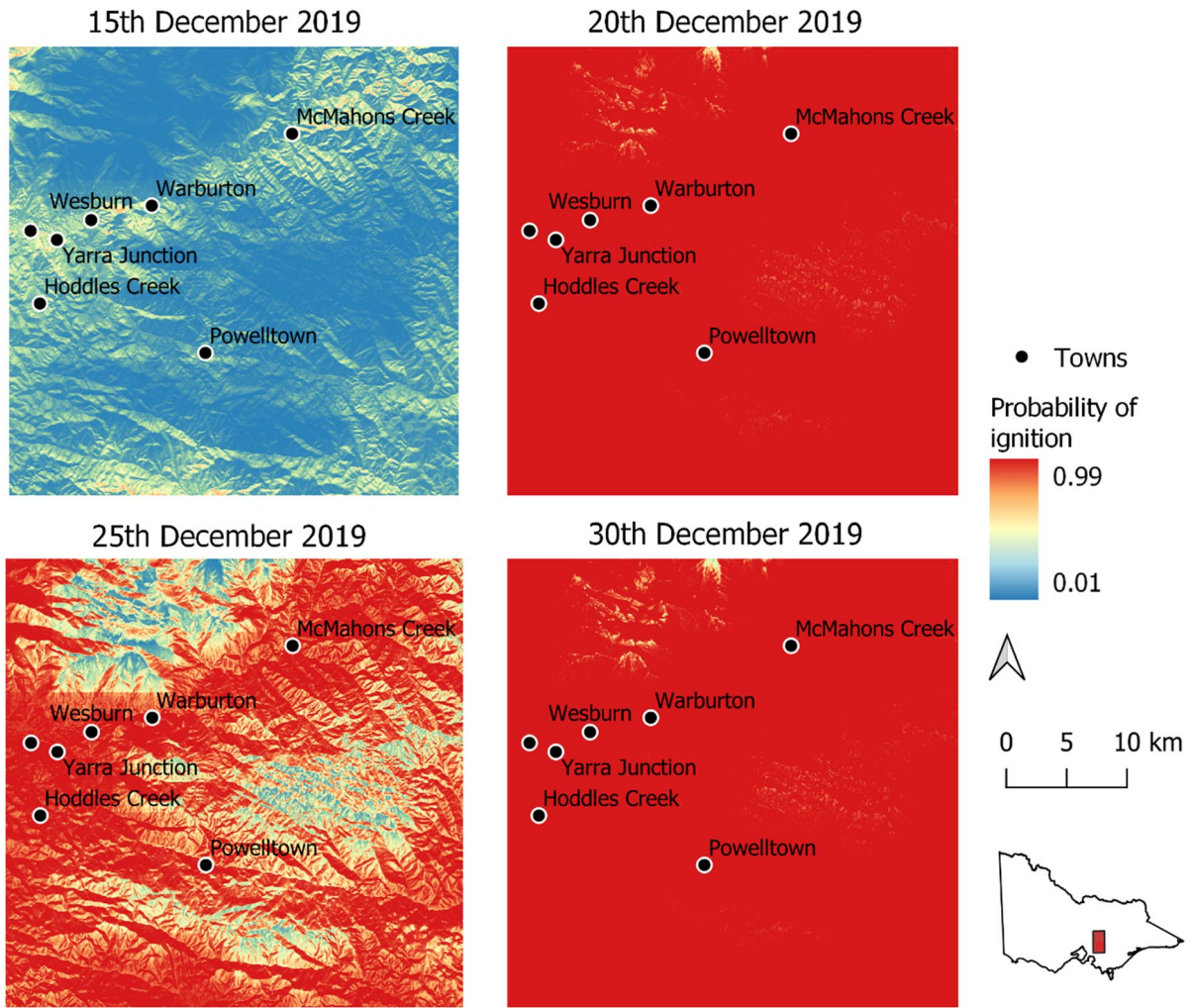
Rank	Variables	Coefficient	s.e.	P-value	df	LogLik	$\Delta$ AICc	Akaike weight	R <sup>2</sup>	AUC
1	Intercept	-9.876	2.279	<0.001***	4	-33.86	0	0.51	0.45	0.91
	Aridity	3.355	1.001	<0.001***						
	SPEI	0.666	0.374	0.075						
	In-forest VPD	3.125	0.652	<0.001***						
2	Intercept	-9.317	2.152	<0.001***	3	-35.61	1.29	0.27	0.42	0.90
	Aridity	2.9874	0.890	<0.001***						
	In-forest VPD	3.1246	0.669	<0.001***						
3	Intercept	-11.264	2.923	<0.001***	5	-33.54	1.6	0.23	0.45	0.91
	Aridity	3.6125	1.058	<0.001***						
	SPEI	0.6619	0.379	0.081						
	Open solar	0.0464	0.058	0.422						
	In-forest VPD	3.0447	0.649	<0.001***						

maximum daily ignitability at a fine resolution to quantify temporal trends in the spatial connectivity of available fuel. Such information could be used by fire managers for gauging wildfire risk and when planning or undertaking prescribed burning.

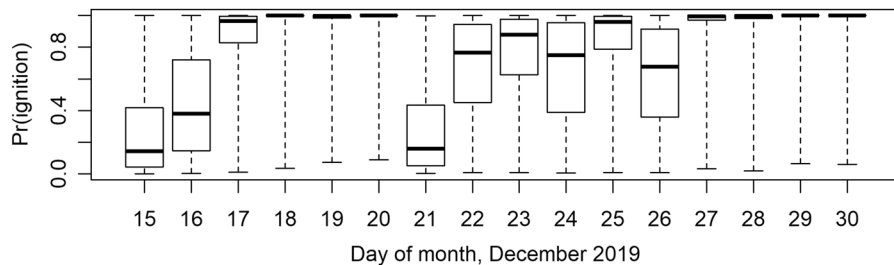
The importance of dead near surface FFMC on ignitability, rather than surface FFMC, was surprising because surface and subsurface FFMC have historically been considered the key drivers of fire activity (e.g. Cheney et al. 2012; McArthur 1967; Sneeuwjagt and Peet 1985). However, our results do not necessarily mean the mechanistic link is stronger between near surface FFMC and ignitability because surface and near surface FFMC were strongly correlated ( $r=0.88$ ). Rather, both surface and near surface FFMC are likely to have contributed to the ‘success’ of the ignition. Most firebrands landed on the surface fuel (88%), therefore its moisture would have influenced the initial ignition. Then, as the flames propagated and incorporated the near surface strata, dead near surface FFMC likely contributed to the likelihood of a sustained ignition. Near surface FFMC is predominantly influenced by atmospheric dryness (Matthews 2014; Nolan et al. 2016b) whereas surface FFMC also depends on soil moisture (Pook and Gill 1993; Zhao et al. 2022) and litter bed structure (Cawson et al. 2020b), potentially making surface FFMC more spatially variable. Therefore, our field estimates of near surface FFMC could have been more precise than our estimates of surface FFMC, leading to a stronger relationship with ignitability. This suggests field measures of near surface dead FFMC

may provide a more reliable indicator of ignitability than field measures of surface or subsurface FFMC. Although there are likely to be some circumstances when the near surface and surface FFMCs do not align (e.g., following light rainfall or high humidity).

In-forest VPD was the strongest microclimatic predictor of ignitability, having indirect (via fuel moisture) effects on ignitability. The strong predictive performance of VPD is consistent with numerous studies globally which have found strong relationships between VPD and fire activity across multiple scales (e.g. Mueller et al. 2020; Resco de Dios et al. 2022; Sedano and Randerson 2014; Williams et al. 2014; Ziel et al. 2020). A unique feature of our research is the use of in-forest VPD as opposed to coarser resolution VPD predicted for open conditions using gridded meteorological data (‘open VPD’). The forest canopy and topography cause in-forest VPD to differ substantially from open VPD, particularly for denser canopied forests (Brown et al. 2022; Davis et al. 2019). Consequently, in-forest VPD is a stronger predictor of ignitability than open VPD (Cawson et al. 2022). Our use of in-forest VPD explains why our ignitability thresholds (ranging from 1 to 1.7 kPa for shrubby foothill and wet forest, respectively) are slightly lower than those reported in other studies using open VPD, e.g., 1.86 kPa for temperate broadleaf and mixed forest (Clarke et al. 2022) and 1.5 kPa for shrubby foothill forest (Burton et al. 2023a). The in-forest thresholds are lower as the effect of canopy cover and topography are accounted for within the metric.



**Fig. 6** Daily maximum predicted ignitability across the Central Highlands landscape over a two-week period during the 2019–2020 “Black Summer” fire season



**Fig. 7** Daily distribution of ignition probabilities across the Central Highlands landscape over a two-week period during the 2019–2020 “Black Summer” fire season. Medians (50th percentile) indicated by solid horizontal line. Box encloses

middle half of data (from 25th to 75th percentile). The whiskers show the minimum and maximum values. Wider box and whiskers indicate more spatial variability, meaning the spatial interconnectedness of ignitable fuel is low

In-forest solar radiation also emerged as a key predictor of ignitability, having both direct and indirect effects. Radiative heating of fine fuel enhances drying rates, making the top layer of fuel more flammable (Countryman 1977; Kreye et al. 2020). Solar radiation also affects ignitability directly by increasing the surface temperature of the fuel, which reduces the amount of heating required to raise the fuel to ignition temperature; although this effect is considered less important than its effects on fuel moisture (Kreye et al. 2020). The strong relationship between in-forest solar radiation and ignitability was not found when open solar radiation was substituted (Table 3). This result suggests that canopy structure and topographic position play an important role in influencing the nature of the relationship between solar radiation and ignitability. Further research to model subcanopy solar radiation across the landscape could be used to improve predictions of fire activity in the future.

Soil moisture had a relatively small effect on the probability of ignition compared with in-forest VPD and solar radiation. The absence of a strong soil moisture effect reflects the high importance of near surface dead FFMFC to ignition, which was mostly a function of in-forest VPD not soil moisture. The absence of a drought (SPEI) effect further highlights the importance of short-term drying for ignitions to occur. Low soil moisture and drought conditions heighten wildfire risk and are associated with the occurrence of large wildfires (Nolan et al. 2021; Krueger et al. 2022). However, our results show they are not essential for point-scale ignitions to occur. This is not unsurprising because ignitions leading to wildfires and prescribed burns occur every year in south-eastern Australia, including drought and non-drought years (Collins et al. 2015); albeit less so in wet forests.

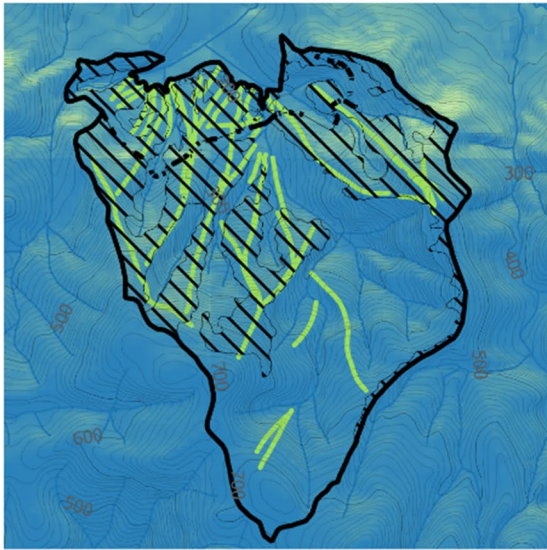
Fuel moisture and VPD thresholds for ignition varied as a function of aridity. Drier conditions were needed for ignitions to occur in more mesic parts of the landscape (i.e., wet and damp eucalypt forests) compared to the more arid locations (i.e., shrubby foothill forest). This result broadly aligns with previous studies that identified differences in VPD thresholds (and other dryness metrics) between vegetation types for fire occurrence and ignitability (Nolan et al. 2016a; Duff et al. 2018b; Newberry et al. 2020). However, the distinction in our study was that the effects of forest structure and landscape position were already accounted for within the near surface FFMFC

and in-forest VPD metrics. Therefore, the changing thresholds as a function of aridity index appear to reflect litter bed structure, and near surface species composition and structure. Traits of the leaves within a litter bed (e.g. size of leaves, leaf thickness, specific leaf area and degree of curl) contribute to differences in flammability, even when the moisture contents of the litter are the same (Plucinski and Anderson 2008; Varner et al. 2015; Burton et al. 2020). Some plant species within the near surface strata ignite and propagate fire more readily than others (Cawson et al. 2023) e.g., the abundance of grasses influences flammability at the interface between savanna and forest (Newberry et al. 2020). Differences in the VPD threshold between forest types could also be due to understorey density. In-forest VPD was measured at screen height (1.2 m), whereas the ignitions occurred on the forest floor. Dense near surface fuel in wet and damp forests likely created a VPD differential between screen height and the forest floor, causing the in-forest VPD threshold for ignition to be higher (Pickering et al. 2021).

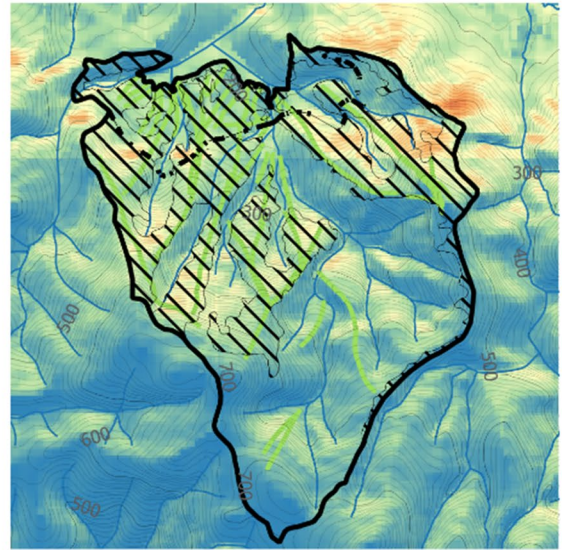
Incorporating ignitability into the estimation of fire risk may be useful, particularly for denser forests where fire occurrence is strongly dependent on fuel moisture (Cawson et al. 2020a). Our landscape-scale ignitability model quantifies the spatial interconnectedness of ignitable fuel where the risk of a large wildfire increases when the median probability of ignition across the landscape is high and the range of values (interquartile range) is narrow. Such conditions indicate that more sheltered parts of the landscape (i.e., wetter forests in gullies and on polar-facing slopes) have a high probability of ignition in addition to the exposed aspects, meaning there are few barriers to the spread of fire across the landscape. This was observed during the 2019-20 Black Summer season (Figs. 6 and 7). Peak ignitability (i.e., uniformly high ignitability across the landscape) on the 20th and 30th December 2019 coincided with days of declared total fire ban and major fire runs in the far east of Victoria (Salkin 2022). There were no moisture barriers to limit fire spread had ignitions occurred on these days in the Yarra District. Measures of the spatial connectivity of available fuel have the potential to provide more insight into the likelihood of a large fire occurring than single values for a larger area (e.g., 5 km resolution), which ignore variability caused by



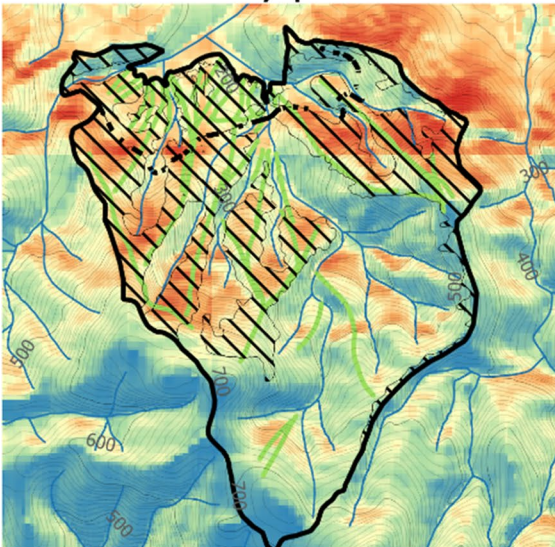
5 days prior



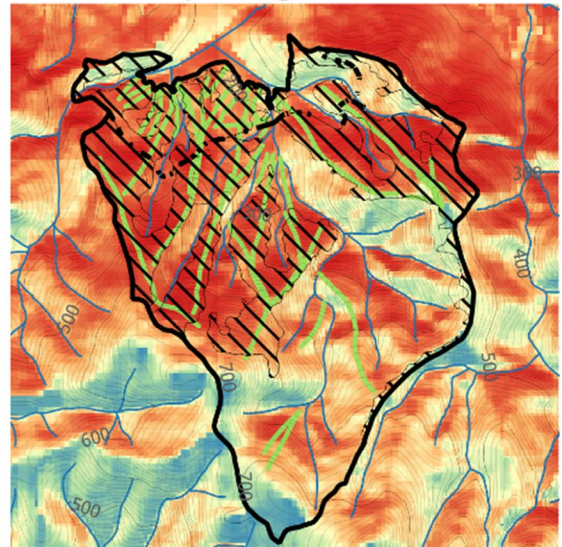
3 days prior



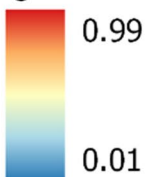
1 day prior



Day of ignition



Probability of ignition



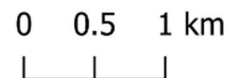
Contours

- 100 m interval
- 20 m interval
- Aerial ignition track log

— Watercourse

□ Burn perimeter

▨ Burnt area



topography and forest type (Caccamo et al. 2012). Our model could be used for this purpose, but testing is required across a broader geographic area

before operational implementation. The methods developed to measure and model ignitability could be applied more broadly across different forest types



◀**Fig. 8** Outcomes of an operational prescribed burn overlaying predicted ignitability. The consecutive maps show daily maximum predicted ignitability across a prescribed burn unit in the days leading up to the burn. The prescribed burn was ignited by fire agency personel using aerial incendiaries along ridgelines (green lines) and handheld drip torches along the perimeter. The prescribed burn was located in the Yarra Fire District and occurred on the 13th March 2023. Burn data were sourced from the Department of Energy, Environment and Climate Action

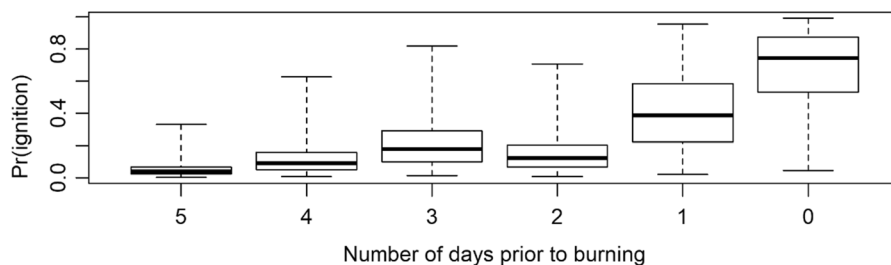
worldwide. However, this would require calibration because thresholds for ignition vary between forests and across an aridity gradient.

In the context of prescribed burning, our landscape-scale ignitability model could help fire managers identify burn windows by providing forecast maps of ignitability across a burn unit. To implement a prescribed burn, fire managers need to understand how fuel availability varies spatially across the burn unit (McCaw and Burrows 2020). Conditions are more conducive for achieving a patchy burn when there is high variability in ignitability across the landscape. Yet, fuel moisture models rarely account for differences in topography and forest type (Matthews 2014). Consequently, fire managers measure fuel moisture manually in a few locations within a burn unit in the days prior to burning and extrapolate those measurements to predict how ignitability may vary within the burn unit. The efficiency and accuracy of this process could be greatly improved with maps forecasting daily maximum ignitability at a 20 m resolution, which

our model provides. Calibration would be required between the firebrand and sources of ignition used in prescribed burning (e.g. drip torches). Furthermore, it may be useful to consider sub daily variations in ignitability. Modelling ignitability at a finer temporal resolution could be a next step for this research as this would allow fire managers to better understand when fuel is likely to be available to ignite during the day. It may also enhance the level of agreement between the ignitability predictions and burn outcomes, as the most notable disagreement in the prescribed burning case study (Fig. 8) were due to ignitions occurring before ignitability had reached its peak for the day.

**Conclusion**

We quantified the direct and indirect effects of a range of moisture variables on ignitability in different types of eucalypt forests. This was achieved by measuring ignitability in the field under varying moisture conditions. Dense forests needed drier fuel and drier in-forest atmospheric conditions to ignite than sparser forests. We used our field data to develop an ignitability model to forecast spatial variations (20 m resolution) in maximum daily ignitability across a forested landscape. An ignitability model could inform fire management decision-making by depicting the spatial continuity of available fuel. Our field methodology could be used



**Fig. 9** Daily distribution of ignition probabilities within the operation prescribed burn (depicted in Fig. 8) for the days leading up to ignition. Medians (50th percentile) indicated by solid horizontal line. Box encloses the middle half of data

(from 25th and 75th percentile). Whiskers show minimum and maximum values. Wider box and whiskers indicate more spatial variability, meaning the spatial interconnectedness of ignitable fuel is low

to develop similar ignitability models in other forest types worldwide.

**Acknowledgements** We acknowledge the Traditional Owners of the land on which this study occurred – the Dja Dja Wurrung and Wurrundjeri peoples. Thank you to Aaron Heap and Dennis Kulatav for assisting with data collection in the field. We gratefully acknowledge the project steering committee: Musa Kilinc (Country Fire Authority (CFA)), Andy Ackland (CFA), Darcy Prior (Department of Energy, Environment and Climate Action (DEECA)), Miguel Cruz (CSIRO), Thomas Duff (CFA). This project would not have been possible without the ongoing support of fire managers and field crews from Forest Fire Management Victoria.

**Author contributions** All authors contributed to the study conception and design. Data collection was performed by JC, JB and BP. Analysis was performed by JC and JB. The first draft of the manuscript was written by JC. All authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

**Funding** Open Access funding enabled and organized by CAUL and its Member Institutions. This project was funded by the Victorian Government's *Safer Together initiative via the Integrated Forest Ecosystem Research program*.

**Data availability** The datasets generated during this study are available from the corresponding author on responsible request.

#### Declarations

**Competing interests** The authors have no relevant financial or non-financial interests to disclose.

**Open Access** This article is licensed under a Creative Commons Attribution 4.0 International License, which permits use, sharing, adaptation, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons licence, and indicate if changes were made. The images or other third party material in this article are included in the article's Creative Commons licence, unless indicated otherwise in a credit line to the material. If material is not included in the article's Creative Commons licence and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder. To view a copy of this licence, visit <http://creativecommons.org/licenses/by/4.0/>.

#### References

- Bain K, Wayne A, Bencini R (2016) Prescribed burning as a conservation tool for management of habitat for threatened species: the Quokka, *Setonix brachyurus*, in the southern forests of Western Australia. *Int J Wildland Fire* 25(5):608–617
- Bradstock RA (2010) A biogeographic model of fire regimes in Australia: current and future implications. *Glob Ecol Biogeogr* 19(2):145–158
- Bradstock RA, Hammill KA, Collins L, Price O (2010) Effects of weather, fuel and terrain on fire severity in topographically diverse landscapes of south-eastern Australia. *Landscape Ecol* 25(4):607–619
- Brehehy P, Burchett W (2017) Visualization of regression models using visreg. *R J* 9:56–71
- Brown TP, Inbar A, Duff TJ, Lane PNJ, Sheridan GJ (2022) The sensitivity of fuel moisture to forest structure effects on microclimate. *Agric Meteorol* 316:108857
- Bureau of Meteorology (2022) Climate statistics for Australian locations. Australian government. [http://www.bom.gov.au/climate/averages/tables/cw\\_086094.shtml](http://www.bom.gov.au/climate/averages/tables/cw_086094.shtml)
- Burnham KP, Anderson DH (2004) Multimodel Inference. Understanding AIC and BIC in Model Selection. *Sociol Methods Res* 33(2):261–304
- Burrows N, Middleton T (2016) Mechanisms enabling a fire sensitive plant to survive frequent fires in south-west Australian eucalypt forests. *Fire Ecol* 12(1):26–40
- Burton JE, Cawson JG, Filkov AI, Penman TD (2020) Leaf traits predict global patterns in the structure and flammability of forest litter beds. *J Ecol* 109(3):1344–1355
- Burton JE, Penman TD, Filkov AI, Cawson JG (2023a) Multi-scale drivers of factors influencing moisture thresholds for litter bed flammability. *Agric Meteorol* 337:109514
- Burton JE, Filkov AI, Pickering BJ, Penman TD, Cawson JG (2023b) Quantifying litter bed ignitability: comparison of a laboratory and field method. *Fire* 6:24
- Caccamo G, Chrisholm LA, Bradstock RA, Puotinen ML (2012) Using remotely-sensed fuel connectivity patterns as a tool for fire danger monitoring. *Geophys Res Lett* 39:1
- Calcagno V (2013) Package 'glmulti.' Model selection and multimodel inference made easy. <https://cran.r-project.org/web/packages/glmulti/glmulti.pdf>
- Cawson JG, Duff TJ (2019) Forest fuel bed ignitability under marginal fire weather conditions in Eucalyptus forests. *Int J Wildland Fire* 28(3):198–204
- Cawson JG, Duff TJ, Tolhurst KG, Baillie CC, Penman TD (2017) Fuel moisture in Mountain Ash forests with contrasting fire histories. *For Ecol Manag* 400:568–577
- Cawson JG et al (2020a) Exploring the key drivers of forest flammability in wet eucalypt forests using expert-derived conceptual models. *Landscape Ecol* 35:1775–1798
- Cawson JG et al (2020b) Estimation of surface dead fine fuel moisture using automated fuel moisture sticks across a range of forests worldwide. *Int J Wildland Fire* 29(6):548–559
- Cawson JG et al (2022) Predicting ignitability from fire-brands in mature wet eucalypt forests. *For Ecol Manag* 519:120315
- Cawson JG, Burton JE, Pickering BJ, Demetriou V, Filkov AI (2023) Quantifying the flammability of living plants at the branch scale: which metrics to use? *Int J Wildland Fire* 32(10):1404–1421

- Cheney NP, Gould JS, McCaw WL, Anderson WR (2012) Predicting fire behaviour in dry eucalypt forest in southern Australia. *For Ecol Manag* 280:120–131
- Clarke H et al (2022) Forest fire threatens global carbon sinks and population centres under rising atmospheric water demand. *Nat Commun* 13:7162
- Collins BM, Kelly M, van Wagtenonk JW, Stephens SL (2007) Spatial pattern of large natural fires in Sierra Nevada wilderness areas. *Landscape Ecol* 22:545–557
- Collins KM, Price OF, Penman TD (2015) Spatial patterns of wildfire ignitions in south-eastern Australia. *Int J Wildland Fire* 24(8):1098–1108
- Collins L, Bennett AF, Leonard SWJ, Penman TD (2019) Wildfire refugia in forests: severe fire weather and drought mute the influence of topography and fuel age. *Glob Change Biol* 00:1–15
- Collins L et al (2021) The 2019/2020 mega-fires exposed Australian ecosystems to an unprecedented extent of high-severity fire. *Environ Res Lett* 16:044029
- Core Team R (2022) R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. URL <https://www.R-project.org/>
- Countryman CM (1977) Radiation effects on moisture variation in ponderosa pine litter, USDA Forest Service. Pacific Southwest Forest and Range Experiment Station, Berkeley
- Cruz MG et al (2012) Anatomy of a catastrophic wildfire: the Black Saturday Kilmore East fire in Victoria, Australia. *For Ecol Manag* 284:269–285
- Cruz MG et al (2015) Empirical-based models for predicting head-fire rate of spread in Australian fuel types. *Australian Forestry* 78(3):118–158
- Cruz MG et al (2022) An empirical-based model for predicting the forward spread rate of wildfires in eucalypt forests. *Int J Wildland Fire* 31(1):81–95
- Davis KT, Dobrowski SZ, Holden ZA, Higuera PE, Abatzoglou JT (2019) Microclimatic buffering in forests of the future: the role of local water balance. *Ecography* 42:1–11
- de Dios VR et al (2022) Convergence in critical fuel moisture and fire weather thresholds associated with fire activity in the pyroregions of Mediterranean Europe. *Sci Total Environ* 806:151462
- Department of Environment Land Water and Planning (2016) Native Vegetation - Modelled 2005 Ecological Vegetation Classes (with Bioregional Conservation Status), Victorian State Government (data.vic.gov.au), Melbourne
- QGIS Development Team (2020) QGIS Geographic Information System. <http://qgis.osgeo.org/>
- Duff TJ, Cawson JG, Penman TD (2018a) Prescribed burning. In: Manzello SL (ed) Encyclopedia of wildfires and wildland-urban interface (WUI) fires. Springer International Publishing, Cham, pp 1–11
- Duff TJ, Cawson JG, Harris S (2018b) Dryness thresholds for fire occurrence vary by forest type along an aridity gradient: evidence from Southern Australia. *Landscape Ecol* 33:1369–1383
- Filkov AI, Duff TJ, Penman TD (2020a) Frequency of dynamic fire behaviours in Australian forests. *Fire* 3(1):1
- Filkov AI, Ngo T, Matthews S, Telfor S, Penman TD (2020b) Impact of Australia's catastrophic 2019/20 bushfire season on communities and environment. Retrospective analysis and current trends. *J Saf Sci Resil* 1:44–56
- Frost AJ, Ramchurn A, Smith A (2018) The Australian landscape water balance model (AWRA-L v6). Technical description of the Australian water resources assessment landscape model version 6., Bureau of Meteorology
- Gill AM, Allan G (2008) Large fires, fire effects and the fire-regime concept. *Int J Wildland Fire* 17(6):688–695
- Gill AM, Zylstra P (2005) Flammability of Australian forests. *Australian Forestry* 68(2):87–93
- Hessburg PF, Agee JK, Franklin JF (2005) Dry forests and wildland fires of the inland Northwest USA: contrasting the landscape ecology of the pre-settlement and modern eras. *For Ecol Manag* 211(1–2):117–139
- Hijmans RJ (2022) Raster: geographic data analysis and modelling
- Hines F, Tolhurst KG, Wilson AAG, McCarthy GJ (2010) Overall Fuel Hazard Assessment Guide, 4th edition. 82, Fire Management Branch, Department of Sustainability and Environment, Melbourne, Victoria
- Jeffrey SJ, Carter JO, Moodie KB, Beswick AR (2001) Using spatial interpolation to construct a comprehensive archive of Australian climate data. *Environ Model Softw* 16(4):309–330
- Keane RE (2015) Wildland fuel fundamentals and application. Springer International Publishing, Switzerland
- Keane RE et al (2008) Ecological effects of large fires on US landscapes: benefit or catastrophe? *Int J Wildland Fire* 17(6):696–712
- Kreye JK, Kane JM, Varner JM, Hiers JK (2020) Radiant heating rapidly increases litter flammability through impacts on fuel moisture. *Fire Ecol* 16(1):1
- Krueger ES et al (2022) Using soil moisture information to better understand and predict wildfire danger: a review of recent developments and outstanding questions. *Int J Wildland Fire* 32(2):111–132
- Lefcheck JS (2016) Piecewise structural equation modelling inR for ecology, evolution, and systematics. *Methods Ecol Evol* 7:573–579
- Matthews S (2014) Dead fuel moisture research: 1991–2012. *Int J Wildland Fire* 23(1):78–92
- McArthur AG (1967) Fire behaviour in eucalypt forests. Department of National Development, Forestry and Timber Bureau, Canberra
- McCaw L, Burrows N (2020) Prescribed fire as a tool for land management in southern Australian forests and woodlands -a land management perspective. In: Leavesley A, Wouters M, Thornton R (eds) Prescribed burning in Australasia. The science, practice and politics of burning the bush. Australasian Fire and Emergency Service Authorities Council Limited, Melbourne, pp 83–94
- Monteith JL, Unsworth MH (2013) Principles of environmental physics. Plants, animals and the atmosphere, 4th edn. Elsevier, Oxford
- Mueller SE et al (2020) Climate relationships with increases in wildfire in the southwestern US from 1984 to 2015. *For Ecol Manag* 460:117861
- Newberry BM et al (2020) Flammability thresholds or flammability gradients? Determinants of fire across savanna-forest transitions. *New Phytol* 228:910–921
- Nolan RH, Boer MM, de Dios VR, Caccamo G, Bradstock RA (2016a) Large-scale, dynamic transformations in fuel

- moisture drive wildfire activity across southeastern Australia. *Geophys Res Lett* 43(9):4229–4238
- Nolan RH et al (2016b) Predicting dead fine fuel moisture at regional scales using vapour pressure deficit from MODIS and gridded weather data. *Remote Sens Environ* 174:100–108
- Nolan RH et al (2021) What do the Australian black summer fires signify for the global fire crisis? *Fire* 4(4):97
- Nyman P, Sherwin CB, Langhans C, Lane PNJ, Sheridan GJ (2014) Downscaling regional climate data to calculate the radiative index of dryness in complex terrain. *Aust Meteorol Oceanogr J* 64:109–122
- Nyman P, Baillie CC, Duff TJ, Sheridan GJ (2018) Eco-hydrological controls on microclimate and surface fuel evaporation in complex terrain. *Agric Meteorol* 252:49–61
- Oliveira SLJ et al (2015) Ecological implications of fine-scale fire patchiness and severity in tropical savannas of Northern Australia. *Fire Ecol* 11(1):10–31
- Pausas JG, Keeley JE, Schwilk DW (2017) Flammability as an ecological and evolutionary driver. *J Ecol* 105(2):289–297
- Pebesma E (2018) Simple features for R: standardised support for vector data. *R J* 10(1):439–446
- Penman TD, Kavanagh RP, Binns DL, Melick DR (2007) Patchiness of prescribed burns in dry sclerophyll eucalypt forests in South-eastern Australia. *For Ecol Manag* 252(1–3):24–32
- Penman TD et al (2011) Prescribed burning: how can it work to conserve the things we value? *Internaional J Wildland Fire* 20:721–733
- Pickering BJ, Duff TJ, Baillie C, Cawson JG (2021) Darker, cooler, wetter: forest understories influence surface fuel moisture. *Agric For Meteorol* 300:108311
- Plucinski MP, Anderson WR (2008) Laboratory determination of factors influencing successful point ignition in the litter layer of shrubland vegetation. *Int J Wildland Fire* 17:628–637
- Pook EW, Gill AM (1993) Variation of live and dead fine fuel moisture in *Pinus radiata* plantations of the Australian Capital Territory. *Int J Wildland Fire* 3(3):155–168
- Resco de Dios V et al (2015) A semi-mechanistic model for predicting the moisture content of fine litter. *Agric Meteorol* 203:64–73
- Ryan KC (2002) Dynamic interactions between forest structure and fire behavior in boreal ecosystems. *Silva Fenn* 36(1):13–39
- Salkin O (2022) Victorian bushfire case studies -. Black Summer final report, Melbourne
- Sedano F, Randerson JT (2014) Multi-scale influence of vapour pressure deficit on fire ignition and spread in boreal forest ecosystems. *Biogeosciences* 11:3739–3755
- Sitters H, Di Stefano J, Christie FJ, Sunnucks P, York A (2015) Bird diversity increases after patchy prescribed fire: implications from a before-after control-impact study. *Int J Wildland Fire* 24(5):690–701
- Slijepcevic A, Anderson WR, Matthews S (2013) Testing existing models for predicting hourly variation in fine fuel moisture in eucalypt forests. *For Ecol Manag* 306:202–215
- Slijepcevic A, Anderson WR, Matthews S, Anderson DH (2015) Evaluating models to predict daily fine fuel moisture content in eucalypt forest. *For Ecol Manag* 335:261–269
- Sneeuwjagt R, Peet GB (1985) Forest fire behaviour tables for western Australia –3rd edition. Western Australian Department of Conservation and Land Management, Perth
- Sullivan AL (2017) Inside the inferno: fundamental processes of wildland fire behaviour. Part 2: heat transfer and interactions. *Curr Forestry Rep* 3:150–171
- Sungmin O, Hou XY, Orth R (2020) Observational evidence of wildfire-promoting soil moisture anomalies. *Sci Rep* 10(1):8
- Varner JM, Kane JM, Kreye JK, Engber E (2015) The flammability of forest and Woodland Litter: a synthesis. *Curr Forestry Rep* 1(2):91–99
- Vicente-Serrano SM, Begueria S, Lopez-Moreno JI (2010) A Multiscalar Drought Index sensitive to global warming: the standardized precipitation Evapotranspiration Index. *J Clim* 23(7):1696–1718
- Williams AP et al (2014) Correlations between components of the water balance and burned area reveal new insights for predicting forest fire area in the southwest United States. *Internaional J Wildland Fire* 24(1):14–26
- Zhao L et al (2021) The influence of soil moisture on surface and sub-surface litter fuel moisture simulation at five Australian sites. *Agric Meteorol* 298:108282
- Zhao L, Yebra M, van Dijk AIJM, Cary GJ, Hughes D (2022) Controlled field experiment clarifies the influence of soil moisture on litter moisture content. *Agric For Meteorol* 314:108782
- Ziel RH et al (2020) A Comparison of Fire Weather Indices with MODIS Fire Days for the Natural Regions of Alaska. *Forests* 11(5):516

**Publisher's Note** Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.