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# Atmospheric dryness removes barriers to the development of large forest fires

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A R T I C L E I N F O

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A B S T R A C T

Large forest fires have far-reaching impacts on the environment, human health, infrastructure and the economy. Forest fires become large when all forest types across a landscape are dry enough to burn. Mesic forests are the slowest to dry and can act as a barrier to fire growth when they are too wet to burn. Therefore, identifying the factors influencing fire occurrence in mesic forests is important for gauging fire risk across large landscapes. We quantified the key factors influencing the likelihood that an active wildfire would propagate through mesic forest. We analysed 35 large forest fires (> 2500 ha) that occurred in Victoria, Australia where mesic and drier eucalypt forests are interspersed across mountainous terrain. We used a random forest model to evaluate 15 meteorological, topographic and disturbance variables as potential predictors of fire occurrence. These variables were extracted for points within burnt and unburnt patches of mesic forest. The likelihood of an active wildfire spreading through mesic forest increased by 65 % as vapour pressure deficit (VPD, i.e., atmospheric dryness) rose from 2.5 to 7 kPa. Other variables had substantially less influence (< 20 % change in fire occurrence) and their effects were further reduced when VPD was very high (> 6.5 kPa). Mesic forests were less likely to burn in areas with lower aridity, shallower slopes, and more sheltered topographic positions. Mesic forests 13–15 years following stand-replacing disturbance had 6 % higher chance of burning than long undisturbed forests (50 years post-disturbance). Overall, we show that topography and disturbance history cannot substantially counter the effects of high VPD. Therefore, the effectiveness of mesic forest as a barrier to the development of large forest fires is weakening as the climate warms. Our analysis also identifies areas less likely to burn, even under high VPD conditions. These areas could be prioritised as wildfire refugia.

## 1. Introduction

Large wildfires have localised and far-reaching impacts on human health, the environment and the economy (Maditinos and Vassiliadis 2011; Stephens et al., 2014; Nolan et al., 2021). Consequently, they are a significant concern for governments, especially as their prevalence increases with warming climates (Abram et al., 2021; Senande-Rivera et al., 2022). An understanding of the key factors driving the development of large wildfires and models to predict their likelihood are essential for effective wildfire management.

High spatial continuity of *available* fuel is one important precursor to large fire development (Miller and Urban 2000; Gill and Allan 2008; Bradstock et al., 2009; Caccamo et al., 2012; Sullivan and Matthews 2013). Fuel is available when it is dry enough to ignite and sustain burning. Large wildfires need available fuel in both exposed and sheltered topographic positions (Sharples 2009; Boer et al., 2020; Resco de Dios et al. 2022). Mesic forests, occurring in sheltered topographic positions and areas with high average annual rainfall, can act as a barrier to wildfire growth when they are too wet (unavailable) to burn (Bradstock 2010). Understanding when these forests transition to a flammable state is imperative for gauging wildfire risk across the broader landscape (Cawson et al., 2024; Gill and Allan 2008). Yet, fire behaviour research has historically focused on drier vegetation types (Cruz et al., 2015), leaving critical gaps in our understanding of large forest fires whose development depends on the flammability of mesic forests (Cawson et al., 2020).

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Fire occurrence in mesic forests is thought to be moisture-limited, rather than fuel-limited, meaning there is usually enough fuel to sustain fire but its moisture content is usually too high (Meyn et al., 2007; Bradstock 2010; Murphy et al., 2013; Cawson et al., 2020). This is supported by field studies in mesic forests where dead fuel moisture variables outperform fuel structural variables as predictors of flammability (Ray et al., 2005; Cawson et al., 2022). There are ample quantities of dead fine fuel (less than 6 mm thick) to sustain a wildfire in mesic forests, except immediately following high intensity fire (Cawson et al., 2018). However, the fuel is usually too wet to burn (Cawson et al., 2017). This reflects the high mean annual rainfall, low evaporative demand, sheltered topographic position and high projected foliage cover of mesic forests (Nyman et al., 2014; Nyman et al., 2015). Disturbance history may also influence fuel moisture in mesic forests via its effects on forest structure and species composition, though there is conflicting evidence about its direction of influence with some studies reporting reduced fuel availability with time since disturbance (Burton et al., 2019; Furlaud et al., 2021; Wilson et al., 2022) and others reporting no long-term relationship between disturbance history and fuel moisture (Cawson et al., 2017; Brown et al., 2021).

Broadscale climate and weather influence fuel moisture patterns across landscapes (Matthews 2014). Drought is an important precursor to major wildfires globally (Littell et al., 2016) as it influences fuel availability by drying dead fuel at the base of the litter bed and by causing vegetative dieback (Ruthrof et al., 2016; Nolan et al., 2020). Soil moisture affects the moisture of litter at the base of the litter bed, particularly in deep litter beds like those in mesic forests (Zhao et al., 2022). Weather conditions determine the evaporative demand and moisture vapour differential between the fuel and atmosphere, and therefore the rate of moisture exchange (Viney 1991; Matthews 2014), particularly for dead fuel exposed to atmospheric conditions at the top of the litter bed and suspended above ground (Resco de Dios et al. 2015). Topographic position can influence moisture conditions on the forest floor, with lower moisture contents on more exposed aspects and ridges (Nyman et al., 2015). Therefore, the effects of topography should be considered when examining relationships between broader meteorological conditions and fire behaviour.

Our objective was to identify the conditions when mesic forests are likely to act as a barrier versus contribute to wildfire spread. We examined the factors influencing the likelihood that an active wildfire will propagate through mesic eucalypt forest in south-eastern Australia. We hypothesized that fire occurrence in mesic forests would depend on a combination of weather and climate, topography and disturbance history (Fig. 1). Specifically, we asked:

- Which combination of variables best predict wildfire occurrence in mesic forests?
- What are the threshold conditions associated with increased fire occurrence in mesic forests?

## 2. Methods

### 2.1. Study area

The study was based in the State of Victoria, in southeastern Australia. Wildfires are common within this region, with frequency and intensity varying as a function of forest type (Murphy et al., 2013). We used mapping of ecological vegetation divisions (EVDs) to identify areas of mesic forest (Cheal 2010). EVDs are based on the fire ecology of the vegetation and mesic forest is represented by 'Tall Mist Forest' (EVD 12). These are Australian native forests with a projected canopy cover of 30–70 % comprising an overstorey of *Eucalyptus regnans* in montane environments or *E. delegatensis*, in subalpine environments. Mature forests are at least 30 m tall and commonly achieve heights of 70 m (Ashton and Attiwill 1994; Tng et al., 2013). Ferns, tree-ferns and broad-leaved trees and shrubs commonly occur within the understorey (Ashton and Attiwill 1994; Florence 1996). At higher elevations (1000–1500 m), where *E. delegatensis* predominates, the understorey may be grassy. Tall mist forests occur predominately in the uplands of central and eastern Victoria, but also in mountainous locations near the coast in the Otway Ranges (on the western coastline of Victoria) and Wilsons Promontory (the southernmost tip of Victoria) (Fig. 2).

Fires occur infrequently in mesic forests relative to adjacent dry eucalypt forests and woodlands. The tolerable fire interval for high severity fire in mesic forests is 80 to 300 years (i.e., the appropriate fire interval for maintaining the floristic composition) (Cheal 2010). The dominant overstorey species, *E. regnans* and *E. delegatensis*, are obligate seeders, meaning they are killed by high severity fire and regenerate from seed, taking 25–30 years to reach maturity (Ashton and Attiwill 1994). Consequently, these forests are sensitive to high frequency, high severity fire (Fairman et al., 2016). In contrast, the surrounding dry sclerophyll forest can tolerate more frequent high intensity fires, e.g. minimum tolerable fire intervals of 15 years for Grassy/Heathy Dry forest and 25 years for Tall Mixed Forest (Cheal 2010).

There have been numerous large (> 2500 ha) forest fires in Victoria since 2003 with many incorporating areas of mesic forest (Fig. 2). The most significant fire seasons over this period were: 2003–04 when the 'Alpine fires' burnt 1.3 million ha in Victoria's high country; 2006–07 when the 'Great Divide' fires burnt 1.2 million ha in eastern Victoria; 2009 when the 'Black Saturday' fires burnt 430,000 ha including mesic forests within Melbourne's water supply catchments; 2019–20 when the

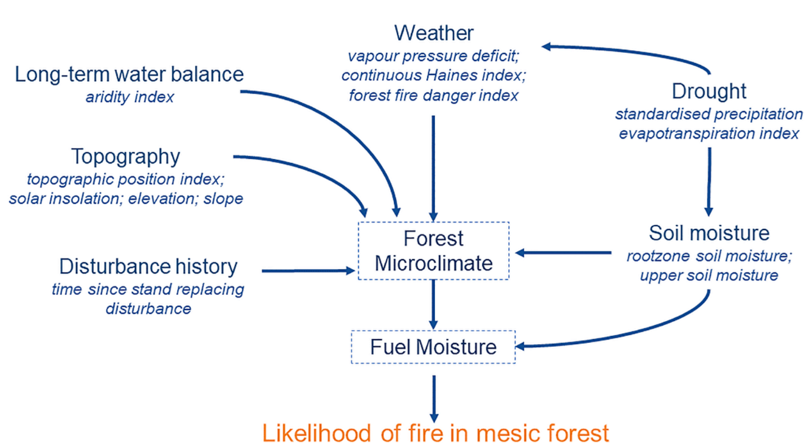


**Fig. 1.** Conceptual model of the key factors hypothesised to influence the probability that an active wildfire will propagate through mesic forest. Variables in italics are evaluated in this study. Factors inside the dashed boxes were not measured directly.

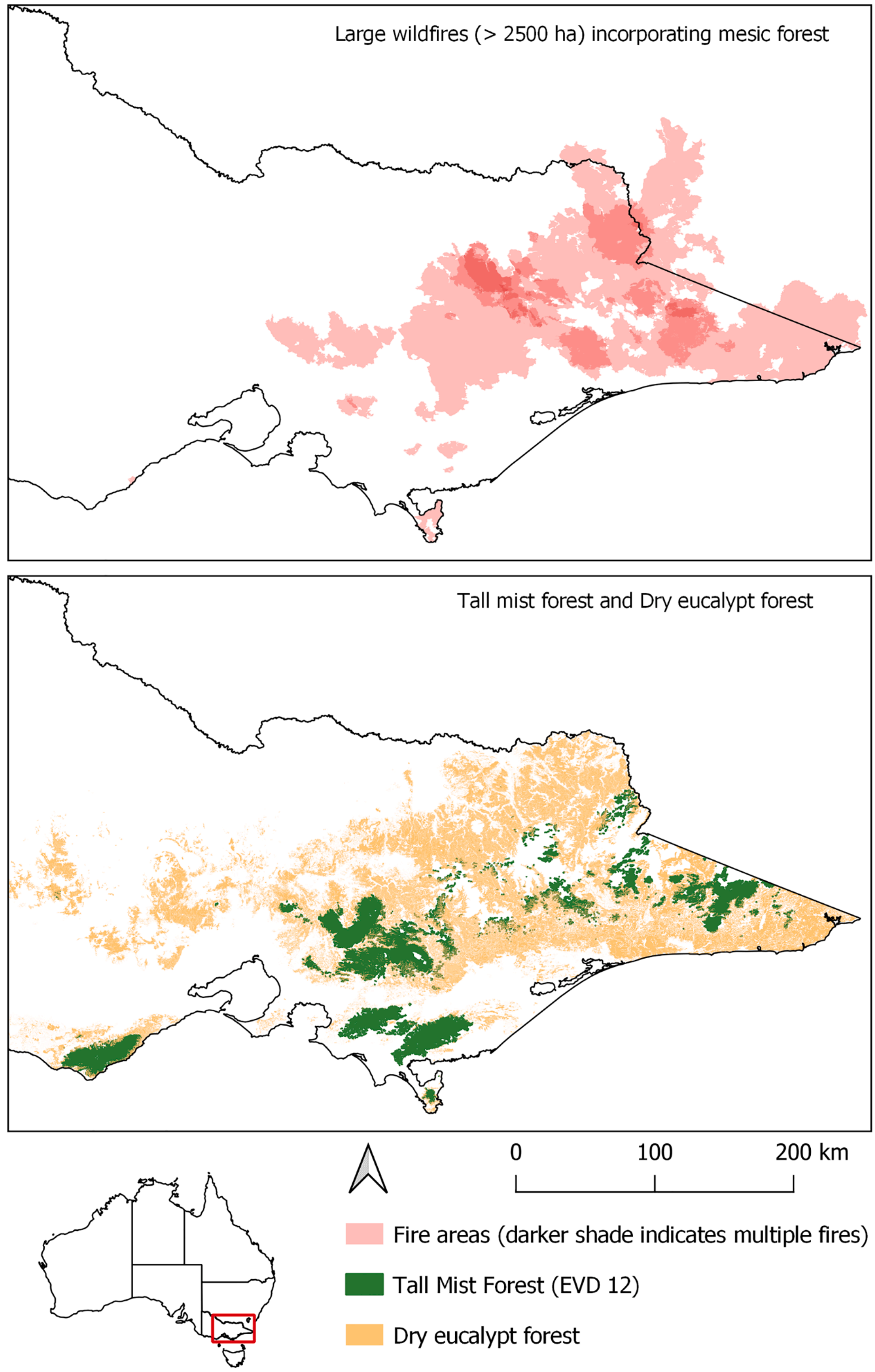


**Fig. 2.** Map depicts the study area in eastern and central Victoria. Green indicates Tall Mist forest (EVD 12); yellow indicates drier eucalypt forest types. Pink shading indicates large fires (> 2500 ha) encompassing Tall Mist Forest from the 2002–03 to the 2019–20 fire seasons. Spatial datasets obtained from data.vic.gov.au.

'Black Summer' fires burnt 1.5 million ha in eastern Victoria.

### 2.2. Fire response variable

We used a binary response variable – burnt vs. unburnt – for areas of mesic forest within the perimeter of large wildfires (> 2500 ha). We utilised fire severity mapping from an earlier study, which comprised a subset of large wildfires in Victoria that occurred from 2000 to 2020 (Collins et al., 2018; Collins et al., 2021). The mapping identified 5 classes of fire severity: 1) unburnt; 2) low canopy scorch (<20 % scorch); 3) moderate canopy scorch (20–80 % scorch); 4) high canopy scorch (>80 % scorch), and; 5) canopy consumption (>20 % canopy consumed). Class 1 (unburnt) was retained in the analysis while the remaining fire severity classes were combined (classes 2 to 5) to produce a binary (burnt vs. unburnt) dataset of points within the fire perimeter. We overlaid the wildfire areas with a grid of sample points spaced 400 m apart (as per Price and Bradstock 2012), a distance that aligns with the typical ridge-gully spacing, and extracted Tall Mist Forest (EVD 12) for each point. We subset the points to select only those that occurred within large (> 50 m radius) patches of mesic forest. We eliminated unburnt points that were more than 200 m from a burnt edge, allowing us to reasonably presume all remaining unburnt points had an opportunity to burn via either short distance spotting or the main fire front (note, spotting is a common mode of fire propagation in eucalypt forests (Cruz et al., 2012)).

Many of the wildfires within the dataset occurred over multiple days. We used MODIS and VIIRS fire detections and the methodology developed by Parks (2014) to map daily progression of each fire at approximately 500 m resolution. This allowed us to determine the likely date of fire for each sample point. Unburnt points were assigned the date of the nearest burnt area. There were 13,586 points in our final dataset (11,393 burnt; 2193 unburnt) across 35 wildfires and 11 fire seasons from 2002/03 to 2019/20.

### 2.3. Predictor variables

We selected 15 predictor variables (Table 1) that characterise the components of the conceptual model outlined in Fig. 1. Values for the predictor variables were extracted using the 'terra' package in R (Hijmans et al., 2023). For daily weather variables, we extracted values for the date when each sample point was most likely to have burnt, or for unburnt points we used the date for the nearest burnt area. Probability density curves for each variable illustrate the distribution of values for burnt vs. unburnt areas of mesic forest within the fire perimeter on the day of fire (Figure S1).

Landscape aridity was used to characterise the long-term water balance associated with landscape position. We used the Nyman et al. (2014) aridity index (AI), a non-dimensional measure of aridity that accounts for the effects of fine-scale (20 m) variations in topography on net solar radiation. AI is a ratio of potential evapotranspiration over precipitation. Thus, higher values indicate a more arid landscape position. Calculation of the aridity index is based on long-term climate data: 20 year record of solar radiation (1990–2012); 30-year record of precipitation (1961–1990); 30 year record of cloud fraction (1976–2005); 100-year record of temperature (1911–2012).

Drought was depicted using the standardised precipitation evapotranspiration index (SPEI), a measure of drought severity derived from precipitation and potential evapotranspiration over a defined temporal window (Vicente-Serrano et al., 2010). We calculated SPEI using a range of temporal resolutions (3, 6, 12, and 24 months) for the months preceding the fire to determine if the length of drought influenced fire occurrence in mesic forests. Input data were obtained from SILO, a 5 km gridded daily climate reconstruction for Australia (Jeffrey et al., 2001). SPEI was calculated using the 'SPEI' package in R (Beguería and Vicente-Serrano, 2023 #757). We extracted upper and rootzone soil moisture data from the Australian Landscape Water Balance Model (Frost et al., 2018). Upper soil moisture (SM_up) is a daily, 5 km gridded metric representing the amount of water in the upper (0–10 cm) soil layer expressed as a fraction of available water whereas rootzone soil moisture (SM_rz) represents the sum of water in the upper and lower soil layers (0–100 cm).

Weather was depicted using the continuous haines index (CHI), forest fire danger index (FFDI) and vapour pressure deficit (VPD). CHI is an index of atmospheric stability, with higher values associated with a greater likelihood of pyro-convective fires (Mills and McCaw 2010). CHI was derived using daily maximum temperature and minimum dewpoint from daily 5 km gridded SILO data (Jeffrey et al., 2001). FFDI is an index of fire weather, integrating measures of soil moisture, fuel availability (drought factor) and wind speed (McArthur 1967). FFDI was extracted from the Australian Gridded Climate dataset (Jones et al., 2009). VPD is the maximum daily deficit between the amount of moisture in the air and amount that it can hold when saturated (Monteith and Unsworth 2013). It is an indicator of fuel moisture (Resco de Dios et al. 2015; Nolan et al., 2016b) and numerous studies demonstrate strong links between VPD and fire activity (e.g. Sedano and Randerson 2014; Williams et al., 2014; Cawson et al., 2022). We calculated daily 5 km gridded VPD from maximum daily temperature and minimum daily relative humidity, which approximates maximum daily VPD. Input data were obtained from the SILO database of Australian climate data (Jeffrey et al., 2001).

Time since disturbance was determined using both wildfire and logging history datasets, with the most recent event identified as the last disturbance (Department of Environment Land Water and Planning 2020a, 2020b). Prescribed burns were excluded because mesic forests are not targeted during prescribed burns and typically remain unburnt or burn at very low intensity when adjacent forests are treated. Time since disturbance defaulted to 100 years for locations with no recorded history of disturbance.

Topographic position was depicted using four metrics – continuous heat insolation load index (CHILI), topographic position index (TPI), elevation and slope. All metrics were derived from the Shuttle Radar Topography Mission (Farr et al., 2007) using the Google Earth Engine platform (Gorelick et al., 2017). TPI is derived by substracting the mean elevation within a 500 m radius from the elevation of the focal pixel. Positive values represent exposed topographic positions (i.e., ridges and upper slopes) where as negative values represent sheltered positions (i. e., gullies and lower slopes). CHILI is a surrogate for the effects of insolation and topographic shading on evapotranspiration with higher values indicating higher levels of solar insolation.

### 2.4. Data analysis

Spearman's Rank correlation coefficient was calculated between all pairs of predictor variables using the *corr* package (Wei and Simko 2017) in the R programming language (R Core Team 2022) (Figure S2). We excluded one variable for pairs that were highly correlated ($r \geq 0.6$). There were four variables excluded (SPEI06, SPEI12, CHI, FFDI). When choosing between highly correlated variables, we chose the variable that was more widely used to predict fire globally (e.g. VPD over FFDI and CHI). The remaining 11 variables were used to build a random forest model to predict the probability that an active wildfire would propagate through mesic forest.

We used the random forest algorithm within the 'randomForest' package in R to model fire occurrence (burnt/unburnt) in mesic eucalypt forests (Liaw and Wiener 2002). Random forest is a machine learning algorithm that combines multiple decision trees (Breiman 2001). It is increasingly being used in fire science as it has a good predictive capacity without overfitting data and can handle non-linear responses between variables. We fit 500 classification trees per iteration and trialed four predictor variables at each node (mtry = 4). To account for the unbalanced number of burnt vs. unburnt sample points, we specified a 50/50 split of burnt/unburnt sample points to build each tree by setting the sample size to 500 for each. This helped ensure the model fit did not preference burnt areas.

Model accuracy was determined using a 'leave-five-fires-out' cross validation approach where five out of the 35 fires were held out at each iteration. A random forest model was built while excluding the sample points from the five fires, then model accuracy was tested by predicting the probability of fire occurrence for the sample points within the excluded fires. This was repeated for all combinations of fires.

We used a cross-validated stepwise procedure to determine which of the 11 remaining variables (Table 1) to include in the final random forest model to reduce overfitting and build the most parsimonious model (Parks et al., 2018). This involved removing variables if they did not provide unique information that improved model fit. Specifically, we used the cross-validation approach (outlined above) to build a *full* model using all variables and a set of *reduced* models with one explanatory variable removed from each. Then, we calculated the cross-validated area under curve (AUC) statistic using the 'pROC' package in R (Sing et al., 2005) for the full and reduced models. If the

**Table 1**
Description of variables evaluated as predictors. Mean, minimum and maximum are values for the samples points extracted for the date the sample point burnt. Variables in bold were retained in the final random forest model after testing for multicollinearity and removing variables with no explanatory power in the stepwise selection procedure.

| Variables evaluated as predictors | Abbrev. | Resolution | Interpretation | Mean | Min, Max |
|---|---|---|---|---|---|
| Aridity index | **AI** | 20 m, long-term average | Higher values indicate greater aridity | 1.6 | 0.5, 3.1 |
| Standardised precipitation-evapo-transpiration index for 3-, 6-, 12- & 24-month time frames | **SPEI03**<br>SPEI06<br>SPEI12<br>SPEI24 | 5 km, monthly | Extreme drought ⟨ −2; Severe drought −2 to −1.5; Moderate drought −1.5 to −1; Mild drought −1 to −0.5; No drought ⟩ −0.5. | −1.7<br>−1.6<br>−1.5<br>−1.5 | −2.5, 0.4<br>−2.5, −0.3<br>−2.9, 0.6<br>−2.7, 0.6 |
| Upper soil moisture (daily) | SM_up | 5 km. daily | Fraction of available water in the soil (0–10 cm depth) | 0.02 | 0, 0.28 |
| Rootzone soil moisture (daily) | SM_rz | 5 km, daily | Fraction of available water in the soil (0–100 cm depth) | 0.24 | 0.01, 0.8 |
| Continuous Haines Index | CHI | 5 km, daily | Higher values indicate higher likelihood of pyroconvective fires | 8.8 | −4, 13.4 |
| Forest Fire Danger Index | FFDI | 5 km, daily | Low danger 0–5; Moderate danger 5–12; High danger 12–24; Very High danger 24–50; Extreme danger 50–100; Catastrophic danger >100 | 41 | 4, 141 |
| Vapour pressure deficit, kPa | **VPD** | 5 km, daily | Higher values indicate drier air | 4.0 | 0.6, 8.7 |
| Time since disturbance, years | **TSD** | 30 m, yearly | Years since last disurbance; No records = 100 years. | 55 | 0, 100 |
| Continuous Heat-Insolation Load Index | **CHILI** | 30 m | Very cool 0; Very warm 255 | 180 | 48, 254 |
| Topographic position index | **TPI** | 30 m | Exposed positions > 0; Sheltered positions < 0; Flat or midslope = 0 | −4.9 | −129, 148 |
| Elevation, m | Elev | 30 m | Metres above sea level | 808 | 42, 1560 |
| Slope, ° | **Slope** | 30 m | Gradient of land surface | 16 | 0, 52 |

AUC *increased* when any given variable was removed (i.e., AUC higher for reduced model vs. full model), it indicated the full model was over-fit and the variable did not provide any unique information. In these cases, the variable that resulted in the largest increase in AUC was permanently removed and the process repeated with the full model having one less variable. This process continued until all variables resulted in a decreased AUC when removed from the full model. As such, all variables in the final reduced model provided unique information. Results are only presented for the final reduced model.

The cross-validated outputs for the final reduced model were used to determine overall model accuracy using the 'caret' package in R (Kuhn 2008) to produce a confusion matrix and derive the overall accuracy and kappa score. Additionally, we calculated the mean AUC statistic. To help identify the most influential predictors in the final model, we extracted 'mean decrease accuracy' from the cross-validated outputs. It is calculated by randomly shuffling the values of a specific variable and then calculating the decrease in model accuracy caused by the perturbation. The larger the decrease the more critical the variable was for predicting wildfire occurrence.

Partial dependence plots were derived to explore the relationship between individual predictor variables and the probability of fire occurrence. For these plots, all variables except the variable of interest were held constant at their mean value. VPD was the most influential variable in the model, so to further examine the effect of the other variables on fire occurrence, we held VPD constant at its 10th and 90th percentile values (from the range of values in the dataset) to calculate additional partial dependence curves for the other values.

## 3. Results

The final random forest model (i.e., the final reduced model rather than full model) had an overall cross-validated accuracy of 0.70, an AUC of 0.61 and Kappa score of 0.21. It performed well for correctly predicting burnt points (precision = 0.87; recall = 0.74; F1 = 0.80) but not as well for correctly predicting unburnt points (precision = 0.32; recall = 0.52; F1 = 0.39) (Table 2).

VPD was the most important predictor with the highest mean decrease accuracy in the final model (Fig. 3). SPEI03 also had a high mean decrease accuracy whereas SPEI12 was omitted from the final reduced model because it did not improve the model fit. Likewise, SM_rz, SM_up and elevation did not improve model fit and were omitted from the final reduced model. AI and TSD were moderately important whereas the topographic variables (CHILI, TPI and slope) had relatively low mean decrease accuracy.

The probability of burning in mesic forest increased by about 65 % as VPD rose from 2.5 to 7 kPa (Fig. 4). AI had a smaller positive effect, with

**Table 2**
Confusion matrix for the final reduced random forest model.

| | | Observed | |
|---|---|---|---|
| | | Burnt | Unburnt |
| Predicted | Burnt | 27,182<br>*True positive* | 4064<br>*False positive* |
| | Unburnt | 9239<br>*False negative* | 4275<br>*True negative* |

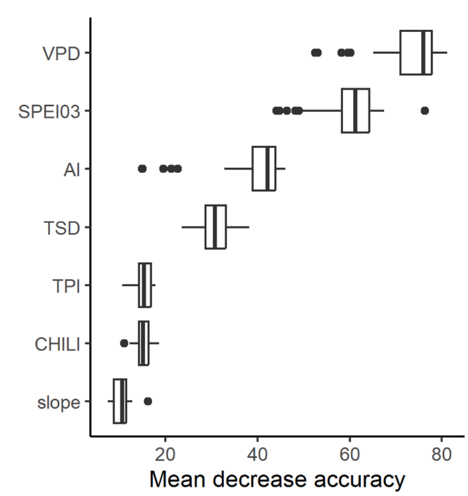


**Fig. 3.** Boxplots depicting median and range of variable importance outputs for the cross-validated random forest model. These results are for the final, reduced model. Variable importance was measured by 'mean decrease accuracy,' a measure of loss in model accuracy when the variable is excluded.

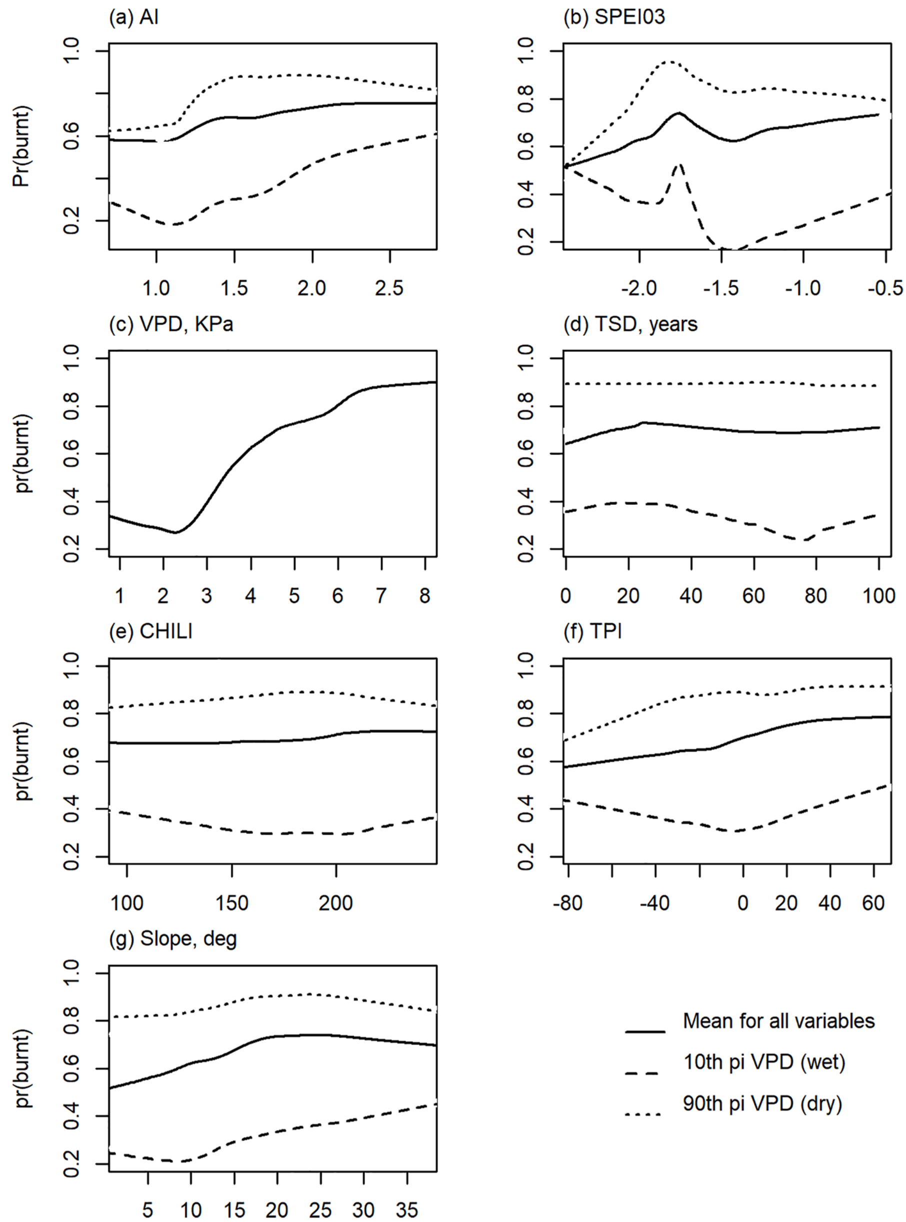


**Fig. 4.** Partial dependence plots showing the relationship between each predictor variable and the probability that mesic forest will burn when all other predictors are held constant at their mean (solid line). These results are for the final, reduced model. The dashed and dotted lines depict model predictions when VPD is held constant at its 10th (1.42 kPa) and 90th (6.73 kPa) percentile values, respectively, and all other predictors are held constant at their mean.

fire occurrence increasing by about 10 % as AI rose from 0.5 to 3 when other values were held at their means. SPEI03 also appeared to have a small positive effect overall with the probability of burning increasing by about 10 % as SPEI03 increased from −2.4 to −0.5 (and other variables were held at their means), but the relationship was erratic. The probability of burning was lowest immediately post-disturbance and then increased by 25 % to peak at 13–15 years before declining gradually 6 % by 50 years post-disturbance. There were small increases in the probability of burning in more exposed topographic positions and on steeper slopes. The probability of burning increased by: 7 % when CHILI increased from 80 to 220; 20 % when TPI increased from −0.90 to 45; and 20 % when slope increased from 0 to 20°.

All variables had a larger effect on the probability of burning when VPD was held constant at its 10th percentile value (1.42 kPa) rather than when VPD was held constant at its 90th value (6.73 kPa).Fires had a high likelihood (pr $\geq$ 0.7) of spreading through mesic forest when VPD exceeded 4 kPa, particularly when combined with an AI exceeding 1.7, TSD of 10–45 years, TPI greater than −1.8, slope exceeding 15° and CHILI exceeding 195 (Fig. 5). Fire spread was only observed in mesic forest when SPEI03 was less than −0.5.

## 4. Discussion

Mesic forests provide a barrier to the development of large fires when they are too wet to burn. However, when their fuel dries they become highly flammable and under these conditions there is a high risk of large wildfires. VPD, a key determinant of fuel moisture, was the strongest predictor of a wildfire propagating through mesic forest. When VPD exceeded 2.5 kPa fire occurrence rapidly increased in mesic forest and when VPD was very high (> 6.5 kPa) it lessened the effect of other variables. As the climate warms and high VPD days become more common (Clarke et al., 2022), the effectiveness of mesic forest as a barrier to the development of large forest fires will weaken.

VPD is a leading determinant of fuel ignitability, fire occurrence and

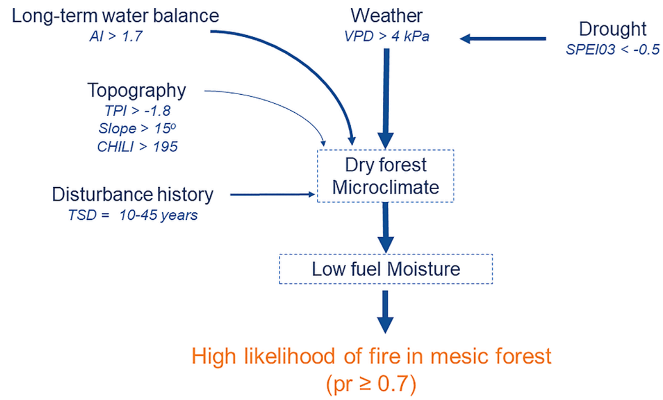


**Fig. 5.** Revised conceptual model of the key factors influencing the probability that an active wildfire will propagate through mesic forest. Variables in italics were identified as important. Values indicate the range of conditions needed for pr > 0.7 of burning in mesic forest with all other variables held at their mean. Variables of higher importance in the modelling are depicted with thicker outbound arrows.
Factors inside the dashed boxes were not measured directly.

burned area when evaluated against other potential predictors in different forest types (Williams et al., 2014; Mueller et al., 2020; Cawson et al., 2022; Resco de Dios et al. 2022). The high importance of VPD is consistent with conceptual models that identify fuel moisture as limiting fire occurrence in mesic forests (Bradstock 2010; Cawson et al., 2020). VPD is strongly correlated with the moisture content of dead fine fuel, especially fuel exposed to the atmosphere (Resco de Dios et al. 2015; Nolan et al., 2016b), and also of live fuels (Griebel et al., 2023). In our modelling, VPD also acted as a surrogate for fire weather as CHI and FFDI were highly correlated with VPD and omitted from the random forest modelling to avoid multicollinearity. Therefore, the dominance of VPD in the model represents the importance of both fuel moisture and short-term weather as drivers of fire occurrence in mesic forests.

The VPD threshold (2.5 kPa) for an increase in fire activity was higher than thresholds identified in other studies in southeastern Australian forests for fire occurrence (1.86 kPa) (Clarke et al., 2022), large-scale wildfires (1.2–2 kPa) (Nolan et al., 2016a) and ignition (~1.5 kPa) (Burton et al., 2023). VPD thresholds for these studies reflect conditions needed for wildfires to occur in drier eucalypt forests, which dominant the landscape. In contrast, our study focuses specifically on thresholds for mesic forests where dense vegetation moderates atmospheric conditions more than in drier forests (Nyman et al., 2018; Pickering et al., 2021). Consequently, a higher VPD (when measured at a 5 km resolution in the open) is needed to overcome these canopy effects and induce sufficient drying to sustain fire within mesic forests. Higher severity wildfires necessitate an even higher VPD threshold, e.g. Benyon et al. (2023) identified a VPD threshold of approximately 5.5 kPa for large, stand replacing fires in wet eucalypt forests. The effects of other variables are lessened when VPD is high (e.g., at its 90th percentile value of 6.73 kPa in our study) and therefore conditions are conducive to a high coverage wildfire (i.e., few unburnt patches). Fire weather is known to overwhelm the effect of other variables on fire behaviour under extreme conditions where the amount of fine fuel is not limiting (Leonard et al., 2014; Tolhurst and McCarthy 2016; Collins et al., 2019; Collins et al., 2023).

The likelihood of fire varied spatially within mesic forests as a function of landscape position, particularly when VPD was below its mean value. The fine-scale aridity index (20 m resolution), which depicts the effects of topography on the long-term water balance, had the largest influence. Forests in less arid parts of the landscape exhibit denser vegetation and a moister microclimate (Nyman et al., 2014) and therefore greater atmospheric dryness (higher VPD) is needed for fire to propagate in these locations (Burton et al., 2023; Cawson et al., 2024). Forests in more sheltered topographic positions (negative TPI) had a lower probability of burning due to less solar exposure and protection from the most desiccating winds, resulting in a moister microclimate; this finding concords with other studies (e.g. Leonard et al., 2014; Storey et al., 2016; Collins et al., 2019; Meigs et al., 2020; Bowman et al., 2021). The positive relationship between slope and the probability of burning partially aligns with other studies (Bradstock et al., 2010; Krawchuk et al., 2016). However, these studies also report less fire on very steep slopes associated with rocky escarpments. Rocky escarpments are not a common feature of mesic forests in Victoria. Rather, steep slopes tend to be associated with more intense fire behaviour as fires spread more quickly upslope (Sullivan 2017).

Mesic forests recovering from a recent stand-replacing disturbance (i.e., < 6 years post-disturbance) had the lowest probability of fire compared with forests at other times post-disturbance, which is consistent with other studies (Taylor et al., 2014; Zylstra 2018). This reflects an initial lack of fuel to carry a fire in the first earlyyears followed by high moisture in the dense regrowth, inhibiting ignition and fire spread (Cawson et al., 2017). The probability of fire increased by 25 % (from 0.5 to 0.75) from zero to 13 years post-disturbance, when all other variables were held at their mean, which is consistent with other studies (Taylor et al., 2014; Bowman et al., 2016; Zylstra 2018). Following this peak there was a reduction of about 6 % (from 0.75 to 0.69) in the probability of fire from 15 to 50 years post-disturbance. This decline is described in the 'moisture model,' a theoretical curve depicting changing flammability with time since disturbance in Ash-dominated eucalypt forests (McCarthy et al., 2001). Declining flammability could reflect increased fuel moisture in older forests due to changes in forest structure and species composition (Burton et al., 2019; Furlaud et al., 2021; Wilson et al., 2022). The magnitude of this decline was significantly smaller than some studies report (Taylor et al., 2014; Zylstra 2018), but in agreement with Bowman et al. (2016). Regardless, fire weather (VPD) had a far greater influence on the probability of fire than disturbance history (Price and Bradstock 2012; Bowman et al., 2021). At high VPD the effects of time since disturbance were negligible whereas at low VPD the effects were more pronounced.

Drought (measured by SPEI) and soil moisture had less influence than expected. Both are frequently cited as important precursors to fire, particularly in mesic forests where substantial drying is needed (Cawson et al., 2020). The relationship between SPEI03 and the probability of fire was inconsistent, which suggests drought severity does not have a consistent effect on fire occurrence in mesic forests. That said, the presence of drought seems important overall because all fires within the study occurred under drought conditions (SPEI < −0.5). The lack of a relationship between drought severity (i.e., SPEI03) and fire occurrence could reflect a bias in our sampling – we limited our study to large wildfires (> 2500 ha) that incorporated mesic forests within their perimeter and large forest fires commonly coincide with dry years (Collins et al., 2022). Soil moisture was omitted during the stepwise procedure because it did not improve the model fit. This result contradicts other studies where soil moisture has been identified as correlated to wildfire occurrence in mesic forests (Cawson et al., 2022; Benyon et al., 2023).

There was a considerable amount of variability not explained in our modelling (overall accuracy 0.70; AUC 0.61), which suggests one or more important explanatory variables were not included. One such variable could be the fire itself in the surrounding landscape, which can influence subsequent fire behaviour (Tolhurst and McCarthy 2016). Leonard et al. (2014) found the likelihood of a point remaining unburnt was strongly influenced by fire intensity in the surrounding landscape. Bowman et al. (2021) included a spatial autocorrelation variable in their modelling and found it be the most important predictor of fire severity for the 2019/20 Australian Black Summer fires. They describe this variable as representing the very rapid expansion of fire under extreme weather conditions, which overwhelms the effect of other variables like topography. Including a fire intensity variable in our model may have improved its accuracy, however, it would have limited the utility of the model, preventing its use as a predictive tool since fire intensity of the surrounding area is only known retrospectively. Other potentially important variables not included in our analysis due to limited data availability were wind speed and sub-canopy microclimate, both of which are associated with fire occurrence in mesic forests.

Model performance was particularly low for the ‘unburnt’ class, which highlights the difficulty of identifying threshold conditions for fire spread in dense canopied forests using broad-scale data. Fine-scale spatial (100 m) and temporal (sub-daily) variations in subcanopy microclimate strongly influence the likelihood of fire spread under marginal conditions (Cawson et al., 2022). The variables used in our study mostly represented much coarser spatial (5 km) and temporal (daily) resolutions, limiting their ability to precisely define fire spread thresholds. In contrast, prediction accuracy was higher for the ‘burnt’ class because this class incorporated numerous days of severe fire weather when fires will spread through all forest types, including mesic forests. Making accurate (true positive) predictions of fire occurrence under severe fire weather conditions is relatively easy and this would have elevated the true positive rate in our model. The poor prediction accuracy under marginal fire weather conditions highlights the importance of continuing to undertake studies that involve in-field microclimate and fire behaviour measurements.

## 5. Implications for fire management

As climates warm, we expect to see mesic forests contribute more often to the development of large wildfires, rather than act as a barrier to their growth. This is due to the higher incidence of high VPD days forecast under future climates (Clarke et al., 2022). Although topographic factors were less important than VPD, an understanding of how topography influences wildfire patchiness could be useful for fire management. Our modelling shows wildfires are less likely to propagate through mesic forests in areas of low aridity, on shallow slopes and more sheltered topographic positions such as gullies and polar slopes. These topographic positions are more likely to become wildfire refugia – unburnt patches within a wildfire footprint – particularly under less severe fire weather. Wildfire refugia are important for the survival of plants and animals vulnerable to frequent fire (Krawchuk et al., 2016). Fire agencies could incorporate the protection of areas with a high likelihood of becoming wildfire refugia into their fire prevention and suppression plans to help preserve key ecological assets. An example of this occurred during Australia’s 2019–20 Black Summer fires to protect a stand of ancient Wollemi pine (Nolan et al., 2021). As wildfires become more frequent, wildfire refugia will be critical for the survival of some species that are intolerant of high frequency fire, including the canopy dominants (*E. regnans* and *E. delegatensis*) within the mesic forests of south-eastern Australia (Bowman et al., 2014; Fairman et al., 2016).

## CRediT authorship contribution statement

**Jane G. Cawson:** Writing – review & editing, Writing – original draft, Visualization, Project administration, Methodology, Funding acquisition, Formal analysis, Conceptualization. **Luke Collins:** Writing – review & editing, Methodology, Data curation, Conceptualization. **Sean A. Parks:** Writing – review & editing, Methodology, Data curation, Conceptualization. **Rachael H. Nolan:** Writing – review & editing, Methodology, Conceptualization. **Trent D. Penman:** Writing – review & editing, Funding acquisition, Conceptualization.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Data Availability

Data will be made available on request.

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## Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.agrformet.2024.109990.

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