Dryness thresholds for fire occurrence vary by forest type along an aridity gradient: evidence from Southern Australia

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Abstract

Context Wildfires are common in localities where there is sufficient productivity to allow the accumulation of biomass combined with seasonality that allows this to dry and transition to a flammable state. An understanding of the conditions under which vegetated landscapes become flammable is valuable for assessing fire risk and determining how fire regimes may alter with climate change

Objectives Weather based metrics of dryness are a standard approach for estimating the potential for fires to occur in the near term. However, such approaches do not consider the contribution of vegetation communities. We aim to evaluate differences in weather-based dryness thresholds for fire occurrence between vegetation communities and test whether these are a function of landscape aridity.

Methods We analysed dryness thresholds (using Drought Factor) for fire occurrence in six vegetation communities using historic fires events that occurred in South-eastern Australia using logistic regression. These thresholds were compared to the landscape aridity for where the communities persist.

Results We found that dryness thresholds differed between vegetation communities, and this effect could in part be explained by landscape aridity. Dryness thresholds for fire occurrence were lower in vegetation communities that occur in arid environments. These communities were also exposed to dry conditions for a greater proportion of the year.

Conclusions Our findings suggest that vegetation driven feedbacks may be an important driver of landscape flammability. Increased consideration of vegetation properties in fire danger indices may provide for better estimates of landscape fire risk and allow changes to fire regimes to be anticipated.

Keywords bushfire; climate; dryness; drought factor; fuel moisture; ignition; KBDI; wildland fire

Introduction

Wildfire is a key disturbance process that shapes many ecosystems globally, occurring where there is a suitable combination of productivity and seasonality (Bradstock 2010; Krawchuk and Moritz 2011; Pausas and Ribeiro 2013). In these environments, wet seasons promote the accumulation of vegetation biomass, and dry seasons facilitate the loss of moisture from this biomass, allowing it to transition to a flammable state (Beverly and Wotton 2007; Dimitrakopoulos et al. 2010).

The spread of fire is governed by fundamental physical processes – given an ignition source, combustion of fuel occurs - this is sustained if heat can effectively transfer to unburnt fuels (Sullivan 2017). In vegetated landscapes, the behaviour of fires is a function of fuel, weather and topography (Byram 1959). This fuel – collectively described as the fuel bed – consists of living and dead biomass including leaf litter, living plants, woody debris, tree bark, dead plant material and soil (Duff et al. 2017; Keane 2015; Riccardi et al. 2007). There has been a substantial body of research to assess factors contributing to flammability at small scales (plant or sub-plant), including evaluating the contributions of structure, energy content, total mass , density, moisture content, volatile oils and fineness (Dimitrakopoulos 2001; Dimitrakopoulos et al. 2010; Dimitrakopoulos and Papaioannou 2001; Duff et al. 2017; Gill and Moore 1996; McAllister and Finney 2014; Murray et al. 2013; Simpson et al. 2016; Wyse et al. 2016). At larger scales (vegetation community), different vegetation properties likely to come into effect (e.g. composition, connectivity, live to dead ratio) to influence the flammability of the vegetation at this scale. Yet, despite wildfires playing a key role in ecosystem processes in many parts of the world (Bond and Keeley 2005), how vegetation properties combine to govern flammability at community scales is still poorly understood (Fernandes and Cruz 2012; Finney et al. 2013; Pausas et al. 2016).

Moisture plays a key role in the transition fuels between non-flammable and flammable states; with high moisture levels inhibiting combustion (Dimitrakopoulos et al. 2010; Larjavaara et al. 2004; Rossa 2017). This effect is evident when considering fire at landscape scales – at times of high fuel moisture, the area burnt by wildfires is constrained (Chuvieco et al. 2004; Dennison and Moritz 2009; Nolan et al. 2016; Weise et al. 2005). Within a vegetation community, moisture is stored in live and dead vegetation, duff and the soil. The moisture content of dead fine fuels exposed to the air fluctuates daily in response to microclimatic conditions – temperature, relative humidity and precipitation. However, fuel components in contact with the soil respond much more slowly – following the wet season, months of drying may be necessary before the fuelbed as a whole is in a condition to sustain fire (Keane 2015; Matthews 2013). The influence of landscape stored moisture is an important consideration of fire behaviour models – models that are used for decision support for fire management (Matthews 2009; Perry 1998; Sullivan 2009).

Fire behaviour models have been broadly adopted and are used operationally by landscape managers to provide wildfire warnings, set preparedness levels and invoke regulations (Taylor and Alexander 2006). In such models, long term landscape drying processes are represented by metrics calculated using account-keeping approaches, whereby water is progressively added (via precipitation) or gradually lost (via evapotranspiration) from a moisture account with a set capacity. An advantage of such approaches is that they require only weather as an input, so can be used in conjunction with weather forecasts to create forward projections of risk. Such metrics include the moisture codes in the Canadian Forest Fire Weather Index (van Wagner 1974), the Drought Factor (DF) in the Australian Forest Fire Danger Index (FFDI) (McArthur 1967; Noble et al. 1980) and the 100 and 1000 hour moisture models of the US National Fire Danger Rating System (Cohen and Deeming 1985). These metrics have been shown to be correlated with the moisture contents of particular components of the fuelbed (e.g. litter (Schunk et al. 2017) and woody debris (Brown et al. 1985)) and have demonstrated value in indicating potential fire behaviour (Krueger et al. 2016; Riley et al. 2013).

Recent studies suggest there are differences between vegetation communities in both the link between dryness metric values and fuel moisture (Beverly and Wotton 2007; Schunk et al. 2017), and the thresholds of dryness that define the area burnt by fire at landscape scales (Beverly and Wotton 2007;

Chuvieco et al. 2004; Nolan et al. 2016). As weather derived moisture indices play an important role in landscape risk planning, it is important that their outputs are representative of fire behaviour in all communities for which they are applied. Given the fire productivity hypothesis (Bradstock 2010; Pausas and Ribeiro 2013), we expect that vegetation communities that have more available water will have greater biomass and consequently larger stores of moisture that need to be depleted before they become flammable. Accordingly, we hypothesise that the thresholds for burning based on weather derived indices of dryness will differ between vegetation communities and that the difference will be a function of site productivity. Prior studies have looked at thresholds relating to area burned (e.g. Dennison and Moritz 2009; Nolan et al. 2016; Pausas and Paula 2012), we look at occurrence to minimise the confounding effect of other factors such as wind and human intervention. We seek to identify and compare fire occurrence thresholds based on DF for fire-prone vegetation communities using historical data derived from over 400 fires that occurred in South-eastern Australia over a 17 year period.

Specifically, by analysing historic fire data, we aim to:

(1) Test for differences in dryness thresholds for fire occurrence between vegetation communities;
(2) Assess whether there is a relationship between the dryness thresholds for fire occurrence and landscape aridity; and
(3) Consider the implications of our findings in relation to the frequency of occurrence of conditions that exceed flammability thresholds

Materials and methods

The approach of this study was to evaluate DF thresholds by determining the lower DF bounds at which historic fires had occurred across a range of vegetation communities. These were then considered in terms of the general aridity under which the vegetation persists and the frequency at which those thresholds are met.

Study area

This study focused on *Eucalyptus* dominated communities in the state of Victoria, Australia. Victoria has a varied climate, with arid areas in inland and temperate conditions at high altitudes and near the coast (Costermans 2009). Annual rainfall varies across the state from approximately 330 to 2,180 mm; with summers being typically warmer and drier. Fires are a periodic occurrence in most *Eucalyptus* forests, although the minimum return interval tolerated can vary greatly (for the vegetation communities considered in this study; from 10 to 80 years for high intensity fire (Cheal 2010)). Uncontrollable wildfires typically occur in the summer months (December to February) (Harris et al. 2017; Murphy et al. 2013). There is substantial variability in the amount of area burnt each fire season, with disproportionately more area burnt under seasonally dry conditions related to the El Niño phase of the El Niño Southern Oscillation (ENSO) (Long 2006). Six vegetation communities across a broad aridity gradient were selected for analysis; communities were only selected if they covered large areas with limited fragmentation due to cleared land (Table 1 and Fig 1). These communities, which account for just under half (49%) of all native vegetation cover in the study area, are: Wet Forest, Damp Forest, Dry Forest, Lowland Forest, Heathy Woodland and Mallee.

Data sources

Fire history and vegetation data were obtained from the data portal of the Victorian Government spatial data repository (source: www.data.vic.gov.au, accessed 1/11/2016) in the form of ESRI shapefiles. The vegetation dataset is entitled 'Native Vegetation - Modelled 2005 Ecological Vegetation Classes (with Bioregional Conservation Status)' (ANZLIC ID: ANZVI0803003495).

These classes are hereon abbreviated as EVCs. EVCs are hierarchically classified vegetation communities mapped at 1:25000 that are widely used for land management and research within the study area (Davies et al. 2002). The EVC dataset represents the state of vegetation communities from mid-way through the study period and there is no compelling evidence of permanent community change that would have greatly altered results. There were some instances of the failed regeneration after fire of some areas of Damp forest (Bowman et al. 2014b), however much of this was ameliorated by remediation activities (Fagg et al. 2013). The high level vegetation community class was used to define vegetation communities; however the community 'Wet or Damp Forest' was split into 'Wet forests' and 'Damp forests' using sub-community definitions as the differing flammability of the wet forests of the study area have been a focus of past speculation about landscape processes (e.g. McCarthy, Gill & Bradstock (2001)).

The fire history data was derived from the dataset entitled 'Fire History Records of Fires primarily on Public Land' which consists of mapped fire areas (wildfires and prescribed burns) that have occurred on public land in the state of Victoria since 1903 (ANZLIC ID: ANZVI0803004741). For this study, only wildfires were considered. This data contains representations of the perimeters of fires mapped to an accuracy of 10-300 m, as curated by the Department of Environment, Land Water and Planning. To maximise the positional accuracy of mapped fire areas, this study was limited to fires that had occurred after 1996 as this was when fires began to be mapped using digital means (GPS and GIS systems). As weather data was available until the end of 2012, the span of the study was June 30, 1996 to December 30, 2012. The perimeters for the study period were predominantly mapped through field survey or aerial imagery. The metadata for each fire contains information about the type of fire (wildfire or prescribed burn), method of data collection and date of ignition. There is no information recorded about the duration of each fire.

Weather parameters used to approximate dryness on the day of ignition for each fire were obtained from a gridded dataset of hourly weather created using a combination of mesoscale modelling, global reanalysis data and surface observations (Brown et al. 2016). The grid resolution of the reconstruction is approximately 4 km for the study area (0.05° latitude). The modelled rainfall didn't correlate well with training observation data used for the reanalysis, so interpolated rainfall maps produced as part of the Australian Bureau of Meteorology Australian Water Availability Project were used to obtain rainfall data (Raupach et al. 2009). Landscape aridity values were obtained from the CGIAR-CSI Global-Aridity database with a spatial grid resolution 30 arc seconds (Zomer et al. 2008) – approximately 1 km for the study area. The average annual aridity value is a ratio between mean annual precipitation and potential evapotranspiration.

The weather data were used to calculate daily maximum values of Drought Factor (DF) from the day of fire occurrence. DF is an index used to represent the proportion of fine fuel at a site in a dry enough state to burn, with 0 representing no fuel available to burn and 10 representing 100% of fuels available. It is derived from the Keetch Byram Drought Index (Keetch and Byram 1968), but includes additional consideration of the effect of recent rain. It is a component of the FFDI (McArthur 1967; Noble et al. 1980)) and is used to forecast forward for a 7 day period at the resolution used in this study using forecast and observed weather for fire planning purposes (Finkele et al. 2006) The DF is calculated from weather alone, but has been found to agree with remotely sensed indices of soil moisture (Holgate et al. 2017). While some of the fires may have burned over multiple days, in the absence of rain events DF changes gradually, so it was assumed the DF from the day of ignition would still be somewhat representative of the burning conditions on later days (Dowdy et al. 2009). The exception would be if a rain event occurred; however it was assumed that rain events sufficient to greatly alter DF were also likely to extinguish any fires burning. DF was calculated using the following formula:

$$\mathrm{DF} = \frac{0.191*(I+104)(N+1)^{1.5}}{(3.52*(N+1)^{1.5}+P-1)}$$

Where I is the Keetch Byram Drought Index (KBDI (Keetch and Byram 1968)), N is the number of days since the last rain event and P is the amount of rain during that event.

Geospatial analysis

Spatial data manipulation was done in ESRI ArcMap version 10.2.2. The fire history data layer was spatially intersected with the EVC layer to create a unique record for every fire/EVC combination. The area of each record was calculated. The centroids of the fire history data and the date of occurrence were used to query the weather database to determine the DF for the day of the fire for each record. Given the scale of the weather data (~4 km), it was assumed that fire centroids would be generally representative of the entire fire event. Although some fires were much larger (for example the great divide fires in 2003 (McCarthy et al. 2012)), each fire was only considered once for each vegetation community and therefore these large fires did not greatly impact results. The historic exposure of each fire location various DF values was determined by computing the DF ranks of all days from within the study period (June 1996 – December 2012) and extracting the values representing the rank percentiles of 0 to 100%. The relative percentile of the DF value for the day of fire occurrence was determined for each record using this data. Extraction of data from the weather database was done in Python 2.7.9 using the packages pandas 0.17.1 (http://pandas.pydata.org) and xarray 0.8.2 (Hoyer and Hamman 2017).

Data processing

The records were imported into R 3.3.4 for analysis (R Development Core Team 2017). The package plyr version 1.8.4 was used to perform database operations (Wickham 2011). Fire data were summarised to find the total polygon area by vegetation community for each unique fire event. As the level of mapping precision for the source data is limited, there is a high likelihood chance of erroneously recognising small areas of unburnt vegetation as burnt at fire edges. To resolve this, only records where at least 5 ha of a vegetation community of interest had been burnt were used for analysis. Additionally, as the date of the 1st of January had been used as a default value for cases where the fire start date was unknown, all fires that started on this date were removed. After data cleaning, a total of 441 fires remained for analysis. The total area burned and the number of instances of each vegetation community being burnt is presented in Table 2.

Statistical analysis

The range of DF values at which fires have occurred and the DF frequency of occurrence of these conditions were represented visually using density plots and two dimensional boxplots - bagplots (Rousseeuw et al. 1999), with statistics calculated using the R package 'aplpack' (Wolf and Bielefeld 2014). To evaluate the thresholds of fire occurrence for each vegetation community, a generalized mixed modelling approach was applied using the R package LME4 (Bates et al. 2015). In this, DF was treated as the fixed effect and vegetation community was treated as the random effect. Modelling was done using a binomial / logit link. As logistic regression requires both presences and absences; absences were created by selecting 100 DF average percentile values for each vegetation type, resulting in similar numbers of presences and absences (441 vs 600) (Barbet-Massin et al. 2012). Three model structures were evaluated and compared using ANOVA. The best model was determined using the Akaike information criterion (AIC) (Burnham 2004). The models were simple linear regression (fire ~ DF), fixed effect with random intercept (fire ~ DF+ 1 | vegetation) and fixed effect with random intercept and slope (fire ~ DF+ (1 + DF | vegetation)). The resultant probability curves for the best model were plotted, including 50% prediction intervals calculated using a bootstrapping approach consisting of 1000 iterations using the R package 'merTools' (Knowles and Frederick 2016). The performance of the best model was evaluated using a 10-fold cross-validation, whereby the model was repeatedly rebuilt and tested using 10% of the training data systematically held out. Performance was evaluated using Specificity (rate of true negatives per modelled negatives), Accuracy (rate of correct predictions per total predictions) and the area under the Receiver Operating Characteristic (ROC) curve (Fawcett 2006). Additionally, a pseudo R^2 value was calculated using R package MuMIn (Barton 2018).

To evaluate links between DF thresholds and aridity, the DF value at which there was less than a 25% probability of fires occurring was determined by algebraically solving the logistic regressions using the R package MASS (Venables and Ripley 2002). A prediction range around this value was estimated using the minimum and maximum 25% DF values drawn from models developed as part of the 10-fold cross validation. The 25% probably threshold DF conditions for fire occurrence were then compared to aridity values using simple linear regression. The likelihood of these thresholds being met were evaluated by regressing the 25% probability thresholds with the rank percentile of occurrence of the DF threshold values.

Results

The density of the occurrence of fires and the rank percentile of these values show distinct differences between vegetation types (Fig 2), with differences apparent in both the thresholds at which fires occur and the frequency at which those thresholds occur. For example, Wet Forests burn predominantly when the DF is above 6, which occurs for relatively infrequently at the sites where Wet forests persist (Fig 2A). In contrast, Mallee burns under a wider range of conditions and those conditions occur often (Fig 2F). There is evidence of bimodality in the density distributions of fire occurrence across DF values for all vegetation types. This was investigated, and it was found that three fire seasons had particularly large numbers of fires under dry conditions (Appendix 1). Two of these were 2002/3 and 2006/7; which were particularly dry years of the Millennium Drought (Harris et al. 2017). The other was 2008/9, a period where there was an extreme heat wave with a number of weather records broken (Cruz et al. 2012b). The percentile values indicated that there have been differences in exposure to the values of DF between the vegetation types. Both Wet (Fig 2A) and Damp Forests (Fig 2B) have very similar distributions of conditions, with a median of approximately 5. Lowland Forest (Fig 2C) and Dry Forest (Fig 2D) have slightly drier conditions, with a median of around 6. The DF density distribution for Heathy Woodlands is further skewed to the left, indicating increasing dryness. Our results indicate that the Mallee is extremely dry, with the DF rarely falling below 8. Despite this, fires have been recorded in Mallee at a wide range of DF values.

The logistic regression analysis found that the mixed model with random slope and intercept (fire ~ DF+ (1 + DF | vegetation) was clearly the best as determined by an information theoretic approach.

The alternative models were not within 2 AIC units, with ΔAIC of 20.1 and 76.6. The diagnostics of the model are presented in Table 3. Using cross-validation, the model was found to have a mean specificity of 0.74 (SD 0.07) and a mean Accuracy of 0.69 (SD 0.05). This indicates the model performs slightly better at predicting true negatives than true positives, as would be expected in cases where absences are generated. The area under the ROC curve was 0.79 (SD 0.03). The pseudo R^2 of the fixed effect was 0.32 and with the random effect 0.42 (Table 3), indicating that the vegetation community accounted for ~25% of the overall explained deviance explained by model.

The probability curves for each vegetation type are presented in Fig 3. These show clear separation of the prediction intervals of the vegetation communities. Fig 4A shows the DF values below which there is less than a 25% chance of fire occurring, plotted against the average aridity for each vegetation community. The minimum DF value at which fires occurred was positively correlated with the climatic aridity of a site, with sites that were less arid requiring conditions to be drier (a high DF) before fires occur ($p = 0.013$, Rho = 0.901). Fig 4B shows the 25% DF threshold plotted against its position in the rank percentile of occurrence for each vegetation community. The DF occurrence as a rank percentile for each site was positively correlated with the threshold value ($p = 0.032$, Rho = 0.85). This indicates that sites that are wetter not only have a high threshold of drying before they are available to burn, but that this threshold occurs less often than in drier sites.

Discussion

Dryness thresholds for fire occurrence as a function of vegetation community productivity

Our results indicate that there are clear differences in the thresholds (as determined by DF) at which different vegetation communities are able to ignite and sustain fire. We found that more productive sites had both a higher drying threshold before fires could occur and, as the sites were on average wetter, these thresholds were met less often. These effects are likely to act in concert to reduce the overall potential for fires occurring in these systems. A study by Pausas and Paula (2012) also identified links between regional aridity and fire thresholds in the Iberian Peninsula, although conversely, they found that higher dryness thresholds were required in more arid areas. As they focused on fire area rather than fire occurrence, their result was a combined outcome of the factors that drive fire occurrence and spread. Their sites were at the fuel limited end of the fire-productivity spectrum, so dryness was less likely to be limiting and the relative importance of spread factors such as wind and vapour pressure deficit may have been greater - fire spread in fuel limited sites requires more extreme weather to provide sufficient flame connectivity between fuel elements (Cruz et al. 2012a). Additionally, human interference may have played a role in limiting area growth in less productive sites – firefighting efficiency reduces with increasing vegetation biomass (McCarthy et al. 2003). Our focus on occurrence was a deliberate attempt to minimise the contribution of fire spread influences to results.

We surmise that the positive correlation between aridity value and the DF based burning thresholds is indicative that differences in DF thresholds between vegetation communities are a predominantly a function of site moisture storage. Site productivity is an important determinant of both biomass and soil depth (Birk and Simpson 1980; Olson 1963). With the exception of Wet and Damp Forests, the average aridity levels of all vegetation communities were below 1, indicating water availability limits productivity across the study area (Table 1). The DF assumes a fixed site moisture storage capacity and was calibrated during development using empirical observations of fires predominantly in Lowland and Dry Forests (McArthur 1967). Accordingly, it would be expected that wetter forests would have greater capacity to store water, so would need more drying before their fuel is dry enough to sustain fire. This would mean that DF would underestimate site moisture, so – as observed - higher thresholds would need to be met before fuels in wetter forests reach the same gravimetric water content as those in Dry Forests.

The effect of moisture storage may be further compounded by feedbacks where higher vegetation cover further limits moisture loss at productive sites by reducing advection and solar radiation driven evaporation (Nyman et al. 2018; Nyman et al. 2017; Walsh et al. 2017; Xu and Singh 2000) and viceversa for sites that are more arid than the forests for which DF was calibrated. This is in agreement with the fire productivity hypothesis, and is supported by findings from South Africa, which found fire occurrence was positively correlated with increasing tree cover up to a threshold, after which it decreased (Archibald et al. 2009). Such feedbacks can also be observed resulting from differences in topographic exposure (Nyman et al. 2018), whereby polar facing slopes that are sheltered from direct solar radiation have greater water availability and consequently greater productivity. This water availability can define the spatial distribution of vegetation communities with feedbacks on fire occurrence (Wood and Bowman 2012). Such effects can occur at relatively small scales, so would not be well recognised using DF at the operational prediction scales (i.e. 4 km) evaluated here. Additionally, topographic effects in varied terrain may result in a mosaic of flammable and non-flammable fuels, resulting in situations where fire growth is constrained by the connectivity of dry patches rather than average dryness (Caccamo et al. 2012). Accordingly, productivity related feedback effects are likely to be a contributing factor to the differences in flammability between communities observed in this study in the short term, and determine the vegetation communities that grow at a locality in the long term.

What remains unclear from our analysis is the role that differences in the ‘fuel’ properties of the fuel bed have in defining flammability. Evolutionary convergence of plant traits to tolerate drought and poor soils have been well described (e.g. mineral contents, leaf sizes, live plant moisture contents etc. (Mooney and Dunn 1970)), and these have been associated with differences in flammability at laboratory scales (Gill and Moore 1996; Pausas et al. 2016). Large differences in fuelbed composition between communities in the same productivity niche (e.g. forests and grasslands) have been shown to result in large differences in flammability (Fletcher et al. 2014; Nowacki and Abrams 2008). In our study, adaptations for moisture deficit will be correlated with productivity differences resulting from moisture storage, so with our data the relative contributions cannot be separated. The question of how to bring together fuel moisture dynamics and other fuel bed properties to determine community level fire behaviour requires further work to be resolved (Fernandes and Cruz 2012).

Potential effects on fire regimes

Our results suggest that all of the vegetation communities evaluated spend a substantial proportion of their existence in a flammable state. Even the Wet forests, which are adapted to infrequent high intensity fire, will on average, spend about 10% of their time above their DF flammability threshold (Fig 2A) - albeit as inter-annual variation in dryness is high, this may vary from year to year (Harris et al. 2017). This suggests that fire occurrence is largely a function of the likelihood of ignitions occurring during this flammable phase. In the study area, the majority of fire ignitions are anthropogenic (Collins et al. 2015; Davies 1997), consequently the future patterns of these ignitions may be an important determinant of the vulnerability communities to inappropriate fire regimes (McWethy et al. 2013). As a result, the maintenance of communities within tolerable fire regimes may require active management intervention to counter excess ignitions, particularly as flammability windows increase with hotter and drier conditions resulting from climate change.

The potential for climate change to increase the frequency and severity of fire weather has been a focus of much recent research (e.g. Clark 1988; Hantson et al. 2015; Hennessy et al. 2005; Pausas 2004; Podur and Wotton 2010; Wotton et al. 2010), however limited consideration has been given to how this may influence fuel properties. Potential changes to production equilibria have been recognised (Matthews et al. 2012; Penman and York 2010), however our results suggest that changes in community composition due to shifting environmental niches may also have large implications for patterns of fire in the landscape. Our findings suggest that feedbacks between climate and vegetation may have an amplifying effect on fire occurrence, whereby a drying climate results in increased fire weather and the encroachment of drought tolerant communities into zones where mesic communities now persist, reducing DF thresholds for fire. Such feedbacks could make landscapes more vulnerable to uncontrollable fire, which may result in further changes in vegetation structure and composition (Bowman et al. 2014c; Kitzberger et al. 2016; Tepley et al. 2018; Tepley et al. 2016).

Study limitations

In this study, we considered the thresholds of dryness that need to be met in a vegetation community before a fire of greater than 5 hectares can occur. However, dryness is not the only threshold that must be met – there must be an ignition, sufficient fuel and a vector to drive spread (i.e. wind) (Bradstock 2010). Towards this, we assumed that all communities had sufficient exposure to ignitions over a range of DF values to allow the effective determination of thresholds, and that other fuelbed properties remained consistent within communities. The highly significant results of this study indicate that our general findings are likely to be robust. However, the potential that other factors add noise to the outcome should be acknowledged. In particular, the Mallee community occurs in exceptional dry environments and so is rarely exposed to DF values below 8 (Fig 2F), making it difficult to determine a minimum threshold (Fig 3). Additionally, there is the potential for flammability to change within a vegetation community as it transitions through growth stages post disturbance. Fuel and moisture dynamics can change greatly as vegetation recovers after fire and response patterns can be a complex function of climatic conditions, disturbance severity and community ecology (Bowman et al. 2014a; Cawson et al. 2018; Cawson et al. 2017; Duff et al. 2012; Gill and McCarthy 1998; Gould et al. 2011; McCarthy et al. 2001). The period for which suitable information were available for this study meant that data were too limited to include post disturbance effects, however as they can be manipulated through management activities (i.e. timber harvesting or prescribed burning), further work in this area is warranted.

Conclusions

We found links between the DF thresholds at which fires have occurred and vegetation communities, and clear evidence that aridity plays a role in shaping this relationship. These interactions suggest that if there is reduced rainfall in response to climate change, weather and vegetation change may act in concert to lower the threshold for fires and increase the number of days when this threshold is reached. Consequently, our findings suggest that current approaches to quantify fire danger based on DF are likely to be producing biased outcomes. Given the differences in fire occurrence thresholds between vegetation communities, further work is required to understand the processes behind these thresholds and determine the relative contributions of moisture dynamics, inherent community flammability properties, disturbance effects and human activity.

Author contributions

TD and JC conceived the ideas and designed methodology; TD and SH collected and analysed the data; TD led the writing of the manuscript. All authors contributed critically to the drafts and gave final approval for publication. All data will be archived on University servers.

Data accessibility

Fire and vegetation data can be accessed at www.data.vic.gov.au

Aridity data can be accessed at http://www.cgiar-csi.org/data/global-aridity-and-pet-database

Australian rainfall data can be accessed at

http://www.bom.gov.au/jsp/ncc/climate_averages/rainfall/index.jsp

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Table 1. Vegetation community descriptions

Vegetation community	Area (ha)	Average Rainfall (mm)	Average Annual aridity (P:E; mm/mm)	Low severity fire return interval (years)	high severity fire return interval (years)	Description
Damp Forest	850,000	1,210	1.12	25	25	Dominated by a tall eucalypt tree layer to 30 m tall over a medium to tall dense shrub layer of broad-leaved species typical of wet forest mixed with elements from dry forest types. The ground layer includes herbs and grasses as well as a variety of moisture-dependent ferns.
Dry Forest	2,717,000	1,160	0.90	10	25	Medium to tall open forest or woodland to 25m tall with a tree layer over a sparse to dense shrub layer. A high cover and diversity of herbs and grasses in the ground layer.
Lowland Forest	616,000	950	0.97	8	25	Eucalypt forest to 20 m tall on relatively fertile, moderately well-drained soils in areas of relatively high rainfall. Characterised by the diversity of life forms and species in the understorey including a range of shrubs, grasses and herbs.
Heathy Woodland	338,464	790	0.68	10	15	Eucalypt-dominated low woodland to 10 m tall lacking a secondary tree layer and generally supporting a diverse array of narrow or ericoid-leaved shrubs except where frequent fire has reduced this to a dense cover of bracken.
Mallee	1,557,000	380	0.25	20-40*	20-40	Low woodland to 7m tall consisting of multi-stemmed *Eucalyptus* trees. Occurs on infertile siliceous sands on minor dunes and undulating sandplains.
Wet Forest	458,000	1,250	1.18	80	80	Tall eucalypt overstorey to 30 m tall with scattered understorey trees over a tall broad-leaved shrubby understorey and a moist, shaded, fern-rich ground layer that is usually dominated by tree-ferns.

Areas and climate data calculated from data used in analysis. Vegetation type descriptions are summarised from the Victorian Department of Environment Land, Water and Planning Ecological Vegetation Type Benchmarks (Planning 2016). Return intervals are derived from Cheal (2010). *Depending on sub community.

Table 2. Total area burned and number of fires within the study period for the vegetation communities analysed

	Area (ha)	n
Damp Forests	433,953	145
Dry Forests	1306,234	386
Heathy Woodlands	55,506	97
Lowland Forests	66,751	132
Mallee	296,637	147
Wet Forests	127,622	66

Table 3. Outputs of the best linear mixed effects model: predicting the probability of a fire occurring from DF (fixed factor) and vegetation community (random factor).

	Random Effects		
Groups	**Variance**	**Std. Dev**	
Vegetation community	3.72	1.93	
DF	0.06	0.25	
(Intercept)	**Intercept**	**Estimate**	
Damp Forests	-0.76	0.12	
Dry Forests	0.01	0.11	
Heathy Woodlands	0.85	-0.16	
Lowland Forests	0.34	-0.05	
Mallee	2.94	-0.40	
Wet Forests	-2.92	0.33	
	Fixed Effects		
	Estimate	**Std. Err**	**p value**
Intercept	-4.00	8.6E-01	3.0E-06
DF	0.54	1.1E-01	1.7E-06
Pseudo R^2	**Fixed Effects**	**Full model**	
	0.32	0.42	

*Statistically significant at $p<0.05$, ** Statistically significant at $p<0.01$, ***Statistically significant at $p<0.001$

Figure Labels

Figure 1. Map of the study area showing the extent of the vegetation communities of interest.

Figure 2. Bagplots representing the rank percentile DF value of fire occurrence (y axis) and absolute value of Drought Factor values for fire occurrence (x axis) for instances where >5 ha was burnt in each vegetation community. Fires are represented as black points; inter-quartile range is shaded in grey. Black lines and tick marks represent density of fire occurrence for each DF value, grey lines represent density of DF occurrence. Vegetation communities represented are A) Wet Forest, B) Damp Forests, C) Lowland Forest, D) Dry Forest, E) Heathy Woodlands and F) Mallee.

Figure 3. Logistic regression plots of fire occurrence at differing Drought Factor Values. 50% prediction intervals are represented by dotted lines.

Figure 4. Scatterplots showing 25% probability threshold Drought Factor plotted against A) Average annual Aridity Index, and B) the rank percentile of the Drought Factor threshold occurrence. Vectors represent standard error. Linear trend-lines are presented in grey. DF error bars represent the range of values obtained through 10-fold cross-validation. Aridity error bars represent the standard deviation of the aridity values for each vegetation community sampled at every fire location.

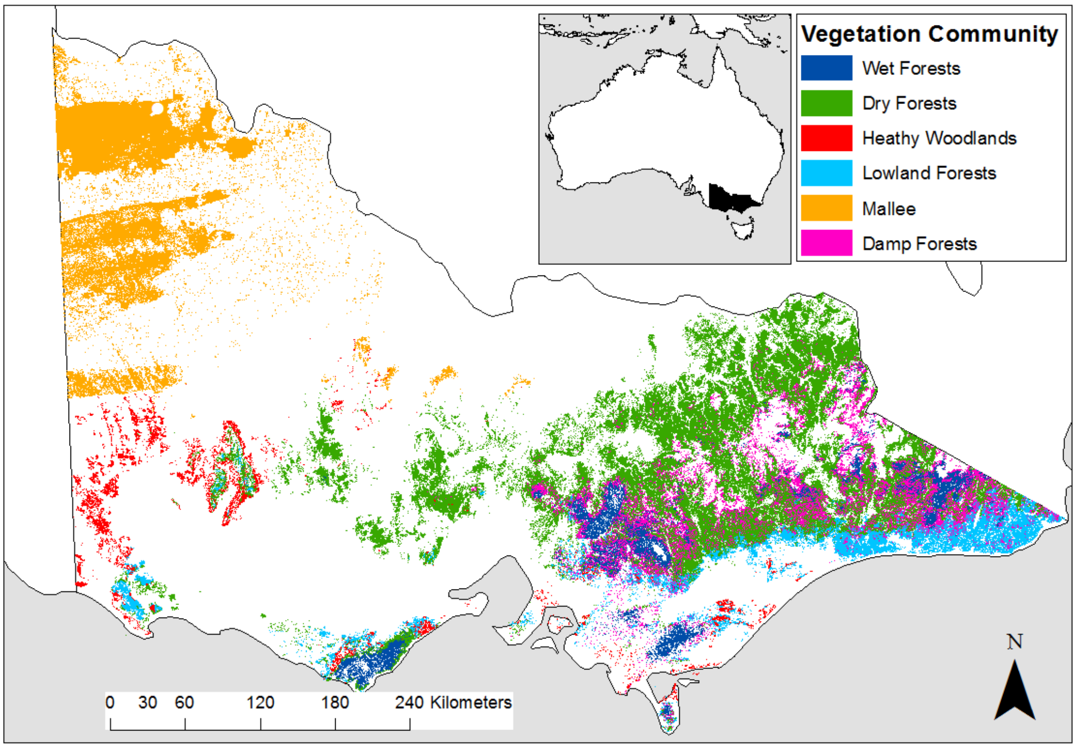
Vegetation Community
Wet Forests
Dry Forests
Heathy Woodlands
Lowland Forests
Mallee
Damp Forests
N
0 30 60 120 180 240 Kilometers

Figure 1.

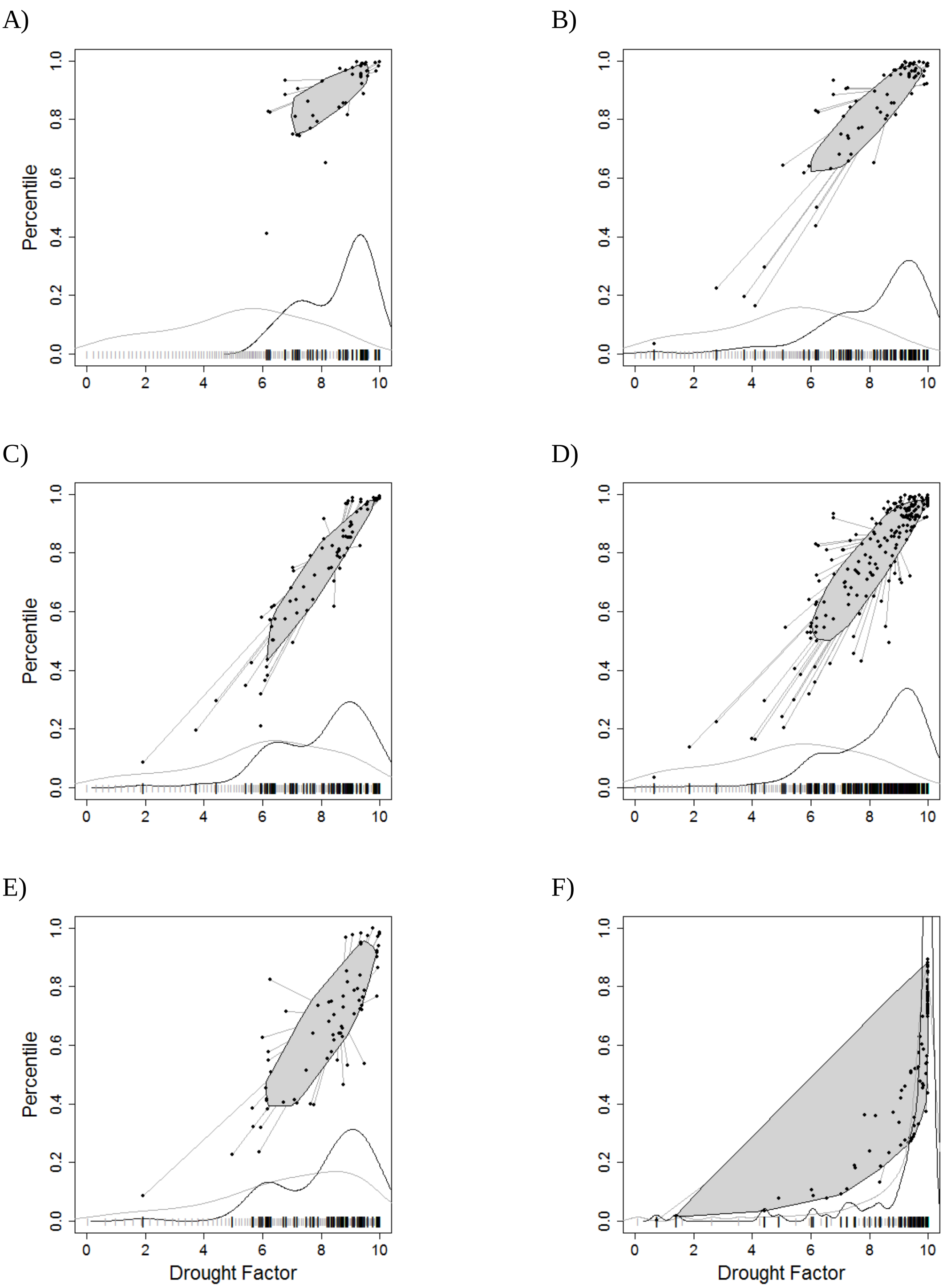

Figure 2.

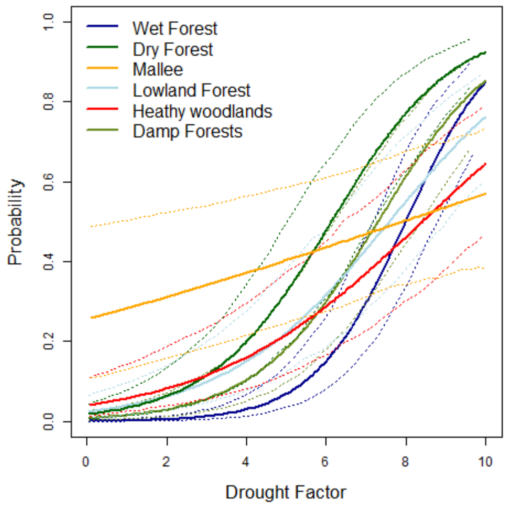
Wet Forest
Dry Forest
Mallee
Lowland Forest
Heathy woodlands
Damp Forests
Probability
0.0
0.2
0.4
0.6
0.8
1.0
0
2
4
6
8
10
Drought Factor

Figure 3.

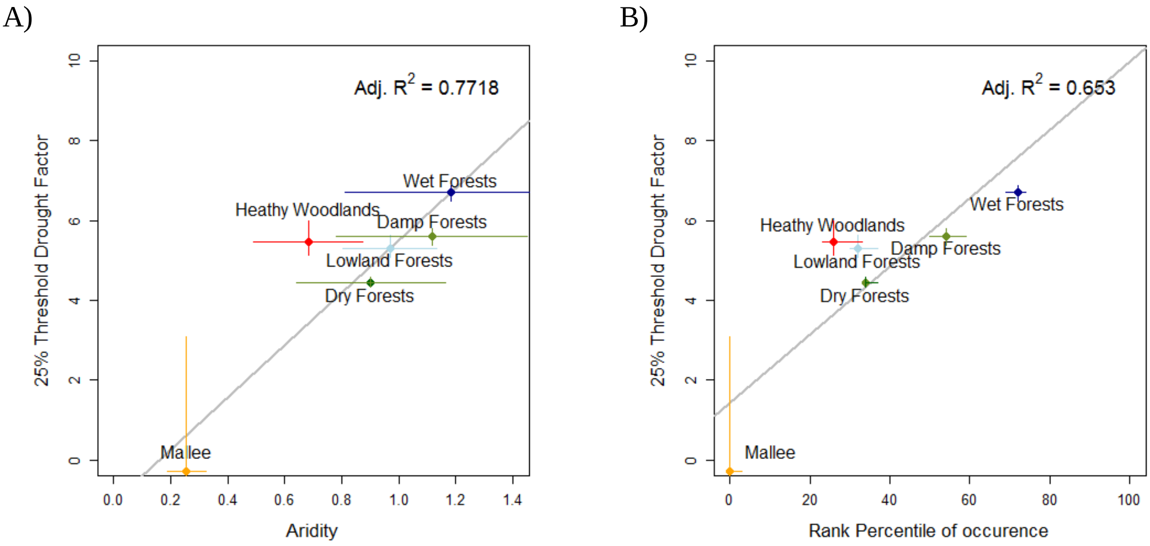
A)
Adj. R² = 0.7718
Wet Forests
Heathy Woodlands
Damp Forests
Lowland Forests
Dry Forests
Mallee
25% Threshold Drought Factor
Aridity
B)
Adj. R² = 0.653
Wet Forests
Heathy Woodlands
Damp Forests
Lowland Forests
Dry Forests
Mallee
25% Threshold Drought Factor
Rank Percentile of occurence

Figure 4.

Appendix 1. Number of fires by season for the state of Victoria, Australia, where at least 5 ha of a vegetation grouping was burnt in a single event

Fire season	Number of fires
1996/7	34
1997/8	40
1998/9	34
1999/2000	27
2000/1	49
2001/2	45
2002/3	74
2003/4	23
2004/5	49
2005/6	41
2006/7	92
2007/8	73
2008/9	148
2009/10	74
2010/11	27
2011/12	67
2012/13	2