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Positive severity feedback between consecutive fires in dry eucalypt forests of southern Australia

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Disciplines

Medicine and Health Sciences | Social and Behavioral Sciences

Publication Details

Barker, J. W. & Price, O. F. (2018). Positive severity feedback between consecutive fires in dry eucalypt forests of southern Australia. *Ecosphere*, 9 (3), 1-14.

Positive severity feedback between consecutive fires in dry eucalypt forests of southern Australia

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Citation: Barker, J. W., and O. F. Price. 2018. Positive severity feedback between consecutive fires in dry eucalypt forests of southern Australia. *Ecosphere* 9(3):e02110. 10.1002/ecs2.2110

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Key words: disturbance; eucalypt forest; feedback effect; fire regime; fire severity.

Received 1 January 2018; accepted 11 January 2018. Corresponding Editor: Debra P. C. Peters.

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INTRODUCTION

Wildfires are a heavily studied natural phenomenon, but many studies treat them as discrete disturbance events, when they are an ongoing natural process (Bowman et al. 2009). This process is termed the fire regime, which represents the history of all fire at a location, comprising the number, severity, and seasonality of fires (Gill 1975). Most studies of fire regimes have looked only at the frequency of fires (Bradstock et al. 1997, Enright et al. 2015, Fairman et al. 2016, Hammill et al. 2016), at the expense of the other aspects of fire regimes (Morgan et al. 2001). Fire severity is a component of the fire regime for which we lack knowledge, especially in the context of broader processes.

Severity is a measure of the vegetation consumed by a fire, making it useful for examining the impact of fire on ecosystems. The severity of a fire affects the ecosystem response and recovery. Fire can result in changes to the relative abundances of species, as well as structural changes in the fuel strata and stand density (Schwartz et al. 2016). High-severity fire can lead to a reduced ability for the vegetation to recover (Ireland and Petropoulos 2015), compared to low-severity fire, but this depends on the recovery method of the species. High-severity fire will be more damaging to resprouting plants than low-severity fire and may result in plant death. This would be expected to reduce post-fire recovery. However, high-severity fires can also stimulate germination in some

re-seeding species through smoke or heat cues (Gill 1981). Some of these species require severe fire events to germinate seeds (Ooi et al. 2006), as has been clearly demonstrated for *Acacia linifolia* (Liyanage and Ooi 2015). This stimulation may result in very vigorous plant growth after a severe fire (Gordon et al. 2017), leading to high fuel loads some time after a fire.

These responses may then influence the severity of subsequent fires. There are two possibilities: a negative (stabilizing) feedback between fires, whereby high severity in the previous fire leads to slow plant recovery (Godwin 2011, Lydersen et al. 2014), and therefore low fuel loads, and ultimately lower severity if a second fire occurs. Alternatively, there may be a positive (runaway) feedback between fires, where initial high-severity fire leads to rapid and dense plant growth, and hence high fuel load (Williams et al. 2012, Clarke et al. 2015), resulting in an increased risk of further high severity if a second fire is to occur. In the negative feedback scenario, plant (and fuel) dynamics are driven mostly by fire-caused mortality which increases with severity. In the positive feedback scenario, dynamics are driven mostly by post-fire recovery and recruitment which increase with severity. These alternatives are illustrated in Fig. 1.

These feedbacks have implications for risk management strategies, as prescribed fire and other fuel reduction processes are commonly used for fire management in Australia (Ellis et al. 2004). The effectiveness of low-intensity prescribed fires on fuel loads has not been fully explored (Bradstock et al. 2010), and while prescribed burning does have a quantifiable effect on subsequent wildfire, these effects can be subtle and dependent on how burning is applied (McCaw 2013). The type of feedback occurring in the system would determine the effect of prescribed burning.

Few studies have examined the effect of the severity of previous fires on the severity of subsequent fire. The handful of studies looking at this have been in North America (Thompson et al. 2007, van Wagendonk et al. 2012, Harris and Taylor 2017), with most only having one response fire, and occurring mostly in conifer forests. These studies have consistently found that fires return at the same or higher severity as the previous fire, supporting the idea of a positive feedback.

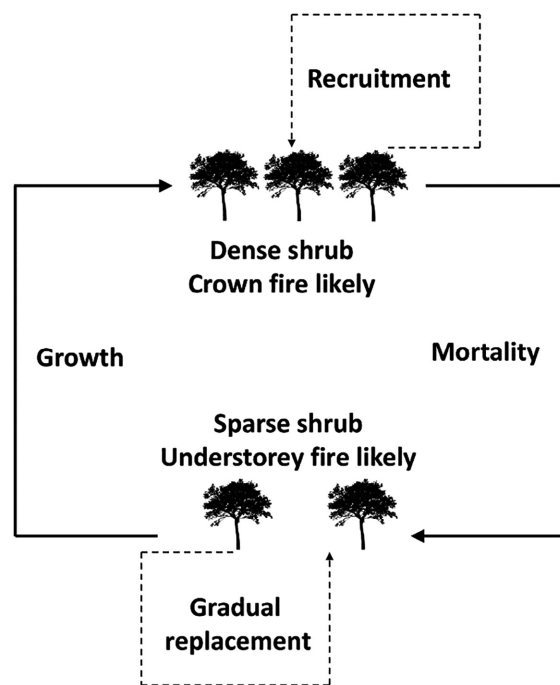


Fig. 1. A conceptual model of forest understory life history, with four processes: gradual inter-fire replacement, post-fire pulsed recruitment, plant growth, and mortality. In a negative fire feedback, growth and mortality dominate: Severe fires kill many plants, and recruitment is weak, so plant density decreases, and hence, future severe fire becomes less likely. Conversely, low-severity fires kill few plants so continued growth increases the likelihood of future severe fire. In a positive feedback, recruitment is more influential, and mortality is less. Severe fire will kill a proportion of the plants, but there is vigorous recruitment, increasing the probability of subsequent severe fire. A low-severity fire does not trigger such a recruitment pulse and so leaves the forest less likely to experience subsequent severe fire. This process would not affect the canopy species unless there is an extremely severe fire, resulting in basal resprouting.

The long-term effects of fire severity on Australian ecosystems are unknown, as few studies have examined this aspect of fire regimes. If the positive feedback effect occurs, then there is a potential spatial divergence in plant communities where some patches would experience a regime of repeated severe fire, with resulting increase in vegetation density, while other patches experience a regime of repeated low-severity fire and lower

vegetation density. Positive feedbacks may also benefit risk management strategies. A low-severity prescribed burn may be able to be used to interrupt a cycle of extreme severity, and reduce the chance of crown fire in subsequent wildfires.

The length of time since the previous fire influences severity due to a gradual recovery of fuel, meaning that the probability of high-severity fire increases over time (Bradstock et al. 2010, Lydersen et al. 2014). This recovery process varies due to differences between vegetation types, the severity of the fire, and the characteristics of the location.

The focus of this study was to determine the relationship between the severity of a fire and severity of previous fires for 53 forest fires in New South Wales (NSW), Australia. The fires spanned a range of years, with differing intervals between the fires. Our two main questions addressed in this study are as follows:

1. How is the severity of a fire influenced by the severity of the previous fire?
2. How is this relationship influenced by the amount of time between the fires?

We hypothesized that initially, severity in the previous fire has a negative effect on severity in the subsequent fire, because high-severity fires remove more fuel, leaving less available for subsequent fires. However, this effect would only be present for a short time (<10 yr) following fire. As the interval between fires increases, the relationship will reverse, and a positive feedback will occur. This is because high-severity fires stimulate more vigorous growth, leading to dense vegetation over time, creating more fuel (i.e., we hypothesize a positive severity feedback).

METHODS

Study area

The study was conducted in a 1.1 million ha area of the Sydney region of New South Wales, Australia. The area encompassed a large part of the Greater Blue Mountains World Heritage Area, extending from Singleton in the north, to Wollongong in the south, reaching as far as Lithgow to the West (Fig. 2). The study area has a temperate climate, with cool winters and warm summers, influenced by proximity to the ocean. Average temperatures range from 16°C in July to

26°C in December (Australian Bureau of Meteorology). The area receives an average rainfall of 1100 mm per year, with late summer months generally having the highest level (Tozer et al. 2010). There is a gradient of rainfall, decreasing from north to south, with orographic effects from the Illawarra escarpment and the Blue Mountains. The region is characterized by periodic drought conditions and extreme fire weather (Bradstock et al. 2009). Elevations range from 0 m to 1215 m across sandstone geology (Doerr et al. 2006). The fire season in this area runs through spring and summer, from October to March.

The vegetation of the region is dominated by dry sclerophyll forests and woodlands, primarily composed of *Eucalyptus* species (Tozer et al. 2010). This is interspersed by smaller areas of wet sclerophyll forest and rainforests, which mainly occur in moister areas such as gullies or south-facing slopes (Keith and Simpson 2010).

Fire severity data

The study was conducted using historical fire severity mapping from a variety of sources, spanning 1982–2013 (Table 1). This dataset represents ~90% of all wildfires that occurred in the study area between 1982 and 2014, but some fires did occur in the intervals between the fires (mostly prescribed burns).

The delta Normalized Difference Vegetation Index (NDVI) was used to measure fire severity in the data used in this study. This index is commonly used for the measurement of fire severity (Escuin et al. 2008, Keeley 2009). The source severity maps were pre-classified from NDVI into severity classes based on the definitions of Keeley (2009) and Ryan and Noste (1985): (1) low to moderate, with little to no effect on the canopy and fire restricted to the lower strata of vegetation; (2) high, with crown scorch and extensive understory burning; (3) very high, for fire involving extensive crown scorch and defoliation; and (4) extreme, for the highest severity, involving complete crown consumption.

We simplified this classification into two binary response variables: very high-/extreme-severity occurrence (severity classes 3 and 4), and low-severity occurrence (severity class 1). High severity was excluded from the analysis as its effects would not be as strong as the two extremes. This approach has been commonly

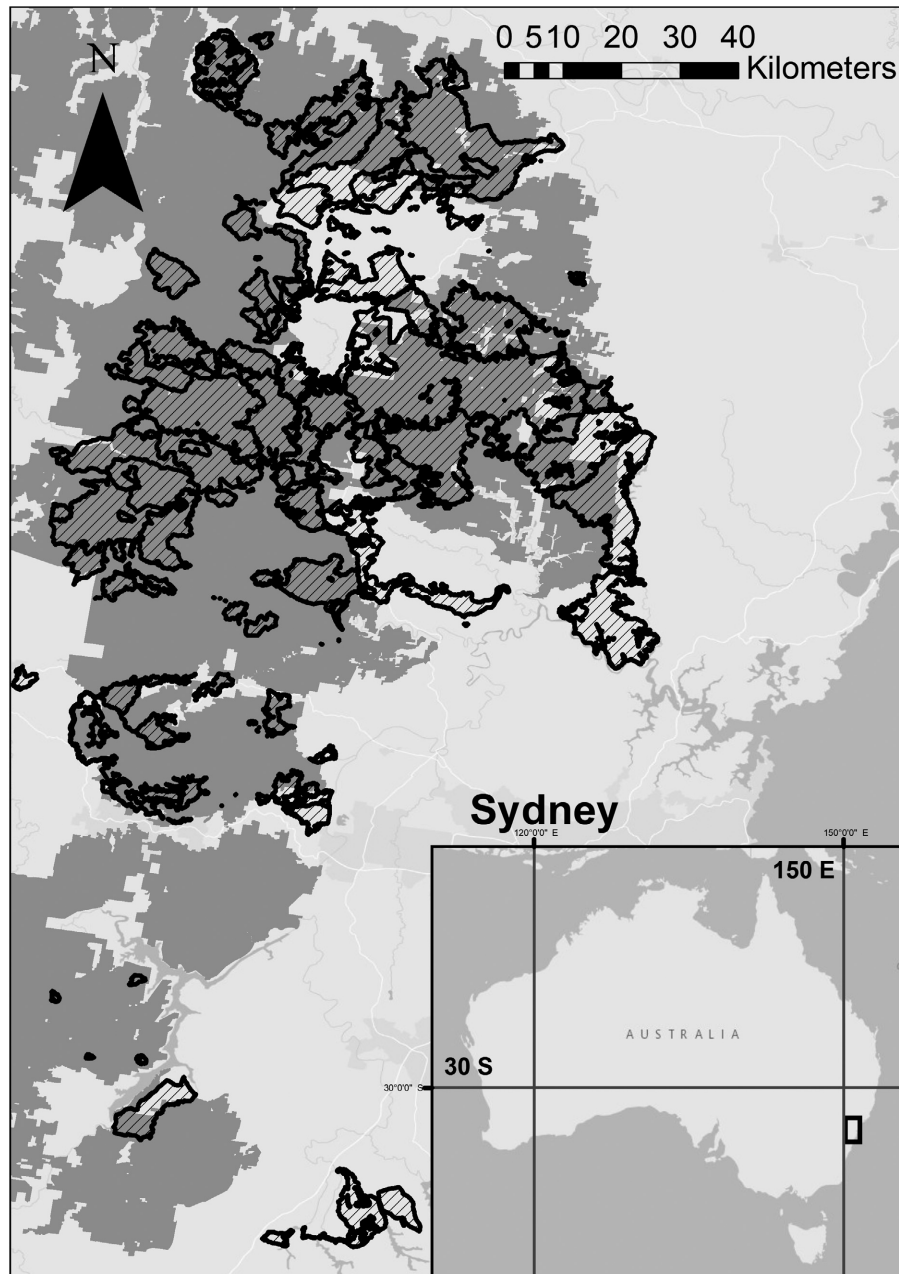


Fig. 2. Map of the study area, with the hatched areas representing the fires. The area is in the Sydney region of NSW and is bounded by Singleton in the north and Wollongong in the south, reaching West to Lithgow. The dark gray area is the Greater Blue Mountains World Heritage Area (mostly intact eucalypt forest).

applied in Australian studies of fire severity (Bradstock et al. 2010, Price and Bradstock 2012, Storey et al. 2016). The method also relates to fire management, since low-severity fires are generally amenable to suppression, while high-severity fires are not (Gill et al. 1987).

The severity maps were intersected to identify areas burned in two fires. The second fire was the study fire, while the first fire, referred to as the previous fire, was a predictor. Unburnt areas in the study fires and areas with a fire between the first and second severity maps were also

Table 1. The GIS severity data which were used in the study.

Data	Sensor	Method	Resolution	References
2013/14 severity	Landsat 7	dNDVI	30 m	Hammill (<i>unpublished data</i>)
	Aerial photo	dNDVI	2 m	Price (<i>unpublished data</i>)
2006/7 severity	Landsat 7	dNDVI	30 m	Hammill et al. (2010)
2002/3 severity	Landsat 7	dNDVI	30 m	Hammill et al. (2010)
2001/2 severity	Landsat 7	dNDVI	30 m	Hammill and Bradstock (2006)
	SPOT 2	dNDVI	10 m	Hammill and Bradstock (2006)
1997/8 severity	Landsat 5	dNDVI	30 m	Hammill et al. (2010)
1993/4 severity	Landsat 5	dNDVI	30 m	Hammill et al. (2010)
1982/3 severity	Landsat 4	dNDVI	30 m	Hammill et al. (2010)

Note: Table shows source data layers and reference for the author of the data.

removed. There were a total of 53 study fires. These data spanned inter-fire intervals from 4 to 33 yr, with most cases being between 7 and 12 yr (Fig. 3). The study fires occurred in four fire seasons, with the most fires occurring in 2002/03.

Ancillary data

Weather has a profound effect on fire severity (Price and Bradstock 2012), and Forest Fire Danger Index (FFDI; McArthur 1967) is often used as

a predictor of risk in bushfires and is a function of wind speed, temperature, humidity, and drought factor (Bradstock et al. 1998). The daily maximum FFDI was used as a summary for fire weather effects for each day of the fires. Forest Fire Danger Index has been used previously in the study of fire severity and other aspects of fire behavior (Price et al. 2015, 2016). Fire progression maps and hotspots were used to estimate the day on which the points in a fire burned.

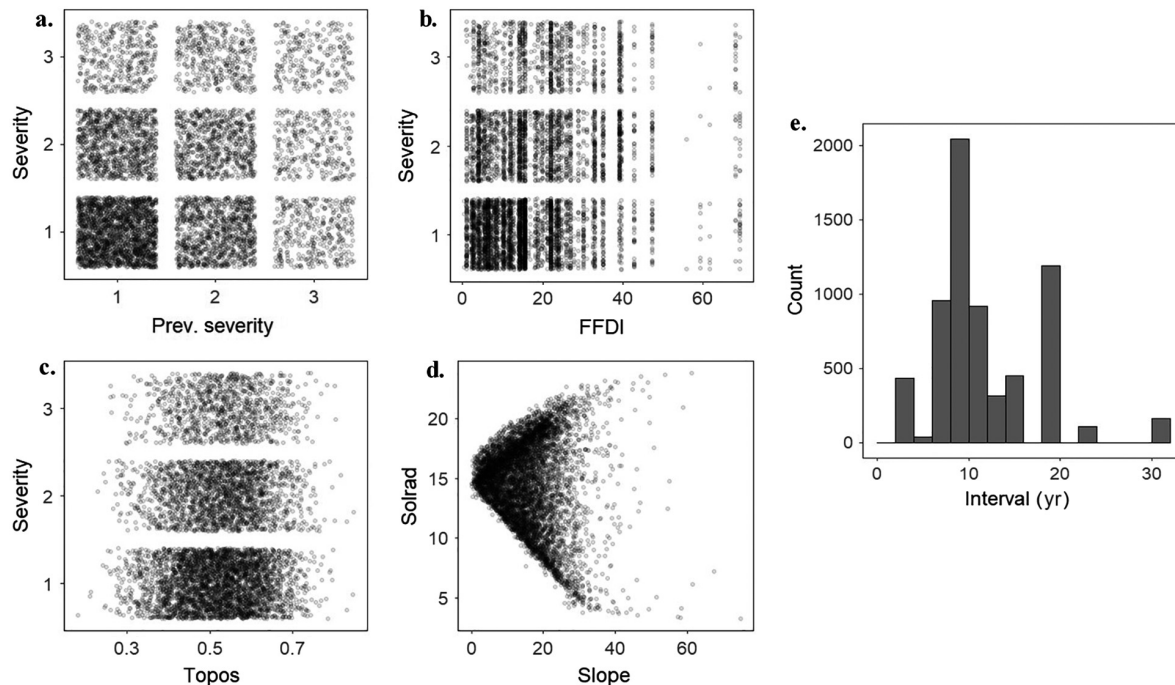


Fig. 3. The data for (a) previous severity, (b) FFDI, and (c) topographic position, all plotted against three levels of severity and jittered to represent the density of points. Slope (degrees; d) is plotted against solar radiation, as the range of values for solar radiation is dependent on slope. The histogram (e) shows the number of sample points for each time since fire.

Progression maps were available for the 2006/7 fire season and some of the 2013/14 fires (Office of Environment and Heritage, *unpublished data*). Moderate-resolution imaging spectroradiometer (MODIS) active fire data (Giglio et al. 2003) were used to determine the dates for the remaining fires. The dates were then used to assign daily maximum FFDI data to each progression polygon. These data were taken from the records of the closest weather station to each fire, adjusted for elevation. Weather data more accurate than daily values were not obtainable from the available data, because the time of day at which each point burned was unknown.

The vegetation classes for each point were extracted from an updated vegetation map for NSW (Keith and Simpson 2010). The data were restricted to include only the shrubby sub-formation of dry sclerophyll forests, to control for the effect different vegetation may have on severity. This formation was the most common vegetation type in the study area. Wet sclerophyll or the grassy sub-formation of dry sclerophyll forests may be expected to have lower severity than shrub dominated dry sclerophyll forest, so this might cause an apparent positive feedback.

Slope, topographic position, and exposure were all derived from the 30-m resolution digital elevation model (DEM) of NSW from Geoscience Australia (available at <http://www.ga.gov.au>). Exposure was calculated using the solar radiation function in ArcMap 10.3 (ESRI 2010) to determine the maximum amount of sunlight received at a point, based on topography. Exposure influences the moisture content of fuels and, combined with slope, may influence the growth of vegetation. Topographic position is the local landscape position, expressed as the percentage elevation in a 500-m window around each cell on the DEM. 100% represents the highest local point. These variables have been found to be related to localized variation in fire severity (Bradstock et al. 2010, Storey et al. 2016).

Analysis

A grid of sample points, 500 m apart, was created over the study area. The 500-m separation used has been found to counter spatial autocorrelation, as it is similar to the ridge–valley distance in landscapes throughout the Sydney region and has been used in previous severity studies

(Bradstock et al. 2010, Price and Bradstock 2012). The severity levels of each overlapping fire, the time between fires, as well as slope, topographic position, FFDI, and exposure to solar radiation, were recorded for each point (Fig. 3).

High severity dominated several fires, with little variation across the fire; low severity similarly dominated others. This may have caused a lack of independence between points within fires. To account for this, the identities of individual fires were included as a random factor in the mixed model method.

The data were split up for the analysis, with 70% used for the training data and the remaining 30% used as testing data. Generalized additive mixed models were used to quantify the effects of previous fire severity, fire interval, and the ancillary variables, FFDI and topography. All possible additive model combinations were examined, and the best model and supported alternatives were identified using the statistical model selection method, based on Akaike weights (Burnham and Anderson 2002). For the best model, all two-way interactions were tested and retained if they increased the weighting. Non-linearity in the response to the predictor variables in the best model was tested by comparing linear terms with smooth terms, which were retained if they increased the explanatory power of the model. Smooth terms were used with the default number of knots ($k = 10$) for most variables, but fewer knots were used for fire interval ($k = 4$) to prevent overfitting.

Although our method minimized spatial autocorrelation, we tested the degree to which it occurred by using variograms and Moran's I , a statistical measure of autocorrelation, to ensure that the proximity of points would not bias the results. All statistical analyses were performed using R 3.3.1 (R Development Core Team 2013). The data are accessible in the Dryad Digital Repository (Barker and Price 2018).

RESULTS

Very high-/extreme-severity fire represented 15.7% of the data, while low-severity fire consisted of 53.2% and the remaining 31.1% of the data were high severity, which was not analyzed. The proportion of very high-/extreme severity was more than double with previous very high/extreme severity than with previous low severity

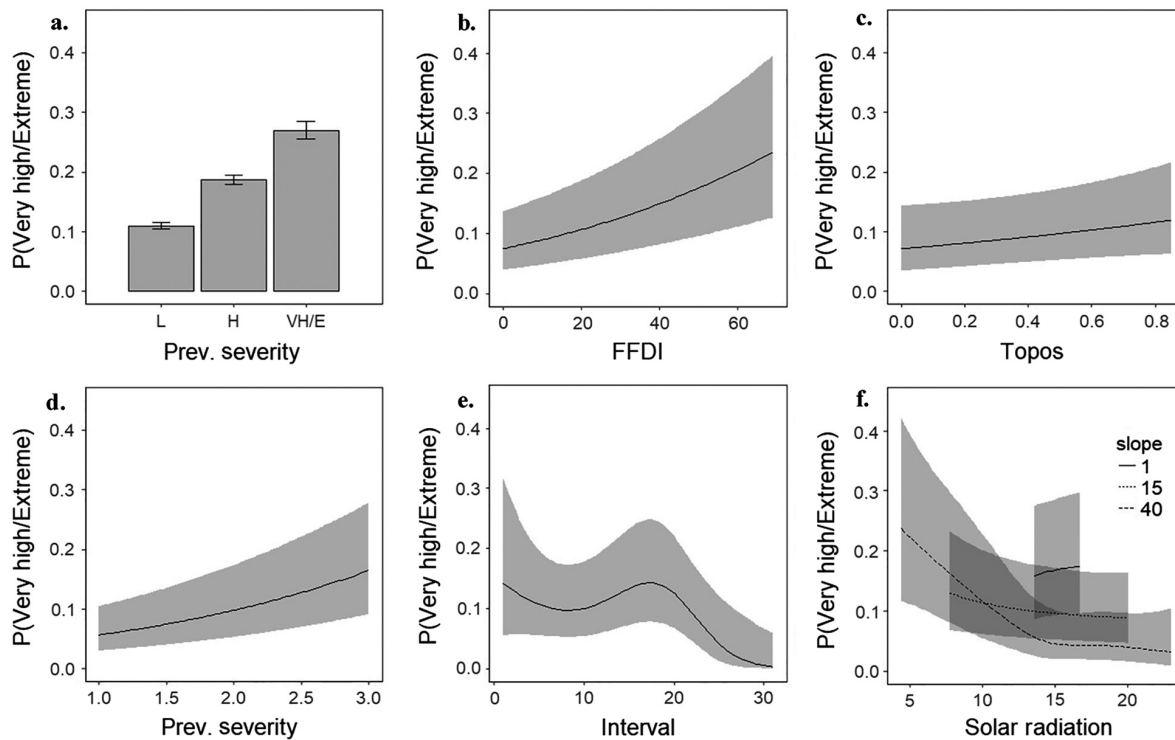


Fig. 4. (a) The proportion of very high/extreme severity for each level of previous severity in the raw data. The model predictions for the independent effect of the variables; (b) FFDI, (c) topographic position, (d) previous severity, and (e) fire interval (in years), and (f) the interactive effect of solar radiation and slope on the probability of very high/extreme-severity occurrence. The shaded areas on the line graphs represent 95% confidence intervals. Values of solar radiation were restricted to those which were physically possible.

(Fig. 4a). Likewise, the proportion of low-severity fire occurring was a third lower with previous very high/extreme severity than with previous low severity (Fig. 6a). The Moran's I test also indicated a low level of spatial autocorrelation ($I = 0.162$, $Z = 13.061$, $P < 0.001$). This suggests that autocorrelation did not substantially influence the models.

Very high/extreme severity

The statistical model determined to be the most meaningful in determining the probability of very high/extreme severity, using Akaike weights, contained every measured predictor variable (Table 2), and explained 14.0% of the deviance. There were no supported alternative models. Previous fire severity was the strongest predictor of crown fire probability ($P < 0.001$; Fig. 4d). The model had an accuracy of 84.6% in the training data, compared to 84.8% in the test data (Fig. 5a, b).

Forest Fire Danger Index had a positive relationship with the occurrence of very high/extreme severity ($P < 0.001$, Fig. 4b). Topographic position had a slight positive effect, but it was not statistically significant ($P = 0.09$; Fig. 4c). Fire interval had a non-linear effect on the likelihood of very high/extreme severity ($P < 0.05$), with a decrease in likelihood after 16 yr; however, the overall

Table 2. The GAM model for very high/extreme severity included all variables.

Variable	df	χ^2	P
Prev. severity	1	125.99	***
topos	1	2.90	0.09
FFDI	1	29.78	***
Interval	2.99	10.70	*
Slope \times solrad	8.38	68.36	***

Note: Prev. severity is the previous severity, Interval is the length of time between fires, topos is topographic position, solrad is solar radiation, and FFDI is Forest Fire Danger Index.
* $P < 0.05$, *** $P < 0.01$.

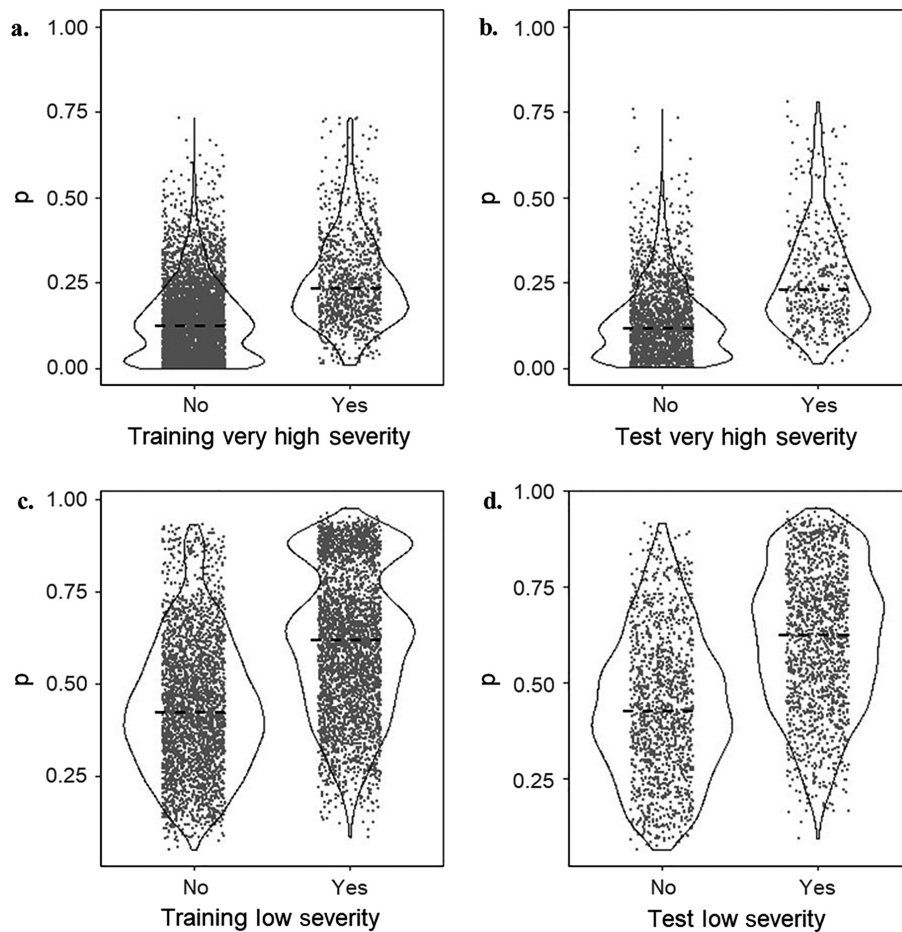


Fig. 5. Predicted values (y -axis) from the fitted models, plotted over the observed values (x -axis) of very high/extreme severity (a, b) and low severity (c, d) for the training and testing data. Violin plots show the probability density, and the dashed line is the median.

effect of interval was small (Fig. 4e). There was an interactive effect of slope and solar radiation on the occurrence of very high/extreme severity ($P < 0.001$). As slope increased, solar radiation had an increasingly negative relationship with very high/extreme severity (Fig. 4f).

Low severity

The low-severity fire model with the highest Akaike weight contained the variables: previous severity, slope, topographic position, fire interval, and FFDI (Table 3), and explained 14.4% of the deviance. This model contained no interactions between variables and there were no supported alternative models. Previous fire severity was the strongest predictor of low severity ($P < 0.001$; Fig. 6d). The model had an accuracy of 67.9% in

the training data, compared to 67.7% in the test data (Fig. 5c, d).

Topographic position, FFDI, and fire interval all had negative effects on the occurrence of low-

Table 3. The best GAM model for low-severity fire likelihood.

Variable	df	χ^2	P
Prev. severity	1	85.32	***
topos	1	4.56	*
Interval	1	7.12	**
FFDI	1	75.83	***
Slope	4.97	71.48	***

Note: Prev. severity is the previous severity, Interval is the length of time between fires, topos is topographic position, solrad is solar radiation, and FFDI is Forest Fire Danger Index. * $P < 0.05$, ** $P < 0.01$, *** $P < 0.001$.

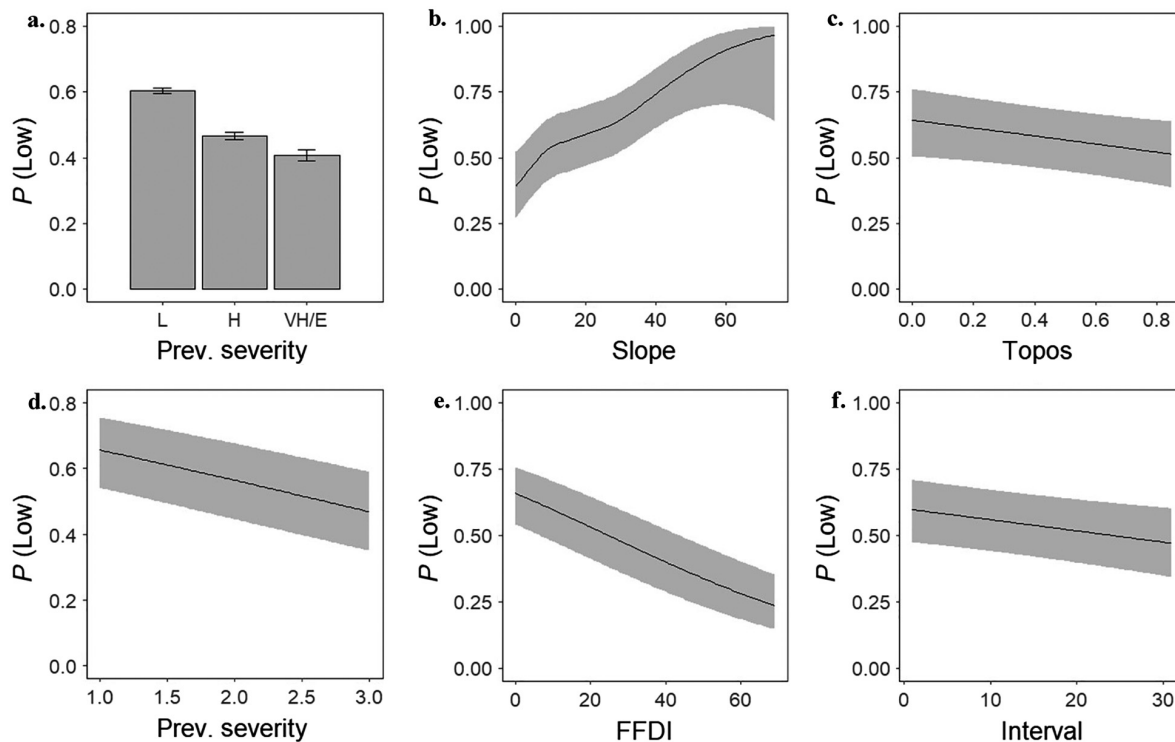


Fig. 6. (a) The proportion of low severity for each level of previous severity in the raw data. The model predictions for the independent effect of each variable; (b) slope, (c) topographic position, (d) previous severity, (e) FFDI, and (f) fire interval (in years), on the probability of low-severity occurrence, with the shaded areas of the line graphs representing 95% confidence.

severity fire ($P < 0.05$, $P < 0.001$, $P < 0.01$, respectively; Fig. 6c, e, f), while slope had a positive and slightly non-linear relationship with the probability of low severity ($P < 0.001$; Fig. 6b).

DISCUSSION

The effect of previous severity

The likelihood of very high/extreme severity was low compared to low severity, but it was significantly more likely after previous very high/extreme severity. Conversely, the probability of fire restricted to the understory decreased with increasing severity in the previous fire. These results support our hypothesized response of a positive feedback and match the relationships found in previous studies from North American conifer forests (Thompson et al. 2007, Thompson and Spies 2010, van Wagtenonk et al. 2012).

Thompson and Spies (2010) found that the pattern of severity was strongly influenced by the shrub layer of vegetation, while the distribution

of the canopy had no effect. The influence of one fire on another may also be mediated through the shrub layer in our Australian Eucalypt forests. Very high-/extreme-severity fire has been found to stimulate rapid regrowth in eucalypt species (Williams et al. 2012), and in species from the shrub layer (Clarke et al. 2015, Gordon et al. 2017). Clarke et al. (2005) found that there is a mass recruitment of understory species after a severe fire in eastern Australian vegetation, and these plants reach maturity within ten years of the fire. A study in Warrumbungle National Park by Gordon et al. (2017) found that shrub growth after a fire was more vigorous in high-severity patches than in low-severity patches. Similarly, in California, Coppoletta et al. (2016) also found an increase in shrub vegetation after severe fire, which promoted further high severity in a subsequent fire. Shrubs may act as ladder fuels, allowing the vertical spread of fire from the understory into the canopy, creating a crown fire (Menning and Stephens 2007). While it may be assumed that

rapid growth in the shrub layer after a fire results in higher fuel loads, leading to an increased probability of future crown fire, the specific effect of shrub cover on fire severity has not been quantitatively examined.

It is unknown if the positive feedback found in our study continues after the second fire, or if there are limits. It may be the case that continued successive crown fire would reduce plants' ability to recover, leading to a reduction in fuel over time. A continued positive effect could lead to patches with divergent fire regimes and ultimately different species next to each other, driven entirely by their fire history. Liyanage and Ooi (2015) found high levels of variation in the germination of individual plants from heat treatments. This suggests that, while the shrub layer may facilitate the relationship between fires, the composition of the vegetation may also introduce further variation.

There is evidence that the fire regime does influence the species composition (Morrison et al. 1995), though only frequency and interval (not severity) have been studied in the past. If plant species composition changes, it might provide further impetus for high-severity fires, like the postulated grass–fire cycle, whereby flammable grasses gradually replace less flammable shrubs through repeated burning (Rossiter et al. 2003, Bowman et al. 2014). Alternatively, the new species might be less flammable and so limit the runaway severity effect. Further studies are required to examine the influence the severity of multiple fires has on subsequent severity, and the effects of severity on vegetation regrowth.

The positive feedback we found in this study also has management implications for the impact of fire on human lives and property, especially with the trends in increasing fire frequency, shortened intervals between fires, and increasing fire extent, due to climate change (Cary et al. 2006, Bradstock 2010, Moritz et al. 2012, Enright and Fontaine 2014). Although the promotion of successive severe fires may potentially increase risk, this study has also revealed a process through which this may be mitigated. Our results suggest that low-severity fire promotes more low-severity fire, so it may be possible to use low-severity prescribed fire to interrupt cycles of high severity and reduce human risk. This may be somewhat dependent on the properties of location, but the

relationship between severities was found to be strong in this study, so there is potential for this to be an effective method.

Fire interval

There was some evidence of a weak non-linear effect of fire interval on very high/extreme severity, and a linear effect on low severity. This is counter to the hypothesis, which predicted an interactive effect between fire interval and severity. The most likely reason for the lack of a strong effect is that the minimum fire interval was four years, so the immediate reduction in severity that was expected was not captured by the data. Gordon et al. (2017) found dense shrub growth 18 months after a fire, and a study of planned burns in Eucalypt forests found that understory vegetation returned to 77% of the pre-fire biomass one year after fire (Jenkins et al. 2016), indicating that much of the revegetation would have already occurred at the four-year interval in the current study. Bradstock et al. (2010) found very little crown fire at time since fire < 5 yr, though Price and Bradstock (2012) found an effect of previous burning lasting up to ~7 yr.

In our study, the probability of very high/extreme severity was low from 4 to 10 yr since the previous fire, after which there was a slight increase. There was then a decrease in very high/extreme severity from 17 to 30 yr. However, this may be an artifact of the data and requires fire occurrence data to validate. However, the curve of the relationship between fire interval and very high/extreme severity does match the relationship found using a fire behavior model (Zylstra et al. 2016). The likelihood of low-severity fire decreased linearly with increasing fire interval. The overall effect of fire interval on severity remained small. Storey et al. (2016) also found a non-linear effect of time since the previous fire on severity in the Sydney region. That study found that severity peaked around ten years since the previous fire, with a distinct decrease after this time. A study in the USA also found that fire severity remained low with less than four years since the previous fire, increasing afterward (Coppoletta et al. 2016). Lydersen et al. (2014) found that severity was also low up to fourteen years since the previous fire, in mixed conifer forests. Neither of these studies found a decline in severity over time. The most likely

explanation of the decline over time in our study and Storey et al. (2016) is that shrubs in dry eucalypt forests begin to thin after about 10 yr, and so gradually reduce the likelihood of very high/extreme severity.

Other variables

The topographic effects suggest that the severity of fires is linked to the inherent properties of a site. This is supported by previous research in NSW (Bradstock et al. 2010, Clarke et al. 2014, Storey et al. 2016).

The probability of low severity increased with slope. This has also been found previously in the Sydney region (Bradstock et al. 2010, Storey et al. 2016). Bradstock et al. (2010) suggest that this is due to rock outcrops being common on steeper slopes, reducing fuel continuity and preventing fire from reaching the canopy. Greater values of topographic position had a reduced probability of low severity, though there was no effect on very high/extreme severity. This provides weak evidence that severity is higher on ridge tops, than in valleys or on hillsides, which has also been found previously (Bradstock et al. 2010, Price and Bradstock 2012). Topographic position is a surrogate for tree height, fuel moisture, and wind exposure. Ridges have shorter trees than valleys and are more exposed to wind (Bradstock et al. 2010), creating a greater chance of fire reaching the crowns of trees. Valleys have higher fuel moisture than ridges, reducing fire risk.

There was an interaction between slope and solar radiation, which affected the probability of very high/extreme severity. At low slopes, solar radiation had a weak positive relationship with very high/extreme severity. As slope increased, this relationship reversed, becoming a distinct negative relationship at a slope of 40°. Generally, it is thought that fires are more intense on uphill runs (Gould et al. 2007). However, slopes are also associated with low moisture (due to rockiness and high runoff). This, in combination with high exposure to solar radiation, may have reduced vegetation cover, compared to flatter areas.

While the effect of previous fire severity was strong, with clear trends, the models only captured a small percentage of deviance (14% for severe fire, 14.4% for low severity). This indicates that other factors, which were not explored, play a role in the observed patterns. The most likely missing

factor was fine-scale variation in weather conditions. The models in this study only included daily maximum FFDI values for weather data, which positively affected very high/extreme severity and negatively affected low severity. While this did have a strong influence, variation in the weather over each day, such as changes in wind speed and temperature, may have affected patterns of severity. Weather has been consistently found to have a strong influence on the behavior of fires (Hammill and Bradstock 2009, Bradstock et al. 2010, Penman et al. 2013, Storey et al. 2016). Fine-scale variation within the vegetation structure caused by topography and soil could also explain additional variability in fire severity. Simple topographic variables do not well describe this variation.

CONCLUSION

There was a positive feedback effect between fires, where high-severity fire increased the likelihood of subsequent severe fire, which has the potential for causing a runaway effect, like the self-reinforcing grass–fire cycle (Rossiter et al. 2003, Bowman et al. 2014). This has ecological and management implications, as a consistent positive feedback across many fires could lead to a change in vegetation communities. The occurrence of a runaway effect cannot be concluded from this study alone, and several consecutive fires would have to be examined to support this hypothesis.

Three key areas have been highlighted, which should be the focus of further study: (1) the ongoing feedback effects in more than two fires, and the impact of the feedbacks on vegetation; (2) the changes in fire regimes due to climate change and other processes; and (3) the potential effect of prescribed burning, and other fuel treatments, to break the feedback effects found in this study.

ACKNOWLEDGMENTS

We thank Phil Zylstra, Mark Ooi, and Meaghan Jenkins for valuable comments at different stages of this work, and Michael Bedward for robust statistical advice.

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