

# Can precipitation influence landscape controls on wildfire severity? A case study within temperate eucalypt forests of south-eastern Australia

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**Abstract.** The environmental, economic and social impacts of wildfires depend on spatial patterns of fire severity. An understanding as to how drivers of fire severity vary across broad vegetation communities exists. However, examination of variation within communities in response to gradients of moisture has received little attention so far. This study examined whether relationships between environmental variables (i.e. fire weather, topography and fuel age) and fire severity were modified by increasing mean annual precipitation. Understorey fires were more likely to occur in young fuels (i.e. <5 years since fire) in drier sites, although this effect diminished as precipitation increased. The probability of occurrence of understorey fires under non-extreme weather and on steep slopes was reduced in wetter areas. Relationships between crown fire and weather, topography and fuel age were largely unaltered by the precipitation gradient, with only a marginally significant interaction occurring between weather and mean annual precipitation. Greater fine fuel accumulation associated with increased precipitation presumably reduced fuel limitations imposed by environmental factors (i.e. fire weather, slope, fuel age), altering their relative control on the probability of understorey fire. The probability of crown fires is predominantly driven by fire weather and is consequently less sensitive to precipitation gradients. Consideration of precipitation gradients will be necessary when identifying controls of fire severity and devising effective fire management strategies.

**Additional keywords:** dry sclerophyll forest, fire management, fire regimes.

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## Introduction

Large wildfires show considerable spatial variability in severity (i.e. the degree of vegetation damage or consumption) across temperate forest ecosystems (Bradstock 2008; Schoennagel *et al.* 2008), which may reflect underlying variations in fire intensity (Keeley 2009). Ecologically, this variability may be beneficial as it can create heterogeneity in forest structure (Franklin *et al.* 2002) and ecosystem function (Schoennagel *et al.* 2008). Furthermore, the spatial arrangement of unburnt and low severity patches may influence the resilience of fire sensitive biota and communities through the provision of fire refugia (Camp *et al.* 1997; Mackey *et al.* 2002; Wood *et al.* 2011). Conditions associated with low severity fire (e.g. moderate fire weather, riparian areas, young fuels) may facilitate fire suppression (Kauffman 2001; Plucinski *et al.* 2012). By contrast, crown fires occurring at the wildland–urban interface can have disastrous implications in terms of loss of life and property (Price and Bradstock 2012). Hence, an understanding of the determinants of variations in fire severity is required to effectively manage risks to ecological and human values.

Weather, fuel availability and topography are key influences on fire severity in temperate forest ecosystems globally (Collins *et al.* 2007; Thompson and Spies 2009; Bradstock *et al.* 2010;

Murphy and Russell-Smith 2010), and are often used to quantify fire risk and wildfire probability across large spatial scales (Bradstock *et al.* 1998; Parisien *et al.* 2012). However, the relative effect that these variables have on fire regimes may vary across landscapes in response to environmental gradients (Schoennagel *et al.* 2004; Krawchuk and Moritz 2011; Perry *et al.* 2011; Price and Bradstock 2012). Landscape variation in vegetation productivity in response to variation in mean annual precipitation or soil fertility may potentially alter the relative influence of weather, fuel age and topography on severity by effects on fuel characteristics (i.e. accumulation rates and total biomass). In much of Australia and other water-limited environments positive associations exist between long-term annual precipitation and tree cover or aboveground biomass (Archibald *et al.* 2009; Keith *et al.* 2009; Pekin *et al.* 2009). Consequently, fuel accumulation and connectivity is generally greater in ecosystems with high annual precipitation than ecosystems with low annual precipitation (Huston 2003; Govender *et al.* 2006; Bradstock 2010). Fire intensity and fuel biomass are likely to be positively related (Gill *et al.* 1987), though fuel structure and moisture will also influence this relationship (Sullivan *et al.* 2012). Variations in rates of fuel accumulation therefore have the potential to affect fire intensity and resultant fire severity.

Fuel reduction burning is utilised across large areas of temperate forest ecosystems to manage wildfire risk (Fernandes and Botelho 2003; Penman *et al.* 2011). This management technique aims to reduce fuel loads and consequently the intensity, and hence severity, of subsequent wildfires, in order to increase the likelihood of suppression by fire crews (Fernandes and Botelho 2003). The frequency at which fuel reduction burns are applied within a landscape is generally predicated on relationships between fuel accumulation, time since fire and fire intensity (Gill *et al.* 1987; Morrison *et al.* 1996; Penman *et al.* 2011). However, studies examining time since fire–fuel relationships are often limited in geographic extent (e.g. Fox *et al.* 1979; Morrison *et al.* 1996; Penman and York 2010) and rarely consider the effect of precipitation gradients across a vegetation community. Spatial variation in fuel accumulation will have important implications for fire management, as it will shape the temporal window of fuel reduction burning effectiveness and overall fire suppression potential across a landscape (Fernandes and Botelho 2003; Schoennagel *et al.* 2004). Broad scale analysis of relationships between fuel age (i.e. time since fire) and fire severity patterns across spatial gradients of precipitation may provide a way of quantifying these effects.

Quantification of the effect of gradients of productivity on fire severity requires measurement of fire severity over large areas (e.g. 100 000 ha). Remote sensing offers the opportunity to undertake such measurements through the use of satellite imagery (Lentile *et al.* 2006). Previous studies have found strong correlations between pre- to post-fire change in reflectance (e.g. Normalised Difference Vegetation Index, difference Normalised Burn Ratio) and field based measures of vegetation consumption (Chafer *et al.* 2004; Hammill and Bradstock 2006; Keeley 2009). Remotely sensed indices of reflectance change have been frequently utilised to identify variables driving spatial patterns of fire severity across forested landscapes (Collins *et al.* 2007; Bradstock *et al.* 2010; Murphy and Russell-Smith 2010).

The aim of this study was to determine whether the effects of key drivers of fire severity (i.e. weather, topography and fuel age) change along a gradient of mean annual precipitation. We anticipate that greater mean annual precipitation will reduce fuel limitations and consequently reduce the influence of key fire severity drivers, in particular fuel age and weather. Our study utilised existing severity data from four large wildfires (>40 000 ha) that burnt within temperate dry sclerophyll forests and woodlands of the Sydney region during summer 2001–02. The fires burnt concurrently under similar weather conditions in comparable environments that differ in mean annual precipitation. Therefore, these fires provide a controlled natural experiment that is appropriate to investigate how drivers of fire severity vary along gradients of mean annual precipitation.

## Methods

### Study area

The Sydney region of south-eastern Australia (Fig. 1) is characterised by large areas of urban development surrounded by expanses of natural bushland. The dry sclerophyll eucalypt forests covering much of this area are highly flammable and characterised by rapid fuel accumulation (Fox *et al.* 1979;

Morrison *et al.* 1996), which accompanied with periodic conditions of drought and extreme fire weather, make this region prone to recurrent large wildfires (Bradstock *et al.* 2009).

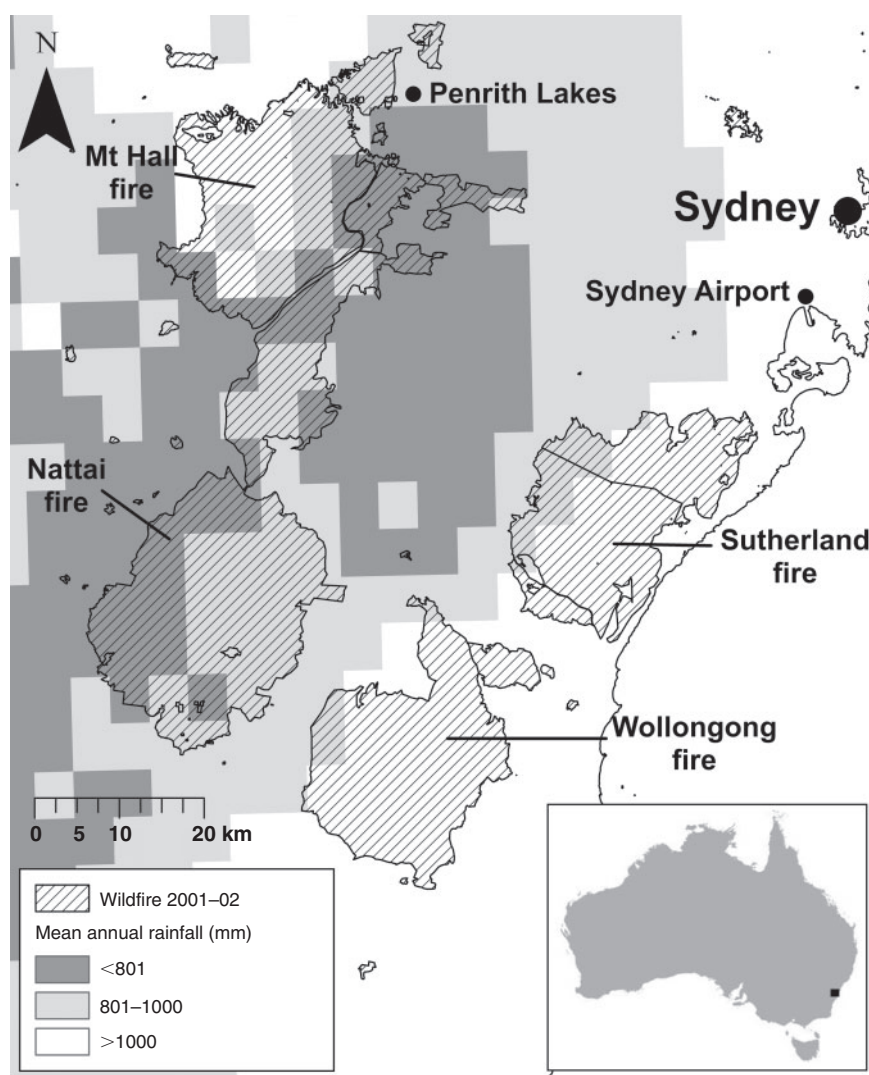
A gradient of decreasing mean annual precipitation occurs from east to west across the study region, inland from the coast. Near the coast (i.e. Sutherland and Wollongong) mean annual precipitation ranges from ~900 to 1500 mm, declining to ~600 to 1000 mm further west on the margins of the Blue Mountains (i.e. Mount Hall and Nattai) (Fig. 1; Bureau of Meteorology, see <http://www.bom.gov.au/jsp/awap/rain/index.jsp>, accessed 2 February 2010). Mean annual precipitation then increases in the Blue Mountains (i.e. within and to the west of the Mount Hall fire perimeter) (Fig. 1). The study focussed on this gradient of long-term average rainfall (Table 1). Mean daily maximum temperatures range from 25 to 31°C in the summer months and mean daily minimum temperatures range from 2 to 10°C in the winter months. Average maximum temperatures are typically greatest at the centre of the study region, declining towards the coast and mountains. Average minimum temperature tends to be greater on the coast than inland (www.bom.gov.au, accessed 7 March 2013).

The region is characterised by locally pronounced relief, consisting of ridges and plateaus that are dissected by networks of gullies and gorges (Fairley and Moore 2000). The average ridge–gully distance across the study area is ~400 m (Bradstock *et al.* 2010). Terrain becomes more deeply incised from the coast to the foothills of the Blue Mountains, which is reflected by the greater average slope and topographic position index (i.e. difference between site elevation and highest elevation within the surrounding 1000 × 1000-m window) in the Mount Hall and Nattai landscapes compared with Sutherland and Wollongong (Table 1). Triassic sandstones are the dominant geological substrate across the study region (Fairley and Moore 2000).

Vegetation across the study area is dominated by dry sclerophyll forest and woodland communities with an open canopy largely comprised of *Eucalyptus*, *Corymbia* and *Angophora* species (Keith 2004). Canopy species in these communities typically resprout following fire by epicormic buds beneath their bark, and have been shown to exhibit low rates of mortality (<5%) following high intensity crown fires (Bradstock 2008). Canopy height typically ranges from 10 to 30 m, and the understorey, dominated by sclerophyllous shrubs, is generally up to 4 m tall (Keith 2004). Variation in the structure and composition of these communities across the study region is driven largely by precipitation and soil fertility (Fairley and Moore 2000). The drier hinterland forests and woodlands (annual precipitation ~650–950 mm) of the study region have similar vegetative structure but a more open and less diverse shrub layer than the wetter coastal forests and woodlands (annual precipitation >1000 mm) (Keith 2004). Evidence suggests that fuel hazard development in dry sclerophyll forest and woodlands of this region is slower in drier cooler climates than wetter warmer climates (Watson *et al.* 2012), as has been found in other areas of southern Australia (Huston 2003).

### The 2001–02 Sydney fires

The study focussed on four large fires (>40 000 ha; the Mount Hall, Nattai, Sutherland and Wollongong fires) that burnt during



**Fig. 1.** Location of the study area and the four study fires within the Sydney region of Australia. The location of the two weather stations (i.e. Penrith Lakes and Sydney Airport) used to calculate the forest fire danger index is also presented.

**Table 1.** Summary of slope, topographic position and mean annual precipitation across the study area

Mean ( $\pm$ s.e.) of slope, topographic position and mean annual precipitation from each of the study fires. Values are based on data from sample points used in the analysis of fire severity patterns. Topographic position is the difference in elevation (metres) between a sample point and the highest local point within a surrounding  $1000 \times 1000$ -m sample window

Fire	<i>n</i>	Slope ( $^{\circ}$ )	Topographic position	Mean annual precipitation (mm)
Mount Hall	692	$19.81 \pm 0.44$	$72.66 \pm 2.12$	$891.12 \pm 3.87$
Nattai	577	$19.21 \pm 0.45$	$101.35 \pm 3.78$	$816.89 \pm 2.56$
Sutherland	582	$9.34 \pm 0.26$	$39.48 \pm 0.95$	$1220.70 \pm 5.23$
Wollongong	468	$10.64 \pm 0.36$	$43.23 \pm 1.33$	$1268.81 \pm 5.71$

late December 2001 and early January 2002 (Fig. 1). All fires burnt under 'Extreme' weather conditions (temperature  $\sim 30$ – $35^{\circ}\text{C}$ ; relative humidity 7–15%; wind speed  $30$ – $40 \text{ km h}^{-1}$ ) on 25 December. Weather conditions eased between 27 and 30 December (temperature  $20$ – $30^{\circ}\text{C}$ ; relative humidity 20–60%; wind speed  $10$ – $30 \text{ km h}^{-1}$ ), resulting in more moderate fire

behaviour (Bradstock *et al.* 2010). The severity of these fires was mapped by Chafer *et al.* (2004) using SPOT 2 (Satellite Pour l'Observation de la Terre) imagery. This involved (i) computing the Normalised Difference Vegetation Index (NDVI) for pre- and post-fire images, (ii) calculating the difference between the pre- and post-fire NDVI ( $\Delta\text{NDVI}$ ; 20-m spatial resolution) and

(iii) classifying  $\Delta$ NDVI into six severity classes based on on-ground measures of vegetation consumption (Chafer *et al.* 2004). The classification had at least 88% accuracy (Chafer *et al.* 2004), with independent verification finding high levels of agreement (Hammill and Bradstock 2006). Bradstock *et al.* (2010) subsequently utilised this severity mapping to examine the relative influence that weather, time since fire, topographic position, slope and aspect had on patterns of fire severity for the Mount Hall and Nattai fires, which occur at the low end of the precipitation gradient (Fig. 1).

Our study utilises fire severity mapping derived by Chafer *et al.* (2004) to examine whether the effect of weather, topography and fuel age on fire severity is dependent upon annual precipitation. Six severity classes were mapped: (1) foliage and stems <10 mm in the shrub and tree canopy layer consumed, (2) shrub foliage consumed and tree canopy partially scorched or consumed, (3) understorey shrub fire with complete tree canopy scorch, (4) understorey shrub fire with partial tree canopy scorch, (5) understorey shrub fire with no tree canopy scorch and (6) unburnt. Binary reclassification was undertaken as per Bradstock *et al.* (2010) to permit two separate analyses focusing on (i) understorey fire (1: classes 3, 4, 5, 6; 0: classes 1, 2) and (ii) crown fire (1: class 1; 0: classes 2, 3, 4, 5, 6). Understorey fires (UF) are confined to the shrub and ground layers, with unburnt patches sometimes present. These fires burn at low to moderate intensity (i.e. <1500 kW m<sup>-1</sup>) and are potentially suppressible. Crown fires (CF) are those that enter the tree canopy (i.e. consuming all vegetation <10 mm thick) and burn at intensities at which fire suppression is not possible (10 000–70 000 kW m<sup>-1</sup>) (Bradstock *et al.* 2010).

### Data

A combination of fire progression data and daily weather observations were utilised in order to identify the climatic conditions under which different parts of the study area burnt. Meteorological data from Penrith Lakes (station number 67113) and Sydney Airport (station number 66037) weather stations (Fig. 1) were used to calculate daily estimates of the McArthur Forest Fire Danger Index (FFDI), which is commonly used to assess fire risk across eucalypt forests (Noble *et al.* 1980). Fire weather was subsequently classified as extreme (EX – maximum FFDI 60–100) or non-extreme (NEX – maximum FFDI <35). A combination of MODIS satellite imagery, NOAA hotspot

data, web fire mapper (<http://firefly.geog.umd.edu/firemap/>, accessed 3 February 2009) and written accounts (NSW Rural Fire Service, unpubl. data) were used to digitise progressive boundaries of the fires, and subsequently identify areas that burnt under EX (1100 hours–~1800 hours 25 December) and NEX (1100 hours 27 December–1100 hours 31 December) weather. The use of MODIS imagery and hotspots has been found to provide estimates of fire progression that are comparable to on-ground mapping (Bradstock *et al.* 2010). In order to increase sample size for NEX observations in the Sutherland fire additional areas that burnt under NEX weather (FFDI <20) between 3 and 6 January 2002 were included. These areas were identified using hotspots and fire progression records (NSW Office of Environment and Heritage, unpubl. data).

Three measures of topography were used in our analysis, namely topographic position, slope and aspect (Table 2). These layers were generated using digital elevation models (25-m resolution) obtained from the NSW Office of Environment and Heritage (OEH). Topographic position (TOPOS) was calculated as the difference in elevation (metres) between a pixel and the highest local point within a surrounding 1000 × 1000-m sample window. This provided a continuous measure of topographic position in which ridges are typically represented by small values and gullies are represented by large values. Slope was calculated using the Spatial Analyst Tool in ArcGIS (9.2). Aspect was calculated as a continuous measure relative to north as described in Penman *et al.* (2007), which resulted in values ranging from 0 to 180° (i.e. values approaching 0° represent northerly aspects, values approaching 180° represent southerly aspects).

Digitised fire history records (NSW OEH, unpubl. data) were used to create a layer of time since fire (TSF) from the 1976–77 fire season to the 2000–01 fire season. Areas with no recorded fires in this period were assigned the maximum TSF of 25 years. A range of fuel ages were recorded across the study sites (0–25 years), though these were heavily distributed towards the older age classes (i.e. >15 years; Table 2). A logarithmic transformation (i.e.  $\ln[x+1]$ ) was performed to TSF, due to the non-linear trend in fuel accumulation within eucalypt forests (Fox *et al.* 1979; Morrison *et al.* 1996; Penman and York 2010). Mean annual precipitation for the period 1977 to 2001 was calculated using monthly rainfall grids (0.05° resolution) obtained from the Bureau of Meteorology

**Table 2.** Predictor variables used in the regression analysis

Variable	Description	Format	Data range (untransformed)
WEATHER	Fire weather: Extreme (EX): maximum FFDI > 60 Non-extreme (NEX): maximum FFDI < 35	Categorical	–
MAP	Mean annual precipitation in millimetres (1976–2001). A precipitation ratio (point value/dataset mean) was used for model fitting (see text)	Continuous	663–1532
TSF	Time since fire (years), $\ln(x+1)$ transformed. This variable included both wildfire and prescribed burns.	Continuous	0–25
TOPOS	Topographic position (see text)	Continuous	0–393
SLOPE	Slope (°)	Continuous	0–72
ASPECT	Aspect relative to north (see text)	Continuous	0–180
SLRV	Spatially lagged response variable (see text)	Continuous	–1.8–3.5



(<http://www.bom.gov.au/jsp/awap/>, accessed 2 February 2010). Details of the derivation of the monthly grids are provided in Jones *et al.* (2009). A proportional measure of mean annual precipitation (MAP) was used in the analyses as it facilitated model fitting. This was calculated by dividing the mean annual precipitation for a sample point by the mean of all sample points (mean = 1032 mm). Back-transformed values of mean annual precipitation are presented in figures for ease of interpretation.

A grid of data points with 400-m spacing was generated using 'Hawths Tools' (v3.27) in order to sample variables used in the analysis. Spacing of 400 m was utilised as it represents the typical ridge–gully distance across the study area, and hence the spatial grain at which fire severity consistently varies (Bradstock *et al.* 2010). Sampling was restricted to dry sclerophyll forest vegetation communities, as defined by Tindall *et al.* (2004), occurring within reasonably undisturbed vegetation located in National Parks, water catchments and military training areas. Sampling was excluded from within 40 m of fire trails and roads, 60 m of powerlines, 20 m of significant water bodies (i.e. dams, lakes, rivers with pooled water) and 100 m of conservation area boundaries. Data were extracted from layers of fire severity, weather, terrain, time since fire and precipitation at each sample point using the Spatial Analyst Tool in ArcGIS (9.2).

### Data analysis

Spatial autocorrelation in fire severity data was assessed using Moran's *I*, which is a measure of correlation between data points at different spatial proximities (Haining 2003). Values between one and six were assigned to each of the six ordinal categories of severity (as described earlier in the text) and used to calculate Moran's *I*. A spatial variogram indicated that data were spatially autocorrelated ( $P < 0.000$ ) up to a distance of 12 000 m, which approximately equates to the size of the sampling area within each fire. This suggests that spatial autocorrelation was only an issue within the perimeter of individual fires. A spatially lagged response variable (SLRV) was derived, as described in Haining (2003), from the classified fire severity data. For each data point, the SLRV represents the sum of the fire severity scores, transformed according to an inverse-distance weighting, within a 12 000-m radius. The following equation was used to calculate the SLRV for a data point (Threlfall *et al.* 2011):

$$SLRV_i = \frac{\sum_j (W_{ij} \times Y_j)}{\sum_j W_{ij}} \quad (1)$$

where *i* represents the focal data point, *j* represents a point within the 12 000-m radius of the focal point, *W* represents the inverse distance between *i* and *j* and *Y* represents the response variable (i.e. fire severity). Low SLRV values will represent points where there is a large area of the surrounding landscape burnt at high severity and high SLRV values will represent areas where there is a large area of the surrounding landscape burnt at low severity. The SLRV was fitted as a model term in all models, in order to adjust model coefficients of predictors to account for the effect of spatial autocorrelation (Haining 2003). If spatial autocorrelation is present, the SLRV will show a significant negative relationship with CF and a positive relationship with UF.

Logistic regression was used to model the probability of occurrence of UF and CF as binary responses. The process used for testing assumptions and model selection was based on methodology described in Logan (2010) and Burnham and Anderson (2002). Prior to model fitting, the Pearson correlation coefficient and variance inflation factor were respectively used to test for correlation and multi-collinearity between predictor variables (Logan 2010). Correlation coefficients between predictor variables were generally small (i.e.  $<0.5$ ), and coefficient estimates did not vary significantly when correlated variables were added to the same model, hence multicollinearity was assumed to be absent. Analyses were done using a randomly selected subset (75%) of the data. For each severity response (i.e. UF, CF) all combinations of weather, topographic position, slope, aspect, time since fire, mean annual precipitation and two way interactions involving mean annual precipitation were modelled. Akaike's information criterion (AIC) was used to select the best model, whereby the model with the lowest AIC is considered to have the best fit (Burnham and Anderson 2002). Models within two AIC points of the model with the lowest AIC score are considered to have strong support and were considered as plausible alternatives, with the most parsimonious model being selected preferentially (Burnham and Anderson 2002).

The discriminative ability and predictive accuracy of each model was examined using the remaining 25% of the data. Discriminative ability of the models was assessed using Receiver Operating Characteristic area under curve (ROC AUC). A ROC AUC value of 1 indicates that a model has perfect discrimination, whereas a value of 0.5 would be the equivalent of a random guess (Pontius and Schneider 2001). The predictive accuracy of the models was assessed by calculating the proportion of data points for which a fire severity class was correctly assigned by each model. This was undertaken using a model cut-off point of 0.5 (i.e. predicted probability  $<0.5$  was classed as 0; predicted probability  $\geq 0.5$  classed as 1). Model derivation, probability plots and ROC AUC analyses were done using the software package R v 2.11.1 (R Development Core Team 2010). The package 'ROCR' (Sing *et al.* 2009) was used to calculate ROC AUC and predictive accuracy.

Following the model selection process, hierarchical partitioning was used to assess how the relative contribution of weather, topography and time since fire to goodness of fit (i.e. root mean square 'prediction' error) changes under different levels of mean annual precipitation. The data were grouped into two precipitation categories ('low',  $\leq 850$  mm; 'high',  $> 850$  mm) and hierarchical partitioning was performed for both UF and CF within each precipitation category. Logistic regression was also performed and the Nagelkerke's  $R^2$  index was calculated to facilitate comparison of the variability explained by each set of predictor variables. The R packages 'hier.part' (Walsh and Mac Nally 2012) and 'Design' (Harrell 2009) were respectively used for hierarchical partitioning and the calculation of  $R^2$  values.

### Results

Understorey fire and crown fire were recorded at 41 and 24% of the 2320 sample locations (Table 3). There was a reasonable spread of sample points within the different levels of fire weather (WEATHER), topographic position (TOPOS), slope

**Table 3. Summary of the data used for analysis**

Sample sizes ( $n$ ) and occurrence of different fire severity classes (UF, CF) for predictor variables used in the analysis. Data have been divided into two precipitation classes: (a)  $\leq 850$  mm and (b)  $> 850$  mm. A description of the variables is contained in Table 2

Variable	Level	$n$	UF	CF
(a) $\leq 850$ (mm)				
WEATHER	EX	419	102	109
	NEX	235	194	3
ASPECT	N (0–90)	350	154	59
	S (91–180)	304	142	53
SLOPE	0–10	174	65	39
	11–25	292	118	56
	$> 25$	188	113	17
TOPOS	0–50	259	87	72
	51–100	161	73	26
	$> 100$	234	136	14
TSF	0–7	75	49	2
	8–15	66	26	12
	$> 15$	513	221	98
(b) $> 850$ (mm)				
WEATHER	EX	857	110	374
	NEX	808	537	62
ASPECT	N (0–90)	952	356	247
	S (91–180)	713	291	189
SLOPE	0–10	776	260	240
	11–25	672	280	169
	$> 25$	217	107	27
TOPOS	0–50	997	340	302
	51–100	499	229	117
	$> 100$	169	78	17
TSF	0–7	95	39	14
	8–15	488	154	126
	$> 15$	1082	454	296

(SLOPE), aspect (ASPECT) and time since fire (TSF) across the range of mean annual precipitation (MAP; Table 3), indicating that the dataset was robust enough to assess interactions involving precipitation.

The best UF model contained TOPOS and interactions between MAP and weather, slope and TSF (Table 4). There were two plausible alternative models (i.e.  $\Delta AIC < 2$ ), which contained the same core variables as the best model and an additional variable (i.e. ASPECT or an interaction between TOPOS and MAP). The alternative models were dismissed as they were more complex and had a lower goodness of fit than the best model. The significant interactions contained in this model indicate that the effect weather, TSF and slope have on the probability of UF decreases with increasing MAP (Fig. 2a–c). Fires of low intensity (UF) were more likely under non-extreme (NEX) weather than extreme (EX) weather (Fig. 2a), as expected. Increasing MAP led to a decreased likelihood of UF under NEX weather, but had little effect on the likelihood of UF under EX weather, as expected (Fig. 2a). In areas of the landscape receiving relatively low MAP (i.e.  $< 850$  mm), UF was more likely to occur in younger fuels (0–5 years since fire) (Fig. 2b). However, as MAP increased (i.e.  $> 1000$  mm), the effect of TSF on the probability of UF diminished (Fig. 2b). Slope had a positive effect on the probability of UF, indicating

**Table 4. Model coefficients for the preferred understorey fire (UF) model**

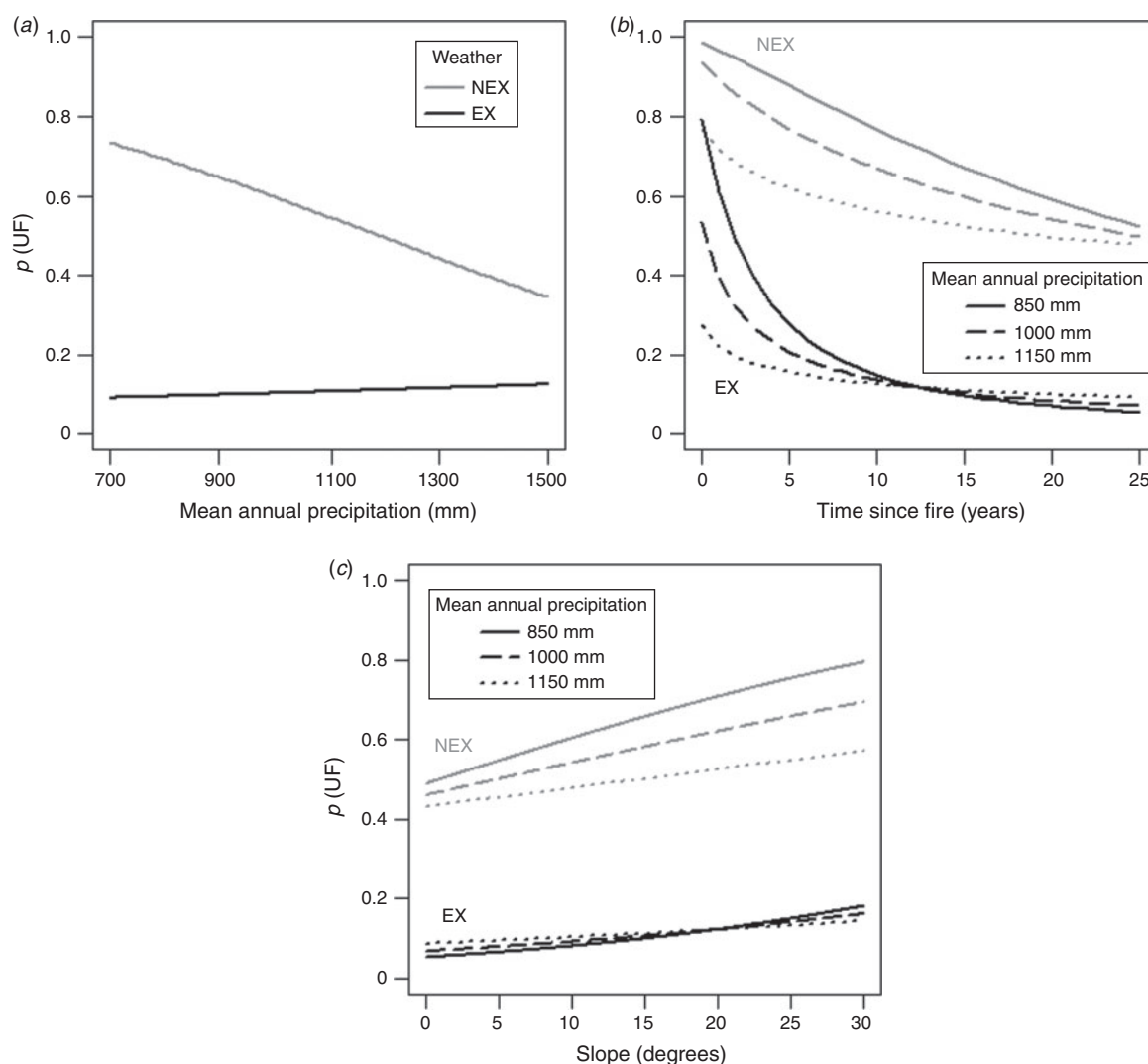
EX is the reference category in WEATHER. A description of the model terms is contained in Table 2

Model term	Coefficient	s.e.	Z-value	P-value
Intercept	5.921	1.738	3.407	0.001
SLRV	0.754	0.112	6.731	0.000
WEATHER (NEX)	5.075	0.827	6.133	0.000
TOPOS	0.009	0.001	6.850	0.000
SLOPE	0.125	0.034	3.645	0.000
TSF	−3.780	0.627	−6.024	0.000
MAP	−6.606	1.832	−3.605	0.000
MAP:WEATHER (NEX)	−2.607	0.783	−3.331	0.001
MAP:SLOPE	−0.092	0.035	−2.593	0.010
MAP:TSF	3.044	0.630	4.834	0.000

that steeper areas were more likely to experience a fire confined to the understorey than flat areas, though the magnitude of change declined as MAP increased (Fig. 2c). The effect of TOPOS remained unchanged by MAP, with gullies (i.e. high TOPOS values) having a greater likelihood of UF than ridges. This model had a very good discriminative ability (ROC AUC = 0.851) and predictive accuracy (76.3%) when applied to the test dataset.

Hierarchical partitioning revealed that for UF the relative contribution of each variable to the model goodness of fit varied with MAP (Fig. 3). TOPOS, slope and TSF accounted for ~30% of explained variance (12.3, 8.1 and 10.6%) at sites experiencing ‘low’ ( $\leq 850$  mm) MAP, but less than 5% (1.3, 2.3 and 0.6%) at sites experiencing ‘high’ ( $> 850$  mm) MAP (Fig. 3). Conversely, the relative contribution of weather and the spatially lagged response variable (SLRV; i.e. the neighbourhood influence) increased with increasing MAP, explaining ~35% of explained variance each under ‘low’ MAP and ~48% each under ‘high’ MAP (Fig. 3). However,  $R^2$  values from logistic regression models fitted to each dataset indicate that a greater amount of deviance in UF is explained under ‘low’ v. ‘high’ MAP (0.624 v. 0.499). This suggests that only the relative contribution of weather and the SLRV is altered by MAP, not the total deviance explained.

The best CF model contained TOPOS, slope, TSF and an interaction between weather and MAP (Table 5). There were five plausible alternative models (i.e.  $\Delta AIC < 2$ ), which contained the same core variables as the best model and an additional variable. However, these models were dismissed as they were more complex and had a lower goodness of fit than the best model. CF was more likely to occur under EX than NEX weather (Fig. 4). However, the likelihood of CF under NEX did increase slightly with increasing MAP (Fig. 4). In general, areas burning under NEX weather were unlikely to experience CF. Hence, the influence of topography and TSF on CF occurrence was only evident under EX weather conditions. TSF had a positive effect on the probability of CF (Table 5), indicating that under EX weather long unburnt areas were more likely to experience CF than recently burnt areas. CF had a negative relationship with slope (Table 5), indicating that flat areas are more likely to experience CF. TOPOS had a positive effect on



**Fig. 2.** Plots depicting the interactive effects of mean annual rainfall and (a) weather, (b) time since fire and (c) slope, on the predicted probability of understorey fire (UF). Grey and black lines respectively depict non-extreme (NEX) and extreme (EX) fire weather. Variables included in the preferred model (Table 4) but not shown in a plot were defined as TSF = 15, SLOPE = 15, TOPOS = 10, SLRV = 0.01. Annual rainfall (RAIN) values have been converted to millimetres for ease of interpretation. Refer to Table 2 for a description of the variables.

CF (Table 5), whereby ridges are more likely to experience CF than gullies. The ROC AUC and predictive accuracy of this model were very good, being 0.878 and 82.9%.

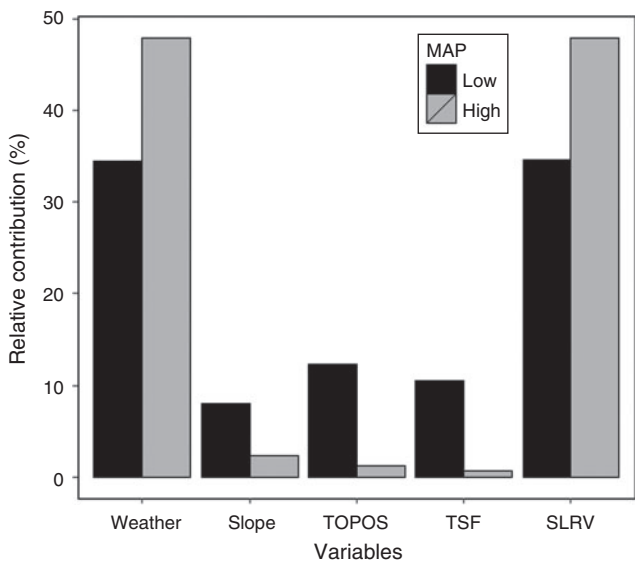
Under 'low' MAP, the severity of neighbouring pixels (i.e. SLRV) accounted for the majority (56.4%) of the explained variance in CF, with TOPOS, weather, TSF and slope accounting for 20.0, 13.9, 6.2 and 3.5% (Fig. 5). The small effect of weather at sites experiencing 'low' MAP can be attributed to the near absence of CF occurrence under NEX weather (Table 3). This result highlights the importance of weather in determining CF. Therefore, there was essentially no variance in CF under NEX weather to which the model could be fitted. It is likely that the effect of weather in the 'low' MAP dataset has been absorbed by the SLRV (Fig. 5), as sample points that are in close spatial proximity typically burnt under the same weather conditions. Under 'high' MAP, weather and the SLRV accounted for 81.5%

of explained variance (Fig. 5). The relative contribution of TSF and slope remained relatively constant across both 'low' and 'high' MAP, whereas the contribution of TOPOS declined with increasing MAP (Fig. 5). Model  $R^2$  values were greater for the 'low' MAP dataset ( $R^2 = 0.571$ ) than the 'high' MAP dataset ( $R^2 = 0.360$ ).

## Discussion

### Fire severity patterns

The effects of weather, slope and fuel age on the occurrence of potentially suppressible fire (i.e. UF) varied spatially with mean annual precipitation across dry sclerophyll forests of the Sydney region of south-eastern Australia. Weather, topography and time since fire can influence patterns in fire behaviour by altering fuel load and moisture, and hence the amount of fuel available to



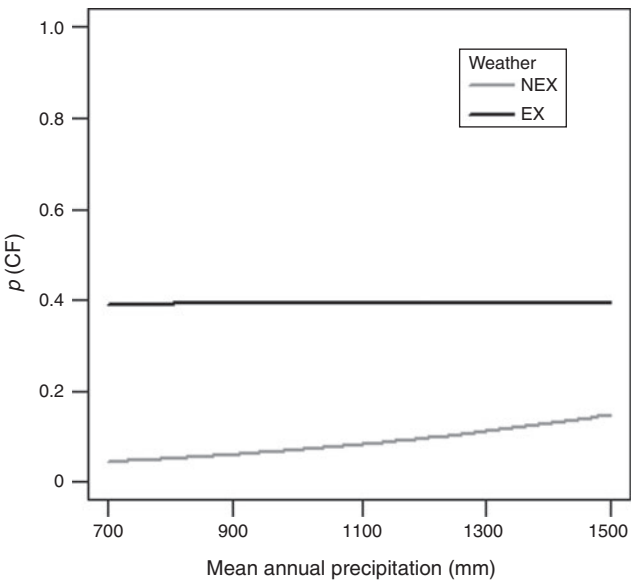
**Fig. 3.** Relative contribution (%) of predictor variables to the overall deviance in understorey fire (UF) explained by models fitted to the ‘low’ ( $\leq 850$  mm) and ‘high’ ( $> 850$  mm) rainfall data subsets. Refer to Table 2 for a description of the variables.

**Table 5.** Model coefficients for the preferred crown fire (CF) model EX is the reference category in WEATHER. A description of the model terms is contained in Table 2

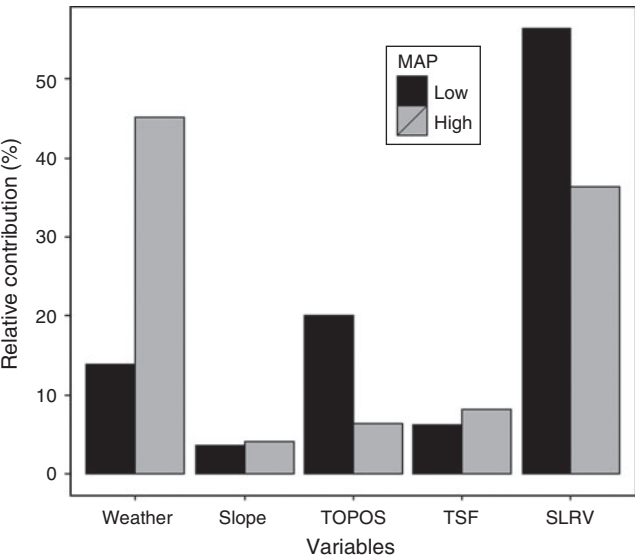
Model term	Coefficient	s.e.	Z-value	P-value
Intercept	−3.386	0.652	−5.192	0.000
SLRV	−0.757	0.120	−6.304	0.000
WEATHER (NEX)	−3.799	0.962	−3.948	0.000
TOPOS	−0.014	0.002	−6.768	0.000
SLOPE	−0.023	0.009	−2.581	0.010
TSF	1.231	0.158	7.770	0.000
MAP	0.019	0.451	0.042	0.967
MAP:WEATHER (NEX)	1.706	0.824	2.070	0.038

burn (Catchpole 2002). The evidence suggested that in environments with high mean annual precipitation the inhibitory effect of young fuel ages on severity, evident in drier environments, were greatly diminished. This is presumably due to more rapid accumulation of fine fuels in wetter environments (Huston 2003). Although decomposition rates have been shown to increase with precipitation (Austin 2002; Penman and York 2010), decreased decomposition rates in the first couple of years following fire (Penman and York 2010) may counterbalance this effect. Drought in the months preceding the 2001–02 Sydney fires ensured fuel across much of the study region was sufficiently dry to burn (Chafer et al. 2004; Caccamo et al. 2012). Thus, differences in fuel moisture were unlikely to have affected severity among the study sites at the time of the fires.

The varied effect of both weather and slope on UF across the gradient of mean annual precipitation probably reflects changes in fuel biomass and connectivity. The likelihood of fire being confined to the understorey (i.e. UF) decreased with increasing mean annual precipitation under NEX weather (Fig. 2a). It is



**Fig. 4.** Plots depicting the interactive effects of annual rainfall and weather on the predicted probability of crown fire (CF). Variables included in the preferred model (Table 5) but not shown in a plot were defined as TSF = 15, SLOPE = 15, TOPOS = 10 and SLRV = 0.01. Annual rainfall (RAIN) values have been converted to millimetres for ease of interpretation. Refer to Table 2 for a description of the variables.



**Fig. 5.** Relative contribution (%) of predictor variables to the overall deviance in crown fire (CF) explained by models fitted to the ‘low’ ( $\leq 850$  mm) and ‘high’ ( $> 850$  mm) rainfall data subsets. Refer to Table 2 for a description of the variables.

likely that greater fuel loads, including a well developed mid-layer of sclerophyllous shrubs, associated with increased precipitation (Huston 2003; Keith 2004) are responsible for this trend. Fire behaviour models for eucalypt forest predict that if weather (i.e. FFDI) is held constant, fire intensity will be greater under higher fuel loads (Gill et al. 1987), which supports our



explanation. Steep slopes were more likely to experience understorey fire than gentle slopes when mean annual precipitation was low and weather was NEX. This is most likely due to discontinuous fuels associated with rock outcropping on steep slopes (Bradstock *et al.* 2010). However, the effect of slope became more benign as annual precipitation increased (Fig. 2c), presumably due to increased fuel continuity associated with wetter areas.

Crown fires are strongly driven by fire weather (i.e. high temperatures, low humidity, strong winds) (Luke and McArthur 1978; Thompson and Spies 2009; Price and Bradstock 2012), which may explain why mean annual precipitation had little effect on the occurrence of these fires. Under NEX weather there was a small increase in the likelihood of crown fire when going from low to high mean annual precipitation (Fig. 4). This probably reflects the influence that the vertical continuity of fuels have on the incidence of CF (Luke and McArthur 1978; Catchpole 2002; Sullivan *et al.* 2012). Tall shrubs and tree bark (i.e. fibrous bark or long bark ribbons) provide vertical continuity between litter and canopy fuels and therefore increase the likelihood of CF (Sullivan *et al.* 2012). Forests within the wetter regions of the study area typically have greater shrub cover than those in the drier regions (Keith 2004). Bark and shrub fuels (i.e. biomass and structure) may also take several decades to fully develop this potential in dry sclerophyll forests and woodlands (Fox *et al.* 1979; Department of Sustainability and Environment 2003). This would explain why there was a greater likelihood of CF in long unburnt areas. Obligate seeders and basal resprouters, which are species that are effectively returned to a juvenile phase following fire, are a major component of the shrub layer within dry sclerophyll forest communities of the Sydney region (Bradstock and Kenny 2003). Therefore, the post-fire recovery of shrub fuel structure will be strongly time dependent, which may help explain why mean annual precipitation had no effect on the relationship between fuel age and CF occurrence.

Topographic position appeared to have a consistent effect on fire severity across the region regardless of mean annual precipitation (Table 4), whereby gullies typically experienced fires confined to the understorey. Although the amount of variance explained by topographic position was lower in areas of 'high' v. 'low' mean annual precipitation (Fig. 3), this merely reflects the tendency for coastal areas with high mean annual precipitation to have lower topographic relief (Table 1). Ridges typically experienced more severe fire, and CF generally only occurred on long unburnt ridges under extreme fire weather. Reduced fire severity and fire occurrence within gullies and riparian areas is commonly reported in temperate forests (Taylor and Skinner 1998; Beaty and Taylor 2001; Penman *et al.* 2007; Wood *et al.* 2011), though variation in this trend may occur across landscapes and fire events (see Dwire and Kauffman 2003). Greater fuel moisture and reduced wind exposure within gullies are the most probable explanations for the patterns observed in our study (Bradstock *et al.* 2010).

The amount of variation in fire severity explained by our models will be inherently limited by the quality and availability of explanatory data (e.g. fire history, fuel moisture), an issue relevant to all studies of this nature. For example, the fire history database used to calculate time since fire contained virtually no information on fire severity and patchiness, which will directly

influence post-fire fuel accumulation rates. This will have generated noise in the modelled relationships between time since fire and fire severity. Similarly, we were unable to directly measure and account for fuel moisture before the fires at an appropriate spatial scale. Satellite imagery has the potential to provide broad scale fuel load and fuel moisture information (e.g. Chafer *et al.* 2004; Caccamo *et al.* 2012), though products with both appropriate spatial resolution (e.g. ~10 m) and return intervals (e.g. days) are not readily available. Fire suppression activities (i.e. backburning, aerial water bombing, on-ground fire fighting), which may influence patterns in fire severity, were not accounted for in our analysis. However, the overall size of the complex of fires burning at the time meant that suppression resources were thinly spread. Therefore, the resultant chance of sampling areas where severity may have been reduced by suppression was probably low.

#### *Management implications and climate change*

The results of our study suggest that the time period over which fuel reduction burning is effective (i.e. reduces fire intensity to potentially suppressible levels) may vary across the dry sclerophyll forests of the study region. Following fire there may be a 0–5 year window within which treated fuels are more likely to reduce fire intensity to potentially suppressible levels (i.e. UF) under extreme weather conditions. This supports the general consensus that fine fuels will approach pre-fire levels 2–5 years following fire in sclerophyll forests and woodlands of temperate Australia (Fox *et al.* 1979; Morrison *et al.* 1996; Penman and York 2010). However, this window of effectiveness appears to shorten as mean annual precipitation increases (Fig. 2b), presumably in response to increased rates of fine fuel accumulation. As time since fire included both wildfire and prescribed burns, the former of which is generally associated with greater fuel consumption, it is possible that the window of hazard reduction burning effectiveness may be shorter than that stated here. Regardless, fire management programs will need to be responsive to such spatial variation in the effectiveness of fuel reduction (Schoennagel *et al.* 2004). For example, if hazard reduction burning only reduces fire severity to potentially suppressible levels within the first couple of years following fire in 'mesic' parts of the landscape, then the broad scale application of this management technique will not be the most effective way to manage fire risk.

The dominant effect of weather on fire severity further emphasises that the effectiveness of fire risk management strategies (e.g. fuel reduction, suppression) will be highly constrained by fire weather conditions (McCarthy and Tolhurst 2001; Fernandes and Botelho 2003; Price and Bradstock 2012). There is some evidence from eucalypt forests in southern Australia that areas recently burnt (i.e. <5–10 years since fire) by prescribed burns and wildfires will alter wildfire behaviour, even reducing the occurrence of CF under very high to extreme weather conditions (Fernandes and Botelho 2003; Bradstock *et al.* 2010). However, analysis of 114 fires by McCarthy and Tolhurst (2001) has shown that the effectiveness of fuel reduction burning (i.e. the capacity to assist suppression) is reduced with increasing severity of fire weather, particularly with a FFDI of ~25–50. Price and Bradstock (2012) revealed that time since fire had negligible effect in terms of reducing fire severity to potentially

suppressible levels under very high (mean FFDI = 36) and catastrophic conditions (mean FFDI = 103) in eucalypt forest during the 2009 fires in Victoria, Australia. Extreme weather conditions pose the greatest threat to life and property (Luke and McArthur 1978; Blanchi *et al.* 2010; Price and Bradstock 2012) and consequently represent conditions when fire management actions need to be effective (Fernandes and Botelho 2003). Therefore, the identification of conditions that constrain the effectiveness of fuel reduction burning will be crucial for enhancing fire management strategies and fire fighter safety.

Climate change is predicted to increase fire occurrence in temperate eucalypt forests of southern Australia, largely due to an increased frequency of extreme fire weather events (Bradstock 2010; Bradstock *et al.* 2012; Cary *et al.* 2012). Our findings, and past research (e.g. Bradstock *et al.* 2010; King *et al.* 2011; Bradstock *et al.* 2012; Price and Bradstock 2012), suggest that increased occurrence of extreme weather events may result in a shift towards fires of greater severity and intensity in temperate eucalypt forests. Projected reductions in annual precipitation (e.g. median decrease of 4–8% for Sydney in 2070; CSIRO and Australian Bureau of Meteorology 2007) and associated declines in fuel production under predicted future climates may partially offset these changes to fire occurrence (Bradstock 2010; Cary *et al.* 2012) and intensity (Fig. 2). As discussed above, the window of fuel reduction burning effectiveness may increase under drier conditions. Therefore, future conditions of reduced precipitation are likely to enhance fuel reduction burning efficacy. However, the short window of fuel reduction burning effectiveness (i.e. <5 years) coupled with the dominant effect of fire weather (Fig. 2), suggests that the potential for broad scale fuel reduction burning to mitigate enhanced fire risk under future climate is likely to remain constrained in temperate dry sclerophyll forests.

## Conclusions

The importance of precipitation regimes in determining the relative influence fire weather, topography and fuel age have on fire regimes has been highlighted across a range of ecosystems globally (Schoennagel *et al.* 2004; Seydack *et al.* 2007; Archibald *et al.* 2009; Bradstock 2010). Our study provides further evidence of this phenomenon, revealing that precipitation regimes can shape these relationships even within a reasonably homogenous expanse of eucalypt forest, whereby the relative effect fire weather, slope and fuel age had on the occurrence of potentially suppressible understorey fire decreased with increasing mean annual precipitation. Fuel production rates, fuel accumulation and biomass are positively related to annual precipitation across a range of fire prone ecosystems (Austin 2002; Huston 2003; Govender *et al.* 2006; Pekin *et al.* 2009), which suggests that our findings will have broader generality. Consequently, fire management strategies will need to be adaptable to spatial variation in mean annual precipitation and in response to future changes in precipitation regimes, as has been suggested for other ecosystems globally (Schoennagel *et al.* 2004; Archibald *et al.* 2009; Bradstock 2010).

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