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Biogeographical variation in the potential effectiveness of prescribed fire in south-eastern Australia

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Abstract

Aim Prescribed fire is a common land management for reducing risks from unplanned fires. However, the universality of such effectiveness remains uncertain due to biogeographical variation in fuel types, climatic influences and fire regimes. Here, we explore biogeographical patterns in the effectiveness of prescribed fire by calculating leverage (the reduction in unplanned area burnt resulting from recent previous area burnt) across south-eastern Australia over a 25 year period. **Location** The 30 bioregions of south-eastern Australia. **Methods** We quantified leverage in each bioregion from fire records from 1975-2009, controlling for variation in annual weather. We also identified potential drivers of variation in leverage by relating the bioregional leverage values to measures of fuel type and growth, climate, and weather extremes. **Results** Leverage was inferred in four bioregions while in the other 26 bioregions no leverage was detected or prescribed fire had the opposite effect (fire-follows-fire). Leverage occurred in the forested eastern section of the study area, where rainfall, fuel load and fire activity is high and fire weather is mild. In all bioregions, weather was a stronger predictor than past-fire extent of area burnt in a particular year. **Main conclusions** Our analysis of leverage shows that the effectiveness of prescribed fire varies regionally in predictable ways, which means that fuel management strategies applied in one region are not necessarily applicable in another. In most bioregions prescribed burning is likely to have very little effect on subsequent extent of unplanned fire, and even in regions where leverage occurs, large areas of treatment are required to substantially reduce the area burned by unplanned fire.

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Original Article

Biogeographical variation in the potential effectiveness of prescribed fire in southeast Australia

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Running Title: Prescribed fire effectiveness in Australia

ABSTRACT

Aim. Prescribed fire is a common land management for reducing risks from unplanned fires. However, the universality of such effectiveness remains uncertain due to biogeographic variation in fuel types, climatic influences and fire regimes. Here we explore biogeographic patterns in the effectiveness of prescribed fire by calculating leverage (the reduction in unplanned area burnt resulting from recent previous area burnt) across south-eastern Australia over a 25 year period.

Location. The 30 Bioregions of south-eastern Australia.

Methods. We quantified leverage in each Bioregion from fire records from 1975-2009, controlling for variation in annual weather. We also identified potential drivers of variation in leverage by relating the Bioregional leverage values to measures of fuel type and growth, climate, and weather extremes.

Results. Leverage was inferred in four Bioregions while in the other 26 Bioregions no leverage was detected or prescribed fire had the opposite effect (fire follows fire). Leverage occurred in the forested eastern section of the study area, where rainfall, fuel load and fire activity is high and fire weather is mild. In all Bioregions, weather was a stronger predictor than past fire extent of area burnt in a particular year.

Main Conclusions. Our analysis of leverage shows that the effectiveness of prescribed fire varies regionally in predictable ways, which means that fuel management strategies applied in one region are not necessarily applicable in another. In most Bioregions prescribed burning is likely to have very little effect on subsequent extent of unplanned fire, and even in regions where leverage occurs, large areas of treatment are required to substantially reduce the area burned by unplanned fire.

INTRODUCTION

The structure and biomass of fuel is commonly manipulated in fire-prone landscapes in order to reduce the incidence, intensity and size of wildfires (Fernandes & Botelho, 2003; Penman *et al.*, 2011), driven by the need to reduce risks posed by wildfires to people, property, ecosystem services and biodiversity. Fuel treatments such as prescribed burning are a core priority for management of fire-prone ecosystems worldwide (Russell-Smith & Thornton, 2013; Moritz *et al.*, 2014), despite debate and uncertainty about their efficacy and effects (Price & Bradstock, 2011; Attiwill & Adams, 2013). Prescribed burning treatment has been expanded across southern Australia in response to recommendations of the Royal Commission into recent loss of life and property in Victoria (Teague *et al.*, 2010; 2011). Expansion of the use of prescribed fire has also been advocated in forested ecosystems in Europe, Australia and western USA, as a measure to mitigate carbon losses and perceived environmental degradation (Wiedinmyer & Hurteau, 2010; North *et al.*, 2012).

Advocacy for prescribed burning is often based on case studies which demonstrate successful mitigation of the spread and intensity of wildfires. In this vein, the results of a long-term prescribed burning program in the Mediterranean-climate forests of south-western Australia have been promoted as providing a general justification for extensive prescribed burning in temperate forest ecosystems in Australia and other continents. For example, Burrows and McCaw (2013) (page e25) asserted that this prescribed burning program provided "an exemplar for fire management in southern Australia… [and] relevant to fire-prone, forested landscapes in temperate environments around the world"; Sneeuwjagt and Stephens (2013) contend that these results from Western Australia were generally applicable to the mixed conifer forests of the Sierra Nevada, in the western USA. The policy decision to annually burn 5% of public lands in Victoria and Tasmania is based on

the assumption that levels of effectiveness of prescribed burning in South Western WA forests (Boer *et al.*, 2009) apply elsewhere in Australia.

Here we examine the generality of prescribed burning effectiveness by scrutinizing how area burnt by wildfires is affected by area of previous burning across the diverse Bioregions of south-eastern Australia. We also examine the degree to which the effect of previous burning on the subsequent area burnt by wildfires is altered by macro-scale, biophysical variation inherent in the fire-prone ecosystems of this portion of the Australian continent.

Leverage is a regional-scale ($100 - 10,000$ km^2) measure of the effectiveness of fuel treatment (Loehle, 2004): i.e. the reduction in area of unplanned fire that results from the prior treated area. In practice, it is quantified by the slope

$$(L = dA_{uf}/dA_f) \qquad\qquad [1]$$

of the relationship between the annual extent of unplanned fire (A_{uf}) and total fire extent (A_f) over the preceding 1 or more years, with the assumption that prescribed and unplanned fires have similar negative effects on subsequent unplanned fire area. If prescribed fire reduces the subsequent area of unplanned fire, then the slope of this relationship should be negative. High efficacy of fuel treatment will be indicated by a relatively steep negative slope, whereas low efficacy will be indicated by a small negative slope. Where the relationship is flat (zero slope) or positive (i.e. fuel treatment promotes wildfire) leverage is effectively absent (i.e. treatment is ineffective in reducing area of wildfires).

Leverage can be expected to be sensitive to variation in biophysical conditions, because relationships between fire and fuel are sensitive to fire weather, fuel dynamics and the

overall rate of occurrence of wildfires (King *et al.*, 2013; Thomas *et al.*, 2014). In arid environments of low productivity, treatment to reduce fuel may have limited potential to reduce fire activity because there is usually too little fuel to carry a fire (Bradstock, 2010). Extensive coverage of herbaceous fuels can develop quickly in response to exceptional rainfall but opportunities for effective treatment will be limited before these fuels senesce and dry out. Hence leverage is low. In contrast, in forested environments of high productivity, fuel is generally abundant and non-limiting to fire spread (Bradstock, 2010), thereby providing more scope for effective treatment (and hence higher leverage).

Fire simulation has demonstrated that leverage is positively related to mean area burnt (by unplanned fire), negatively related to the rate of fuel accumulation and also negatively related to the point-scale probability of fire spread (Price, 2012), factors that all exhibit large scale biogeographic variation (e.g. Thomas *et al.,* 2014). The area burnt effect reflects the influence of the encounter rate: i.e. the more fire there is in a landscape, the higher the chance that any wildfire will encounter a recently burnt area. The fuel accumulation effect augments the effect of the encounter rate by determining the length of time that a burnt patch will potentially influence subsequent fires. Geographic variation in mean annual area burnt and fuel recovery rates are a function of primary productivity (Bradstock, 2010; Thomas *et al.*, 2014).

Probability of fire spread is also sensitive to fire weather and fuel continuity (Price, 2012). It is commonly assumed that fuel has the predominant effect because this is explicit in commonly-used fire behaviour models. For example, in the McArthur Mk 5 fire behaviour model (Noble *et al.*, 1980), fire line intensity scales linearly with the Fire Danger Index (weather) but with the square of fuel load (Gill *et al.*, 1987). However, several empirical

studies from Australian forests have found that weather is the most important determinant of such factors as fire spread (Price & Bradstock, 2010), fire size (Boer *et al.*, 2008), annual area burnt (Price & Bradstock, 2011) and fire severity (Price & Bradstock, 2012). Thus, we predict that leverage will be strongest where severe fire weather is less frequent, but also that annual area burnt will be more sensitive to weather than fuel age (time since fire). Other factors such as disjunctions in fuel continuity that arise from either natural variation in landscape structure (e.g. terrain, rockiness, streams) or human intervention (e.g. clearing, roads) can also affect leverage (Price 2012).

Leverage has been recently examined in a variety of ecosystems and considerable variation in values has been reported (Boer *et al.*, 2009; Price & Bradstock, 2011; Vilen & Fernandes, 2011; Price *et al.*, 2012a). For example, in Mediterranean-climate eucalypt forests in Western Australia, leverage is approximately 0.25 (Boer *et al.*, 2009), while similar values have been reported for eucalypt forests of the Sydney region of south-eastern Australia (Price and Bradstock 2011, Bradstock *et al.* 2012). However, wider variations in leverage have been reported both across Australia (e.g. leverage circa. 1 with high potential to influence fire patterns in tropical savannas, Price *et al.* 2012a) and elsewhere (e.g. zero leverage in chaparral shrublands of southern California, (Price *et al.*, 2012b). This geographic variation in leverage is proximately driven by variation in annual area burnt and fuel recovery, both factors that are strongly influenced by primary productivity because productive ecosystems have high fuel loads and high rates of fuel accumulation (Bradstock, 2010). Thus the gradient in leverage values in the cases mentioned is reflected in an annual rainfall gradient: 1200 mm in the Australian savannas, 900 mm in eucalypt forest in Sydney and Western Australian and 450 mm in California. This variation in leverage is implicitly

incorporated by fire management agencies with levels of prescribed fire treatment being greatest in savannas, rare in California and intermediate in Australian forests (Price & Bradstock, 2011; Price *et al.*, 2012a; Price *et al.*, 2012b; Burrows & McCaw, 2013). A systematic appraisal is required to test the hypothesis that productivity has a consistent, widespread effect on leverage.

Based on current understanding of the diversity of vegetation, climate, terrain and fire activity evident across south-eastern Australian ecosystems (Pausas & Bradstock, 2007; Murphy *et al.*, 2013; Bradstock *et al.*, 2014) we expected the leverage values to exhibit variations that reflect causal variations in fire weather, overall productivity, fuel accumulation, discontinuity and rates of wildfire incidence. We made a number of specific predictions:

1) leverage will be weak or absent in low-productivity ecosystems, where fuel limitation generally inhibits fires anyway, compared to high-productivity ecosystems. This fundamental control on leverage will also be apparent in relationships with proximate drivers that are themselves related to productivity:

2) Leverage values will be positively related to the mean annual area burnt;

3) Leverage values will be negatively related to fuel accumulation rate.

4) Leverage values will be negatively related to the frequency of severe fire weather, because the relative influence of fire weather compared to other factors on rate of fire spread increases with the severity of fire weather;

As a consequence, we predict that the potential effectiveness of prescribed burning as a management tool will vary across regions as a function of biophysical context. Prescribed

burning solutions that are effective in one particular region may not be effective elsewhere unless there is strong similarity in vegetation types, fire weather, fuel accumulation and ignition rates.

MATERIALS AND METHODS

Study Area

The study area comprised the south-eastern Australian states of Victoria, New South Wales, Australian Capital Territory and South Australia, an area of 2.0 million km^2 (Fig.Fig. 1). The vegetation and fire regimes in these regions reflect systematic variation in climate (temperature, rainfall amount and seasonality) and elevation (Murphy *et al.*, 2013). The dominant vegetation formations range from arid grassy shrublands, through grassy woodlands, tall open forests, closed rainforests to alpine grasslands. The sample units were 190 sub-regions of the 32 Interim Biogeographic Regions of Australia (Bioregions) situated in this part of the continent, defining zones of similar geology, landform and biota (Hutchinson *et al.*, 2005) (Table 1). The number of subregions in each Bioregion varied from 1 to 19 (median 5).

Analysis 1: Leverage estimation

Fire perimeter data were sourced from State Government agencies for the years 1975-2009 (New South Wales Office of Environment and Heritage, Victorian Department of Environment and Primary Production, South Australian Department of Environment, Water and Natural Resources, unpublished data). In each case, these comprised the final

boundaries of all planned (or 'prescribed') fires and unplanned (or 'wild') fires with a spatial accuracy of approximately 100 m. The combined database contained ~38,000 fires. The percentage of the vegetated land that was burnt by unplanned fire in each sub-region in each year, and by any fire in the preceding 1, 2 and 5 years were calculated from this database, using State-based vegetation maps to define the vegetated land.

Gridded daily weather data (Jeffrey *et al.*, 2001) were used to calculate the maximum temperature, number of days above 35°C, number of days with relative humidity below 15% and July-Dec and Jan-May rainfall anomaly (Standardised Precipitation Index (SPI) (McKee, 1995; Caccamo *et al.*, 2011)) for each sub-region in each year. The weather data were derived at 10 km resolution (Clarke *et al.*, 2013) from a regional climate simulation using the Weather Research and Forecasting (WRF) model (Evans & McCabe, 2010), forced by a reanalysis dataset (Kalnay *et al.*, 1996). These data were also used to calculate the mean annual rainfall for each bioregion.

For each Bioregion the presence and value of leverage was estimated via an analysis of the effect of previous fire on area burnt in each year using generalised linear mixed modelling (GLMM) with each year in each subregion as the statistical sample. The models specified a gamma error distribution rather than a normal distribution because the area burnt values were skewed toward zero. Sub-region was specified as a random variable because the samples were repeated measures for each sub-region. The annual weather variables (temperature, humidity and rainfall anomaly) were used to partition the variation in area burnt that was due to meteorological rather than past-fire causes, as in previous studies (Price & Bradstock, 2011; Price *et al.*, 2012a; Bradstock *et al.*, 2014). Year was also included

to control for significant temporal change in area burnt, which could have obscured the leverage effect (Bradstock *et al.*, 2014). For each Bioregion, 64 models were compared: all variable combinations were tested subject to the condition that any model could only contain one of the time periods for assessment of past fire effects (i.e. 1, 2 or 5 years), and either the annual maximum of daily maximum temperature or of the number of days above 35^oC. Thus, five variables was the maximum permitted (one past fire variable + one temperature variable + rainfall + dry days + year). In this analysis, leverage is the negative of the slope estimate of the past fire term (should it be present in the preferred model).

Model selection techniques (Burnham & Anderson, 2002) were used to identify the model with the lowest value of Akaike's Information Criterion (AIC) and all other models with an AIC within 2 units of the lowest (supported alternative models). Based on these models, we classified the Bioregions according to whether leverage was detected. For Bioregions where leverage was detected (i.e. a negative past fire effect was included as a predictor in the preferred model), we estimated effect sizes of past fire and weather predictors by re-fitting the model with the lowest AIC with standardised variables (re-scaled within the range 0-1). Two Bioregions (Australian Alps and South Eastern Highlands) were amalgamated because data were sparse and vegetation and fires are often contiguous between these two bioregions and the Finke Bioregion was excluded because fires only occurred in two of the 25 years. This analysis was conducted using the LME4 package (Bates *et al.*, 2014) in the R statistical software (R Core Team, 2013).

Analysis 2: Biogeography of leverage

This analysis related the levels of leverage observed across the Bioregions to a range of biophysical attributes derived for each Bioregion. The national NVIS 1:1000,000 vegetation map (ESCAVI, 2003) was used to identify the dominant vegetation type for each Bioregion (there were 62 mapped vegetation types within the study area). Two parameters describing the recovery of fuel post-fire were derived from the literature for each dominant vegetation type. The parameters were the asymptotic or maximum fuel load (X_{ss}, in tonnes/ha) and the *k* parameter from an Olson curve (Olson, 1963):

$$X_t = X_{ss}(1 - e^{-kt})$$

Parameter *k* is the rate at which fuel loads accumulate towards the maximum (X_{ss}) and is also equal to the annual fuel input divided by asymptotic fuel load. Values were assigned to the closest matching type from a review of NSW forest and woodland vegetation types (Watson, 2012) and from specific references for other vegetation types: *Acacia* shrublands (Burrows, 1976), Mallee with hummock grasslands (Noble, 1989), Mallee with shrubby understory (Burrows, 1976), tussock grasslands (Friedel, 1981) and hummock grasslands (Russell-Smith *et al.*, 2010).

The fire history data were used to calculate the overall mean area burnt per annum for each Bioregion as a percentage of the vegetated area. The mean annual rainfall for each Bioregion was calculated using a 0.01° resolution Worldclim climatic grid surface (Hijmans *et al.*, 2005). The 99th percentile of the daily Forest Fire Danger Index (FFDI) was derived at a 10 km grid resolution (Clarke *et al.*, 2013) from a regional climate simulation using the Weather Research and Forecasting (WRF) model (Evans & McCabe, 2010). FFDI is a commonly used measure of fire weather incorporating recent rainfall, temperature, relative humidity and wind speed (Noble *et al.*, 1980) . The 99th percentile grid represents the

highest value to be expected 4 days per year. The topographic roughness of each Bioregion was calculated as the standard deviation of elevation values (across the bioregion) from the national GEODATA 9 second Elevation Model (downloaded from Geoscience Australia (www.ga.gov.au) July 2012).

A Kruskal-Wallis non-parametric ANOVA test was used to examine the influence of the biophysical variables on the presence of leverage among Bioregions (conducted using the R statistical software (R Core Team, 2013)). Because many of these predictors are interrelated, sometimes causally (e.g. rainfall may drive fuel dynamics and forest cover), we also examined the correlation matrix among the variables, using Spearman's rank correlation. This provided further insight into the underlying causes of the observed relationships with leverage. For this analysis, rainfall can be considered to be a proxy for Net Primary Productivity (NPP), since there was a correlation of 0.97 (n = 30, p<0.001) between mean Bioregion values for rainfall and NPP (derived from Raupach *et al.* (2001)).

RESULTS

Most of the Bioregions had a low level of fire activity. The mean annual % burnt was 0.54% and only one Bioregion exceeded 3% burnt per year (Table 1). Fire activity was higher toward the south and east coast and generally below 0.5% per year in the arid interior (Fig. 1 a).

Scatterplots for the relationship between % area burnt and % area burnt in the preceding one and five years are shown for three example bioregions in Fig. 3 and for all 30 bioregions

in Appendix S1. Four Bioregions exhibited leverage: i.e. a negative effect of previous fire on area burnt by unplanned fire in any given year was present in the selected model (Table 1, Fig. 1b, Fig. 3a). In sixteen Bioregions, there was no evidence of leverage: i.e. either no effect of past fire (e.g. 11 Bioregions, Table 1, Fig. 3c), or; a positive relationship between past fire and subsequent fire (e.g. five Bioregions, Table 1, Fig. 3b). In the remaining 10 Bioregions data were insufficient for analysis (Fig. 1b). These 10 were Bioregions that: i) contained only one year with large area burnt, across all sub-regions, with very low fire activity for the remainder of the period, or; ii) where there was no area burnt in more than 80% of years (Table 1).

The four Bioregions with leverage formed a band along the east coast (Fig. 1b), which corresponds to the forested mountains of the Great Dividing Range. The leverage value in these regions ranged from 0.09 for the Australian Alps/SE Highlands to 0.36 for the New England Tablelands. Most of the Bioregions with inadequate data for analyses were in inland arid areas. The Bioregions with no detected leverage were mostly semi-arid woodland types, but this group also included two east-coast Bioregions (South East Queensland and South East Corner) with extensive forest cover (Table 1).

For the 20 Bioregions containing sufficient area burned data for analysis, the best models for 18 of these included a significant effect of one or more of the weather variables (Table 1). There was a negative relationship with Jan-May SPI in 13 Bioregions and July-Dec SPI in three Bioregions. For three of the four Bioregions with leverage (Australian Alps/South East Highlands, NSW North Coast, Sydney basin), the effect size of the weather predictors was an order of magnitude larger than the effect size for past fire (Table 2), and for the other (New

England Tablelands) the effect sizes were similar among the rainfall, relative humidity and past fire variables present in the model (0.003, 0.003 and 0.005 respectively).

The dominant vegetation type was forest in all four of the Bioregions where leverage was present but leverage was absent in six other forested Bioregions (Table 1). The classification of Bioregions into those with or without leverage was strongly discriminated by rainfall, topography and maximum fuel load, but also by percentage forest, annual percentage area burnt and 99th percentile FFDI (Table 3, Fig. 2, Fig. 3). Bioregions with leverage had significantly higher rainfall, fuel loads, percentage forest, percentage area burnt and lower FFDI than Bioregions without leverage. The percentage vegetated and the fuel accumulation rate k were lower in Bioregions with leverage, but not significantly different (at $p<0.05$, Table 3). The best four predictors could discriminate between Bioregions with and without leverage with overall accuracy of at least 80%. Rainfall was strongly correlated with maximum fuel load, percentage forested, topography and FFDI ($r>0.7$, Table 4) and moderately correlated with percentage area burnt ($r >0.6$). Therefore, the strong effects on leverage reflected associated phenomena: high rainfall leading to the dominance of forest, with high fuel loads that burn relatively frequently.

DISCUSSION

Leverage only occurred in the forests of the Great Dividing Range in south-eastern Australia. In all other Bioregions, past fire had no inhibitory effect on the area burnt by subsequent unplanned fire: there was either no detectable effect or else too little fire activity to analyse (which in practical terms is no detectable effect). There were clear biophysical differences between the Bioregions with leverage and those without. The Bioregions with leverage

were those with high rainfall (productivity), less severe fire weather, dominated by forest, with high maximum fuel loads and with relatively frequent fire.

This pattern was consistent with three of our specific predictions: that leverage would be positively related to productivity and mean area burnt and negatively to fire weather. We also predicted that fuel accumulation rates (k) would be lower in Bioregions with leverage because the recovery of sufficient mass and connectivity will impose limits on the spread of fire. The results indicated a trend consistent with this prediction (Table 3) but differences were not significant.

The leverage value of 0.16 for the Sydney Basin Bioregion estimated in this study was lower than the values reported for empirical (Price & Bradstock, 2011; leverage = 0.3) and simulation (Bradstock *et al.*, 2012a; leverage = 0.25) studies for the same region. These differences may be because the previous studies examined smaller areas within the Sydney Basin Bioregion, which had a larger proportion of dry forested vegetation. Leverage in wet Tasmanian landscapes containing varied forest and shrubland communities was estimated at 0.19 using simulation (King *et al.*, 2013). This estimate is within the range for forested Bioregions reported here (Table 1). Likewise, empirically derived leverage in eucalypt forests in Western Australia was approximately 0.25 (Boer *et al.*, 2009). Even though our empirical study showed no evidence of leverage in arid regions, simulation studies suggested leverage could occur in arid environments of Central Australia (Bradstock *et al.*, 2006; King *et al.*, 2013). King *et al.* (2013) reported a leverage value of 0.09 for a simulation study of hummock grassland landscapes in the West MacDonnell Ranges (Northern Territory), with similar rainfall and vegetation to many of the arid zone Bioregions studied here. Simulation studies overcome the problem posed by relatively high variation in fire activity and a short

time series of fire history evident in these ecosystems. Hence relatively weak leverage for arid environments may only be readily detectable in simulation studies. A similar argument may account for the absence of leverage in an empirical analysis of southern California shrublands (Price *et al.*, 2012b): leverage may in fact be present, but at a very low level which is not detectable with the method used (i.e. analysis of 29 years of historical fire records).

Five of the bioregions showed a positive relationship between past and subsequent unplanned fire (the opposite of leverage), including three forested bioregions (South East Corner, South Eastern Queensland and South East Coastal Plain). The main reason for this result is the prevalence of points with zero past fire and zero unplanned fire, which constrains the relationship to pass close to the origin rather than the negative relationship expected from leverage (see Appendix S1, Fig. S1d). These cases reflect years when no unplanned fire occurs even though there has been no recent planned or unplanned fire. Where this is common, such as in subregions where fires rarely occur, planned fire treatment cannot substantially reduce subsequent fire since there would be very little unplanned fire anyway. Rather than interpreting these cases as evidence of fire-follows-fire, we conclude that these bioregions simply show no leverage effect.

Our results suggest that the contention of Burrows and McCaw (2013) and Sneeuwjagt *et al.* (2013) that prescribed fire is universally effective is not supported by historical fire records in southeast Australia, even when restricted to forests. Although leverage was detected in four forested Bioregions, it was not detected in the other six forested Bioregions or in any of the six eucalypt woodland Bioregions. In all Bioregions, measures of weather variation had a stronger influence on area burnt than did past fire area. It seems that strong effects of past

fire on area burnt are the exception rather than the rule. The principal reason is that in most Bioregions, fuel loads in treated areas will have returned to levels that support fire spread before a subsequent fire occurs. In turn, such an effect primarily reflects relatively low fire activity. Our results imply that in most Bioregions in southeast Australia, the potential for prescribed burning to significantly reduce the area of unplanned fire is limited. Therefore recent policy initiative to increase prescribed burning rates across all Bioregions (Teague *et al.*, 2010; Government, 2011) may only have limited effects in reducing the risks from unplanned fires to people and property, unless such treatments are strategically targeted close to the margins of developments and infrastructure (Bradstock *et al.*, 2012a; Gibbons *et al.*, 2012).

While high area burnt, relatively mild fire weather, high fuel loads and long recovery periods appear to be important for leverage, not all of them are needed for leverage to occur, nor does the presence of one of them guarantee leverage. For example, Australian tropical savannas are characterized by high leverage (i.e., $L \approx 1$), yet they have low fuel loads, rapid fuel recovery (Russell-Smith *et al.*, 2009), and relatively severe fire weather (the 99th percentile FFDI for three Bureau of Meteorology stations in western Arnhem Land (Jabiru, Katherine and Bulman) is 38, 49 and 40). However, the combination of high rainfall (between 900-1500 mm) and annual drought result in a large area burnt each year (approximately 30%). So in savannas leverage is high despite low fuel loads and rapid fuel recovery, because fire is so extensive. In Southern California, by contrast, leverage was not detected using analyses of fire records (Price *et al.*, 2012b). There, fuel recovery in the predominant chaparral shrublands is relatively slow (Keeley *et al.*, 2011), but there is sufficient recovery for fires to re-occur after only one year (Keeley, 2009). This, in

combination with low rates of burning (<2% per year) results in leverage being effectively absent (Price *et al.*, 2012b). Some of the factors that modify leverage have clear biogeographic patterns: rainfall seasonality is high in the Australian tropics (monsoonal summer rain) and Mediterranean (coastal South Australia and Western Australia, winter rain). Other factors, such as areas where annual grasses proliferate after fire, do not have such clear geographic patterns.

Future risk management implications

Although most Bioregions in southeast Australia did not show leverage, fuel treatment via prescribed fire or effects of recent burning on fuel loads has the potential to affect the rate of spread and intensity of subsequent unplanned fires at local scales. The results provide insight into the spatial and temporal resolution of potential effects of fuel treatment using prescribed fire for management of risks to assets. Where leverage was low or absent, the average long-term effects on fire size at a Bioregional scale of such local-scale influences are small or non-existent. A recently burnt patch may slow or stop an unplanned fire should one occur, but low encounter rates make this unlikely. The most efficient use of prescribed fire is applying it to the immediate proximity of assets, where a resultant reduction of fire intensity can be of immediate benefit in terms of impacts on structures and ease of suppression (Price & Bradstock, 2010, 2012). In low-productivity, rainfall-limited systems, effectiveness may be increased by applying prescribed fire once herbaceous fuels have accumulated after a rainfall event. However, opportunities for doing this before such fuels are fully cured may be limited.

These results also provide insight into geographic variation in the potential for use of prescribed fire to reduce emissions of greenhouse gases through reduction of area burnt and intensity of unplanned fire (Narayan *et al.*, 2007; Hurteau & North, 2009). Such reductions are only likely to come about where leverage is high (i.e. circa 1) because otherwise prescribed burning increases the total area burnt and so potentially increases emissions (Bradstock *et al.*, 2012b). Based on our results there may be limited scope for use of prescribed fire to reduce emissions in this way across the south-eastern Australian mainland.

The results of this study conform with an emerging understanding that can be used to predict leverage and hence prescribed burning effectiveness in different Bioregions as a function of mean annual area burnt, recovery rate of the fuels and fire weather (Price, 2012). Thus there is potential to explore and model leverage explicitly through wider investigation of global-scale data for these key determinants of fire (Chuvieco *et al.*, 2008; Archibald *et al.*, 2013). For example, Net Primary Productivity and temperature patterns have been found to have a strong, non-linear (i.e. "humped") influence on global burnt area (Krawchuk *et al.*, 2009; Pausas & Ribeiro, 2013). We predict that at the global scale trends in leverage will be similar because of a positive relationship between Net Primary Productivity (rainfall) and leverage.

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SUPPORTING INFORMATION

Additional Supporting Information may be found in the online version of this article:

Appendix S1: Scatterplots of past and subsequent area burnt for each Bioregion

DATA ACCESSIBILITY

Data used can be obtained by emailing the author: T. Penman (trent.penman@unimelb.edu.au) for

leverage estimation among bioregions; and O. Price (oprice@uow.edu.au) for data used for

analysing the biogeography of leverage.

BIOSKETCH

The team brings together expertise in plant fire ecology, landscape ecology, meteorology and spatial

and statistical analysis, focussed through the Centre for Environmental Risk Management of

Bushfires at the University of Wollongong. The team members have a combined interest in resolving

the potentially conflicting role of fire management in maximising biodiversity and minimising human

fire risk both currently and in the future. We have collaborated on several past and current projects

and each have individual interests in a range of fields broadly related to wildfire ecology and

management.

Editor: Kate Parr

Table 1: The 32 Bioregions of south-eastern Australia showing biophysical characteristics in the first eight columns and leverage and weather terms from the selected models in the two right-hand columns. The leverage column shows the opposite of the linear relationship between past fire and subsequent area as determined for fire history mapping from 1975-2009. A positive leverage reflects a negative effect of past fire; negative value means a positive effect of past fire; a zero value means no effect was detected; and "N/A" means there was too little fire to analyse. All entries of 'SPI' in the Weather column refer to a significant negative relation with Jan-May SPI except those with *, which have a negative relationship with July-Dec SPI. TMAX is the maximum recorded daily temperature for the year and NHOT is the number of days > 35 ^{o}C. 'ns' in this column means there was no significant weather variable. The vegetation type is a simplified vegetation classification of the most common (by area) NVIS vegetation type within the Bioregion. % Burnt is the mean annual % of vegetated land burnt. FFDI99 is the 99th percentile Forest Fire Danger Index for the bioregion .

| Bioregion | Vegetation type | Biophysical Characteristics | | | | | | | Modelling Results | |
		% Burnt	% Vegetated	% Forest	Rainfall (mm)	FFDI99	Fuel k[#]	Fuel max. (t/ha)[#]	Leverage	Weather
Broken Hill Complex	Chenopod	0.01	100.0	0.0	233	65.9	0.458	2.4	N/A	N/A
Channel Country	Chenopod	0.16	99.6	0.0	230	63.7	0.458	2.4	N/A	N/A
Cobar Peneplain	Eucalypt Woodland	1.46	83.0	0.6	419	54.5	0.4	10.0	N/A	N/A
Darling Riverine Plains	Eucalypt Woodland	0.01	68.4	9.7	467	57.0	0.4	10.0	N/A	N/A
Flinders	Eucalypt Forest	1.77	98.7	38.7	827	7.3	0.17	16.4	N/A	N/A
Gawler	Acacia woodland	0.11	99.9	0.0	201	65.3	0.47	4.5	N/A	N/A
Mulga Lands	Acacia woodland	0.18	99.5	1.0	376	63.4	0.47	4.5	N/A	N/A
Riverina	Chenopod	0.01	56.0	2.7	412	56.7	0.458	2.4	N/A	N/A
Simpson Strzelecki Dunefields	Hummock Grassland	0.43	99.6	0.0	174	64.8	0.15	10.0	N/A	N/A
Stony Plains	Chenopod	0.03	99.7	0.0	160	65.6	0.458	2.4	N/A	N/A
New England Tablelands	Eucalypt Forest	1.08	16.0	11.5	896	25.4	0.17	16.4	0.363	SPI ,RH
NSW North Coast	Eucalypt Forest	2.00	15.7	11.7	1220	22.1	0.35	19.0	0.285	SPI
Sydney Basin	Eucalypt Forest	3.48	64.7	31.2	976	30.5	0.17	16.4	0.163	SPI
Australian Alps / South Eastern Highlands	Eucalypt Forest	1.69	36.0	21.5	1034	26.9	0.35	19.0	0.086	SPI, TMAX
Brigalow Belt South	Eucalypt Woodland	0.82	53.7	2.7	654	45.0	1.00	4.7	0	SPI*
Central Ranges	Acacia woodland	0.37	100.0	0.0	255	65.6	1.00	4.7	0	RH
Eyre Yorke Block	Mallee	0.43	30.5	0.1	376	47.4	0.35	8.7	0	SPI
Great Victoria Desert	*Acacia* woodland	0.50	99.8	0.0	196	65.6	0	0	0	SPI
Kanmantoo	Eucalypt Woodland	1.10	11.0	2.2	628	35.5	0.4	10	0	SPI

Murray Darling Depression	Mallee	0.54	28.5	0.0	337	59.5	0.3	5.77	0	ns
Nandewar	Eucalypt Forest	0.17	36.9	16.1	742	36.4	0.17	16.4	0	SPI
Naracoorte Coastal Plain	Eucalypt Woodland	0.74	18.1	0.5	611	36.3	0.4	10	0	SPI*
Nullarbor	Chenopod	1.38	99.9	0.0	214	47.4	0.458	2.38	0	SPI*
Victorian Midlands	Eucalypt Forest	0.61	29.0	18.1	696	39.3	0.17	16.4	0	SPI
Victorian Volcanic Plain	Wetlands	0.77	6.2	1.9	679	33.2	0.35	19	0	SPI
Flinders Lofty Block	Chenopod	0.06	79.8	1.6	314	61.4	0.458	2.38	-0.181	SPI, TMAX
South East Corner	Eucalypt Forest	2.10	85.6	65.7	920	21.2	0.17	16.4	-0.202	SPI,TMAX
South Eastern Queensland	Eucalypt Forest	2.09	32.2	17.1	1129	24.6	0.3	11	-0.288	NHOT
South East Coastal Plain	Eucalypt Forest	0.42	18.2	6.7	814	23.4	0.17	16.4	-0.366	SPI
NSW South Western Slopes	Eucalypt Woodland	0.43	17.1	3.8	652	43.9	1	4.7	-0.461	ns

Values in these columns are derived from the literature and hence vary in the number of significant Fig.s.

Table 2: Effect sizes for fire and weather variables from the best models in the leverage detection analysis for the four Bioregions where leverage was detected. The effect size values are the predicted change in annual area burnt for each unit of the standardised predictor variable. Thus, in the Sydney Basin the effect of SPI is 2.8 times that of past fire.

Bioregion	Effect Size		
	SPI	Past Fire	Other weather terms
New England Tablelands	-0.00309	-0.00503	0.00326 Relative Humidity
NSW North Coast	-0.01237	-0.00512	
Sydney Basin	-0.01602	-0.00565	
Australian Alps / South Eastern Highlands	-0.01227	-0.00208	0.00039 Max Temp

Table 3: Predictor variables used for the drivers of leverage analysis, showing the mean values for Bioregions with and without leverage, and results of a Kruskal-Wallace test of the differences.

Variable	Leverage Bioregions	No-leverage Bioregions	Kruskal $\chi2$	Kruskal p
Rainfall	1031	489	8.578	0.003
Topography	6.54	1.96	7.897	0.005
Fuel Maximum	17.7	8.40	7.409	0.006
% Burnt	2.06	0.64	6.268	0.012
% Forest	19.0	7.28	5.477	0.019
FFDI_99	26.2	48.1	5.376	0.020
Fuel k	0.26	0.43	2.788	0.095
% Vegetated	19.0	31.1	1.206	0.272

Table 4: Spearman rank correlation matrix among the predictor variables for drivers of leverage analysis (sample is 30 south-east Australian bioregions). Significant correlations are in bold.

	Rainfall	Topography	Fuel Maximum	% Forest	% Burnt	FFDI99	Fuel K
Topography	**0.781**	-					
Fuel Maximum	**0.827**	**0.665**	-				
% Forest	**0.922**	**0.713**	**0.739**	-			
% Burnt	**0.654**	**0.640**	**0.639**	**0.529**	-		
FFDI99	**-0.911**	**-0.736**	**-0.802**	**-0.840**	**-0.734**	-	
Fuel K	**-0.535**	**-0.362**	**-0.741**	**-0.563**	**-0.441**	**0.617**	-
% Vegetated	**-0.545**	**-0.378**	**-0.510**	**-0.409**	**-0.155**	**0.520**	0.279

Fig. Legends

Fig. 1: a) The area burnt per year (as a percentage of the vegetated area) for south-eastern Australian bioregions for the period 1975-2009 and b) leverage values derived from the analysis. Leverage values were obtained in forested regions with high rainfall along the dividing range. Coordinate system is decimal degrees (datum GDA94).

Fig. 2: Spatial patterns in a) 99th percentile FFD; b) annual rainfall and c) the standard deviation of elevation for bioregions in south-eastern Australia. Presented values are the mean for each bioregion. Bioregions for which leverage could not be calculated are shaded in cross-hatching. Map projection is decimal degrees (datum GDA94).

Fig. 3: Example scatterplots of past v subsequent fire for three bioregions: a) with strong leverage (Sydney Basin); b) with positive past v subsequent fire relationship (South East Coastal Plain); and c) with no leverage detected (Nandewar). The left-hand plot is for the past one year and the right-hand plot is the mean of the past 5 years. Each sample point is one year in one sub-region.
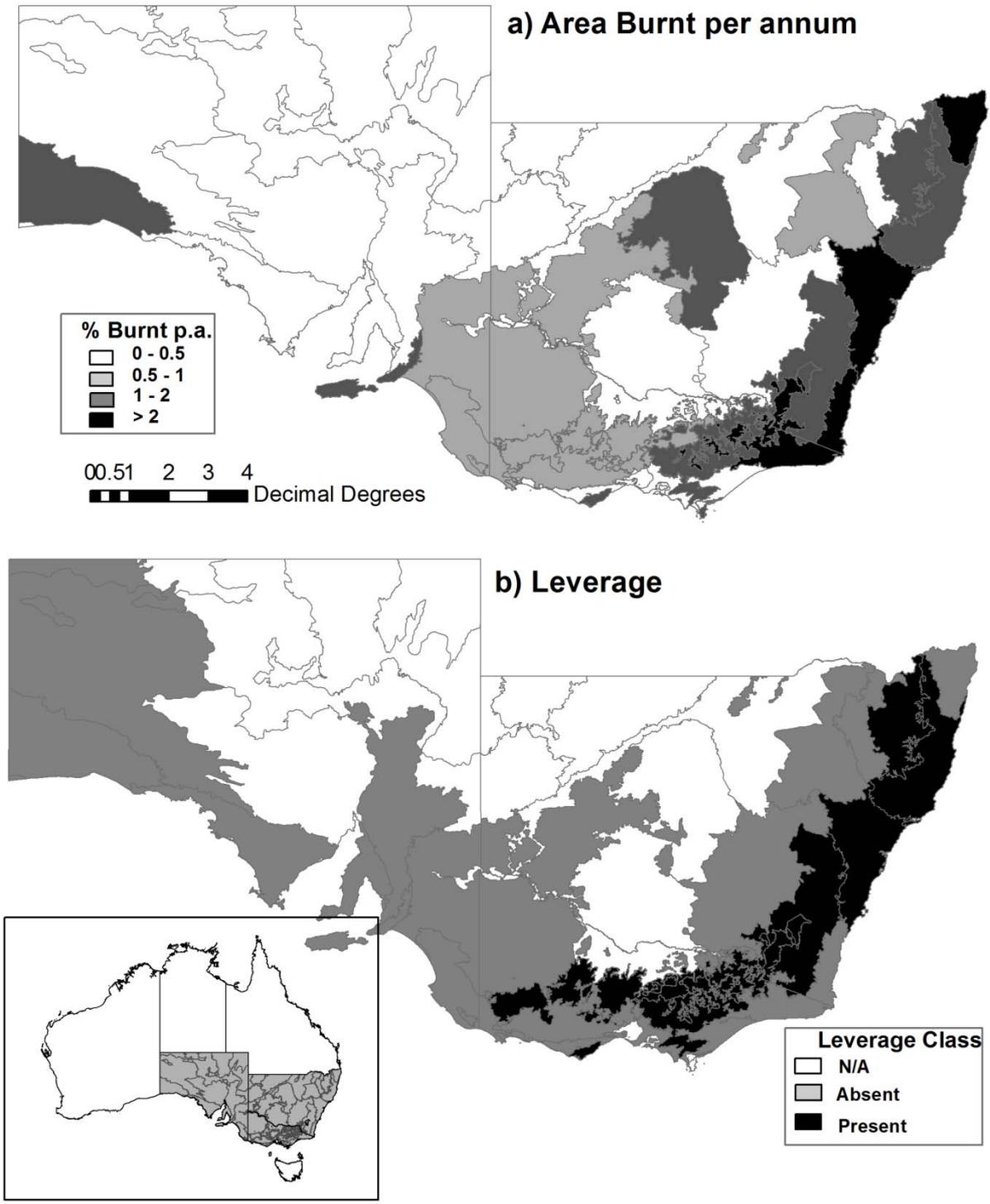
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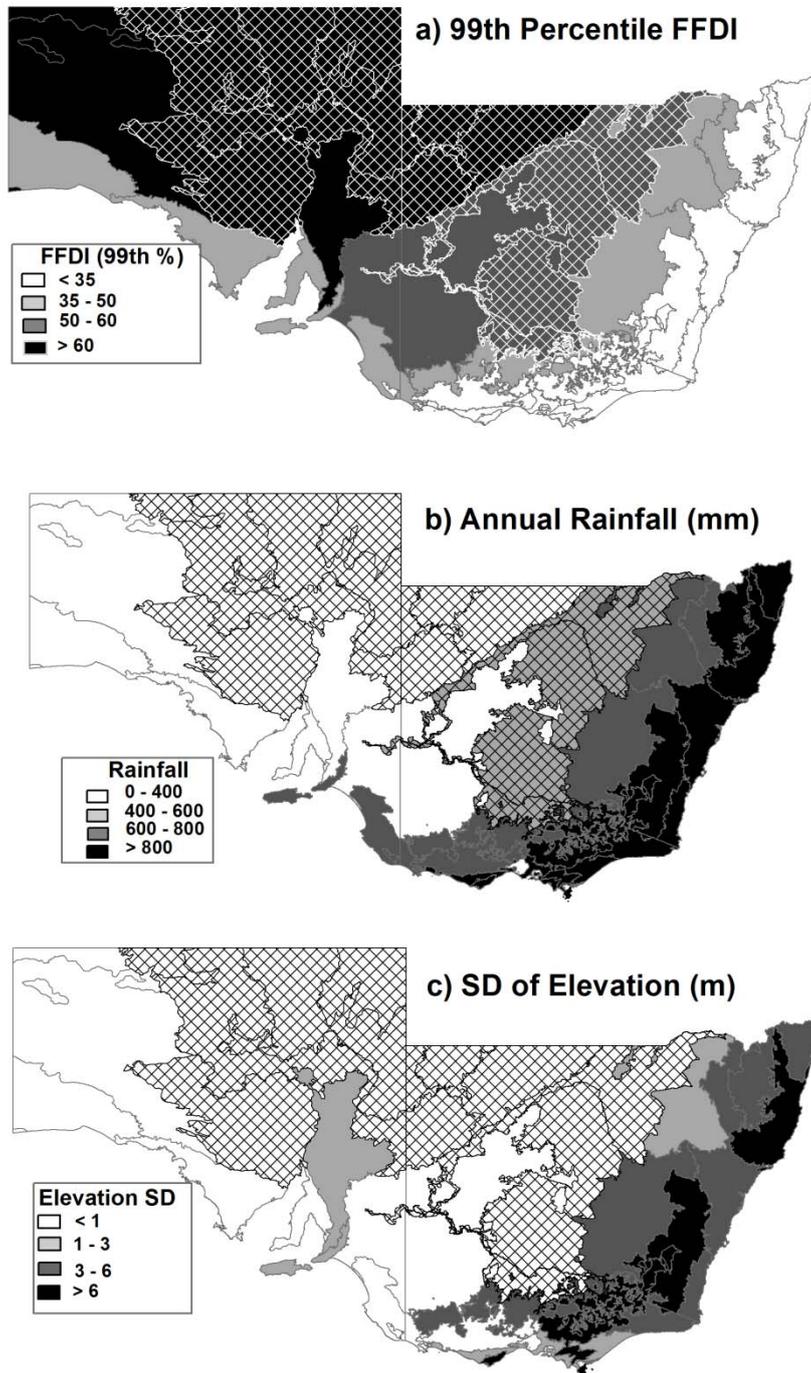
Fig. 2: Spatial patterns in a) 99th percentile FFD; b) annual rainfall and c) the standard deviation of elevation across the study area. Presented values are the mean for each bioregion. Bioregions for which leverage could not be calculated are shaded in cross-hatching. Map projection is decimal degrees (datum GDA94).
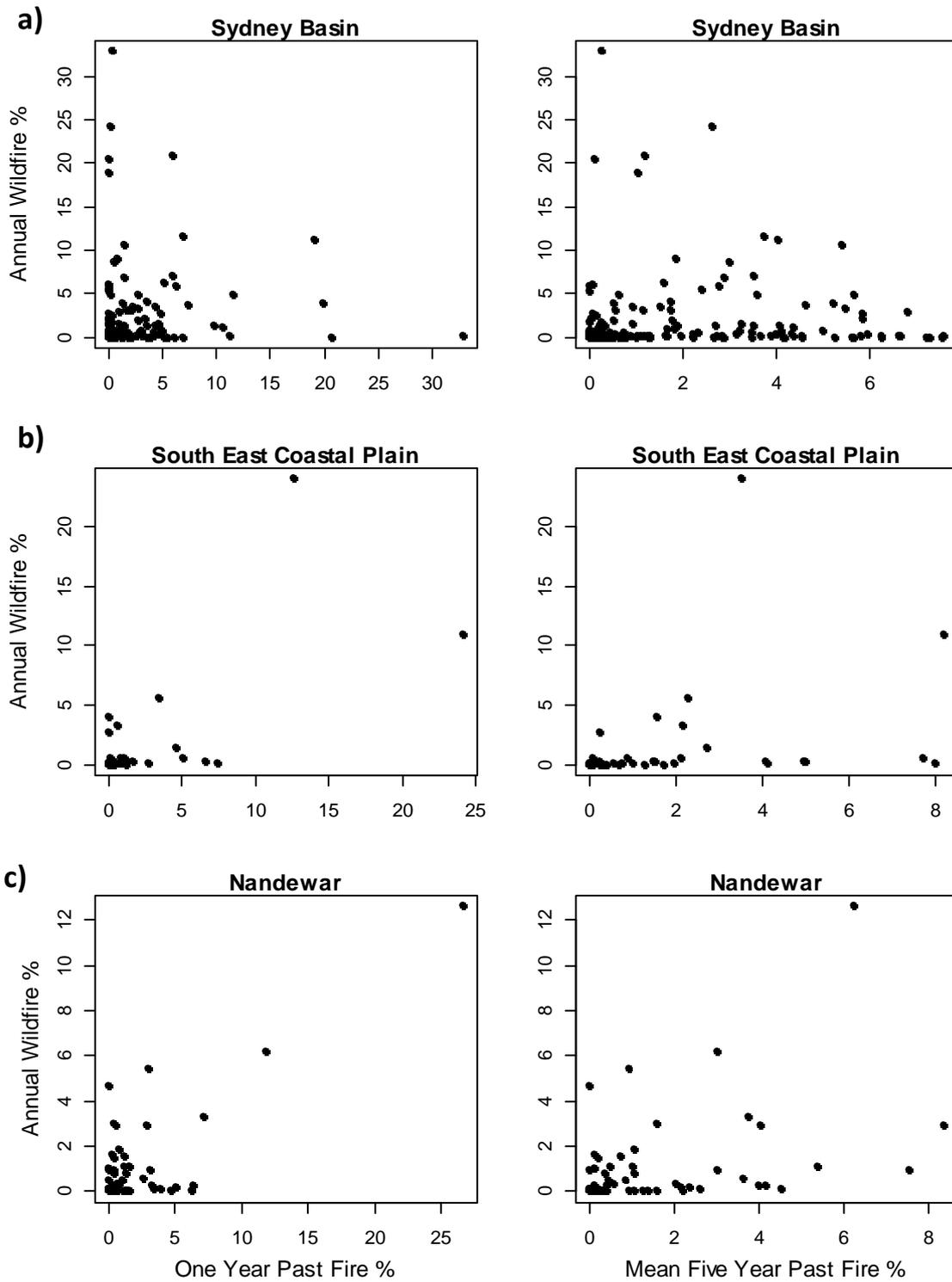
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