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This document was created in response to a Freedom of Information request made to CSIRO.

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Date: 8 January 2020

Request: Any reports, documents, minutes, briefings or similar provided to federal minister/s from 2018 onwards on the links between climate change and bushfires; and any specific warnings about the 2019-20 bushfire season.

Document(s): 1-4

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Document 1

[redacted] s22

From: Plucinski, Matt (L&W, Black Mountain)
Sent: Friday, 16 February 2018 11:54 AM
To: 'senator.siewert [redacted] s22
Cc: MPLO
Subject: Science Meets Parliament meeting
Attachments: FISJ 2218_Plucinski_2014.pdf; WF13090_final.pdf

Dear Senator Siewert
Thank you for participating in Science Meets Parliament and meeting with me in your office on Wednesday. It was a great experience and I enjoyed learning about the inner workings of parliament.

Further information on the work that CSIRO does on bushfires can be found at https://www.csiro.au/en/Research/Environment/Extreme-Events/Bushfire.

I have attached two of recent research papers of work that I have undertaken in Western Australia which may be of interest to you. These studies used incident data from the Departments of Fire and Emergency Services and Biodiversity, Conservation and Attractions which has been analysed and modelled with weather observations. The first gives a profile of temporal ignition patterns and the second presents models for predicting the number of daily human caused fires within management regions in the south-west.

Thanks again,

Matt Plucinski

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The timing of vegetation fire occurrence in a human landscape

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ABSTRACT

Vegetation fires in urban and peri urban (human) landscapes damage property and infrastructure, threaten lives and incur considerable suppression costs. This study investigated the timing of fires burning in vegetation within and around the city of Perth, Western Australia. The timing of fires from 16 different cause types were investigated at hourly, daily, monthly and annual scales, and using fire danger indices and fuel moisture. Ignitions from most causes were shown to have hourly and monthly profiles that reflect fire danger and fuel availability. Some causes with low heat outputs, such as cigarettes and sparks from cutting and welding, were more sensitive to fire danger and fuel availability than others. Causes related to arson and recreational activities, such as camp fires, were more likely to occur on weekends and public holidays. Arson prevention measures appear to have reduced the incidence of deliberately lit fires, and may have reduced the number of fires occurring on days of total fire ban, although these days have much higher rates of ignition than other days. High profile fire events also increase public awareness and reduce ignition rates. Lessons learned from analyses of fire occurrence can help fire agencies more effectively apply prevention and mitigation programs.

1. Introduction

Vegetation fires burning within and around urban areas threaten life and property and require significant resources to manage. These fires originate from a range of causes and occur in a variety of areas, such as parks, reserves, gardens and road verges. Knowl edge of the temporal patterns of vegetation fires that originate from different causes assist fire prevention and response by allowing fire agencies to proactively focus their efforts at times when fires are more likely to start [3,15].

Fire agencies undertake a range of activities to prevent fire ignitions. These include implementing fire restrictions, such as total fire bans, issuing permits for private burns, and undertaking public education and awareness campaigns. Total fire bans are declared on days where the weather is conducive to ignition and rapid fire growth, and are set when the forecast daily maximum level of the Forest or Grassland Fire Danger Index [22,23] exceeds a critical point (usually 50) [8]. For most jurisdictions it is illegal to ignite outdoor fires or undertake some activities that may cause a fire for the 24 h period of a day of total fire ban. Restrictions are also used to prevent agricultural and fuel reduction burns on private land from being undertaken on days of elevated fire danger, when the chance of escape is high. Public fire education campaigns are mostly undertaken during the fire season to increase fire safety awareness, reduce accidental ignitions and to increase the reporting of suspicious behaviour related to deliberate ignitions.

The ease and sustainability of ignition of vegetation is related to fuel moisture content [26] particularly for dead fuels [30,12]. The occurrence of wildfire ignitions has been linked to the moisture content of dead surface fuels in many analyses of wildfire incident data [37,41,42,35,20]. The moisture content of dead fuels vary with that of the surrounding atmosphere and typically undergo a diurnal cycle with the highest values attained in the morning and lowest values attained in the mid afternoon.

Many studies focussed on wildfire occurrence have tended to consider anthropogenic and lightning ignitions separately (e.g.: [38,35,42,20]). These have generally not investigated the different anthropogenic cause categories, other than some that have specifically focussed on the timing of arson ignitions (e.g. [32,33]).

There has been little research on the effect of timing and weather on the occurrence of fires in vegetation from different causes in human landscapes. Some studies have investigated spatial and temporal distributions of a range of fire incidents in urban areas (e.g. [9,3,11]; Wuschke et al., [43]) but have not considered how these vary with cause. Structure fires occur more frequently during winter periods and vegetation fires occur more often in summer and during drier conditions [7,18,10,11]. While some of these studies have considered vegetation fires, they have

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not specifically considered variation in timing due to ignition cause, weather or fuel availability.

This research investigated the timing of vegetation fires from different causes in the urban and peri-urban areas within and surrounding the city of Perth, Western Australia. Timing was considered at hourly, daily, monthly and annual scales and with weather variables related to wildfire danger and fuel availability. Ignition causes with unusual time profiles were identified and investigated. The long-term influence of fire prevention measures on ignition rates and the impact of a high profile fire event on fire occurrence were also examined and discussed.

2. Study area and data

Perth is the largest city in Western Australia with a current population of 1.9 million people [1]. The city has experienced rapid economic and population growth over recent decades with significant urban expansion along the coast and the outer fringe (Fig. 1). There are considerable amounts of public open space within these areas including sections with remnant native vegetation [16]. The greater area considered in this study also covers a variety of other land uses, including forest and conservation reserves and agricultural and industrial areas. Vegetated areas in and around the city take a variety of forms including pasture grasses, dry eucalypt forest and woodlands, shrubland and suburban parks and gardens. It is these areas where the fire ignitions considered in this study have occurred.

The region experiences a Mediterranean climate with a long dry period over the summer and autumn and a wildfire season extending from mid-October to mid-May. The majority of fires and emergencies are managed by the Department of Fire and Emergency Services (DFES[1]), while bushfires that occur on state owned land are managed by the Department of Parks and Wildlife (DPaW[2]).

Records for fires burning in vegetation were obtained from DFES for the three metropolitan management regions. The records used in this analysis cover the period from 1 July 2004 until 30 June 2012 and conform to the Australian Incident Reporting Standard (AIRS) [2], a national data standard that many fire agencies in Australia use for collecting, recording and reporting information about fire incidents.

The AIRS data fields used here were 'ignition heat form', 'ignition factor' and 'report time'. The ignition heat form field lists the heat source that caused the ignition, and may include items such as matches, cigarettes or hot sparks. The ignition factor field categorises the reasons for ignition heat sources combining with combustible material and starting fires. Both of the ignition fields require the ignition point to be located and assessed by a senior firefighter who has undertaken fire investigation training. The assignment of an ignition factor requires some judgement to be made in order to determine if human caused fires were accidental or deliberate.

The report time field identifies the time (to the nearest minute) that the agency was notified of the fire, typically by the public as an emergency phone call. In most cases detection and reporting are likely to come soon after ignition due to the relatively dense population in the study area, however some ignitions may lead to smouldering fires or may grow very slowly and go undetected for some time. Some ignition sources, such as campfires and pre-existing fires that are not fully extinguished, may persist for long periods before initiating a fire spreading in vegetation.

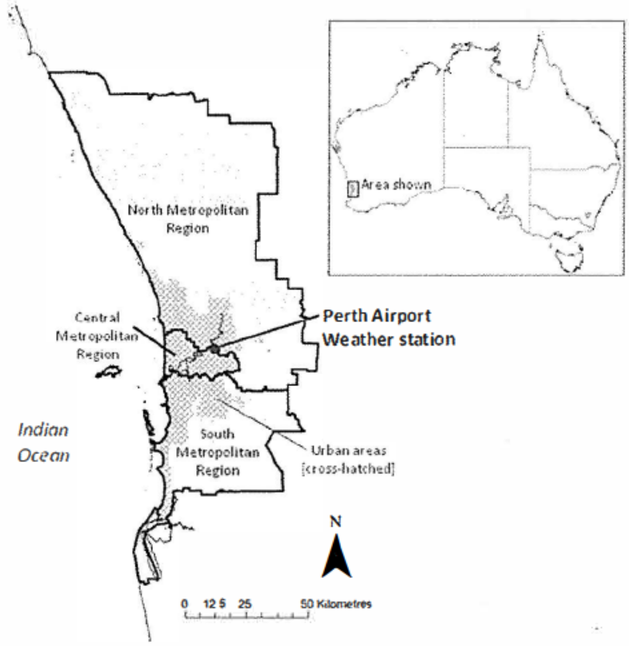

Fig. 1. Location of the study area and the weather station used. The cross-hatching shows urban areas.

The DFES database contained 87 specific ignition heat form types and 85 specific ignition factor types. These were used to determine 16 ignition cause categories (Table 1), including two natural, three deliberate and 10 accidental categories. There were two other categories for ignitions that were either listed as "other" or where the cause was not determined. The ignition cause categories were the smallest categorical units that the data could be broken down into based on the AIRS fields. Records from DPAW were not used because they had fewer categories for ignition cause and these did not readily translate to those available in the DFES database, particularly with the many types of accidental ignition cause. DPAW fires only comprised of 5.5% of the total vegetation fires that occurred in the study region and timeframe.

Day type attributes were compiled for each fire in the database. These were day of the week and binary categorical descriptors based on the occurrence of work days (all days except public holidays and weekends) and school days (all days except public holidays, weekends and school holidays).

Hourly weather data were obtained from the Perth Airport Bureau of Meteorology weather station (31.93°S, 115.98°E) for the period from 1 January 2000–30 June 2012. Missing weather observations were supplemented with observations from the nearby Perth Metropolitan weather station (31.92°S, 115.87°E). These were used to calculate Grassland Fire Danger Index (GFDI) [22], Forest Fire Danger Index (FFDI) [23] and fuel moisture content for the study period, with early observations (pre July 2004) used to stabilise drought indice inputs. GFDI and FFDI were calculated using Noble et al., [27] equations, with GFDI calculations based on an assumption that grass was constantly in a fully cured state. This assumption was required as there were no records of curing available to the study and would have led to a significant over estimation of GFDI in the cooler and wetter times of the study period. The drought factor input for FFDI was calculated using the Soil Dryness Index [25], which is the preferred drought index for Western Australian fire agencies [5]. The surface fuel moisture content (SFMC) of the litter layer was used to indicate the

[1] The Department of Fire and Emergency Services was known as the Fire and Emergency Services Authority until 31 October 2012.

[2] The Department of Parks and Wildlife was known as the Department of Environment and Conservation until 30 June 2013.

Table 1
Descriptions for the different ignition cause categories considered in this analysis.

Cause type	Cause category	Description
Natural	Lightning	Heat for ignition attributed to lightning strikes.
	Spontaneous combustion	Spontaneous combustion of materials such as mulch or other organic debris.
Deliberate	Incendiary	Arson, where a legal decision had been made or physical evidence could be used to prove that the fire was deliberately set.
	Suspicious (known cause)	Circumstances indicated that fires were likely to be deliberately set (i.e. probably arson), with the ignition source identified.
	Suspicious (unknown cause)	Circumstances indicated that fires were likely to be deliberately set (i.e. probably arson), however the ignition source was not, or could not be identified.
Accidental	Cigarettes and smoking material	Accidentally ignited by a cigarette or other smoking material.
	Small open fires	Accidentally ignited by a small open fire, such as a camp fire, bonfire, or rubbish fire.
	Escapes from planned burns	Escapes from fires deliberately ignited for a management purpose, such as reducing fuels, removing stubble or pasture improvement.
	Cutting or welding	Heat for ignition attributed to cutting or welding equipment.
	Matches or lighter	Heat for ignition attributed to matches and other lighters, such as cigarette lighters.
	Fireworks and explosives	Heat for ignition attributed to fireworks or explosives.
	Electrical failure	Ignition heat form attributed to malfunctioning electrical equipment, including powerlines and electrical devices.
	Mechanical failure	Ignition heat form attributed to malfunctioning machinery, including vehicles, that caused ignition through the generation of sparks, arcs, or heat.
	Re-kindled from a previous fire	Re-ignition from a previously extinguished unplanned fire
Undetermined	Other	Other minor ignition causes not categorised elsewhere in the database
	Undetermined or not reported	Ignition cause was not able to be determined or was not reported

Table 2
The number, percent and mean number of vegetation fires per day on all days for each cause category.

Cause categories	Total number	% of total	Cause type
Lightning	171	0.55	Natural (1.03%)
Spontaneous combustion	150	0.48	
Incendiary	3322	10.62	Deliberate (55.25%)
Suspicious (known cause)	11,227	35.90	
Suspicious (unknown cause)	2728	8.72	
Cigarettes and smoking material	3955	12.65	Accidental (29.81%)
Small open fires	252	0.81	
Escapes from planned burns	786	2.51	
Cutting or welding	165	0.53	
Matches or lighter	1206	3.86	
Fireworks and explosives	112	0.36	
Electrical failure	496	1.59	
Mechanical failure	756	2.42	
Re-kindled from a previous fire	1593	5.09	
Other	925	2.95	Undetermined (13.92%)
Undetermined or not reported	3427	10.96	

availability of the fuel for ignition SFMC and was determined using Matthews' [21] process model.

3. Analysis methods

The timing of vegetation fires from each cause category were investigated at four scales: annual (8 years, considered for the local bushfire season from July 1 to June 30); month of the year; day of the week; and hour of the day. The proportions of fires occurring in each element (year, month, day, hour) within these time scales were determined for all fires in the dataset and for fires from each cause category to establish time profiles for each individual cause class and for fires from all causes. Time profiles were also established for GFDI, FFDI and inverse SFMC, by determining the proportion of total sum for each of these that occurred within each time element. SFMC was inversed so that it would have a profile shape similar to the fire danger indices and ignitions. Each ignition cause profile was compared to the three weather profiles in order to determine the relationship between them. This was done using mean squared error (MSE, [40]), which provided a suitable relative measure at each time scale. All analyses were conducted in R [34].

Relationships between each of the cause categories and weather were further investigated by converting hourly GFDI, FFDI and SFMC values to deciles and determining the proportion of fires from each cause category occurring in each decile. This was done to produce profiles similar to those developed for the time scales. GFDI, FFDI and SFMC were considered as deciles because they have highly skewed distributions and this allowed the formation of groups with equal portions of time within the study period.

Cause categories that had unusual timing (i.e. different to the timing of fires from all cause categories) were identified using a method based on the MSE weighted by the number of observations in each group (see: [39]). MSE comparisons that are not weighted by observation size would suggest that cause categories that have few observations are more likely to be unusual than those that have higher sample sizes. The MSEs between each cause profile and the profile for all causes were determined. These were then weighted by applying a linear model to the log of the number of fires and the log of the MSE for each cause category. The residuals from the linear model provided an estimate of the difference between the time profiles for fires from one cause category and that for fires from all cause categories. The MSEs for fire causes that make up large portions of the total dataset are small and using the residuals from the log–log linear model with

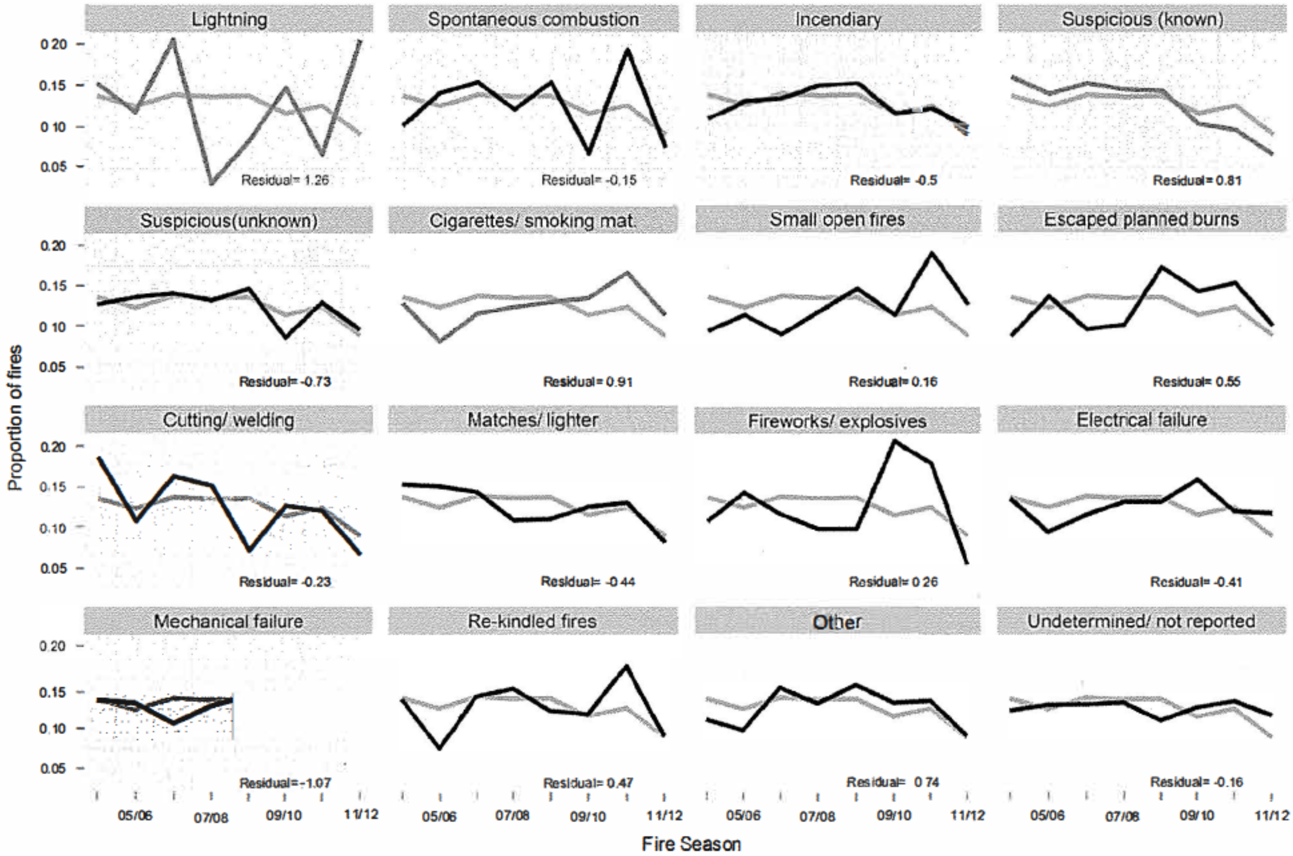

Fig. 2. Annual profiles for cause categories (black). The cause categories that had time profiles different to those for all causes (residual > 0.75) are shown in red and the inter-fire season time profile for all causes is shown in grey. The residual of a linear model applied to the log of the number of fires and the log of the MSE is given for each cause. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

number of fires provides a means of mitigating the effect of sample size. The cause categories with the highest residuals are those with the most unusual time profiles. In this study most of the residual plots for the different time scale and weather deciles had a break in residuals centred around 0.75 with only a few points greater than this. For this reason cause categories with residuals greater than 0.75 were considered to have timing profiles that were different to that of those for all causes in this study.

The effect of total fire bans was investigated by comparing the daily mean number of fires per day for all days to the number of fires experienced on days where the GFDI exceeded 50. This is the cut off used for setting total fire bans in the study area and had to be used in the absence of records of days that were declared total fire bans. Total fire ban declarations are made by DFES using forecast weather conditions across the study region, but may also consider other factors, such as resource availability and existing incidents. Unfortunately there were no available records listing days that were actually declared to be total fire bans during the study period. The majority of declared total fire ban days that occurred during the study period would have had GFDIs greater than 50, so would have been identified using this method.

The effect of a high profile fire on ignition rates was investigated by comparing daily ignition rates before and after it. The fire occurred on 6 February 2011 and destroyed 71 homes in the suburbs of Roleystone and Kelmscott within the study area. It was attributed to sparks from an angle grinder [19]. The mean numbers of daily fires before and after this fire for for each cause categories were compared for all days and for days when the GFDI was very high or above. These comparisons were made using the Wilcoxon rank sum test [17] as the data was non-parametric.

4. Results

There were 31271 vegetation fires that occurred in the DFES Metropolitan fire management regions during the eight year period (2922 days) in the DFES database. The majority (55.2%) of these were attributed to one of the three deliberate cause categories, with suspicious fires from known causes being the most common individual cause category (Table 2). In contrast to this, there were very few fires (1.2%) from natural causes. Fires attributed to accidental causes comprised 29.8% of the data, with cigarettes and smoking material being the most common of these. Fires with unknown causes comprised 13.9% of the dataset.

4.1. *Annual profiles*

The number of fires per season varied between 2803 and 4308 over the study period, with a decreasing trend (Fig. 2). The mean fire danger and fuel moisture conditions experienced during each fire season within this period were relatively uniform, other than slightly higher fire danger indices and lower fuel moisture contents during the 2010/11 season and lower fire danger indices during the 2005/06 season.

The cause categories that had time profiles that were most different to that for all causes, once samples size had been considered, were lightning, cigarettes and smoking materials and suspicious fires of known causes (Fig. 2). The suspicious fires of known cause appear to have a declining trend that is greater than that for fires from all causes over the eight fire seasons considered. The highly variable profile within the lightning plot reflects the fact that lightning fires occur on very few days, but these days

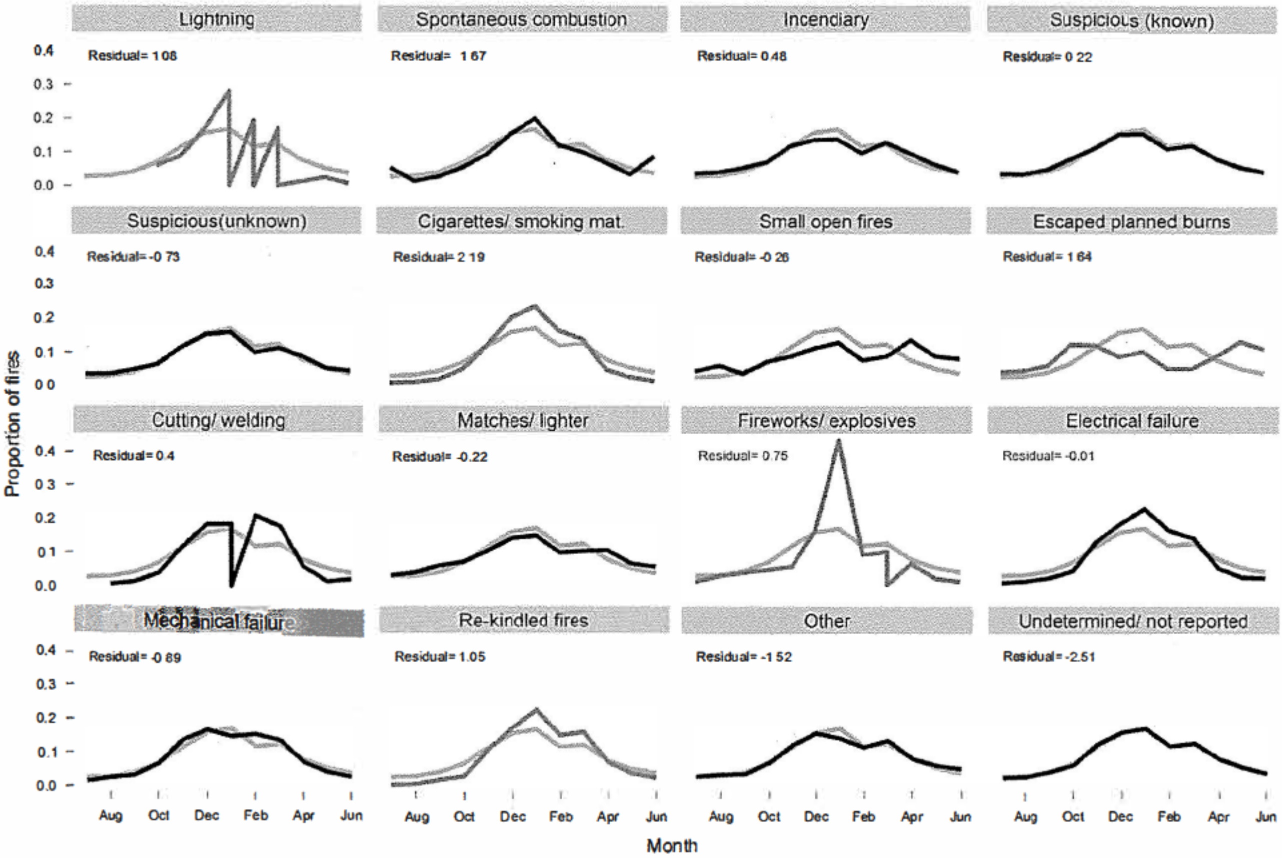

Fig. 3. Monthly profiles for cause categories (black). The cause categories that had profiles that were different to those for all causes (residual > 0.75) are shown in red and the profile for all causes is shown in grey. The residual of a linear model applied to the log of the number of fires and the log of the MSE is given for each cause. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

usually have multiple lightning ignitions [13,24]. Some cause categories (e.g. fireworks and explosives and re-kindled fires) have variable profiles but low residuals because of the small number of fires attributed to them.

4.2. Monthly profiles

The monthly time profile for vegetation fires from all cause categories sees the majority of ignitions occurring during the warmest months (Fig. 3), which is when the fire danger is highest and fuels are at their driest.

There were five cause categories that had monthly profiles different to that for all causes (Fig. 3). Four of these (lightning, cigarettes and smoking materials, fireworks and explosives and rekindled fires) had exaggerated seasonal profiles with higher proportions of fires in the summer months and fewer in the cooler months. Of these the most exaggerated was the fireworks and explosives cause category. The fires attributed to escaped planned burns occurred mostly in autumn and spring which are the times of the year that most planned burns are undertaken in this region. Fuels are usually too wet to sustain planned burns in winter and they are restricted in summer because the risk of escape is high.

4.3. Daily profiles

The daily profile for vegetation fires from all cause categories show that fires are more likely to occur on weekends than during the week (Fig. 4). The profile for weather was flat across the days of the week similar to that for fires attributed to cigarettes and smoking material.

The cause categories that had daily profiles most different to that for all cause categories were lightning, suspicious fires of known cause, cigarettes and smoking material, cutting and welding and fireworks and explosives (Fig. 4). Lightning caused fires had a highly variable daily profiles, which is likely to be related to the dataset containing a few randomly distributed days with multiple lightning caused fires. Similarly, fires caused by cutting and welding activities had peaks on Mondays and Wednesdays, but were only based on only 165 fires. Suspicious fires from known causes had slightly more ignitions on weekends and fewer on weekdays. Most ignitions attributed to fireworks and explosives occurred on Fridays, Saturdays and public holidays.

Fires from most cause categories have greater occurrence rates on weekends, public holidays, days when children were not at school and days where the fire danger rating was very high ($32 < \mathrm{GFDI} < 50$) or extreme ($\mathrm{GFDI} > 50$) (Table 3). There were 64 days within the study period where the GFDI exceeded 50 and total fire bans were likely to have occurred. Fires from all cause categories had higher rates of occurrence on these days. For these days, fires attributed to electrical failures, fireworks and explosives, rekindled previous fires, cigarettes and smoking materials and lightning had daily occurrence rates that were four or more times greater than for all days. Fires caused by cutting and welding, small open fires, incendiary arson and lightning had higher rates of occurrence on days of very high fire danger than days of extreme fire danger. This reduction in ignition from cutting and welding and small open fires is probably a result of total fire bans being declared.

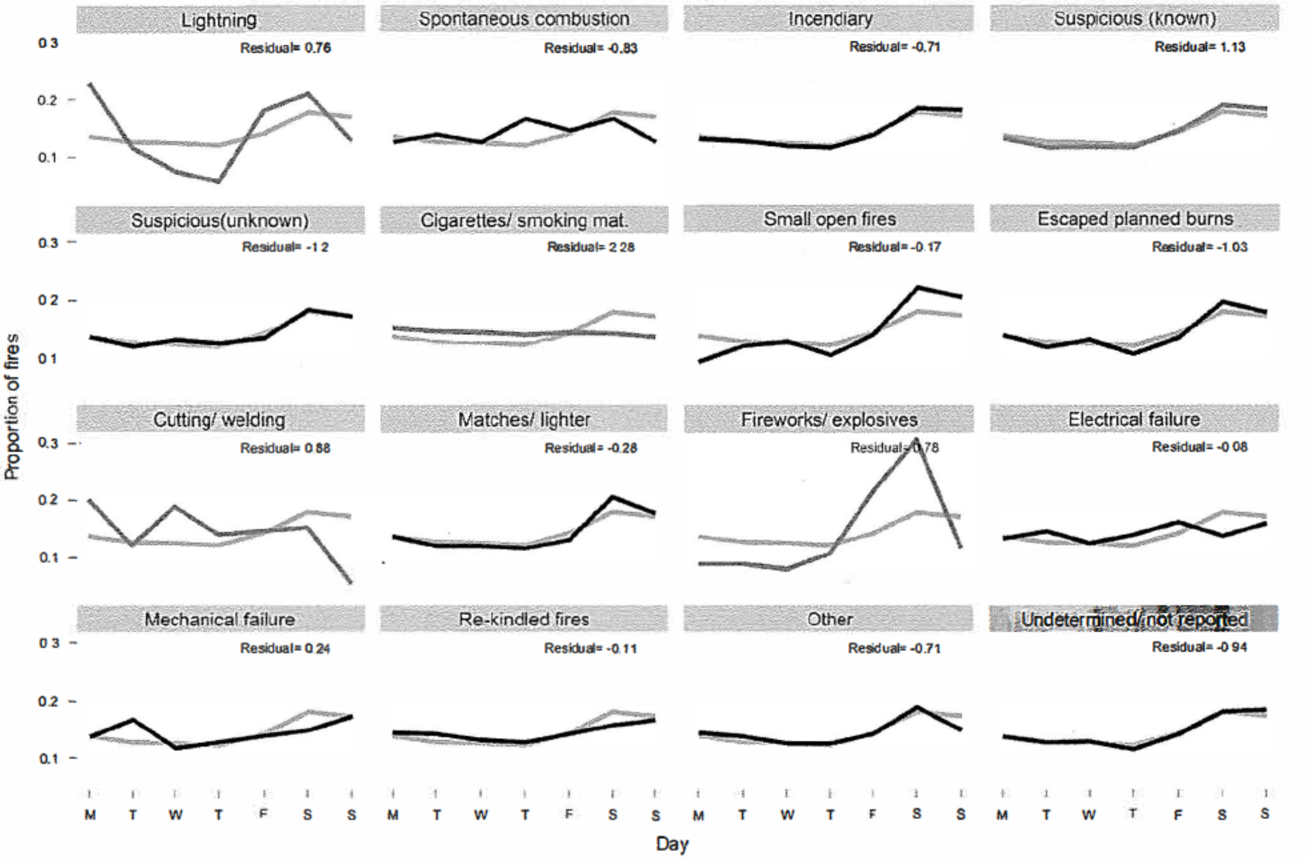

Fig. 4. Daily profiles for cause categories (black). The cause categories that had daily profiles different to those for all causes (residual > 0.75) are shown in red and the profile for all causes is shown in grey. The residual of a linear model applied to the log of the number of fires and the log of the MSE is given for each cause. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 3
Mean number of fires per day type by cause category.

Cause category	All days	Week-ends	Public holidays	Non-school day	GFDI < 32 (Low, mod, high)	32 < GFDI < 50 (Very high)	GFDI > 50 (Extreme/total fire ban)
Lightning	0.06	0.07	0.06	0.07	0.03	0.28	0.23
Spontaneous combustion	0.05	0.05	0.03	0.06	0.05	0.09	0.14
Incendiary	1.14	1.45	1.73	1.40	1.03	2.11	1.91
Suspicious (known cause)	3.84	4.98	5.92	4.84	3.47	7.07	7.67
Suspicious (unknown cause)	0.93	1.15	1.61	1.15	0.83	1.79	2.17
Cigarettes and smoking material	1.35	1.31	1.81	1.57	1.02	3.92	5.83
Small open fires	0.09	0.13	0.18	0.11	0.08	0.07	0.09
Escapes from planned burns	0.27	0.35	0.55	0.32	0.26	0.35	0.29
Cutting or welding	0.06	0.04	0.06	0.05	0.05	0.16	0.09
Matches or lighter	0.41	0.55	0.57	0.52	0.39	0.64	0.74
Fireworks and explosives	0.04	0.06	0.16	0.06	0.03	0.07	0.19
Electrical failure	0.17	0.18	0.32	0.20	0.13	0.48	0.84
Mechanical failure	0.26	0.29	0.37	0.29	0.22	0.62	0.61
Re-kindled from a previous fire	0.55	0.61	1.12	0.66	0.41	1.61	2.39
Other	0.32	0.37	0.49	0.37	0.27	0.68	0.73
Undetermined or not reported	1.17	1.47	1.90	1.44	1.00	2.46	3.52
Number of days	2922 (100%)	835 (28.6%)	77 (2.6%)	1395 (47.7%)	2630 (90%)	228 (7.8%)	64 (2.2%)

4.4. *Hourly profiles*

The hourly profile for all vegetation fires is similar to the diurnal profile for inverse SFMC, which shows a 1–2 h lag behind the fire danger indices (Fig. 5). Fires attributed to electrical and mechanical failures, rekindled fires and undetermined causes had hourly profiles that were very similar to those for FFDI and GFDI (Fig. 6). The fire cause types that had hourly profiles that were most different to that for all causes were those caused by cigarettes and smoking material, cutting and welding, fireworks and explosives and re-kindled previous fires (Fig. 6). The hourly profiles for fires caused by cigarettes and smoking material and cutting and welding exhibited exaggerated peaks, while re-kindled fires tended to occur earlier in the day than those from other causes. Fires caused by fireworks and explosives were more common at night, particularly in the hour following midnight. The profiles for fires attributed to deliberate causes showed higher representations during the night hours than for fires from all cause types. Fires attributed to rekindled previous fires, escaped planned burns and electrical and mechanical failures were less common at night than fires from all cause types.

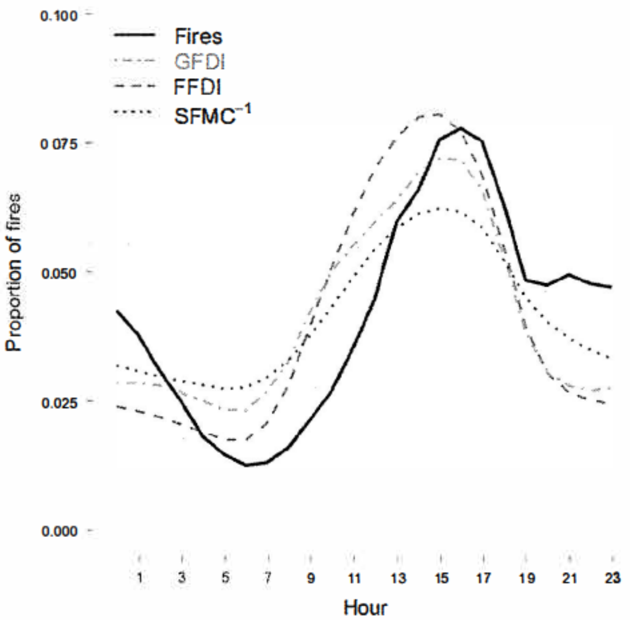

Fig. 5. Hourly profile of fires for all cause types compared with profiles for GFDI, FFDI and inverse SFMC.

4.5. *Fire danger and fuel moisture profiles*

Fires from all cause categories had positive relationships with GFDI and FFDI deciles (Figs. 7 and 8) and a negative relationship with SFMC (Fig. 9). Fires caused by cigarettes and smoking material and cutting and welding had GFDI, FFDI and SFMC decile profiles that were different to those for all causes, while those resulting from re kindled fires were sensitive to GFDI and FFDI. Ignitions attributed to these three cause classes are more sensitive to weather conditions than those from other causes, probably because they have a lower heat output making them more difficult to cause fires. Fires that resulted from electrical failures showed a similar, though less significant, trend to these. The number of daily fires attributed to cutting and welding on days of total fire ban are much lower than those on days of high or very high fire danger (Table 3) presumably due to fewer people using this sort of equipment as a result of the total fire ban declaration.

4.6. *Impact of a high profile fire on ignition rates*

A comparison of data from before and after the Roleystone–Kelmscott fire shows a reduction in the number of fires per day for most cause categories (Table 4), with significant reductions in fires

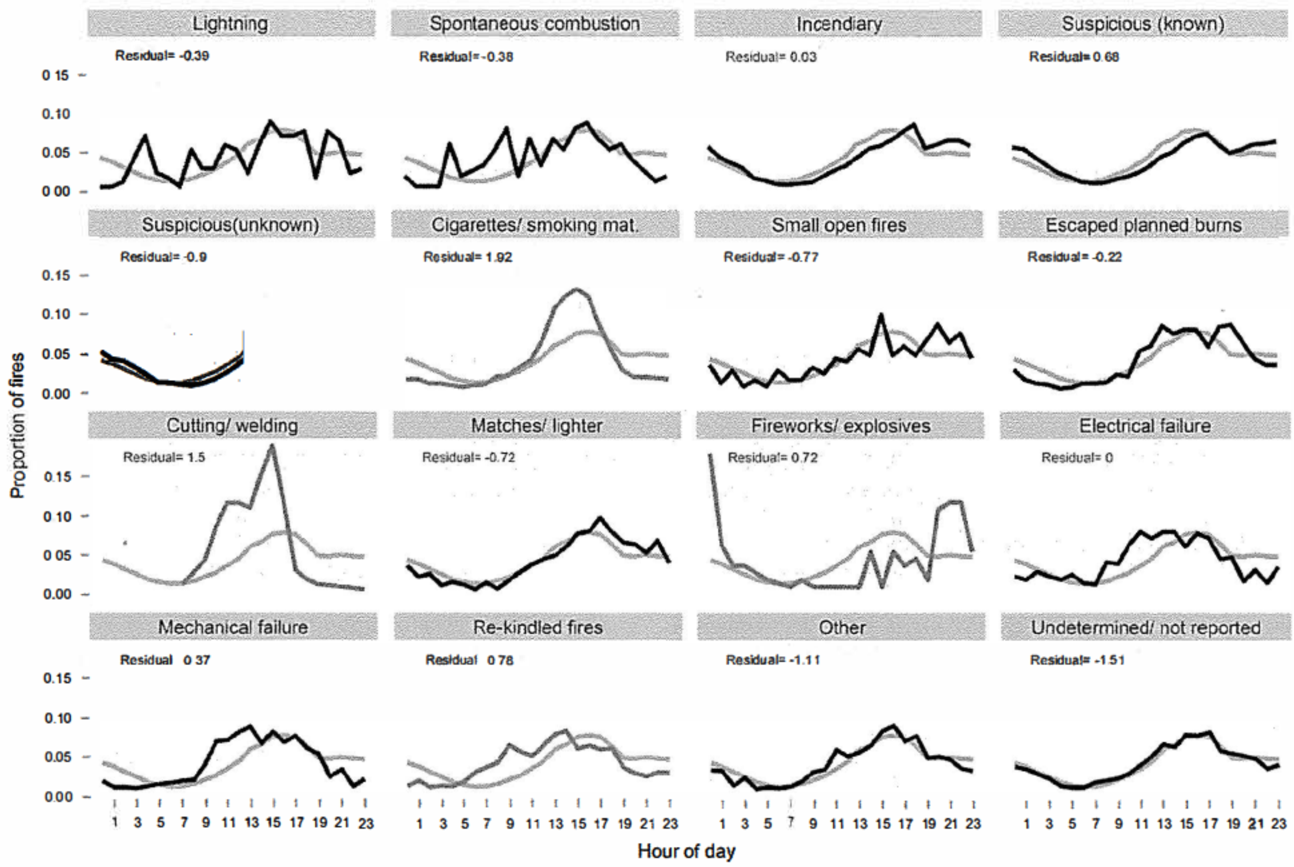

Fig. 6. Hourly profiles for cause categories (black). The cause categories that had hourly profiles different to those for all causes (residual > 0.75) are shown in red and the hourly profile for all causes is shown in grey. The residual of a linear model applied to the log of the number of fires and the log of the MSE is given for each cause. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

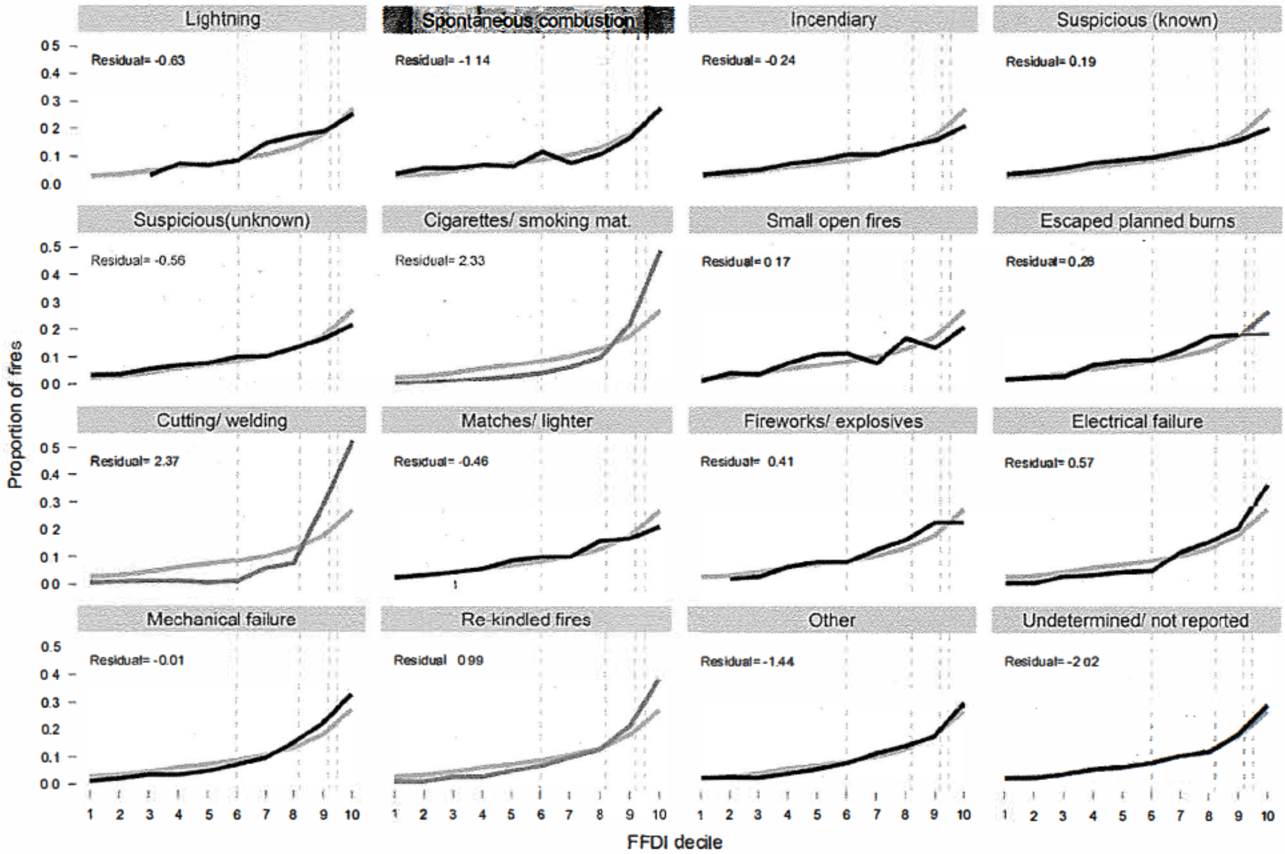

Fig. 7. GFDI decile profiles for cause categories (black). The cause categories that had profiles different to those for all causes (residual > 0.75) are shown in red and the GFDI decile profile for all causes is shown in grey. The residual of a linear model applied to the log of the number of fires and the log of the MSE is given for each cause. The dashed vertical lines indicate the breaks for the different fire danger rating classes (low, moderate, high, very high, extreme (total fire ban)). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

from the three deliberate causes as well as those attributed to matches and lighters, other causes and cutting and welding.

5. Discussion

The incidence of vegetation fires within the Perth region is strongly related to fire danger and fuel moisture conditions, with ignitions from all cause categories being more frequent during periods of elevated fire danger. The different cause categories had a range of sensitivities to fire danger and fuel moisture. Some causes that have small heat outputs, such as cigarettes, cutting and welding, were more restricted to periods with elevated fire danger conditions and low fuel moisture than other causes.

The timing of vegetation fires is also dependant on the presence of the ignition source. In terms of human caused fires this relates to human activity, which varies according to day type, as indicated by the increased rates of ignition on weekends, public holidays and non-school days (Table 3). These relationships are consistent with the findings of previous studies that have investigated the timing of deliberate and accidental fires (e.g.: [7,18,6,3,10,11,31]). The high incidence of fires attributed to arson related (deliberate) causes found in this study is consistent with that reported by Bryant [6] for this region, who found Western Australia to have a higher proportion of arson ignitions than other Australian states. This high rate of arson is similar to that reported in some European countries (e.g [35,15]), but is much greater than that reported in North American studies (e.g. [32,42,20]).

The rate of ignitions on days that are likely to have been total fire bans is considerably higher for most cause categories (Table 3). There are likely to be multiple reasons for this. Firstly, fuels are much more ignitable on total fire ban days, and for this reason ignition sources are more likely to successfully ignite fuels, including sources that have low heat outputs (e.g. cigarettes and sparks from cutting and welding equipment) that tend not to ignite fuels on other days. Secondly, there may be some undetected fires ignited on previous days that have been smouldering or burning slowly. These fires can quickly develop into detectable size in response to rising fire danger conditions as would occur on the mornings of total fire ban days. Finally, it has been hypothesised that deliberate fires may be more common on these days as some arsonists may be alerted to the potentially devastating impacts of fires due to the increased awareness of fire danger [32,6,11,33]. Total fire ban restrictions limit the number of fires caused by cutting and welding and small open fires, which have considerably higher occurrence rates on days of very high fire danger than total fire bans (Table 3).

Interestingly the number of ignitions attributed to lightning is lower on days of total fire ban than on days of Very High fire danger. This is likely to be due to the low incidence of storms on total fire ban days due to the meteorological conditions associated with them. Fires ignited by lightning can burn slowly and remain undetected for many days [14], often being detected on days of total fire ban in some regions (e.g. [28]). Slow burning lightning ignitions are less likely to occur in southern Western Australia than other regions because of the general lack of moisture during the long dry summers.

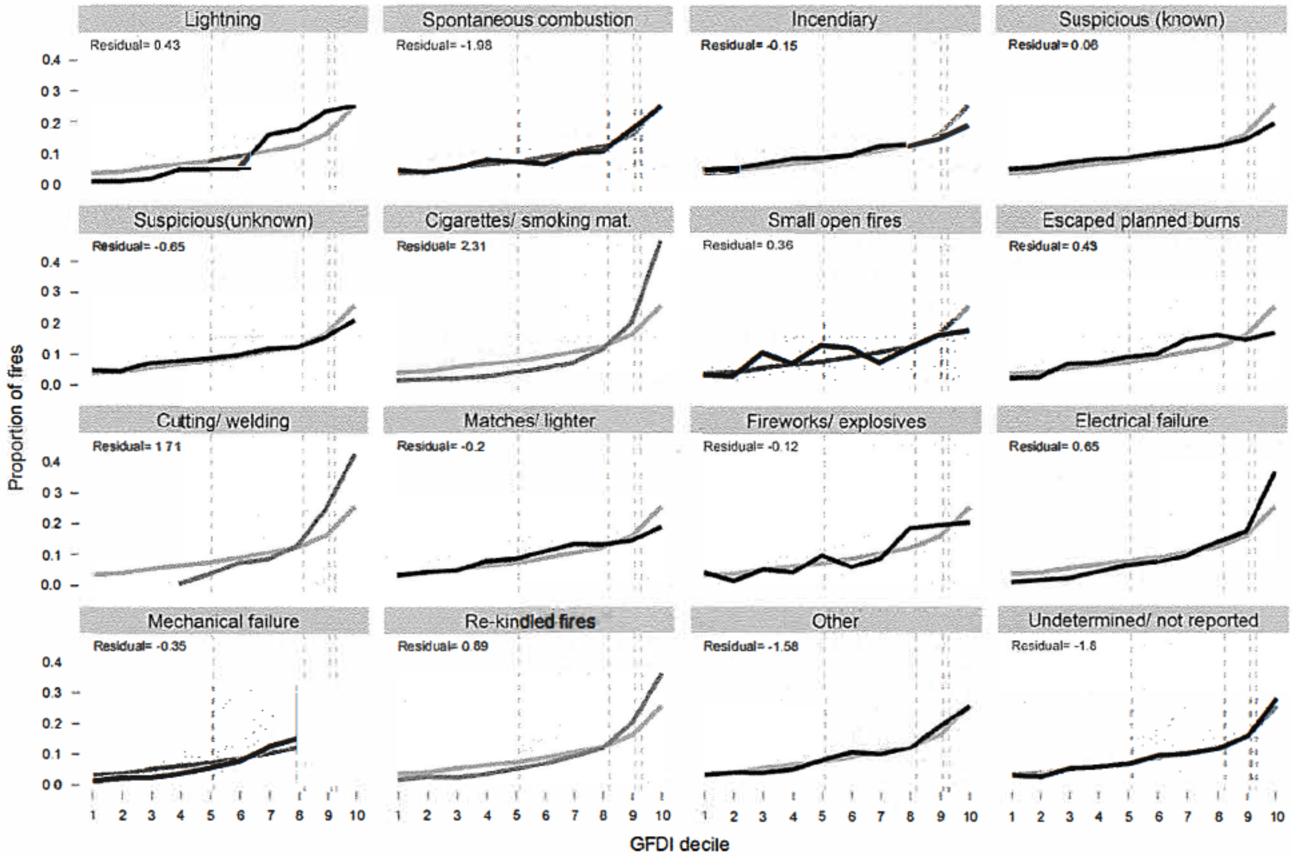

Fig. 8. FFDI decile profiles for cause categories (black). The cause categories that had profiles different to those for all causes (residual > 0.75) are shown in red and the FFDI decile profile for all causes is shown in grey. The residual of a linear model applied to the log of the number of fires and the log of the MSE is given for each cause. The dashed vertical lines indicate the breaks for the different fire danger rating classes (low, moderate, high, very high, extreme (total fire ban)). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

The high rate of ignitions on days of very high and extreme grassland fire danger is of concern given that the frequency of these days is predicted to increase under climate change [29]. Continued population growth along the urban–bushland interface may also lead to higher ignition rates and fire restrictions. Prevention and suppression strategies may need to be adjusted to counter the adverse effects of these.

There was a general decline in the annual number of ignitions throughout the study period, which is mainly due to the reduction in deliberately caused fires (Fig. 2). DFES, DPAW and the Western Australian Police have been implementing arson reduction activities in the study region since late 2001 [36]. These include a range of public education and fire awareness programs that are targeted at the whole community with an emphasis on children and their parents [4]. The Western Australian police also undertake patrols of areas with high arson rates on days of total fire ban. These are likely to curb deliberate ignition rates on these days. The education and awareness programs have developed over time and it is highly likely that the cumulative effect of these prevention efforts is influencing the decline in arson, which is independent of annual variations in fire danger and fuel availability (Fig. 2).

The analysis of the daily fire occurrence rates before and after the high profile Roleystone–Kelmscott fire shows that the publicity from this event led to reductions in the rates of fires attributed to arson, matches and lighters and cutting and welding (Table 4). While the duration of this reduction in these ignitions cannot be determined, this result indicates that these events can serve as opportunity for fire prevention messages to be more effectively understood and abided by.

5.1. Management implications

While the impact of increased public awareness due to arson reduction programs and high profile fire events are likely to have prevented fires a range of causes, it may be possible to further reduce fires by focussing the maximum preventative efforts on very high and extreme fire danger days that coincide with weekends and public holidays and by targeting specific causes. Fire agencies could use the publicity associated with high profile fires as opportunities to communicate fire prevention messages at a time when the public are more likely to listen to them.

Targeted awareness campaigns would be most effective if they focussed on the fire causes that result in the greatest number of ignitions (in this case arson and cigarettes). These campaigns could be timed to coincide with the peak times when ignition causes are most likely to occur based on meteorological conditions and day type. For example an awareness campaign aimed at reducing ignitions caused by discarded cigarettes could be specifically focussed on the peak hours of days with very high and above fire danger, particularly on days of total fire ban since there was no reduction in this ignition type of these days (Table 3). Such a campaign could use police to specifically enforce cigarette littering during these times, with the actions and results (e.g. convictions) of these being widely publicised and the public encouraged to report on those discarding cigarettes at these times. Other actions that may further reduce unwanted vegetation fires could include the patrolling of recent fires during the morning of very high and extreme fire danger which is a time when re-ignitions are more likely to occur (Fig. 6).

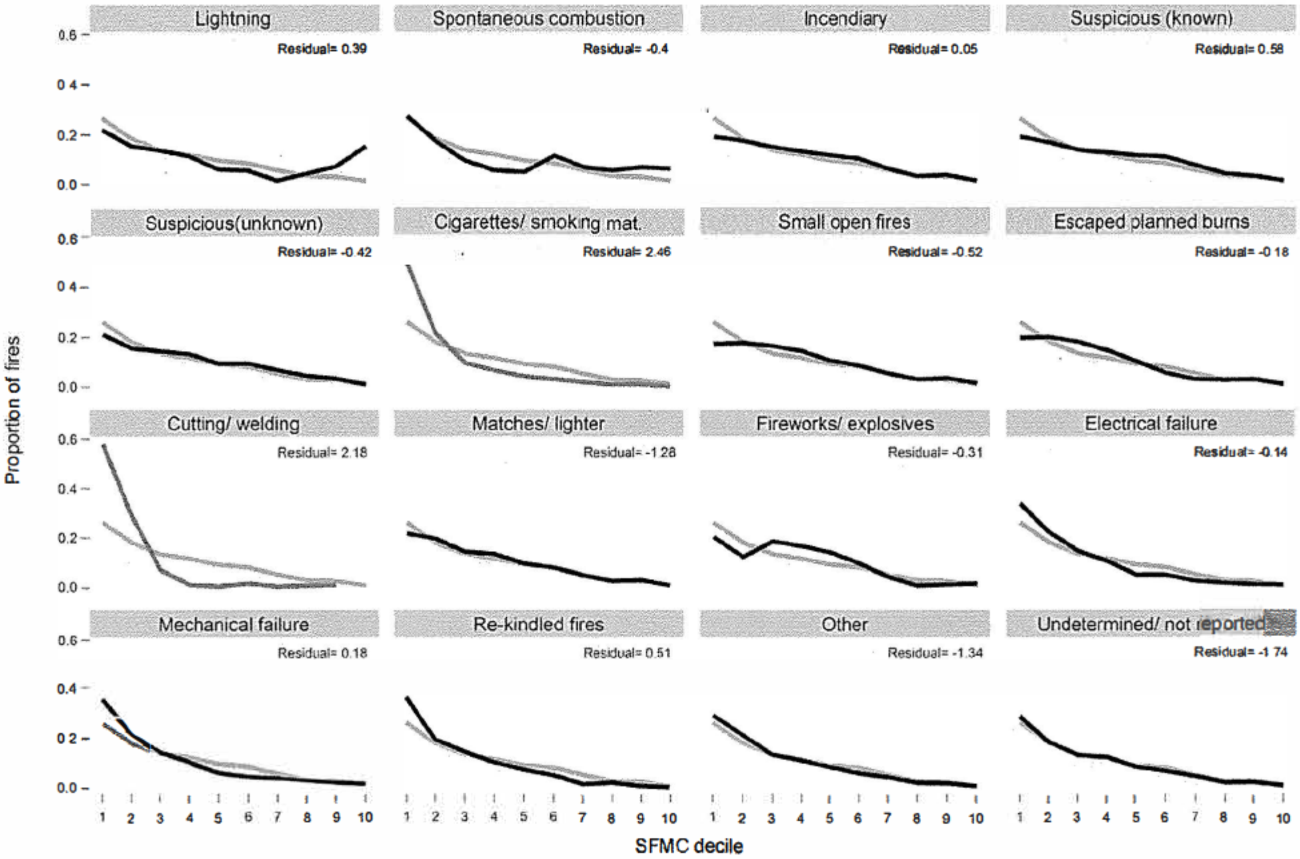

Fig. 9. SFMC decile profiles for cause categories (black). The cause categories that had profiles different to those for all causes (residual > 0.75) are shown in red and the SFMC decile profile for all causes is shown in grey. The residual of a linear model applied to the log of the number of fires and the log of the MSE is given for each cause. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 4
Mean numbers of fires per day before (1 July 2004–6 Feb 2011) and after (7 Feb 2011–30 June 2012) the Roleystone–Kelmscott fire.

	All days		Days with GFDI > 32	
Cause category	Before	After	Before	After
Lightning	0.05	0.09	0.25	0.35
Spontaneous combustion	0.05	0.04	0.11	0.09
Incendiary	1.19	0.89***	2.23	1.46**
Suspicious (known cause)	4.21	2.10***	8.11	4.03***
Suspicious (unknown cause)	0.97	0.78**	1.90	1.78
Cigarettes and smoking material	1.37	1.25	4.36	4.28
Small open fires	0.08	0.09	0.15	0.17
Escapes from planned burns	0.28	0.23	0.38	0.18*
Cutting or welding	0.06	0.04*	0.18	0.03**
Matches or lighter	0.44	0.30***	0.73	0.45*
Fireworks and explosives	0.04	0.03	0.11	0.05
Electrical failure	0.18	0.14	0.62	0.35*
Mechanical failure	0.27	0.22	0.66	0.51
Re-kindled from a previous fire	0.56	0.49	1.91	1.34*
Other	0.33	0.24**	0.77	0.45**
Undetermined or not reported	1.19	1.10	2.76	2.46
Number of days	2412	510	227	65

*,**,***, signify where groups are significantly different using the Wilcoxon two sample test at the $p=0.05$, 0.01, and 0.001 levels respectively.

6. Conclusion

The timing of vegetation fires is strongly influenced by weather conditions, with ignition rates increasing as fuels become drier and fire danger increases. Fires originating from sources that have low heat outputs, such as cigarettes and sparks from cutting and welding, are more sensitive to weather conditions than other causes, and mostly occur on dry days with very high fire danger. Fire timing is also influenced by the presence of ignition sources, which is related to human behaviour and varies with day type. Fire prevention measures should be targeted toward cause that contribute the most to the total fire count, with the greatest effort applied on days with the highest fire danger, particularly when these coincide with weekends, public holidays and school holidays. Efforts should be made heighten public awareness during the peak afternoon hours of days with very high and extreme fire danger.

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Predicting the number of daily human-caused bushfires to assist suppression planning in south-west Western Australia

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Abstract. Data from bushfire incidents in south-west Western Australia from the Departments of Parks and Wildlife and Fire and Emergency Services were used to develop models that predict the number of human-caused bushfires within 10 management areas. Fire incident data were compiled with weather variables, binary classifications of day types (e.g. school days) and counts of the number of fires that occurred over recent days. Models were developed using negative binomial regression with a dataset covering 3 years and evaluated using data from an independent year. A common model form that included variables relating to fuel moisture content, the number of recent human-caused bushfires, work day (binary classification separating weekends and public holidays from other days) and rainfall was applied to all areas. The model had reasonable fit statistics across all management areas, but showed enough day-to-day prediction variability to be of practical use only in the more densely populated management areas, which were dominated by deliberate ignitions. The findings of this study should be of interest to fire managers in Mediterranean climatic regions where a variety of practices are used to manage wildfires.

Additional keywords: accidental ignitions, deliberate ignitions, fuel moisture, negative binomial regression, wildfire occurrence.

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Introduction

Most bushfires that occur in populated parts of the world are caused by humans. It is well established that human-caused ignitions are spatially concentrated around areas of human activity and infrastructure such as suburbs and roads (e.g. Syphard *et al.* 2008; Catry *et al.* 2009, Penman *et al.* 2013). The temporal distribution of unintentional human-caused ignitions is more complex as it depends on fuel ignitability and human activity (Wotton *et al.* 2003, 2010). Fuel ignitability is a product of fuel moisture content (Anderson 1970) and varies with atmospheric conditions (Nelson 2001). The influence of human activity on the daily number of ignitions differs according to the causal activity. However, many studies have found higher ignition rates when people are more likely to be undertaking recreational activities, such as during school holidays, weekends and public holidays (e.g. Prestemon and Butry 2005, Bryant 2008, Albertson *et al.* 2009).

Fire management agencies undertake daily planning activities to minimise the incidence and effects of bushfires. During periods of anticipated bushfire activity, more resources are deployed for detection, rapid initial response and arson prevention, and warnings are broadcast to the public. Predictions of the number of likely bushfires and the potential fire behaviour to occur in a management area on a day allow suppression agencies to more accurately determine their resource needs (Haines *et al.* 1983; Tithecott 1992; Wotton and Martell 2005; Vilar *et al.* 2010*a*; Wotton *et al.* 2010) and thereby help to increase the probability of initial attack success (Podur and Wotton 2010; Wotton *et al.* 2010) and assess and manage the costs of over-preparedness against the consequences of under-preparedness (Magnussen and Taylor 2012).

Predictions of the number of bushfires expected on a given day have traditionally been based on the experience and intuition of senior managers with the aid of fire danger rating systems (Martell 1982; Martell and Boychuk 1997). These systems integrate information about the environment into numerical indices that provide an indication of the potential ignitibility, fire behaviour, suppression difficulty and damage caused by bushfires on a day (Chandler *et al.* 1983). They are used by fire authorities to determine preparedness levels and warn the public (Cheney and Gould 1995), but do not directly indicate the probability or number of unplanned bushfires on a given day. Several studies have been undertaken to determine the most suitable index for a region based on their relationship with fire occurrence and other related statistics determined from fire records (e.g. Viegas *et al.* 1999; Andrews *et al.* 2003; Vasilakos *et al.* 2009; Padilla and Vega-García 2011).

Models have been developed to predict the probability of a day with one or more bushfires and to estimate the number of daily ignitions that may occur within one or more defined regions (e.g. Cunningham and Martell 1973; Vega-Garcia *et al.* 1995; Wotton *et al.* 2003, 2010; Wotton and Martell 2005; Albertson *et al.* 2009). These models are typically based on variables related to fuel availability and causal agents. Variables associated with causal agents include lightning activity, recent bushfire activity and day type variables. The latter classifies days based on designations such as public holidays, weekends and school holidays, and may relate to the general abundance and activities of people in bushfire-prone areas. The factors that influence bushfire ignitions vary for different causes and for this reason most studies have only considered bushfires attributed to a single cause class (e.g. Wotton *et al.* 2003; Wotton and Martell 2005; Padilla and Vega-García 2011) or have considered bushfires from lightning and human causes separately (e.g. Reineking *et al.* 2010; Vilar *et al.* 2010*b*; Wotton *et al.* 2010; Magnussen and Taylor 2012). Some temporal bushfire occurrence models have also considered spatial variables by considering fires within grid cells across a landscape (e.g. Preisler *et al.* 2004; Reineking *et al.* 2010; Padilla and Vega-García 2011; Magnussen and Taylor 2012).

Investigations of day-to-day fire occurrence in regions with Mediterranean climates have come mainly from southern Europe (e.g. Vilar *et al.* 2010*a*, 2010*b*; Padilla and Vega-García 2011), where fire is mainly used for agricultural purposes on small private lots and escapes from these comprise a large proportion of the wildfires experienced, particularly in rural areas. None of these studies has developed prediction tools for operational planning. The present study considers south-west Western Australia, which also experiences Mediterranean climate but has a different cultural and land management context to those in the European study areas. This region has one of the most proactive landscape prescribed burning programs in the world (Burrows and McCaw 2013), which aims to mitigate the scale and effect of unplanned wildfires by limiting the amount of fuel that is available.

This study is concerned with the day-to-day variation in bushfire occurrence and aims to develop and evaluate the reliability of models that predict the number of daily human-caused bushfires in fire management areas within south-west Western Australia. Such models can be used to provide forecasts to assist daily fire management planning and have not been previously developed in Australia. This study explored the key relationships that affect fire management planning at the regional level, similar to the studies of Cunningham and Martell (1973) and Martell *et al.* (1987). It demonstrates methods that could be applied in other regions with adequate fire incident and meteorological records to develop simple practical operational predictive tools. The work presents a set of independent models including variables that provide maximum statistical goodness of fit (the common approach in most fire occurrence studies), together with a set of coefficients for a common model framework for the entire management region. This latter approach, which also led to models with high goodness of fit, provides a spatially large agency with a consistent framework for predicting occurrence, a valuable outcome from both an implementation and training perspective.

Methods

Study area and data

South-west Western Australia is characterised by a range of fuel types including annual pasture grasses, dry eucalypt forest and woodland, and shrubland. The region experiences a Mediterranean-type climate with annual drought in summer and autumn. The peak fire season extends from October through to May in most years, and tends to be shorter along the wetter southern coast. This region experiences ~1000 bushfire ignitions per year, with more than 90% of these caused by humans, including ~70% suspected to have been deliberately lit (Bryant 2008); For this reason, our study only considered human-caused ignitions. The highest density of ignitions occurs in the bushland adjoining the Perth metropolitan area and the urbanised coastal strip south of Perth, which has a population of 1.9×10^6 people (Australian Bureau of Statistics 2014). In Western Australia, bushfires are managed by two state government agencies with distinctly different roles and responsibilities. The Department of Parks and Wildlife (DPAW[A]) is responsible for the management of public land (including national parks and state forests) and has a responsibility for fire management and suppression on these lands. The Department of Fire and Emergency Services (DFES[B]) coordinates emergency services for a range of natural disasters and emergency incidents that threaten life and property, including bushfires on private land.

Fire incident records from DPAW and DFES have been used to form datasets that contain the number of daily bushfire ignitions for 10 management areas. The management areas include six DPAW districts (Swan Coastal, Perth Hills, Wellington, Blackwood, Donnelly and Frankland) and four DFES regions (North Metropolitan, South Metropolitan, South West and Lower South West) that overlap the DPAW districts (Fig. 1). All bushfires that occurred in each management region within the study period have been considered regardless of the land tenure or responding agency.

This study is concerned with bushfire ignitions in grass, shrubland and forest fuels that can potentially burn considerable areas. Urban areas have been omitted from each area used in this study: fires in these areas are typically small in extent as they are located in isolated patches of fuel such as gardens, vacant lots,

[A]The Department of Parks and Wildlife was known as the Department of Environment and Conservation (DEC) until 30 June 2013.

[B]The Department of Fire and Emergency Services was known as the Fire and Emergency Services Authority (FESA) until 31 October 2012.

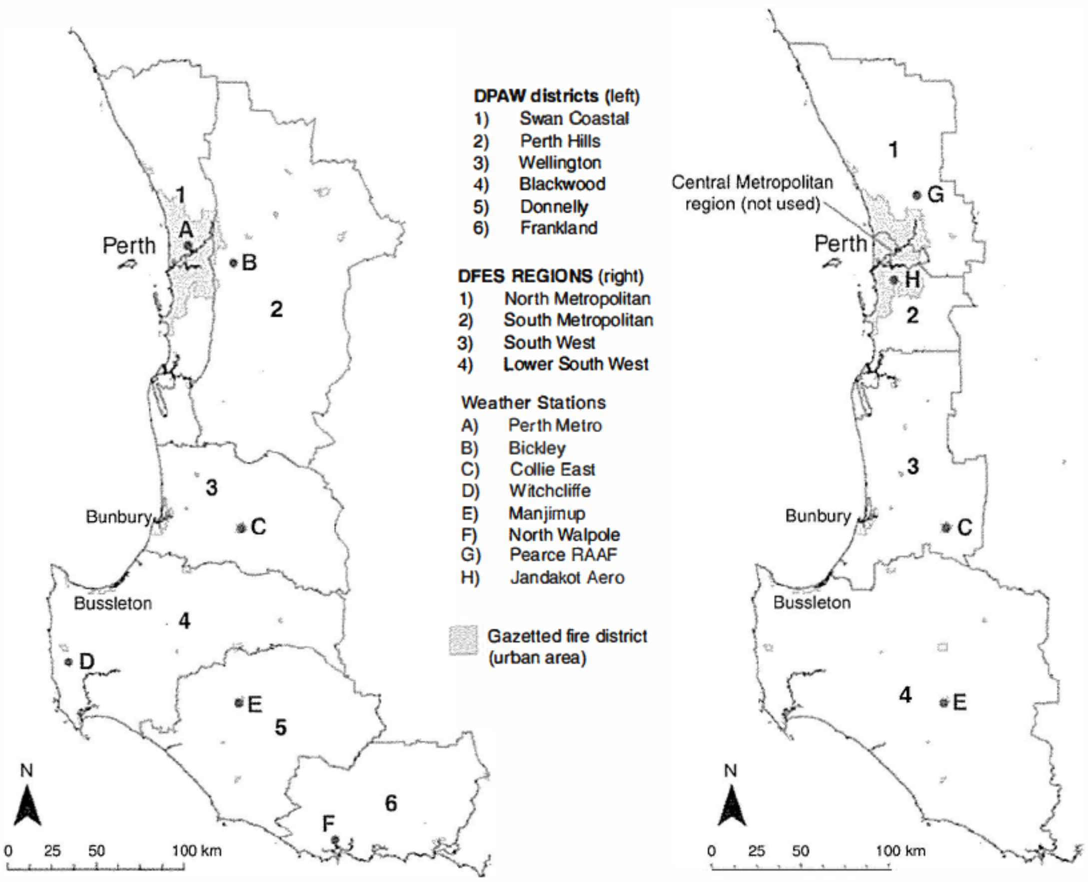

Fig. 1. Location and extent of Department of Parks and Wildlife (DPAW) districts (left) and Department of Fire and Emergency Services (DFES) regions (right) considered in this study. Grey shaded areas show the urban areas (identified using DFES's gazetted fire district areas) omitted from the analysis. Points show the locations of the primary weather stations used (Bureau of Meteorology). The Central Metropolitan region (DFES) was not used in this analysis as it was classified entirely as urban.

urban parks and road verges. Urban areas were identified using DFES's 'gazetted fire district' boundaries (grey areas in Fig. 1). These included all areas where the primary response came from an urban fire brigade whose primary role is structural fire-fighting. The DFES Central Metropolitan region was not included in this study because it is entirely within the gazetted fire district.

The main part of this study was restricted to a period where data were available from both state organisations. This limited our data to four fire seasons (2008–09, 2009–10, 2010–11 and 2011–12), where a fire season covers a full year from 1 July to 30 June. The DFES data from seasons before 2008–09 did not have sufficient location information to determine in which management areas fires occurred and whether they were in gazetted districts.

The first three seasons were used as a training dataset for model development and the 2011–12 season was reserved for model evaluation. Fire incident data with suitable location information were available in the DPAW dataset for 10 fire seasons starting from 2002–03, and were used to investigate the importance of the duration and age of the training dataset.

Human-caused bushfires were categorised as deliberate, accidental or of unknown cause. Deliberate ignitions included arson and suspected arson fires where the ignition site was within vegetation or burned from another location (e.g. dumped stolen vehicles) into vegetation. Accidental ignitions were those attributed to a range of unintentional causes such as malfunctioning machinery, escaped campfires and escaped prescribed burns. The unknown ignition category comprised fires of unknown cause, but when lightning was not suspected. We investigated deliberate and accidental ignitions independently and developed models for these to determine if there are different factors driving them, and the influence of these factors.

Other data

The fire incident data were compiled with data related to day type, recent bushfire activity and weather conditions. Day type variables were used to categorise days into groups based on different human activities. These were day of the week and the binary categorical variables separating public holidays, weekends, work days (all days except public holidays and weekends)

Table 1. Weather, drought, fire danger and fuel moisture variables considered in this study
FD, fire danger; FM, fuel moisture

Attribute (units)	Group	Daily format(s)	Reference(s)
Air temperature (°C)	Weather	max	
Relative humidity (%)	Weather	min	
Wind speed (km h $^{-1}$)	Weather	max	
Gust wind speed (km h $^{-1}$)	Weather	max	
Rainfall[A] (mm)	Weather	daily total	
Days since last rainfall	Drought	count	
Keetch Byram Drought Index (KBDI)	Drought	daily figure	Keetch and Byram (1968)
Soil Dryness Index (SDI)	Drought	daily figure	Mount (1972), Burrows (1987)
Drought factor (calculated with KBDI)	Drought	daily figure	McArthur (1967), equation in Noble *et al.* (1980)
Drought factor (calculated with SDI)	Drought	daily figure	McArthur (1967), equation in Noble *et al.* (1980)
Forest Fire Danger Index (FFDI) (calculated with KBDI)	FD	max, mean, 10am, 12pm, 3pm	McArthur (1967), equation in Noble *et al.* (1980)
FFDI (calculated with SDI)	FD	max, mean, 10am, 12pm, 3pm	McArthur (1967), equation in Noble *et al.* (1980)
Grassland Fire Danger Index (assuming 100% curing)	FD	max, mean	McArthur (1966), equation in Noble *et al.* (1980)
Forest Fire Behaviour Table index for Northern Jarrah forest	FD	max, mean	Sneeuwjagt and Peet (1985), FMC equations in Viney (1991), index equations in Beck (1995)
Forest Fire Behaviour Table index for Karri forest	FD	max, mean	Sneeuwjagt and Peet (1985), FMC equations in Viney (1991), index equations in Beck (1995)
Canadian Fire Weather Index	FD	daily index	Van Wagner (1987)
Build Up Index	FD	daily index	Van Wagner (1987)
Initial Spread Index	FD	daily index	Van Wagner (1987)
Fine Fuel Moisture Code	FD	daily index	Van Wagner (1987)
Duff Moisture Code	FD	daily index	Van Wagner (1987)
Drought Code	FD	daily index	Van Wagner (1987)
Fosberg Fire Weather Index (FFWI)	FD	max	Fosberg (1978)
FFWI modified to include drought effect	FD	max	Goodrick (2002)
Simple fire danger index	FD	max	Sharples *et al.* (2009*a*)
Simple fire danger index with drought	FD	max	Sharples *et al.* (2009*a*)
McArthur Grassland FMC (%)	FM	min	McArthur (1966), equation in Sullivan (2010)
McArthur Forest FMC (%)	FM	min	McArthur (1967), equation in Viney (1991)
Simard FMC (%)	FM	min	Simard (1968)
Matthews Simple FMC (%)	FM	min	Matthews *et al.* (2010)
Matthews process surface FMC (%)	FM	min, mean, 10am, 12pm, 3pm	Matthews (2006)
Matthews process profile FMC (%)	FM	min, mean 10am, 12pm, 3pm	Matthews (2006)
Vesta FMC (%)	FM	min	Gould *et al.* (2007)
Sharples fuel moisture index	FM	min	Sharples *et al.* (2009*b*)

[A]Measured for the 24 h to 0900 hours.

and school days (all days except public holidays, weekends and school holidays). The influence of recent bushfire activity was considered by constructing variables that summed the total number of bushfires occurring over the previous 2–14 days within each region. These recent bushfire activity variables were made for both the total number of bushfires (all causes) and those attributed to human causes.

Weather data were sourced from a representative Bureau of Meteorology weather station within each area (Fig. 1). Records beginning in January 2000 were used to allow time for drought indices to stabilise before the start of the study period (1 July 2003). The weather stations were selected based on their location within the area and the completeness of their data.

Hourly observations from each station included air temperature, relative humidity, wind speed, rainfall and mean sea level pressure. Missing data were dealt with as follows. Estimates for missing daily rainfall and maximum temperature data were obtained from the SILO database (http://www.longpaddock.qld.gov.au/silo/about.html (Jeffrey *et al.* 2001)). This allowed for the continuous drought indices to run for the entire period. Data that were missing for less than 5 consecutive hours were interpolated, but data missing for 5 or more consecutive hours were estimated from the most representative nearby station. None of the stations used had more than 5% missing hourly data within the main study period. Corrected data were used to calculate a range of fire danger and drought indices and to model fuel moisture content (FMC). These were converted into relevant daily summary formats (e.g. the maximum hourly reading for a day) for model development and are listed in Table 1.

Modelling

Models developed to predict daily bushfire occurrence have typically used Poisson regression (e.g. Cunningham and Martell

1973; Wotton *et al.* 2003, 2010; Prestemon and Butry 2005; Prestemon *et al.* 2012). Preliminary modelling was undertaken using Poisson regression, but the mean deviance of these models was much higher than is expected with a Poisson distribution, as a result of the overdispersion from the zero count within the data (Bolker *et al.* 2009). Following this, negative binomial regression models of the common NB2 variety (where the variance is assumed to be a function of the square of the mean) (Cameron and Trivedi 1998) were tested. Negative binomial regression is similar to Poisson regression except that it relaxes the assumption of the equality of the mean and variance by adding an extra parameter to model overdispersion (Greene 2008). Negative binomial models were found to suit the data as they had mean deviances close to 1, so were selected for this preliminary study.

Negative binomial models of daily fire occurrence were developed for each bushfire management area using a common model form that included the same group of variables but had unique coefficients for each management area. These models predict the number of human-caused bushfires occurring in the region regardless of their cause (e.g. deliberate, accidental, unknown), land tenure or responding agency. A common model form is useful from an implementation perspective as it provides consistency in the input variables that need to be calculated in each area and the ability to easily compare relative fire occurrence potential across regions. In addition, we relaxed this model form constraint and fitted the best overall combination of predictors for each bushfire management unit. This latter approach provides a means of obtaining the best fit in each area and also a means of assessing how predictors vary in their importance and statistical significance across the entire study area. The general form used for both these models was:

$$N_f = \exp(\beta_0 + \beta_1 V_1 + \beta_2 V_2 + \ldots + \beta_n V_n) \qquad (1)$$

where N_f is the number of fires in each fire management area per day, $\beta_0, \ldots, \beta_n$ are the coefficients and $V_1, \ldots, V_n$ are the variables.

The common form model was developed by combining data for each agency from the training period into a single dataset for all areas and determining the most important variables using a stepwise process that considered all combinations of non-correlated variables. The avoidance of highly correlated variables ($r > 0.5$) limited models to a maximum of one variable related to drought, fire danger, FMC (Table 1), day type and recent fire activity. The best five models were identified using the Akaike Information Criterion (AIC) (Sakamoto *et al.* 1986). These model forms were then applied to each area dataset to determine the form that could be best applied to all management areas. Individual management area models were developed using the same stepwise procedure but with data from only a single area. Negative binomial models were constructed using the glm.nb function in the MASS package (Venables and Ripley 2002) in R (R Development Core Team 2012).

The most significant predictor variables influencing the number of deliberate fires and the number of accidental fires were identified by developing negative binomial models with a common form for all areas using only the data from each cause class with the same procedure that was used to develop the common form model for all human-caused bushfires.

The 95% confidence interval for each model prediction was used to determine a prediction band, which was rounded to the nearest integer, hence providing a daily range of predicted bushfires. This provides the user with worst- and best-case estimates for each day, and the differences between them give a measure of the reliability of the prediction (Boyle *et al.* 2012).

Model performance was assessed using the evaluation dataset in two ways. First, the proportion of daily human-caused bushfires within the predicted 95% confidence interval was determined (accuracy rate), as were the proportions that were under predicted and over predicted (under- and over-prediction rates). Second, distance measures were used to quantify the magnitude of the forecast error and to determine model bias. The distance measures used here were the root mean square error (RMSE) and the mean absolute error (MAE), and bias was measured using the mean bias error (MBE) (Willmott 1982).

In order to evaluate the sensitivity of predictions to the duration and age of the training dataset, common form negative binomial models predicting the daily number of human-caused bushfires attended by DPAW were developed for each of the six DPAW management areas using three independent training periods: the common period (2008–09 to 2010–11), an early period of the same duration (2003–04 to 2006–07) and the longest available period (2003–04 to 2010–11). These models were evaluated on the human-caused bushfires in the DPAW database for the 2011–12 season. Models developed using the common period and early period were compared to investigate the influence on fits of age of the training dataset. Models developed using the common period were compared to those developed using the longest available period in order to investigate the influence of the duration of the training period. Comparisons were based on distance measures, because models developed on longer duration datasets have narrow confidence intervals and therefore narrow prediction bands.

Results

There are large differences in the number of fires and the proportion of deliberately lit fires across the study area. Management areas in the more densely populated northern parts of the study area experience considerably more human-caused ignitions and days with human-caused bushfires per season than do those in the south (Table 2). The peak days in these areas also had more ignitions, with higher proportions of these deliberately lit. The 2008–09 season had the largest number of fires in the majority of management areas. The number of annual fires attributed to each cause type did not vary much other than for deliberate fires, which were much more prevalent in the 2008–09 season (Fig. 2).

Modelling number of bushfires per day in fire management areas

The common model form for predicting the number of daily human-caused bushfires in all areas included the variables FMC (predicted using Viney's 1991 equation for McArthur's 1967 table), number of human-caused bushfires that occurred within the area over the previous 14 days, the binary work day classification and daily rainfall (measured at 0900 hours). The coefficients and fits for this model form in each fire management area are given in Table 3 and graphical examples of the model fit

Table 2. Median fire season statistics for fire management areas during the study period (2008 09 to 2011–12)

	Median number of human-caused bushfires per year				Median number of days with human-caused bushfires per year		Number of daily human-caused bushfires	
	All	Deliberate	Accidental	Unknown	Number	%	Mean	Max
DPAW district								
Swan Coastal	270	134	50	86	149	40.8	0.78	7
Perth Hills	397	112	89	196	174	17.6	0.96	12
Wellington	164	46	37	81	99	27	0.39	9
Blackwood	177	30	63	84	105	28.7	0.47	8
Donnelly	28	4	13	11	21	5.7	0.07	4
Frankland	28	5	11	12	18	4.9	0.06	4
DFES region								
North Metropolitan	391	169	66	156	181	49.4	1.02	13
South Metropolitan	150	57	29	64	97	26.6	0.41	6
South West	217	56	55	106	125	34.2	0.58	8
Lower South West	194	27	71	96	105	28.7	0.48	9

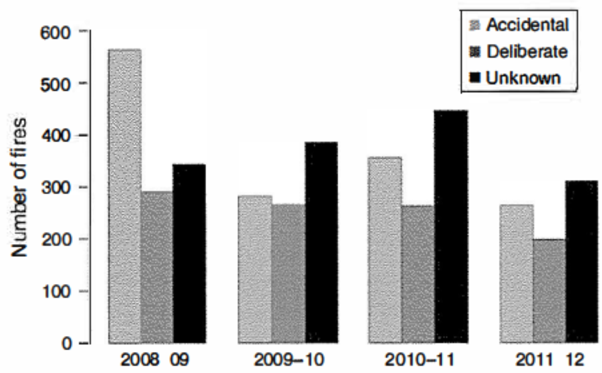

Fig. 2. The number of fires per season by cause across the study area.

to the areas with the highest, median and lowest mean daily number of fires during the evaluation season (2011–12) are given in Fig. 3. Model forms developed independently for each management area are presented in Table 4 along with their fit statistics. The number of fires per day (N_f) in each fire management area can be determined using Eqn 1 where β_0, β_1 and β_n are the coefficients listed in each management area columns in Tables 3 and 4, and V_1, V_2 to V_n are the associated variables.

The fits of the common form models (Table 3) show high prediction rates with 81–99% of daily fire occurrences from the 2011–12 season fitting within the predicted 95% confidence band.

Models fitted individually to areas had slightly improved fit and distance measures (Table 4) than those from the common form models (Table 3). The MBE of these models indicate that they had a stronger positive bias than the common form models. The individual area models listed in Table 4 contain 25 unique variables, with FMC variables selected first in all but one.

Model forms that excluded recent observed fire history variables were also assessed, as these variables may be troublesome for operational forecasts of fire activity several days into the future: for any future days leading up to the day of interest, fire occurrence numbers can only be estimated, likely using the model itself as a source. Models similar to those presented in Tables 3 and 4 that did not include recent fire history variables had much higher coefficient standard errors and as a result, very wide confidence intervals. Prediction bands developed using the 95% confidence interval were too wide to be of practical use, and the use of smaller confidence intervals resulted in reduced accuracy predictions.

Effect of duration and age of the training dataset

The models developed using the independent training periods (2003–04 to 2006-07, 2008–09 to 2010-2011 and 2003–04 to 2010–11) in the DPAW data all showed very similar goodness of fit with the evaluation data (Table 5), indicating that there is very little difference in the models developed from these datasets. In most cases the training datasets contained seasons that had more and fewer fires than the evaluation season (2011–12). The relative fits of these models may have been different if this were not the case.

Difference between deliberate and accidental ignitions

The best model form for predicting the number of deliberate fires per day in all 10 management areas (Table 6) contained the same variables, in the same order, as the common form model for all types of human ignitions (Table 3), which perhaps reflects the high prevalence of this cause type in the overall dataset. This is probably because there are nearly twice as many deliberate ignitions as accidental ones across the entire study area in the training dataset (Table 2). The best model form for predicting the number of daily accidental fires contained similar variables (Table 6). These were mean daily profile moisture content calculated using the Matthews (2006) model, the number of human-caused bushfires in the area over the previous 7 days, minimum daily relative humidity and school day, which indicated that accidental ignitions were more likely on non-school days. The distance measures for the cause-specific models were generally higher than those for the model for all human-caused fires indicating poorer fits. This is probably because of the higher frequency of days without fires in the individual cause-specific subsets. The distance measures for accidental ignition models were generally higher than those for deliberate

Table 3. Coefficients (standard errors), dispersion parameter (Θ) and fit statistics for the common model (Eqn 1) form predicting the daily number of human-caused fires (all cause types) applied to the 10 bushfire management areas

Probabilities are significant at: *, $0.01 < P < 0.05$; **, $0.001 < P < 0.01$; ***, $P < 0.001$

	Swan Coastal	Perth Hills	Wellington	Blackwood	Donnelly	Frankland	North Metro	South Metro	South West	Lower South West
Coefficients (standard error)										
Intercept [β_0]	1.439***	1.178***	0.647**	0.848***	−0.604	−0.553	1.404***	0.912***	0.811***	0.602**
	(0.195)	(0.171)	(0.232)	(0.256)	(0.471)	(0.460)	(0.182)	(0.242)	(0.208)	(0.211)
Minimum hourly equilibrium FMC (McArthur 1967) (%) [β_1]	−0.279***	−0.178***	−0.238***	−0.205***	−0.310***	−0.282***	−0.237***	−0.325***	−0.216***	−0.189***
	(0.027)	(0.019)	(0.031)	(0.028)	(0.066)	(0.064)	(0.026)	(0.068)	(0.026)	(0.021)
Number of human-caused fires in previous 14 days [β_2]	0.026***	0.018***	0.047***	0.046***	0.151	0.162*	0.020***	0.039***	0.036***	0.046***
	(0.006)	(0.004)	(0.011)	(0.009)	(0.082)	(0.076)	(0.004)	(0.011)	(0.008)	(0.009)
Workday (binary 1 = workday) [β_3]	−0.504***	−0.313***	−0.351**	−0.335**	−0.067	−0.299	−0.530***	−0.284**	−0.312**	−0.255*
	(0.078)	(0.082)	(0.116)	(0.113)	(0.277)	(0.279)	(0.076)	(0.107)	(0.098)	(0.116)
24 h rainfall to 0900 hours (mm) [β_4]	−0.045*	−0.078***	−0.184**	−0.139***	−0.098	−0.288	−0.122***	−0.025	−0.168***	−0.022
	(0.195)	(0.022)	(0.062)	(0.034)	(0.119)	(0.216)	(0.033)	(0.021)	(0.047)	(0.023)
Θ	3.303	1.744	1.254	1.253	1.404	0.444	2.194	2.429	1.694	1.121
Fits (to 2011/2012 evaluation data)										
Accuracy rate	**0.885**	**0.809**	**0.970**	0.932	0.984	**0.995**	**0.861**	0.940	**0.937**	0.913
Under prediction rate	**0.066**	**0.068**	**0.019**	0.046	0.016	**0.005**	**0.049**	0.057	**0.041**	0.066
Over prediction rate	**0.049**	**0.123**	**0.011**	0.022	0	**0**	**0.090**	0.003	**0.022**	0.022
RMSE	**0.972**	**0.974**	**0.551**	0.878	0.427	**0.257**	**1.073**	0.761	**0.801**	0.886
MAE	**0.670**	**0.681**	**0.390**	0.577	0.159	**0.107**	**0.730**	0.489	**0.537**	0.559
MBE	**0.078**	**0.145**	**0.095**	0.096	−0.027	**0.009**	**0.149**	−0.012	**0.069**	0.035

ignitions, which may be related to the higher frequency of days with no fires.

Discussion

This paper presents new models that predict the daily number of human-caused bushfires at the scale of management areas used for administrative purposes by Western Australian government agencies and demonstrates a method that could be applied to other regions to develop similar operationally focussed models. The models have reasonable fit statistics (Tables 3, 4), but only those developed for areas that experience high numbers of fires (i.e. >0.25 fires day^{-1}) showed enough day-to-day prediction variability to be of practical use. The models for these areas (Swan Coastal, Perth Hills, Wellington, North Metropolitan, South Metropolitan, South West and Lower South West) are suitable for agencies to use to inform their daily operational resource planning.

Models produced for the management areas that experience few fires (i.e. Donnelly and Frankland) showed little day-to-day variability in their predictions. Although these models appeared to have good fit statistics (Table 3) a constant prediction for between 0 and 1 bushfires every day would have performed just as well in these areas. There are no reliable relationships to identify days with fires in these areas and, because of the small number of fires in these regions overall, it is unlikely that a reliable model that would meet operational needs could be developed for these areas.

The most common problems regarding the fit of the models related to the days with under-predicted fire numbers. These were often those with the highest number of fires. This is a major weakness in the application of this model as these are the days when more initial attack resources are required and when preparedness planning is crucial. Under prediction is a common feature of fire count modelling using relatively simple model forms such as Poisson or negative binomial because of the large number of days with zero counts, and a variety of counts occurring on days with similar conditions. This is part of the compromise between trying to choose a region that is large enough to experience a reasonable number of fires, but small enough to justify the assumption that weather can be reasonably represented by a single point. This problem has been discussed previously by Todd and Kourtz (1991) and Tithecott (1992), who also explained how fire managers are comfortable with predictions that provide a reliable indication of the severity of the day and do not expect models to provide exact numbers.

Models that were developed independently for individual management areas (Table 4) performed slightly better than those with the common form for all areas (Table 3). However, common form models are typically preferable because they are simpler to implement and provide a common explanatory framework and understanding of the important drivers of the process across the entire organisation (with multiple management areas). The individual area models contained 25 unique variables, so would be much more difficult to implement operationally than the common form models. Both modelling approaches have limitations in prediction accuracy due to the random nature of human-caused ignitions and the limited ability of empirical models to account for this with day type and fire history variables. All models under predicted the number of fires on peak days.

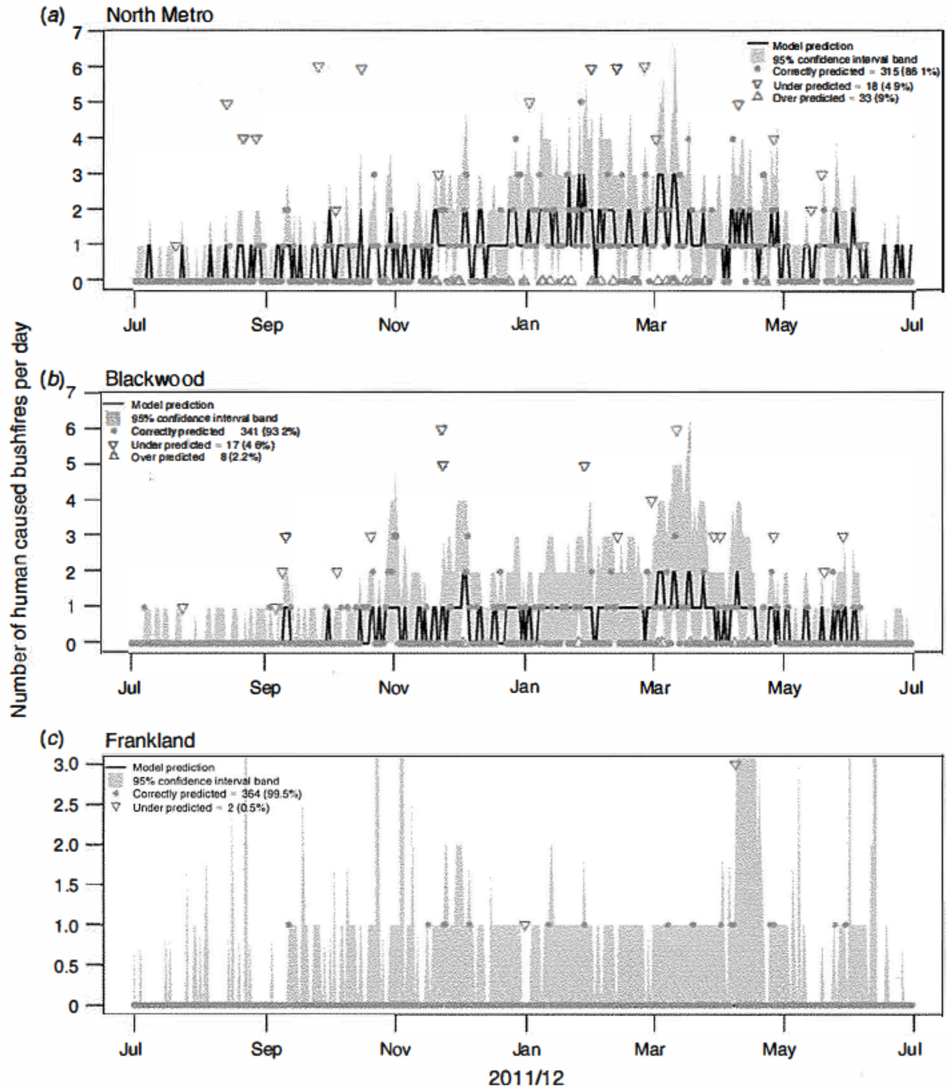

Fig. 3. Graphical examples of the model fit to the areas with the highest (North Metropolitan, DFES), median (Blackwood, DPAW) and lowest (Frankland, DPAW) number of median daily fires during the 2011 12 evaluation season using the common models given in Table 3.

Most models included variables related to fuel moisture, day type and recent fire activity. Fuel moisture variables were consistently selected first during stepwise variable selection procedures. The moisture content of surface litter is strongly linked to the sustainability of ignition and the availability of fuels to support combustion (e.g. Anderson 1970; Nelson 2001), and is a key environmental predictor in most existing daily fire occurrence models (e.g. Cunningham and Martell 1973; Wotton *et al.* 2003, 2010; Wotton and Martell 2005).

Variables related to day type and recent fire activity have been included in previous models (e.g. Prestemon and Butry 2005; Albertson *et al.* 2009; Prestemon *et al.* 2012). The day type variables in the models presented here indicate that fires are more likely to start on weekends, school holidays and public holidays, which is consistent with the findings of previous studies (Prestemon and Butry 2005; Albertson *et al.* 2009; Prestemon *et al.* 2012). This was true for both deliberate and accidental ignitions. Daily rates of deliberate fires in Western Australia have been found to be strongly associated with day of the week in an investigation of bushfire arson trends (Bryant 2008). Recent fire activity variables have previously been used in arson studies, where it has been suggested that they could indicate to copycat arsonists a low chance of prosecution (Prestemon *et al.* 2012).

The 3 year training period was much shorter than many of those used in previous studies based on fire incident records (e.g. Wotton *et al.* 2003, 2010; Wotton and Martell 2005; Albertson *et al.* 2009; Reineking *et al.* 2010; Magnussen and Taylor 2012), although some have relied on similar data durations (Viegas *et al.* 1999; Vilar *et al.* 2010*a*, 2010*b*; Padilla and Vega García 2011). Our analysis of the effect of the duration of the training dataset found very little difference in the model outcomes (Table 5). This is an interesting finding that suggests

Table 4. Variables, coefficients and fit statistics for models (Eqn 1) predicting the daily number of human-caused fires (all cause types) that were developed independently for each management area

Significances of the test statistic values are designated as follows: *, 0.05; **, 0.01; ***, 0.001

	Swan Coastal	Perth Hills	Wellington	Blackwood	Donnelly	Frankland	North Metro	South Metro	South West	Lower South West
Coefficients and variables										
Intercept (β_0)	0.620	5.886***	−0.869***	−0.455**	−28.619***	3.177	1.847***	1.265**	0.562***	−0.540**
β_1 (V_1)	0 285*** (Min FMC McArthur 1967)	0.069*** (FFMC)	−0.022*** (Mean profile FMC Matthews 2006)	0.017*** (Mean profile FMC Matthews 2006)	0.307*** (FFMC)	0.036 (CFWI)	0.285*** (MinFMC McArthur 1967)	0.432*** (Min FMC – McArthur 1967)	0.024*** Mean profile FMC (Matthews 2006)	−0.014*** (Mean profile FMC Matthews 2006)
β_2 (V_2)	0.467*** (School day)	0.024*** (Number of accidental bushfires in previous 9 days)	0.179*** (Number of deliberate bushfires in previous 7 days)	0.040*** (Max daily FFDI calculated with SDI)	0.052*** (CFWI)	0.831 (Number of deliberate bushfires in previous 5 days)	0.552*** Work day	0.008*** (Number of accidental bushfires in previous 7 days)	0.105*** (Number of deliberate bushfires in previous 14 days)	0.032*** (Max daily FFDI calculated with SDI)
β_3 (V_3)	0.032*** (Number of bushfires in previous 9 days)	0.313*** (School day)	0.446*** (Weekend day)	0.068*** (Number of bushfires in previous 6 days)	0.003*** (DC)	0.062 (Mean surface FMC Matthews 2006)	0.023*** (Number of human-caused bushfires in previous 11 days)	0.026** (FFDI at 1200 hours)	0.375*** Weekend day	0.073*** (Number of bushfires in previous 6 days)
β_4 (V_4)	0.083** (DF calculated with SDI)	0.0001*** (DMC)	0.022** (Maximum daily FFDI calculated with SDI)	0.393*** (Work day)	0.089* (Maximum temperature)		0.127*** 24-h rainfall	0.329** (Weekend day)	0.021*** (Max daily FFDI calculated with SDI)	0.300** (Work day)
β_5 (V_5)							0.0001*** DMC	0.010** (Number of days since last rain)		
Fits (to 2011 12 evaluation data)										
Accuracy rate	0.970	0.984	0.945	0.858	1.000	0.992	0.877	0.970	0.885	0.874
Under-prediction rate	0.030	0.016	0.055	0.079	0.000	0.008	0.038	0.030	0.101	0.079
Over-prediction rate	0.000	0.000	0.000	0.063	0.000	0.000	0.085	0.000	0.014	0.046
RMSE	1.009	1.049	0.285	1.041	0.185	4.480	1.201	0.610	0.614	1.008
MAE	0.688	1.024	0.534	1.020	0.431	2.117	1.096	0.781	0.784	1.004
MBE	0.074	0.715	0.372	0.635	0.161	0.264	0.759	0.486	0.492	0.615

Table 5. Goodness of fit of the models developed using DPAW independent training datasets when applied to the evaluation dataset

	Swan Coastal	Perth Hills	Wellington	Blackwood	Donnelly	Frankland
Early period (2003 04 to 2006 07)						
RMSE	0.656	0.516	0.365	0.413	0.386	0.248
MAE	0.373	0.302	0.211	0.227	0.172	0.078
MBE	0.003	0.025	0.041	0.007	0.061	−0.014
Common period (2008 09 to 2010 11)						
RMSE	0.652	0.514	0.366	0.412	0.388	0.247
MAE	0.400	0.312	0.217	0.237	0.163	0.080
MBE	0.054	0.001	0.049	0.026	0.050	−0.012
Long period (2003 04 to 2010 11)						
RMSE	0.663	0.517	0.366	0.417	0.383	0.252
MAE	0.368	0.302	0.205	0.224	0.182	0.081
MBE	−0.007	0.021	0.033	0.000	0.074	0.012

Table 6. Variables and fit statistics for common form models developed for predicting the daily number of deliberate and accidental fires

	Deliberate fires	Accidental fires
Variables used	Minimum hourly equilibrium FMC (McArthur 1967) (%) Number of human caused bushfires in previous 14 days Work day 24 h rainfall to 0900 (mm)	Mean profile FMC (Matthews 2006) Number of human caused bushfires in previous 7 days Minimum hourly relative humidity (%) School day
Median accuracy (range)	0.918 (0.866 1.000)	0.940 (0.833 1.000)
Median under prediction (range)	0.082 (0.000 0.134)	0.049 (0.000 0.167)
Median over prediction (range)	0.000 (0.000–0.008)	0.000 (0.000 0.128)
Median RMSE (range)	0.909 (0.264 1.130)	0.912 (0.256 1.285)
Median MAE (range)	0.463 (0.063 0.666)	0.466 (0.087 0.715)
Median MBE (range)	0.282 (0.379 0.045)	0.289 (0.568 0.014)

that the factors driving human-caused ignition are relatively constant and that fitting a model to more years of data may not necessarily improve predictions. This finding should be further investigated when data from all fires in a region are available over a longer period. As dataset length increases and data from further in the past is used, the comparability of models to current fire activity may also be affected by changes in ignition factors, such as policies related to the setting of fire restrictions, laws related to arson, changes in population distribution and density resulting from urbanisation, and changes in land use.

Our study considered weather variables at a coarse scale using a single station to represent each management area, so is unlikely to represent local weather factors such as sea breezes and discrete rainfall events, or adequately reflect strong gradients in rainfall, temperature and humidity associated with distance from the ocean. However, the single measure of moisture for each area provides an index of the relative ease of ignition. This approach has been used in previous studies such as Wotton and Beverly (2007), who showed that the Fine Fuel Moisture Code tracked moisture across a range of forest types and could thus be used as a good relative indicator of day-to-day change in moisture content. Many studies have applied gridded approaches (e.g. Reineking *et al.* 2010; Padilla and Vega García 2011; Magnussen and Taylor 2012) that have interpolated weather variables to predict the spatio-temporal probability of fire occurrence across broader areas, such as an entire state, province or country. These studies predict a daily probability of one or more fires in each grid cell and have estimated daily fire numbers by summing cell probabilities. These studies are not suited to the daily level of operational application sought by our study.

This study has relied on fire incident records, and demonstrates the importance of high-quality data for allowing similar sorts of analyses and modelling. In order to predict occurrences for all sources of ignition, future work should develop models predicting lightning ignitions within this region, such as those developed for other regions (Wotton and Martell 2005, Dowdy and Mills 2012). Daily fire occurrence models could be developed across Australia and be used to inform pre-emptive resource sharing between management regions. This would maximise the efficient use of national firefighting resources. Further work on this topic should consider the spatial issues related to fire occurrence in south-west Western Australia. Other topics for further study include investigating similar relationships for lightning ignitions and the timing of fire reports within a day.

The models presented in Table 3 could be implemented as decision support aids in the relevant management areas following some small system developments. First, the simple equilibrium fuel moisture input (McArthur 1967) could be estimated from weather forecasts that can provide the minimum daily relative humidity and corresponding air temperature for the days required. The rainfall input could also be estimated from weather forecasts or determined from morning observations. The number of human caused fires in the previous 14 days could be readily determined from recent regional incident records for a current or next day forecast, but would require some estimation when being used to predict daily fire counts beyond this. The further ahead the forecast day is, the more error there would be in the prediction and we would not recommend using these models more than 6 days ahead.

This study shows how simple practical models can be developed to assist day-to-day fire management operations. Similar models could be developed in other regions given the availability of suitable fire incident records and corresponding meteorological observational data. The common model form for multiple management areas approach resulted in fits that were only slightly lower than regionally specific independent models and would be a suitable approach for agencies that cover multiple regions. It is likely that models developed in other regions would experience similar under-prediction issues on peak days due to the regression method, and this problem will be greater in regions that experience few fires.

Conclusion

The number of daily human-caused bushfire ignitions is related to fuel moisture content, recent fire activity, day type and rainfall. Models presented here can be used to provide guidance for predicting the daily number of human-caused fires for the southwest Western Australia management areas with moderate to high ignition rates (Swan Coastal, Perth Hills, Wellington, Blackwood, North Metropolitan, South Metropolitan, South West and Lower South West), thereby improving daily fire preparedness planning. These models predict the range of daily human-caused fires, but tend to under predict the number of fires on peak days. The use of longer training datasets is unlikely to improve models. The methods presented here can be used to develop similar predictive tools for day-to-day fire planning operations in other regions with suitable fire incident and metrological records.

Acknowledgements

We are grateful to DPAW and DFES for making their incident data available for this study and acknowledge the assistance of Craig Carpenter, Carole Dowd and Jared Ebrall. Funding for this research was provided by the Bushfire Cooperative Research Centre. The CSIRO Capability Development Fund supported an initial meeting for this project. Xunguo Lin, Andrew Sullivan, Stuart Matthews and Nick Nicholls helped with coding for calculating weather variables and modelling. Jenny Carter, Steve Taylor, Sadanandan Nambiar, the Associate Editor and anonymous reviewers provided helpful comments that improved draft versions of the manuscript.

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Document 2

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From: Shrives, Kimberley (CorpAffairs, Black Mountain)
Sent: Thursday, 13 December 2018 8:46 AM
To: Acworth, Celia
Cc: Rolph, Angus; Zielke, Judi (Executive, Black Mountain); MPLO
Subject: HPRM: State of the Climate 2018 - additional comms information
Attachments: Joint BoM-CSIRO Letter to Parliamentarians BOM CEO approved.docx; SotC-MediaRelease-Embargoed 0001 19 Dec.docx; SOTC 2018 FaQ.docx; 18-00336 OA StateoftheClimate2018 WEB 181212.pdf

Hi

Following up on our discussion yesterday, I've attached the following material:

- The final version of the report,
- The draft Media Release,
- The current CSIRO frequently asked questions, and
- The Joint BoM/CSIRO covering letter to Parliamentarians.

s 22 [redacted]

Cheers

K

Kimberley Shrives
CSIRO

s22 [redacted]

Australian Government
Bureau of Meteorology

[CSIRO crest]

[Name]
[Position]
[Electorate]
[Address]
[SUBURB STATE POSTCODE]

[date]

Dear [name]

On behalf of the Bureau of Meteorology and CSIRO, we are pleased to provide you with a copy of the *State of the Climate 2018*.

The *State of the Climate* is co-produced by our organisations every two years and provides a comprehensive analysis of Australia's climate. The *State of the Climate 2018* is the fifth in the series.

Key findings in the *State of the Climate 2018* include:

- Australia's climate has warmed by just over one degree since 1910, leading to an increase in the frequency of extreme heat events.
- Oceans around Australia have warmed by around one degree since 1900, contributing to longer and more frequent marine heatwaves.
- There has been an increase in extreme fire weather, and a longer fire season across large parts of Australia.
- Rainfall between April and October has declined across parts of southern Australia.
- Rainfall has increased across parts of northern Australia since the 1970s.
- Seas around Australia have become more acidic and sea levels have risen.
- Carbon dioxide (CO2) concentrations in the atmosphere are above 400 parts per million (ppm) and the CO2 equivalent of all greenhouse gas has reached 500 ppm.
- Emissions from fossil fuels are the main contributor to the observed growth in atmospheric CO2.

The *State of the Climate 2018* is available on either www.bom.gov.au or www.csiro.au.

Yours sincerely

Dr Andrew Johnson FTSE FAICD
CEO and Director of Meteorology

Dr Larry Marshall
Chief Executive of the CSIRO

Australia's National Meteorological Service
Level 16, 32 Turbot Street, Brisbane QLD 4000 | T: +61 7 3239 8700 | www.bom.gov.au | ABN 92 637 533 532

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State of the Climate 2018
Media Release

Australian Government
Bureau of Meteorology

CSIRO

EMBARGOED UNTIL 0001 WEDNESDAY 19 DECEMBER, 2018

Click here for report figures and summary video.

State of the Climate 2018 shows continued warming of climate and oceans

More frequent extreme heat events and marine heatwaves, an increase in extreme fire weather, and declining rainfall in the southeast and southwest of the continent are some of the key observations showing Australia's changing climate, as detailed in the latest State of the Climate report released today by CSIRO and the Bureau of Meteorology.

Drawing on the latest climate observations, the biennial report provides a comprehensive analysis of Australia's climate and how it is changing.

Since 1910, Australia's climate has warmed by just over 1°C, and sea surface temperatures in the oceans surrounding Australia have increased by around 1°C.

"In line with global trends, our data shows that Australia's climate is continuing to warm, with eight of the 10 warmest years on record occurring since 2005," Director of CSIRO's Climate Science Centre Dr Helen Cleugh said.

"This warming is caused by increased greenhouse gases, such as carbon dioxide, in the atmosphere.

"Measurements taken over the past 40 years at Tasmania's Cape Grim Baseline Air Pollution Station show that carbon dioxide levels in the atmosphere have been steadily increasing, with levels now consistently above 400 parts per million since 2016.

"Globally, carbon dioxide levels have increased 46 per cent since pre-industrial times (around 1750), and are likely the highest they've been in at least the past two million years.

"The main contributor to this observed growth in atmospheric carbon dioxide is the continued increase in emissions from burning fossil fuels."

The Bureau of Meteorology's Manager of Climate Monitoring Dr Karl Braganza said the warming trend in Australia was contributing to an increase in extreme fire weather and the length of the fire season.

"Fire weather in Australia is largely monitored using the Forest Fire Danger Index, which estimates fire danger on any given day," Dr Braganza said.

"Monitoring of the FFDI shows there has been an increase in the frequency and severity of fire weather in recent decades.

"This trend in fire weather is particularly noticeable through southern and eastern parts of Australia."

Dr Braganza said declining rainfall in the southwest and southeast of the continent was another key change to Australia's climate over recent decades.

"While Australia's rainfall is highly variable and influenced by major climate drivers, such as El Niño and La Niña, there has been a noticeable decline in rainfall between April and October through southern parts of the country," he said.

"In 17 of the past 20 years, April to October rainfall in southern Australia has been below average."

The report also provides projections for Australia's future climate. These include:

- Further increases in sea and air temperatures, with more hot days and marine heatwaves, and fewer cool extremes.
- Further sea level rise and ocean acidification.
- Decreases in rainfall across southern Australia, with more time in drought, but an increase in intense heavy rainfall throughout Australia.

State of the Climate 2018 is the fifth report in a series published biennially by CSIRO and the Bureau of Meteorology, which together play an integral role in monitoring, measuring and reporting on weather and climate.

The State of the Climate 2018 report can be found on the Bureau of Meteorology and CSIRO websites.

Fast facts:

- Australia's climate has warmed by just over 1 °C since 1910, leading to an increase in the frequency of extreme heat events.
- Surface temperatures in the oceans around Australia have warmed by around 1 °C since 1910, contributing to longer and more frequent marine heatwaves and mass coral bleaching events.
- Sea levels are rising around Australia, increasing the risk of inundation.
- The oceans around Australia are acidifying (the pH is decreasing).
- April to October rainfall has decreased in the southwest of Australia. Across the same region May–July rainfall has seen the largest decrease, by around 20 per cent since 1970.
- There has been a decline of around 11 per cent in the April–October rainfall in the southeast of Australia since the late-1990s.

- Rainfall has increased across parts of northern Australia since the 1970s.
- Since the 1970s, streamflow has decreased across southern Australia and increased in northern Australia, where rainfall has increased.
- There has been a long-term increase in extreme fire weather, and in the length of the fire season, across large parts of Australia.

Contacts

Chris Gerbing, Communication Manager, CSIRO Oceans and Atmosphere

T: [redacted] s22

Bureau's media team

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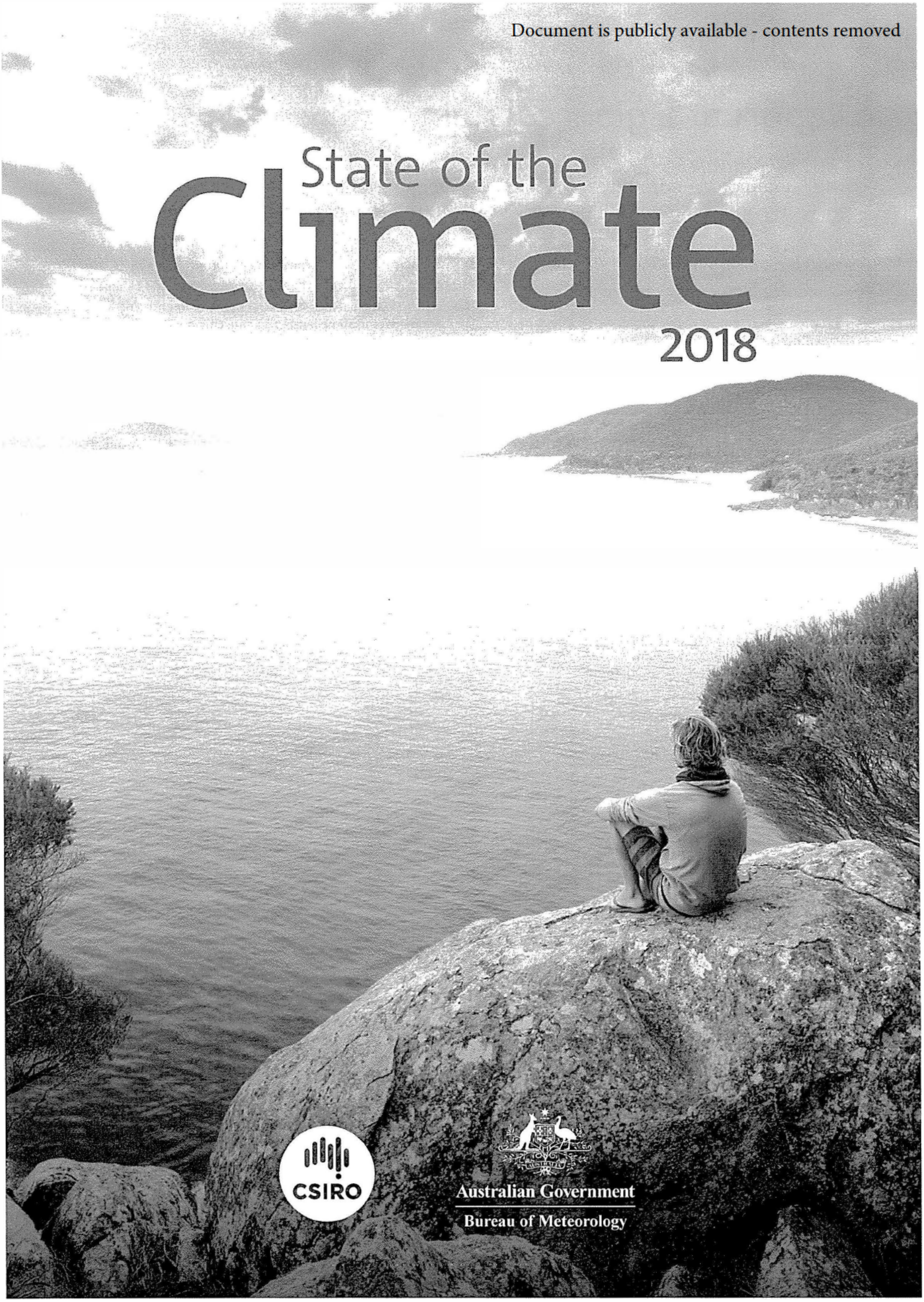
State of the Climate 2018



CSIRO

Australian Government

Bureau of Meteorology

[redacted] s22

From:	Scott, Hannah (CorpAffairs, Black Mountain)
Sent:	Friday, 22 March 2019 10:13 AM
To:	Acworth, Celia
Cc:	MPLO; Zielke, Judi (Executive, Black Mountain)
Subject:	Overview of CSIRO's environmental research
Attachments:	CSIRO environment FINAL.pdf
Categories:	Informal notifications

Hi Celia,

Here's a snapshot of CSIRO's work in the environment space, including some examples of projects currently underway.

Please let me know if you have any questions, or would like further information on any of the projects referenced.

Apologies for the delay in getting this to you.

Cheers, H

Hannah Scott
Manager, Ministerial Liaison Office
CSIRO

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www.csiro.au

CSIRO Environment

Our research

s 22 [redacted]

CSIRO works to:

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- help Australia better understand, respond to and prepare for extreme events and emergency situations, such as bushfires, floods, cyclones and drought.

s 22 [redacted]

Case studies

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Fire

CSIRO has a strong history in observing the way in which bushfires impact on people and their environment and has contributed to new building regulations to better protect homes.

CSIRO has also evaluated bushfire spread models to develop a practical guide for predicting the rate of fire spread in different Australian vegetation types under different conditions. > Read more about the team's work

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AT CSIRO, WE DO THE EXTRAORDINARY EVERY DAY

We innovate for tomorrow and help improve today – for our customers, all Australians and the world.
We imagine. We collaborate. We innovate.

FOR FURTHER INFORMATION
CSIRO Ministerial Liaison Office
Hannah Scott
t [redacted]
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e
s22

[redacted]

From: Methorst, Laura (CorpAffairs, Black Mountain)
Sent: Tuesday, 30 July 2019 3:55 PM
To: Buzza, Keegan; daniel.glover[redacted]Acworth, Celia
Cc: MPLO; Zielke, Judi (Executive, Black Mountain); Bowes, Tanya (CorpAffairs, North Ryde)
Subject: Health Impacts of Climate Change report - release tomorrow (Wednesday)
Attachments: From Townsville to Tuvalu_the health impacts of climate change EMBARGOED.pdf; FINAL Press Release Health Impacts of Climate Change 250719.docx; From Townsville to Tuvalu 12072019.pdf

Categories: Informal notifications

Hi Celia, Keegan and Dan,

Just wanted to give you a heads up about the release of a report by the Global Health Alliance Australia (a peak body of 47 Global Health organisations) report *Health and Climate Change: from Townsville to Tuvalu.*

The report is scheduled to be released tomorrow at an event in Melbourne.

[redacted]

Laura

Laura Methorst
Senior Advisor
Ministerial Liaison Office
CSIRO
E [redacted]
CSIRO Black Mountain Science and Innovation Park, Canberra, ACT 2601
www.csiro.au

Document is publicly available - contents have been removed

Health and climate change in Australia and the Asia Pacific region

"From Townsville to Tuvalu"

GLOBAL HEALTH ALLIANCE AUSTRALIA

www.glham.org

Major report from health peak body: health impacts of climate change in Australia and the Pacific needs whole-of government attention

31 July 2019, Melbourne: Australia and neighbouring countries in our region are experiencing more deaths, illnesses and injuries from heatwaves, cyclones and other extreme weather events because of climate change.

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"Most Australians know about the devastating deaths of 173 people because of the Black Saturday bushfires of February, 2009. What is less well known is that during the heatwave, which included three days over 43 degrees Celsius, there were 374 more deaths than expected in a normal week, probably from heat stroke."

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[redacted]

GLOBAL HEALTH ALLIANCE AUSTRALIA

MONASH University

s 22 [redacted]

Media contact

Ranya Alkadamani
Impact Group International
s22 [redacted]

NOTE TO EDITORS – KEY FINDINGS:

s 22 [redacted]

Australian Impacts

s 22 [redacted]

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Global and Indo-Pacific impacts

- In the Indo Pacific region, climate change is raising sea levels, exacerbating the severity of natural disasters, reducing nutrition levels in food and increasing disease produced by unclean water. If neighbouring health systems prove inadequate, pressure on Australia to provide assistance, even a safe haven for climate refugees, will grow.
  Around the world, yields from crops such as maize, wheat, rice and soybeans are expected to drop by as much as 10% between 2000 and 2050. Ozone toxicity has been shown to substantially reduce rice production in South and Southeast Asia, with significant implications for the supplies of staple food and nutrition for millions of people. Higher Co2 concentrations in crops are also stripping protein, Vitamin A, folate, zinc and iron from the nutrient content of stable crops.
  ****Dr Rob Grenfell, Director of Health and Biosecurity, CSIRO available to discuss****

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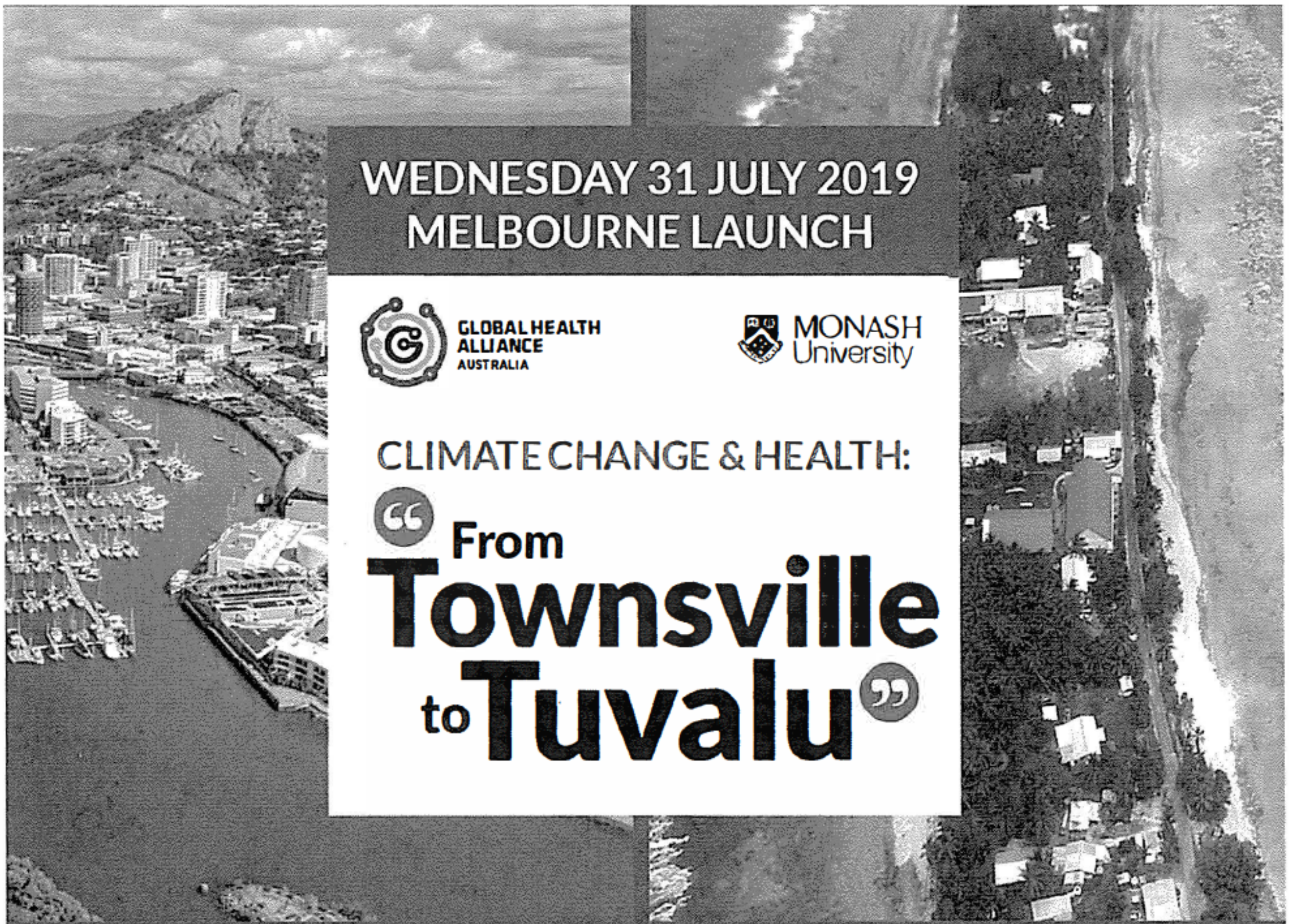

WEDNESDAY 31 JULY 2019
MELBOURNE LAUNCH

GLOBAL HEALTH ALLIANCE AUSTRALIA

MONASH University

CLIMATE CHANGE & HEALTH:

"From Townsville to Tuvalu"

Join the **Global Health Alliance Australia** and **Monash University** for the launch of a policy paper that details the impacts of climate change on the health of Australians and of our neighbours in the Indo-Pacific region, and proposes ways to reduce these impacts.

EXPERTS:

Professor Rebekah Brown Senior Vice Provost and Vice Provost (Research), Director of Revitalising Informal Settlements and their Environments, Monash University

Laureate Professor Peter Doherty Nobel Prize winner, Doherty Institute for Infection and Immunity

Dr Elizabeth Finkel AM Science Journalist, 2019 Australian Society for Medical Research Medallist, Founder and Editor-in-Chief 2013 -2018 Cosmos Magazine

Dr Helen Haines MP (via video from Parliament House)

Professor Karin Leder School of Public Health and Preventive Medicine, Monash University

Ms Sarah Newton Pro Vice-Chancellor (Enterprise); Deputy Dean, External Relations, Monash University

Professor John Thwaites Climate Works Australia, Monash Sustainable Development Institute

Professor Sophia Zoungas Head of School, Public Health and Preventive Medicine, Monash University

The launch will be chaired by Professor Jane Fisher Finkel Professor of Global Health, Monash University.

JOIN US!

www.trybooking.com/BDHOA

When: Wednesday 31 July 2019, 10.30 12.30pm

Where: Ground Floor, 553 St Kilda Rd, Melbourne 3000

RSVP: Wednesday 24th July via TryBooking

Please stay for a light networking lunch after the launch from 12.30-1.30pm

For enquiries, please contact Shana on [redacted] s22

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These Gold and Bronze sponsors of the Alliance are acknowledged for their support and global health leadership.