Department of
Sustainability and
Environment

Establishing a link between the power of fire and community loss: **The first step towards developing a bushfire severity scale**

Fire and adaptive management

report no. 89

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Published by the Victorian Government Department of Sustainability and Environment Melbourne, June 2011

Authorised by the Victorian Government, 8 Nicholson Street, East Melbourne, Victoria, Australia.

Printed by Stream Solutions
Printed on 100% Recycled paper

ISBN 978-1-74287-069-4 (print)
ISBN 978-1-74287-070-0 (online)

For more information contact the DSE Customer Service Centre 136 186

Accessibility
If you would like to receive this publication in an accessible format, such as large print or audio, please telephone 136 186, 1800 122 969 (TTY), or email customer.service@dse.vic.gov.au

This document is also available in PDF format on the Internet at www.dse.vic.gov.au

Acknowledgements

We gratefully acknowledge the contributions of the following:

- **Funding**: Department of Sustainability and Environment (DSE) and Office of Emergency Services Commissioner (OESC) – Department of Justice
- **Project management and facilitation**: Bushfire CRC, DSE, Country Fire Authority (CFA) and Monash University
- **Data**: Bushfire CRC, CFA, DSE, Department of Environment and Climate Change (DECC), University of Tasmania (UTAS) and Monash University
- **Review**: Andrew Sullivan (CSIRO), Lachie McCaw (DECC), Miguel Cruz (CSIRO), Jim Gould (CSIRO), Robin Hicks (Bureau of Meteorology), Richard Thornton (Bushfire CRC) and Graham Hepworth (University of Melbourne, Statistical Consulting Centre)
- **Additional statistical methods and ideas**: Dave Anderson.

We also wish to thank the following for their data and ideas:

- Nic Gellie (DSE), Kelsy Gibos (DSE), Nigel Tapper (Monash University), Alen Slijepcevic (DSE), Michael Reeder (Monash University), David Packham (Monash University), Francis Hines (DSE), Andrew Bennet (DSE), Brian Potter (USFS), Ralph Nelson (USFS retired), Lachie McCaw (DECC), Lyndsey Wright (Bushfire CRC), David Nichols (CFA), Jon Marsden Smedley (UTAS), Salahuddin Ahmad (DSE), Andy Ackland (DSE), Allen Beaver (DSE), Mark Garvey (CFA), Jude Kennedy (CFA), Reza Amira (Monash University), Vaibhav Gupta (Monash University), Anh Phan (Monash University) and Thu Phan (Monash University)

Front cover image: Isochrones showing the fire spread of the 2009 Murrindindi fire. Gellie *et al*. (Forthcoming). Fire and Adaptive Management report series. Department of Sustainability and Environment.

Australian Government
Attorney-General's Department
Emergency Management Australia

We gratefully acknowledge the Attorney General's Department of the Australian Government that part funded this project through the Natural Disaster Mitigation Program.

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Fire and adaptive management

One: Abstract

Current fire danger scales do not fully reflect the potential destructive force of a resulting bushfire and therefore do not provide the community with an adequate warning for the potential loss of human life and property. The well known fire danger meters used in south-eastern Australia, the McArthur forest and grassland fire danger meters, were designed for general fire danger forecasting and rely on simple weather data inputs. For the last 50 years, these meters have been widely used to determine fire preparedness, and have repeatedly proven useful for this purpose. However, they do not necessarily relate to community loss or to the destructiveness of fire.

With a growing database of fire statistics covering Australia's long history of destructive fires, a review of available observations and estimates of fire weather, fuel loading, fire behaviour and community loss is warranted. A new bushfire scale that incorporates the potential damage or destructive force may better inform and prepare the community of the dangers associated with bushfires. The potential for a fire to impact on communities (as measured by the loss of life and property) may correlate better (or be linked) to the rate of energy release than to traditional fire danger ratings. This project tests a framework for developing a bushfire severity scale based on community loss.

To determine whether a link exists between energy release from a fire and community loss, this project reviewed observations of 81 wildfires (from 1939 to 2009) across Victoria and other southern states. Fire behaviour, fire weather, community loss and fuel loading datasets were compiled for these wildfires. These datasets were combined in a spatial database to enable the analysis of possible relationships between community loss and fire power. The community loss information was also compared to the calculated McArthur fire danger indices, with various adjustments to the indices for fuel loading and slope.

This study found that a relationship exists between the power of the fire and community loss that is stronger than the relationship between McArthur's fire danger indices and community loss, particularly when house or population density is incorporated into the statistical model. Results also showed that the relationship between community loss and the Forest Fire Danger Index (FFDI) adjusted for fuel loading (FFDIF) was stronger than that between community loss and the unadjusted FFDI, for a given house or population density. An alternative predictor of house loss was given by FFDIF and the number of houses at risk as determined from the product of the fire area and house density. Models for predicting fatalities and economic losses fitted the data better than those predicting house losses, but they were strongly influenced by a small number of fires with high losses.

The database developed for this study and the relationships established are essential for undertaking future studies that require observations and estimates of past fire behaviour and losses; and also to form the basis for developing a new severity scale. Further research that incorporates other fires, fuel and fire behaviour factors and a more detailed spatial analysis is also warranted.

2

Two: Introduction

Australia has a long history of destructive fires, particularly in the inhabited forest and grasslands of the southern states. Some of the most destructive fires recorded include Black Friday (1939), Dwellingup (1961), Hobart (1967), Ash Wednesday (1983), Como Janelli (1994), Canberra (2003) and, more recently, Black Saturday (2009). These fires impacted communities for many reasons described in a range of inquiries and commissions, the latest being the Royal Commission into the Black Saturday Bushfires (see Teague *et al* 2010). Underpinning all of these events are particular weather conditions, fuel type, fuel condition and the intersection of the fires with communities.

How these and other fires evolve and behave has (in some cases) been well researched and documented in the literature. Such research has led to fire-behaviour prediction models, which have been very useful when combating fire events. These models use site-specific information for predicting the rate of spread, spotting distance, crowning potential, flame height and intensity of a fire. At the forefront of this research was the work conducted by McArthur (1962; 1966; 1967) in the 1950's and 1960's on grass and forests of southern Australia, and simultaneously by Peet (1965; 1967) on forests in Western Australia. More recent research in fire behaviour and the development of models and prediction tools, has been conducted by Cheney *et al.* (1993; 1998); Cheney and Gould (1995) which focused on fire spread in grasslands and by Gould *et al.* (2007a; 2007b) which focused on dry eucalypt forests. The models have become more sophisticated as more data has become available, leading to a greater understanding of fire behaviour.

The term 'fire danger' has a long history and has had a number of definitions. According to Chandler *et al.* (1983 p.450) fire danger is the result of 'factors affecting the inception, spread and difficulty of control of fires and the damage they cause'. Cheney and Gould (1995) comment that if any of these factors are absent, then there is no fire danger. Furthermore, a 'fire danger rating' is 'a fire management system that integrates the facets of selected fire danger factors into one or more qualitative or numerical indices of current protection needs' (Chandler *et al.* 1983 p.450). Fire danger rating systems are used to assess the potential for bushfire occurrence, fire spread and difficulty of suppression (McArthur 1967; Sharples *et al.* 2009). Although many examples of fire danger ratings (and indices) exist, this report focuses on the McArthur fire danger meter because it is a widely used index in south-eastern Australia (Noble *et al.* 1980; Sharples *et al.* 2009) where the greatest losses of life and property have occurred. This rating system is used for declaring fire bans, informing people of the risk of fire and for planning and allocating resources (McArthur 1967; Sharples *et al.* 2009).

The McArthur Forest and Grassland Fire Danger Rating Systems (FDRS), which are based on forest and grass fire danger indices (FFDI and GFDI, respectively), were developed in the 1950s and 1960s using available science, case study evidence and expert opinion (Lucas *et al.* 2007; McArthur 1967). The FFDI and GFDI represent the predicted rate of spread of a fire on flat ground in standard fuel, and so are linked to the McArthur fire spread predictions. They are non-linear functions of simple weather and drought variables that include temperature, relative humidity, wind speed and drought factor (DF). Forest and Grassland Fire Danger Ratings (FFDR and GFDR) are categorical ratings determined from non-linearly increasing ranges of the FFDI and GFDI. Although the McArthur FDRS have been in use for over 50 years, there are some inherent weaknesses in the underlying system. Firstly, while being based on scientific data, experimental studies largely focused on many small-scale fires in generally low open forest types around the Australian Capital Territory, under moderate weather conditions and on a number of experimental fires conducted in dry open sclerophyll jarrah forest in Western Australia (see McArthur (1966; 1967)). These small experimental fires were supplemented with ad hoc observations on a small number of wildfires, some of them poorly documented. Secondly, the most severe conditions represented by both forest and grass meters (FFDI and GFDI values of 100) were based on known worst-case fires, the 1939 Black Friday for forests, and the 1952

Mangoplah for grasslands. Weather conditions for these fires have since been exceeded a number of times (e.g. Ash Wednesday 1983, Black Saturday 2009). These two important weaknesses limit the applicability of the McArthur FDRS in situations where the conditions may be out of the range of those in the meters. A third problem arises when relating fire danger to community losses because fire danger is deemed to be on a regional basis and factors that affect fire behaviour, such as topography and fuel hazard, are not included in the FDRS.

Clearly, there is scope to improve McArthur's FDRS so that more informed decisions can be made in forecasting fire danger to aid government departments, as well as the public in protecting livelihoods and assets. One such approach is to adjust the FFDI and GFDI to relate to a local area by incorporating the slope and fuel load, so that the adjusted FDI is proportional to the predicted rate of spread from the McArthur meter. Another approach is to use more recent fire spread model predictions to predict fire danger on a regional and local scale. However, doing so requires a greater understanding of the fire behaviour factors that influence damage potential.

While the McArthur FDRS has been an essential component of fire danger warnings in Australia it makes more sense that a fire danger rating system should transparently reflect how fire behaviour characteristics determine not only difficulty of suppression, but also the potential for damage to a community and other assets. Many natural hazards have a scale or rating that can be directly related to the destructive force or potential power of the hazard. For example, earthquakes use the open-ended Richter scale which is based on the amount of seismic energy released by the earthquake (USGS 2010). For hurricanes the Saffir Simpson Hurricane Wind Scale is used. This scale is made up of five categories distinguished by the intensities of their sustained winds and is primarily used for measuring the potential damage upon landfall (NOAA 2010). Both of these increase by an order of magnitude in impact from one level to another and are potentially linked to the amount of damage caused by the hazard (Simpson and Riehl 1981). While these rating systems are measures during or after an event (not a forecast of conditions prior to one eventuating), such methods of linking energy of the event to its destructive force should be considered for categorising bushfire events before any effort can be made to improve forecasting methods. A scale that refers to loss due to a bushfire is necessary for assessing events and measuring its impact. This information can later be used to manage and prepare for future bushfires.

In designing a scale to rate the severity of bushfires, or 'wildfire threat', as termed by Cheney *et al.* (1990), the severity of an event should ideally relate to order of magnitude of destructive power, which then must be further related to the potential for loss. There have been very few studies conducted in Australia that analyse the relationship between community loss and actual fire events. This is primarily due to the lack of compiled data. However, a recent study by Blanchi *et al.* (2010) demonstrated that a relationship between fire weather severity and house loss does exist. Loss of life and property depends on a range of factors, such as the magnitude and behaviour of fires; the number and exposure of people and property to the fire; and their level of ability to avoid or withstand bushfire impacts. Thus a bushfire severity scale should provide an estimate of the destructive nature of a fire and its potential to impact on communities and their assets. This is complex and any framework that does arise from a scientific analysis of available information should initially establish a link between community loss and the intensity or power (energy release rate) of the fire.

Fireline intensity is defined as the rate of heat released per unit length of fire front (Byram 1959). The idea of a link between fireline intensity and community loss has had numerous mentions in the literature (e.g. Middelmann (2007) and Wang (2006)). Early observations by McArthur (1962) showed that vegetation damage is closely related to fire intensity.

Gill (1998) even theorised developing a 'Richter-like' scale for fires based on intensity as the variable associated with destructive force and loss. While this relationship has been hypothesised to exist, no data has been compiled and analysed to support this theory. This is because estimates of fire intensity are difficult to make and require information on many attributes of the fire and the environment. However, with a growing, and increasingly improving, database of fire statistics covering Australia's long history of destructive fires, a review of current fire danger ratings can now be conducted using the latest observations.

Our understanding of the magnitude (energy release), temporal and spatial variability of individual fire events has been greatly enhanced over the last 50 years. However, there is currently a lack of collective fire characterisation in Australia, and internationally, which largely stems from inadequate data collection and insufficient pooling and sharing of resources and information. Furthermore, there is a lack of integrated research by fire behaviour scientists and engineers. For example, the southern states of Australia have a long history of destructive fires and although relevant fire behaviour characteristics are generally collected after fire events, this information is scattered between research bodies, literature and government organisations. Such problems have limited the opportunities to analyse data in the form of a synthesis, and increase the uncertainties in estimating the impacts of a fire on communities.

The inability to accurately predict the destructive potential of fire limits the capability of fire agencies to quantify and assess the potential of fire events. Addressing the limitation will assist in reducing bushfire impacts on communities. It is essential that current methods and ideas be tested in the form of a synthesis. Therefore, a comprehensive spatial database of forest and grass fires in Australia has been assembled, which includes fire danger indices (FFDI and GFDI), measures of fire severity (Byram's fireline intensity and fire power), fire behaviour characteristics (e.g. rate of spread, spotting distance, fire area), community loss (number of fatalities, houses destroyed and economic cost of the fire), site information (e.g. vegetation and fuel loading), and ancillary information such as weather characteristics. This should enable a measure of fire severity, or potential destructive force focused on community impact to be developed by improving current fire danger rating systems, or as a standalone scale. Such a scale would need to be consistent with our knowledge of fire intensity, power and its effect on communities. This project hypothesises that fire power, the total rate of energy release, may provide a better measure of the destructive force of fires on local communities than existing fire danger ratings.

Three: Aim and objectives

This project aims to explore the relationship between measures of fire strength and community loss; and make recommendations for modifying existing indices or developing a new bushfire severity scale through the use of a national archive of past bushfires and their impacts on communities. This aim will be achieved through three main steps:

- Determining the impact of major fires in Australia in relation to community loss
- Calculating fire behaviour indices, fire intensity and the power of each fire
- Determining the relationship between fire behaviour indices, fire intensity and the power of fire with community loss.

This work will provide an understanding of the impacts of bushfires on communities, as well as an improved quantification of existing fire danger systems and of the key processes driving catastrophic bushfires. Such work will allow better fire and community management frameworks to be developed and adopted to protect lives and assets. While this research focuses on improving local scale predictions, broad regional scales should also benefit from this research by combining local predictions with advances in spatial predictive models.

4

Four: Study site

4.4 Vegetation

South-eastern Australia experiences frequent major fires, with the bushfire danger becoming serious in some parts of Victoria every two to three years (Luke and McArthur 1978). This is because of the regular occurrence of extreme weather, steep topography and flammable vegetation, as well as occasional severe droughts (all of which influence fire behaviour and fire spread) (Long 2006).

Eucalypts are the dominant fuel type of the forested areas of Australia (McArthur 1967). In Victoria specifically, there are a range of biomes. The Victorian Alpine regions are comprised of a mosaic of treeless alpine shrub and grasslands and sub-alpine woodlands. In the central highlands, dry and wet montane forests occupy most of the area. In the dry Mallee regions towards the west of the state, Sandplain and Mallee Heath, scrub woodlands and yellow gum woodlands dominate the vegetation. Vegetation in the east of the state is characterised by lowland damp forests, Banksia woodlands and Riparian scrub, which are interspersed throughout the foothills. In the upper altitude regions of eastern Victoria, wet forest ecosystems dominate the landscape (e.g. *Eucalyptus regnans* and *Eucalyptus obliqua*) (Source: EVC (Ecological Vegetation Classes) combined into major fuel types by K Tolhurst, courtesy of DSE). The major vegetation types across Australia are displayed in Fig. 1.

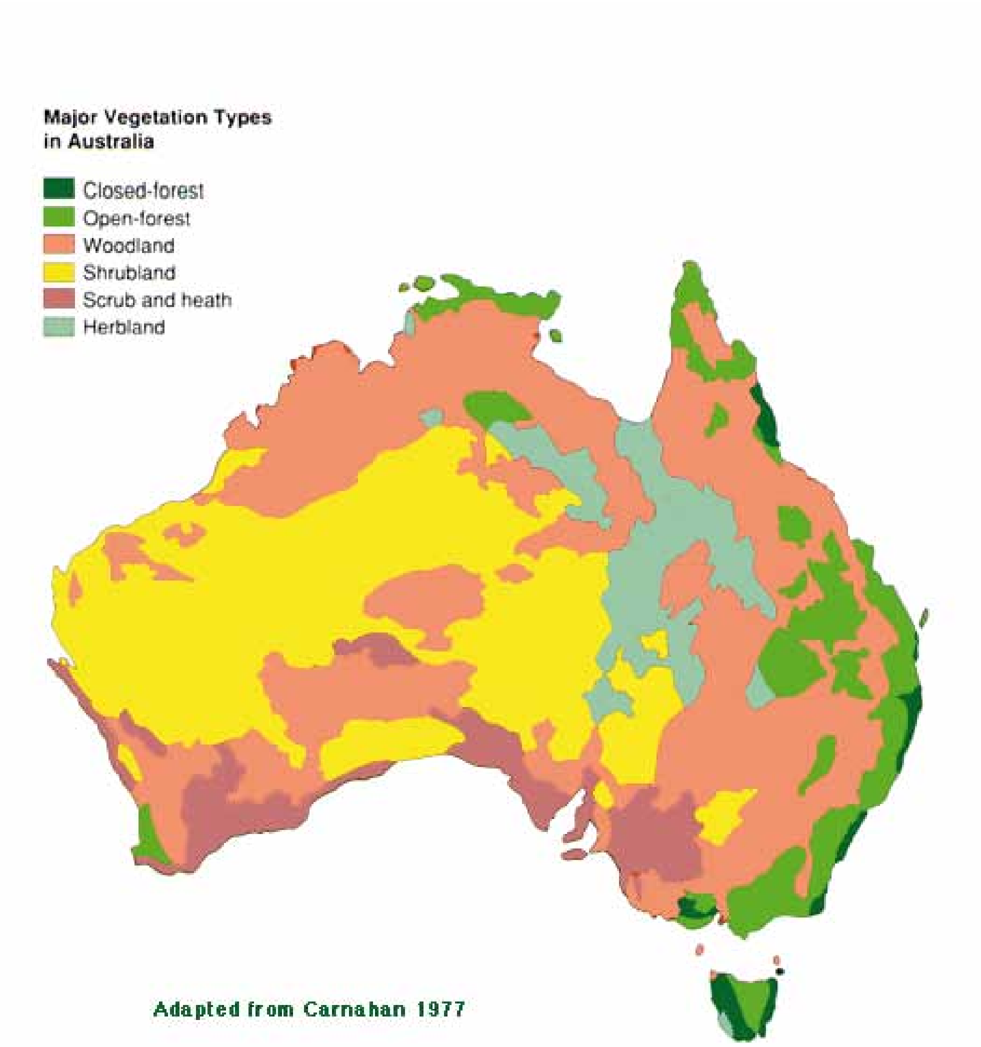


Figure 1: A simplified version of Australia's vegetation (Australian National Botanic Gardens 2007).

4.2 Major fire events in Australia

A number of significant fire events have occurred in Australia over the last 70 years, including Black Friday (1939), Dwellingup (1961), Hobart (1967), Ash Wednesday (1983), Como Janelli (1994), Canberra (2003) and Black Saturday (2009). These were all fires that caused major to catastrophic consequences to communities and the environment. However, many more bushfires have repeatedly impacted the communities of the southern states of Australia, with extensive loss of life and property. In the past 70 years, at least 7300 houses have been destroyed and 375 people have lost their lives. More specifically, Black Friday in 1939 affected the states of Victoria, NSW and ACT and resulted in 66 fatalities in Victoria (Sun 1939). The Dwellingup fire in Western Australia caused the loss of 116 houses (McArthur 1961), and the Tasmanian fires that affected the city of Hobart in 1967 caused the deaths of 62 people and destroyed over 1000 houses (Chambers and Bettingham-Moore 1967). Ash Wednesday affected both South Australia and Victoria in 1983 and caused 61 fatalities and the loss of over 2000 houses (Country Fire Authority 1983; Keeves and Douglas 1983). The Como Janelli fire in NSW resulted in four lives lost and 99 houses destroyed (Sullivan 2004). In terms of fatalities, the most severe fires were those that occurred on Black Saturday in 2009 in Victoria, claiming 173 lives and destroying over 2000 houses (Teague *et al.* 2010). The locations of the major bushfires analysed in this report are shown in Fig. 2.

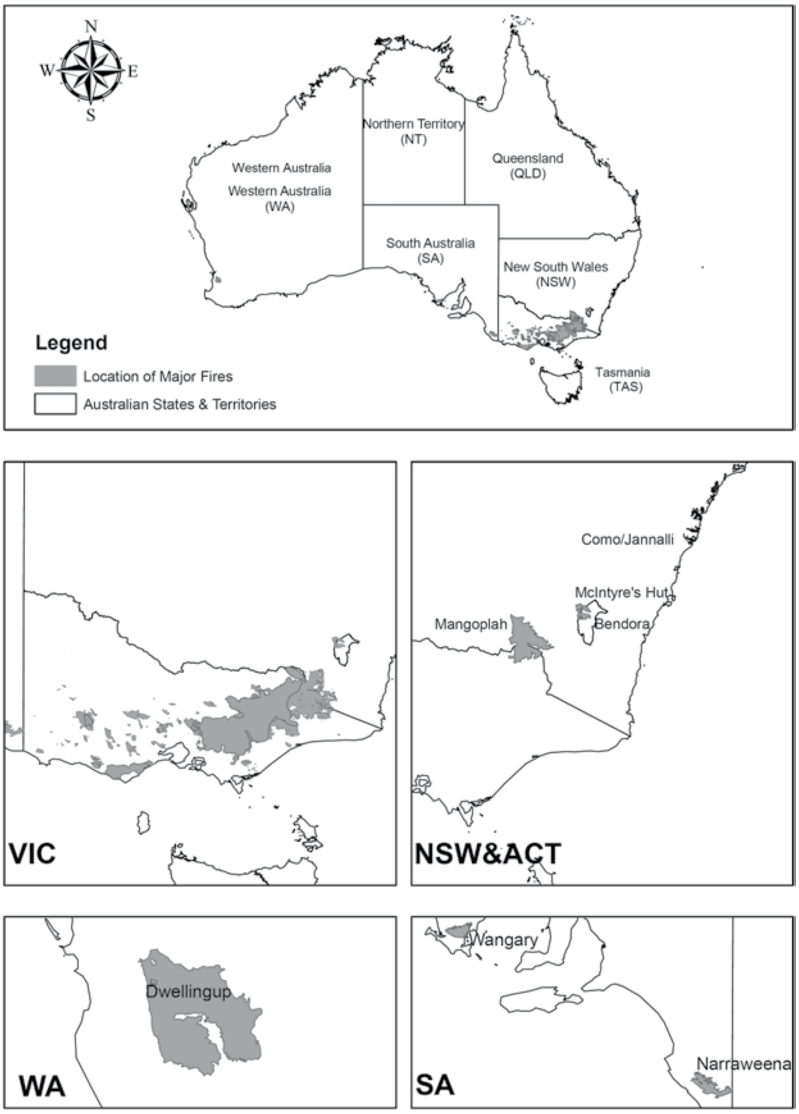
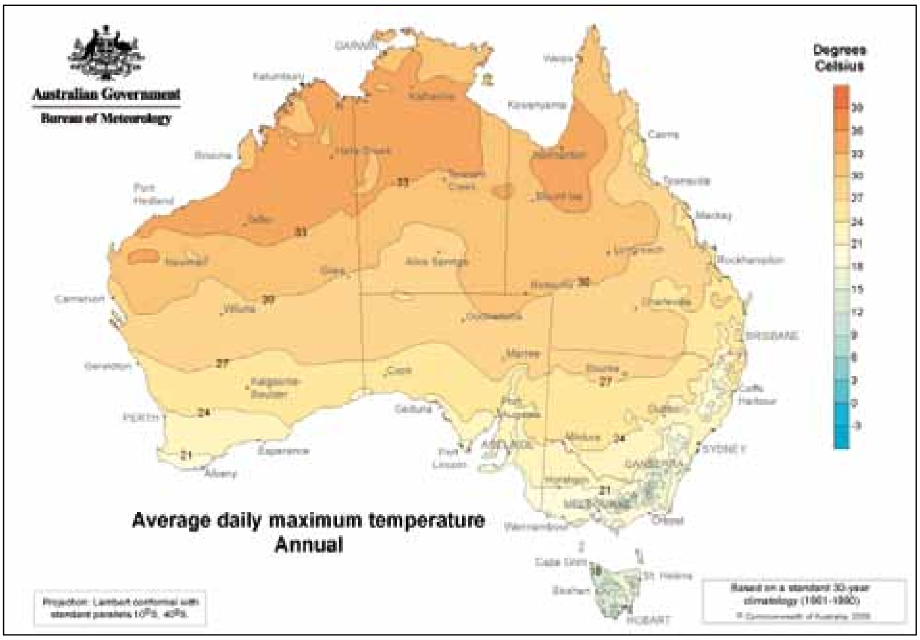


Figure 2: The locations of the major bushfires analysed in this report.

4.3 Weather and climate

The climate of Victoria varies from semi-arid and hot in the north-west (Mallee region), to temperate and cold in the Central Highlands. The climate is highly influenced by seasonal weather patterns and topographic features, such as the Great Dividing Range, which produces a montane climate in the highlands of Victoria. The Mallee region typically has the highest maximum temperature, with the lowest towards the north-east of the state (Fig. 3a). Due to the variability in climate, annual median rainfall reaches up to 2000 mm in the east and north-east of the state, and below 300 mm in the Mallee region (BOM 2010) (Fig. 3b). In South Australia, the climate is characterized by a Mediterranean climate, with wet winters and hot summers, much like that of southern Western Australia. New South Wales experiences a temperate climate, with maximum temperatures and lowest rainfall averages in the north-west of the state.

a.



b.

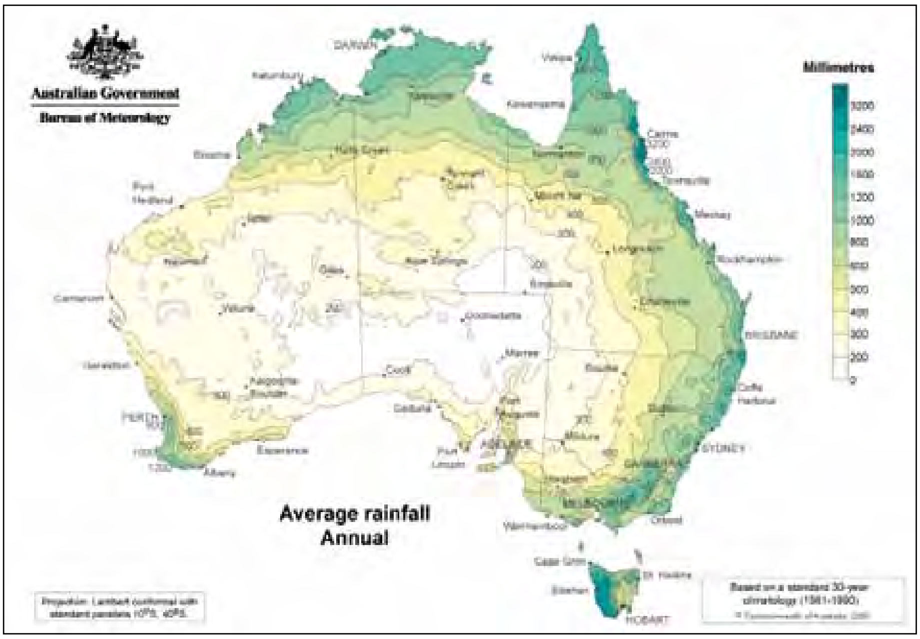


Figure 3: (a). Average annual maximum temperature and (b). average annual rainfall (**www.bom.gov.au/climate/averages/maps.shtml** accessed: 10/10/10).

4.4 Climate, weather and fire

Due to the natural climate variability in Australia, and specifically in Victoria, large areas are prone to bushfires. Long periods of hot weather, coupled with low rainfall affect vegetation dryness and often cause drought and tinder conditions throughout the state (Bureau of Meteorology 2009). Additionally, if these drought conditions are preceded by high spring rains, the summer bushfires in more grassy communities can be intense due to high grass curing and additional fuel load on the surface (Bureau of Meteorology 2009). Fire seasons throughout the country vary according to latitude. For example, most of southern Australia is affected by bushfire threat in summer and early autumn (December to March), whereas northern Australia experiences fires during winter and spring (June to November) (Fig. 4).

Natural climate variability also impacts the fire regime, particularly the phenomenon known as the El Niño-Southern Oscillation (ENSO). Australia is one of the countries most affected by ENSO (Cai *et al.* 2001). Widespread drought occurs during the El Niño phase and heavy rains take place during the La Niña phase (Cai *et al.* 2001). These phases alter the vegetation, such as the build up of fuel and desiccation, which impacts the fire regime (Kitzberger 2002). Stern and Williams (1989) identified a strong relationship between ENSO and fire danger in Victoria. Despite this strong relationship being identified, few studies have been conducted in the southern states of Australia on the relationship between actual fire events and ENSO. One such study, by Nicholls and Lucas (2007), identified a relationship between the coincident ENSO summer rainfall and the area of Tasmania burned through wild fires. Further work is needed to examine the relationship between bushfire behaviour and climate indices in other states.

Although most of northern Australia experiences high amounts of burning each year, the fires are usually not severe and do not cause damage to assets or human lives. The bushfires in southern Australia are very dangerous when most of the vegetation dries out in mid to late summer. High risk weather patterns occur in the form of vigorous cold fronts entering a slow moving high-pressure system in the Tasman Sea (Bureau of Meteorology 2009). In south-eastern Australia, these weather events are associated with very hot, dry and gusty north westerly winds. The passage of the cold front causes the winds to suddenly shift direction, which leads to dangerous conditions when the flank of the fire becomes the fire front (Bureau of Meteorology 2009). Such conditions feature in bushfires that cause vast amounts of damage to communities and the landscape, such as the Ash Wednesday fires of 1983 and the recent Black Saturday fires of 2009.

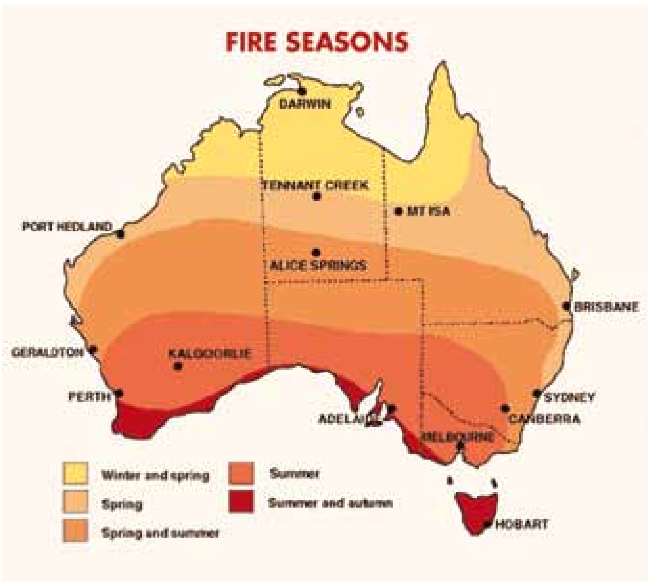


Figure 4: Australian fire season map (Luke and McArthur 1978).

Five: Data and methods

To assess the relationship between loss and the destructive power of the fires studied, several datasets were examined. Fire weather, fire behaviour, vegetation type, fuel loading, topography, community loss and house and population density information were collected for each fire. The datasets were compiled from a range of sources and each dataset is discussed separately. The spatial layers and the tabular data were linked spatially so that where possible, spatial information could be extracted for analysis. Several fires were included that had no community loss recorded so that the risk of loss could be assessed for given weather conditions.

5.1 Fire perimeters and fire behaviour mapping

Fire perimeters have been deduced for major fires for many years. Originally in Victoria (pre-1980s), fire perimeters were created from ground assessments and eyewitness observations; these have now been transferred from hard copy to digital data for the purposes of this study. Currently, fire perimeters are collected using 'classic' fire reconstruction techniques, as well as aerial and satellite remote sensing, Global Positioning Systems and aerial photo interpretation. A Victorian fire history database, created by the Country Fire Authority (CFA) and the Department of Sustainability and Environment (DSE), containing a digital perimeter for many fires was used, however some older fires (pre-1980s) and fires from other states were found in paper maps. These were scanned, digitised, geometrically rectified and then added to the Geographical Information Systems (GIS) spatial database. This database also used more detailed fire reconstruction information from the Black Saturday fires. Many of the fires occurred over several days and/or consisted of several fires that eventually combined into one large fire. This study attempted (when known) to use the fire perimeter for the day of the fire that caused the corresponding damage.

Isochrones, or contours of equal time, were obtained where possible for each fire. These contours detail the spatial spread of the fire perimeter over temporal scales, ranging from 10-minute to daily intervals. Such detailed information is essential to track fire propagation pre- and post-frontal change, as well as quantifying the rate of spread at various points across the fire. The level of detail for each fire varied depending on the source and age of the fire. Unfortunately, very few fires had highly detailed isochrone information (such as those available for the 2009 fires). Fig. 5 reveals the varying complexity of isochrones used in this project.

Figure 5: Examples of the different complexities/accuracies of the isochrones information collected, (a) Murrindindi (2009) (Gellie *et al*. Forthcoming), (b) Avoca (1985) (Maynes and Garvey 1985) and (c) Monivale (1983) (Country Fire Authority 1983).

5.2 Fire weather variables

Weather variables were obtained from the Bureau of Meteorology's automatic weather station data, and from government reports that described data from manual and automatic weather stations. These data included temperature, relative humidity, rainfall and wind speed and direction. Often, the weather stations were a long distance from where the fire occurred and the conditions (topography/elevation) may have been very different. Therefore, the distance between the fire and the weather station was calculated so that this could be incorporated into the analysis. Data corresponding to the time of highest daily FFDI were used in this study.

This study only accounted for surface weather conditions, but it is acknowledged that the vertical structure of the atmosphere is likely to contribute to fire behaviour and therefore the energy released during an event (Potter 2002). Further investigation is required to understand how the vertical structure of the atmosphere influences, or is influenced by, catastrophic bushfires.

5.3 Slope

Slope data were calculated from the VicMap DEM20 (resolution of 20 m) for Victorian fires and GEODATA 9 Second digital elevation model (DEM-9S) Version 3 (**www.ga.gov.au/meta/ANZCW0703011541.html**) (resolution approx 250 m) for all other states.

5.4 Fuel types and loads

McArthur (1962) states that the amount of fine fuel available on the forest floor is one of the most significant factors affecting fire behaviour and largely determines the rate of spread and intensity of a fire burning under a given set of meteorological conditions. Even though recent research (Burrows 1999; Cheney *et al.* 1993; Gould *et al.* 2007b) indicates that fuel load is not as important in determining spread rate as fuel structure, fireline intensity is a function of fuel load. Therefore it was essential that accurate estimates of fuel load were included in the database. Fig. 6. shows the vertical distribution classification of fuels considered.

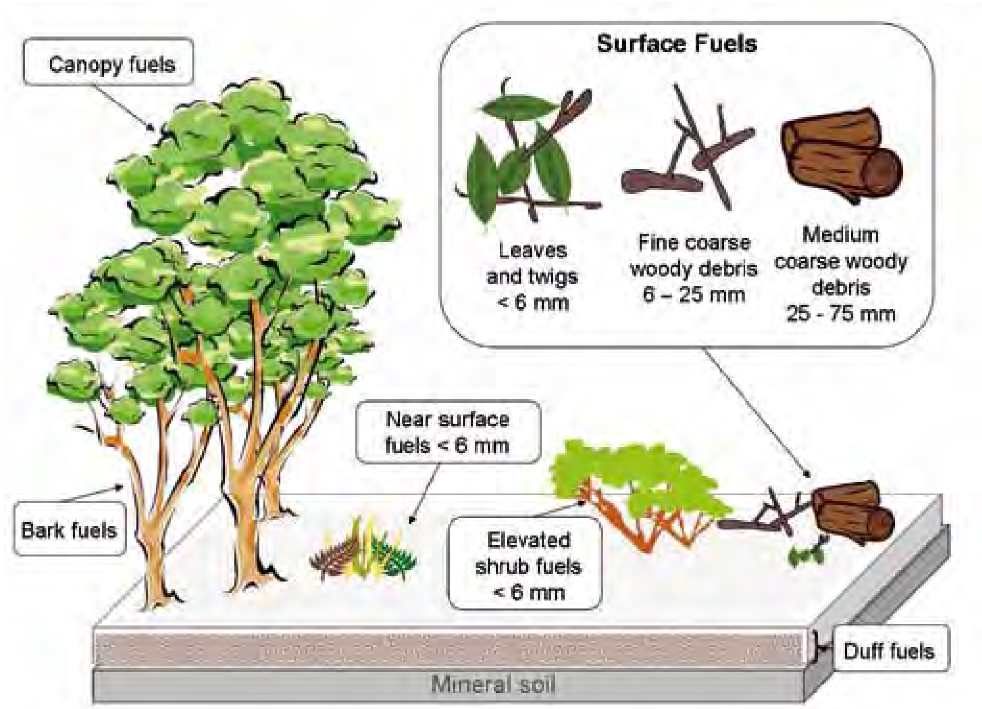


Figure 6: Fuel structure of ecologically mature eucalyptus forests in Victoria (Gellie *et al.* 2010).

Unfortunately, accurate fuel information was not readily available for each fire. Best estimates were taken from the literature, although some areas lacked any estimate. In such cases, modelled fuel loads were used. Modelled fuel loads were created using fuel types, fire history and accumulation curves. More information about the grouping of fuel types and the fuel accumulation rates can be found in Tolhurst (2005) and McCarthy *et al.* (2009). These data were used to produce estimates of the bark load, surface load and elevated load. For consistency with the literature data, only surface fine fuel estimates from the modelled data were incorporated into the analysis. Where there were no estimates for fuel load in the case-study reports or modelled data, estimates were taken from Gellie *et al.* (2010).

Elevated fuels, near surface fuels, bark fuels, coarse woody debris and canopy were not included in the analysis. Therefore any calculation of the energy released from these fires is only partial, particularly in those fires that burned in the canopy.

5.5 Community loss and density

The number of fatalities, houses lost and economic loss are essential in determining the impact of a fire on a community. Community loss data was collected in two formats, tabular and spatial. Tabular data came from a range of sources, many of which were already compiled by the CFA (see CFA 2010). Sources included newspaper articles, reports, books and journal articles.

For the fires analysed in this study, the number of firefighter deaths was not always known. For fires with available information, the percentage of fire fighter deaths was approximately 5% of all fatalities in the analysis. It is acknowledged that the conditions under which firefighters are killed in a bushfire may vary from those determining civilian deaths, however the percentage of firefighter fatalities was considered small enough not to remove them from the analyses.

Detailed spatial data were only available for a few of the fires. These included fatality and house loss data of the 2009 Black Saturday fires, available from the Bushfire CRC. The fatality data were supplied by the Victorian police, and the house-loss data were created using aerial photography accessed through Geosciences Australia. House-loss data for four regions of the Ash Wednesday fires were also acquired, and these were estimated from aerial photography. Additionally, various paper maps that marked where house losses occurred were identified. These were digitised and geocoded. Finally, some documents revealed address points of fatalities and house losses and these were also incorporated in the analyses. In total, there were spatial data for 17 fires with house loss and five fires with fatalities.

Estimates of economic loss were also used in analyses. For the Victorian fires in this study, which occurred between 1939 and 2008, economic figures were acquired from the CFA and DSE. These data were constructed according to the State Emergency Risk Assessment Methodology (State Emergency Mitigation Committee 2005) and were originally 'corrected' to modern costs (2004). These were further corrected to 2008 Australian dollars to match the 2009 dataset. Economic data for the 2009 fires were acquired from a recent economic loss assessment (Stephenson 2011), which is based on methods developed by the OESC (2008). These economic figures were converted to 2008 Australian dollars. This framework was also used to calculate economic costs for fires other than those in Victoria.

To assess the community loss, house and population density information was examined. In order to be more representative in describing the impact of house loss, fatalities and economic loss in fire-affected communities, average densities were calculated over the fire affected area only. For house density, where possible, aerial photography obtained over a fire-affected region around the time of the fire was collected. These images were georectified, collated as a mosaic and then each property was digitised to establish the housing density (Fig. 7).

Aerial photography was not available for all regions and was not always feasible for ascertaining house density and for estimating the population density. Consequently, Australian Bureau of Statistics (ABS) population and housing census data were incorporated. This was achieved by using statistical local boundaries, local government or census districts to provide the best available estimate of broad population and housing densities using the proportion of area burnt and proximity to towns. The ABS dataset at the closest time to the fire event was used.

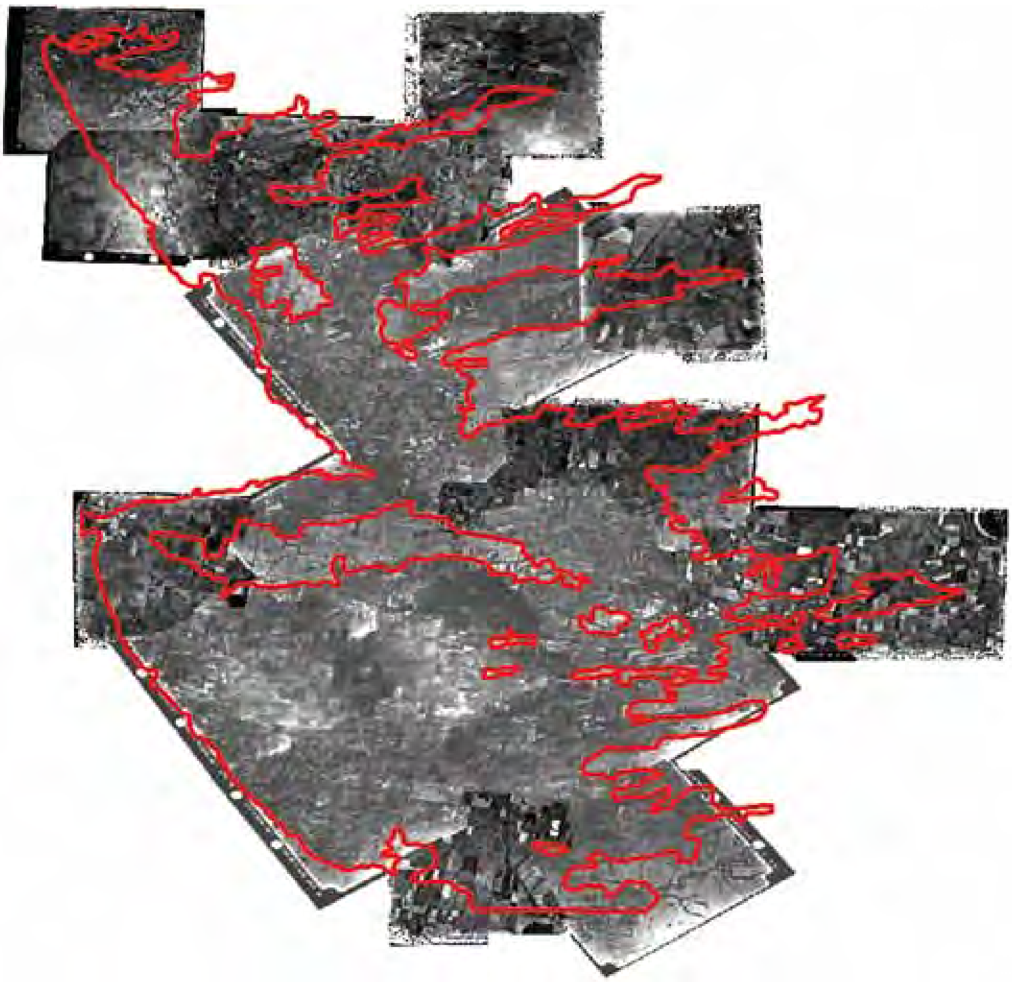


Figure 7: Orthophotos covering populated regions of the Cudgee 1983 fire (Country Fire Authority 1983).

5.6 Fire danger indices

The weather data discussed in Section 5.2 were used to calculate McArthur's fire danger indices. To test the applicability of McArthur's fire danger meter on community loss, FFDI (Mk V) and GFDI (Mk IV) were calculated for each fire using the same methods as used by the Bureau of Meteorology (2006).

Both FFDI and GFDI are functions of temperature, humidity and wind speed at a height of 10 m. The GFDI includes a measure of grassland curing, whereas the FFDI includes a measure of 'fuel availability' reflected in the drought factor (DF), which is a measure of long-term drying. The DF is a function of the Keetch-Byram Drought Index (KBDI), which measures the cumulative moisture deficiency in the upper soil layers, and it also incorporates information about the rainfall record. Equations used to determine FFDI were those given in Noble *et al.* (1980), however the drought factor was determined using Griffin's algorithm (Griffiths 1999). The equation to determine the GFDI was that given in

Purton (1982). Note that both forms of the indices assume standard fuel loadings, being 4.5 t/ha for grasslands (Luke and McArthur 1978) and 12.5 t/ha for forests (McArthur 1967).

5.7 Adjusted fire danger indices

Slope and fuel loading/structure affect fire behaviour (Luke and McArthur 1978). However, these factors are not included in the McArthur Fire Danger Indices. To better reflect the fire behaviour over the fire area, FFDI and GFDI were adjusted to account for fuel loading and slope in a way that reflects the Mark V Forest Meter and Mark V Grassland Meter spread rate predictions.

Fuel adjustment

$$\mathrm{FFDIF} = \mathrm{FFDI} \times \left(\frac{w}{1.25}\right), \qquad (1)$$

$$\mathrm{GFDIF} = \mathrm{GFDI} \times \left(\frac{w}{0.45}\right), \qquad (2)$$

where w is the average fuel load over the fire area in kg/m^2, 1.25 is the standard fuel loading for the FFDI (12.5 t/ha) converted to kg/m^2 and 0.45 is the standard fuel loading for the GFDI (4.5 t/ha) converted to kg/m^2. Note that the formula in Purton (1982) would result in an adjustment of $(w/0.45)^{1.027}$, but the adjustment used here is in line with the equation for the Mark V grassland meter (Noble *et al*. 1980), which includes fuel loading. In the case of forests, recent research (Gould *et al*. 2007b) has shown spread rate to be less dependent on fuel load than the McArthur Mark V meter predicts, while in grasslands it has been shown that spread rate does not depend directly on fuel load (Cheney *et al*. 1993). However, it was decided that the adjustments to the indices were worth considering as they reflect differences in intensity between fires at the same FFDI and GFDI.

Slope adjustment

$$\mathrm{FFDIS} = \mathrm{FFDI} \times \exp(0.069\theta), \qquad (3)$$

$$\mathrm{GFDIS} = \mathrm{GFDI} \times \exp(0.069\theta), \qquad (4)$$

where θ is the average slope encountered by the head fire in degrees. The multiplier $\exp(0.069\theta)$ is given in Nobel *et al*. (1980) as an approximation to the increase in no-slope rate of spread in the Mark V Forest Meter when the slope angle is θ degrees.

Fuel and slope adjustment

$$\mathrm{FFDIFS} = \mathrm{FFDI} \times \left(\frac{w}{1.25}\right) \times \exp(0.069\theta), \qquad (5)$$

$$\mathrm{GFDIFS} = \mathrm{GFDI} \times \left(\frac{w}{0.45}\right) \times \exp(0.069\theta). \qquad (6)$$

These adjustments were used as predictor variables for community loss to see whether they would be better predictors than the unadjusted FFDI or GFDI.

Accounting for such features is very important because the steepness of the slope affects both the rate of spread and direction of the fire. For example, fires typically move faster uphill because the flames are closer to the fuel, and wind currents are uphill, which forces the flames towards the unburnt fuels. A recent study by Hammill and Bradstock (2006), which investigated the effects of terrain on fire behaviour, found that fire severity was greatest at moderate slopes of between 6 and 15 degrees. Similarly, the amount of fuel on the surface also greatly influences the severity of the fire, with higher fuel loadings being associated with higher intensity.

5.8 Intensity and power measures

The most commonly used measure of the 'strength' of a fire is Byram's fireline intensity, I_B, which is the rate of heat release per unit length of the active fire front (Byram 1959). It is calculated as

$$I_B = hw_a R, \tag{7}$$

where w_a (kg/m²) is the fuel available for burning in the fire front, h (kJ/kg) is the heat yield of the available fuel and R is the forward rate of spread (m/s). Fireline intensity is thus the rate of energy release over the depth of flame behind unit length of the fire front.

Intensity does not include a measure of the size of the fire. A simplistic improvement on just using intensity is to multiply the energy release rate per unit length by some characteristic fireline length for which the intensity is reasonably large. This gives an estimate of the power of the fire. Thus the first measure of fire power considered is given by

$$\mathrm{PWR}_1 = I_B \times \alpha P, \tag{8}$$

where the perimeter of the fire, P, is given by Equation 36 (section 9.2), and α is given by Equation 34 (Appendix 9.2).

Catchpole *et al.* (1982) extended the definition in Equation 7 to intensity around the perimeter of a fire, where R is replaced by the rate of spread normal to the perimeter. The spread rate, and thus the intensity, varies round the perimeter, as discussed in Catchpole *et al.* (1982). A more accurate estimate of the power of the fire, PWR_2, is given by integrating the intensity around the fire perimeter which is shown in Catchpole *et al.* (1982) to be

$$\mathrm{PWR}_2 = \int I_B ds = hw_a \frac{dA}{dT}, \tag{9}$$

where dA/dT is the rate of area growth with time. The area, A, of an elliptical fire with length D_T and length to breadth ratio LB is

$$A = \frac{\pi D_T^2}{4LB}. \tag{10}$$

The distance D_T can be expressed as $D_T = 2fR_0T$ (see Fig. 17 in section 9.2). Thus

$$A = \frac{\pi f^2 R_0^2 T^2}{LB}.$$

hence

$$\frac{dA}{dT} = \frac{2\pi f^2 R_0^2 T}{LB}. \tag{11}$$

Substituting for fR_0 in terms of D_T gives

$$\frac{dA}{dT} = \frac{\pi}{2LB}\frac{D_T^2}{T}, \tag{12}$$

thus

$$\mathrm{PWR}_2 = \frac{\pi h w_a}{2LB}\frac{D_T^2}{T}. \tag{13}$$

Note that this assumes the heat yield and available fuel remain constant around the fire, whereas recent studies (e.g. Linn and Cunningham (2005)) suggest that the combustion processes are different for heading, flanking and backing fires, and thus h and w_a would vary somewhat around the perimeter.

5

To calculate the power of the fire for fires that have a 'blow-out' due to a wind change a number of different equations are required. The methods used to calculate the power of the fire from these blow-outs can be found in the appendix (sections 9.3–9.5).

5.9 Byram's definition of 'power of the fire'

Byram (1959) introduced the concept of 'power of the fire', PF, to determine the strength of the fire, and as a comparison with the 'power of the wind', PW. He suggested comparing the ratio PF/PW with unity to determine whether the buoyant forces exceeded the inertial forces at some height above the ground. In this case, extreme fire behaviour and blow-out characteristics were assumed likely to occur. The ratio PF/PW is also known as the convection number, NC (Nelson Jr 1993). The two measures, PF and NC, were considered; the first as a measure of the strength of the fire, and the second as a measure of possible extreme fire behaviour.

PF is given by Equation 14 below (Nelson Jr 2003).

$$\mathrm{PF} = \frac{gI_B}{c_p T_a}, \qquad \textbf{(14)}$$

where g is gravitational acceleration (9.8 m/s^2), c_p is the specific heat of dry air at constant pressure (1.005 kJ/kg K), and T_a is air temperature (°K). Note that PF is the rate at which buoyant air does work in ascending unit vertical distance of the convection column (Nelson Jr 2003). It differs from I_B from fire to fire only in the term T_a which is in degrees absolute. Only the surface temperature could be used for T_a as this study lacked information on the vertical temperature profiles. Since absolute temperature only varies by about 7% in the range between 22°C and 46°C (the range of temperatures in the fires analysed) PF was very highly correlated with I_B (r = 0.99), so only the latter was used in the analysis (as it is more well-known to fire agencies).

The convection number, NC is dimensionless and it is shown by Nelson (1993) to be given by

$$\mathrm{NC} = 2gI_B / \rho_a c_p T_a (U\text{-}R)^3, \qquad \textbf{(15)}$$

where U is wind speed (m/s), R is forward rate of spread (m/s) and ρ_a is air density (1.2 kg/m^3). The wind speed, U, was taken as the wind speed used to calculate the fire danger indices while R was taken as the average spread rate over the whole fire area.

5.10 Applying shapes to actual fire events

To apply the power equations of ellipses and blow-outs, given in the appendix, to actual fire events, shapes were fitted to each fire. This was done to consistently calculate the energy released from a fire and to also incorporate the energy released after (if) a change in the weather occurred. Fires form different shapes because of topography, vegetation and the weather, but most often (particularly in south-eastern Australia) the fire forms an ellipse as it is pushed by strong north-westerly winds. Many of these fires are then altered by strong south westerly winds following the passage of a cold front, and depending on the topography, vegetation, weather and fire management, these blow-out fires can form shapes such as triangles, squares, several ellipses and partial squares and triangles. This makes calculating the energy released from a fire difficult.

In a GIS, each fire was divided into the relevant shapes so that the appropriate equations could be applied to calculate the energy released. Firstly, an ellipse shape was fitted from the start point of the fire and extended out to the end of the fire before the wind change arrived. Then various shapes were used to capture the post change shapes which began from the ellipse and extended to the end of the fire. Examples of these are shown in Fig. 8. While each fire does not follow a precise shape this method was the most consistent and efficient at encapsulating and representing each fire event. Additionally, this method can be applied to the shapes formed by spotting (see appendix). When more accurate fire perimeters are available for all fires, future studies are advised to develop equations that can be applied to the actual fire perimeters.

a.

b.

c.

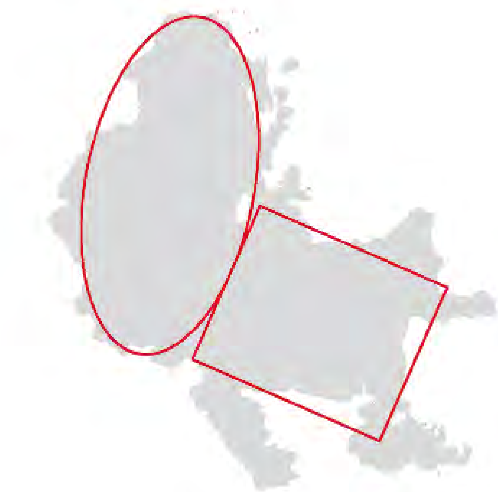


Figure 8: (a). Ellipse (Anakie 1985),(b). Ellipse and triangle (Avoca 1985), (c). Ellipse and rectangle (Coopers Creek 2006) (Source: Maynes and Garvey, (1985); DSE, (2010b)).

5.11 Extracting data for calculating power and intensity

To apply the power equations various measurements and timings of the fire needed to be made. This included the start and end times associated with the main ellipse (usually the part of the fire driven by strong north-westerly winds ahead of the front) and also the start and end times associated with the blow-out part of the fire (caused by the winds following the front). These times, along with the appropriate distances, were used to calculate the rate of spread (*R*) of each part of the fire. Additionally from the fire shapes, the area of each section of the fire was extracted along with the length and breadth measurements for calculating the length-to-breadth ratio (Fig. 9).

The average fine-fuel load (*w*) was extracted from either the literature or the modelled data for the fire-affected area. For the heat yield of available fuel (*h*) used in the power and intensity calculations, 20,000 kJ/kg is regarded as a reasonable average for the range of fuels commonly consumed by bushfires (Luke and McArthur 1978). Following Nelson and Adkins (1986), this was corrected for a nominal 20% energy loss due to radiation and a nominal 5% loss due to the evaporation of moisture (assuming a moisture content of 5%) from Table 3.2 in Byram (1959). The power and intensity values were then calculated using the various timing and dimension measurements, fuel load estimates and heat yield. Finally, the average slope was calculated by taking the mean slope within the fire perimeter in a GIS. Average values over the fire were used because the positions of the losses were largely unknown.

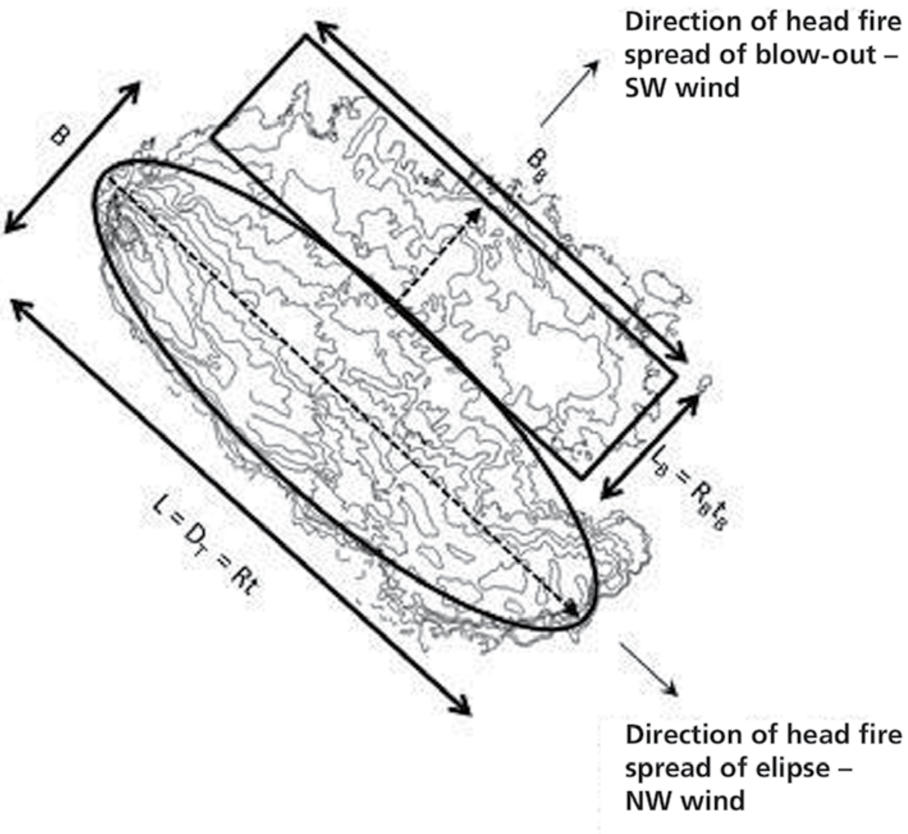


Figure 9: One example of applying shapes to actual fire events, in this case the Murrundindi fire (Gellie *et al*. Forthcoming): B is breadth of ellipse, L is length of ellipse, B_B is the breadth of the blow out (in this case a rectangle) and L_B is the length of the blow-out

5.12 Fire-related variables

A list of fire-related variables used to predict community loss, together with their definitions, is given in Table 1.

Table 1: Fire related variable used to predict community loss, together with their definitions

Variable	Terminology	Source
FFDI	Forest Fire Danger Index	Noble *et al*. (1980)
FFDIF	FFDI corrected for fuel load	Eq. 1
FFDIS	FFDI corrected for slope	Eq. 3
FFDIFS	FFDI corrected for fuel load and slope	Eq. 5
GFDI	Grass Fire Danger Index	Purton (1982)
GFDIF	GFDI corrected for fuel load	Eq. 2
GFDIS	GFDI corrected for slope	Eq. 4
GFDIFS	GFDI corrected for fuel load and slope	Eq. 6
IBAV	Average Byram's intensity for main ellipse and blow-out	Eq. 7
PRW1TOT	Total PWR1 for main ellipse and blow-out	Eq. 8, 37, 39
PWR2TOT	Total PWR2 for main ellipse and blow-out	Eq. 13, 38, 40
NC	Convection number	Eq. 15

5.13 Data accuracy classification system

The data were classified into categories that represented the reliability and uncertainties of the data used in the analysis (Table 2). These classifications were based on previous studies such as Cheney *et al.* (1998) and Bushfire CRC (2009). The numerical weights associated with each category were estimates of the relative reliability determined when setting up the database. These weights were used in the statistical analysis of the relationships, as described in the statistical methods section.

Table 2: Data accuracy classification system

Data accuracy classification system		
Rating		Magnitude
	Weather data	
1	Weather station within 25 km of fire	1.00
2	Reference from a report	0.95
3	Weather station within 50 km of fire	0.90
4	Weather station greater than 50 km from fire	0.85
	Fuel load information	
1	Report – thorough fuel load examination with measurement errors	1.00
2	Report – thorough fuel load examination	0.90
3	Modelled fuel hazard layer	0.80
4	Report – general observation	0.70
5	Fuel load inferred from vegetation type and fuel age (Gellie *et al.* 2010)	0.40
	Fire behaviour – Rate of spread (ROS)	
1	ROS estimated from map (detailed map, isochrones, high temporal resolution)	1.00
2	ROS estimated from map (detailed map, isochrones, low temporal resolution)	0.90
3	ROS estimated from fire perimeter only	0.80
4	ROS estimated using weather data (McArthur's method)	0.70
	Housing and population densities	
1	Spatial layer (ortho photos, address points)	1.00
2	Australian Bureau of Statistics – Census Districts	0.70
3	Estimate from expert	0.40
	Economic loss data	
1	Figures from economic loss assessment OESC method (Stephenson 2011)	1.00
2	Figures from CFA/DSE fire history database (Country Fire Authority 2010)	0.70
3	Calculated using DSE Economic loss assessment spreadsheet	0.20

5.14 Statistical methods

The aim was to establish whether there was a relationship between either of the FDIs (raw or adjusted) or any of the measures of the strength of the fire (the independent variable *x*) and community loss (the dependent variable *Y*), and, if so, which measure of strength (or FDI) gives the strongest relationship. In the case of house loss or fatalities, the dependent variable, *Y,* is a count. The basic regression model for count data is a generalised linear model (McCullagh and Nelder 1989) where the dependence of the conditional mean of *Y* (μ) at a fixed value of *x* is specified as

$$g(\mu) = \eta = b_0 + b_1 x, \tag{16}$$

where *g(.)* is called the link function, and b_0 and b_1 are regression coefficients. Usually for count data the link function is the natural logarithm, (see Agresti (2002) for a good account of modelling count data). Regression coefficients are usually estimated by the method of maximising the likelihood using iteratively weighted least squares. Equation 16 may be extended to more than one regressor variable, e.g. for two regressor variables x_1 and x_2 the regression equation with the log link is

$$\log(\mu) = \eta = b_0 + b_1 x_1 + b_2 x_2 \tag{17}$$

For standard linear regression with a continuous dependent variable the conditional distribution of *Y* for fixed values of the predictor variables is taken to be a normal distribution. For count data the simplest distribution to use is a Poisson distribution. This arises naturally by assuming that the probability of an event happening to one of a large number, *N*, of items is proportional to 1/*N* (in this case the items may be houses or people). This assumption is obviously not valid in this case because of the variation in population density across a landscape.

The Poisson distribution is restrictive because the conditional variance of *Y* is equal to the mean. In practice, in regression for count data, the variance of *Y* about the regression line is often found to be larger than the mean, so tests of hypothesis about the significance of the regression coefficients, and confidence intervals for the regression line are not valid. This overly large variance may arise because only a relatively small amount of variability in the data has been explained by the regressor variables or because of spatial clustering. A way of dealing with this is to use the same mean function, but let

$$\mathrm{var}(Y) = \theta\mu\ , \tag{18}$$

where var(*Y*) is the variance of *Y*, and $\theta > 1$. The parameter θ is estimated from the data. This is known as the 'quasi-Poisson model', and θ is called the 'dispersion parameter' (Agresti 2002).

Another way of accounting for the overly large variance is to use the two parameter 'negative binomial model'. Here, for fixed μ, the dependent variable has a Poisson distribution, but μ itself has a gamma distribution. In this case

$$\mathrm{var}(Y) = \mu + \kappa\mu^2\ , \tag{19}$$

where $\mu > 0$ and $\kappa > 0$. Here the over-dispersion (the amount in excess of μ) is the multiplicative factor $1 + \kappa\mu$ which depends on μ (in contrast to the quasi-Poisson distribution).

In addition to overly large variation, count data may contain more zeros than would be allowed for by a Poisson or negative binomial distribution. There is also the possibility of under-representation of zeros because of the bias towards including fires with some losses.

One class of model capable of dealing with these situations is the 'hurdle model' originally proposed by Mullahy (1986). Zeileis *et al*. (2008) give a good account of the application of this and other models to deal with inflated zeros. In the hurdle model there are two component models: a truncated count model, such as a Poisson or negative binomial model which is used for the positive counts, and a hurdle component which models zero-versus positive counts. In the case of fatalities, for example, the hurdle model may be interpreted as there being one process that determines whether there was a fatality on a fire and another process which determines how many fatalities there were, given that there was at least one fatality. A binomial model (where the probability of a zero is constant for fixed values of the regressor variables) is often used for the zero-hurdle component. Different regressor variables may be used for the two model components. For the binomial model, a logit link function is generally used of the form $\log[\pi/(1-\pi)]$ where π is the probability of a non-zero loss. Thus for two explanatory variables in the binomial model

$$\log[\pi/(1-\pi)] = \eta^* = c_0 + c_1x_1 + c_2x_2 , \qquad \textbf{(20)}$$

where, c_0, c_1, and c_2 are regression coefficients. For the hurdle model with log link the mean regression relationship is given by

$$\log(M) = \eta + \log(1 - f_Z(0,\pi)) - \log(1 - f_C(0,\mu)) , \qquad \textbf{(21)}$$

where M is the mean loss, η is a function of the regression coefficients as in Equations 16 and 17, $f_Z(0,\pi)$ is the probability of no losses in the zero-hurdle model and $f_C(0,\mu)$ is the probability of no losses in the positive count model. For example, in the case of the hurdle model with a Poisson positive count model and a binomial zero-hurdle model $f_Z(0,\pi) = (1-\pi)$ and $f_C(0,\mu) = \exp(-\mu)$. Equation 21 is used to predict mean loss.

The software did not allow a quasi-Poisson hurdle model. However the estimates of the coefficients from the quasi-Poisson model are the same as those for the Poisson model, although the standard errors are larger (Agresti 2002). Thus the hurdle Poisson model was used to fit the data, and the standard errors were calculated using the sandwich covariance matrix estimator (White 1994), to test for the significance of the coefficients. The models were fitted using the software R (R Development Core Team 2008) with the extra packages *pscl* (Jackman 2010) and *sandwich* (Zeileis 2004; Zeileis 2006) included for analysis of the hurdle model and for the sandwich covariance estimator.

The economic loss data was continuous and highly skewed to the right. One method of analysing this type of data is to use a generalised linear model with a normal distribution and a log link which essentially assumes a normal distribution of the logarithm of the data. On the other hand the economic loss data is highly correlated with the house loss and fatalities data, as assuming an average cost of house loss and human life, the economic loss is a multiplier of the weighted sum of house loss and fatalities. As an approximation, the economic loss was rounded to the nearest million dollars and hurdle Poisson and negative binomial models fitted.

The models were assessed using several goodness-of-fit statistics: the root mean squared error (RMSE), the mean absolute error (MAE) and the mean bias error (MBE) (Willmott 1982). The RMSE and MAE both give an estimate of combined bias and precision, but the MAE is less affected by outliers. The MBE measures only bias. For a non-dimensional standardised measure of goodness of fit the correlation, *r*, between the observed values and the fitted model predictions was used, as recommended by Agresti (2002). The formulae for the various goodness-of-fit statistics are given below, as Equations 22–25.

5

$$\mathrm{RMSE} = \sqrt{\frac{\sum_i (y_i - \hat{y}_i)^2}{n}} \qquad \textbf{(22)}$$

$$\mathrm{MAE} = \frac{\sum_i |y_i - \hat{y}_i|}{n} \qquad \textbf{(23)}$$

$$\mathrm{MBE} = \frac{\sum_i (y_i - \hat{y}_i)}{n} \qquad \textbf{(24)}$$

$$r = \frac{\sum_i (y_i - \bar{y}_i)(\hat{y}_i - \bar{\hat{y}}_i)}{\sqrt{\sum_i (y_i - \bar{y}_i)^2 \sum_i (\hat{y}_i - \bar{\hat{y}}_i)^2}} \qquad \textbf{(25)}$$

In the above equations, y_i is the observed value of Y (on the original scale), $\hat{y}_i$ is the predicted value of y_i, $\bar{y}_i$ is the mean value of the y_i, $\bar{\hat{y}}_i$ is the mean value of the $\hat{y}_i$ and n is the number of observations. It was not possible to use the residual deviance or Akaike's Information criterion (see Agresti (2002)) to compare models because of the use of quasi-likelihood models which do not produce a maximised likelihood.

For house loss, fatalities and economic loss data the two models, hurdle Poisson with sandwich covariance matrix estimator, and hurdle negative binomial, were used in the analysis. For the economic data, a normal distribution with a log link was also considered. The potential dependent variables were number of fatalities, total number of houses lost or economic loss. House damage was not included as there were several cases with no available damage information. The main regressor variable was one of the fire danger indices (either raw or adjusted), Byram's intensity or one of the measures of power of the fire. The regressor variables were fitted both untransformed and using a logarithmic transformation. The logarithm of house or population density was used as a covariate regressor variable, depending on whether the independent variable was house loss, fatalities or economic loss. For comparison of models the regressions were unweighted (apart from economic loss, which had different reliabilities in the Y variable), but in the final model development the regressions were weighted. The weighting was done using the product of the relevant fuel, fire behaviour and density weights (as given in Table 2) as this was presumed to reflect the way the errors compounded in the variables. If spread rate was estimated from the McArthur equations, or if one of the FDIs (raw or adjusted) was the regressor variable, the weather reliability weighting was included in the weighting. Sensitivity to the weighting was examined by fitting a non-weighted model and comparing the results.

Further analysis was carried out relating loss, fatalities and economic loss to the number of people or houses exposed in the fire and one of the fire-related variables. Each variable was considered in turn to determine which had the best relationship with loss when exposure was used as a covariate.

The analyses were supplemented by residual plots: residuals against fitted values, normal quantile plots of the standardised deviance residuals, square root standardised deviance residuals against fitted values and standardised Pearson residuals against leverage (see Davidson and Snell (1991) for details).

Six: Results

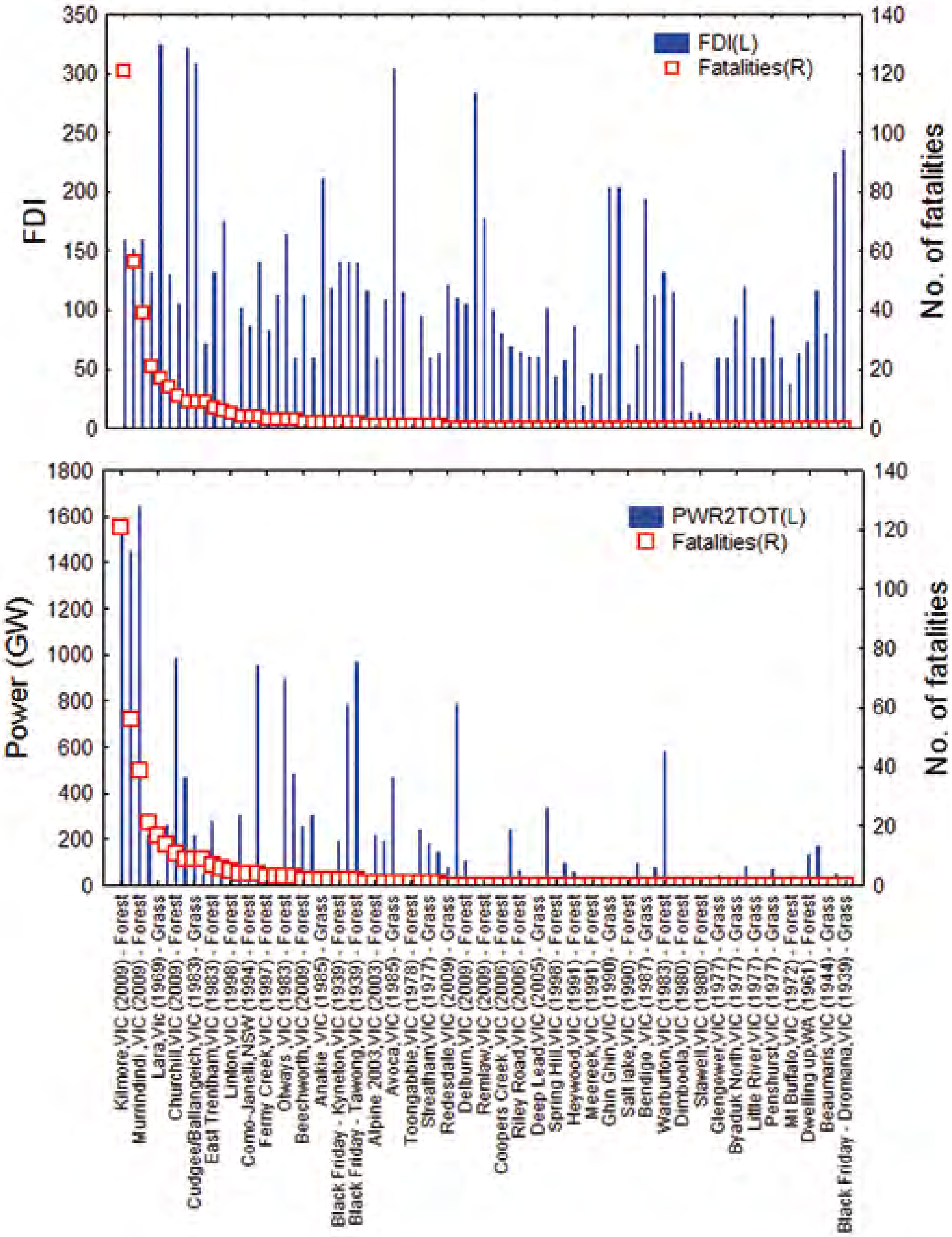
6.1 Summary of fires in the southern states of Australia

This project analysed 81 fires (see Table 10 in section 9.1). This number was largely restricted by data availability. Most of the fires were in Victoria (74); one in Western Australia, two in South Australia, two in New South Wales and two in the Australian Capital Territory. Because of a lack of data, the 1967 Hobart fire could not be included in the analysis. Of the 81 fires, 49 of these were in forested regions and 32 were in grass. Of the fires studied, 36 had one or more fatalities during the event, 25 of these fires occurred in forest and 11 in grass. In terms of house loss, 59 of the fires analysed had one or more houses destroyed; 36 of these being in forest and 23 in grass. The fires that had 10 or more fatalities occurred in Kilmore (2009), Murrindindi (2009), Churchill (2009), Cockatoo (1983), Narraweena/Clay Wells (1983), Lara (1969), and Black Friday (Central and North) (1939). The fire that resulted in the greatest house loss was Kilmore (2009), with over 1200 houses lost. Economic costs greater than $100 million AUD (year 2008) were found in the Murrindindi, Kilmore and Churchill fires in 2009, Canberra fires in 2003, Otways and East Trentham fires in 1983 and the Dandenongs fires in 1962. Note that the economic loss is dependent on how the fire is divided up; for example, the combined economic cost of the Alpine 2006 fire would exceed $100 million dollars, but in this study these fires are divided up into individual fires and therefore individual costs.

The average fuel load for the fires that occurred in forested regions was 1.4 kg/m^2, with a maximum fuel load of 4.45 kg/m^2 at the Mt Buffalo fire in 1972 (Table 3). For grass fires, the average fuel load was 0.4 kg/m^2, with a maximum fuel load of 0.9 kg/m^2 found at the Avoca fire in 1985. The average drought factor was 9.3 and the average rate of spread for all fires was 1.1 m/s. The maximum FFDI for forest fires was 177 during the Remlaw fire (2009) and the maximum GFDI for grass fires was 324 for the Lara fire (1969). Murrundindi, Kilmore and Black Friday (Central and North) had the largest PWR2TOT values (greater than 1400 GW).

Of the 81 fires analysed, 19 (of the 49) in forested regions had a 'blow-out' following the wind change and 10 (out of 32) of the grass fires had a blow-out. Other fires may have had blow-outs following the change, but data was not available for these. Out of the total 29 blow-outs, 48% caused one or more deaths, whereas 90% destroyed one or more houses. Fig. 10 shows fatalities and house loss in relation to FDI and PWR2TOT for each fire.

a.


FDI
No. of fatalities
FDI(L)
Fatalities(R)
Power (GW)
No. of fatalities
PWR2TOT(L)
Fatalities(R)
Kilmore,VIC (2009) - Forest
Murrindindi ,VIC (2009) - Forest
Lara,Vic (1969) - Grass
Churchill,VIC (2009) - Forest
Cudgee/Ballangeich,VIC (1983) - Grass
East Trentham,VIC (1983) - Forest
Linton,VIC (1998) - Forest
Como-Janelli,NSW (1994) - Forest
Ferny Creek,VIC (1997) - Forest
Otways ,VIC (1983) - Forest
Beechworth,VIC (2009) - Forest
Anakie ,VIC (1985) - Grass
Black Friday - Kyneton,VIC (1939) - Forest
Black Friday - Tawong,VIC (1939) - Forest
Alpine 2003,VIC (2003) - Forest
Avoca,VIC (1985) - Grass
Toongabbie,VIC (1978) - Forest
Streatham,VIC (1977) - Grass
Redesdale,VIC (2009) - Grass
Delburn,VIC (2009) - Forest
Remlaw,VIC (2009) - Forest
Coopers Creek ,VIC (2006) - Forest
Riley Road,VIC (2006) - Forest
Deep Lead,VIC (2005) - Grass
Spring Hill,VIC (1998) - Forest
Heywood,VIC (1991) - Forest
Meereek,VIC (1991) - Forest
Ghin Ghin,VIC (1990) - Grass
Salt lake,VIC (1990) - Forest
Bendigo ,VIC (1987) - Grass
Warburton,VIC (1983) - Forest
Dimboola,VIC (1980) - Forest
Stawell,VIC (1980) - Forest
Glengower,VIC (1977) - Grass
Byaduk North,VIC (1977) - Grass
Little River,VIC (1977) - Grass
Penshurst,VIC (1977) - Grass
Mt Buffalo,VIC (1972) - Forest
Dwelling up,WA (1961) - Forest
Beaumaris,VIC (1944) - Grass
Black Friday - Dromana,VIC (1939) - Grass

b.

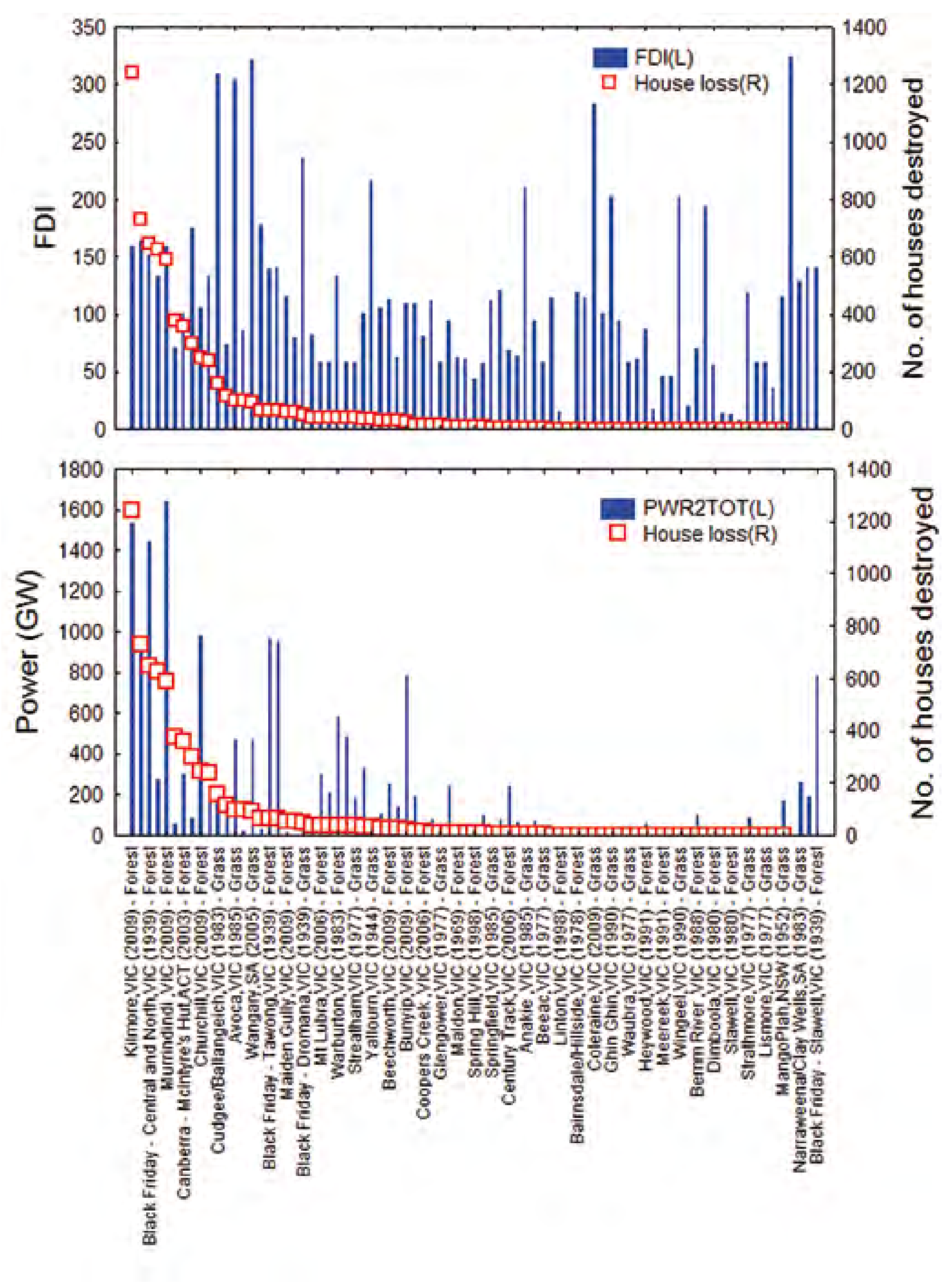


Figure 10: Fatalities (a) and houses destroyed (b) in relation to FDI (FFDI or GFDI depending on the vegetation type) and PWR2TOT.

Fire and adaptive management

Table 3: Descriptive statistics (means and standard deviation)

	Forest				Grass			
	N	Mean (± SD)	Min	Max	N	Mean (± SD)	Min	Max
Slope (°)	49	7.9 ± 5.2	0.4	19.2	31	3.1 ± 2.8	0.3	12.6
Fuel (kg/m^2)	49	1.4 ± 0.7	0.1	4.5	31	0.4 ± 0.2	0.2	0.9
Fire Area (km^2)	49	632.7 ± 2972.1	0.1	20830.1	31	181.7 ± 366.0	1.8	1897.3
Main ellipse PWR 1 (GW)	49	226.2 ± 404.0	0.1	1990.7	31	96.8 ± 129.7	1.1	449.6
Main ellipse PWR 2 (GW)	49	177.2 ± 298.8	0.1	1446	31	82.3 ± 105.3	0.8	346.1
PWR1TOT(GW)	46	342.4 ± 513.0	0.2	1990.7	27	93.4 ± 128.4	1.6	572.8
PWR2TOT (GW)	49	289.4 ± 432.4	0.1	1642	31	105.5 ± 141.7	1.3	482.6
IB Average (kW/m)	49	16714.3 ± 16065.3	73.5	53187.6	31	8880.8 ± 6720.1	630	22711.7
NC	49	0.72 ± 0.89	0.01	5.35	31	0.42 ± 0.56	0.01	2.22
Fatalities	49	6.3 ± 19.5	0	121	32	1.9 ± 4.2	0	17
House loss	47	132.4. ± 253.1	0	1244	30	21.9 ± 37.0	0	157
Economic Loss ($mil AUD)	32	102.8 ± 235.5	1.6	1172	27	12.0 ± 18.3	0.1	65.7
FFDI or GFDI	49	87.4 ± 46.8	4.6	177.2	32	145.0 ± 89.1	59	324.3
FFDIF or GFDIF	49	93.3 ± 69.4	1.8	317.0	31	120.8 ± 111.9	32.8	595.9
FFDIS or GFDIS	49	174.8 ± 128.3	4.8	571.4	31	181.3 ± 125.3	61.9	484.0
FFDIFS or GFDIFS	49	197.2 ± 190.1	1.9	844.5	31	156.9 ± 148.8	34.4	708.0

6.2 Summary of descriptive results

FFDI, GFDI and the power of fire were affected by weather attributes. The data were binned into 5% intervals for relative humidity (RH) and 5°C intervals for temperature to show the means of the variables in response to environmental drivers. Low RH was associated with generally high mean fire measures with a maximum (for RH ≤ 5%) of 150, 220 and 310 GW for FFDI, GFDI and PWR2TOT, respectively (Fig. 11). FFDI and GFDI increased approximately linearly, and tripled in value when the RH decreased from 25% to 5%, but PWR2TOT almost tripled (from 100 to 270 GW) when RH decreased from 15% to 10%, and then showed only a small increase with decreasing RH. All three scales of fire severity were low for RH values above 25%. Similarly binning FFDI, GFDI and PWR2TOT to 5°C temperature intervals showed that FFDI and GFDI increased, for the most part, linearly with temperature, but PWR2TOT increased dramatically above 35°C and then remained relatively constant. Temperatures below 25°C were associated with relatively low FFDI, GFDI and PWR2TOT values.

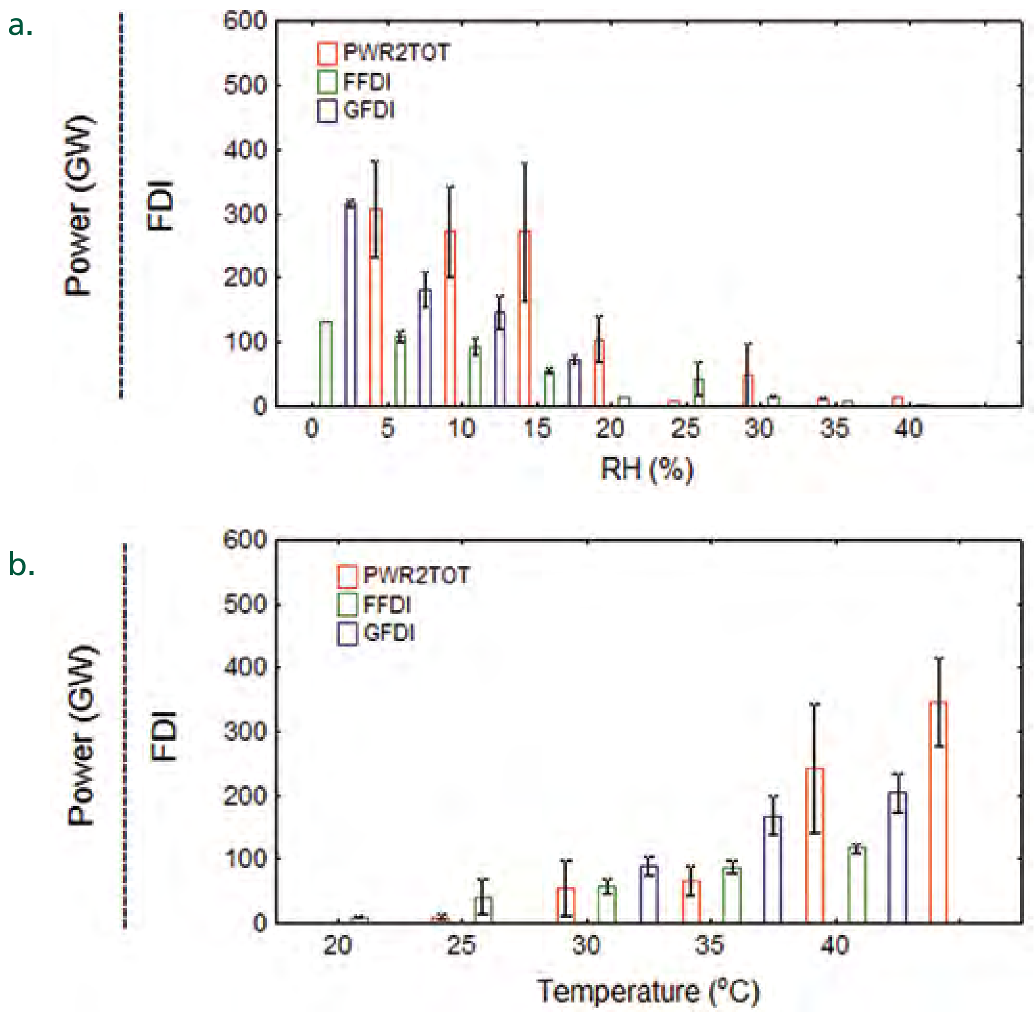


Figure 11: (a) RH binned to 5% intervals and (b) temperature binned to 5°C intervals. Standard error bars are shown.

6.3 Statistical relationship between loss and fire-related variables

Scatterplots showing the relationship between community loss (house loss, fatalities and economic loss) and the variables in Table 1 are shown in the appendix as Fig. 25–27. These show generally greater losses with larger values of the fire related variables, apart from the convection number, NC, for which high losses are seen at low values of NC and vice versa. However, it is not apparent from the scatter plots which variable is the best predictor of loss, and the relationship between loss and the fire related variables is complicated by the different house and population densities associated with each fire.

A preliminary analysis was done to compare the predictive ability of the various fire related variables. This consisted of fitting generalised linear models using number of houses lost, number of fatalities or economic loss as the dependent variable, and one of the fire variables as the independent variable, including the logarithm of either house density or population density, as a covariate. The independent variable was fitted as a linear function and as a log function. The full dataset was used, and then forest and grass fires were considered separately. Adjusted FFDI values were used for forest and adjusted GFDI values were used for grass. The Poisson and negative binomial hurdle models were fitted in each case for the house loss data. The Poisson hurdle model, which gave more weight to higher losses, was used for the fatalities data. For the economic data, residual analysis for the normal model gave poor results: non-normality of the standardised deviance residuals and patterns in the plots of the residuals versus fitted values. Thus only the hurdle Poisson model was used. No weighting was used so that models could be compared, except for weighting the '*Y*' variable (economic loss) in the economic loss analysis. The significance of the coefficients in the hurdle models was not tested in the first stage. This was done when the final models were developed. The correlation between the observed and fitted values was used to compare the models.

6.3.1 House Loss

Using an unweighted analysis for house loss the hurdle Poisson model always performed as well as, or better than, the hurdle binomial model (see Table 4). The logarithmic form of the independent variable was generally better than the linear form, but not in every case. The adjusted FFDI and GFDI (particularly when adjusted for fuel alone) were better than the unadjusted values. In the combined dataset and in forest alone, PWR2TOT was better than the best of the adjusted indices. In grassland, the GFDIF and GFDIFS performed much better than PWR2TOT. It should be noted that house losses in grass fires are generally much lower than those in forest fires, and the models using GFDIF and GFDIFS are strongly influenced by the Cudgee/ Ballangeich fire (with a loss of 150 houses) for which adjusting for fuel and slope did not improve the predictions. PWR1TOT was always worse than PWR2TOT and had the added disadvantage that it could not be calculated for triangular blow-outs. IBAV was not a particularly good predictor when compared to the power variables and the adjusted fire indices. NC was a very poor predictor.

Table 4: Correlation between observed and predicted values for hurdle Poisson and hurdle negative binomial models predicting house loss from house density and fire-related variables (unweighted). Log and linear functions of the fire-related variable (V) are shown. Blank entries correspond to non-convergence of the GLM algorithm

		Hurdle Poisson		Hurdle negative binomial	
		V	log(V)	V	log(V)
Forest and grass	FFDI	0.47	0.50	0.46	0.48
n = 76 (68)*	FFDIF	0.73	0.76	0.70	0.73
	FFDIS	0.61	0.68	0.53	0.67
	FFDIFS	0.69	0.73	0.64	0.72
	GFDI	0.48	0.50	0.48	0.50
	GFDIF	0.61	0.73	0.51	0.73
	GFDIS	0.74	0.72	0.72	0.68
	GFDIFS	0.64	0.75	0.53	0.74
	IBAV		0.57	0.60	0.48
	PWR1TOT	0.72	0.73	0.67	0.57
	PWR2TOT	0.82	0.77	0.80	0.65
	NC	0.20	0.28	0.17	0.19
Forest	FFDI	0.62	0.65	0.60	0.63
n = 46(42)	FFDIF	0.72	0.76	0.71	0.74
	FFDIS	0.60	0.68	0.52	0.68
	FFDIFS	0.68	0.73	0.64	0.72
	IBAV		0.63	0.59	0.61
	PWR1TOT	0.72	0.72	0.70	0.66
	PWR2TOT	0.82	0.77	0.82	0.72
	NC	0.27	0.30	0.27	0.09
Grass	GFDI	0.77	0.64	0.73	0.59
n = 30(26)	GFDIF	0.49	0.51	0.43	0.51
	GFDIS	0.38	0.42	0.36	0.42
	GFDIFS	0.44	0.42	0.42	0.42
	IBAV	0.39	0.36	0.31	0.28
	PWR1TOT	0.46	0.43	0.26	0.38
	PWR2TOT	0.66	0.63	0.59	0.57
	NC	0.22	0.22	0.22	0.10

* Numbers in parenthesis are for PWR1TOT which was not calculated for triangular blow-outs

In the following analyses the best models for the combined dataset were developed using weighted data, as appropriate, and the terms in the zero-hurdle model were tested for significance.

6.3.1.1 Using PWR2TOT as the predictor variable

Hurdle Poisson and hurdle negative binomial models were fitted using PWR2TOT as the predictor variable. Only those fires with complete information for the predictor variables and housing density could be used. The numbers used in each model are shown in Table 5. The positive count component of the hurdle model used models of the form:

$$\eta_H = b_0 + b_1 f(\mathrm{PWR2TOT}) + b_2 \log(\mathrm{HDENS}), \quad \textbf{(26)}$$

where the subscript H indicates houses lost, HDENS is the housing density, $f(.)$ is either the identity or the logarithmic function, and b_0, b_1 and b_2 are regression coefficients. Note that to predict the mean number of houses lost, M_H, it is necessary to add the hurdle component to the right hand side of Equation 26 as in Equation 21. Weighting was done using reliabilities for fire behaviour, fuel, house density and weather (if fire behaviour was predicted from a model). Only the intercept was significant in the zero-hurdle model in each case. All coefficients in the positive count part of the hurdle model were significant in all models (using a sandwich test for the Poisson model). The predicted values are plotted against the observed values for the models in Fig. 12(a)–(d). Fig. 12(b) is on a different scale to show the large over-predictions for Kilmore and Murrindindi for the linear negative binomial model. For the logarithmic models, loss in the Kilmore fire was quite badly under-predicted. The goodness-of-fit statistics for the four models, and for all other models developed in the later analyses, are given in Table 5. The Poisson linear model is clearly the best model; even though the r value is similar to the linear negative binomial model the latter is badly biased. The regression diagnostics favoured the negative binomial model, but as pointed out by Ver Hoef and Boveng (2007), the quasi-Poisson model gives more weight to larger losses, while the negative binomial distribution gives more weight to losses than the quasi-Poisson model below the point where $\mu/\theta = \mu/(1+\kappa\mu)$ and after that the weights are virtually constant. Using a quasi-Poisson model and a negative binomial model without hurdle components gave the estimates $\theta = 118$ and $\kappa = 0.0.4237$. Thus $\theta = (1 + \kappa\mu)$ represents a loss of 200, which is relatively small compared to the highest losses. Since it is critical to model high losses accurately the quasi-Poisson model is preferable. Accordingly, all further analysis was carried out with the hurdle Poisson model (with sandwich tests for the count model coefficients).

The regression coefficients (and their standard errors) of the quasi-Poisson linear model, and all models developed in the later analyses, are given in Table 6.

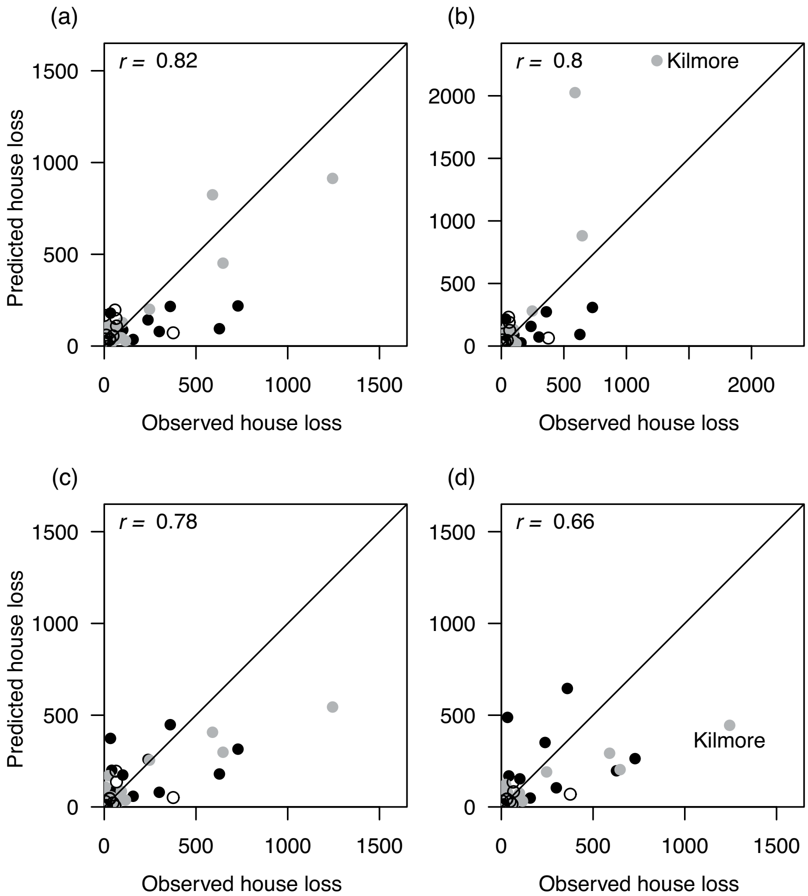


Figure 12: Predicted values plotted against observed values for the equation in house loss in terms of PWR2TOT and HDENS (Equation 26) for (a) hurdle Poisson model (linear), (b) hurdle negative binomial model (linear), (c) hurdle Poisson model (log) and (d) hurdle negative binomial model (log). Fire reliability is shown by shading in the symbols: black-filled circles, weight greater than or equal to 0.55, grey-filled circles, weight less than 0.55 and greater than or equal to 0.35, and open circles, weight less than 0.35.

Table 5: Goodness of fit statistics for the fitted regression models in Equations 26, 27, 29, 31 and 32

	n	Model	*r*	RMSE	MAE	MBE
House loss versus HDENS and PWR2TOT (Eq. 26)	76	hurdle Poisson (linear)	0.82	119	64	7.4
		hurdle neg. bin.(linear)	0.80	230	86	-31.4
		hurdle Poisson (log)	0.78	137	64	18.8
		hurdle neg. bin. (log)	0.66	156	70	21.1
		hurdle Poisson (linear) unweighted	0.82	122	62	15.9
House loss versus HDENS and FFDIF (Eq. 27)	76	hurdle Poisson (linear)	0.74	140	70	9.7
House loss versus HRISK and FFDIF (Eq. 29)	76	hurdle Poisson (linear)	0.85	108	54	-3.5
Fatalities versus PDENS and PWR2TOT (Eq. 31)	79	hurdle Poisson (linear)	0.91	7	3	0.0
Economic loss versus PRISK and PWR2TOT (Eq. 32)	59	hurdle Poisson (linear)	0.99	25	18	-0.9

Table 6: Coefficients and standard errors for fitted regression models in Equations 26, 27, 29, 31 and 32. Standard errors are given in parenthesis. Standard errors for the hurdle Poisson count model are sandwich standard errors

		Count model			Zero-count model		
		intercept	*f*(V)	ln(CV)	intercept	*f*(V)	ln(CV)
House loss versus HDENS (CV) and PWR2TOT(V) (Eq. 26)	hurdle Poisson linear	3.2984 (0.2933)	0.002148 (0.000154)	0.3537 (0.05925)	1.2384 (0.3965)		
House loss versus HDENS(CV) and FFDIF(V) (Eq. 27)	hurdle Poisson linear	3.1061 (0.3620)	0.0122 (0.00172)	0.1950 (0.05924)	1.2811 (0.3882)		
House loss versus HRISK(CV) and FFDIF(V) (Eq. 29)	hurdle Poisson linear	1.1666 (0.4285)	0.009265 (0.001709)	0.3980 (0.05525)	-1.1262 (0.9524)		0.6015 (0.2303)
Fatalities versus PDENS (CV) and PWR2TOT(V) (Eq. 31)	hurdle Poisson linear	-0.1295 (0.6633)	0.002429 (0.0002845)	0.3557 (0.1457)	-0.9945 (0.4699)	0.004790 (0.002273)	
Economic loss versus PRISK (CV) and PWR2TOT(V) (Eq. 32)	hurdle Poisson linear	0.04196 (0.1663)	0.002120 (0.00003727)	0.4257 (0.02173)	2.1936 (0.7323)		

6

6.3.1.2 Effect of weighting

The effect of weighting was examined on the house loss model in Equation 26 by comparing the weighting used with equal weighting in the hurdle Poisson linear model. The change had only a small effect on the resulting model coefficients. The coefficient for the intercept, for instance, changed from 3.2948 to 3.1766, a difference of about 3%. Table 5 shows that the *r* values, RMSE and MAE are quite similar, but the bias is greater in the unweighted model (15.9 as opposed to 7.4).

6.3.1.3 Using FFDIF as the predictor variable

To determine whether a reasonable model could be developed using a modification of the FFDI, the modification with the best *r* value from Table 4 (FFDIF) was chosen, and the hurdle Poisson model was then fitted to the combined fire data using a function of FFDIF as the predictor variable. The models for the positive count component of the hurdle model were of the form

$$\eta_H = b_0 + b_1 f(\text{FFDIF}) + b_2 \log(\text{HDENS}) \ , \qquad \textbf{(27)}$$

where $f(.)$ is either the identity or logarithmic function and HDENS is the housing density. Weighting was done using reliabilities for fuel, house density and weather. Only the intercept was significant in the zero-hurdle part of the models. The linear model in HDENS had a slightly lower *r* value than the log model ($r = 0.74$ as opposed to $r = 0.75$), but the other error statistics were better. Notably, the bias was 9.7 compared with 11.6, and the predictions were better for larger house loss. In contrast to using Equation 26 with the hurdle Poisson model, the goodness-of-fit statistics were poorer apart from the MBE (see Table 5), but the model has the advantage that it can be applied without predicting the fire area. Predicted values are plotted against the observed values in Fig. 13.

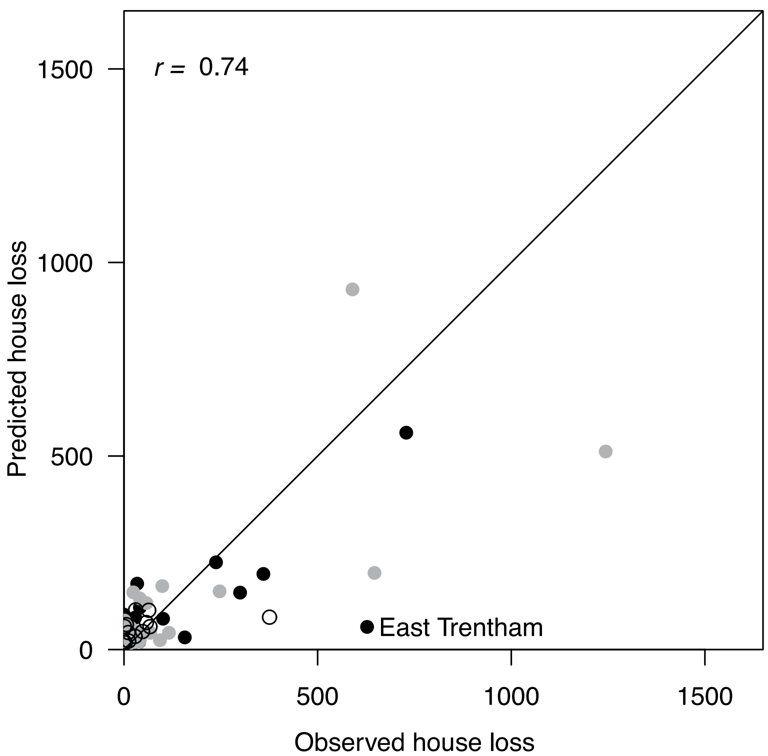


Figure 13: Predicted values plotted against observed values for the equation for house loss in terms of FFDIF and HDENS (Equation 27) for the hurdle Poisson model (linear). Fire reliability is shown by shading in the symbols: black-filled circles, weight greater than or equal to 0.55, grey-filled circles, weight less than 0.55 and greater than or equal to 0.35, and open circles, weight less than 0.35.

6.3.1.4 Alternative model for house loss

Another way to explain house loss is to model it in terms of number of exposed houses and some measure of the strength of the fire. So a possible model is

$$\eta_H = b_0 + b_1 f(\mathrm{V}) + b_2 \log(\mathrm{HRISK}), \tag{28}$$

where HRISK is the number of houses at risk (equal to the product of fire area and housing density), V is one of the predictor variables and $f(.)$ is the identity or log function. This equation was fitted using the hurdle Poisson model. To be comparable with the previous analysis the combined dataset was used. Correlations between observed and predicted values for the unweighted models are given in Table 7. For this model the fuel-adjusted FFDI and GFDI were better than PWR2TOT. The best models were given by using GFDIF and FFDIF. As forest fire losses are generally heavier than grass fire losses, the model in FFDIF was considered more appropriate. This model with the linear form of FFDIF was then fitted again using weights (weather, fuel and house density). The fitted model was

$$\eta_H = b_0 + b_1 \mathrm{FFDIF} + b_2 \log(\mathrm{HRISK}). \tag{29}$$

For this model, FFDIF was not significant in the zero-hurdle model which was determined by log(HRISK) alone. The predicted values are plotted against the observed values for this model in Fig. 14. This model had slightly better error statistics than the model using PWR2TOT and HDENS (see Table 5).

Table 7: Correlations between observed and expected values for models predicting house loss from house risk and fire-related variables (unweighted). Log and linear functions of the fire-related variable (V) are shown. Blank entries correspond to non-convergence of the GLM algorithm.

n = 76 (68) *	V	log(V)
FFDI	0.71	0.70
FFDIF	0.85	0.82
FFDIS	0.60	0.66
FFDIFS	0.69	0.74
GFDI	0.75	0.72
GFDIF	0.87	0.85
GFDIS	0.67	0.72
GFDIFS	0.75	0.79
IBAV		0.78
PWR1TOT	0.63	0.70
PWR2TOT	0.75	0.73
NC	0.54	0.57

* Number in parenthesis is for PWR1TOT, which was not calculated for triangular blow-outs

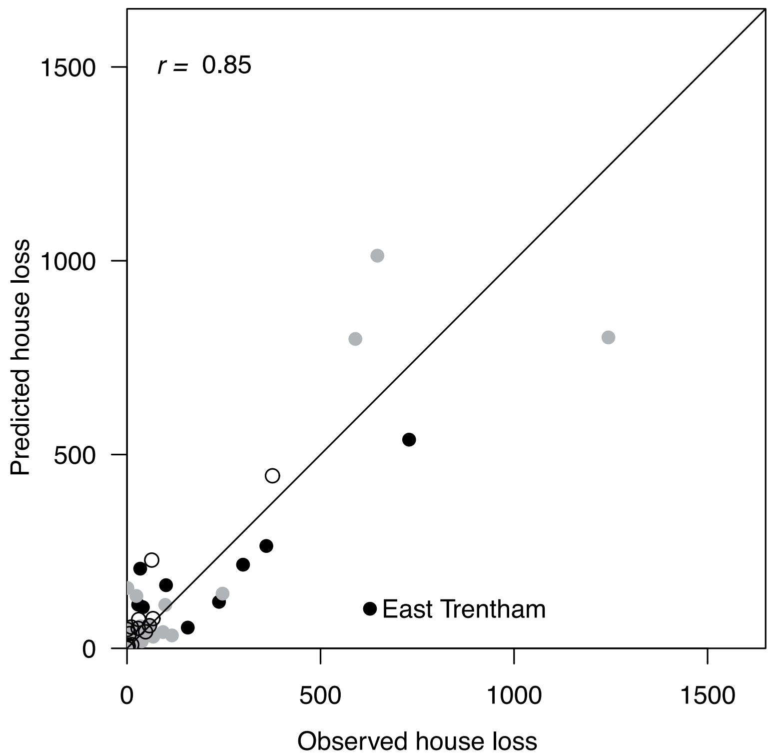


Figure 14: Predicted values plotted against observed values for the hurdle Poisson model (linear) for house loss for the equation in FFDIF and HRISK (Equation 29). Fire reliability is shown by shading in the symbols: black-filled circles, weight greater than or equal to 0.55, grey-filled circles, weight less than 0.55 and greater than or equal to 0.35, and open circles, weight less than 0.35.

6.3.2 Fatalities

The positive count regression model was

$$\eta_F = b_0 + b_1 f(\mathrm{V}) + b_2 \log(\mathrm{CV}), \qquad \textbf{(30)}$$

where the subscript *F* refers to fatalities, CV is either the population density or the number of people at risk (equal to the product of fire area and population density), V is one of the fire-related variables and $f(.)$ is the identity or log function. The hurdle Poisson model was used in preference to the hurdle negative binomial model to ensure the highest fatalities were modelled well. Models were fitted using each fire variable in turn and the results are shown in Table 8.

Adjusting the FDIs improved predictions in the forest and combined data sets but not in grassland (primarily due to the dominance of Cudgee/Ballangeich and Wangary with 9 fatalities each). It is important to note that the combined data set was also dominated by three high fatality fires (Murrindindi, Kilmore and Black Friday – Central and North) thus any model for fatalities may not be robust. A model was created using PWR2TOT, which gave the best correlations for forest, grass and the combined data set, but it should be regarded with caution.

The fitted model was of the form

$$\eta_F = b_0 + b_1 \mathrm{PWR2TOT} + b_2 \log(\mathrm{PDENS}) \ , \qquad \textbf{(31)}$$

where PDENS is the population density. Weighting was done using reliabilities for fire behaviour, fuel, house density and weather (if fire behaviour was predicted from a model). For this model log(PDENS) was not significant in the zero-hurdle model. The predicted values are plotted against the observed values for this model in Fig. 15.

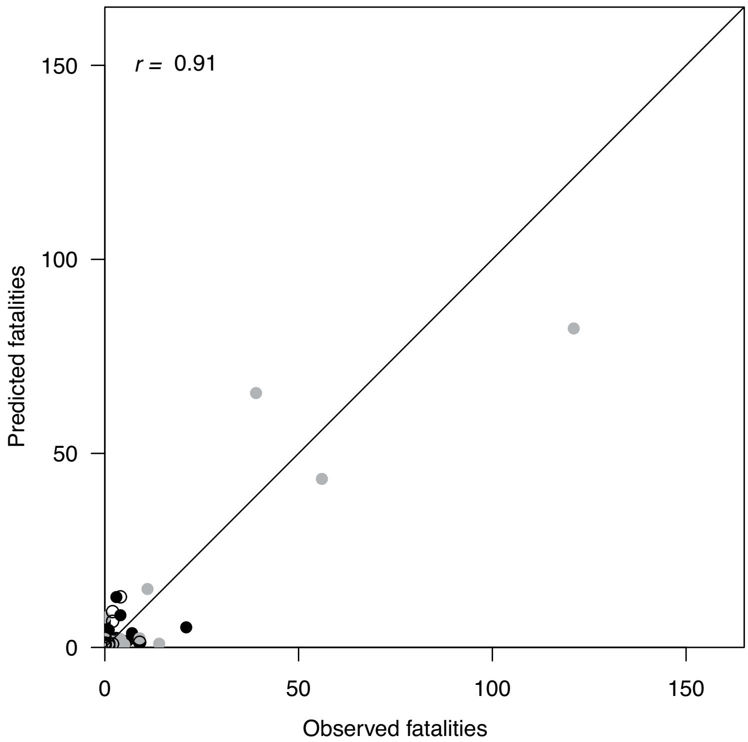


Figure 15: Predicted values plotted against observed values for the equation for fatalities in terms of PWR2TOT and PDENS (Equation 31) for the hurdle Poisson model. Fire reliability is shown by shading in the symbols: black-filled circles, weight greater than or equal to 0.55, grey-filled circles, weight less than 0.55 and greater than or equal to 0.35, and open circles, weight less than 0.35.

Table 8: Correlation between observed and predicted values for models predicting fatalities from population density and fire-related variables, and from population risk and the fire-related variables (both models unweighted). Log and linear functions of the fire-related variable (V) are shown. Blank entries correspond to non-convergence of the GLM algorithm.

		Population density		Population risk	
		V	log(V)	V	log(V)
Forest and grass n = 79 (71)*	FFDI	0.32	0.36	0.63	0.62
	FFDIF	0.60	0.62	0.81	0.77
	FFDIS	0.55	0.58	0.56	0.60
	FFDIFS	0.64	0.64	0.67	0.69
	GFDI	0.35	0.39	0.71	0.68
	GFDIF	0.46	0.55	0.85	0.83
	GFDIS	0.70	0.68	0.67	0.79
	GFDIFS	0.58	0.64	0.74	0.76
	IBAV		0.39		0.65
	PWR1TOT	0.70	0.63	0.63	0.64
	PWR2TOT	0.91	0.81	0.84	0.73
	NC	0.04	0.08	0.40	0.40
Forest n = 48 (44)	FFDI	0.34	0.45	0.72	0.69
	FFDIF	0.60	0.68	0.83	0.82
	FFDIS	0.54	0.59	0.55	0.58
	FFDIFS	0.63	0.72	0.66	0.69
	IBAV		0.36		0.66
	PWR1TOT	0.68	0.62	0.62	0.63
	PWR2TOT	0.95	0.85	0.84	0.72
	NC	0.09	0.07	0.41	0.40
Grass n = 31 (27)	GFDI	0.44	0.53	0.40	0.37
	GFDIF	0.17	0.32	0.11	0.22
	GFDIS	0.22	0.32	0.21	0.24
	GFDIFS	0.13	0.18	0.06	0.10
	IBAV		0.55		0.40
	PWR1TOT	0.63	0.61	0.53	0.49
	PWR2TOT	0.77	0.73	0.60	0.64
	NC	0.39	0.31	0.51	0.41

* Numbers in parenthesis are for PWR1TOT, which was not calculated for triangular blow-outs

6.3.3 Economic loss

It was not clear whether housing or population density was the best covariate to use for economic loss, and they were highly correlated in the economic data set (r = 0.99). It was found that population density performed slightly better, so it was used for the comparisons. The possible covariates are log(population density) and log(population risk). The normal distribution model with the log link had poor diagnostic plots, indicating that the model was unsatisfactory. The economic data were rounded to the nearest million dollars. The hurdle Poisson model was used in preference to the hurdle negative binomial model to ensure the highest economic losses were modelled well. Loss was weighted by the economic reliability given in Table 2. Models were fitted using each fire variable in turn and the results are shown in Table 9.

For the forest data, the algorithm for the hurdle model did not converge. In the combined data using PDENS, the model using PWR2TOT performed best. Using PRISK as the covariate, the variable PWRTOT performed even better, but it was closely followed by PWR1TOT, FFDIF and GFDIS. Like the fatalities data the economic loss data were dominated by two very high losses (Murrindindi and Kilmore), which influenced the correlations. (There was no economic loss data for Black Friday – Central and North.) A model was developed for PWR2TOT, but again it should be regarded with caution.

The positive count regression model was of the form

$$\eta_E = b_0 + b_1 \mathrm{PWR2TOT} + b_2 \log(\mathrm{PRISK}), \qquad \textbf{(32)}$$

where the subscript *E* refers to economic loss which is measured in millions of dollars. Weighting was done using reliabilities for fire behaviour, fuel, house density and weather (if fire behaviour was predicted from a model) as well as economic reliability. For this model only the intercept was significant in the zero-hurdle model. The predicted values are plotted against the observed values for this model in Fig. 16.

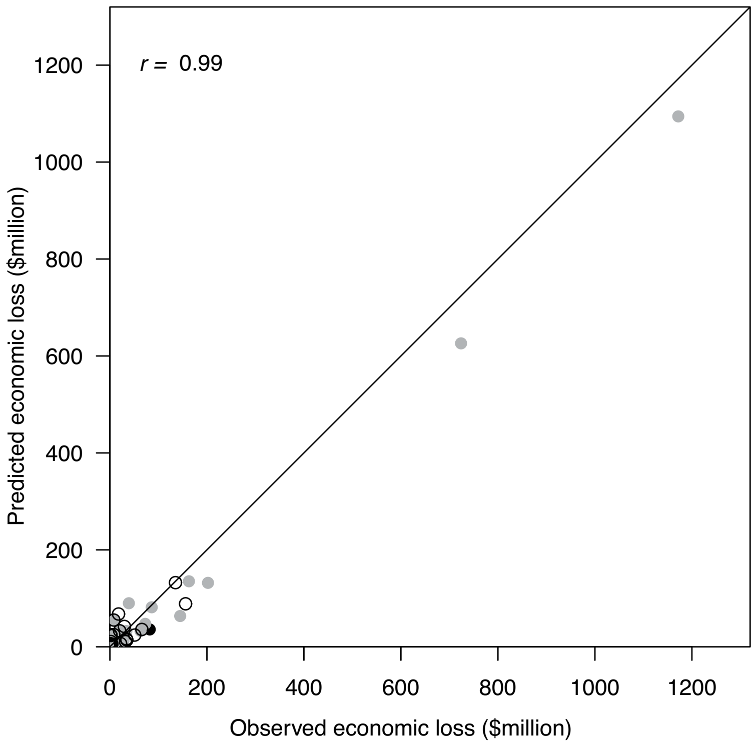


Figure 16: Predicted values plotted against observed values for the equation for economic loss in terms of PWR2TOT and PRISK (Equation 32) for the hurdle Poisson model. Fire reliability is shown by shading in the symbols: black-filled circles, weight greater than or equal to 0.55, grey-filled circles, weight less than 0.55 and greater than or equal to 0.35, and open circles, weight less than 0.35.

Table 9: Correlation between observed and predicted values for models predicting economic loss (rounded to the nearest million dollars) from population density and fire-related variables and from population risk and fire-related variables (both models unweighted). Log and linear functions of the fire-related variable are shown. Blank entries correspond to non-convergence of the GLM algorithm

		Population density		Population density x fire area	
		V	log(V)	V	log(V)
Forest and grass n = 59 (51)*	FFDI	0.32	0.36	0.61	0.63
	FFDIF	0.78	0.79	0.93	0.92
	FFDIS	0.62	0.63	0.88	0.87
	FFDIFS	0.72	0.77	0.89	0.90
	GFDI	0.47	0.46	0.67	0.66
	GFDIF	0.82	0.83	0.95	0.93
	GFDIS	0.82	0.77	0.96	0.93
	GFDIFS	0.74	0.82	0.91	0.94
	IBAV		0.60		0.72
	PWR1TOT	0.89	0.78	0.98	0.93
	PWR2TOT	0.97	0.89	0.99	0.95
	NC	0.11	0.16	0.29	0.33
Grass n = 27 (23)	GFDI	0.80	0.76	0.82	0.83
	GFDIF	0.53	0.61	0.75	0.75
	GFDIS	0.55	0.61	0.80	0.81
	GFDIFS	0.52	0.57	0.76	0.76
	IBAV		0.67		0.77
	PWR1TOT	0.52	0.67	0.81	0.87
	PWR2TOT	0.61	0.73	0.74	0.76
	NC	0.38	0.45	0.75	0.76

* Numbers in parenthesis are for PWR1TOT which was not calculated for triangular blow-outs

6.4 Interpretation of coefficients of regression equations

The coefficients in Table 6 can be interpreted in terms of the effect on loss of changes in the variables or covariates. For example, consider Equation 26 relating house loss to PWR2TOT using HDENS as a covariate. With PWR2TOT used in a linear form, Equation 26 for the non-zero count data model can be written as

$$\eta_H = b_0 + b_1 \mathrm{PWR2TOT} + b_2 \log(\mathrm{HDENS}) \ . \qquad \textbf{(33)}$$

Mean house loss is predicted by taking the exponent of Equation 21 and using Equation 33 for η. From Table 6 the coefficient b_2 in Equation 33 is 0.3537. If house density is doubled for the same PWR2TOT, house loss is predicted to increase by $2^{0.3537} \approx 1.3$†, or by approximately 30%. Using the standard error in Table 6 to obtain an approximate 95% confidence interval for b_2 the percentage increase is expected to lie between 18% and 39%. For example, at Kilmore, with PWR2TOT = 1537 GW, and a density of 3.8 houses per square km the house loss was predicted to be 914 (actual loss 1244), whereas if the density had been 7.6 houses per km^2, the loss would have been predicted to be 1168 with 95% confidence interval (1076, 1268).

† The intercept, the term in PWR2TOT and the hurdle term drop out of the calculation, and for predictions of η_H greater than about 5 (medium to high loss) the last term in Equation 21 is close to 0. The small amount of bias introduced by estimating a function of the estimate (see Neyman and Scott (1960) and Snowdon (1991)) has been ignored.

The coefficient b_1 in Equation 33 is 0.002184. Increasing PWR2TOT by ΔPWR2TOT has the effect of multiplying loss by exp(0.002184 × ΔPWR2TOT). Thus, increasing PWR2TOT by 500GW is predicted to cause nearly three times the house loss. Again, using the standard error to obtain an approximate confidence interval for b_1, the predictions are expected to lie between 2.5 and 3.4 times the loss for an increase of 500 GW. For Kilmore, if PWR2TOT was increased by 500 GW to 2037 GW (resulting from an extra fuel load of 30%) the loss could be expected to be 2675 houses with 95% confidence interval (2293, 3120).

For the fatalities model in Equation 31, using the same reasoning, doubling the population density is also predicted to multiply loss by about 30%, with a 95% confidence interval of between 5% and 55%. Increasing PWR2TOT by 500GW is predicted to cause about 3.4 times the fatalities (confidence interval 2.5 to 4.5). For Kilmore, fatalities were predicted to be 82 (actual fatalities were 121). If PWR2TOT had increased by 500 GW to 2037 GW the fatalities could be expected to be around 277 (confidence interval 208 to 368).

The zero-hurdle component of the model describes the probability of a loss or fatality. The logit link used in the binomial part of the model implies that the probability of loss, π, is determined by $\pi = 1/(1 + \exp(-\eta^*))$ where η^* is determined from the hurdle regression equation. In Equation 26 for house loss, from Table 6 $\eta^* = 1.2384$, so the probability of some loss is 0.775 (which is partly a function of how the fires were selected). The 95% confidence interval is (0.61, 0.88). For fatalities, from Equation 31 and Table 6, $\eta^* = -0.9945 + 0.00479 \times \text{PWR2TOT}$, so the value of π can be determined through η^* for any value of PWR2TOT. With PWR2TOT = 100 GW, π is predicted to be 0.37 (0.22, 0.56), while for PWR2TOT = 1000 GW, π is predicted to be 0.98 (0.44, 0.9996). This is a large interval as the variance of η^* increases with η^*.

7

Seven: Discussion

7.1 Fire characterisation and limitations

The southern states of Australia have a long history of destructive fires, yet information on each event is scattered among research bodies, government organisations and research publications. Because of this, a single database that details individual fires on the national level does not exist. This study has compiled many observations and estimates on past fires that include fire behaviour, fire weather, fuel loading and community loss. This dataset provides the basis for categorising fires and the development of a community fire information and warning system.

While every effort was made to obtain the most reliable data for each variable for each fire, improvements will (and should) inevitably be made. This will undoubtedly enhance the results. One example of how the dataset could be improved would be to use remotely sensed data to map exact perimeters of the burn, and the patchiness of past burns, to improve fire size measures and fuel load estimates. This is feasible using Landsat imagery, which has coverage for almost the last 40 years (available: http://landsat.usgs.gov/, accessed 01/07/2010). Additionally, more detailed information could be included in the database for analysis, such as the design features and materials used in the construction of the houses destroyed, since these have been linked to the number of houses damaged or destroyed (Leonard and Bowditch 2003). Not only should the database be updated and improved, but additional fires should be added, particularly fires from states other than Victoria. This project examined over 70 fires from Victoria, yet there are numerous destructive fires that have occurred in the southern states of Australia.

The dearth of fires from other states obviously biases the analysis, as the sampling is not random. The analysis is also biased because a disproportionately smaller number of fires that did not cause damage are in the database. These fires would be generally small fires, and the bias would affect the estimation of the hurdle model parameters, by underestimating the probability of no losses. In addition to this, the modelling is conditional on there being an ignition. This could be extended in future work.

The method of down-weighting poor data is crude and neither takes account of whether the error was in the dependent or independent variable nor uses an estimate of the magnitude of the error. Accounting for these aspects of error will be covered in future analysis.

Using the independent variable (power of the fire or the adjusted FFDI) in a linear form in the equation for the logarithm of loss (such as Equation 26) results in exponential form of the independent variable in the prediction equation for loss. Thus non-zero loss is predicted for zero-values of the independent variable which is obviously incorrect. The problem is exacerbated as the values of the covariate (density or risk) are increased. However it is not unusual to get quite high losses for small values of PWR2TOT when the house or population density is high or the fire area in large. As an example, the Dandenongs fire (1962) had a low value of PWR2TOT of 54.4 GW but a high population density (50 houses/km^2) and a very large fire area (1709 km^2). It had an economic loss of $135 million (median 9 in the data set) and the model in Equation 32 predicted $146 million.

This report introduced two new methodologies to estimate fire severity, or potential destructive force, through measuring the power of fire. These methods proved useful for measuring the power of the fire at various stages of development. This research shows that the method based on integrating the intensity of the fire around the perimeter proved much better than standard fire danger indices, and better than an approximation based on assuming Byram's intensity at the head of the fire over a proportion of the perimeter. This is because it could be used for all blow-out shapes and it was better correlated with community loss. It tends, however, to overestimate the power of the fire as not all the perimeter of the mapped fire area is alight at any one time. On the other hand, the power of the fire is underestimated because of the omission of the consumption of medium-to-coarse woody and canopy fuels.

To develop a more thorough understanding of the impacts of fire on communities, future estimates of the power of a fire would benefit from focusing on the region of the fire that caused the damage to a community, as this may provide critical information on the performance of such a model. An estimate of the power of the fire along a given isochrone could be obtained by integrating Equation 7 in Catchpole *et al.* (1982) for the rate of spread (and hence intensity) of a point on an arbitrary fire front along the isochrone. Also, more complete measurements of fire behaviour could be made by adding fuel estimates for coarse woody debris, canopy and live/dead components like those modelled by Keith *et al.* (2010). This would better quantify the total amount of power released by the fire as it considers all available fuels rather than only surface fuels. Furthermore, the vertical atmospheric structure, and how that plays a role in influencing the power of fire (Potter 2002), should be incorporated. Other methods of estimating the energy released during a fire event should also be further investigated, such as those methods developed by Wooster *et al.* (2005), which estimate fire radiative energy (FRE) and fire radiative power (FRP) from remotely sensed data. Other important knowledge gaps exist that need to be addressed. These include how the scale of a fire event changes the efficacy of both mitigation strategies (such as planned burning), and communities and fire agencies' responses.

7.2 Performance of the predictor variables

7.2.1 FFDI and GFDI

FFDI and GFDI were found to perform poorly in relation to community loss when compared with the adjusted values and the power of fire variables, PWR1TOT and PWR2TOT. This is almost certainly due to inherent limitations of the FFDI and GFDI, which are meant for broad-scale application and solely rely on meteorological input data, and are therefore not suitable for a range of fuel loads and topographic regions. It should also be noted that FFDI and GFDI were designed as predictors of fire initiation, fire spread and ease of suppression, and not of community loss.

7.2.2 FFDI and GFDI adjusted

Since FFDI and GFDI were poor predictors of community loss, these indices were adapted to account for slope and fuel. This was achieved by adjusting the indices to the fuel loading and slope of the area of each fire using the spread equations in Noble *et al.* (1980).

Adjusting FFDI and GFDI for fuel gave the best predictions. Adjusting for slope and fuel provided better predictions than the unadjusted indices, but not as well as those for fuel alone (except for fatalities and economic loss in grasslands, where the slope and fuel-adjusted GFDI were best). The problem may be that the adjustment for average slope over the whole fire does not capture the fire behaviour at the site of the losses. Using density (house or population) as a covariate, the fuel-adjusted indices were not quite as good predictors as the power variables, but using exposure risk as a covariate they were almost equal to or better than the power variables in predicting community loss. This is probably because the fire area information incorporated into PRW2TOT is being used in the covariate. FFDIF and HRISK provided the best model for house loss (r = 0.85). GFDIF was a slightly better predictor than FFDIF for the combined grass and forest fires, but was not used as losses are more prevalent in forests. The model using FFDIF and HDENS could be used on a local area basis using only FFDI, house density and fuel loading, without needing predictions of fire area.

7.2.3 Byram's intensity

Byram's fireline intensity has been shown to have great practical value as an indicator of fire severity for fire control purposes (Catchpole *et al.* 1982) and ecologically the index has been used to relate damage of trees to fire severity (McArthur and Cheney 1966; Van Wagner 1972). However, Byram's intensity was found to be a relatively poor predictor of community loss, and was about the same in predictive power as the unadjusted FFDI and GFDI.

7.2.4 Byram's convection number

Byram's convection number, NC, was a very poor predictor of community loss. For Kilmore, with a loss of 1244 houses, NC was 0.55; for Canberra-McIntyre's Hut, with a loss of 360, NC was 1.6; and for the small fire at Meereek with no loss, NC was 5. Nelson (1993) points out the assumptions of stability and non-entrainment that are inherent in the derivation of NC which may affect the results. In addition, NC was calculated at ground level rather than up to a level of about 1km as proposed by Byram (1959). More sophisticated models, such as that proposed by Nelson (2003), may yield an improvement in predictive power, but more detailed inputs would be needed.

7.2.5 Power of the fire

PWR2TOT was the best predictor of house loss when using density as a covariate, and was only slightly worse than the fuel-adjusted fire danger indices when using exposure risk as a covariate. It provided the best model for predicting fatalities (with population density), and the best model for predicting economic loss (with risk of exposure). PWR1TOT was not as good a predictor as PWR2TOT and could not always be calculated.

PWR2TOT needs predictions of time since ignition and fire area, and the risk of exposure covariate needs predictions of fire area. Emerging tools, such as Phoenix (Rapid Fire), can now be used to estimate the area and time since ignition of a fire through simulation and fire behaviour prediction models. This could be used to provide predictions of possible loss on a local area basis.

7.2.6 Implications for developing a fire severity scale

This study demonstrates that various estimates of the strength of past bushfires correlate better than fire danger indices with the impact of fire on communities. The relationship between the strength of a bushfire and community loss is similar to other natural disaster severity scales.

The current FDRS is not adequate for predicting community loss. Further improvements could be made to better predict both fatalities and property loss. Initial steps to make improvements to the current FDRS would be to determine which of the meteorological variables in the FFDI are most strongly correlated with loss, and whether a different combination or even the addition of new driving variables would give a better predictor of loss. This report suggests simple modifications to the FFDI through incorporating slope and fuel loading factors (especially fuel). Doing so increases the predictive power of FFDI. However, the public and fire managers would further benefit from a rating system that is based on the power of a fire. This would require further research into what variables and to what extent different variables influence the power of a fire, through intensive spatial analysis and incorporation of the vertical atmospheric structure. This report provides an initial insight into establishing a new methodology to describe fire through reconstructing the power released at certain parts of the fire. However, to fully understand and make use of this methodology as a fire severity scale, it is necessary to move from reconstruction to prediction.

The implications that this research, combined with further work, will have on policy decisions is considerable. The ability to calculate the power of the fire, and then at a local scale use it to predict the number of fatalities and house losses (within a range) would provide communities with more targeted advice to leave in advance of Code Red/Catastrophic bushfire days and therefore may result in reducing the number of fatalities. However, the community impacts captured in the data reflect a culture where many in the community stay and defend. It is likely that policy and practice changes resulting from the lessons of Black Saturday will alter future outcomes. It is hoped that this will include significantly less loss of life, but fire agencies and communities will need to prepare for increased house and property damage.

Predicting the behaviour of natural phenomena such as fire requires robust fire behaviour models. Computationally, local fire behaviour prediction is becoming more possible through advancements such as Phoenix RapidFire, but the predictions produced are still only a function of the quality of the data and models that underpin them. This research highlighted the importance of this knowledge in informing fire agencies and community decision making. Such knowledge is especially important when events of unprecedented scale and magnitude occur. Additionally, events such as those on Black Saturday will invariably occur in a warming and drying climate (Lucas *et al.* 2007), and making predictions about what might happen involves considerable uncertainty. This uncertainty can be reduced if a solid scientific base can be built that captures what is known from past events (which is not currently the case). A contemporary view and understanding of fire – how it behaves, how it can be described, and how it can impact on communities – is therefore needed.

For this to occur, a contemporary fire science research agenda is required. Additional research that improves the understanding of the destructive potential of future bushfires and the ability to predict community consequences is listed in the appendix in Section 9.7. This includes better understanding of the aspects of fire weather and fire behaviour such as fire categorisation, fire and atmospheric interactions, fuel categorisation, fuel moisture change and better prediction of thresholds that lead to impacts on communities and the things they need and value.

In saying this, enough is known to improve current approaches. The current understanding of fire and the best prediction of its destructive potential is better than no framework, or one that relies on simple fire danger ratings. This report has provided considerable information for the development of an interim framework, be it the use of adjusted fire danger rating, or the use of systems such as Phoenix RapidFire to estimate power, even though considerable knowledge gaps exist.

7.3 Future research opportunities

The project highlights the need for more detailed research into a contemporary fire danger rating system that not only meets traditional fire agency needs of preparedness, decision making and impact to forest and rural values, but also includes the potential for bushfires to impact on communities. It shows that physical measures that relate to community impacts exist and are an improvement on existing fire danger indices and the standard Byram's fireline intensity. It also confirms that bushfire behaviour (rate of spread, fire shape and size, fuel consumption and power) and community attributes (such as settlement density) affect bushfire risk, and that improved science and data will improve fire danger rating and risk assessments.

The Attorney Generals Department, supported by State fire agencies, the Bushfire CRC and key researchers are currently scoping a research project designed to develop a contemporary fire danger rating system. Some critical knowledge gaps relevant for consideration, identified by this project are detailed in the appendix (section 9.7). In the meantime, this project has discussed current approaches to fire danger rating for community information and warning. It highlights that further gains are possible through the use of fuel adjustments in forests, and that in Victoria at least, the use of Phoenix

RapidFire to estimate the power of fire and community impacts should be trialled alongside existing approaches.

In the interim, extension of this work warrants consideration. This research drew heavily on Victorian information, but considerable case study information from other jurisdictions exists. Furthermore, outputs from project VESTA (Gould *et al.* 2007b) fire behaviour models for dry forests, and grassland fire behaviour models (Sullivan 2008) could be tested for their ability to predict fire behaviour and relationships with community impacts. The simple extension of the comprehensive historic bushfire database compiled by this project will enhance this and future research.

Eight: Summary and conclusions

Developing more robust theories and models of fire behaviour and the impacts of fire on communities is critical for current and future fire risk management. To date, much of Australia's fire history has not been collated and considered in an integrated way, yet this information provides an insight into the nature and intensity of fires that result in the loss of life and assets. This study has compiled the most comprehensive database to date of observations and estimates on fires that have occurred in the southern states of Australia available today. The database includes information on fire behaviour, fire weather, fuel loading and community loss associated with fire. These data were linked with a GIS, where fire perimeters and isochrones could be used to calculate the power of the fire using various shapes and adaptations to fire intensity equations. Meteorological data were also used to calculate McArthur's fire danger indices, FFDI and GFDI. Additionally, these were adjusted to incorporate the local fuel and slope conditions. These fire behaviour related measures of power – FFDI, GFDI and the adjusted FFDI and GFDI – were used as predictors of community loss caused by each fire together with house (or population) density or with fire exposure risk (density multiplied by fire area).

This study found that an estimate of the power of the fire was the best overall predictor of community loss. The fuel-adjusted FFDI was the next-best predictor and exceeded power of the fire in predicting house loss when combined with risk exposure. The original FFDI and GFDI performed poorly. These results suggest that the current fire danger rating systems could be adjusted to improve the warning system so that it better relates to community loss. However a better approach would be to base a new bushfire threat warning system on the power of the fire. Given the importance of accurately predicting bushfire threats, future research should make improving the measures and predictability of fire power a priority in bushfire research in Australia.

Nine: Appendix

9.1 Fires analysed, associated losses and power, intensity and FFDI calculations

Table 10. Fires analysed in this study and the associated losses

Location, state, year, veg	Fire Name	Fatalities	House loss	Economic loss (AUD $ mil)	FFDI	GFDI	IB Avg (kW/m)	PWR2TOT (GW)	Tmax (°C)	RH (%)	Wind speed (km/h)	Mean slope (°)	Fuel (kg/m²)	Drought factor	References fatalities and house loss data (L), economic loss data (E), weather data (W) and fuel data (F)
Beechworth,VIC (2009) – Forest	Beechworth	2	29	82.48	113	118	12776	255	44.1	7	41	14	1.30	10	L: Teague et al. (2010), E: Stephenson (2011), W: BOM (2010), F: McCaw et al. (2009)
Bunyip,VIC (2009) – Forest	Bunyip	0	24	85.57	110	130	33449	785	42.9	10	46	11	2.00	10	L: Teague et al. (2010), E: Stephenson (2011), W: BOM (2010), F: McCaw et al. (2009)
Churchill,VIC (2009) – Forest	Churchill	11	247	202.08	105	112	43710	984	44.5	10	42	14	2.00	10	L: Teague et al. (2010), E: Stephenson (2011), W: BOM (2010), F: DSE (2010a)
Coleraine,VIC (2009) – Grass	Coleraine	0	1	2.68	170	283	4087	10	43.0	9	63	6	0.52	10	L: Teague et al. (2010), E: Stephenson (2011), W: BOM (2010), F: McCaw et al. (2009)
Delburn,VIC (2009) – Forest	Delburn	0	30	33.78	105	112	13725	108	44.5	10	42	8	1.50	10	L: Teague et al. (2010), E: Stephenson (2011), W: BOM (2010), F: McCaw et al. (2009)
Kilmore,VIC (2009) – Forest	Kilmore	121	1244	1172.00	159	293	53188	1537	39.6	11	68	12	2.00	10	L: Teague et al. (2010), E: Stephenson (2011), W: BOM (2010), F: DSE (2010a)
Maiden Gully,VIC (2009) – Forest	Maiden Gully	1	58	24.39	116	120	7790	12	44.9	7	41	4	1.00	10	L: Teague et al. (2010), E: Stephenson (2011), W: BOM (2010), F: McCaw et al. (2009)
Murrindindi ,VIC (2009) – Forest	Murrindindi	39	590	723.94	159	293	51118	1642	39.6	11	68	14	2.50	10	L: Teague et al. (2010), E: Stephenson (2011), W: BOM (2010), F: DSE (2010a)
Redesdale,VIC (2009) – Grass	Redesdale	0	7	13.90	116	120	22712	75	44.9	7	41	6	0.84	10	L: Teague et al. (2010), E: Stephenson (2011), W: BOM (2010), F: DSE (2010a)
Remlaw,VIC (2009) – Forest	Remlaw	0	68	27.88	177	266	5008	28	45.4	6	57	0	0.34	10	L: Teague et al. (2010), E: Stephenson (2011), W: BOM (2010), F: DSE (2010a)
Upper Ferntree Gully,VIC (2009) – Forest	Upper Ferntree Gully	0	1		100	92	143	1	45.5	9	37	6	0.09	10	L: Teague et al. (2010), E: No data, W: BOM (2010), F: DSE (2010a)
Mt Lubra,VIC (2006) – Forest	Mt Lubra	2	41	17.34	59	74	13358	302	39.3	20	42.5	7	0.87	9.3	L: CFA (2010), E: Stephenson (2011), W: BOM (2010), F: DSE (2010a)
Coopers Creek ,VIC (2006) – Forest	Coopers Creek	0	17	3.65	81	103	1530	23	34.4	10	46	10	1.70	9.8	L: CFA (2010), E: Stephenson (2011), W: BOM (2010), F: DSE (2010a)
Century Track,VIC (2006) – Forest	Century Track	0	6	1.55	69	92	20351	242	42.4	18	44	9	1.45	8.8	L: Smith (2006), E: CFA (2010), W: BOM (2010), F: DSE (2010a)
Riley Road,VIC (2006) – Forest	Riley Road	0	6	1.55	64	63	15281	64	34.2	11	37	4	1.67	10	L: CFA (2010), E: CFA (2010), W: BOM (2010), F: DSE (2010a)
Carranballac,VIC (2005) – Grass	Carranballac	0	0	0.11	39	61	5591	26	33.8	15	39	1	0.45	6.7	L: Smith (2005), E: EMA (2010), W: BOM (2010), F: Conservative Estimate

Location, state, year, veg	Fire Name	Fatalities	House loss	Economic loss (AUD $ mil)	FFDI	GFDI	IB Avg (kW/m)	PWR2TOT (GW)	Tmax (°C)	RH (%)	Wind speed (km/h)	Mean slope (°)	Fuel (kg/m²)	Drought factor	References fatalities and house loss data (L), economic loss data (E), weather data (W) and fuel data (F)
Deep Lead, VIC (2005) – Grass	Deep Lead	0	11	3.22	60	60	4349	29	33.9	12	37	4	0.25	9.8	L: No loss, E: Stephenson (2011), W: BOM (2010), F: DSE (2010a)
Wangary, SA (2005) – Grass	Wangary	9	93	29.85	188	322	15018	469	42.0	3	60	2	0.25	10	L: Smith (2006), E: Stephenson (2011), W: BOM (2010), F: DSE (2010a)
Canberra – Bendora, ACT (2003) – Forest	Canberra – Bendora	0	34	18.00	101	131	48030	333	36.9	8	48.2	11	1.50	10	L: Doogan (2006), E: Stephenson (2011), W: BOM (2010), F: ACT State Coroner (2006)
Canberra – McIntyre's Hut, ACT (2003) – Forest	Canberra – McIntyre's Hut	4	360	156.00	101	131	45275	305	36.9	8	48.2	8	1.50	10	L: Doogan (2006), E: Stephenson (2011), W: BOM (2010), F: ACT State Coroner (2006)
Alpine 2003, VIC (2003) – Forest	Alpine 2003	1	41	32.16	59	34	7234	214	37.0	6	22	19	1.50	10	L: Wareing and Flinn (2003), E: Stephenson (2011), W: BOM (2010), F: DSE (2010a)
Linton, VIC (1998) – Forest	Linton	5	2	7.81	15	27	4223	10	23.5	21	32	6	1.00	5.4	L: CFA (2010), E: CFA (2010), W: BOM (2010), F: DSE (2010a)
Spring Hill, VIC (1998) – Forest	Spring Hill	0	11	2.37	43	27	1764	8	31.5	11	24	4	0.84	10	L: Ferguson and Edgar (1999), E: CFA (2010), W: BOM (2010), F: DSE (2010a)
Ferny Creek, VIC (1997) – Forest	Ferny Creek	3	41	21.97	82	121	6346	10	36.0	15	52	17	1.55	9.8	L: Victorian State Coroner (1997) , E: CFA (2010), W: BOM (2010), F: DSE (2010a)
Berringa, VIC (1995) – Forest	Berringa	0	9	1.93	57	42	8102	96	36.7	7	26	6	1.23	9.2	L: Chatto (1999), E: CFA (2010), W: BOM (2010), F: Chatto, 1999
Como–Janelli, NSW (1994) – Forest	Como-Janelli	4	99	51.00	86	107	6646	20	36.0	10	46	2	1.50	9.9	L: Gill and Moore (1998), E: EMA (2010), W: BOM (2010), F: Conservative Estimate
Heywood, VIC (1991) – Forest	Heywood	0	0		87	145	3649	59	35.0	13	55.4	2	1.35	9.2	L: No loss, E: No data, W: BOM (2010), F: Wouters, 1993
Meereek, VIC (1991) – Forest	Meereek	0	0		46	26	16731	16	41.0	17	22	1	1.70	10	L: No loss, E: No data, W: BOM (2010), F: Buckley, 1994
Mt William, VIC (1991) – Forest	Mt William	0	0		46	26	402	0	41.0	17	22	2	0.60	10	L: No loss, E: No data, W: BOM (2010), F: Grant and Wouters (1993)
Patrol Track, VIC (1991) – Forest	Patrol Track	0	0		18	13	1591	1	34.0	30	19	5	1.44	8.3	L: No loss, E: No data, W: BOM (2010), F: Grant and Wouters (1993)
Ghin Ghin, VIC (1990) – Grass	Ghin Ghin	0	1	0.56	109	203	1815	10	35.0	15	65	13	0.30	9.9	L: Jordan et al. (1990), E: CFA (2010), W: BOM (2010), F: Jordan et al. (1990)
Salt lake, VIC (1990) – Forest	Salt lake	0	0		20	33	6663	12	34.0	33	35	1	1.16	7	L: Jordan et al. (1990), E: CFA (2010), W: BOM (2010), F: Jordan et al. (1990)
Strathbogie, VIC (1990) – Forest	Strathbogie	1	17	8.74	109	203	17219	189	35.0	15	65	15	0.60	9.9	L: No loss, E: CFA (2010), W: BOM (2010), F: Jordan et al. (1990)
Wingeel, VIC (1990) – Grass	Wingeel	0	0	0.15	95	203	1154	42	35.0	15	65	1	0.30	8.6	L: No loss, E: No data, W: BOM (2010), F: Buckley (1990)

Location, state, year, veg	Fire Name	Fatalities	House loss	Economic loss (AUD $ mil)	FFDI	GFDI	IB Avg (kW/m)	PWR2TOT (GW)	Tmax (°C)	RH (%)	Wind speed (km/h)	Mean slope (°)	Fuel (kg/m²)	Drought factor	References fatalities and house loss data (L), economic loss data (E), weather data (W) and fuel data (F)
Bemm River ,VIC (1988) – Forest	Bemm River	0	0		70	368	24553	97	28.0	27	95	9	2.08	6	L: No loss, E: No data, W: Buckley (1990), F: Grant and Wouters (1993)
Bendigo ,VIC (1987) – Grass	Bendigo	0	0		91	194	5776	37	37.4	12	60	5	0.50	7.7	L: No loss, E: No data, W: BOM (2010), F: Billing (1987)
Anakie ,VIC (1985) – Grass	Anakie	2	5	5.71	113	211	7313	42	40.0	7	56	3	0.27	8.1	L: Maynes and Garvey (1985), E: CFA (2010), W: Maynes and Garvey (1985), F: Maynes and Garvey (1985)
Avoca,VIC (1985) – Grass	Avoca	1	101	39.23	148	305	19781	469	41.0	11	68	3	0.88	8.9	L: Maynes and Garvey (1985), E: CFA (2010), W: Maynes and Garvey (1985), F: DSE (2010a)
Springfield,VIC (1985) – Grass	Springfield	3	7	6.41	87	112	2904	28	41.0	10	44	7	0.27	8.9	L: Maynes and Garvey (1985), E: CFA (2010), W: Maynes and Garvey (1985), F: Maynes and Garvey (1985)
Melton,VIC (1985) – Grass	Melton	0	14	8.46	88	112	7808	78	41.0	10	44	2	0.43	9	L: Maynes and Garvey (1985), E: CFA (2010), W: Maynes and Garvey (1985), F: Maynes and Garvey (1985)
Belgrave ,VIC (1983) – Forest	Belgrave	6	300	73.22	133	175	10847	86	41.0	4	48	9	1.15	10	L: Keeves and Douglas (1983), E: No data, W: BOM (2010), F: Conservative Estimate
Branxholme,VIC (1983) – Grass	Branxholme	1	1	1.72	94	114	1409	2	39.5	11	46	2	0.25	10	L: CFA, 1983, E: Stephenson (2011), W: BOM (2010), F: CFA (1983)
Cockatoo,VIC (1983) – Forest	Cockatoo	21	238	33.74	133	175	18268	218	41.0	4	48	10	1.35	10	L: CFA, 1983, E: Stephenson (2011), W: BOM (2010), F: DSE (2010a)
Cudgee/Ballangeich,VIC (1983) – Grass	Cudgee/ Ballangeich	9	157	63.23	186	309	8539	216	43.0	5	61	1	0.30	10	L: CFA, 1983, E: Stephenson (2011), W: BOM (2010), F: Billing (1983)
East Trentham,VIC (1983) – Forest	East Trentham	7	628	145.33	133	175	25053	276	41.0	4	48	12	0.54	10	L: CFA, 1983, E: Stephenson (2011), W: BOM (2010), F: CFA (1983)
Monivae ,VIC (1983) – Grass	Monivae	0	3	1.14	94	114	2899	11	39.5	11	46	1	0.25	10	L: CFA, 1983, E: Stephenson (2011), W: BOM (2010), F: CFA (1983)
Narraweena/Clay Wells,SA (1983) – Grass	Narraweena/ Clay Wells	14			113	129	20928	262	44.4	10	45	0	0.30	10	L: CFA, 1983, E: Stephenson (2011), W: BOM (2010), F: CFA (1983)
Otways ,VIC (1983) – Forest	Otways	3	729	162.69	164	283	51112	895	43.0	9	63	11	2.00	9.7	L: CFA, 1983, E: Stephenson (2011), W: BOM (2010), F: CFA (1983)
Warburton,VIC (1983) – Forest	Warburton	0	41	8.81	133	175	45674	583	41.0	4	48	16	1.25	10	L: CFA, 1983, E: Stephenson (2011), W: BOM (2010), F: CFA (1983)
Daylesford,VIC (1980) – Forest	Daylesford	0	0		14	11	5321	11	28.0	33	20	5	1.38	8.6	L: no loss, E: No data, W: BOM (2010), F: Billing (1981)
Dimboola,VIC (1980) – Forest	Dimboola	0	0		56	66	8382	37	35.7	16	40	1	1.00	9.2	L: no loss, E: No data, W: BOM (2010), F: DSE (2010a)

Location, state, year, veg	Fire Name	Fatalities	House loss	Economic loss (AUD $ mil)	FFDI	GFDI	IB Avg (kW/m)	PWR2TOT (GW)	Tmax (°C)	RH (%)	Wind speed (km/h)	Mean slope (°)	Fuel (kg/m²)	Drought factor	References fatalities and house loss data (L), economic loss data (E), weather data (W) and fuel data (F)
Stawell, VIC (1980) – Forest	Stawell	0	0		13	47	7611	15	23.9	34	48.2	5	2.25	4.7	L: No loss, E: No data, W: BOM (2010), F: Billing (1981)
Bairnsdale/Hillside, VIC (1978) – Forest	Bairnsdale/ Hillside	2	1	8.31	119	179	486	4	39.1	10	55.4	1	0.54	9.9	L: EMA (2010), E: CFA (2010), W: BOM (2010), F: DSE (2010a)
Toongabbie, VIC (1978) – Forest	Toongabbie	1	2	1.95	5	7	74	0	22.2	64	22.3	1	0.49	9.5	L: EMA (2010), E: CFA (2010), W: BOM (2010), F: DSE (2010a)
Stawell, VIC (1978) – Forest	Stawell	0	0		8	13	8345	15	21.8	38	25.9	1	2.00	6.3	L: No loss, E: No data, W: BOM (2010), F: Billing (1981)
Beeac, VIC (1977) – Grass	Beeac	0	4	0.99	49	59	5299	14	33.3	19	40.7	1	0.25	9.6	L: McArthur et al. (1982), E: CFA (2010), W: BOM (2010), F: DSE (2010a)
Byaduk North, VIC (1977) – Grass	Byaduk North	0	1	0.35	63	94	4178	15	35.0	20	50	1	0.25	9.6	L: McArthur et al. (1982), E: CFA (2010), W: BOM (2010), F: McArthur et al. (1982)
Glengower, VIC (1977) – Grass	Glengower	0	14	3.44	46	59	6542	44	33.3	19	40.7	4	0.25	9	L: McArthur et al. (1982), E: CFA (2010), W: BOM (2010), F: McArthur et al. (1982)
Lismore, VIC (1977) – Grass	Lismore	0	0	0.18	49	59	9258	41	33.3	19	40.7	3	0.50	9.6	L: McArthur et al. (1982), E: CFA (2010), W: BOM (2010), F: McArthur et al. (1982)
Little River, VIC (1977) – Grass	Little River	0	0	0.13	46	59	5209	18	33.3	19	40.7	2	0.25	9	L: McArthur et al. (1982), E: CFA (2010), W: BOM (2010), F: McArthur et al. (1982)
Penshurst, VIC (1977) – Grass	Penshurst	0	5	1.36	63	94	12638	69	35.0	20	50	2	0.50	9.6	L: McArthur et al. (1982), E: CFA (2010), W: BOM (2010), F: McArthur et al. (1982)
Pura Pura, VIC (1977) – Grass	Pura Pura	1	13	10.59	76	95	16651	238	38.0	14	45	1	0.50	9.6	L: McArthur et al. (1982), E: CFA (2010), W: BOM (2010), F: McArthur et al. (1982)
Strathmore, VIC (1977) – Grass	Strathmore	0	0	0.76	71	119	11337	83	35.0	20	55.4	2	0.50	9.6	L: McArthur et al. (1982), E: CFA (2010), W: BOM (2010), F: McArthur et al. (1982)
Streatham, VIC (1977) – Grass	Streatham	1	38	24.33	46	59	22252	184	33.3	19	40.7	1	0.50	9	L: McArthur et al. (1982), E: CFA (2010), W: BOM (2010), F: McArthur et al. (1982)
Wallinduc, VIC (1977) – Grass	Wallinduc	3	39	20.25	46	59	20236	483	33.3	19	40.7	1	0.65	9	L: McArthur et al. (1982), E: CFA (2010), W: BOM (2010), F: McArthur et al. (1982)
Waubra, VIC (1977) – Grass	Waubra	0	1	0.30	46	59	4565	23	33.3	19	40.7	5	0.25	9	L: McArthur et al. (1982), E: CFA (2010), W: BOM (2010), F: McArthur et al. (1982)
Mt Buffalo, VIC (1972) – Forest	Mt Buffalo	0	0		37	27	2651	16	34.5	14	24.1	9	4.45	8.5	L: No loss, E: No data, W: BOM (2010), F: Dexter (1977)
Daylesford, VIC (1969) – Forest	Daylesford	1	29	7.70	62	83	5670	143	37.1	6	37.1	4	0.90	7.4	L: EMA (2010), E: No data, W: BOM (2010), F: No data
Lara, Vic (1969) – Grass	Lara	17			139	324			38.4	10	70.6			8.3	L: CFA (2009), E: CFA (2010), W: BOM (2010), F: DSE (2010a)

Location, state, year, veg	Fire Name	Fatalities	House loss	Economic loss (AUD $ mil)	FFDI	GFDI	IB Avg (kW/m)	PWR2TOT (GW)	Tmax (°C)	RH (%)	Wind speed (km/h)	Mean slope (°)	Fuel (kg/m²)	Drought factor	References fatalities and house loss data (L), economic loss data (E), weather data (W) and fuel data (F)
Maldon,VIC (1969) – Forest	Maldon	0	12	2.57	62	83	990	3	37.1	6	37.1	4	0.30	7.4	L: CFA (2009), E: CFA (2010), W: BOM (2010), F: DSE (2010a)
Dandenongs,VIC (1962) – Forest	Dandenongs	9	376	135.24	71	77	6683	54	39.2	12	38.9	13	1.35	9.3	L: CFA (2010), E: CFA (2010), W: BOM (2010), F: DSE (2010a)
Dwelling up,WA (1961) – Forest	Dwelling up	0	116	35.00	73	69	13563	136	41.1	14	37	3	1.25	10	L: McArthur (1961), E: CFA (2010), W: BOM (2010), F: McArthur (1961)
MangoPlah,NSW (1952) – Grass	MangoPlah	0	0		91	116	4765	169	41.0	15	48	6	0.30	10	L: No loss, E: No data, W: BOM (2010), F: Conservative Estimate
Beaumaris,VIC (1944) – Grass	Beaumaris	0	58	19.70	78	80	630	1	37.6	7	37	2	0.20	9.5	L: Barrow (1944), E: CFA (2010), W: Barrow (1944), F: DSE (2010a)
Yallourn,VIC (1944) – Grass	Yallourn	0	34	65.74	135	216	12012	52	39.6	6	55.8	3	0.22	9.5	L: SEC (1944), E: CFA (2010), W: BOM (2010), F: DSE (2010a)
Black Friday – Central and North,VIC (1939) – Forest	Black Friday – Central and North	56	647		152	221	10715	1446	44.6	9	56	19	1.64	10	L: Sun (1939), E: No data, W: Foley (1947), F: DSE (2010a)
Black Friday – Colac,VIC (1939) – Forest	Black Friday – Colac	4	64		140	207	26724	952	42.2	9	56	8	1.31	10	L: Sun (1939), E: No data, W: Foley (1947), F: DSE (2010a)
Black Friday – Dromana,VIC (1939) – Grass	Black Friday – Dromana	0	48		163	236	7650	28	45.6	8	56	8	0.30	10	L: Sun (1939), E: No data, W: Foley (1947), F: DSE (2010a)
Black Friday – Kyneton,VIC (1939) – Forest	Black Friday – Kyneton	2			140	207	30024	189	42.2	9	56	12	1.39	10	L: Sun (1939), E: No data, W: Foley (1947), F: DSE (2010a)
Black Friday – Stawell,VIC (1939) – Forest	Black Friday – Stawell	2			140	207	35802	784	42.2	9	56	10	1.08	10	L: Sun (1939), E: No data, W: Foley (1947), F: DSE (2010a)
Black Friday – Tawong,VIC (1939) – Forest	Black Friday – Tawong	2	67		139	201	35150	965	46.0	13	56	13	1.07	10	L: Sun (1939), E: No data, W: Foley (1947), F: DSE (2010a)

9.2 Derivation of equation for PWR1TOT

For convenience, the notation from Catchpole *et al.* (1982) is used here, and their Figure 3 is reproduced here as Fig. 17.

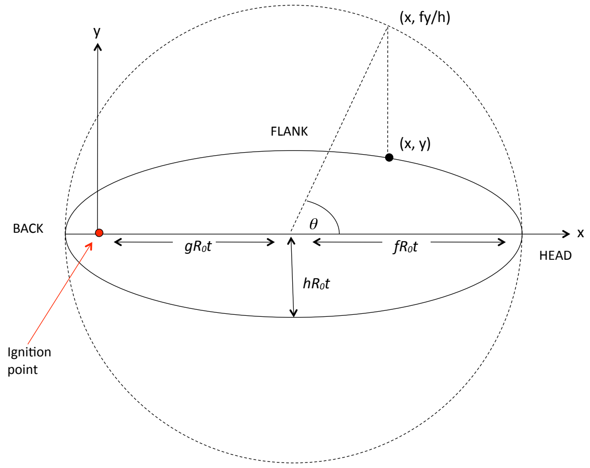


Figure 17: Reproduction of Figure 3 from Catchpole et al. (1982) giving notation.

Catchpole *et al.* (1982) assume an elliptical fire shape and describe how the intensity varies around the fire perimeter. They plot intensity versus non-dimensional arc length in their Figure 6 for two different length to breadth ratios (f/h) of 2 and 4. The fires examined in this project had length to breadth ratios ranging from 3 to 10. The parameter g was close to f (back fire spread rate negligible compared to forward spread rate). For length-to-breadth ratios between 1.5 and 10 and g = 0.99f, the normalised intensity is plotted in Fig. 18 versus non-dimensional arc-length measured from the head fire end of the major axis. For a length-to-breadth ratio of 4, for example, the intensity is reduced to one quarter by 1/5 of the arc length from the head fire to the back fire. For a length to breadth ratio of 10, the intensity is reduced to one quarter by 1/25 of the arc length from the head fire to the back fire. The intersection point of the curves in Fig. 18 with one quarter of the maximum intensity were plotted against length to breadth ratio, and (using log linear regression with R^2 =0.999) expressed as a function of length to breadth ratio as

$$\alpha = \exp\left(1.285\text{-}1.422\sqrt{\mathrm{LB}}\right), \qquad \textbf{(34)}$$

Here α is the fraction of the ellipse perimeter at which the intensity drops to one quarter of the maximum intensity, and LB is the length-to-breadth ratio. One quarter was chosen arbitrarily; as the proportion of the intensity increases the arc length used decreases and PWR1 becomes equal to IB when the arc length is unity. If necessary α could be adjusted to use a different cut-off value.

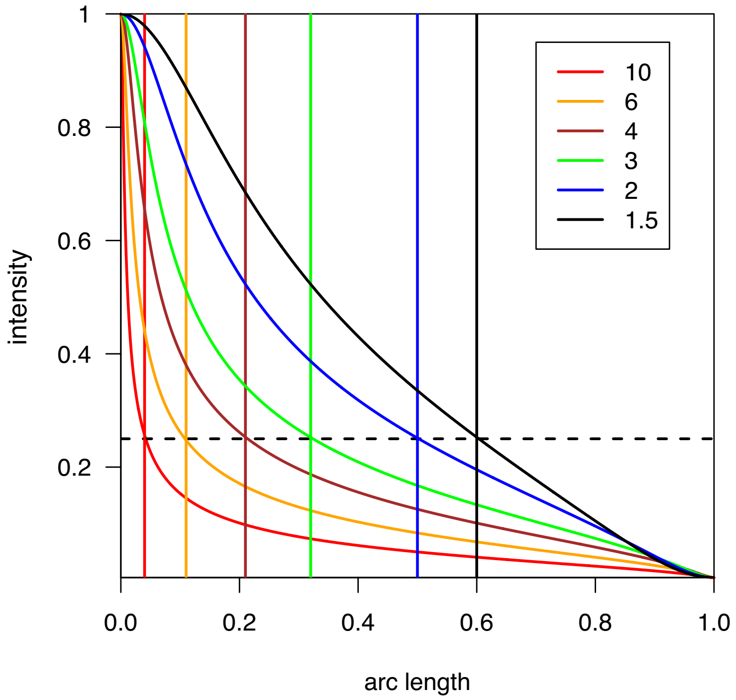


Figure 18: Normalised intensity versus non-dimensional arc length measured from the head fire end of the major axis for fires with length-to-breadth ratios between 1.5 and 10. The horizontal line represents a quarter of the head fire intensity.

Multiplying Equation 7 by α times the perimeter length is a possible measure of fire strength. This is a measure of the power of the fire in units of total rate of heat release. The perimeter, *P*, of an ellipse can be approximated by the first few terms of the Gauss-Kummer series (Linderholm and Segal 1995)

$$P = \pi(a+b)\left[1 + m^2/4 + m^4/64 + m^6/256 + 2m^8/16384 + 49m^{10}/65536 + \ldots\right], \qquad \textbf{(35)}$$

where *a* and *b* are the semi-major and semi-minor axes of the ellipse, respectively, and $m = (a - b)/(a + b)$.

The first two terms of the series in square brackets have been used by Forestry Canada Fire Danger Group (1992) in their Equation 87 to give the equation of the perimeter of an ellipse in terms of the length to breadth ratio LB (= *a*/*b*) and the total fire spread distance D_T at time *T*. (Note that D_T is the sum of the head and back fire spread distances). Using a slightly more accurate formula including the first three terms of Equation 35 gives

$$P = \pi \frac{D_T}{2}\left(1 + \frac{1}{\mathrm{LB}}\right)\left[1 + \frac{1}{8}\left(\frac{\mathrm{LB}-1}{\mathrm{LB}+1}\right)^2\right]^2. \qquad \textbf{(36)}$$

With a length to breadth ratio of 10:1 this gives an error of only 0.1% of the true perimeter.

9.3 Blow-outs due to wind change

To approximate the energy release after a cool change in Victoria, where the north east flank of the fire burning under a north-west wind changes to a fast-moving head fire with a south-west wind behind it, a rectangle or an elliptical approximation can be used.

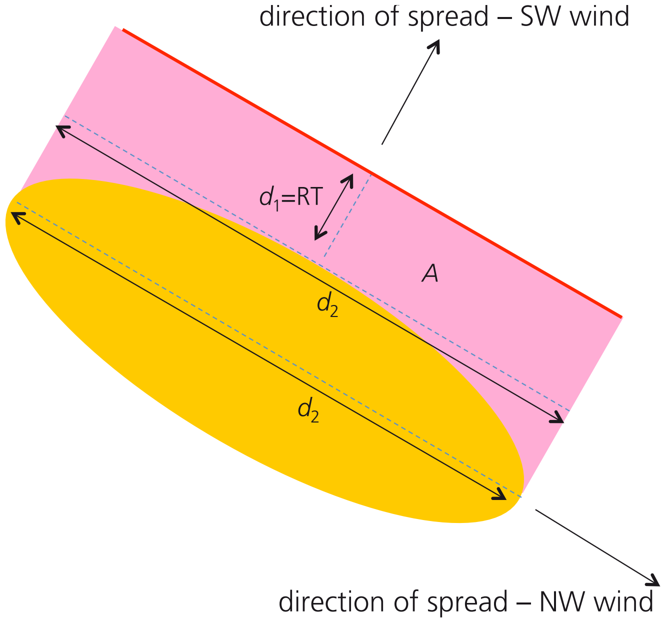


Figure 19: Rectangular shape for estimating power, based on a 90 degree wind change.

In the case of the rectangular approximation it is assumed that there is negligible flank fire spread immediately after the change, and so the leading edge of the rectangle is probably the best characteristic distance to use (see Fig. 19). PWR_1 in Equation 8 can be replaced by.

$$\mathrm{PWR}_{\mathrm{B1}} = I_{\mathrm{B}} d_2 = hwRd_2 = hwd_1 d_2 / T \,, \qquad \textbf{(37)}$$

where PWR_{B1} is PWR_1 for the blow-out part of the fire.

The blow-out area is approximately a rectangle of area A (see Fig. 19). The area of this rectangle is $A = RTd_2$, so $\frac{dA}{dT} = Rd_2$ and Equation 9 thus gives

$$\mathrm{PWR}_{\mathrm{B2}} = hwRd_2 = hwd_1 d_2 / T \,, \qquad \textbf{(38)}$$

where PWR_{B2} is PWR_2 for the blow-out part of the fire.

Note that for the rectangle approximation $PWR_{B2} = PWR_{B1}$.

Using Huygen's principle (Anderson *et al.* 1982) the fire growth can be represented as the envelope of a series of ellipses with origins at every point on the fire front (see Fig. 20). The resulting approximate fire shape is shown in Fig. 21.

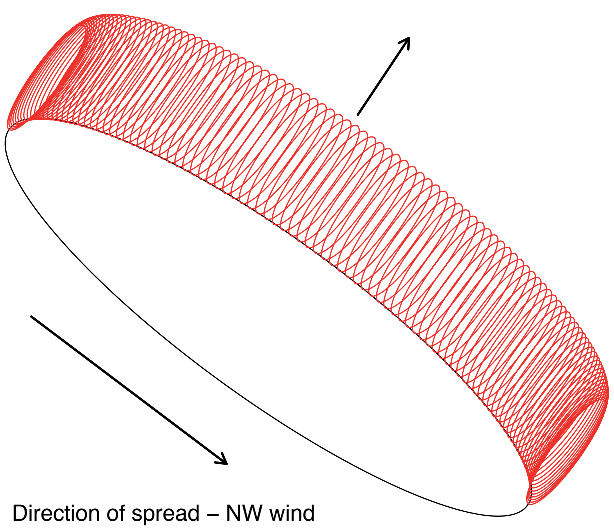


Figure 20: Huygen's principle applied to the new front for a 90 degree wind change

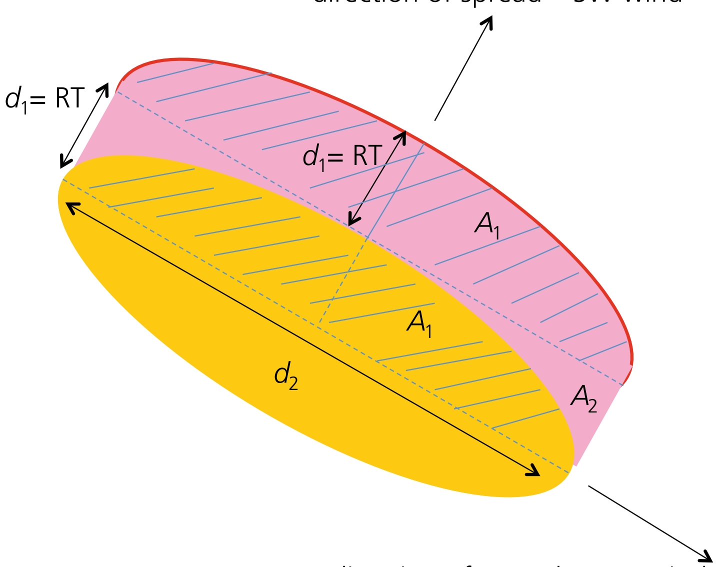


Figure 21: Elliptical shape derived from Huygen's principle for estimating power, based on 90 degree wind change.

Assume negligible fire growth along the new flanks. The fire front can then be represented by the perimeter of half the original ellipse. The distance d_2 (the major axis of the original ellipse) is known. To obtain PWR_{B1} the characteristic distance can be taken as the semi perimeter of the original ellipse.

$$\mathrm{PWR}_{B1} = I_B \times \frac{P}{2}, \tag{39}$$

The area of new growth is $2(A_1 + A_2)$, which can be seen to equal $d_2 d_1 = RTd_2$, so again $\frac{dA}{dT} = Rd_2$ and again PWR_{B2} is given by Equation 38, which justifies the rectangular approximation.

9.4 Partial Blow-outs

Some of the fires were observed to have partial blow-outs on the side of the ellipse near the leading edge of the fire. These could be approximated by rectangles or triangles.

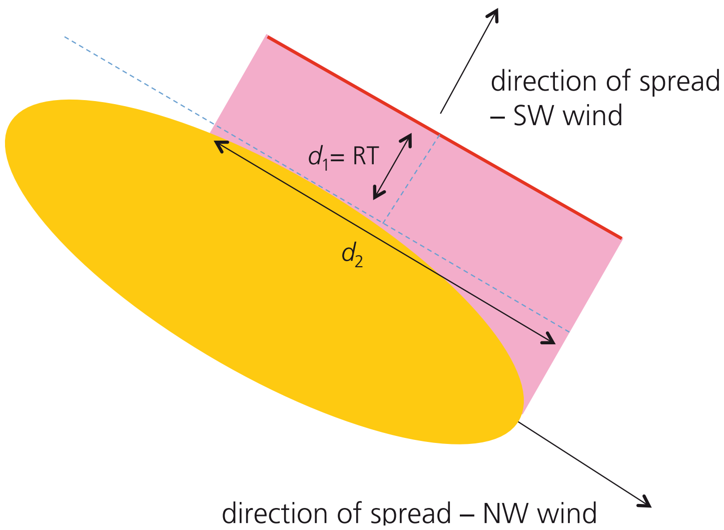


Figure 22: Rectangular shape for estimating power for a partial blow-out.

The case of a rectangular blow-out is given in Fig. 22 which can be seen to be similar to Fig. 19 except that d_2 is not as long as the major axis of the original ellipse. Again $PWR_{B2} = PWR_{B1}$ and the measures of power are given by Equations 37 and 38.

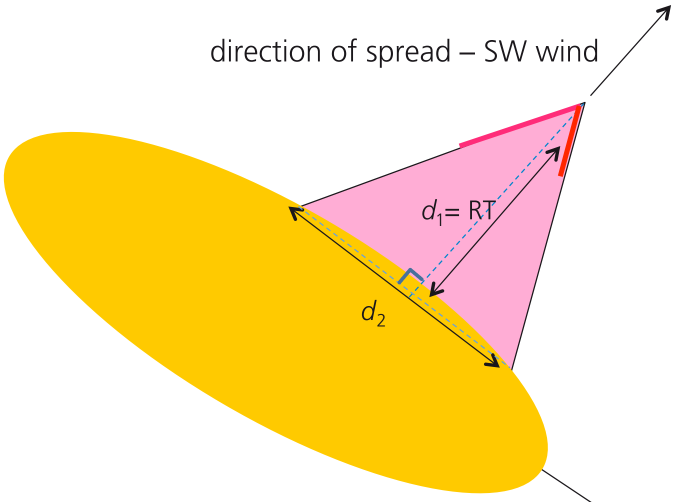


Figure 23: Triangular shape for estimating power for a partial blow-out.

The case of a triangular blow-out is given in Fig. 23. In this case the spread rate is maximum at the tip and drops off along the sides depending on the shape of the triangle. Some characteristic distance, like that shown in red, could be determined, but it would depend on the triangle shape. This seems unnecessarily complicated, so PWRB1 is not calculated.

The area of a triangle is half base times perpendicular height, so the area of the triangle is $A = \frac{1}{2} d_2 RT$, so $\frac{dA}{dT} = \frac{1}{2} R d_2$ and Equation 9 then gives

$$\mathrm{PWR}_{B2} = \tfrac{1}{2} hwRd_2 = \tfrac{1}{2} hwd_1 d_2 / T \quad , \qquad \textbf{(40)}$$

which is half of that of Equation 38 (as the area of the triangle in Fig. 23 is half of the area of the rectangle in Fig. 22)

9.5 The influence of spotting on fire shape

The shape of the fire front after a change may be more irregular than that approximated by either an ellipse or a rectangle in the immediate period after a change. Mass spot-fires can break out after the change, igniting at various distances from the north-east flank. In some cases, the area burning out in this period could almost be considered a stationary fire, with multiple ellipses burning out within a given perimeter (Fig. 24). This can be represented by either a square or an ellipse, as given before.

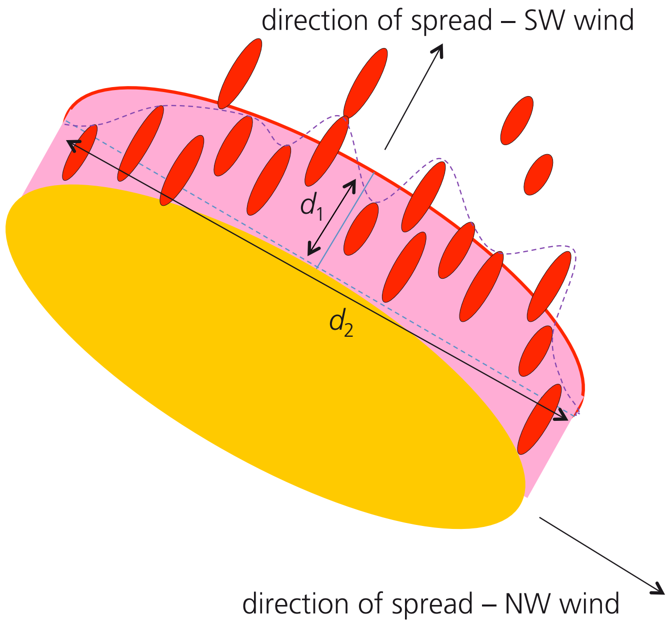
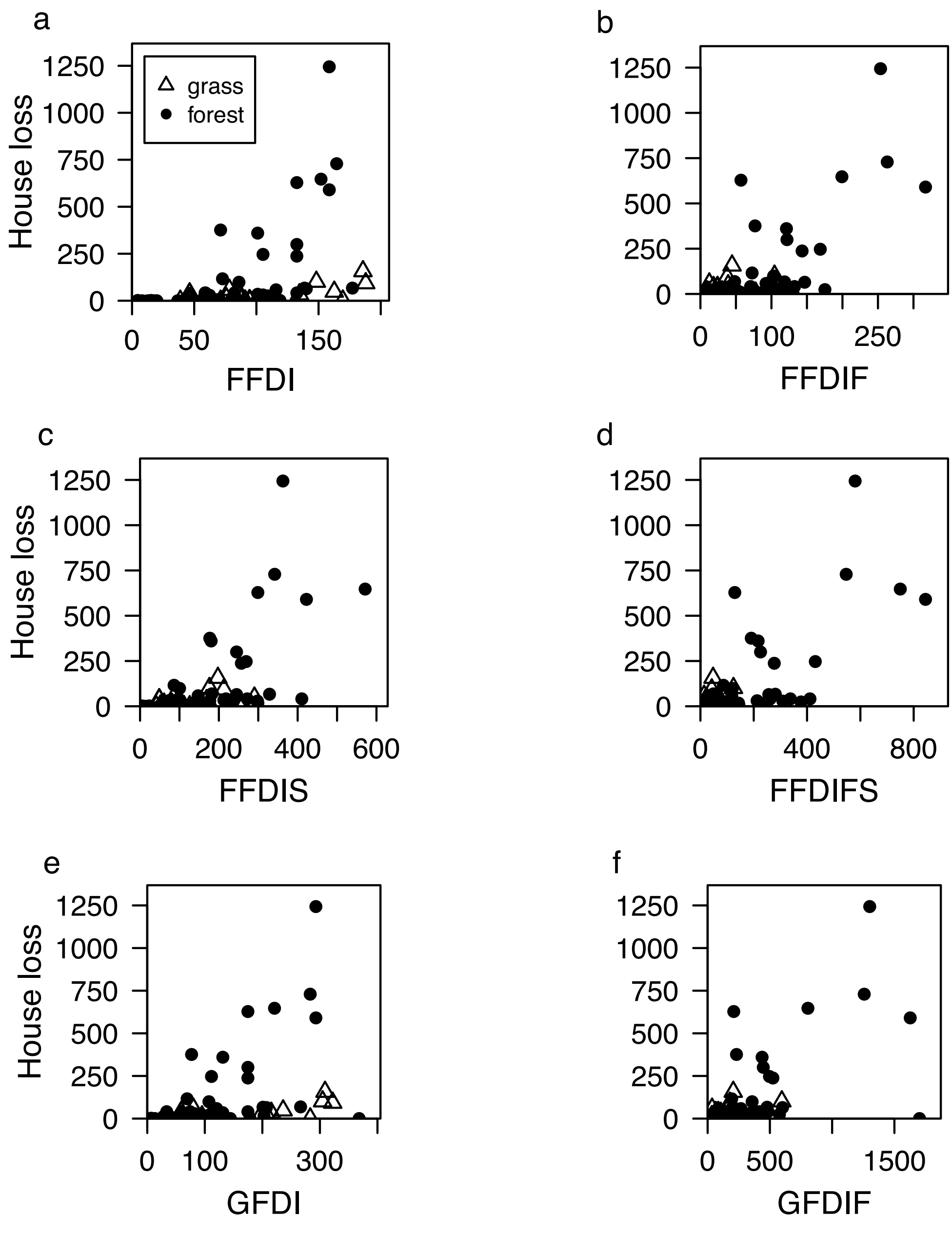


Figure 24: Multiple spot fires burning out within an immediate period after a 90 degree wind change. The purple line represents the boundary of the irregularly shaped head fire perimeter after the change has caused the fire to alter direction.

9.6 Statistical analysis – scatter plots



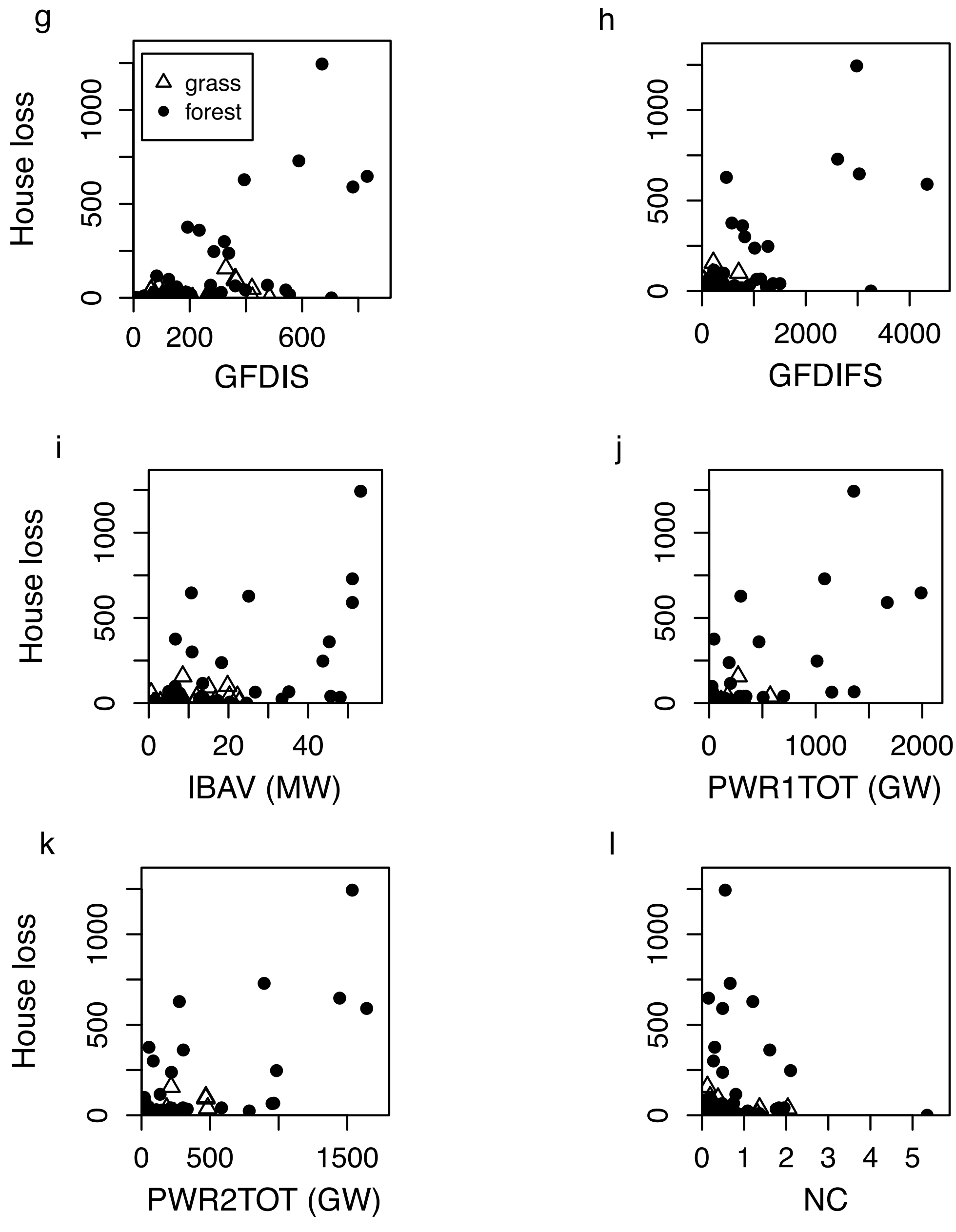
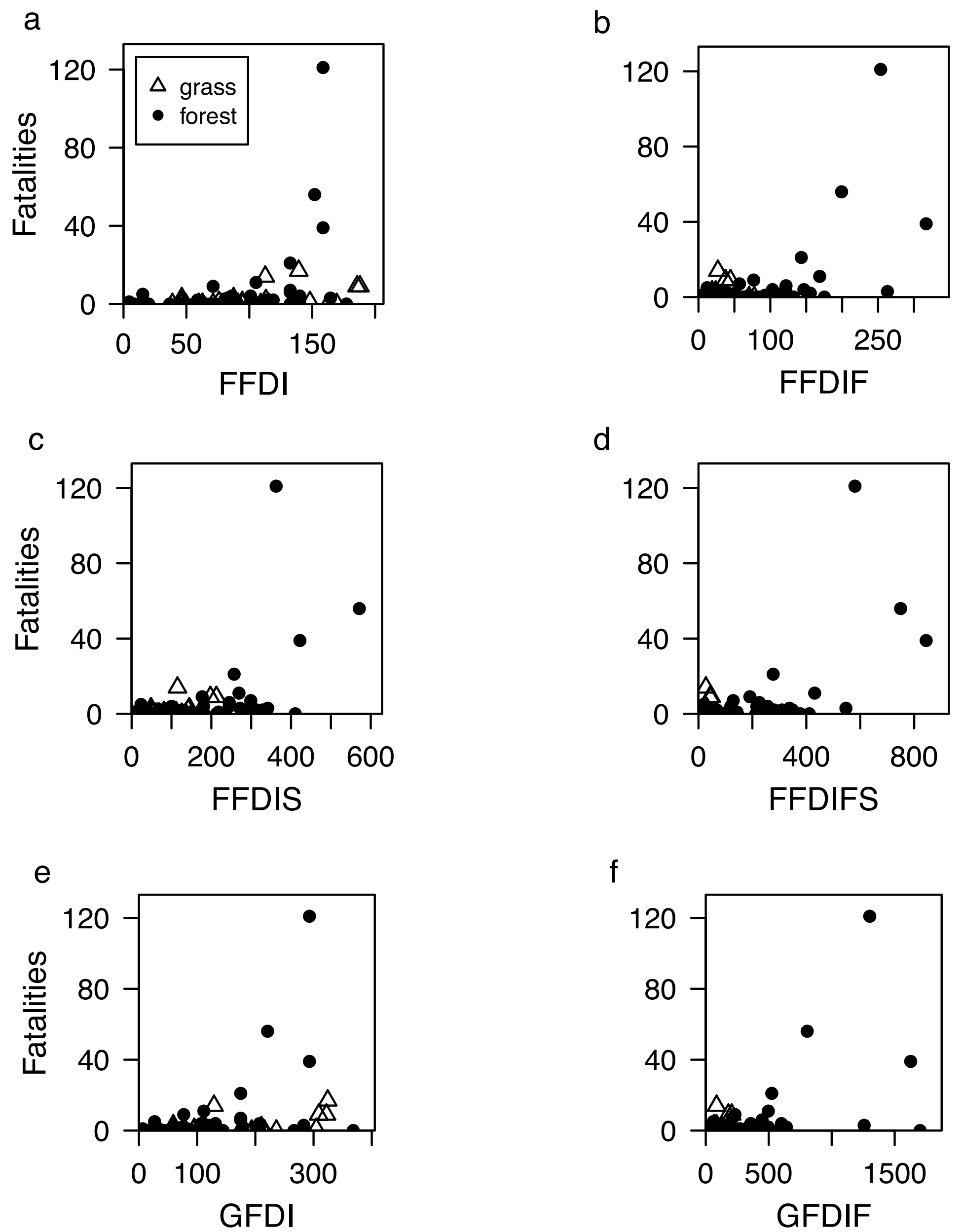


Figure 25: House loss plotted against (a) FFDI, (b) fuel-adjusted FFDI (FFDIF), (c) slope-adjusted FFDI (FFDIS), (d) fuel- and slope-adjusted FFDI (FFDIFS), (e) GFDI, (f) fuel-adjusted GFDI (GFDIF), (g) slope-adjusted GFDI (GFDIS), (h) fuel- and slope-adjusted GFDI (GFDIFS), (i) average Byram's intensity (IBAV), (j) total PWR1 (PWR1TOT) and (k) total PWR2 (PWR2TOT), (l) convection number NC.


a
Fatalities
grass
forest
FFDI
b
FFDIF
c
Fatalities
FFDIS
d
FFDIFS
e
Fatalities
GFDI
f
GFDIF

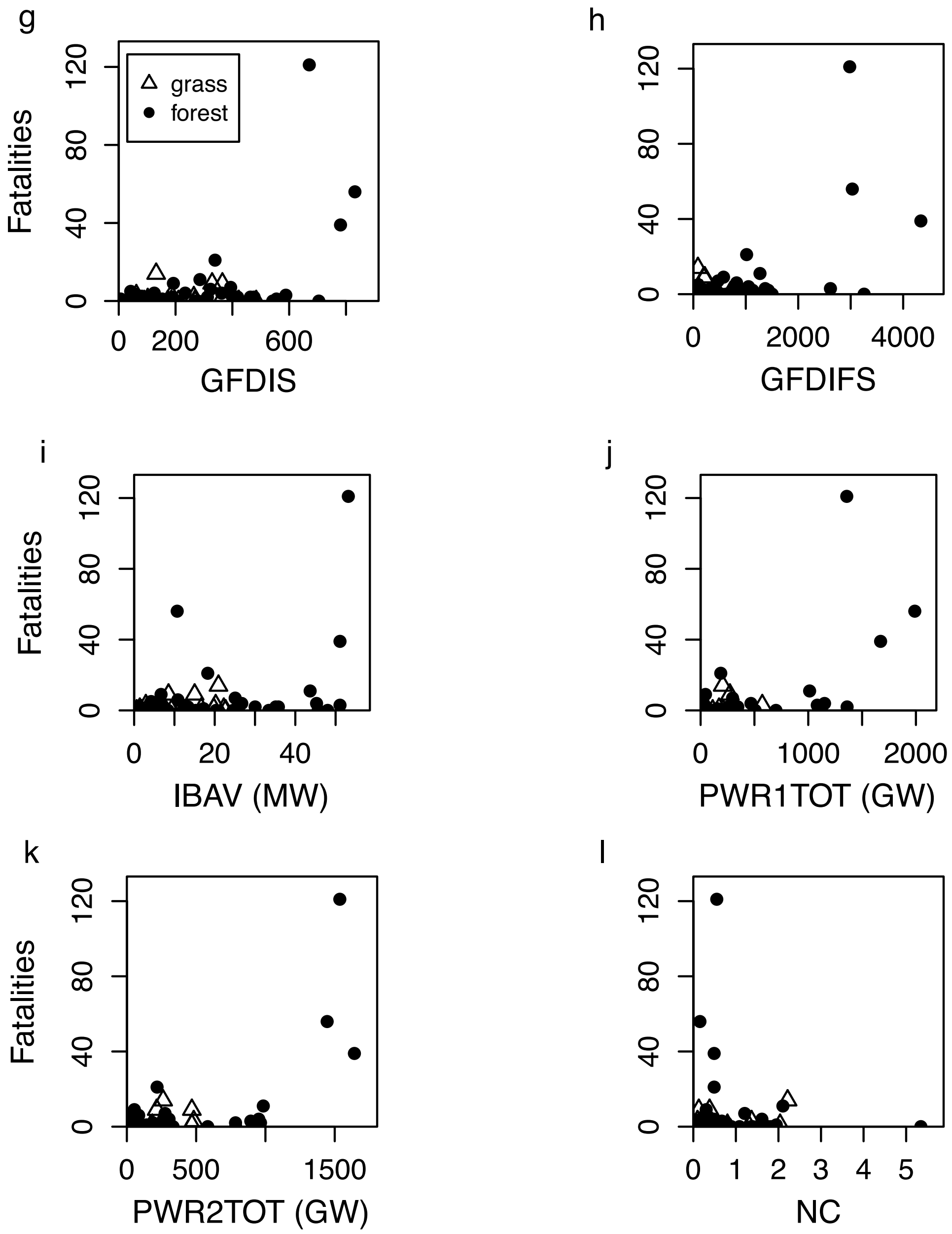
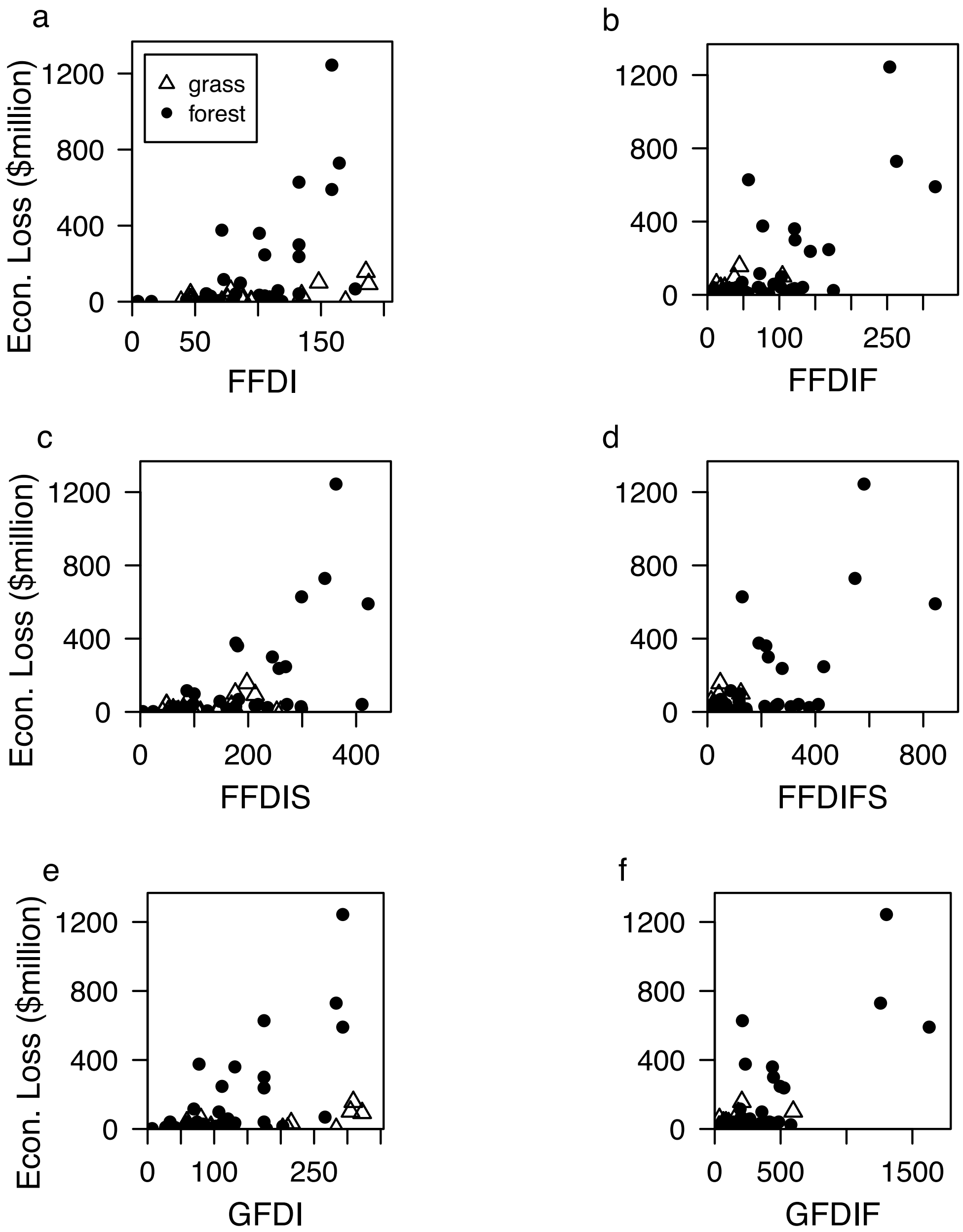


Figure 26: Fatalities plotted against (a) FFDI, (b) fuel-adjusted FFDI (FFDIF), (c) slope-adjusted FFDI (FFDIS), (d) fuel- and slope-adjusted FFDI (FFDIFS), (e) GFDI, (f) fuel-adjusted GFDI (GFDIF), (g) slope-adjusted GFDI (GFDIS), (h) fuel- and slope-adjusted GFDI (GFDIFS), (i) average Byram's intensity (IBAV), (j) total PWR1 (PWR1TOT) and (k) total PWR2 (PWR2TOT), (l) convection number NC.


a
grass
forest
Econ. Loss ($million)
1200
800
400
0
0
50
150
FFDI
b
1200
800
400
0
0
100
250
FFDIF
c
Econ. Loss ($million)
1200
800
400
0
0
200
400
FFDIS
d
1200
800
400
0
0
400
800
FFDIFS
e
Econ. Loss ($million)
1200
800
400
0
0
100
250
GFDI
f
1200
800
400
0
0
500
1500
GFDIF

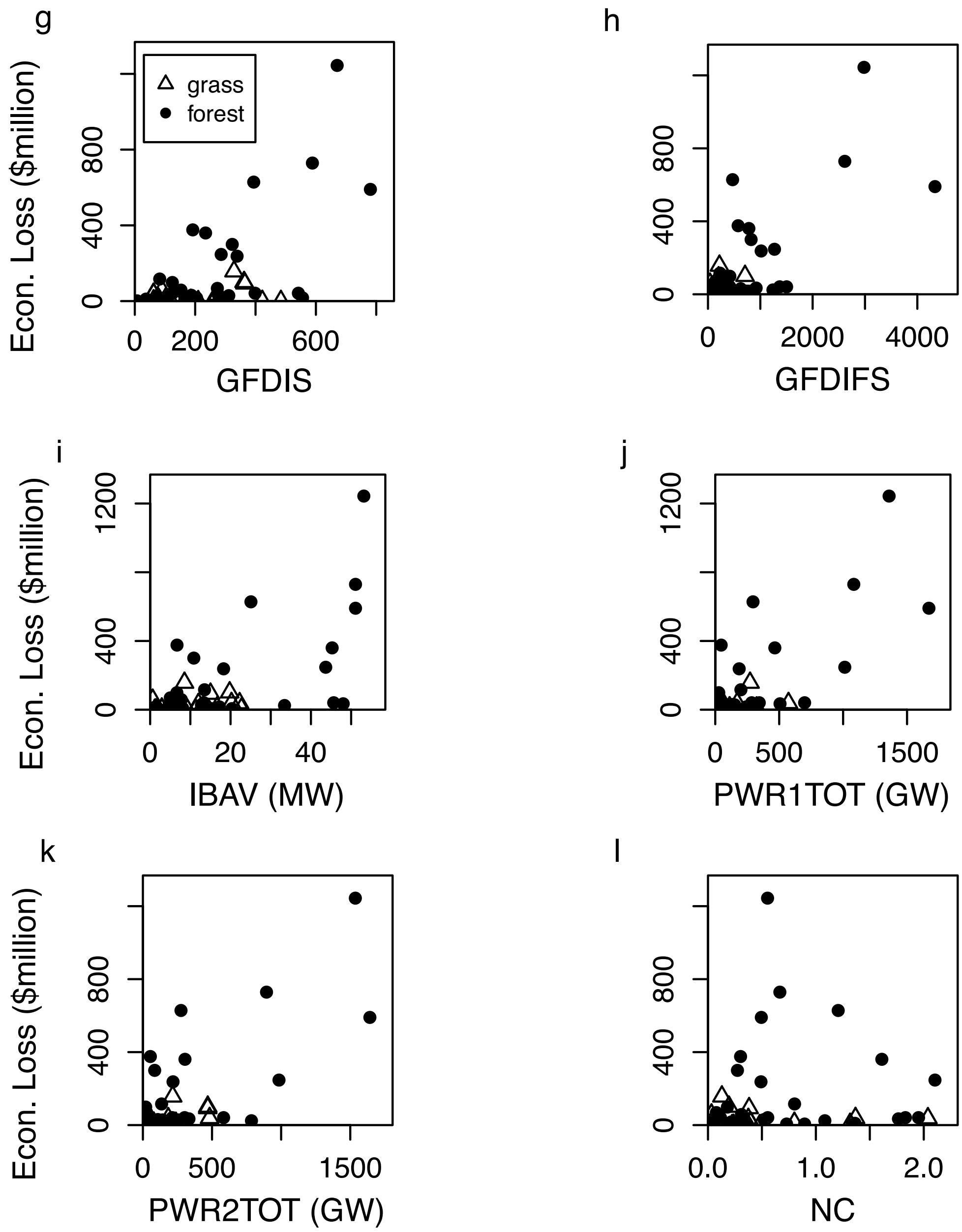


Figure 27: Economic loss plotted against (a) FFDI, (b) fuel-adjusted FFDI (FFDIF), (c) slope-adjusted FFDI (FFDIS), (d) fuel and slope adjusted FFDI (FFDIFS), (e) GFDI, (f) fuel adjusted GFDI (GFDIF), (g) slope adjusted GFDI (GFDIS), (h) fuel- and slope-adjusted GFDI (GFDIFS), (i) average Byram's intensity (IBAV), (j) total PWR1 (PWR1TOT) and (k) total PWR2 (PWR2TOT), (l) convection number NC.

9.7 Additional recommendations for further work

Additional research that would improve our understanding of the destructive potential of future bushfires and our ability to predict community consequences is given below.

9.7.1 Weather and climate

- Incorporate vertical atmospheric structure of each fire and establish how this contributes to the power of the fire.
- Identify the contributing climate conditions such as ENSO, heat waves preceding climate events etc.
- Include other fire weather information such as frontal system movement.
- Apply moisture-lag effects where on days of high temperature and low humidities, the dryness of the fuel will lag behind actual meteorological conditions by an hour or more (McArthur 1967) .

9.7.2 Fuel condition

- Improve fuel type and fuel accumulation rate estimates with intensive field surveys.
- Fuel loads in this study used homogenous fuels. Incorporate modelled fuel loads spatially to create more accurate fire propagation estimates and therefore improve energy release estimates.
- Use remotely sensed data and field surveys to estimate the patchiness and severity of the burn to reveal the remaining fuel loads, which can be used in modelling risks for future fires.
- Combine remotely sensed data (both lidar and reflectance) to develop algorithms for fuel load mapping.
- Use remotely sensed data to estimate fuel moisture content (FMC) to accurately assess the influence of FMC on past fires. This will help understand future fire risk, e.g. NDWI (Normalised Differenced Water Index) using NIR and SWIR channels.
- Incorporate canopy fuels and a portion of the coarse fuels into the fuel consumption.

9.7.3 Community loss and density

- Include more detailed loss information – preparedness, house materials, proximity of houses to trees and other houses, house age, houses destroyed due to spotting, number and cause of injuries and deaths etc.
- Investigate the influence of spotting in each fire on community loss.
- Orthorectify and digitise additional aerial images to map housing density to gain a more accurate measure of the community affected by the fire. Additionally, where data are available use change detection methods of pre- and post-fire aerial images to create spatial information on the houses that were lost during the fire.
- Calculate economic loss using the consistent and comprehensive framework discussed by Stephenson (2011).
- Assess and, if necessary, revise DSE criticality framework based on the findings of this report.

9.7.4 Fire behaviour

- Use remotely sensed data to establish the burn severity of past fires along with fire history (based on patchiness of past fires), fuel load, and fuel moisture content.
- Analyse high fire danger risk days where no fires occurred to determine probability of ignitions occurring.
- Use remotely sensed data to measure Fire Radiative Power (FRP) and Fire Radiative Energy (FRE), (see Wooster *et al.* (2005)) to improve energy release estimates.
- Compare results with VESTA equations, which requires information on fuel hazard scores and near-surface height.
- Determine which of the meteorological variables in the FFDI are most strongly correlated with loss, and whether a different combination of these variables is a better predictor of loss.
- Improve the power measurement of each fire by accounting for spotting. See theoretical method in appendix.
- Improve power measurement of each fire by calculating the power of a specific isochrone. This can be applied using a GIS as an arbitrary front.
- Concentrate fire behaviour, weather and topography information on area of community loss.
- Improve FDRS analysis by standardising by time, for example, the length of the high FFDI.
- Add ember loading (1–2 km) from homes for spot fires.
- Use discriminant analysis to see whether variables such as FFDI and power can be broken into intervals that relate to increasing average loss.
- Group FFDI into warning classes (low, moderate, high etc.) and test relationship with loss. Also do this for Power and Byram's fireline intensity

10

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