Fire in arid and semi-arid Australia
1998 – 2004

NOTE:
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Chapter 6

SPATIAL INDICATORS OF FIRE RISK
IN
THE ARID AND SEMI-ARID ZONE OF AUSTRALIA
Abstract

Fire plays a role in determining the shape of the earth’s ecosystems, impacts socio-economic issues, and influences our climate. In arid and semi-arid Australia (70% of the continent), individual fires frequently exceed 1 million ha, and have collectively burnt up to 9% of the total area in a single year, associated with antecedent periods of above average rainfall which boost the fuel load. People affected by these fires - Federal and State governments, pastoralists, Aboriginal communities, larger towns, conservation park managers and tourist operators - all have different outlooks and priorities about these phenomena. Little objective information about the fire regime and its drivers has been available for this vast area with its very low population density. A predictive understanding of the spatial and temporal pattern of risk of large uncontrollable fires is needed to promote pro-active management.

We present a conceptual framework which serves both to summarise existing knowledge and to reduce the complexity for a quantitative statistical analysis. This conceptual framework contains four main groups of independent variables; biomass, curing, ignition source, and fire weather. For these groups of variables we identified direct data sources or spatial surrogates. To quantify different aspects of the fire regime, interpretation of NOAA-AVHRR satellite imagery was employed, which identifies both fire hotspots (FHS) and fire affected area (FAA). For temporal variables, we present a surface displaying relationships for different combinations of lag/phase. This highlights different patterns for each region, and the most appropriate timeframes to use in modelling.

Results of exploratory regression analysis in arid and semi-arid Australia show that the strongest influence is exerted by biomass or fuel load. As this is highly dependent on antecedent rainfall, we can anticipate a strong effect of climate change on the fire regime. The strongest combinations of relationships may be used as spatial indicators in the development of long-lead fire risk models for these areas. This can help improve the timing of pro-active strategies to manage fire, and in the allocation of sparse funds and resources. Our analysis has highlighted regional patterns of fire across different land tenures. Heightened awareness of these patterns may encourage a more cooperative and coordinated approach to fire management amongst stakeholders.
6.1 Introduction

Few studies (Holm et al., 2003; Jafari et al., 2008; Ludwig et al., 2007; Odeh and Onus, 2008; Southgate and Carthew, 2007) have used Geographical Information Systems (GIS) and remotely sensed data to create spatial indicators of ecological conditions or processes in arid or semi-arid Australia, despite the fact that this can be the most cost- and time-effective method of accessing these vast, remote and under-populated areas, comprising 70% (5.5 million km²) of the continent.

Fire is one of the pivotal processes in these landscapes, affecting the distribution and abundance of a unique and diverse range of plants and animals (Kershaw et al., 2002). Historically, lightning and burning by Aboriginal people produced a fine grain mosaic of burnt patches at different seral states (Bowman, 1998; Burrows et al., 2006a; Latz and Griffin, 1978). Fire regimes have changed with the cessation of traditional Aboriginal burning over large areas, and are now characterised by pulses of large intense wildfire following above average rainfall (Allan and Southgate, 2002; Bradstock and Cohn, 2002; Craig, 1999), ranging between a few years to over 20 years apart (Allan and Southgate, 2002; Edwards et al., 2008).

Over 9% of arid and semi-arid Australia burned in both 2000 and 2001, and 7% in 2002 (Chapter 5, see also Turner et al., 2008). Fires threatened homesteads, sacred and cultural sites, damaged infrastructure, destroyed pasture and fences, killed cattle and other animals, and posed health risks to the public (Allan and Tschirner, 2009; Edwards et al., 2008; Ellis et al., 2004). They also killed mature mulga plants, increasing the opportunity for spinifex to invade these fire sensitive communities, and they contributed to soil erosion and significant greenhouse gas emissions. Fire age was homogenised over very large areas, which may lead to significant biodiversity problems.

A pro-active burning program in the preceding years could have mitigated many of the adverse impacts of these fires (Edwards et al., 2008). However, as these periods of large intense wildfire are infrequent in these environments, it is difficult for individuals to develop skills to manage them, and few explicit fire management strategies have been developed. Fire management is also constrained by limited resources of manpower and equipment, the vastness and remoteness of many areas, poor accessibility, and imperfect knowledge of fire behaviour and fire effects (Edwards et al., 2008; Ellis et al., 2004). Here, if a large fire develops, it is often next to impossible to contain it.

Fire forecasting tools, such as the widely used Fire Danger Index (FDI) for eucalypt forest or continuous grasslands (Cheney et al., 1998; McArthur, 1966, 1967), or the recently developed fire danger rating system for discontinuous spinifex grasslands (Burrows et al., 1991; Burrows et al., 2006c), are largely based on empirical data from experimental fires, but few of these experiments have been conducted in arid or semi-arid environments. Predictions are specific for a particular time and place, and are updated daily. Short-term predictions like these are most useful as a
decision support mechanism for tactical planning of management fires, or the allocation of resources for firefighting by operational fire fighting centers, of which there are very few in arid and semi-arid Australia.

What has been lacking is a means to predict when fire risk warrants, or necessitates, early pro-active intervention in these areas. An ability to predict wildfire variability with long-lead forecasting (seasonal to annual leads) at a regional and national level can assist strategic long-term planning, and the chance of timely and cost-effective intervention initiatives such as patch-burn strategies and buffer burns, to benefit biodiversity and limit the impact of wildfires, while maximizing the limited available funding and resources.

This approach has recently been adopted throughout Australia, with the inaugural Seasonal Bushfire Assessment produced for 2006-2007 (Lucas et al., 2006). Each year, following a number of workshops around the country, a report and map are produced indicating the fire potential during the active part of the upcoming fire season for a given region (Bushfire CRC, 2007, 2008; Lucas et al., 2006). These outlooks are based on considered expert assessments from climatologists, meteorologists and state-based fire-agency personnel.

But, little objective information about the fire regime and its drivers has been available for arid and semi-arid Australia in the past. One of the first attempts to characterise the causes, seasonal incidence, distribution and size of wildfires in central Australia was carried out by Griffin et al. (1983), using statistics from records of fires reported on pastoral properties between 1970 and 1980. They found that the total area burnt was best explained by the rainfall of the preceding 2 years. An assessment of fire patterning, using the fire affected area (FAA) and fire hotspot (FHS) data derived from National Oceanographic and Atmospheric Administration’s (NOAA) Advanced Very High Resolution Radiometer (AVHRR) imagery (Craig et al., 2002; Marsden et al., 2001), has recently been completed by Russell-Smith et al. (2007b) for all of Australia from 1997 to 2005. In this study, statistical modelling was used to relate the spatial variation of fires to a variety of static biophysical variables. This revealed that rainfall seasonality substantially explains fire patterns at a continental scale. Temporal variations were modelled using measurement of antecedent rainfall, Normalized Difference Vegetation Index (NDVI), and prior fire. In the arid and semi-arid regions, annual rain in the preceding year explained most variance. The current authors have demonstrated that the main trends in fire distribution follow latitudinal rainfall and temperature in arid and semi-arid Australia, and also established a broad-scale positive temporal relationship between categorised antecedent rainfall and area burnt in the following year, as part of their initial analysis of regional fire patterns in these areas, using the NOAA-AVHRR FAA data between 1998 and 2004 (Chapter 5, see also Turner et al., 2008).

Building on our earlier work (Chapter 5, see also Turner et al., 2008), this paper reports the results of finer-scaled and more extensive exploratory analysis and modelling in the entire arid and semi-
arid regions of Australia. We use computational experimentation to test how varying model scenarios drive model outcome, in an effort to better understand the complex system. This predictive understanding of the independent variables behind the spatial and temporal pattern of risk of large uncontrollable fires is needed to promote pro-active management. We examine the feasibility of long-lead fire prediction in these regions, in the hope that automatic seasonal forecasts could eventually be developed, to support the current system which is based largely on expert opinion.

In this paper, we present a conceptual framework which serves to summarise existing knowledge of the climatic, edaphic and anthropogenic factors which affect fire risk. This conceptual framework contains four main groups of independent variables. Indices for biomass, curing, and ignition source are developed using the NOAA-AVHRR FAA dataset, while the fire weather index uses the FHS data as the dependant variable, as the exact date of fires is unknown from the FAA data.

We elucidate the relative strength of influence, and predictive capability, of 140 independent variables (antecedent rainfall, recent rainfall and temperature, soil, vegetation, land use, NDVI, lightning, road networks, population density, land tenure, and current temperature, wind, relative humidity and rainfall) on 7 years of fire data, at both a continental and regional scale, throughout arid and semi-arid Australia. We present a surface displaying 40 relationships between antecedent rainfall and FAA (combining lags of 0, 3, 6, 9 and 12 months, and phases in 3 month increments from 3 to 24 months) for the entire study area, and for each region. This serves to highlight the different patterns for each region, and the most appropriate timeframe to use in modelling. A similar methodology is used when modelling NDVI. The strongest combinations of relationships are used as spatial and temporal indicators of the risk of large fires, both overall and on a regional basis, in the final models.

6.2 Study site

Our study area is delineated by the Australian Bureau of Meteorology’s ‘dry climate’ zones. This uses a modification of Köppen’s classification of world climates, based upon differences in the seasonal distribution of mean annual temperature and precipitation measured over 30 years (figure 6.1) (Stern et al., 2000).

These arid and semi-arid lands, often referred to as rangelands, occupy 70% of Australia (5.5 million km$^2$) and are inhabited by less than 3% of the population (over 500,000 people) (Brown et al., 2008). They are characterised by low average rainfall which is highly variable (Bureau of Meteorology, 2005), infertile soils over extensive areas (Bureau of Rural Science, 1991), and sparse vegetation (National Land and Water Resources Audit, 2001). Fire is characterised by pulses of large intense wildfire following above average rainfall in preceding years (Allan and Southgate, 2002; Edwards et al., 2008).
6.3 Conceptual framework and data

We present a conceptual framework (figure 6.2) which serves both to summarise existing knowledge and to reduce the dimensionality for a quantitative statistical analysis. This conceptual framework contains four main groups of independent variables: biomass, curing, ignition source, and fire weather.

Biomass (fuel load) is a product of the amount of vegetation that has grown in an area, and any intervention on that vegetation through management practices or disturbances such as fire or flood (Bowman et al., 2007; Dyer and Stafford Smith, 2003). The rate of plant growth depends on the type of vegetation in question, the underlying soil type and conditions, and climatic conditions (particularly antecedent rainfall) (Orians and Milewski, 2007; Winslow et al., 2003).

On pastoral lands, grazing by animals, including termites, generally keeps the fuel loads low. In the perennial tussock grasslands (e.g. Mitchell grass (Astrebla spp.), palatable annuals and ephemerals will normally be eaten out leaving bare ground between tussock (Cheney and Sullivan, 2008). After extended periods of widespread rain however, growth can far exceed consumption (Hodgkinson, 2002). In the drought-resistant, unpalatable, perennial hummock grasses - commonly soft spinifex
Figure 6.2 Conceptual framework
(Triodia pungens), hard spinifex (Triodia basedowii), or feathertop spinifex (Triodia schinzii) - fuel loads accumulate in association with the variable rainfall (Allan and Southgate, 2002). Hummocks grow up to 30-60 cm high and 30-100 cm in diameter, and occupy 30-50% of the ground area, with the ground between them normally bare. While highly flammable, fire spread is normally restricted by wind speeds capable of spreading flames at a low angle across the hummocks. After rain however, a sparse cover of short grasses or forbes may grow between the hummocks, facilitating rapid fire spread (Cheney and Sullivan, 2008).

On pastoral land, fire suppression has been the main focus of management, for protection of people and assets (Edwards et al., 2008; Griffin et al., 1983), although fire has been used for fuel reduction and pastoral land management to a limited extent in recent years (Craig, 1999; Letnic, 2004; Myers et al., 2004; Vitelli and Pitt, 2006). Traditionally, Aboriginal communities used fire in hunting and “fire-stick” farming, as well as for cooking, warmth and signalling (Bird et al., 2005; Bowman, 1998; Fensham, 1997; Latz, 1995). Although fire management is still culturally important today, the opportunities for getting out on country to burn are constrained (Edwards et al., 2008). This being said, roadside ignitions by Aboriginal travellers were responsible for many of the fires in Central Australia during the 2000-2002 fire events, causing considerable animosity from pastoralists (Edwards et al., 2008). In conservation areas, fire management is aimed at protecting physical assets, cultural sites and human life, as well as protecting biodiversity from wildfire, and enhancing biodiversity through prescribed burning (Duguid et al., 2009; Edwards et al., 2008; Gill et al., 2002a; Keith et al., 2002).

The Normalized Difference Vegetation Index (NDVI) (Tucker, 1979) has been used for many years to measure and monitor plant growth (vigour), vegetation cover, and biomass production from multispectral satellite data. It is based on brightness values of the near-infrared and red bands, and is a representation of the "greenness" of vegetation at the time the satellite passes over a designated area. NDVI is now calculated fortnightly for the entire country, and has been utilised in a number of arid and semi-arid environments (Hobbs, 1995; Holm et al., 2003; Jafari et al., 2007).

Curing is also a measure of pasture ‘greenness’, and is defined as the percentage of material in the sward that is dead. Following the growth season and seed production, pastures die or become dormant and dry out. The degree of curing has an effect on flammability and the potential rate of fire spread (Cheney and Sullivan, 2008). The curing process is affected by variable characteristics such as rainfall and temperature, as well as vegetation and soil types (Allan et al., 2003; Cheney and Sullivan, 2008). Hummock grasses become particularly flammable, as they accumulate a dense core of coarse dead material over a number of years.
A number of studies have derived relationships between NDVI and ground-based estimates of curing within Australia (Allan et al., 2003; Chladil and Nunez, 1995; Dilley et al., 2004; Paltridge and Barber, 1988), though not in the dry climate zones. Grassland curing indices are now produced for a number of areas (for southeast Australia by the Bureau of Meteorology, and for the Kimberly and southwest region of Western Australia by Landgate, Western Australian Land Information Authority), using the same basic algorithms as the NDVI. Currently, the most common method for quantifying curing is still visual estimation in the field, although the Bushfire Cooperative Research Centre is in the process of developing a new satellite vegetation index to access grassland curing across Australia and New Zealand (Bushfire CRC, 2009).

Fire ignition sources can be from either lightning or humans. There is a high level of lightning activity in the northern parts of Australia, and a decrease in total flash density occurs southward (Kuleshov et al., 2006). Lightning tends to strike higher ground along peaks and ridges (Kilinc and Beringer, 2007), while anthropogenic fires are more likely to occur near settlements and along roads and tracks (Burrows et al., 2006a; Edwards et al., 2008). Fires can be lit for traditional purposes, fuel hazard reduction, sustainable land use, or ecosystem management. Others may be lit maliciously, or simply burn out of control. In arid and semi-arid Australia, it is difficult to know for certain how many fires are started by lightning and how many by humans, as many are not attended, or reported in official statistics.

Weather conditions such as low relative humidity, high temperatures, strong winds, and lack of rain all contribute to increased fire danger. These factors contribute to the rate of spread and intensity of a fire, which affects the total area burned. They are used in the Fire Danger Index (FDI), widely used throughout the country in areas of eucalypt forest or continuous grassland (Cheney et al., 1998; McArthur, 1966, 1967). In patchy fuels such as spinifex, fire spread can usually only be sustained if conditions are such that the flames from burning hummocks can breach the inter-hummock gaps and ignite the adjacent hummock (Cheney and Sullivan, 2008). A number of models to predict rate of spread in discontinuous spinifex communities have been developed in Australia (Burrows et al., 1991; Burrows et al., 2006c; Griffin and Allan, 1984, 1993), but none of these models are currently operational.

The datasets used in our analysis are summarised in table 6.1. Land tenure is used as an indicator of the type of fire management that is most likely to be employed. Because the fire datasets only cover 7 years, it was not possible to calculate the time since last burnt for most locations, so this variable was not included in our analysis. The real-time ground-based detection data, Lightning Positioning and Tracking System (LPATS), used by Kilinc and Beringer (2007) for their analysis was unfortunately not available for our use. Instead we used the Bureau of Meteorology’s average annual lightning ground flash density data (1995-2002) (Kuleshov et al., 2006).
<table>
<thead>
<tr>
<th><strong>Table 6.1 Project datasets</strong></th>
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<tbody>
<tr>
<td><strong>Name</strong></td>
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<tr>
<td>Climate Zones</td>
</tr>
<tr>
<td>Fire Affected Areas (FAA)</td>
</tr>
<tr>
<td>Fire Hot Spots (FHS)</td>
</tr>
<tr>
<td>Monthly Rainfall</td>
</tr>
<tr>
<td>Monthly Maximum Temperature</td>
</tr>
<tr>
<td>Normalized Difference</td>
</tr>
<tr>
<td>Vegetation Index (NDVI)</td>
</tr>
<tr>
<td>Soils</td>
</tr>
<tr>
<td>Vegetation</td>
</tr>
<tr>
<td>Road Network</td>
</tr>
<tr>
<td>Lightning</td>
</tr>
</tbody>
</table>
6.4 Methodology

The accuracy of the NOAA-AVHRR FAA and FHS datasets has been assessed in arid and semi-arid regions using Landsat-derived interpretations by the authors (Chapter 4, see also Turner et al., 2009a).

6.4.1 FAA indicators

Fire affected area (FAA) was used for the biomass, curing, and ignition source indices. The FAA dataset contains mapped burnt patches from 1998 to 2004, and the dates of detection. The data were aggregated to 50 km x 50 km grids (2,096 cells), giving the percentage of each cell burnt for each year/month (2,096 cells x 7 years x 12 months = 176,064 records). The climate zone of each cell was also included (figure 6.1).

Monthly rainfall data were aggregated to 50 km x 50 km grids, using mean values. This was then summed in various combinations to form a 5 x 8 matrix for each cell, with lags of 0, 3, 6, 9 and 12 months and phases in 3 month increments from 3 to 24 months, for inclusion in the biomass index. For example, a lag of 0 and a phase of 6 shows the cumulative rainfall for 6 months before the year/month in question, while a lag of 3 and a phase of 12 shows the cumulative rainfall between 3 and 15 months before the year/month in question.

Cumulative values for the previous 1, 2, and 3 months were calculated for both monthly rainfall and monthly maximum temperature data, for inclusion in the curing index.

To model a separate NDVI-based biomass index, the maximum NDVI was calculated for each month at the 1 km resolution. This monthly maximum NDVI data were then aggregated to 50 km x 50 km grids, using mean values. A 40 variable matrix similar to the rainfall data was formed.

To model a separate NDVI-based curing index, the NDVI value in the previous month was subtracted from the highest value for the previous 12 months (50 km x 50 km grid values), as an indication of ‘loss of greenness’.

These 87 dynamic variables were then linked to the FAA data by cell location/year/month.

A separate 50 km x 50 km grid was created for each of the 11 soil types, 23 vegetation types, and 16 land tenure classes present in the study area, calculating the percentage of that type or class in each cell. Lastly, 50 km x 50 km grids were created of the mean number of lightning ground flashes per km2, as well as the total length of road, and the total population per cell. These 53 static variables were linked to the FAA data by cell location.

The resulting GIS file of 176,064 records was imported into the S-PLUS (MathSoft, 1999) statistical software package for modelling, with the percentage of area burnt (PercentFAA) as the
dependent variable, and 140 possible independent variables. Examination of the data suggested the use of a generalised linear model (McCullagh and Nelder, 1989).

For the biomass index, the first step was to establish the rainfall lag/phase that was the best predictor or indicator of PercentFAA for the entire area, and also for each of the nine climate zones (figure 6.1). A glm model was fitted for each of the 40 lag/phase independent variables in turn, using the Poisson family with a log link.

The percentage of deviance explained by each model was calculated using the formula:

\[
\% \text{ deviance explained} = \frac{(\text{null deviance} - \text{residual deviance})}{\text{null deviance}} \times 100
\]

Analysis by individual climate zones revealed that there was insufficient fire data in some zones for the results to be statistically significant \((p < 0.05)\). The data were re-grouped into four climate categories - north (hot, winter drought, zone 13 and 22), west (hot, summer drought, zone 14 and 23), central (hot, persistently dry, zone 15 and 24), and south (warm, summer drought or persistently dry, zones 11, 12 and 21).

The models were then run for each climate category, and for the entire area, as were all other models thereafter.

The same methodology was used to establish the cumulative NDVI lag/phase that was the best predictor of PercentFAA.

Glm models were run using rainfall and maximum temperature in the previous 1, 2 and 3 months, and curing NDVI.

An individual glm model was run for each of the soil types, measuring the relationship between PercentFAA and the percentage of the soil type in each cell. Variables were considered significant if they had a \(p\) value < 0.05. As the data had been aggregated up to 50 km x 50 km grids, soil types with small areas gave some meaningless results and were not included in further analysis. Stepwise glm models were then run, using only the most common soil types (up to a total of six types).

The same process, as for soil, was followed for the vegetation types and tenure classes.

A separate glm model was run for each of the other three variables – population totals, road length and lightning ground flash density.
6.4.2 FHS indicators

For the fire weather index, the fire hotspot (FHS) dataset was employed, as the exact date of the detected fires is known, unlike the FAA data (Craig et al., 2002; Yates and Russell-Smith, 2002). Unfortunately, many fires miss detection due to the timing of the satellite overpass or atmospheric conditions on the day (Craig et al., 2002; Gill et al., 2002b; Chapter 4, see also Turner et al., 2009a).

Daily observations of precipitation, relative humidity, maximum and minimum temperatures and mean wind speed from the Australian Bureau of Meteorology weather stations were used in creating the fire weather index. While there were almost 2,000 locations recording rainfall, only 178 of these also recorded the other measurements. For each of these stations, a record was created for each day that all five observations were recorded. The average of the (usually 3 hourly) daily relative humidity readings was used for our analysis. Very few sites have a complete unbroken record of climate information, which resulted in a total of 404,612 records.

To avoid error introduced by extrapolation, the presence or absence of fire hotspots within a 25 km radius of the weather stations was calculated for the daily records at each site.

A glm regression was fitted for each of the five weather variables, for the entire study area and each climate category, using the binomial family with a logit link.

6.4.3 Complete model

Transformations of the independent variables, and interactions between variables were examined.

Finally, stepwise glm models were run for each index, using the combination of variables deemed most suitable (see section 6.5), for the entire study area and each climate category.

6.5 Results

The distribution, seasonality, frequency and minimum return value, and number and extent of our FAA and FHS datasets are described in detail in our initial analysis of the data (Chapter 5, see also Turner et al., 2008).

6.5.1 FAA indicators

In this section the term ‘current year’ refers to the previous 12 months.
6.5.1.1 Fire affected area

Between 1998 and 2004 almost 27% (over 1.5 million km$^2$) of arid and semi-arid Australia was mapped as burnt at least once. This ranged from a low 1.6% in 2003, to over 9% in both 2000 and 2001, with some areas burnt repeatedly (figure 6.3).

![Figure 6.3 Number of times area burnt between 1998 and 2004](image)

6.5.1.2 Rainfall and temperature

The average annual rainfall ranges from ~800 mm in the north, 250 mm in the south and 500 mm in the east, but can be very variable with up to 2,000 mm in the north at times. Mean annual daily maximum temperatures are hottest in the north (over 30° Celsius), graduating to warm in the south (in the low 20s) (Bureau of Meteorology, 2005).

For the entire study area, cumulative rainfall between 3 and 12 months beforehand (lag of 3, and phase of 9), is the best predictor of percentage of area burnt, with 22.8% of the deviance explained (Table 6.2 and 6.3, Figure 6.4). But cumulative rainfall in the previous 2 years is almost as good a predictor - lag/phase 3/18, 3/21, 6/15 and 6/18 all explain over 20% of the deviance. By comparison, cumulative rainfall in the previous quarter (0/3) explains less than 2%, and cumulative rainfall in the previous year (0/12) only 16%.
Table 6.2 Percentage of deviance explained by antecedent rainfall using glm regression for all regions

Dependent variable = PercentFAA

Independent variables = cumulative rainfall for each lag/phase period (see text for details)

The best result is highlighted

* = negative relationship with PercentFAA

<table>
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<tr>
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<th>3</th>
<th>6</th>
<th>9</th>
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<td>3</td>
<td></td>
<td>1.88</td>
<td>2.20</td>
<td>19.52</td>
<td>4.59</td>
<td>* 0.23</td>
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<tr>
<td>6</td>
<td></td>
<td>0.13</td>
<td>16.48</td>
<td>19.47</td>
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<tr>
<td>9</td>
<td>11.24</td>
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<td>17.70</td>
<td>15.52</td>
<td>11.79</td>
<td>9.42</td>
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Figure 6.4 highlights a number of different patterns when modelling antecedent rainfall by climate category. The best predictive power for each region ranges from 11% of deviance explained in the south and 15% in the north, to 22% and 23% in the mid and west. Rainfall in the north is most reliable, producing adequate biomass to burn each year, while in the south, rainfall is consistently low, resulting in little biomass and very infrequent fires. It is in the mid and west, where rainfall can be highly variable, that a stronger relationship between percentage burnt area and antecedent rainfall can be established.

Rain in the north is influenced by the Top-End’s very distinctive monsoonal wet season (about October to April in the Northern Territory, but shorter in other areas). Above average rainfall events in the mid region also tend to be associated with the summer monsoon season (Bureau of Meteorology, 2005). The greatest percentage of area burnt in both the north and mid regions occurred between September and November at the end of the dry season (Chapter 5, see also Turner et al., 2008). The best predictor of PercentFAA is from the current year’s wet season (15% in the north, and over 21% in the mid region). The lag of 3 to 6 months indicates that the vegetation in these regions can reach critical mass in a short time following rain. Lags of 9 and 12 months have very little predictive power, particularly in the north, where they correspond to the dry season. In the mid region, cumulative rainfall in the previous 24 months with a lag of 3 or 6 months still explains 15-20% of the deviance.
Figure 6.4 Percentage of deviance in PercentFAA explained by antecedent rainfall and NDVI using glm regression

(See Table 3 caption for details)
Table 6.3 Percentage of deviance explained individually by each independent variable using glm
regression for dependent variable PercentFAA

The best results for recent rainfall, recent temperature, soil, vegetation, and land tenure are highlighted

* = negative relationship with PercentFAA
ns – result not significant, \( p \) value < 0.05

<table>
<thead>
<tr>
<th>Independent variables</th>
<th>North</th>
<th>West</th>
<th>Mid</th>
<th>South</th>
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<td><strong>Antecedent Rainfall</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cumulative rainfall (best lag/phase)</td>
<td>15.14</td>
<td>23.47</td>
<td>22.17</td>
<td>10.70</td>
<td>22.81</td>
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<td><strong>Recent Rainfall</strong></td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total rainfall in previous 1 month</td>
<td><em>6.79</em></td>
<td><em>2.89</em></td>
<td><em>3.26</em></td>
<td><em>1.78</em></td>
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</tr>
<tr>
<td>Total rainfall in previous 2 months</td>
<td><em>6.14</em></td>
<td><em>5.75</em></td>
<td><em>4.37</em></td>
<td><em>1.30</em></td>
<td><em>2.88</em></td>
</tr>
<tr>
<td>Total rainfall in previous 3 months</td>
<td><em>4.78</em></td>
<td><em>8.99</em></td>
<td><em>5.72</em></td>
<td><em>2.49</em></td>
<td><em>1.88</em></td>
</tr>
<tr>
<td><strong>Recent Temperature</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean maximum temp in previous 1 month</td>
<td><em>0.01</em></td>
<td>7.94</td>
<td>0.29</td>
<td>7.38</td>
<td>1.97</td>
</tr>
<tr>
<td>Mean maximum temp in previous 2 months</td>
<td><em>1.37</em></td>
<td>4.99</td>
<td><em>0.06</em></td>
<td>4.46</td>
<td>0.52</td>
</tr>
<tr>
<td>Mean maximum temp in previous 3 months</td>
<td><em>4.51</em></td>
<td>2.62</td>
<td><em>0.71</em></td>
<td>1.98</td>
<td>0.04</td>
</tr>
<tr>
<td><strong>NDVI</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Curing NDVI (Loss of vegetation greenness)</td>
<td>0.28</td>
<td>1.27</td>
<td>0.78</td>
<td><em>0.09</em></td>
<td>0.88</td>
</tr>
<tr>
<td><strong>Percentage of Soil Type</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 Sands</td>
<td>1.75</td>
<td><em>0.90</em></td>
<td></td>
<td>4.92</td>
<td>6.79</td>
</tr>
<tr>
<td>2 Massive and structured earths</td>
<td>0.50</td>
<td><em>0.83</em></td>
<td><em>0.11</em></td>
<td>ns</td>
<td>0.12</td>
</tr>
<tr>
<td>3 Loams</td>
<td><em>0.61</em></td>
<td>1.74</td>
<td><em>0.06</em></td>
<td><em>0.91</em></td>
<td><em>1.22</em></td>
</tr>
<tr>
<td>4 Cracking clays</td>
<td><em>3.75</em></td>
<td>2.68</td>
<td><em>3.47</em></td>
<td><em>3.67</em></td>
<td><em>1.36</em></td>
</tr>
<tr>
<td>5 Red duplex soils</td>
<td><em>0.52</em></td>
<td>0.07</td>
<td><em>1.01</em></td>
<td><em>0.24</em></td>
<td><em>1.89</em></td>
</tr>
<tr>
<td>6 Calcarous earths</td>
<td><em>0.15</em></td>
<td>ns</td>
<td>2.36</td>
<td>ns</td>
<td>2.64</td>
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<tr>
<td>7 Yellow duplex soils</td>
<td>0.06</td>
<td><em>0.50</em></td>
<td><em>0.05</em></td>
<td>0.55</td>
<td>0.01</td>
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<tr>
<td><strong>Percentage of Vegetation Type</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 Hummock grasslands</td>
<td>0.11</td>
<td>18.94</td>
<td>8.04</td>
<td><em>0.21</em></td>
<td>3.57</td>
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<tr>
<td>2 Acacia shrublands</td>
<td>0.42</td>
<td><em>1.66</em></td>
<td><em>0.53</em></td>
<td><em>0.73</em></td>
<td><em>0.68</em></td>
</tr>
<tr>
<td>3 Acacia forests and woodlands</td>
<td>0.35</td>
<td><em>6.98</em></td>
<td>0.02</td>
<td><em>1.69</em></td>
<td><em>0.41</em></td>
</tr>
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<td>4 Chenopod, samphire</td>
<td><em>1.23</em></td>
<td><em>3.23</em></td>
<td><em>4.20</em></td>
<td><em>4.54</em></td>
<td><em>5.61</em></td>
</tr>
<tr>
<td>5 Tussock grasslands</td>
<td><em>3.00</em></td>
<td>2.29</td>
<td><em>2.64</em></td>
<td><em>6.65</em></td>
<td><em>0.42</em></td>
</tr>
<tr>
<td>6 Eucalypt woodlands</td>
<td>0.31</td>
<td><em>0.07</em></td>
<td><em>1.70</em></td>
<td>4.60</td>
<td>0.12</td>
</tr>
<tr>
<td>7 Eucalypt open woodlands</td>
<td>0.17</td>
<td><em>1.31</em></td>
<td><em>0.16</em></td>
<td>2.78</td>
<td>1.06</td>
</tr>
<tr>
<td>8 Mallee woodlands and shrublands</td>
<td><em>0.01</em></td>
<td><em>0.60</em></td>
<td><em>0.11</em></td>
<td><em>2.71</em></td>
<td><em>0.85</em></td>
</tr>
<tr>
<td>9 Acacia open woodlands</td>
<td><em>1.07</em></td>
<td><em>0.67</em></td>
<td><em>0.35</em></td>
<td><em>0.81</em></td>
<td><em>0.81</em></td>
</tr>
<tr>
<td>10 Other shrublands</td>
<td><em>0.30</em></td>
<td><em>4.47</em></td>
<td><em>0.47</em></td>
<td>9.02</td>
<td><em>0.87</em></td>
</tr>
<tr>
<td><strong>Percentage of Land Tenure Class</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 Private leasehold</td>
<td><em>0.02</em></td>
<td><em>1.00</em></td>
<td><em>3.87</em></td>
<td><em>3.09</em></td>
<td><em>0.47</em></td>
</tr>
<tr>
<td>2 Other crown land, vacant</td>
<td><em>ns</em></td>
<td>3.65</td>
<td>1.32</td>
<td>10.84</td>
<td>0.29</td>
</tr>
<tr>
<td>3 Private freehold</td>
<td><em>1.16</em></td>
<td><em>1.38</em></td>
<td><em>0.96</em></td>
<td><em>6.52</em></td>
<td><em>1.72</em></td>
</tr>
<tr>
<td>4 Private freehold, Aboriginal, non-agri.</td>
<td>0.63</td>
<td>1.56</td>
<td><em>0.11</em></td>
<td>2.11</td>
<td></td>
</tr>
<tr>
<td>5 Nature conservation areas</td>
<td><em>0.01</em></td>
<td><em>0.15</em></td>
<td><em>0.29</em></td>
<td>0.73</td>
<td><em>0.87</em></td>
</tr>
<tr>
<td>6 Reserved crown land, Aborig. reserve</td>
<td><em>0.23</em></td>
<td><em>0.08</em></td>
<td>1.50</td>
<td></td>
<td>0.05</td>
</tr>
<tr>
<td>7 Reserved crown land, not elsewh. class.</td>
<td><em>0.08</em></td>
<td>ns</td>
<td><em>0.02</em></td>
<td><em>1.73</em></td>
<td><em>0.02</em></td>
</tr>
<tr>
<td>8 Private leasehold, Aboriginal</td>
<td>0.20</td>
<td>0.86</td>
<td>ns</td>
<td>0.16</td>
<td>0.52</td>
</tr>
<tr>
<td>9 Private leasehold, Aboriginal, non-agri.</td>
<td><em>0.01</em></td>
<td>ns</td>
<td>0.68</td>
<td></td>
<td>0.03</td>
</tr>
<tr>
<td>10 Private freehold , Aboriginal</td>
<td><em>ns</em></td>
<td><em>0.09</em></td>
<td><em>0.74</em></td>
<td><em>0.11</em></td>
<td></td>
</tr>
<tr>
<td><strong>Other Independent Variables</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total road length</td>
<td><em>2.01</em></td>
<td><em>3.33</em></td>
<td><em>3.60</em></td>
<td><em>9.89</em></td>
<td><em>4.72</em></td>
</tr>
<tr>
<td>Total population</td>
<td><em>0.02</em></td>
<td>0.09</td>
<td><em>0.00</em></td>
<td><em>2.99</em></td>
<td><em>0.12</em></td>
</tr>
<tr>
<td>Lightning ground flash density</td>
<td>1.34</td>
<td>9.00</td>
<td>1.30</td>
<td>0.87</td>
<td>6.75</td>
</tr>
</tbody>
</table>
Cumulative rainfall and mean maximum temperature in the previous 1, 2 and 3 months were examined as variables for the curing index (table 6.3). For all categories, rainfall in the previous 1, 2 or 3 months has a negative impact on PercentFAA, as rainfall during this period adversely affects curing. Generally, rainfall in the previous 3 months explains the most deviance (2-9%), except in the north where rainfall in the previous month is a better indicator.

The relationship with temperature is more complex. In the west and south it is a positive relationship, with the previous month explaining the greatest amount of deviance (7-8%). There is a much greater range of temperature in these regions (from below 20 degrees Celsius in the winter to mid 30’s in the summer.) The greatest area burnt occurs in the hot summer months in these regions. In the north and mid regions the relationship between PercentFAA and temperature is generally negative (except for the previous month in the mid region). Here the hottest months occur during the rainy season, while more area is burnt at the end of the dry season, when it is slightly cooler.

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### 6.5.1.3 NDVI

NDVI values are scaled between -1 and 1. Water typically has an NDVI value less than 0, bare soils between 0 and 0.1 and vegetation over 0.1, with values over 0.5 indicating dense vegetation. In our data, the mean value for monthly maximum NDVI for the entire study area is 0.17 (0.20, 0.18, 0.17 and 0.22 in climate categories 1, 2, 3, and 4 respectively). Only 4% of NDVI values are above 0.3, and 0.5% have values greater then 0.4, while there are few values between 0.5 and 0.6 in any climate category. Approximately 6% of all the maximum monthly NDVI values are less then 0.1.

Cumulative NDVI is used as an indicator of biomass.
For the entire study area, cumulative NDVI from 3 to 6 months beforehand (lag of 3, and phase of 3), is the best predictor of PercentFAA, with almost 9% of the deviance explained (Table 6.3, Figure 6.4). The previous 6 or 9 months cumulative (without any lag), and a lag/phase of 3/6 all explain ~8% of the deviance.

The best lag/phase period of cumulative NDVI for each climate category explains 13% of the deviance in PercentFAA in the north, 4% in the west, 5% in the mid climate category, and 10% in the south. For both the north and south, the results are similar to those for cumulative rainfall (15% and 11%). For the west and mid climate categories however, cumulative rainfall is a far better predictor of PercentFAA (23% and 22%) than cumulative NDVI. The surfaces of NDVI lag/phase results do not show as strong patterns as those for rainfall (Figure 6.4).

In the north, NDVI peaks during the first half of the dry season, generally between April and June. In years of above average rainfall, the NDVI values are greater and the growing season longer. This is than followed by more FAA than normal in the late dry season (Chapter 5, see also Turner et al., 2008). The cumulative NDVI reflects this with the best lag /phase value of 3/3, and those for 3/6, 0/6, and 0/9 almost as good. Lags of 6 and 9 months have little predictive powers, as these correspond to the wet season.

Similarly, in the mid region, NDVI also tends to peak in the winter months (between April and July), and FAA in September to November. The pattern is influenced by the above average rainfall events of 1999-2001. In this region, the best predictor of percentage area burnt is from the previous year’s cumulative NDVI (lag/phase 12/6 explains 5% of the deviance). There is not a great variation in % deviance explained between the lag/phase results however, with the majority between 2.5% and 4%.

In the west, NDVI generally peaks in late winter/early spring (July-September). Rainfall was generally less than 400mm per annum throughout our study period for this area. Values for cumulative NDVI here show little pattern, and have very poor predictive power, with the majority ranging from almost 0% to 2%. The best predictor of PercentFAA is lag/phase 12/9 which explains less than 4% of the deviance.

NDVI peaks in the spring in the south (September-October) and FAA in summer (December-February). Cumulative NDVI in the previous 3 to 21 months (lag/phase 3/18) is the best predictor of FAA in this region, explaining 10% of the deviance. Those with a lag of 0 or 3 and a phase between 12 to 24 months all have values between 8% and 10%. This, like the cumulative rainfall results, reflects the fact that vegetation takes longer to grow in these cooler areas.
Loss of greenness was examined as a possible indicator of curing. The results of fitting maximum NDVI in the previous 12 months minus the previous month’s NDVI as the independent variable are displayed in Table 6.3.

For the entire area, almost 85% of records had a reduction in NDVI of less than 0.1 (~70% for the north and south climate categories, 80% for the west, and 90% in the mid region). The predictive capability of this data was very poor. For the complete study area it explained less than 1% of the deviance. The best result was for the west (1.3%), with the worst in the south (0.1%)

### 6.5.1.4 Soil, vegetation and land tenure

Generally, less than 5% of deviance is explained by any individual soil, vegetation or land tenure variable with a few exceptions (Table 6.3).

Over a third of the study area is composed of sands, the most fire prone soil (Figure 6.5a and b). Approximately 30% burnt once, and a further 16% twice or more, accounting for over 61% of the total FAA. Almost 30%, 20% and 10% of the areas covered by massive and structured earths, loams, and cracking clays burned at least once, resulting in ~ 20% 9% and 4% respectively of the total FAA. In the low fire years of 1998 and 2003, generally less than 3% of each soil type burnt, but with proportionally more fire on sands, and massive and structured earths (Figure 6.5c). In the high fire years, up to 16% of sands and 12% of massive and structured earths burnt, with maxima of 4-8% on most other soils.

Sands explained the greatest percentage of the deviance in PercentFAA amongst the individual soil types for the entire area, and in the mid and south regions (5-7%) (Table 6.3). While sands are the most common soil type in the north, it is cracking clays which explained more of the deviance in PercentFAA, with a negative relationship. Cracking clays also explained the greatest percentage of the deviance of individual soil types in the west, but they cover a very small area and were not included in further analysis, leaving loams as the best indicator of PercentFAA (Table 6.3 and 6.4). Massive and structured earths explained little deviance in any region.

Eucalypt open woodlands, hummock grasslands and eucalypt woodlands were the most fire prone vegetation types (Figure 6.6a and b). Almost half the hummock grasslands (30% of the study area) were burnt at least once, accounting for 50% of the total FAA, while 42% of the eucalypt open woodlands contributed a further 10%. In tussock grasslands 14% burned (4% 2-3 times), producing almost 5% of the total FAA. The chenopod shrubs, samphire shrubs and forblands occupy almost 10% of the study area, but less than 3% of these burned, accounting for only about 1% of the total FAA. In the low fire years, less than 2% of most vegetation types burned, but up to 5% of eucalypt woodlands and eucalypt open woodlands (Figure 6.6c). While approximately the same proportion of hummock and tussock grasslands burnt in the low fire years (~2%), 6 times proportionately more hummock grasslands burnt in 2000 (3% vs. 18%).
Figure 6.5 (a) Major soil types (Bureau of Rural Science, 1991); (b) Proportion of soil types burnt 1998-2004; (c) Area burnt each year by soil type
Figure 6.6 (a) Major veg types (National Land and Water Resources Audit, 2001); (b) Proportion of veg types burnt 1998-2004; (c) Area burnt each year by veg type

Note: Chenopod, samphire* = Chenopod shrubs, samphire shrubs and formlands.
Figure 6.7 (a) Major land tenure classes (Stewart et al., 2001); (b) Proportion of land tenure classes burnt 1998-2004; (c) Area burnt each year by land tenure class

Note: PF = Private freehold, PL = Private leasehold, RCL = Reserved crown land.
Hummock grasslands in the west explained the most deviance (19%) of any of the individual independent vegetation variables, and were also the best predictor in the mid region and overall (Table 6.3). In the north, although hummock grasslands were extensively burnt, tussock grasslands explained more of the deviance, while in the south other shrublands were the most important vegetation type, explaining 9% of the deviance.

Together, private leasehold and private freehold land tenures comprise 62% of arid and semi-arid Australia, vacant crown land 16%, Aboriginal tenures 14%, and nature conservation areas a further 7% (Figure 6.7a and b). Aboriginal lands were the most fire prone tenures with 43-61% burnt at least once, and some more frequently (Figure 6.7b). The exception was Aboriginal private freehold land, where only 1% of the land burnt in total. On vacant crown lands 31% burnt once and another 9% twice or more, while 14% of conservation areas burnt at least once. Almost 44% of the total FAA was on private leasehold property, although only 22% of this land was burnt. Most of the other fire occurred on vacant crown land and Aboriginal non-agricultural private freehold (~20% each of the total FAA). Regardless of the year, a far greater proportion of Aboriginal private leasehold burnt than any other land tenure (from 7% to 23%) (Figure 6.7c). Between 1% and 3% of most other tenures burnt in the low fire years. In other years, high percentages burnt on Aboriginal non-agricultural private leasehold (33%), Aboriginal non-agricultural private freehold (26%), Aboriginal reserves (23%) and vacant crown land (17%).

The individual land tenure that explained the most deviance in the percentage of area burnt was vacant crown land in the south (almost 11%) (Table 6.3). It was also the best indicator of PercentFAA in the west. Private freehold explained most in the north, private leasehold in the mid region, (both negative relationships), while non-agricultural Aboriginal private freehold was best for the entire study area. Nature conservation areas explain less than 1% of the deviance in all areas.

Table 6.4 shows the formulae output from stepwise glms of the six most common soil types, vegetation types and land tenure classes, the percentage deviance explained by the first three variables from each formula, as well as the total. Invariably, adding more than three variables did not increase the deviance explained by more than 0.5%.

When combined in the stepwise glm, the first three soil variables explain more than vegetation or tenure in the north, while vegetation is the best indicator of percentage area burnt in the west, mid and south, and similar to soil for the entire study area (Table 6.4). In the north, the first variable in each formula has a negative relationship with percentage area burnt. As so much of the north was burnt, the best explanation of the percentage of deviance came from those areas less prone to fire (cracking clays, tussock grass, or private freehold).
Table 6.4 Percentage of deviance explained by soil, vegetation and land tenure using stepwise glm models

Dependant variable = PercentFAA

Independent variables = % of up to 6 most common soil types, vegetation types or land tenure classes

* negative relationship with PercentFAA

See table 6.3 for legends of soil, vegetation and tenure

<table>
<thead>
<tr>
<th>Region</th>
<th>Independent variables passed to stepglm</th>
<th>Independent variables output from stepglm</th>
<th>% dev explained by first 3 variables</th>
<th>Total % dev explained</th>
</tr>
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<tbody>
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<td>Most common soils</td>
<td></td>
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<tr>
<td>North</td>
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<td>3 + 2 + 1 + 5</td>
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<td>Mid</td>
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<td>1 + 4 + 6 + 5</td>
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<td>7.97</td>
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<td>1 + 2 + 6 + 5</td>
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<td>1 + 5 + 7 + 6 + 2 + 3</td>
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<td>10.49</td>
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<td>10 + 6 + 7 + 8 + 2 + 4</td>
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<td>18.17</td>
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<td>1 + 4 + 6 + 3 + 2 + 5</td>
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<td>7.75</td>
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<tr>
<td>North</td>
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<td>2.07</td>
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<td>Mid</td>
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<td>4 + 3 + 5 + 1 + 2 + 6</td>
<td>4.15</td>
<td>4.80</td>
</tr>
</tbody>
</table>

6.5.1.5 Other variables

The relationship of PercentFAA with total population, total road length, and lightning ground flash density were also examined (table 6.4).

Arid and semi-arid Australia is characterised by a low population density (Brown et al., 2008). In the 2001 census, there were 265 population centres with over 200 people, half of them in the south climate category. Six major towns had populations of 20,000-30,000, while another 48 centres had over 2,000 people (figure 6.8). Outside of the major service centres and mining towns, the majority of the population is indigenous. Much of the population is very mobile, and there has been a recent emergence of numerous, dispersed, small and discrete settlements on Aboriginal lands (outstations) (Brown et al., 2008).

The road network is most dense around the population centres and in pastoral areas. There are few roads through Aboriginal lands, vacant crown land or conservation areas (figure 6.8).
Figure 6.8 Population and road density

Population
- 200 - 2,000
- 2,000 - 10,000
- 10,000 - 20,000
- 20,000 - 30,000
- Climate categories

Roads
- Road
There was generally a negative relationship of the percentage of area burnt with both the total population and the total length of roads, the exception being population in the west (table 6.4). The relationship with population density explained practically none of the deviance, while that with roads explained 2-10%.

Although the greatest density of lightning is in the north (figure 6.9), the most deviance in percentage area burnt was explained by lightning in the west (9%), with only ~1% for the north, mid and south. All were positive relationships.

### 6.5.2 FHS indicators

Of over 400,000 daily weather observation records, 5,077 had associated fire hotspots spread across 170 of the 178 weather station locations (Figure 6.10).

Daily precipitation readings ranged from 0 to 366mm. Almost 85% of observations recorded no precipitation, 10% less than 5mm, with less than 1% over 30mm. On fire days, the values ranged from 0 to 80mm, with over 95% with 0 precipitation, and 3.5% less than 5mm.
Mean relative humidity had a normal distribution with values between 2% and 100%, a standard deviation (SD) of 19.6% and a mean of 51.8%. Values on fire days ranged from 7% to 100%, but were skewed towards the lower values with a mean of 41.4%.

Results of glm regression reveal negative relationships with both precipitation and relative humidity in all regions (table 6.5). Relative humidity is a better predictor than rainfall, but still explains only 4% of the deviance at most (in the north).

Maximum temperatures ranged from 6.50°C to 50.50°C with a normal distribution (mean and median ~28.50°C, SD = 7.60°C). The maximum temperatures on fire days varied between 13.10°C and 46.30°C, with a mean of 32.30°C and SD of 5.60°C, with a slight skew towards the higher temperatures with a median of 29.70°C.

Daily minimum temperatures ranged from -6.10°C to 35.50°C with a normal distribution (mean = 14.20°C, median = 14.70°C, SD = 7.20°C). The records associated with fires had values between -5.60°C and 31.40°C, a mean of 16.40°C and SD of 6.00°C. The distribution is skewed slightly towards the higher temperatures with a median of 12.90°C.

Both maximum and minimum temperature had a positive relationship with fire hotspot incidence, apart from minimum temperature in the north (table 6.5). Maximum temperature explains more of
the deviance in fire occurrence, but no more than 2%. Minimum temperature explains less than 1% of the deviance in any area, with results for the south not significant.

Daily mean wind speeds as fast as 86.3 km/h were recorded, but less than 2% are above 30 km/h and the mean is 12.0 km/h. The fire related records show a very similar pattern with less than 1% above 30 km/h and a mean of 11.5 km/h. Wind speed did not prove to be a good indicator of fire in arid and semi-arid Australia, explaining a maximum of 0.1% of the deviance in any region (table 6.5).

6.5.3 Complete model

Both the dependant and independent variables input into the stepwise glm regressions, used to construct the biomass, curing, ignition source, and fire weather indices, are listed in table 6.5. A decision was made not to use NDVI derived data for the final biomass or curing model, as the other independent variables which contribute to biomass and curing are better predictors of fire extent.

Transformations of the variables were examined. Where a single term model of the transformed independent variable improved the deviance explained by 2% or more, from that of a single term model of the un-transformed variable, the transformation was included in the final model. Including these 15 transformations in the final models improved them by between 2-8% overall.

The percentage of deviance explained by interactions between rain, soil and vegetation were also examined as part of the biomass index, and between rain, temperature, soil and vegetation for the curing index. As stepwise glm calculates the main terms first, interactions contributed little extra to the deviance explained by the main terms, and were not included in the final models.

The results of the final models are reported in table 6.6. Only the first three terms output from the stepwise glm are listed, as there is little extra deviance explained by addition of more terms.

Overall, the biomass indices explained the highest proportion of deviance in PercentFAA (22% in the north, and 27% to 32% in the other regions). Regardless of the region, antecedent rainfall, with either vegetation or soil, explains the vast majority of deviance.

The curing index explains 13% of the deviance in the north, 32% in the west, 24% and 31% in the mid and south regions, and 21% overall. Recent rainfall (a negative relationship with percentFAA), in combination with either the first vegetation or soil type, has the best predictive power, except in the south where recent temperatures are more influential than recent rainfall.

The first tenure class, and/or lightning strike density, are among the first two terms output by the stepwise glm regression for all of the ignition source indices. A negative relationship between roads and percentFAA is most important in the north, although individually it only explains 2% of the deviance. These ignition source indices explain 4-17% of the deviance.
Table 6.5 Percentage of deviance explained by individual variables used in full model, including transformations

Dependant variable for Biomass, Curing and Ignition Indices = PercentFAA
Dependant variable for Weather Index = Burnt(Y/N) FHS
Transformations: \( L = \log(1+X) \), \( S = \sqrt{X} \), \( 2 = X^2 \)

* negative relationship with PercentFAA
ns – result not significant, p value < 0.05

See table 6.3 for legends of soil, vegetation and tenure

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Table 6.6 Full Model - Percentage of deviance explained using stepwise glm models for each index
Dependant variable for Biomass, Curing and Ignition Indices = PercentFAA
Dependant variable for Weather Index = FHS (Y/N)
Transformations: $L = \log(1+X)$, $S = \sqrt{X}$
* negative relationship with dependant variable
See table 6.5 then table 6.3 for legends of soil, vegetation and tenure

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<tr>
<th>Model Output</th>
<th>North % explained</th>
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<th>Mid % explained</th>
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<td>Lightning</td>
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<td>Rel. Humidity*</td>
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The fire weather indices add little to the explanation of deviance. The highest percentage of deviance explained is for the north (over 4.5%), and the lowest for the south (1%). Relative humidity explains most of the deviance in the north, west and overall, while maximum temperature explains most in the mid and south regions.

In general, although a greater percentage of the northern region was burnt, the indices (apart from the fire weather index) were able to explain less of the deviance for this region than any other.

6.6 Discussion

Results of our analysis show that the strongest influence on the percentage of area burnt (PercentFAA) is exerted by biomass or fuel load, with a strong dependence on antecedent rainfall, and then either vegetation or soil. Surfaces, developed from a matrix of rainfall lag/phase periods, highlighted discernable regional differences. In the north and mid climate categories, the best predictor of FAA extent is from rainfall in the previous 12 months, while in the west and south cumulative rainfall in the previous 24 months is the best predictor (with differing lag/phases). These results are in general agreement with findings from other studies.

Russell-Smith et al. (2007b) performed a quantitative assessment of the spatial variance (using static variables) of the FAA and FHS data, on a similar scale to this study (0.50° × 0.50°, n = 3,025), with reference to broad seasonal rainfall classes (10 classes derived from unsupervised classification of 35 years of quarterly rainfall data). They found that RAINCLASS alone explained ~60% of the deviance in annual average FAA extent for the entire country in their best landscape model, with measures of dominant fuel type and land parcel size explaining a further 10%.

Griffin et al. (1983) found that total area burnt by fires in central Australia (the southern half of the Northern Territory) between 1970 and 1980 was best explained by rainfall in the preceding 2 years. However, they only included fires that had been reported on pastoral properties, and fire regimes in this area have changed in recent years (Edwards et al., 2008). In contrast, Turner et al., (2008) (Chapter 5) examined temporal variations in fires on a broad scale between 1998 and 2004 throughout all arid and semi-arid Australia, and established a positive linear relationship between annual rainfall categories (10 categories at 200 mm intervals) and the percentage of FAA in each category the following year (n = 41, r2 = 0.86). While not the main focus of their study, Russell-Smith et al. (2007b) also examined temporal variation in fire extent for each RAINCLASS. They modelled the dynamic variables rainfall, NDVI and prior fire against variations in annual FAA. Annual rain in the preceding year (not the same year as the fire) explained the most deviance in fire extent in the northern semi-humid, central arid and southern arid RAINCLASS categories (which correspond generally to our study area). Coupled with various combinations of prior fire, annual rain in the preceding year explained 21% of deviance in the north, 18% in the centre, and 11% in the south.
This compares well with our biomass index results. Using a different approach (we did not include prior fire, but did include both spatial (static) and temporal (dynamic) indicators of the risk of fire), we were able to improve on the results of Russell-Smith et al. (2007b). Antecedent rainfall, with either vegetation or soil, explained the majority of deviance (22%, 32%, 29% and 27% of deviance explained in our north, west, mid and south climate categories respectively). We have demonstrated the importance of employing a systematic comparison of different lag/phase combinations to find the best predictor for each region (lag/phase 3/9 explained 18% of deviance in the north, 6/18 23% in the west, 6/6 22% in the mid, and 9/15 11% in the south). This variable alone produced similar results to the temporal models of Russell-Smith et al. (2007b) for these areas. Displaying this type of analysis as a surface for the first time has revealed the patterns for each region. Our analysis has shown that simply choosing cumulative rainfall from one season, or an entire year, does not adequately reflect the differences in rainfall, vegetation growth, curing, and fire seasonality between regions (see results section for details).

Various combinations of soil, vegetation and tenure accounted for the remainder of deviance explained by the biomass index. We have also illustrated that the relationship with the dominant soil, vegetation or tenure in a region is not necessarily the best predictor of fire extent. For example, while hummock grasslands and sands dominate the north and are the most fire prone areas, it is the individual negative relationships with tussock grasslands and cracking clays which are better predictors of fire extent. Once again, this shows the importance of a systematic examination of all major variable types within a region when building a model.

The curing index we developed (based on recent rainfall, recent temperature, soil, and vegetation type) was able to explain 13% of deviance in the north, and ~30% of deviance in all other regions. There would be some overlap with the biomass index however, as they both use soil and vegetation types as independent variables. There are no other studies modelling curing in arid and semi-arid Australia with which to make comparisons.

The ignition source index explained between 5% (north) and 17% (south) of deviance in fire extent. The lightning data explained little of the deviance, except in the west. Unfortunately, our data does not indicate the timing of the lightning (Kuleshov et al., 2006). Using real-time lightning data from the World Wide Lightning Location Network (Lay et al., 2004), Russell-Smith et al. (2007b) found poor temporal associations comparing FAA and lightning seasonality in their northern semi-humid region, better in the central arid region, and relatively good in the southern arid region.

One hypothesis is that anthropogenic fires are more likely to occur near settlements and along roads and tracks. However, Russell-Smith et al. (2007b) hypothesised that the use of fire as a management tool is expected to be greater in landscapes where property sizes are large, and that wildfire would also be greater here, as the capacity to exclude or control it is lower. They modelled this using property sizes over 40 ha to eliminate most urban developments. Our modelling of
population and road density seems to support this theory at first glance, with negative relationships with FAA, apart from population density in the west. However, the deviance explained by population density is minimal, and although the relationships with road density were all negative, examination of the individual FAA records revealed that while a few fires were more than 100 km from the nearest road, over 50% of mapped burnt patches were in contact with a road, a further 10% within 1 km (the pixel size of the original FAA data), and yet another 10% within 3 km. In Central Australia, during the 2000-02 fire event, roadside ignitions by Aboriginal travellers were responsible for many of the large fires (Edwards et al., 2008).

The weather index explained least deviance in fire occurrence overall. The current fire danger indices based on empirical analysis are still the most appropriate for short-term predictions (Cheney et al., 1998; McArthur, 1966, 1967). These however could be improved for our study area by incorporating research already carried out in some areas of arid and semi-arid Australia (Burrows et al., 1991; Burrows et al., 2006c; Griffin and Allan, 1984, 1993), as well as new research.

Measurements of NDVI were treated as separate models, to test if NDVI captures variation in seasonal shifts in vegetation condition (biomass accumulation and curing) better than combinations of other variables. The best result for an NDVI biomass index was the 13% deviance explained in the north. For the NDVI curing index, the best result was 3% in the west. It should be remembered that a loss of greenness does not necessarily indicate curing, it could also be reflecting other factors such as consumption of vegetation by animals (domestic livestock, native or feral), or removal by humans or fire. This NDVI curing index presented here (highest value for the previous 12 months minus value from previous month) would only apply to annual vegetation species. No attempt was made to model curing in perennial vegetation. Compared to both the NDVI biomass and NDVI curing indices, previous rainfall alone, proved to be a far better indicator of PercentFAA. Russell-Smith et al. (2007b) also found variations in rainfall to be a better predictor in these regions, although NDVI was better in some other environments (e.g. southern mesic and east coast semi-humid).

NDVI and many other widely used vegetation indices are inappropriate in arid and semi-arid environments of Australia where perennial vegetation dominates. These plants often lack the contrast between red and infrared reflectance upon which the common vegetation spectral indices are based, making them difficult to distinguish from red coloured soils (Jafari et al., 2007). Several alternative multispectral indices that place less emphasis on vegetation infrared response may be more appropriate (O’Neill, 1996; Pickup et al., 1993). The new index under development by the Bushfire Cooperative Research Centre, to access grassland curing across Australia and New Zealand, will also hopefully prove to be more useful (Bushfire CRC, 2009).
Overall, our rigorous, systematic, exploratory approach to modelling, making few pre-conceived assumptions about relationships between the fire data and independent variables, has proved very useful in building the best model possible from the available data.

As an exploratory exercise, the findings of this research are not intended to be used directly in predicting future large wildfire events. But they can serve as a basis for dialogue about which climatic, edaphic and anthropogenic factors are most important for assessment of fire risk in different regions of arid and semi-arid Australia during the seasonal bushfire assessment workshops (Bushfire CRC, 2007, 2008; Lucas et al., 2006). Our models have shown some skill in forecasting, which demonstrates that further research in this direction is worth pursuing. This research provides guidelines for the development of the structure and spatial detail of more robust long-lead predictive models, following refinement of the techniques put forward in this paper.

Our research has highlighted areas where better data is required. It was fortunate that the Bureau of Meteorology’s lightning data coincided fairly closely with the timeframe of our fire data (Kuleshov et al., 2006), although it does not contain information on the seasonality and timing of lightning strikes. The on-going development of the LPATS system in more remote areas should see the availability of far more accurate lightning data in the not too distant future. Within the vegetation dataset, buffel grass (Cenchrus ciliaris) is not yet mapped. This perennial grass, which was introduced to Australia for pasture and landscape rehabilitation, is rapidly taking over new environments, and has the potential to change fire regimes in many areas (Butler and Fairfax, 2003; Friedel et al., 2006; Pitt, 2004). As already stated, vegetation indices more suited to arid and semi-arid environments should be investigated. The most obvious limitation of this study however, is that the fire data covers only seven years, while fire return intervals in much of this dry country can vary from a couple of years to 30-50 years. We were fortunate in the fact that the data does cover years of average fire activity, as well as a period of widespread fires following above average rainfall in parts of the country, and that it covered all of arid and semi-arid Australia. While we were unable to model past fire (time since last burnt), the fire data does show that, given adequate rainfall, even in arid regions biomass accumulation can be sufficient to burn again soon after a previous fire (figure 6.3). This has important implications for strategic long-term management. A longer time series of fire data will provide further insight.

Long-lead forecasts can help mitigate the effects of large wildfire seasons by offering a window of opportunity for strategic planning. With a better understanding of the factors in play, we may also be better able to predict when prescribed fires will burn effectively but not uncontrollably. It may also be possible to alter and manipulate some of the environmental and social factors that play a part in the process.

The goal of developing a better awareness of regional patterns across different land tenures, can hopefully be utilised to encourage a more cooperative and coordinated approach to fire
management between political jurisdictions, landowners and managers, cultures and individuals, and prevent the animosity which arose between Aboriginal land owners and pastoralists during the 2000-02 fires. There is the opportunity to actively involve the many Aboriginal communities throughout these lands, who have a great desire to care for country, in fire management. The challenge is for conservation and land management agencies to develop processes that enable Aboriginal people to participate in land management in a meaningful and mutually beneficial manner (Burgess et al., 2005; Burrows et al., 2006c).

This work may also serve as the foundation for simulation models of future wildfire distribution, to test the effects of changes in climate, vegetation, land tenure, population demographics, or management strategies on the fire regimes in different areas. The fire regime has already been altered significantly in parts of the country following the departure of Aboriginal people and the cessation of traditional burning (Burrows and Christensen, 1991). Evolution is continuing, and even since the previous large fire event in central Australia in the 1970’s much has changed. Australia has experienced increases in rainfall across the north-west, but decreases over much of the south-east, and a rise in average temperatures (Pittock, 2003). There has been an invasion of fire-prone buffel grass (Cenchrus ciliaris), which has the potential to change fire regimes in many areas (Butler and Fairfax, 2003; Friedel et al., 2006; Pitt, 2004). A substantial amount of land has been transferred back to Aboriginal ownership or stakeholder interest, and more is likely through future land purchase and native title claims (Pollack, 2001). With this has come the emergence of numerous outstations (dispersed, small and discrete settlements on Aboriginal lands) (Brown et al., 2008). Between the 1996 and 2001 population census, the overall indigenous population of arid and semi-arid Australia grew, while the non-indigenous population declined, although patterns are vastly different in various regions (Brown et al., 2008), and there has been an increase in accessibility to remote areas (Edwards et al., 2008). In central Australia, there was an increase in fire activity in the cooler months of March-August during the 2000-02 fires, compared to those of 1974-77. Most of these cool season fires originated along roads, and were likely to have been started by human ignition, given the absence of storms (Edwards et al., 2008). All of these changes have the potential to alter fire regimes. Research must continue, and better databases need to be developed. Basing predictions of what is likely to happen in the next severe fire season in arid and semi-arid Australia, purely on what happened in 2000-02, would be very short sighted!
Chapter 7

CONCLUSIONS
7.1 Conclusions

As discussed in the introduction to this dissertation, due to the lack of objective knowledge of past and current fire regimes in arid and semi-arid Australia, and the complicated relationships between fire regime and its drivers, management of fire in these areas has been hampered. This dissertation makes a marked contribution to this knowledge gap. After validating the NOAA AVHRR fire databases in the arid and semi-arid areas for the first time, significant advances are made in describing the current patterns of fire for the entire area, as well as in experimental modelling of spatial indicators of the processes involved in producing these patterns. These will be discussed below within the context of the aims and objectives of this dissertation.

Arid and semi-arid Australia are remote and sparsely populated areas, where rainfall is low and unpredictable, and the terrain is too inhospitable for sustainable cropping or timber harvesting. The pastoral industry is the major land user, utilising the saltbush, mulga and grassy plains. Aboriginal lands are most often associated with the spinifex-covered sand plains and stony deserts, while nature conservation parks and reserves form another significant landuse. Pulses of heavy rain over weeks at a time occur rarely, but can lead to widespread wildfires following increased fuel loads and fuel continuity. Although little knowledge has been gained about past fire regimes in these dry climate zones, it is believed that both natural and Aboriginal burning created fire regimes upon which many of the areas highly unique and diverse range of plants and animals from these regions depend.

Since European settlement, fire regimes have altered, and are continuing to do so, through changes in landuse and tenure, vegetation, population demographics and accessibility. Management priorities and objectives (including traditional Aboriginal management, suppression, or prescribed burning for fuel reduction, sustainable land use, biodiversity or research) are different for the major stakeholders, and also vary between regions. But these too have changed over time. Many Aboriginal communities are now at risk of loosing their knowledge of traditional burning, while other Australians struggle to understand the processes at work, and adapt their management styles with increasing knowledge.

Much of arid and semi-arid Australia is now suffering from severe degradation or desertification, with the replacement of perennial grasses by inedible woody shrubs a major problem in many pastoral areas. It has also been affected with major extinctions and contractions of range among its native biota. Nearly half of the rangelands’ original native mammals are now gone, and some birds and reptiles are declining. There has been a gradual loss of fire sensitive woodland and shrubland that is being replaced by spinifex grassland in many areas. These problems are due in
part to the altered fire regimes. But it is now recognised that prescribed fire is one of the few cost-effective tools available for maintaining that biological diversity, and controlling woody weeds.

Formal fire management acts, policies, guidelines and plans have evolved greatly in the last few decades nationwide, but particularly in the past few years. Individual states are generally aiming for a holistic adaptive management approach, but are all at different stages of achieving this goal. The arid and semi-arid regions are usually not high on the priority list in this formal process, due to the relative infrequency of large fire events here; while operationally, the lack of funding, manpower, resources and access often means that wildfires are left to burn unless they are perceived to be directly threatening life or property. There is also a lack of empirical knowledge of both past and present fire regimes in these regions, and the ecological effects that different regimes have in the various landscapes. It is therefore difficult to know what the ‘appropriate’ regimes for the present might be.

Until recently the greatest majority of the rangelands had no mapped fire history. The availability of two fire datasets, (active fire - Fire Hotspots (FHS) and burnt area - Fire Affected Area (FAA)), derived from NOAA AVHRR satellite imagery, have now given us a continuous picture of fire events across the entire continent since 1998 at a 1 km resolution. This data has been developed by Satellite Remote Sensing Services at Landgate (the Western Australian Land Information Authority; formerly known as the Western Australian Department of Land Information (DLI), and before that, the Department of Land Administration (DOLA)), and used operationally for a number of years to produce publicly available fire locations online.

Seven years of FHS and FAA data was purchased from Landgate for this project (1998-2004). In order to perform the analysis for this dissertation it was necessary to assemble other fire data for validation, as well as a suitable comprehensive digital spatial database of climatic, edaphic and anthropogenic variables on which to base assessments. For these variables, direct data sources were identified where possible, and spatial surrogates substituted elsewhere. Databases were acquired from various government agencies mostly. An attempt was made to purchase some additional data from private sources (particularly lightning data), but to no avail. Most datasets underwent manipulation to some degree, to conform to the format and standards required for analysis. Various parameters within the assembled database were used in various analyses in this dissertation.

Although the FHS and FAA data is used operationally across the country, there has been nothing published on validation of the data in the arid and semi-arid regions (70% of the continent). This dissertation compares the FHS and FAA data with higher resolution Landsat-derived fire maps at 11 sites, using a number of different approaches which have been used elsewhere in the published
literature. Despite the fact that rigorous validation was not possible for much of the data as there was no ground-truth data available, this analysis still gives a good indication of the reliability and accuracy of the data. It also highlights some of the difficulties in mapping lower intensity fires in discontinuous fuels in the highly reflective desert soils in particular.

Taking these limitations into consideration, both the FAA and FHS datasets were analysed within a GIS (Geographic Information System) framework, to quantify some aspects of fire regime (distribution, seasonality, frequency and extent of fires) for the whole of arid and semi-arid Australia for the first time. This was done at a number of different scales, for the period 1998 to 2004. Other fire regime metrics such as fire intensity, internal patchiness, or return interval could not be measured from this data. While this is a fairly short time frame, it is very significant because it captured, for the first time, the extent of burning in the whole of arid and semi-arid Australia following a period of above average rainfall. This analysis highlights similarities and differences between regions, giving policy makers and managers a basis from which to make more informed decisions in the present, and with which to compare future regimes.

A major problem in these areas is predicting if, and when, mitigating action needs to be taken to avert large wildfires, as resources are often not available to bring them under control once underway. As these events have been relatively infrequent in the past, it is difficult to alert people, who may not have experienced such an event in the past, to the danger, (especially when there was no mapped record of such events). There are a range of fire models available at different temporal and spatial scales, for a variety of forecasting and modelling purposes, none of which have been used to any great extent in arid and semi-arid Australia. In the original project proposal, the author suggested that long-lead seasonal forecasting, as had just been instated in the US, was the way forward for arid and semi-arid Australia. During the course of this project, this has become a reality. There have now been three annual workshops, where experts from around the country gather to produce the Fire Potential Outlook for the entire country for the upcoming fire season. This will assist strategic long-term planning, and the chance of timely and cost-effective intervention initiatives when necessary. This could also help to maximize the limited available funding and resources.

This type of seasonal forecasting has brought about a new type of statistical regression model, producing spatial indicators of seasonal wildfire risk, using many different techniques and fire-climate relationships, in an effort to refine predictions. It has been stated many times that rain is the driving force behind desert fires in Australia with a number of localised studies showing a significant relationship between the occurrence of fires, and rain in the preceding two to three years. In this dissertation, initial regression analysis of the 1998-2004 data on a broad scale (10
rainfall categories in 200mm steps), showed a strong relationship between fire and rainfall in the previous year.

A more in-depth analysis of the 1998-2004 fire data was then undertaken, at both a continental and regional level. A conceptual framework was developed on which to base geo-statistical analysis, and experimental regression analysis modelling. This is the first such analysis of fire in arid and semi-arid Australia as a whole. The results provided new insights into the complexities of the driving forces of fire in these areas, and the differences between periods of low fire activity compared to a less frequent high fire episode. Systematic analysis of the relationship between FAA and antecedent rainfall (using various combinations of time lag and phase) was performed. Presenting this large amount of data visually helps identify the most important relationships for different regions. Analysis of the other independent variables was performed to elucidate their relative strength of influence, and predictive capability on forecasting FAA in arid and semi-arid Australia on a regional basis. The strongest combinations were included in a final model, which is different for each region. This analysis was undertaken at a finer scale than the initial broad-scale analysis of rainfall categories above. This resulted in much smaller $r^2$ values, reflecting the stochastic nature of the fire data at this scale. Results from this analysis may help in refining the annual Fire Potential Outlook for these areas. This analysis has highlighted regional patterns of fire across different land tenures. Heightened awareness of these patterns may encourage a more cooperative and coordinated approach to fire management amongst stakeholders.

Overall, this dissertation cannot totally define the fire regimes of arid and semi-arid Australia, due to the short time span of the data. Nor does it attempt to provide a definitive model for long-lead fire forecasting for these areas. Rather, a significant scientific contribution has been made towards these goals, and to the development of a structure under which to do it.

7.2 Future Directions

Strategic fire planning is essential in the arid and semi-arid rangelands of Australia, as fire management is constrained by limited resources, and the vastness and remoteness of these regions, with poor accessibility to many areas. But management is hampered by imperfect knowledge of fire regime, fire behaviour and fire effects. In the past, there has been little impetus from individual landowners and land managers to manage for wildfire, as they are a relatively rare occurrence on individual properties. An ability to predict fire danger for an upcoming season is fundamental to proactively managing fire in these regions, such as implementing patch-burn strategies and buffer burns to benefit biodiversity and to limit the impact of wildfires when it is necessary. Studies such as this one must continue to advance our knowledge of fire regimes and their drivers, to provide support for strategic planning and geographic priority-setting.
NOAA-AVHRR imagery has provided a database of fire activity over the continent for the last decade, and these datasets are now being complimented by the higher resolution MODIS data. Definition of current fire regimes is improving through analysis and interpretation of this satellite imagery, but we must continue to map both active fires and burnt area at a continental scale to build up our knowledge of fire regimes. Areas of particular interest should also be continually mapped at a fine scale resolution.

“Variability and heterogeneity in fire regimes are seldom quantified. Yet they have profound implications for the ecological effects of fire, and our ability to infer and understand fire regimes themselves, especially over large areas and long times (Keane et al. 1990; McKenzie et al. 1996b; Lertzman et al. 1998; Schmoldt et al 1999)” (Allan, 2003).

Analysis of these databases over time will increase our understanding of the high variability of fire regimes in arid and semi-arid regions. It will help quantify the three kinds of heterogeneity in the fire regimes: internal heterogeneity of individual fires, and both the spatial and temporal heterogeneity of fire regimes. Analysing this information on a regional basis will reduce the use of widespread generalisation with regard to fire regimes that are not relevant in many regions. It will also give us insight into how these regimes are continually evolving over time through changes in landuse and tenure, vegetation types, population demographics, accessibility, management strategies and climate change.

This dissertation has highlighted some unique issues with mapping fire in arid and semi-arid Australia, but more funding needs to be allocated to rigorously validate this data in these regions. While it can be difficult to organise the collection of ground truth data in these remote areas at times of infrequent fire, a coordinated effort must be made to do so, which is representative of all landscape types and climate zones in these regions. The results of such validation should then be used to improve the algorithms used in fire detection where possible.

Following on from the immediate aftermath of major fires around the country at the turn of the century, and recommendations put forward by a number of ensuing enquiries, there have been great advances made in updating laws and policies, and developing fire management strategies and plans, in the last few years. The challenge now is to continue that impetus in times of lesser fire activity in arid and semi-arid regions. It remains to be seen how well these will be implemented, monitored and altered where necessary, within an adaptive management framework.
Hazard reduction burning is recognised as one of the most cost-effective methods of controlling wildfires in arid and semi-arid Australia. The models put forward from exploratory regression analysis in this dissertation can help to identify the areas most at risk for an upcoming fire season. But these models could be greatly improved upon. With increased funding, other datasets and models could be incorporated into the analysis. The models could be used to test the effects that changes in climate or management strategies, for example, might have on the fire regimes. Understanding these changes will help address future management issues. There is also a need for analysis and simulation of the effectiveness of programs of controlled burning in reducing bushfire risk at the landscape scale (Cary, 2005).

It is imperative that anthropogenic fire is reintroduced into some landscapes to prevent further declines in ecosystem health, and to maintain or increase diversity of resident biota. But care must be taken to ensure that its use is not continuing the observed decline in environmental value and biodiversity. While responses of some taxa and communities to fire regimes are reasonably well-known, considerable challenges still remain in defining optimal fire regimes for others. More research is needed to improve our understanding, including detailed studies of interactions between declining floral and faunal species and fire regimes, empirical fire regime experiments, and computer modelling. This should be tempered with insight from traditional owners and other experts. While many agencies have recently produced some form of fire regime guidelines, this research is still in its infancy. Many rely on the best expert knowledge available, and are in fact, yet-to-be tested hypotheses. Until our understanding increases through adaptive management in a cycle of testing, monitoring and improving these postulated regimes, a conservative approach should be taken.

There are currently not enough trained people or resources in sparsely settled arid and semi-arid regions to implement mosaic burning on a large scale. Part of the solution is to train and provide resources to Indigenous ‘fire teams’ where appropriate. This is currently happening in a number of areas through Working on Country projects, which are part of Caring for our Country, the Government's new natural resource management initiative (DEWHA, 2008). Such projects provide applied education, employment opportunities and natural resource management outcomes. They also have the potential to provide other health (both physical and mental), social, cultural, economic, and environmental benefits to people, by them routinely being on their land (Burgess et al., 2005; Johnston et al., 2007b). There are many more Aboriginal communities in arid and semi-arid Australia, with detailed complex knowledge and skills in fire management, and the desire to pass this onto the younger people so they can care for country, who could benefit from such opportunities (Burrows et al., 2006c). It is imperative that such projects take into account the diverse nature of individual communities, and take time to understand local situations,
social structures, culture, politics and land rights issues. De-centralized decision-making processes should be adopted that give the appropriate indigenous people a real say in managing the land (Aslin and Bennett, 2005). Special attention should be paid to fire management of outstations, which have not been managed by traditional burning for some time, and where traditional knowledge may have been lost.

Satellite-derived fire datasets are currently used to estimate biomass burning and greenhouse gas emissions in the savannas (AGO, 2006; Beringer et al., 1995; Meyer, 2004; Meyer et al., 2008; Russell-Smith et al., 2003b; Russell-Smith et al., 2009). In 2008, prescribed burning of savanna (i.e. emissions associated with the burning of tropical savanna and temperate grasslands for pasture management, fuel reduction, and prevention of wildfires) accounted for almost 2% of Australia’s national greenhouse gas inventory (DCC, 2009). The fires in arid and semi-arid Australia between 2000 and 2002 would also have contributed to significant greenhouse gas emissions. Efforts need to be made now in estimating emissions from fires in the arid and semi-arid zones, and modelling how these may alter in the face of climate change.

The success of fire management in arid and semi-arid Australia relies on continued funding and increased resources, for planning, coordination and implementation, and for further research. This dissertation may help to highlight the importance of maintaining the momentum in these regions to politicians, in the fight for the limited funding available nationwide.


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NOTE:
The appendices are on a CD included with the print copy of the thesis held in the University of Adelaide Library.