Understanding Wildfire Patterns in the South-Eastern Australia

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Understanding Wildfire Patterns in the South-Eastern Australia

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Wildfires affect ecological processes, threaten human lives and cause economic losses. Understanding of fire patterns is required to better support the planning of sustainable fire management and risk reduction activities. Fire occurrence and fire size are two essential fire pattern components that describe the distribution of fires and the impacts of fires on landscapes and ecosystems. They vary substantially within and between regions due to variation in weather, fuel, topography and ignition sources. In this thesis, remotely sensed and administrative records as well as Generalised Linear Models and Generalised Additive Models have been used to understand fire occurrence patterns in the south-eastern part of Australia, as well as to obtain knowledge on the patterns of fire occurrence and fire size in the inland semi-arid riverine area.

The results suggest that in the south-eastern Australia, wildfires are more likely to occur in mountainous areas, forests, savannas, and in areas with high vegetation coverage and near human infrastructures, while they are less likely to occur on grasslands and shrublands. Environmental variables are strong individual predictors while anthropogenic variables contribute more to the final model. Fire-ignition drivers and their effects vary across ecoregions. There are non-linear relationships between the probability of fire ignition and some of its drivers e.g. the Normalized Difference Vegetation Index.

This study also reveals that on the NSW side of the Riverina bioregion, human-caused fires mostly occur in spring and summer while natural fires are clustered in summer. Forested wetlands and dry lands experience summer and spring-summer fire regime, respectively. Fire probabilities are higher in forested wetlands than in dry lands and in areas with intermediate inundation frequencies. Weather, fuel and ignition sources are comparably important in regulating human-caused ignitions, while weather contributes more than fuel in driving natural ignitions. Larger-size Fires that burned Entirely in forested Wetlands (FEW) are associated with higher ambient rainfall conditions of the 6th, 13-14th and 17-18th months before fires. Fire danger index is more powerful than other ambient weather factors in explaining the FEW size. The contributing and the most effective factors become different when fires burned in dry lands are incorporated.

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List of Publications

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Posters and Presentations

ZHANG, Y., LIM, S. & SHARPLES, J. J. Contributing Factors to Wildfire Size in the Inland Riverine Environment of Australia. Global Security PLuS, 19 July 2017, UNSW, Sydney, Australia.

'Drivers of Wildfire Occurrence Patterns in Wetlands of Riverine bioregion in New South Wales, Australia' European Geosciences Union General Assembly 2017, 23-28 April 2017, Vienna, Austria.

'What is Happening in Inland Wetlands?' Bushfire and Natural Hazards Cooperative Research Centre Research Advisory Forum, 17-19 Oct 2016, Canberra, Australia.

'Development of spatial models for bushfire occurrence in South-Eastern Australia' 21st International Congress on Modelling and Simulation, 29 Nov - 4 Dec 2015, Gold Coast, Australia.

Abstract

Wildfires affect ecological processes, threaten human lives and cause economic losses. Understanding of fire patterns is required to better support the planning of sustainable fire management and risk reduction activities. Fire occurrence and fire size are two essential fire pattern components that describe the distribution of fires and the impacts of fires on landscapes and ecosystems. They vary substantially within and between regions due to variation in weather, fuel, topography and ignition sources. In Australia, understanding of fire occurrence patterns in the south-eastern part of the continent is important since fires can cause massive life and property losses in this densely populated area. Knowledge on the occurrence and size of fires in the inland semi-arid riverine area of the south-eastern Australia is also required because fires have distinctive impacts on this particular environment. The main purpose of this thesis is to explore fire patterns and their regulating factors in the above-mentioned two landscapes. Insights obtained from this study are expected to support strategic and tactical levels of decision-making in terms of fire management in the south-eastern Australia.

This thesis investigated the relationships between fire patterns and their determinants using Generalised Linear Models and Generalised Additive Models. Remotely sensed and administrative records have been used as sources of fire observations. The results of the broad-scale fire activity analysis reveal that in New South Wales (NSW), Australian Capital Territory (ACT) and Victoria (VIC), wildfires are more likely to occur in mountainous areas, forests, savannas, and in areas with high Normalized Difference Vegetation Index (NDVI) and near human infrastructures, while they are less likely to occur on grasslands and shrublands. Environmental variables are strong individual predictors while anthropogenic variables contribute more to the final model. The ecoregion-based fire ignition analysis suggests that the fire-ignition drivers and their effects vary across regions of NSW and ACT. Findings throughout this study include

that spatial effects are key regulators of fire ignition in all the ecoregions, vegetation factors drive fire ignition in most of the ecoregions, climate gradients affect fire ignition in ecoregions with relatively broad areas, and anthropogenic factors are fire-ignition regulators in the most populated and two sparsely populated ecoregions. Fires tend to start from areas with low annual precipitation and high mean January maximum or July minimum temperature. They are less likely to ignite from rainforests or wet sclerophyll forests than in dry sclerophyll forests. There is a non-linear relationship between NDVI and the ignition probability, with small to medium levels of NDVI showing a positive effect on the chance of a fire getting started. Fires are also likely to occur near human facilities and at non-protected areas in some ecoregions, but away from roads in one ecoregion.

The study on the ignition of fires on the NSW side of the Riverina bioregion reveals that the largest number of fires occur in summer, with human-caused fires mostly occur in spring and summer while natural fires are clustered in summer. Forested wetlands and dry lands experience summer and spring-summer fire regime, respectively. Fire probabilities are higher under severe weather conditions, in areas with higher annual rainfall, in forested wetlands than in dry lands, as well as in areas with intermediate inundation frequencies. The ignition of human-caused fires is strongly associated with the human accessibility to the natural landscape. Weather, fuel and ignition sources are comparably important in regulating the ignition of human-caused fires, while weather contributes more than fuel in driving the ignition of the natural fires. In terms of fire size, higher cumulative rainfall conditions of the 6th, 13-14th and 17-18th months before fires are associated with larger size of Fires that burned Entirely in forested Wetlands (FEW), while the cumulative rainfall after the 18th month before fires positively affect the size of fires when Fires burned Partly in forested Wetlands (FPW) and Fires that did Not burn in forested Wetlands (FNW) are incorporated. A larger fire extent is also driven by severer ambient weather conditions, with fire danger index more powerful in explaining the size of FEW, while the daily temperature becomes more effective when FPW and FNW are gradually incorporated.

Abbreviations

ABS: Australian Bureau of Statistics

ACLUMP: Australian Collaborative Land Use and Management Program

ACT: Australian Capital Territory

AIC: Akaike Information Criterion

ALUM: Australian Land Use and Management

ASEC: Australian State of the Environment Committee

ASTER: Advanced Spaceborne Thermal Emission and Reflection Radiometer

AUC: Area Under the Curve

AVHRR: Advanced Very High Resolution Radiometers

BOM: Bureau of Meteorology

CFA: Country Fire Authority

CLUM: Catchment scale Land Use of Australia Map

COAG: Council of Australian Governments

DA: Department of Agriculture

DAWR: Department of Agriculture and Water Resources

DEE: Department of the Environment and Energy

DELWP: Department of Environment, Land, Water and Planning

DF: Drought Factor

DSEWPaC: Department of Sustainability, Environment, Water, Population and Communities

DX: Deserts and Xeric shrublands

ENSO: El Niño-Southern Oscillation

EVI: Enhanced Vegetation Index

FFDI: Forest Fire Danger Index

FFMG: Forest Fire Management Group

FSR: Fire Spread Reconstruction

GA: Geoscience Australia

GAM: Generalized Additive Model

GCV: Generalized Cross Validation

GDEM: Global Digital Elevation Model

GFDI: Grass Fire Danger Index

GLM: Generalized Linear Model

GWR: Geographically Weighted Regression

FEW: Fires burned Entirely in forested Wetlands

FPW: Fires burned Partly in forested Wetlands

FMI: Fuel Moisture Index

FNW: Fires that did Not burn in forested Wetlands

IBRA: Interim Biogeographic Regionalisation for Australia

IGBP: International Geosphere Biosphere Program

KBDI: Keetch-Byram Drought Index

LGA: Local Government Area

MF: Mediterranean Forests, woodlands and shrubs

MG: Montane Grasslands and shrublands

MODIS: Moderate Resolution Imaging Spectroradiometer

NDVI: Normalized Difference Vegetation Index

NOAA: National Oceanic and Atmospheric Administration

NRC: Natural Resources Commission

NSW: New South Wales

OEH: Office of Environment and Heritage

OSM: OpenStreetMap

REML: REstricted Maximum Likelihood

RFS: Rural Fire Service

ROC: Receiver Operating Characteristics

SPOT: Satellite Pour l'Observation de la Terre

SPP: Spatial Point Process

TB: Temperate Broadleaf and mixed forests

TG: Temperate Grasslands, savannas and shrublands

TM: Thematic Mapper

TSG: Tropical and Subtropical Grassland, savannas and shrublands

VIC: Victoria

VIF: Variance Inflation Factor

WUI: Wildland Urban Interface

WWF: World Wildlife Fund

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Chapter 1 Introduction

1.1 Background

Wildfires have occurred across the globe, especially during the past decade (Bradstock *et al.* 2012). Wildfires affect ecological processes such as vegetation and animal community structures, biogeochemical cycles and the climate (Bowman *et al.* 2009), threaten human lives and cause substantial economic loss (Gill 2005; Taylor *et al.* 2013). Understanding wildfire patterns is essential for planning risk reduction and ecologically friendly fire management. Fire occurrence and size have been used to describe fire patterns. Fire occurrence depicts the ignition or activity of fires within a particular spatial and temporal unit (Romme 1980; Finney 2005; Plucinski 2011) and is a key concept in understanding the distribution of fires. Fire size describes the pattern and extent of a fire that has spread within a landscape (Ryan 2002) and is an essential component of fire regime that determines the impact of fires on landscape dynamics and ecosystem processes (Turner *et al.* 1997; Turner 2010). Both measures are important for fire management planning and risk reduction activities (Chuvieco *et al.* 2010; Price and Bradstock 2011; Fang *et al.* 2015).

Australia is recognised as one of the most flammable continents in the world. Fires that occur in the south-eastern part of Australia are major concerns because they can result in massive life and property losses in this densely populated area (Russell-Smith *et al.* 2007). In particular, New South Wales (NSW), the Australian Capital Territory (ACT) and Victoria (VIC) have been identified as three of the most fire-prone regions in Australia (e.g. Collins *et al.* 2015). Therefore, broad-scale fire patterns that cover these three regions are worthy of exploration. In the semi-arid riverine plain of south-eastern Australia, fires are known to be beneficial for some native species (Gill 1975; Bond and Keeley 2005), however they also threaten fire-sensitive species such as *Eucalyptus camaldulensis* (river red gum), which is an iconic vegetation species in inland riverine areas (Dexter 1978, as cited in CSIRO 2004). Fires in this environment may also lead to soil degradation, bank erosion, channel migration, increased weed invasion and the loss of timber (Allen 2000; Owens *et al.* 2013). The impact of wildfires on the wetland environment and local communities may be exacerbated by climate change and urban expansion (Schneider and Sutherland undated). Therefore, the regional scale fire pattern in the semi-arid riverine environment of Australia warrants special attention.

Wildfire patterns are generally controlled by top-down and bottom-up processes that reflect variations in weather, fuel, topography and ignition sources across multiple scales (Moritz *et al.* 2005; Gill and Taylor 2009; Parisien and Moritz 2009; Parks *et al.* 2012). Weather-related factors regulate wildfire patterns by affecting short-term and long-term fuel moisture and availability (Sullivan *et al.* 2012). These factors include ambient and antecedent weather/climatic conditions that affect the distribution of fire occurrence and the overall area burned (Bradstock 2010; Turner *et al.* 2011; Cary *et al.* 2012); the area burned is positively correlated with the size of an individual fire (Gill and Allan 2008). Ambient weather conditions such as temperature, relative humidity, precipitation and derived indices such as the moisture content of fuels, drought conditions and level of fire danger regulate the chance of a fire by providing the moisture condition suitable for a fire to ignite (Chou 1992; Bradstock *et al.* 2009; Vilar *et al.* 2010a; Taylor *et al.* 2013). They also affect fire activity and size by influencing spread rate, fire intensity and the probability of containment (McArthur 1967; McCarthy and Tolhurst 1998; Catchpole 2002). Antecedent climatic conditions such as antecedent rainfall and temperature, as well as the seasonal rainfall, affect the rate of fuel accumulation by influencing biomass growth and litter fall, and consequently affect the fire pattern (e.g. Veblen *et al.* 2000; Heinl *et al.* 2006; Orians and Milewski 2007; Littell *et al.* 2009; Price and Bradstock 2011; Turner *et al.* 2011). In addition to weather/climate factors, fire patterns are also regulated by the type of fuel/vegetation present (Gumming 2001; Moreira *et al.* 2009; Oliveira *et al.* 2014), the proximity to water (Penman *et al.* 2013), as well as the frequency of inundation (Pettit and Naiman 2007; Douglas *et al.* 2016) because of their connections with the load, moisture and flammability of fuels. Vegetation indices have also been used as indicators of biomass or fuel load in the practice of fire danger prediction (Russell-Smith *et al.* 2007; Turner *et al.* 2011). Topography influences fire patterns by affecting general weather patterns, fuel availability and conditions, creating microclimates, and affecting the probability of lightning (McRae 1992; Pyne *et al.* 1996; Heyerdahl *et al.* 2001; Podur *et al.* 2003; Sharples 2009). Fires have different sources of ignition, with humans accidentally or deliberately causing some fires and lightning being the common cause of natural fires (Kourtz and Todd 1991; McRae 1992; Anderson *et al.* 2000; Pew and Larsen 2001; Syphard *et al.* 2008; Vilar *et al.* 2010b; Magnussen and Taylor 2012; Penman *et al.* 2013). Human activities also affect fire size by influencing the chance of a fire being controlled (Catchpole 2002).

Patterns of wildfires have been studied with the support of data sources and modelling methods. These studies primarily relied on administrative fire records and on remotely sensed observations. Administrative records commonly contain detailed information on ignitions and causes of fires. They have been used in both regional (e.g. Preisler *et al.* 2004; Bradstock *et al.* 2009) and broad-scale (e.g. Littell *et al.* 2009; Fernandes *et al.* 2016b) studies. The satellite-based products, such as the Moderate Resolution Imaging Spectroradiometer (MODIS) active fire product (Giglio *et al.* 2003), provide precise and reliable historical information on fire activity, and have been used in understanding broad-scale patterns of fires (e.g. Hawbaker *et al.* 2013; McRae and Featherstone 2015). The Generalised Linear Model (GLM, Nelder and Baker 1972) and Generalised Additive Model (GAM, Hastie and Tibshirani 1986) are two empirical models that have been widely used in fire pattern analyses. GLM is a parametric model that quantifies the linear relationship between variables, whereas GAM is an extension of GLM that allows for non-linear relationships between variables. When using fine spatial and temporal units, fire activity and ignition are Bernoulli processes in that their probabilities can be modelled using GLM or GAM with a logic link (e.g. Chou 1992; Preisler *et al.* 2004). These models have also been used to investigate relationships between fire sizes and their determinants (e.g. Viedma *et al.* 2009; Hantson *et al.* 2015).

Studies on fire occurrence have been conducted in many countries, mainly in North America (Brillinger *et al.* 2003; Preisler *et al.* 2004; Syphard *et al.* 2008; Parisien *et al.* 2012; Curt *et al.* 2015), Europe (Chuvieco *et al.* 2010; Oliveira *et al.* 2012a; Fuentes-Santos *et al.* 2013), and Australia—where some fire occurrence studies specifically addressed relatively small areas such as the ACT (McRae 1992), the Mallee woodlands and heathlands of VIC (Krusel *et al.* 1993), the Sydney region (Bradstock *et al.* 2009; Penman *et al.* 2013) and the south-west Western Australia (Plucinski 2014; Plucinski *et al.* 2014). Other studies have looked at larger regions such as the whole of VIC (Dowdy and Mills 2012a; Dowdy and Mills 2012b) and south-eastern Australia, which covers three fire-prone states (Collins *et al.* 2015). These studies investigated the effects of environmental and anthropogenic factors on the spatial (e.g. Penman *et al.* 2013) and temporal patterns (e.g. Plucinski 2014) of fire occurrence. Studies on fire occurrence patterns at a broad scale that cover fire-prone states in south-eastern Australia are relatively rare. Also, the differences of fire occurrence drivers across ecoregions of south-eastern Australia are not well understood.

Studies aiming to model relationships between fire sizes and their driving factors have also been conducted worldwide (Russell-Smith *et al.* 2007; Slocum *et al.* 2010; Price and Bradstock 2011; Turner *et al.* 2011; Loepfe *et al.* 2014; Fang *et al.* 2015; Fernandes *et al.* 2016b). In Australia, Russell-Smith *et al.* (2007) conducted a continental-scale fire pattern analysis and quantified the role of biophysical variables, especially rainfall seasonality, to explain fire extent in each climate region. Nicholls and Lucas (2007) found relationships between the current and prior climate conditions and the annual area burned in Tasmania. Price and Bradstock (2011) quantified the effect of fuel age and weather on fire extent in four subregions of the Sydney region. Turner *et al.* (2011) specifically looked at drivers of fire extent in arid and semi-arid areas of Australia, whereas King *et al.* (2013) compared climate drivers of fires in a mesic and an arid ecosystem in Australia. The complexity and variations in climate-fire relationships in different regions suggest the need for localised analyses rather than generalising results from other studies (Nicholls and Lucas 2007).

Forested wetlands differ from neighbouring landscapes in their vegetation types and moisture regimes, therefore fire characteristic, the driving factors of fire occurrence and size, as well as their relative importance are expected to be different than their adjacent areas. This may lead to the need for different forest and fire management efforts at different landscapes and under different climate scenarios. A few published studies have investigated the properties of wetland fires and their determinants around the world (Dwire and Kauffman 2003; Heinl *et al.* 2006; Pettit and Naiman 2007). Dwire and Kauffman (2003) summarised the fire regimes in riparian areas and the characteristics of riparian zones that influence fire properties in western North America. Heinl *et al.* (2006) compared fire characteristics on floodplains and their adjacent dry lands in southern Africa. Pettit and Naiman (2007) reviewed characteristics of riparian fires and their ecological consequences. However, there are very few scientific publications and government reports that systemically characterise wildfires in Australian wetland ecosystems (Douglas *et al.* 2003; Country Fire Authority [CFA], 2014; Douglas *et al.* 2016; Schneider and Sutherland undated). This is a concern given the risk that wetland wildfires pose to rural communities, their role as a natural disturbance that can affect ecological processes, and their importance in timber production, water supply and regulation. Specifically, there is very little information regarding the patterns of fire occurrence and size and their driving factors in the inland semi-arid riverine area of south-eastern Australia. These issues therefore require further exploration.

1.2 Aims and Objectives

This thesis aims to provide knowledge on fire patterns across two different scales in south-eastern Australia. Specifically, it will explore patterns of wildfire activity and ignition on a broad scale that covers fire-prone states, whereas patterns in wildfire ignition and size will be investigated at a regional scale that covers the NSW side of the Riverina Bioregion. These patterns will be modelled by incorporating satellite-based and administrative fire records and factors such as weather conditions, fuel, topography and ignition sources within the framework of statistical modelling methods i.e., GLM and GAM. This study hypothesises that there are significant variations in fire patterns, and in the effects and relative importance of fire-pattern drivers, in different landscapes. This thesis will provide a comprehensive understanding of fire patterns in the target areas to support agencies as they prepare and plan for fire and land management activities in south-eastern Australia.

This thesis specifically addresses the following questions:

(1) What are the broad-scale wildfire activity patterns in South-Eastern Australia; what are the effects and relative contributions of environmental and anthropogenic factors that regulate these patterns; and how can the MODIS active fire product be incorporated into wildfire modelling?
(2) What are the wildfire ignition patterns across different ecoregions of South-Eastern Australia; are there any non-linear relationships between these patterns and their determinants; and how do the relationships vary spatially?
(3) What are the spatial and temporal patterns of fires with different causes and different vegetation types in the inland semi-arid riverine environments; how do their determinants affect these patterns; and what are the relative contributions of different factor groups to fire ignition?
(4) What are the properties of wildfires and their sizes in inland forested wetlands and adjacent dry lands; how do ambient weather and antecedent rainfall affect the size of these fires; and which are the most important factors that govern fire sizes in these environments?

Corresponding to these questions, the main objectives of this thesis are:

(1) To develop spatial models incorporating the MODIS active fire product in order to better understand wildfire activity patterns, their regulating factors, and the relative contributions of these factors in NSW, ACT and VIC;
(2) To model spatial patterns of wildfire ignition in relation to their determinants over five ecoregions of NSW and ACT;
(3) To develop spatiotemporal models for understanding factors that regulate patterns of human-caused and natural fire ignitions in forested wetlands and their adjacent dry lands in the NSW part of the Riverina bioregion; and
(4) To identify the ambient weather and antecedent rainfall factors which are most effective in explaining the wildfire size, and to evaluate their relative importance in two diverse environments in the NSW part of the Riverina bioregion.

1.3 Research Significance

The significance of this study is three-fold. First, this thesis provides information on broad-scale fire occurrence patterns in south-eastern Australia. It identifies environmental and anthropogenic factors driving the spatial distributions of fire activity and ignition; it also demonstrates differences in the contributions of these factors and variation in their effects across different ecoregions. These issues have rarely been systematically explored. Second, the thesis provides knowledge about patterns of fire ignition and size in the inland semi-arid riverine environment of Australia, which are understudied (Douglas *et al.* 2016). This study identifies factors regulating the ignition and size of fires and demonstrates the differences in effects of these factors in forested wetlands and dry lands. Third, this thesis contributes to the understanding of fire regime and risk, and its results have clear implications for land and fire management practices. It is envisaged that findings from this study can help fire managers target suppression efforts, plan fire risk reduction practices, and develop more effective regional conservation plans and management strategies.

1.4 Thesis Structure

The thesis comprises eight chapters. Chapter 1 provides an overview of the context of the thesis, including a general introduction on the background, as well as the main aim, objectives, significance and structure of the thesis. Chapter 2 reviews the key concepts of wildfires related to the thesis, including the environmental and socio-economic impacts of fires and management options, the concept of fire patterns—especially those of fire occurrence and size, the determinants of fire patterns, and the means of obtaining fire relevant observations. Chapter 3 briefly describes the study area, the methods used for fire modelling and the conceptual framework. Chapters 4 to 7 present the four major findings regarding the fire patterns at two different scales in south-eastern Australia, including patterns of fire activity and ignition and their determinants on a broad scale in south-eastern Australia, as well as patterns of fire ignition and size and their driving factors in the semiarid riverine environment of Australia. Chapter 8 draws together the conclusions of each chapter and discusses the contributions, limitations and directions for future research.

Chapter 2 Review of Wildfire Ecology and Management

2.1 Fire Impacts and Management

Wildfires affect ecosystems, threaten human lives, and cause socio-economic loss (Bowman *et al.* 2009). In this section, the importance of wildfires as an ecological disturbance and their effects on human societies and economies, as well as the aims and objectives of fire management activities, are reviewed.

2.1.1 Environmental and Ecological Impacts

Fires are natural disturbances that have profound effects on the distribution and structure of flora and fauna, soil and water (Pyne *et al.* 1996; Bowman *et al.* 2009; Gill *et al.* 2012). The effect of fires on plant communities can be positive or negative, depending on the species, fire characteristics and environmental conditions (Australian State of the Environment Committee [ASEC] 2006). Fires can assist some native species with regeneration, germination and establishment (Gill 1975; Bond and Keeley 2005). For example, *Eucalyptus regnans* (mountain ash), a valuable Eucalyptus forest species normally grown in south-eastern Australia, is dependent on fire for its regeneration (Gill 1975). On the other hand, wildfires may injure or kill fire-sensitive vegetation species such as the river red gum (Dexter 1978, as cited in CSIRO 2004). They threaten animal species directly by causing deaths during fire events, or indirectly by reducing feeding resources (Gill *et al.* 2012). Wildfires affect soil through changes in soil temperature, structure, as well as the ability to absorb and store water (Pyne *et al.* 1996), and affect water via changes in water flow, temperature, acidity/alkalinity (pH), chemistry and bottom sediments (Lyon and O'Connor 2008).

At the global scale, fires influence carbon cycle and the global climate by affecting the exchange of carbon between the land and the atmosphere (Bowman *et al.* 2009). Carbon transfer and stock are affected by fires via three basic mechanisms: the carbon transfer from biosphere to atmosphere, between terrestrial pools and from atmosphere to the biosphere (Williams *et al.* 2012). Biomass burnings accelerate the decomposition and respiration (Bowman *et al.* 2009) and emit trace gases and aerosols that contribute to the variation in atmospheric chemistry (Andreae and Merlet 2001), including the variability of greenhouse gases and the associated global warming (Marston *et al.* 1991). Biomass burnings, together with domestic and industrial fires and fossil-fuel combustions, also generate black carbon aerosols that absorb solar radiation and contribute to the global warming (Bond *et al.* 2013).

2.1.2 Socio-economic Impacts

Wildfires also have a significant socio-economic impact. The impact of wildfires can result from direct contact with the event such as asset damages, deaths and injuries, smoke-related diseases, culture and heritage damages, ecological services, loss of water supply, and greenhouse gas emissions; whereas indirect impacts are those induced as a consequence of the event such as business disruptions, fire responses, and relief to the regional area (Stephenson *et al.* 2013). For example, a number of catastrophic wildfires related to the 1997-1998 El Niño-Southern Oscillation (ENSO) event swept through most regions around the world (Moore 2001). In South East Asia, fires damaged hundreds of thousands of hectares of land, of which more than 9.5 million ha were burned in Indonesia, with an estimated economic loss of $U.S. 5-10 billion. Additionally, the health of 70 million people was adversely affected by the smoke from the fires (Moore 2001). In Latin America, 70 Mexican firefighters and 700 Brazilian Amazon people were killed by the smoke, and at least 9.2 million ha of land was burned, causing an estimated damage of $U.S. 10 to 15 billion (Cochrane 2002).

In Australia, the majority of socio-economic impacts of fires occur in the south-eastern part of the continent where the majority of infrequent, high-intensity and large wildfires occurred (Cheney 1976; Murphy *et al.* 2013) and the population density is the highest. For instance, one of the most devastating wildfires, the 2009 Black Saturday Fires in VIC, burned a total area of more than 400,000 ha, caused 173 deaths, destroyed more than 2,030 houses, and displaced over 7,562 people, resulting in an estimated cost of more than $4 billion (Teague *et al.* 2010). Generally, periods of high fire danger are predicted to be more frequent under the scenarios of global change (Cary *et al.* 2012). The expansion of cities and human communities into rural areas increases the potential impact of fires across Australia.

2.1.3 Fire Management

Although fires are destructive and therefore a significant concern in terms of life and property protection, they are also an essential and irreplaceable ecological process (Ellis *et al.* 2004). The adverse impact of wildfires needs to be mitigated through effective actions. In some cases, fires can be a valuable tool in achieving land management objectives. Consequently, the management of fires must be integrated into land management activities to meet the desirable goals (Barney 1975, as cited in Conedera 2009).

The meaning of "fire management" has been changing and is not uniformly used in different contexts (Hardy 2005; Conedera 2009). In the National Inquiry on Bushfire Mitigation and Management prepared for the Council of Australian Governments (COAG), fire management is defined as "all activities associated with the management of fire-prone lands, including the use of fires to meet land management goals and objectives" (Ellis *et al.* 2004 p.388). According to National Bushfire Management Policy Statement for Forests and Rangelands (Forest Fire Management Group [FFMG] 2014), the management of fires has a number of strategic objectives, such as effectively managing the lands with fires to reduce fire risk and enhance the health, biodiversity and resilience of ecosystems; improving community involvement and public education; enhancing partnerships of management agencies and capacities of risk mitigation; developing active and adaptive risk management approaches and knowledge. Specifically, the objectives of fire risk reduction and mitigation, as well as minimising the adverse ecological impact of fires, can be partially achieved by employing some of fire control activities/treatments such as restriction of unwanted fire starts (e.g., human access), and effective fire suppression and fuel management (e.g., prescribed burning or non-fire treatments) (Ellis *et al.* 2004; Gill *et al.* 2012; NSW OEH2015).

2.2 Fire Occurrence and Size

Fire risk mitigation and ecologically sustainable fire management cannot be effectively achieved without a solid understanding of fire behaviour and regime. This section reviews existing knowledge on the property and behaviour of individual fires, as well as concepts of fire regime and risk.

2.2.1 Fire Behaviour, Regime and Risk

The knowledge of the property of an individual wildfire and its behaviour in a landscape is fundamental. "Fire behaviour" refers to "the manner in which a fire reacts to the variables of fuel, weather and topography" (FFMG 2014). A wildfire can go through several phases, including ignition, development, spread at a steady-state rate, potential exhibition extreme fire behaviour (e.g., high-intensity crown fire and spotting), and extinction (Pyne *et al.* 1996; Sullivan 2014). The fire "imprint", which is dependent on the behaviour of a particular fire event, can be characterized by the fire probability, fire shape and size, the horizontal and vertical burning pattern, as well as the spotting pattern (Catchpole 2002).

"Fire regime" describes the characteristics of sequences of fire events (Gill *et al.* 2012). Therefore the behaviour of an individual fire and the landscape fire regime are closely related (Cary 2002). The concept of fire regime was introduced by Gill (1975) to gain a better understanding of the long-term effects of fire on ecosystems. Gill (1975) identified fire regime components as intensity, frequency, seasonality and type (above-ground or below-ground). Heinselman (1981) summarised fire regime elements as type and intensity (crown/severe surface fires vs. light surface fires), size (area), frequency or return interval and seasonality. Bond and Keeley (2005) modified the fire regime concept defined by Gill (1975) to include fuel consumption and fire spread patterns (ground/surface/crown fires and fire size/patchiness), intensity, severity, frequency and seasonality. The inclusions of severity and size distinguish Bond and Keeley's (2005) fire regime definition from that of Gill (1975). Fire regime provides an integrated way of describing diverse spatial and temporal patterns of fires and their impacts on an ecosystem or landscape (Gill 1975; Bradstock *et al.* 2002; Bond and Keeley 2005; Keeley 2009) and is also an important concept in supporting decision-making for risk mitigation and management (Keeley 2009; Gill *et al.* 2012). For example, fire frequency is the incidents of fires for a given time and region (Bond and Keeley 2005); high-frequency fires may result in the loss of plant (especially shrub) species, reduction in vegetation structure and subsequent loss of animal species (Gill 1975; Bradstock *et al.* 1997). Fire intensity is energy output of the fire line (Byram 1959) or energy released from organic matter during the combustion process (Bond and Keeley 2005; Keeley 2009). Intensity is expected to be related to the short-term effects on vegetation types (especially forests) because low-intensity fires may only consume litter fuels whereas high-intensity fires are more likely to affect the tree canopy, the understorey and the soil organic layers (Gill 1975). The loss and damage of socio-economic assets are also expected to be related to fire intensity because of its connection with flame radiation, firebrand density and flame contact, which influence the potential for structure ignition (Wilson and Ferguson 1986; Blanchi and Leonard 2008; Gill *et al.* 2012).

In this thesis, the term "fire pattern" is used to describe the behaviour and regime of fire across multiple scales. The understanding of fire pattern is important to systematically consider a wide range of environmental, ecological and socio-economic values in the management of fire risk. Fire risk has been defined by Chuvieco *et al.* (2010) as the combination of two components—the fire occurrence probability and the potential damage. The former component is constituted by the probability of a fire igniting in a given place and the potential for a fire to propagate over an area. The latter component describes the probable outcome of a fire, including the negative effects of fires on the socio-economic value and the ecological value. Taylor *et al.* (2013) reviewed a number of fire risk components to inform fire management, including fire ignition and occurrence, growth, size, area burned and frequency, over a range of spatial and temporal scales. In Section 2.2.2, knowledge on fire occurrence and size is reviewed.

2.2.2 Fire Occurrence and Size

The term "fire occurrence" is not uniformly used throughout time and by different organisations/authors. For example, US Department of Agriculture (Romme 1980 p.135) defined it as "one fire event taking place within a designated area during a designated time (Boolean; either yes, a fire occurs, or no, a fire does not occur)", which is similar to the description of Flannigan *et al.* (2009 p.495) who sees fire occurrence as "a relatively simple measure of fire activity that quantifies the presence or absence of an event". Finney (2005 p.98) used the definition "the frequency of fires that have been reported and recorded within a finite area and historical period of time (e.g., number of fires/ha/year)". Plucinski (2011 p.2) used a more general definition that "fire occurrence is used to describe the presence and frequency of fires within a finite time and space".

According to these definitions, the occurrence of fire is, at times, considered the ignition of fire within a certain spatiotemporal unit (Cunningham and Martell 1973; Preisler *et al.* 2004; Syphard *et al.* 2008; Wotton *et al.* 2010; Penman *et al.* 2013); while in other cases, it is referred to as the activity/burning of fire within a spatiotemporal unit (Krawchuk *et al.* 2009; Chuvieco *et al.* 2010; Oliveira *et al.* 2012a; Renard *et al.* 2012; Hawbaker *et al.* 2013). For the former, fire occurrence has the same meaning as the (detected) fire ignition; in the latter case, it includes both the ignition and the propagation of a fire (Chuvieco *et al.* 2010). The definition of fire occurrence is largely dependent on the specific context and purpose of a study, as well as the quality of the fire dataset (accuracy, completeness, consistency, form, source e.g., agency- or satellite-based observation).

Fire occurrence is a fundamental concept in understanding the spatial and temporal distribution of fires. It is also an essential component of fire risk (Chuvieco *et al.* 2010; Taylor *et al.* 2013) and is an attribute of a fire regime (Cary *et al.* 2012). Understanding fire occurrence patterns is critical for fire and land managers in planning for sustainable land management strategies and fire prevention activities (e.g., the timing and allocation of fuel treatment), setting up fire suppression resources, as well as the restoration of burned areas (McRae 1992; San-Miguel-Ayanz *et al.* 2003; Finney 2005; Syphard *et al.* 2008; Oliveira *et al.* 2012a; Chuvieco *et al.* 2014). Therefore, despite the varying definitions of fire occurrence definitions in different contexts, both ignition and activity are important from the perspective of risk mitigation and sustainable land management, and are worthy of exploration.

Fire size (area) describes the extent of a fire as it spreads in a landscape (Ryan 2002). It is an essential component of both fire risk (Taylor *et al.* 2013) and fire regime (Turner *et al.* 1997; Turner 2010). Fire size is driven by spread rate and the probability of timely containment, and the latter is determined by the intensity, remoteness and the spread rate of fire (Catchpole 2002). This suggests the association between fire sizes and suppression effectiveness (Taylor *et al.* 2013). The ecological consequence of a fire is directly affected by the fire size through area related effects (Turner *et al.* 1997; Bond and Keeley 2005). For example, the size of a fire fundamentally determines how much a vegetation type or species is influenced by fire (Turner *et al.* 1997). The area burned is positively correlated with the size of individual fire effects on the carbon cycling and emissions at broader scales (Conard *et al.* 2002; Turetsky *et al.* 2011). From this perspective, understanding the property of fire size and its driving factors is important for planning ecologically sustainable fire management and risk reduction activities (Price and Bradstock 2011; Fang *et al.* 2015).

2.3 Fire Determinants

Wildfires are regulated by top-down and bottom-up factors across a range of spatial and temporal scales (Bowman *et al.* 2009; Flannigan *et al.* 2009; Parisien and Moritz

2009; Bradstock 2010). Weather is considered as a ‘top-down’ control on fire because it affects fire patterns across large areas, whereas fuel, topography and ignition sources are ‘bottom-up’ controls because they are spatially more variable and are associated with local fire patterns (Gill and Taylor 2009; Parks *et al.* 2011). These fire determinants are described in the following sections.

2.3.1 Fire Triangles

The relationships between fire and its determinants may vary with the spatial scales i.e. these relationships are scale-dependent (Moritz *et al.* 2005; Falk *et al.* 2007; Parks *et al.* 2011). The influence of bottom-up factors is site-specific while top-down (weather- or climate- related) factors prevail regionally (Pearson *et al.* 2004). This is because bottom-up factors (e.g., topography) are spatially more heterogeneous i.e., they affect the type, arrangement, moisture, and connectivity of fuels (Gill and Taylor 2009), and therefore affect local fire patterns (Turner 2005). One example of this is that the association between the wildfire pattern and one bottom-up factor i.e. aspect becomes unobvious as the scale becomes coarser (Parks 2011). The scale-dependent fire controls highlight the need of conducting analysis at multiple scales.

A number of conceptual frameworks, notably the fire triangles, have been proposed to describe the change of fire pattern determinants across scales. Moritz *et al.* (2005) presented a fire triangle conceptual model that describes dominant factors affecting fire behaviour and regime at multiple spatial and temporal scales, which is an extension of the traditional fire environment triangle concept (Countryman 1972; Pyne *et al.* 1996). At finer scales, physical-based knowledge is important in understanding the fire fundamental (Rothermel 1972). The fire fundamental triangle includes three interacting factors (heat, oxygen and fuel) that control the fire flame (Pyne *et al.* 1996). When a fire starts, it will continue burning only if all these three legs are available and adequate. At landscape and subregional scales, knowledge of fire behaviour that explains the way fuel ignites, develops and spreads is important. The three components of fire environment triangle (topography, fuel and weather) collectively regulate and interact with the behaviour of fire, such as the spread rate and fireline intensity (Countryman 1972; Pyne *et al.* 1996). At regional and continental scales, the understanding of fire regime, which describes the broad-scale and long-term fire activity pattern, is vital (Moritz *et al.* 2005; Parisien and Moritz 2009). The three components of the fire regime triangle (climate/atmospheric conditions, vegetation/resources to burn and ignition patterns) are the dominant factors affecting the fire pattern at coarse scales (Krawchuk and Moritz 2011; Moritz *et al.* 2012).

Similar with the fire triangle model stated by Moritz *et al.* (2005) and Parisien and Moritz (2009), Bradstock (2010) proposed that the biogeographical variation of fire regime patterns in Australia is regulated by four processes. Bradstock described the fire regime triangle in the form of four "switches": biomass growth (B), availability for burning (A), ambient fire weather and its affected fire spread (S) and ignitions (I), with "B" denoting the vegetation leg and "A" and "S" collectively corresponding to the weather leg in the fire regime triangle (Cary *et al.* 2012). This concept model has been intensively discussed in fire pattern studies, especially those conducted in landscapes of Australia (e.g. Penman *et al*. 2013, Bradstock *et al*. 2014, Gibson *et al*. 2015).

Although the above discussed models are well-defined and conceptually useful, finding out the true fire determinants of a given environment has not been easy, especially at intermediate spatial scales. This is because at these scales interactions between bottom-up and top-down controls are complex and variable (Meyn *et al.* 2007; Bradstock 2010; McKenzie *et al.* 2011; Moritz *et al.* 2012; Parks *et al.* 2012). In addition, the relationships between fire and its determinants not only vary with scales, but also by region (Littell *et al.* 2009). These all make site-specific case studies necessary.

2.3.2 Weather/Climate

The weather or climate factors are top-down controls on fire that has been highlighted in a number of regional and continental studies (Russell-Smith *et al.* 2007; Bradstock *et al.* 2009; Littell *et al.* 2009). They include the ambient weather (or fire weather) that depicts atmospheric conditions on a particular day or during a short period, and the antecedent weather or climate that depicts the climatic conditions that synthesise the weather conditions over a longer period (Pyne *et al.* 1996; Bradstock 2010; Sullivan *et al.* 2012). Ambient weather elements include temperature, relative humidity, precipitation, wind speed and direction. They affect the flammability/availability of fuels (“A”), the behaviour of fire such as the spread rate (“S”), as well as the probability of containment and therefore influence the ease of ignition and fire size (Flannigan and Harrington 1988; Pyne *et al.* 1996; Catchpole 2002; Bradstock *et al.* 2009; Bradstock 2010). For example, wind speed strongly affects the propagation of fire by increasing the radiative heat transfer (McArthur 1967; Catchpole 2002). The antecedent weather conditions, e.g., antecedent rainfall and temperature, affect the rate of biomass accumulation (“B”) by affecting the rate of natural vegetation growth and the amount of litter fall, and therefore affects the occurrence and extent of fire in following seasons (Heinl *et al.* 2006; Orians and Milewski 2007; Russell-Smith *et al.* 2007; Littell *et al.* 2009; Price and Bradstock 2011; Turner *et al.* 2011). For example, in the American Southwest, above-average rainfall and/or cooler temperature leads to higher fine fuel production and continuity that results in high fire activity during the subsequent year(s) (Swetnam and Betancourt 1998; Veblen *et al.* 2000; Littell *et al.* 2009). The most effective rainfall accumulation period that drive fires can be different for different regions (Russell-Smith *et al.* 2007; Littell *et al.* 2009; Turner *et al.* 2011). Seasonal rainfall patterns can also regulate the process of fuel accumulation.

There are several fire danger indexes that have been used to integrate weather information to predict fire behaviour and inform fire potential. In Australia, the McArthur Fire Danger Index (FDI) is the most widely used. It includes two types of indexes: the Forest Fire Danger Index (FFDI) for forests and the Grass Fire Danger Index (GFDI) for grasslands (McArthur 1967; Luke and McArthur 1978). Temperature, relative humidity and wind speed are factored into FFDI directly or via calculations of Keetch-Byram Drought Index (KBDI, Keetch and Byram 1968), a soil moisture deficit measurement reflecting the amount of effective rainfall needed to saturate 200 mm of soil, and Drought Factor (DF) that quantifies how ready fine fuels are to ignite (Noble *et al.* 1980). These indexes provide qualitative (low, medium, high, extreme) predictions of fire risk and are representatives of ambient weather conditions to a large extent.

2.3.3 Fuel/Vegetation

"Fuel is the burnable live and dead vegetation that may be consumed in the passage of the fire" (Sullivan *et al.* 2012 p.55). Fuel or vegetation factors are bottom-up controls on fire patterns (Russell-Smith *et al.* 2007; Syphard *et al.* 2008; Parks *et al.* 2012; Fernandes *et al.* 2016b). Fuel type and fuel load vary at small scales and are two primary considerations that affect a number of fire pattern properties (Catchpole 2002; Cary *et al.* 2012). The type of fuel influences the ease of ignition, the spread and intensity of fire (Catchpole 2002). The behaviours of fires that burn in forests and grasslands are considerably different and thus are often described separately. Grassland fires have higher rates of spread and combustion and they are more sensitive to wind speed change, whereas forest fires tend to burn more intensively especially under extreme weather conditions (Sullivan *et al.* 2012). The amount of fuels affects flame height and depth, fire intensity and sometimes the fire spread.

Fuel moisture content (i.e., the amount of moisture present in fuels) also affects the ignition probability and the spread of fire (Pyne *et al.* 1996; Catchpole 2002). It is a highly dynamic measurement that varies throughout the day. The higher the moisture content, the less likely a fire ignites from or spread through the fuel. Fuel moisture content depends on a number of factors such as weather conditions and vegetation types. Sharples *et al.* (2009) derived a simple index, namely the Fuel Moisture Index (FMI), that can be easily calculated using temperature and relative humidity obtained from weather stations. Other sources of information on fuel moisture content are satellite-based products such as the Normalised Difference Vegetation Index (NDVI, Hardy and Burgan 1999; Chuvieco *et al.* 2004; Caccamo *et al.* 2012).

The relationship between fire activity/pattern and aridity/moisture (and its associated primary productivity/biomass) is non-linear (Bond and Keeley 2005; Meyn *et al.* 2007; Littell *et al.* 2009; Bradstock 2010; Krawchuk and Moritz 2011; Murphy *et al.* 2011; Moritz *et al.* 2012). In arid areas where productivity is low, factors that support the biomass growth (e.g., high level of antecedent rainfall) are the primary contributing factors, whereas in mesic areas where biomass is abundant, severe ambient weather (e.g., high temperature, low moisture content, high wind speed) primarily governs the fire pattern. For example, Littell *et al.* (2009) found that the summer drought in (mesic) forested ecosystems and antecedent winter rainfall in (arid/semi-arid) shrub and grassland ecosystems are important in regulating area burned in the western United States.

There are other factors that regulate fire patterns indirectly by affecting fuel conditions and dynamics. For example, the proximity to water influences fuel moisture, which consequently affects the likelihood of a fire (Penman *et al.* 2013) and the spread of fire across landscape. In wetland or riverine areas, fire activities are influenced by the patterns of disturbance events such as flooding, which also contribute to relative humidity, fuel moisture and biomass accumulation dynamics (Pettit and Naiman 2007; Douglas *et al.* 2016).

In riparian areas, the fuel accumulation and drying out mechanisms are not always equivalent to those in uplands because of the interactive relationship between fire and flooding. The high availability of water in riparian areas results in high net primary productivity and the associated fuel load (Dwire and Kauffman 2003). What's more, the uprooting and deposit of riparian trees during large flood events contribute to the subsequent accumulation of woody fuels and thus increase the fire risk in the semi-arid Sabie River of South Africa (Pettit *et al.* 2005). The destruction of trees by flood also exposes fuels to greater radiant heat that accelerates the drying-out procedure of fuels (Cochrane 2003). The higher load and faster drying-out of fuels will lead to higher fire risk, however frequent flooding will inhibit vegetation growth and the build-up of fuel, thus reducing the risk of fire, therefore Pettit and Naiman (2007) suspected a non-linear relationship between fire and flood frequency, with fire frequency being highest at intermediate flooding frequencies.

2.3.4 Topography

Topographic factors are complex and highly variable controls that exert their influence on site-specific fire patterns (Hawbaker *et al.* 2013). They influence fire behaviour directly by affecting the rate and direction of fire spread (Rothermel 1983) and indirectly by modifying general weather patterns and creating localised weather conditions that consequently affect fuel type and moisture content (Pyne *et al.* 1996; Heyerdahl *et al.* 2001; Sharples 2009). They have also been used to predict areas prone to lightning ignitions (McRae 1992). Topographic factors normally include elevation, slope and aspect. Higher or moderate elevations contribute to higher probabilities of storm occurrence, which leads to higher probability of lightning fire incidence (McRae 1992; Podur *et al.* 2003); slope affects flame length and spread rate of fire (Rothermel 1984); aspect influences the reception of solar exposure and wind, and consequently affects fuel moisture content and its flammability (Mouillot *et al.* 2003; Mermoz *et al.* 2005).

2.3.5 Ignition and Suppression

Wildfires can be caused by natural and human activities. Natural fires may be ignited by lightning strikes, volcanicity, rock fall sparks and spontaneous ignitions (Scott 2000). Lightning is the most common source of natural ignition in forest and remote regions (McRae 1992; Anderson *et al.* 2000). Dry lightning (lightning that occurs without accompanying significant precipitation) is especially important (Pyne *et al.* 1996) because of the strong relationship between ignition survival and fuel moisture (Dowdy and Mills 2012a). Human-caused fires are dominant in Mediterranean Europe (Romero-Calcerrada *et al.* 2008) and south-eastern Australia (Collins *et al.* 2015). Anthropogenic sources of ignition include equipment sparks, arcing from electrical lines, escaped campfire brands, arson, etc. (Pyne *et al.* 1996; Taylor *et al.* 2013). The proximity to human activities, as represented by distance to roads, is found to be significant in predicting fire locations (Romero-Calcerrada *et al.* 2008; Vilar *et al.* 2010b). Land use also affects wildfire activities because of its relationship with fire use or control (Russell-Smith *et al.* 2007).

Human activities affect not only the incidence and activity of fire but also fire size through their influence on the chance of a fire being controlled (Catchpole 2002). For example, Fernandes *et al.* (2016b) found out that fire suppression-related metrics (building density + road density) govern fire size, although their overall contribution is not as great as those of weather and fuel, but is greater than that of topography. Hantson *et al.* (2015) found that the spatial trend of fire size distribution across the globe is driven primarily by climate and human activities (i.e., cropland cover and population density).

2.4 Fire Observations

Fire datasets are essential in studies exploring fire patterns. Taylor *et al.* (2013) summarised eight major sources of fire datasets, including records maintained by management agencies (administrative records), historically reported records, outdoor experiments, case studies, laboratory experiments, numerical modelling, remote sensing and vegetation proxies. In this section, the usage of administrative records and remote sensing observations in fire pattern modelling is described because such information is relevant to the spatial and temporal scales of work presented in this thesis.

2.4.1 Administrative Records

Fires can be reported, investigated and recorded by fire management agencies. These administrative records are the most widely used data source in modelling fire patterns (e.g. Stocks *et al.* 2002; Brillinger *et al.* 2003; Preisler *et al.* 2004; Bradstock *et al.* 2009;

Littell *et al.* 2009; Slocum *et al.* 2010; Martínez-Fernández *et al.* 2013; Penman *et al.* 2013; Plucinski *et al.* 2014; Collins *et al.* 2015; Fernandes *et al.* 2016a). For example, Littell *et al.* (2009) utilized three sources of wildfire-area-burned datasets, including annual fire statistics reports obtained from USDA Forest Service, a 1°×1° gridded dataset developed by Westerling *et al.* (2003) and a large fire dataset to quantify climatic controls on the area burned in the western United States ecoprovinces. The second dataset was compiled from fire reports maintained by the U.S. Department of Agriculture's Forest Service, the U.S. Department of the Interior's Bureau of Land Management, the National Park Service, and the Bureau of Indian Affairs. In south-eastern Australia, which covers NSW, ACT and VIC, the majority of fire records are maintained by the NSW Rural Fire Service (RFS), the NSW Office of Environment and Heritage (OEH), the ACT Rural Fire Service, as well as the CFA and the Department of Environment, Land, Water and Planning (DELWP) in VIC. The advantage of using administrative records is obvious: They normally contain detailed information such as the ignition (location and timing) and cause (e.g., natural or arson) of a fire. However, there are limitations such as the limited accuracy of older records (Taylor *et al.* 2013), the difficulty of collection and compilation of data from multiple agencies and the lack of reported/investigated fires in less populated areas. For example, in the rangeland of Australia, many fires are not attended or reported to the agency (Turner *et al.* 2011), which affects the results of fire occurrence studies in these sparsely settled areas.

2.4.2 Remotely Sensed Observations

In the past a few decades, the remote sensing technique has become an important tool for fire management because of its capacity in assessing uniformly environmental conditions before, during and after fires across various spatial and temporal scales (Lentile *et al.* 2006). It has been used in detecting actively burning fires (e.g. Giglio *et al.* 2003), mapping fire propagation, extent (e.g. Loboda and Csiszar 2007; Veraverbeke *et al.* 2014) and burned area (e.g. Riaño *et al.* 2007; Giglio *et al.* 2013), estimating fuel load and structure (e.g. Skowronski *et al.* 2007), curing (e.g. Allan *et al.* 2003) and moisture content (e.g. Danson and Bowyer 2004; Yebra *et al.* 2013), examining post-fire responses (e.g. Kokaly *et al.* 2007) and emissions from biomass burning (e.g. Kaufman *et al.* 1990), etc. There are two primary methods for obtaining fire pattern information from remote sensing imagery: 1) the detection of active fires from optical and/or thermal bands and 2) the assessment of post-fire effect via the mapping of area burned /surface change as interpreted from a wide variety of aerial and satellite sensors (Lentile *et al.* 2006; Maier and Russell-Smith 2012). Fire patterns that cover board spatial scales (e.g. a continent) are normally detected by Advanced Very High Resolution Radiometers (AVHRR) on the National Oceanic and Atmospheric Administration (NOAA) satellites (Flannigan and Haar 1986) and the Moderate Resolution Imaging Spectroradiometer (MODIS) on the NASA Terra (1999) and Aqua (2002) (Justice *et al.* 2002a) etc., while the Thematic Mapper (TM) on Landsat, the Satellite Pour l'Observation de la Terre (SPOT), etc. are commonly used to detect regional-scale (e.g. a state) fire patterns. MODIS has been found to be the most precise and reliable system in terms of accuracy and completeness of target detection (Justice *et al.* 2002b).

A number of studies have been conducted to monitor and subsequently model fire patterns with the support of satellite imagery (e.g. Chafer *et al.* 2004; Oliveira *et al.* 2012b; Liu *et al.* 2013; Fang *et al.* 2015). In some cases, satellite-based observations and administrative records were used collectively. For example, Craig *et al.* (2002) and Russell-Smith *et al.* (2007) evaluated the continental-scale fire patterns of Australia using images extracted from Advanced Very High Resolution Radiometer (AVHRR). Oliveira *et al.* (2012b) derived a digital fire atlas containing annual fire perimeters in Portugal from Landsat TM and Enhanced TM Plus. Fernandes *et al.* (2016a) used the official database of individual fires together with the digital fire atlas to explore the characteristics of extremely large fires and their sizes in response to the variation of concomitant fuel and weather conditions in Portugal. Chafer *et al.* (2004) computed the NDVI from pre- and post-fire images from SPOT-2 to map the severity and intensity of the Christmas 2001 wildfires in the greater Sydney Basin, Australia. This dataset was then used by Collins *et al.* (2014) to quantify how relationships between environmental variables and fire severity vary with gradients of moisture. Liu *et al.* (2013) mapped fire boundaries according to both the fire dataset obtained from forest fire prevention agency and the Landsat TM imagery, and modelled the pattern of burned patch size in a boreal forest landscape in the Great Xing'an Mountains of North-eastern China. Renard *et al.* (2012) used MODIS active fire observations (Giglio *et al.* 2003) from 2003-2007 to quantify the environmental factors that govern the spatial pattern of forest fires in parts of India. This product has also been used in other fire pattern studies (e.g. Hawbaker *et al.* 2013; Curt *et al.* 2015; McRae and Featherstone 2015).

Chapter 3 Methodology

In this chapter, the study area and the modelling methods are described and a conceptual framework regarding how each chapter is linked is presented.

3.1 Study Area

In Australia, more than 300,000 km^2 are affected by fire annually, making it one of the most fire-prone continents in the world (Craig *et al.* 2002; Russell-Smith *et al.* 2007). The activities of fire differ with variations in environments and vegetation types (Gill 1975; Luke and McArthur 1978). The hazardous fires occur most frequently in the south-eastern part of the continent (Commonwealth of Australia 1996). NSW, ACT and VIC are three fire-prone and densely settled regions where wildfires result in tremendous losses of life and property. During the period of 1939-2007, these three states experienced house losses of 1,530, 521 and 6,861, respectively, accounting for 80% of the total house loss caused by fires in Australia during that period (calculated from Table 1 of Blanchi *et al.* 2010). Fires in these states also resulted in 80% of the total life loss caused by fires during 1901-2011 (calculated from Fig.1 of Blanchi *et al.* 2014).

The Riverina bioregion (Department of Sustainability, Environment, Water, Population and Communities [DSEWPaC], 2012) covers an area of around 90,000 km^2, 77% of which is located in NSW and the rest lies in Victoria (Eardley 1999). Maintaining forest health through management activities (e.g., protection from wildfire) is one of the objectives of the ecologically sustainable forest management in this region (Forests NSW 2008). This can be achieved by conducting strategic fire management through fuel management and wildfire suppression programs.

Chapters 4 and 5 look at fire patterns at relatively broad scales that cover fire-prone states of south-eastern Australia -- the study area of Chapter 4 covers NSW, ACT and

VIC (Figure 3.1 (*b*)), while Chapter 5 covers NSW and ACT. The scale of Chapters 6 and 7 is relatively small that covers a bioregion of south-eastern Australia: the NSW side of the Riverina bioregion (Figure 3.1 (*c*)). Nevertheless, both scales are intermediate in view of the effects of top-down and bottom-up controls on fire patterns (Moritz *et al.* 2005; Parisien and Moritz 2009; Bradstock 2010; McKenzie *et al.* 2011). Details on the selection, the geographical and environmental conditions of each study area will be specified in each individual chapter.

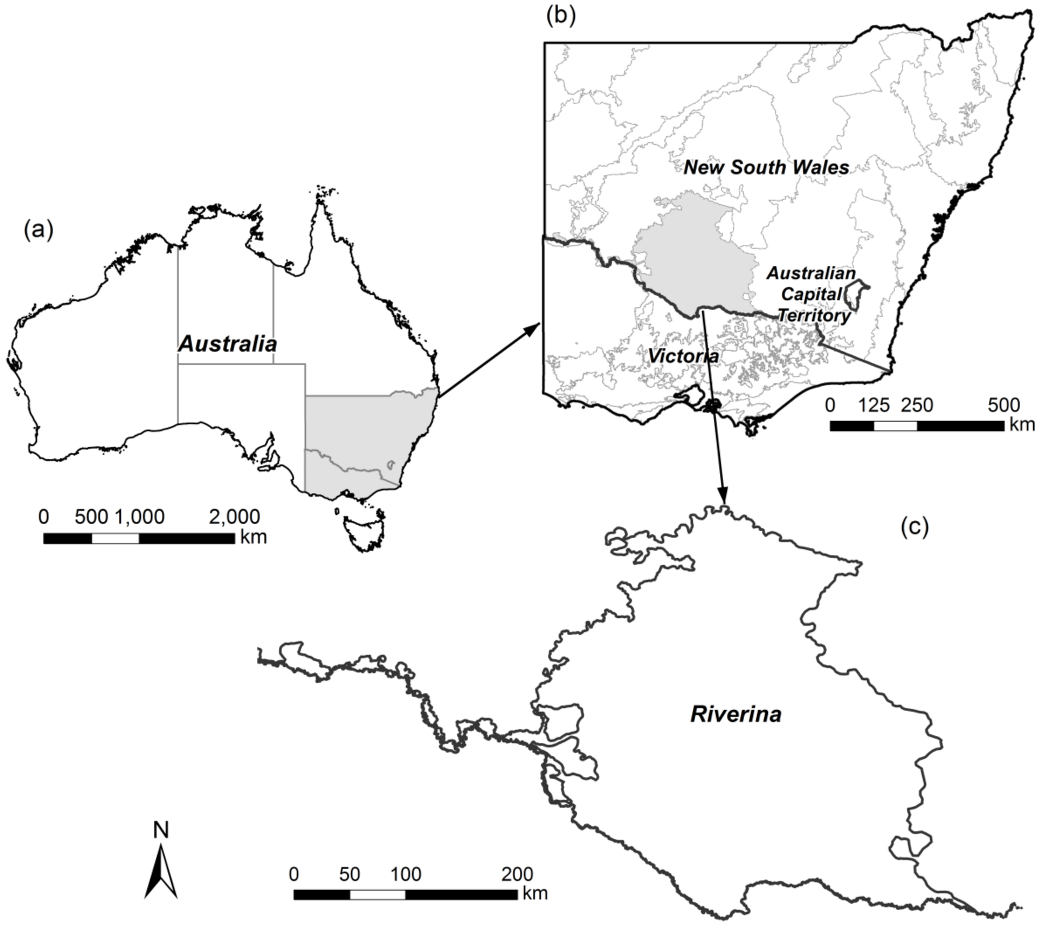

Figure 3.1 Maps showing boundaries of (a) Australia; (b) the south-eastern Australia and (c) the New South Wales side of the Riverina bioregion.

3.2 Modelling Methods

3.2.1 A Review of Wildfire Modelling Methods

Preisler and Weise (2013) summarised three types of wildfire models, i.e., fire risk models used for pre-fire planning, fire behaviour models for fire suppression, as well as fire effects and economy models for post-fire evaluation. Fire risk models can include indexes qualifying levels of fire danger (Section 2.3.2), or empirical models quantifying fire risks (e.g. Brillinger *et al.* 2006; Turner *et al.* 2011; Price and Bradstock 2013; Ager *et al.* 2014; Hernandez *et al.* 2015). Fire behaviour models are most commonly classified as empirical models, semi-physical (or semi-empirical) models and physical models. Empirical models used regression methods and environmental conditions (e.g., wind speed) to predict the rate of spread, such as that used in the Canadian Forest Fire Behaviour Prediction (FBP) System (Forestry Canada Fire Danger Group 1992). Semi-physical models incorporate physical knowledge into mathematical equations. For example, the fire spread rate formulas developed by Rothermel (1972) are subsequently used in BehavePlus (Andrews 2007), Fire Area Simulator (FARSITE) (Finney 2004), Prometheus (Tymstra *et al.* 2010), and others. Physical models are more complex, computational fluid dynamic and combustion models that allow for the dynamic simulation of fire spread and growth in a three-dimensional lattice. These models include FIRETEC (Linn *et al.* 2002), Fire Dynamic Simulator (Mell *et al.* 2007), and a fire-behavior module based on Weather Research and Forecasting (WRF-FIRE) (Mandel *et al.* 2011). Fire effect models estimate effects of fire on ecosystem processes using mathematical equations (Campbell *et al.* 1995) or statistical analysis (e.g. Bradstock *et al.* 1997).

There are primarily three methods used in empirical-based fire risk/pattern studies: the traditional statistics (including Bayesian statistics), spatial statistics and machine learning algorithms. The selection of a model is largely dependent on the nature of the dataset and the objective of a study. In Sections 3.2.1 and 3.2.2, the empirical models for two fire risk components—fire occurrence and size—are described.

Fire Occurrence Models

The occurrence of fire is a stochastic process that can be modelled using a point process framework with a conditional intensity function (Taylor *et al.* 2013). The framework is commonly used to model the probability or number of fire occurrence per period (e.g., day) and per spatial unit (e.g., grid or region), as a function of explanatory variables. A number of models such as Bernoulli, Poisson, negative binomial process models have been used in fire occurrence modelling in different situations. On a very fine spatial and temporal unit, a Bernoulli process can be modelled using a GLM with a logit link, which is mostly referred to as the logistic regression. The dependent variable of a logistic regression is either 1 or 0, meaning that the probability of the presence of a fire is being modelled. For example, Chou (1992) developed a logistic regression model to generate the distribution of the probability of fire occurrence in California. Syphard *et al.* (2008) used logistic regression to model and map spatial patterns of fire ignition in the Santa Monica Mountains. Krawchuk *et al.* (2006) employed logistic regression to quantify the independent effects of weather and forest composition on fire ignition patterns in Alberta, Canada. A Poisson-based model, which is a GLM model with a log link, is commonly used to model the fire count in relation with its determinants. Compared with logistic regression models that connect local covariates with each individual fire, Poisson models relate counts of fires with averaged values of covariates over a larger region (Taylor *et al.* 2013). For example, Mandallaz and Ye (1997) presented the application of Poisson models in forest fire occurrence predictions and illustrated the theory via case studies in France, Italy, Portugal, and Switzerland. Wotton *et al.* (2010) developed a number of Poisson-based models to connect the daily number of fires with weather information within ecoregions of Canada. Negative binomial regression is a generalisation of Poisson-based model but adds a parameter to model over-dispersion in order to assume that the equality of the mean and variance made by Poisson-based models is loosened. For example, Plucinski *et al.* (2014) used negative binomial regression to model the number of daily human-caused fires within 10 management areas of Western Australia, assuming the variance to be a function of the square of the mean. Bayesian modelling methods have also been employed in fire occurrence studies. For example, Bradstock *et al.* (2009) employed a Bayesian logistic regression with uninformed prior knowledge to explore the association between large-fire ignition day probability and its driving weather factors in Sydney Basin, Australia. Dilts *et al.* (2009) used weights of evidence, a data-driven approach from Bayesian statistics, to derive fire occurrence probabilities based on the association between occurrence and landscape-scale evidence layers in Nevada.

GLM is a parametric model that quantifies the linear relationship between covariates and the probability or number of fire occurrence. GAM (Hastie and Tibshirani 1986) is an extension of GLM that allows for non-linear relationships for covariates. Logistic GAM is the dominant GAM that has been used in a number of fire occurrence analyses. These models can be spatiotemporal-based. For example, Brillinger *et al.* (2003) used a spatiotemporal GAM with a logit link to estimate forest fire occurrence as (nonparametric) smooth functions of the spatial effect (location), seasonal effect (day of the year) and elevation in federal lands in Oregon. Preisler *et al.* (2004) used the same technique to build logistic GAMs in estimating three probabilities regarding fire risk and produced probability maps for the entire state of Oregon. This technique has been subsequently used in many spatiotemporal fire occurrence studies (e.g. Vilar *et al.* 2010b; Woolford *et al.* 2014). Logistic GAM has also been used to build spatial fire occurrence models without considering the temporal effects (e.g. Braun *et al.* 2010) or to model long-term trends of fire occurrence, mostly at board spatial scales (e.g. Woolford *et al.* 2014).

Spatial statistics such as the spatial point process (SPP) models (Turner 2009) and geographically weighted regression (GWR) models (Fotheringham *et al.* 2003) have been used to model fire occurrence. SPP models commonly include two types of analysis: the explanatory data analysis that assesses patterns to determine whether they exhibit patterns of complete spatial randomness, and the parametric model used to model relationships between covariates and fire patterns, considering the (possibly) inhomogeneous process. For the first type of analysis, Wang and Anderson (2010) used *K*-function and kernel estimation to evaluate the spatial and temporal patterns of lightning- and human-caused ignitions in forested areas of Alberta, Canada. For the second type of analysis, Yang *et al.* (2007) employed an inhomogeneous Poisson process model to model quantify the effects of land cover, topography, roads, municipalities, ownership, and population density on fire occurrence in the Missouri Ozark Highland forests, in the United States. Another spatial statistical method is the GWR, which allows for the analysis of spatial variation of the driving factors associated with wildfire patterns. For example, Martínez-Fernández *et al.* (2013) identified the driving factors of human-caused fire occurrence in Spain using two statistical methods: the GWR to model fire presence/absence, as well as ordinary least squares regression and binary logistic regression to model fire density. Rodrigues *et al.* (2014) used geographically weighted logistic regression (GWLR) to analyse the spatial variation in the explanatory factors of human-caused wildfires in continental Spain.

Except for statistical methods, a number of machine learning algorithms have been applied in fire occurrence modelling. For example, Oliveira *et al.* (2012a) applied random forest and multiple linear regression to model spatial patterns of fire occurrence in Mediterranean Europe. Müller *et al.* (2013) estimated the probability of a forest fire being ignited by relevant lightning flashes using a decision tree and related decision matrices. Rodrigues and de la Riva (2014) compared the performance of logistic regression with that of three machine-learning algorithms—random forest, boosting regression trees, and support vector machines—in modelling human-caused wildfire occurrences in Spain. Bar Massada *et al.* (2013) compared the performance, variable importance and spatial patterns of predicted occurrence probabilities of logistic regression, random forests and Maximum Entropy (MaxEnt) in the Huron-Manistee National Forest of Michigan. Data-mining techniques are principally superior to parametric methods because of their greater accuracies; however, they have obvious limitations such as the lack of transparency and the possible problem of overfitting (Magnussen and Taylor 2012).

Natural or human-caused fires are caused by different processes (Section 2.3.5), therefore spatial patterns of their occurrence in relation to their driving factors are usually modelled separately. For natural fires, Wotton and Martell (2005) employed logistic regression to model the probability that a lightning strike causes a sustainable ignition on the forest floor and the probability of an ignition being detected and reported to the fire management agency for each ecoregion in the province of Ontario, Canada. Ordóñez *et al.* (2012) used generalised spatial linear models to predict spatially distributed probabilities for fire occurrence in locations where storms featuring lightning occurred in northwest Spain. Woolford *et al.* (2014) assessed the long-term trend of natural fire occurrence and its associations with air temperature and duff moisture anomalies using logistic GAM in a part of north-western Ontario, Canada. Pew and Larsen (2001) examined spatial and temporal patterns of human-caused wildfires in the temperate rainforest of Vancouver Island, Canada. Vilar *et al.* (2010b) developed a spatiotemporal model for human-caused wildfire occurrence prediction in central Spain by using logistic GAM. Romero-Calcerrada *et al.* (2008) used weights of evidence model to model socio-economic data to produce predictive maps in central Spain.

Fire Size Models

Fire size has been studied from several aspects, including its distribution as well as the effects and relative importance of its regulating factors. The distribution of fire sizes has been characterised by empirical models as exponential (Baker 1989), power-law (Lin and Rinaldi 2009; Jiang *et al.* 2010; Slocum *et al.* 2010; Dowdy and Mills 2012b), truncated Pareto (Cumming 2001; Holmes *et al.* 2008) and log-normal (Hantson *et al.* 2016). For example, Slocum *et al.* (2010) conducted power-law statistics to characterise the fire size frequency distribution in south-central Florida. Hantson *et al.* (2015) used the same statistics and concluded that power-law gave a good fit globally.

They then systematically tested the distribution of fire sizes in eight selected areas over the globe and found that fire size data was better fitted by log-normal in most cases, while in only two of eight cases power-law (a particular case of the log-normal) was not rejected (Hantson *et al.* 2016).

The influence of factors such as weather/climate, topography, and vegetation on fire size has been quantified in a number of regions and across multiple scales (e.g. Viedma *et al.* 2009; Slocum *et al.* 2010; Liu *et al.* 2013; Loepfe *et al.* 2014; Fang *et al.* 2015; Hantson *et al.* 2015; Fernandes *et al.* 2016a; Fernandes *et al.* 2016b). These relationships have been built with traditional statistics or machine learning algorithms. For example, Viedma *et al.* (2009) used GLM to find relationships between fire sizes (log ha) and landscape properties and weather conditions in central Spain. Hantson *et al.* (2015) used GAM to find relationships between the distribution of global individual fire sizes and the climate and human activity. Slocum *et al.* (2010) conducted a cross-scale analysis using quantile regression to quantify effects of climatic conditions on fire sizes at different spatial scales. Liu *et al.* (2013) used boosted regression trees, which combine the strengths of regression trees and boosting, to quantify the relative importance of factors regulating fire sizes at continuous spatial scales. Fernandes *et al.* (2016b) used the same method to identify effects of bottom-up variables on a large-size fires in Portugal and evaluated their relative importance globally and across the fire-size range.

3.2.2 Methods used in this Thesis

Since the present thesis aims to provide knowledge on fire patterns of the study area, the empirical-based fire risk models are most appropriate. Among all the above-reviewed fire risk models, GLM and GAM are selected as the modelling methods. Although other methods, e.g., machine learning techniques, may be theoretically superior, the lack of transparency is a drawback (Magnussen and Taylor 2012). Specifically, the probability of fire occurrence is modelled using GLM or GAM with a logit link, depending on whether non-linear relationships between the dependent variable and the explanatory variables are expected, and whether the sample size is large enough to support non-linear regressions. The relationships between fire size and its determinants are modelled with GLM using natural-log transformed fire size as the dependent variable. Details on the modelling approach will be specified in Chapters 4-7. All the variables were constructed within a Geographical Information System (GIS) framework. All statistical analyses were conducted using R packages version 3.1.1 (R Development Core Team 2014) or version 3.2.3 (R Development Core Team 2015).

3.3 Conceptual Framework

The conceptual framework of this thesis is presented in Figure 3.2. This thesis examines fire patterns and their determinants by conducting four individual case studies, each of which targets one objective specified in Section 1.2. Since these studies look at fire patterns across two intermediate spatial scales (see Section 3.1), both top-down and bottom-up controls that exert complex and interactive influence on fire patterns (see Section 2.3) have been evaluated using GLM and GAM in all the case studies. These factors include weather (ambient and antecedent weather), fuel (fuel moisture, fuel type, biomass, etc.), topography (elevation, slope, aspect, etc.) and ignition sources (road network, population, protection, etc.). The inclusion of a specific factor is also subject to the availability of data in each individual study. Remotely sensed fire observations, i.e. the MODIS active fire detections and the administrative fire observations sourced from fire management agencies, are used as dependent variables in the modelling processes of the broad-scale and the small-scale studies, respectively. This framework allows the thesis to assess the scale-dependent and site-specific effects of top-down and bottom-up factors on fire patterns within each study area.

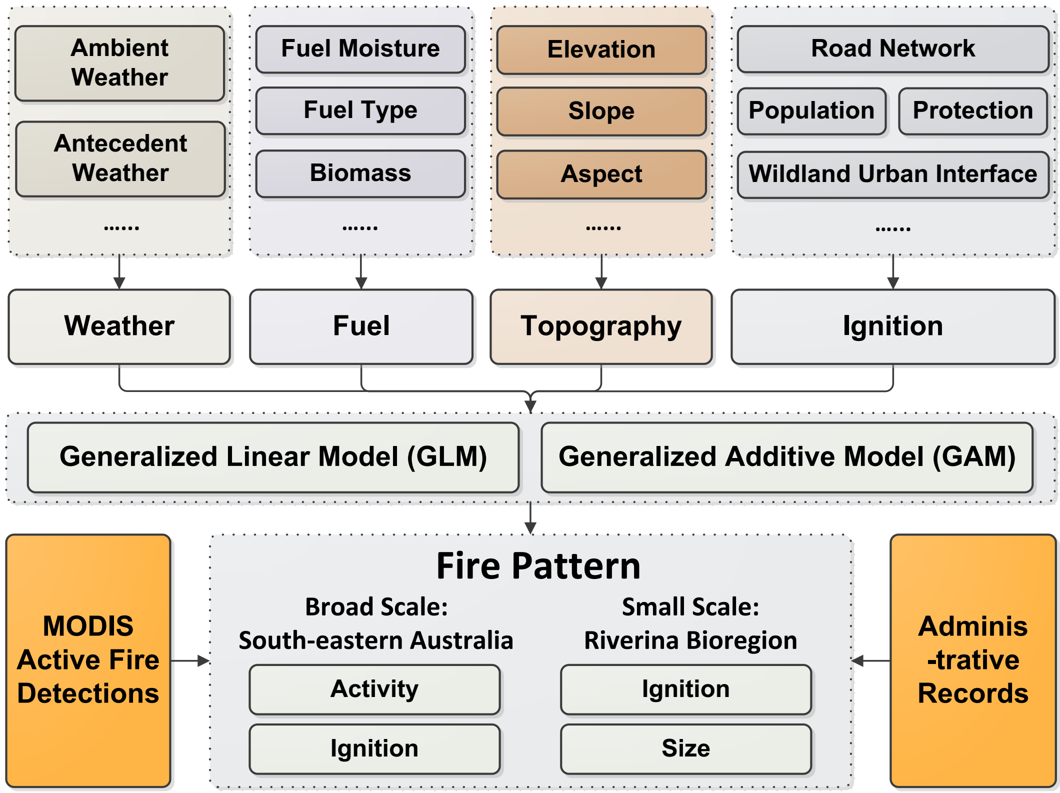

Figure 3.2 Conceptual framework of the thesis.

This thesis first describes the development and validation of spatial models for wildfire activity at a broad scale that covers NSW, ACT and VIC (Chapter 4). The objective is to quantify the effects of environmental and anthropogenic factors on the spatial distribution of fire activities and their relative contributions for the prediction of future fires. To achieve these objectives, the probability of at least one fire within a 1 km^2 grid cell over an 11-year period (2003-2013) has been estimated using MODIS active fire product and logistic GLM. Land cover, vegetation indexes, elevation, slope, aspect, distance to zero residual contours, distance to road, distance to railway, distance to Wildland-Urban Interface (WUI) and population density are considered as contributing factors. Univariate and multiple regression analyses have been conducted for the evaluation of independent and partial effects of these factors on fire activity pattern. The contribution of each factor has been evaluated, and a resulting fire probability map has been generated.

The previous study assumes no difference among fire drivers of different regions and linear relationships between response and explanatory variables. The work presented in Chapter 5 aims to provide localised and more precise information on fire risk assessment, and so can be viewed as an extension of the work of the previous chapter. The primary objective is to quantify the regional variation in the effects of factors on fire ignition pattern in NSW and ACT, Australia. Ecoregions are selected as the landscape segmentation system. This is because (1) an ecoregion is identified to be biologically coherent, so that fire management suggestions are ecologically and strategically meaningful; and (2) each ecoregion covers a large area of the landscape with enough samples, so that statistically significant results can be obtained. Rather than using all the MODIS active fire detections, fire ignition points were identified from the dataset using a Fire Spread Reconstruction (FSR) algorithm. These ignition points, together with environmental and anthropogenic factors, were used to build ecoregion-based models to estimate probabilities of at least one fire within a 1 km^2 grid cell. Logistic GAMs are used to model non-linear relationships between fire probability and its explanatory variables.

As stated in Section 1.1, a better understanding of fire regime pattern is required given the dense population of fire-sensitive species such as *Eucalyptus camaldulensis* in the riverine environment of south-eastern Australia. The objective of the study of Chapter 6 is to characterise wildfire occurrence patterns in inland wetlands and their neighbouring dry lands, and to identify effects and relative contributions of these fire-occurrence drivers in the NSW side of the Riverina Bioregion. Administrative wildfire records from 1970-2016 sourced from several fire management agencies are used for the construction of the dependent variable. A number of human-caused and natural wildfires occurred in this area each year, allowing for quantitative analysis on a causality basis. The distributions of Fires burned Entirely in forested Wetlands (FEW), Fires burned Partly in forested Wetlands (FPW) and Fires that did Not burn in forested Wetlands (FNW) are explored separately in the descriptive analysis. Univariate and multiple logistic GLMs have been built to understand weather, vegetation (e.g., FEW or

FNW) and ignition sources acting on the occurrence of both human-caused and natural fires.

The study presented in Chapter 7 subsequently models the driving factors of wildfire size in the same area as Chapter 6. The objective is to investigate wildfire characteristics and the effects and relative contributions of ambient weather and antecedent rainfall on fire size in forested wetlands and the surrounding dry lands. As in the previous step, descriptive analysis has been conducted to explore distributions of sizes of FEW, FPW and FNW. Univariate and multiple GLM was used to quantify relationships between fire size and its determinants, with natural-log transformed fire size being used as the dependent variable. The three fire categories are progressively incorporated into the modelling process to explore the change of effects and contributions of factors as the fuel type changes from litter/grass to shrub/grass. Chapters 6 and 7 collectively provide information on fire occurrence and size in in the riverine environment of south-eastern Australia. Information obtained from both studies are vital to fire risk reduction and sustainable land and fire management. They may also be extended and compared with knowledge on fire patterns in wetlands and their neighbouring dry lands in arid or semi-arid areas across the world.

Chapter 4 Wildfire Activity Patterns in South-Eastern Australia

In this chapter, the term "fire occurrence" refers to the activities of fire within a spatiotemporal unit (see definition in Section 2.2.2). The spatial patterns of wildfire occurrence in an area that covers NSW, ACT, and VIC are explored by estimating the probability of at least one fire within a 1 km x 1 km grid cell under specific sets of environmental and anthropogenic conditions. Fire occurrence points are sourced from the MODIS active fire product. Univariate and multiple logistic GLMs are used to predict where fires are likely to occur in South-Eastern Australia on a broad scale.

4.1 Study Area

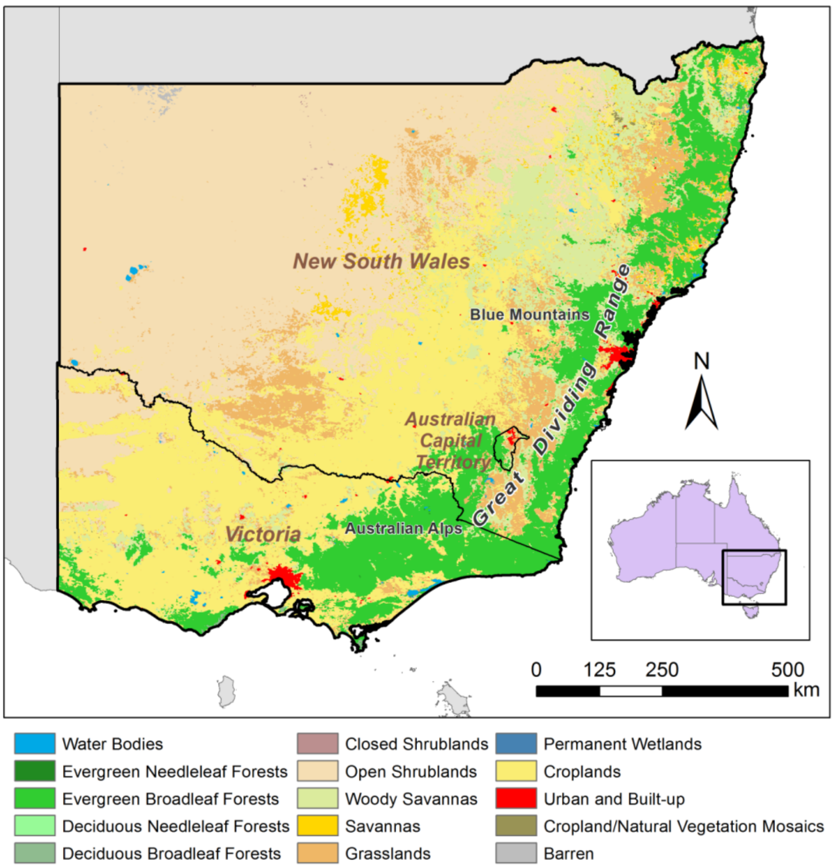

Figure 4.1 Location and land cover types of South-Eastern Australia.

As defined in this section, South-Eastern Australia contains the mainland states of NSW, VIC, and ACT, covering an area of 1,030,000 km^2 (Figure 4.1). The dominant land cover types in this region are open shrublands (39%), croplands (26%), evergreen broadleaf forests (13%), and woody savannas (10%), as calculated by the authors. The climate in this region is temperate: cold and damp in winter, hot and dry in summer. Low frequency, high intensity fires occur in this area due to the latitudinal gradient in summer monsoon rainfall activity (Murphy *et al.* 2013).

4.2 Data Description

A range of datasets were collected and transformed for the purposes of this study. Some were used for statistical analysis (Table 4.1) while others, e.g. the Catchment-scale Land Use of Australia Map (CLUM) (Department of Agriculture and Water Resources [DAWR] 2014) (Section 4.2.1), were used as filters for identifying fire occurrence points.

4.2.1 Land Use

The CLUM dataset was collected by state and territory partners of the Australian Collaborative Land Use and Management Program (ACLUMP), published by the Department of Agriculture (DA), and updated in March 2014. Land use in CLUM is mapped at the detailed catchment scale (1:25,000-1:100,000). This data is classified according to the Australian Land Use and Management (ALUM) Classification version 7 (DAWR 2010), and shows a single dominant land use for a given area based on the major management objective. There are six primary classes of land use: (1) conservation, natural environments; (2) production from relatively natural environments; (3) production from dryland agriculture and plantations; (4) production from irrigated agriculture and plantations; (5) intensive uses; (6) water. The 50 m resolution CLUM dataset was resampled to 1 km for consistency with the resolution of MODIS hotspots and to reduce the size of the dataset needed to cover an area of 1,030,000 km^2. Resampling was performed using the majority algorithm.

Table 4.1 Sources and descriptions for variables included in regression models explaining fire occurrence in South-Eastern Australia. All variables were generated or resampled at a resolution of 1 km.

Variable	Source	Description of Original Data
Explanatory variables		
Land cover	NASA	MODIS 500 m MCD12Q1, 2003
		Six primary classes (forests; shrublands; savannas; grasslands; permanent wetlands; croplands, water bodies and others)
NDVI	NASA	MODIS 1 km MYD13A3 NDVI, Collection 5, January 2003
EVI	NASA	MODIS 1 km MYD13A3 EVI, Collection 5, January 2003
Elevation	NASA	ASTER 30 m GDEM, V2
Slope	NASA	Derived from elevation grid
Northwestness	NASA	Derived from elevation grid
		NW = con ([aspect] == - 1 , 0 , cos (([aspect] + 45) * π / 180))
Distance to zero residual contours	NASA	Derived from elevation grid, m
Distance to primary road	OSM	Mean Euclidean distance, m
Distance to secondary road	OSM	Mean Euclidean distance, m
Distance to railway	OSM	Mean Euclidean distance, m
Distance to WUI	OSM	WUI, m; wildland–urban interface Derived from CLUM land use
Population density	ABS	LGA units, 2003
Dependent variable		
Fire occurrence	NASA	Derived from MODIS 1 km MCD14ML, Collection 5

4.2.2 Land Cover

The MODIS 500 m Land Cover Type product (MCD12Q1) (NASA LP DAAC 2003a) based on the classification system defined by the International Geosphere Biosphere Program (IGBP) was used for filtering of fire occurrence points and subsequent statistical analysis. The classification system consists of 17 classes (11 natural vegetation classes, three developed and mosaic land classes, and three non-vegetated land classes) at a global scale. These were reclassified into six primary classes to consider the influence of primary vegetation types on fire occurrence in the study area: (1) forests; (2) shrublands; (3) savannas; (4) grasslands; (5) permanent wetlands; (6) croplands, water bodies and others. MCD12Q1 data from 2003 was chosen because that year had the highest number of fires in the study area. The data was also resampled from a resolution of 500 m to 1 km using the majority algorithm for consistency with the resolution of MODIS hotspots.

4.2.3 Vegetation

The 2003 Collection 5 MODIS global monthly Vegetation Index product series (MYD13A3) (NASA LP DAAC 2003b) was used as an indicator of fuel load in the study area. This data is provided monthly at a 1 km spatial resolution as a gridded level-3 product. Two types of vegetation index were used: NDVI and a new Enhanced Vegetation Index (EVI). NDVI is the index most commonly used to assess live fuel moisture content (Hardy and Burgan 1999; Chuvieco *et al.* 2004; Caccamo *et al.* 2012); however, it can experience saturation under high-density vegetation conditions (Sellers 1985). EVI minimizes canopy background variation and has improved accuracy in high biomass regions.

4.2.4 Topography

Topographical variables considered included elevation, slope, transformed aspect index (northwestness), and distance to zero residual contours. The elevation layer was resampled at 1 km resolution from the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) Global Digital Elevation Model Version 2 (GDEM V2) 30 m data (NASA LP DAAC 2011). Resampling was carried out by calculating the mean of the cell values within each 1 km^2 rectangular block. Slope (in percentage) and aspect (in degrees) maps were derived from elevation data. Because aspect is a circular variable that cannot be used in linear statistics, that layer was cosine-transformed to obtain a linear index of 'northwestness' which can better distinguish xeric exposures (high index values) from mesic exposures (low index values) (Franklin *et al.* 2000). Another topographical variable tested in this study was the distance to zero meso-scale elevation residual contours, as suggested by McRae (1992). These contours were produced by generating a macro-scale surface using an ordinary kriging interpolation method and then subtracting it from a finer-resolution elevation surface, producing a zero meso-scale elevation surface. Because the resolution of the explanatory variable in this study should not be finer than 1 km, the meso-scale contours are coarser than those used in McRae's study.

4.2.5 Anthropogenic Data

Most wildfires are of anthropogenic origin, either deliberate or accidental, which indicates a potential relationship between fire occurrence and anthropogenic factors such as WUI (Section 3.3 and Table 4.1), distance to roads and railways, and population density. In this study, WUI was defined as the boundary between wildlands and urban areas. Wildland (Section 4.2.6) and urban residential areas were derived from the 50 m resolution CLUM map. A raster map representing the distance to the nearest WUI was generated at a 1-km resolution. Primary roads, secondary roads, and railways were extracted from OpenStreetMap (OSM), a collaborative project to provide open, freely available, and worldwide geographic data (Neis *et al.* 2011), and 1 km resolution distance maps were generated based on Euclidean distance to the nearest road. A population density layer with spatial units corresponding to Local Government Areas (LGAs) (Australian Bureau of Statistics [ABS] 2003) was used in this analysis.

4.2.6 Fire Occurrence

The dependent variable – wildfire occurrence – was originally derived from the Collection 5 MODIS global monthly fire location product (MCD14ML) (NASA LANCE FIRMS 2003-2013) using a contextual algorithm (Giglio *et al.* 2003). This data is the combination of the Terra and Aqua MODIS Level 2 swath 5 min MOD14 / MYD14 active fire products, hence it contains precise dates and times for those fires that are active (hotspots) when MODIS passes over. The spatial resolution of the dataset is 1 km.

Validation of the MODIS active fire product against the ASTER imagery shows a commission error of between 2% and 3% globally (Morisette *et al.* 2005; Csiszar *et al.* 2006; Schroeder *et al.* 2008), though high commission errors are generally found in low fire activity areas such as urban sites and agricultural locations (Hantson *et al.* 2013). Each fire activity data point has a corresponding detection confidence level (low, medium or high); this study included data of all confidence levels because while low-confidence hotspots have slightly higher commission errors, they provide useful additional information (Hantson *et al.* 2013).

In addition to commission errors, the MODIS active fire product has other limitations. First, it does not distinguish between fire causes (lightning or human), which makes it impossible to analyse each explanatory variable in the context of its causality. Furthermore, it has been shown to have an omission error of 18% related to fire patch size (Hawbaker *et al.* 2008); namely, the majority of human-caused fires may not be large enough to be detected by MODIS sensors, and so a bias toward natural fires should be expected. Moreover, the fact that prescribed burning and other non-wildfires were also recorded makes it necessary to filter the data.

The study period covered from January 2003 to December 2013, including all years for which both MODIS Aqua and Terra data products are available. There were data missing in 2007 from mid-August through the end of the year, on part of 21 April 2009, and on 22 April 2009. The total number of MODIS hotspots in this dataset was 176,884.

As mentioned above, it was inappropriate to use all MODIS hotspots in the models because the dataset included fires that occurred on non-wildland areas. A mask representing wildland areas was generated using both CLUM Land use and MODIS land cover data, then applied to filter out hotspots in non-wildland areas. The pixel value of the binary raster was 0 if located in land cover class (6), as well as at land use classes (3), (4), (5), and (6) except for plantation forestry; it was 1 if located somewhere else. This process additionally minimized the influence of commission errors.

A histogram representing the monthly distribution of fire hotspots is shown in Figure 4.2. The majority of fires occurred from November to February, when fire danger levels are highest. Slight fluctuations are evident across spring and autumn months due to the influence of prescribed burning programs, which are generally conducted during cooler periods (autumn and early spring in the study area). In order to mitigate the influence of prescribed burning on results, only fire data within the typical fire season (November to February) was analysed.

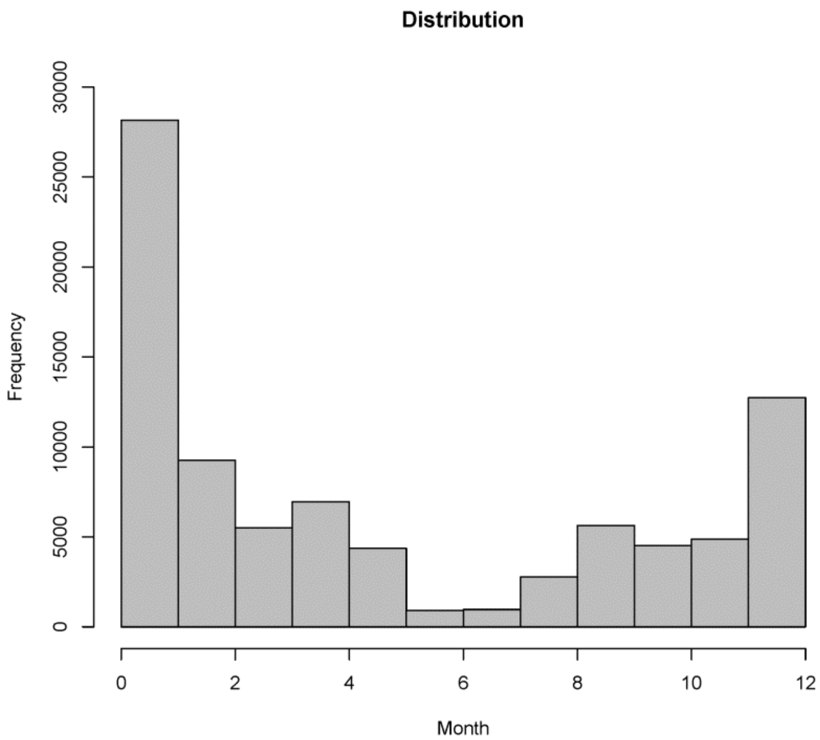

Figure 4.2 Monthly distribution of fire hotspots from 2003 to 2013 for South-Eastern Australia.

A continuous 1-km spatial resolution density map was created by calculating the number of fires occurred during the 11 fire seasons of 2003-2013 that fall within each cell of wildland areas. All the non-zero values were converted to 1 so that the value of each point denotes the presence of at least one fire within each cell. And the absence of fire within a cell is denoted by zero (0). In total, there were 538,690 data points in the density map which included 28,761 presence points and 509,929 absence points. Data analysis was conducted based on sample statistics in order to reduce the data volume. Among many sampling methods, the stratified sampling method was utilized i.e. the ratio of presence to absence is preserved. 10,000 samples (which include 596 presence and 9,404 absence points) were randomly selected. That is, 1.86% of the population is sampled.

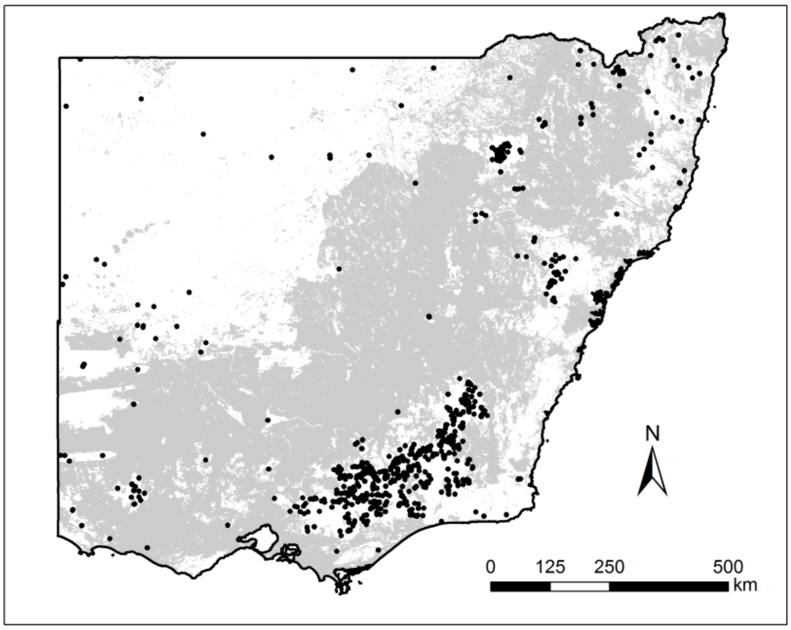

Figure 4.3 Map showing distribution of the dependent variable (black dots), representing the presence of fire in South-Eastern Australia. The grey colour represents non-wildland areas.

4.3 Modelling Approach

To estimate the probability P of at least one fire occurring within a cell, a multiple logistic regression model was developed. Let P_i be the probability of at least one fire occurring in cell i, and x_{ij} be the value of the jth covariate in cell i. The logistic regression can then be defined as:

$$P_i = \exp(\beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \cdots + \beta_n x_{ni})/(1 + \exp(\beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \cdots + \beta_n x_{ni})) \quad (1)$$

where β_0 is an intercept and β_n are coefficients for the explanatory variables x_{ni}. All wildland fire occurrence points were used to fit the model. The ratio of ones to zeros was 1:24.6.

Univariate logistic regression models were developed for each explanatory variable to evaluate their independent influences on fire occurrence. Following the suggestions of Serneels and Lambin (2001), the performance of quadratic or logarithmic versions of the continuous variables was also tested. The final model was chosen by implementing the Akaike information criterion (AIC) in a backwards stepwise algorithm (Venables and Ripley 1999).

To avoid the effects of multicollinearity, Spearman's rank correlation was used to compare continuous explanatory variables (Table 4.2). Correlations above 0.6 (Wintle *et al.* 2005) variables were found between NDVI and slope (r=0.65, P<0.001), NDVI and population density (r=0.81, P<0.001), NDVI and EVI (r=0.97, P<0.001), EVI and population density (r=0.84, P<0.001), slope and elevation (r=0.67, P<0.001), and distance to WUI and population density (r=0.62, P<0.001). Therefore, EVI, slope, and population density were excluded from further analyses. A diagnostic procedure was also implemented using the variance inflation factor (VIF), a measure that shows how much the variance of a coefficient is increased due to collinearity (Belsley *et al.* 1980). Instead of comparing correlations between pairs of variables, VIF calculates the linear relationship between one variable and all other variables. VIFs ranging from 1.01 to 8.29 were considered to indicate no evidence of multicollinearity, as recommended by Belsley *et al.* (1980).

To determine the optimal discrimination threshold for predicting fire occurrence, receiver operating characteristic (ROC) curves were computed for all models. Specifically, model accuracy was evaluated by plotting the true positive rate (sensitivity) against the false positive rate (specificity). The area under the curve (AUC) was used to evaluate model fit, with a measure of 0.9-1 being excellent, 0.8-0.9 good, 0.7-0.8 fair, 0.6-0.7 poor, and 0.5-0.6 fail (Swets 1988). To validate the performance of the final model, a ten-fold cross-validation approach was used (Breiman *et al.* 1984). In this procedure, the original samples were randomly partitioned into ten groups of approximately equal sizes, with a single group reserved as validation data and the remaining nine used as training data. The process was repeated ten times, leaving out a different group each time, AUCs calculated for each validation set. A statistical summary of all ten AUCs was calculated in order to determine the uncertainty related to occurrence location. The mean of the AUCs was taken as the overall cross-validated AUC estimate.

Logistic regressions were fitted using a GLM. VIFs, ROCs, and cross-validated AUCs were computed using R modules *fmsb* (Minato 2014), *pROC* (Robin *et al.* 2011), and *cvAUC* (LeDell *et al.* 2014), respectively.

The contribution of each variable was calculated by conducting a jackknife procedure based on the change in AUC (Bar Massada *et al.* 2013), namely the ten-fold cross-validated AUC. The approach consists of removing individual explanatory variables from the full model and recalculating the cross-validated AUC. The difference between AUC values denotes the loss of explanatory power of the model in the absence of the given factor. In addition, AUC values were computed for univariate models, and the variables were ranked accordingly.

Table 4.2 Correlation matrix for continuous variables.

	NDVI	Elevation	Slope	Northwest -ness	Distance to zero residual contours	Distance to primary road	Distance to secondary road	Distance to railway	Distance to WUI	Population Density
EVI	0.97	0.52	0.59	0.01	-0.30	-0.32	-0.33	-0.45	-0.55	0.84
NDVI		0.56	0.65	0.002	-0.32	-0.29	-0.31	-0.44	-0.52	0.81
Elevation			0.67	0.03	-0.35	-0.25	-0.14	-0.22	-0.35	0.41
Slope				-0.03	-0.45	-0.27	-0.18	-0.29	-0.39	0.53
Northwestness					-0.01	-0.004	0.03	0.002	0.02	0.002
Distance to zero residual contours						0.15	0.11	0.12	0.26	-0.26
Distance to primary road							0.06	0.45	0.39	-0.39
Distance to secondary road								0.25	0.34	-0.34
Distance to railway									0.58	-0.58
Distance to WUI										-0.62

4.4 Results

According to the univariate logistic regression modelling results (Table 4.3), all explanatory variables are statistically significant ($P \leq 0.05$) except for northwestness ($P = 0.37$). In terms of MODIS land cover categories, wildfires were most likely to occur on forests and savannas, but least likely to occur on shrublands and grasslands. NDVI values also showed the expected positive relationship with the response variable. Fire occurrence was positively related to elevation, and negatively related to the distance to zero meso-scale elevation residual contours. Fire occurrence was also negatively related to all anthropogenic variables (distance to primary road, distance to secondary road, distance to railway, and distance to WUI), which suggests that fires are more likely to occur close to human facilities and urban areas.

The final model for fire occurrence included four environmental variables (land cover, NDVI, elevation, northwestness) and three anthropogenic variables (distance to primary road, distance to secondary road, and distance to WUI). AUC values from the ten-fold cross-validation procedure ranged from 0.858 to 0.906, with a standard deviation of 0.014 (Table 4.4). As all values were in the good to excellent range, the AUC variability acceptable, although it clearly can be affected by the locations of the points. The overall cross-validated AUC estimate was 0.886, which supports that the model performs well in predicting fire occurrence.

According to the AUC values of the univariate models (Figure 4.4), NDVI had the strongest predictive power, followed by elevation and land cover. The jackknife estimate of variable importance (Figure 4.4) showed slightly different results, with elevation contributing the most to wildfire occurrence prediction; this result coincides with the variable's performance in the univariate model. Distance to WUI and land cover were ranked second and third by jackknife estimate, respectively. The remaining variables were ordered by jackknife estimate as follows: distance to primary road, NDVI, distance to secondary road, and northwestness.

Table 4.3 Univariate logistic regression results for variables explaining wildfire occurrence in South-Eastern Australia.

Explanatory Variable	Coefficient	Standard Error	***P*** value	95% Confidence Interval	
Land cover			<0.001		
Forest (Intercept)	-1.44	0.05	<0.001	-1.54	-1.34
Shrublands	-3.73	0.18	<0.001	-4.10	-3.40
Savannas	-0.83	0.12	<0.001	-1.07	-0.60
Grasslands	-2.35	0.36	<0.001	-3.14	-1.71
Permanent Wetlands	-12.12	267.7	0.964	NA	18.57
Vegetation index					
NDVI	0.00060	0.00002	<0.001	0.00055	0.00064
Topography					
Elevation	0.0033	0.0001	<0.001	0.0031	0.0036
Northwestness	0.05	0.059	0.37	-0.06	0.17
Distance to zero residual contours	-0.00047	0.00005	<0.001	-0.00056	-0.00038
Anthropogenic data					
Distance to primary road	-0.000017	0.000002	<0.001	-0.000021	-0.000014
Distance to secondary road	-0.000031	0.000003	<0.001	-0.000037	-0.000025
Distance to railway	-0.0000093	0.0000009	<0.001	-0.0000011	-0.0000076
Distance to WUI	-0.000042	0.000002	<0.001	-0.000047	-0.000037

Table 4.4 Summary of AUCs values from ten-fold cross-validation.

Min	Max	Median	Mean	Standard Deviation	Variance	Range
0.858	0.906	0.885	0.886	0.014	0.0002	0.048

Note: The mean of AUC values is the cross-validated AUC estimate.

A 1 km resolution fire occurrence probability map was generated by applying the coefficients of the final model to raster layers corresponding to the explanatory variables (Figure 4.5(*a*)). Relatively high wildfire probabilities (greater than 0.2) were found in forestry areas and in high elevation areas close to urban areas, while low probabilities (less than 0.2) were found in inlands and mountainous areas. The largest area of high wildfire probability was in the Great Dividing Range along the study area coastline. The most flammable areas were located in the forestry areas of the Australian Alps, extending across eastern VIC, southeastern NSW and the ACT; these were followed by the wildland-urban interface areas at the New England Range in northeastern NSW and the Blue Mountains above the Sydney Basin. Natural conservation regions such as Mount Kaputar National Park in northeastern NSW and Grampians National Park in western VIC were also predicted more likely to burn. In addition, ten prediction maps corresponding to the ten-fold cross-validation procedure were generated and converted into a standard deviation map (Figure 4.5(*b*)), provided insights into the spatial distribution of the uncertainty of the final model. Variability was found to be primarily distributed in high fire probability areas, e.g. the Australian Alps.

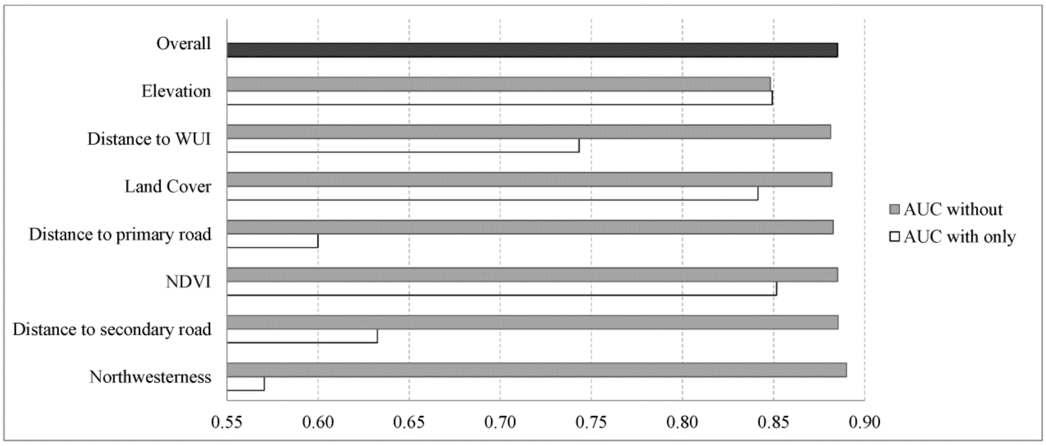

Figure 4.4 Jackknife estimations of variable importance for the final model. Bars denote the area under the receiver operator characteristic curve (AUC). The black bar represents the full-model AUC, white bars represent the AUCs of univariate models, and grey bars represent the AUCs of models excluding the corresponding variables.

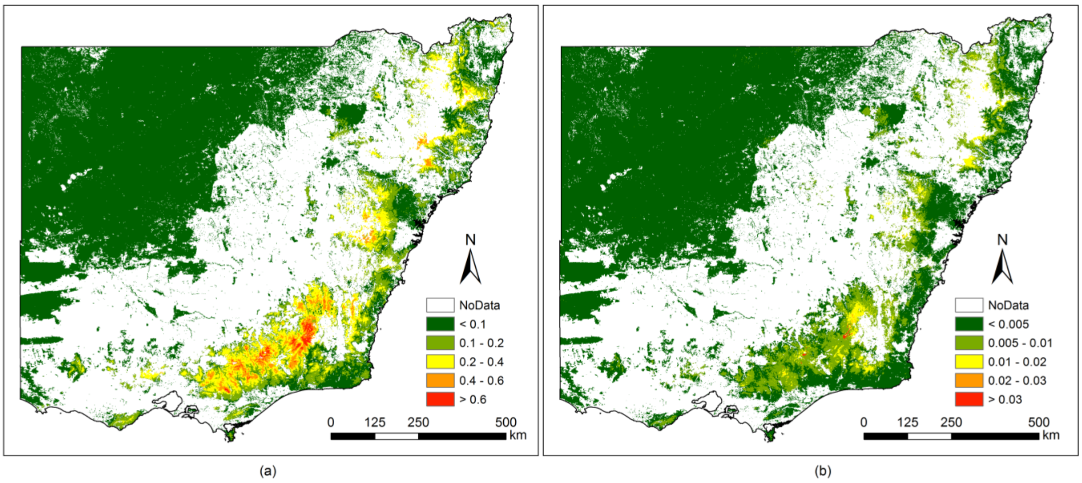

Figure 4.5 Maps showing (a) the predicted probability of wildfire occurrence in South-Eastern Australia and (b) the standard deviation of probability maps corresponding to the ten-fold cross-validation procedure.

4.5 Discussion

The model is able to describe the spatial pattern of wildfire occurrence in South-Eastern Australia over the 11-year period from 2003 to 2013. Wildfire locations in the study area were found to be significantly influenced by land cover types. Forests were most susceptible to fire due to the dominance of fire-prone eucalyptus-related vegetation and heavy fuel loads. Savannas were ranked the second most susceptible, probably due to ease of ignition relating to their inherent features (Murphy *et al.* 2013). Shrublands were least susceptible to burning due to the lower predominance of grass components in those areas (Murphy *et al.* 2013). These results were slightly inconsistent with findings from other landscapes (e.g. Mermoz *et al.* 2005; Oliveira *et al.* 2014), possibly because of the low level of shrub canopy cover (<60%) in most shrub areas of South-Eastern Australia.

As expected, model results indicated fires were more likely to occur in areas with high vegetation index values; this index has a strong relationship with fuel flammability (Caccamo *et al.* 2012). Fires were also more likely to occur in areas with higher elevations. This can be explained by the fact that in the study area, the spatial distribution of vegetation corresponds with elevation, which means there is more vegetation to be burned at higher elevation. When it comes to the influence of aspect on fire occurrence, some researchers have found that a southerly aspect in the northern hemisphere (or a northerly aspect in the southern hemisphere) is more flammable because those slopes receive longer and more direct solar exposure, decreasing fuel moisture content and enhancing its flammability (Mouillot *et al.* 2003; Mermoz *et al.* 2005). Others have found that northern slopes are more fire prone because much more water is available and results in heavier fuel loads (Carmo *et al.* 2011; Oliveira *et al.* 2014). However, in this study, aspect was not predictive of fire occurrence. This may be because the coarse spatial resolution used fails to provide sufficient or correct information on solar exposure and fuel load. This study did determine that fires tend to be distributed in areas near the zero meso-scale elevation residual contour, generated by removing micro- and macro-scale variation in elevation. This finding is consistent with those of McRae (1992) regarding natural ignitions in the ACT area. This unobvious pattern is able to provide practical information for fire risk mapping. Finally, fires were found to be preferentially located in areas near human infrastructure (roads and railways) and WUIs, consistent with the results of other studies at small landscape scales (e.g. Penman *et al.* 2013).

Most environmental factors (NDVI, elevation, and land cover) were found to be informative when analysed independently, which is expected because their spatial patterns correspond with the distribution of wildfires at broad spatial scales. On the other hand, some factors (e.g. land cover) had low variable contributions because much of the information they provided was included in a relatively more influential variable (e.g. elevation).

Anthropogenic variables did not exhibit good predictive power in univariate analyses. There are likely several reasons for this. First, the indistinguishability of ignition sources in the MODIS active fire product may reduce the apparent contributions of anthropogenic variables. Second, due to not all human-caused fire occurrences being retrieved, the independent predictive powers of anthropogenic factors are possibly being underestimated in this study. Third, the fire occurrence points contain information for both ignition and spread. Although fire ignitions in Australia have been proven to be strongly influenced by human activities (Willis 2005), fire spread is fundamentally a function of fuel, climate, and terrain (Pyne *et al.* 1996). Distance to WUI was found to contribute more predictive power than NDVI and land cover, which supports the influence of human activities in fire occurrence. Therefore, anthropogenic variables should not be ignored in fire risk assessments at broad landscape scales. Moreover, the association between human activity and fire occurrence indicates threat from wildfire to human lives and assets. Reducing fuel loads near densely-settled areas that are close to fire-prone bushlands is therefore an essential issue in the context of wildfire management.

The fire probability map produced from the final model illustrates the most fire-prone locations in South-Eastern Australia. The relatively high uncertainty and limited predictive capacity of logistic regression in high fire occurrence areas (Rodrigues and de la Riva 2014) suggests that fire probability has possibly been underestimated. Nevertheless, the prediction map still provides useful information regarding areas where environmental and anthropogenic conditions enhance the likelihood of fire occurrence. According to this map, long-term resources for firefighting and fire prevention should be allocated close to mountainous areas, forests, and savannas, as well as lands with heavy fuel loads. Areas close to WUIs and transport networks should also be emphasized.

MODIS data was used in this study rather than administrative records because the former are globally accessible, which makes it possible to conduct the study at a broad spatial scale, apply the method to other regions of the world, assess the suitability of the model, and explore the variation of spatial patterns in different study areas. MODIS fire data is especially useful for data-poor regions. However, researchers should bear in mind the inherent drawbacks of the MODIS active fire product such as the existence of commission error (which can be minimized by introducing controlling factors), the indistinguishability of ignition sources, and the bias towards natural fires.

Another defect of the model is that the explanatory variables only represent the environmental and anthropogenic conditions of the study area for a short period of time, even though the active fire data covers 11 years. To reduce the impact of this temporal mismatch, data recorded at the most appropriate times were chosen (e.g. January 2003). Furthermore, the overall goodness of fit of the final model is satisfactory. The model could be further improved by using precise occurrence data that has lower omission error or that can identify ignition types. Adding more explanatory variables, especially climate variables, would also be helpful.

4.6 Summary

In this work, logistic regression was used in combination with land cover, vegetation index, and topographic and anthropogenic information to characterize the spatial pattern of fire occurrence on a 1 km^2 grid in South-Eastern Australia over the period of 2003-2013. The models and the final map suggest that mountainous areas, forests, savannas, and lands with high vegetation coverage would be most fire-prone, while grasslands and shrublands can be less vulnerable to wildfire in the study area. Wildfires also tended to occur in areas near human infrastructure and WUIs. Environmental variables were found to be powerful in predicting fire occurrence when analysed individually, while anthropogenic variables contributed more to the final model. The study also demonstrates that the MODIS active fire product is a useful data source for studying environmental and anthropogenic controls on the distribution of wildfires, although attention should be paid to data manipulation procedures and the interpretation of the modelling result. Ultimately, extended knowledge about the influence of environmental and anthropogenic conditions on wildfire occurrence and the spatial pattern of wildfires in the mainland NSW, VIC, and ACT can help fire agencies in these three regions better arrange their limited resources and target management activities.

Chapter 5 Wildfire Ignition Patterns in Ecoregions of NSW and ACT

The work presented in this chapter is an extension of Chapter 4 (see Section 3.3 for the description of the relationship between Chapters 4 and 5). Notably, the term "fire occurrence" in this chapter refers to the occurrence of fire ignition within a spatiotemporal unit (see the definition in Section 2.2.2), which is different from the definition used in Chapter 4. This chapter specifically aims to address the following questions: What are the key types of environmental and anthropogenic factors driving the spatial patterns of wildfire occurrence in different ecoregions? What are the effects of these factors, are they linearly related with wildfire occurrence probabilities, and are these relationships consistent with the prior knowledge? These questions are particularly important for end-users such as fire managers and others investigating wildfire risk assessment, since a better understanding of fire patterns and their drivers will help minimise fire impacts.

5.1 Study Area

South-Eastern Australia, which includes NSW, ACT and VIC, is one of the most fire-prone regions in Australia. The study area covers NSW and the ACT, including coastal plains, eastern highlands (the Great Dividing Range), and western lowlands (Figure 5.1(*a*)); this area amounts to 803,000 km^2 in total. VIC was excluded because a comprehensive and state-wide vegetation classification map covering VIC was not able to be obtained at the time of this study. Within the study area, six ecoregions (Section 5.2.1, Figure 5.1(*b*)) can be found: temperate broadleaf and mixed forests (TB); montane grasslands and shrublands (MG); tropical and subtropical grassland, savannas and shrublands (TSG); temperate grasslands, savannas and shrublands (TG); Mediterranean forests, woodlands and shrubs (MF); and deserts and xeric shrublands (DX). According to the major groups of the Köppen climate classification system, the four major climate zones of this area are: temperate in the east, subtropical in part of the north-east, grassland in the middle, and desert in the west. The dominant vegetation formations (Section 5.2.2, Figure 5.2) are arid shrublands (20%), semi-arid woodlands (20%), dry sclerophyll forests (10%), and wet sclerophyll forests (4%), as calculated by the authors. Human activities are concentrated in the populated coastal and nearby inland areas (Collins *et al.* 2015). Fires occur primarily in spring and summer, with more in the spring in the north and more in the summer in the south (Russell-Smith *et al.* 2007).

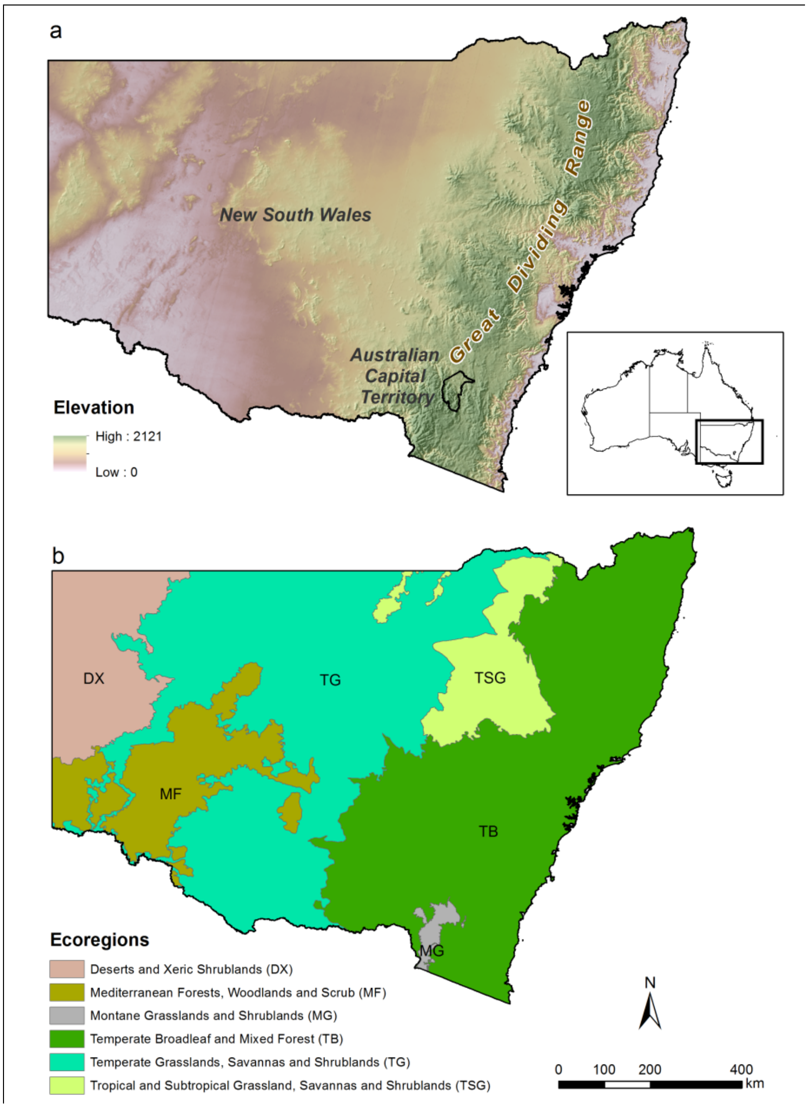

Figure 5.1 Maps of New South Wales and the Australian Capital Territory showing (a) location and topography and (b) ecoregions. The latter are reclassified from the Interim Biogeographic Regionalisation for Australia (IBRA) Version 7 (Department of Sustainability, Environment, Water, Population and Communities 2012) according to the classification system originally developed by the World Wildlife Fund.

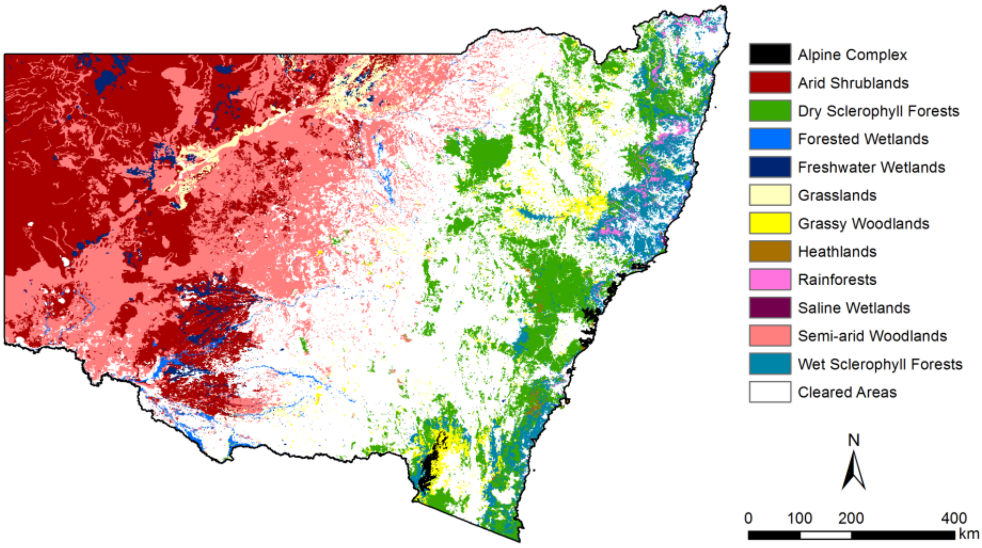

Figure 5.2 Vegetation formations in New South Wales and the Australian Capital Territory, adapted from Keith and Simpson (2012).

5.2 Data Description

A number of datasets were compiled for this study, including the ecoregion layer used for data stratification, the land use layer (Section 4.2.1) used to filter fire points and generate other anthropogenic variables, and other layers (Table 5.1) used for statistical modelling. Some of the datasets have been introduced in Section 4.2, and the rest are described in the following sections.

Table 5.1 Variables included in generalized additive models explaining wildfire occurrence in NSW and the ACT. Fire occurrence is the response variable and all others are explanatory variables. The spatial resolution of all variables is 1 km.

Variable type	Variable	Source	Description
Spatial Effect	Location	NASA	Locations of fire occurrence points, decimal degree
Vegetation	Vegetation type	OEH	Categorical variable, including 12 vegetation formations (Keith 2004): rainforests; wet sclerophyll forests; grassy woodlands; grasslands; dry sclerophyll forests; heathlands; alpine complex; freshwater wetlands; forested wetlands; saline wetlands; semi-arid woodland; and arid shrublands
	Normalized Difference Vegetation Index (NDVI)	NASA	Median value of NDVI representing the average biomass condition
	Distance to drainage line	GA	Mean Euclidean distance to the nearest drainage line, km
Climate	Annual precipitation	BOM	Mean annual precipitation, mm
	January maximum temperature	BOM	Mean January maximum temperature, mm
	July minimum temperature	BOM	Mean July minimum temperature, mm
Topography	Elevation	NASA	Elevation grid
	Slope	NASA	Calculated from elevation grid
	Northwestness (NW)	NASA	Transformed aspect index, calculated from elevation grid NW = cosine ((aspect+45) * π/180)
Anthropogenic variables	Distance to road	GA	Mean Euclidean distance to the nearest road, km
	Distance to track	GA	Mean Euclidean distance to the nearest track, km
	Distance to railroad	GA	Mean Euclidean distance to the nearest railroad, km
	Distance to wildland-urban interface (WUI)	GA	Mean Euclidean distance to the nearest WUI, km
	Distance to recreational area	GA	Mean Euclidean distance to the nearest recreational area
	Distance to powerline	GA	Mean Euclidean distance to the nearest powerline
	Population density	ABS	Population density in each Local Government Area (LGA) unit in 2003
	Protected area	DEE	Binary variable representing the presence of protective management
Response variable	Fire occurrence	NASA	Binary variable, identified from MODIS active fire detections

Note: OEH, NSW Office of Environment and Heritage; GA, Geoscience Australia; BOM, Bureau of Meteorology; ABS, Australian Bureau of Statistics; DEE, Department of the Environment and Energy

5.2.1 Ecoregion

Ecoregions were reclassified from the Interim Biogeographic Regionalisation for Australia (IBRA) Version 7 (DSEWPaC 2012) according to the classification system originally developed based on IBRA 4.0 by the World Wildlife Fund (WWF). This classification system provides a more comprehensive conservation tool than simply looking at ecosystem types or biomass based on climate and vegetation. This system defines a total of 14 ecoregions across the globe, eight of which are found in Australia and six in NSW and the ACT (Figure 5.1 (*b*)).

5.2.2 Vegetation

Version 3.03 of the NSW vegetation formation map (Keith and Simpson 2012) was used to filter fire points and to conduct statistical analysis. The 12 vegetation formations (Figure 5.2) defined by Keith (2004) group together vegetation that has similar flammability properties. This data was resampled from a 200 m resolution to 1 km resolution by the majority rule.

NDVI (Section 4.2.3) is a highly variable factor that reflects the biomass or fuel load through time and across the landscape. Considering the broad spatial and temporal scale of this study, it is more appropriate to use values representing the average biomass condition. Thus, the median NDVI during the period of 2003-2013 was calculated on a pixel-by-pixel basis to avoid the bias that would be introduced to mean values by greenness loss after a burning event.

Additionally, drainage information was derived from the 1:2.5 million scale topographic dataset GEODATA TOPO 2.5M 2003 (Geoscience Australia [GA] 2003). The distance to a drainage line can affect fuel moisture content and thus influence the probability of wildfire occurrence (Penman *et al.* 2013). A 1 km resolution map of distance to the nearest drainage line was produced via calculation of the Euclidean distance (in km).

5.2.3 Climate

Weather condition is a key driving factor of fire potential (Pyne *et al.* 1996). As discussed in section 5.2.2, instead of relating each fire occurrence with the weather conditions before or at that occurrence, variables representing integrated weather conditions are more appropriate for the scale of this study. Three climate variables were tested: (1) annual precipitation (Bureau of Meteorology [BOM] 2016b), which depicts regulation of the spatial distribution of wildfire occurrence through the effects of the precipitation gradient on the amount and type of vegetation; and (2) January maximum temperature (BOM 2006-2013a) and (3) July minimum temperature (BOM 2006-2013b), which together reflect the upper and lower limits that maximise the spatial variability of temperature gradients (Syphard *et al.* 2008). All layers were resampled at a resolution of 1 km using the nearest-neighbour rule.

5.2.4 Anthropogenic Data

Most wildfires in South-Eastern Australia are human-caused (Collins *et al.* 2015), indicating a potential connection between fire occurrence and factors representing the accessibility of wildland areas to human activities. Some of these factors have been introduced in Section 4.2.5 (e.g. distance to WUI, distance to roads, distance to railway, population density); others include distance to recreational area, distance to powerline, etc. In this study, roads and railroads were derived from GEODATA TOPO 2.5M 2003. Tracks, powerlines and recreational areas were derived from a 1:250,000 topographic dataset, GEODATA TOPO 250K Series 3 (GA 2006). As in 4.2.5, 1 km resolution distance maps to the nearest human infrastructure were produced via calculation of Euclidean distances in km. Additionally, fire occurrence is possibly affected by the creation of protected areas where human interventions are strictly or moderately controlled for the conservation of biodiversity; fewer human-caused fires are expected in these areas. Protected areas were derived from the Collaborative Australian Protected Areas Database, CAPAD (Department of the Environment and Energy [DEE] 2014), and then transformed into a 1 km resolution binary layer representing the presence of protective management.

5.2.5 Fire Occurrence

As described in 4.2.6, the MODIS active fire product was used as the source of fire observations. To mitigate the influence of prescribed burnings, which primarily occur during autumn and early spring, this study used fire incidents from November to February in forestry areas (rainforests, dry and wet sclerophyll forests), from September to May in grassy areas (grassy woodlands and grasslands), and from all seasons in other lands.

A MODIS active fire detection does not necessarily represent the time and location that a fire ignited, hence burning events were identified using the FSR method (Loboda and Csiszar 2007) and detected fire points with the earliest time stamp within each event were assumed to be the ignition points. FSR identifies burning events by grouping fire points based on spatial and temporal proximity between pairs of fire detections, which were set as 4 km and ten days in the present study. The number of fire detections for a burning event ranged from 1 to 4,723. A map was created representing the presence (Figure 5.3) or absence of at least one fire occurrence point within each 1 km resolution cell.

The MODIS active fire product does not contain information regarding the causes of fires, hence it is not possible to analyse each explanatory variable in the context of causality. Furthermore, small fires have been found to have high omission error (Hawbaker *et al.* 2008); therefore, a bias towards large or natural fires should be acknowledged, and that most human-caused fires may be too small to be detected. In addition, there may exist multiple ignition points in a given group identified by FSR; these are either the real fire occurrence points that a large event ignites from or clusters of the earliest-detected burning points that include unknown ignition points. A spatial sampling scheme (Section 5.3) was implemented to reduce the bias introduced in the latter case.

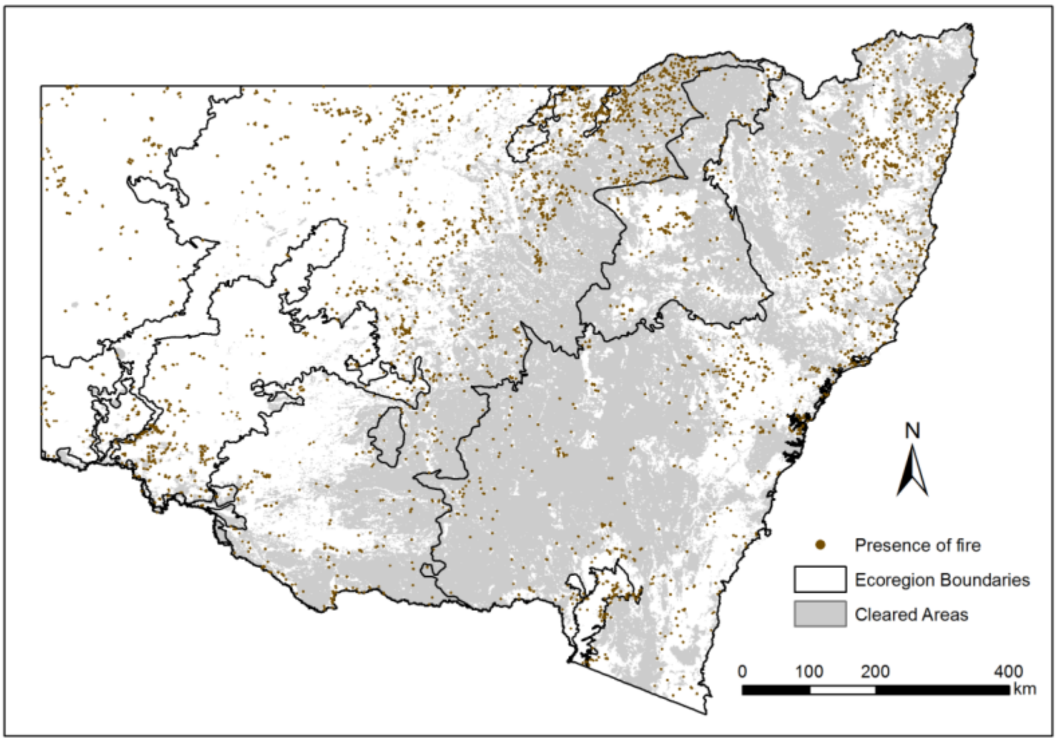

Figure 5.3 Distribution of the response variable representing the presence of fire occurrence.

5.3 Modelling Approach

In the present study, a series of ecoregion-based empirical models were developed to address the research questions. Separate models for regions rather than a single integrated model were developed because fire pattern drivers can vary among regions, i.e. a significant fire driver in one region can be insignificant in another. By developing separate models, the varying effects of factors among regions can be more precisely explained. Ecoregions TB and MG were combined due to the lack of occurrence points in ecoregion MG. This consolidation is not expected to influence the modelling result because the vegetation formation categories preserve important differences between these two ecoregions.

As explained in Chapter 4, Spearman's rank correlation was used to account for the correlations among variables and avoid the effects of multicollinearity. A threshold of 0.6 (Wintle *et al.* 2005) was used as the criterion for removing a correlated variable. Because the assumption of linearity was not met between some explanatory variables and the logit of the response variable , a GAM with a binomial distribution was used to model wildfire occurrence. The advantage of a GAM is that it allows for a non-linear relationship by generating 'smooth functions'.

Let $p(s_1, s_2)$ be the probability of at least one fire occurring at location (s_1, s_2), where s_1 denotes longitude and s_2 denotes latitude. The GAM model can be defined as:

$$logit\{p(s_1, s_2)\} = \beta_0 + \sum_{i=1}^{I} \beta_i x_i + g_1(s_1, s_2) + \sum_{m=1}^{M} g_{m+1}(x_{m+I}) \qquad (2)$$

where β_0 is an intercept and each β_i is the coefficient for each explanatory variable x_i, which have fixed effects; $g_1(s_1, s_2)$ is a nonparametric spatial effect term; g_{m+1} is a smooth spline representing the non-linear relationships between response and explanatory variables x_{m+I}; I and M distinguish x that have fixed and non-linear effects, respectively. The spatial effect term (Table 5.1) is meant to capture unknown topographic or vegetation information that is not included in each model; it also handles dependencies between nearby points. Smoothing parameters were selected by restricted maximum likelihood (REML) estimation, which allows for more accurate smooth term estimation than does generalized cross validation (GCV) smoothness selection (Marra and Wood 2011).

The model was built by initially fitting a model that included all explanatory variables, and then iteratively refitting that model after dropping one non-significant term until no non-significant terms resulted. All smoothing functions except for that of the spatial effect term were limited to three effective degrees of freedom to better represent the underlying processes and to avoid overfitting.

To reduce the influence of spatial autocorrelation and the bias introduced by FSR, a spatially-stratified sampling scheme similar to that suggested by Hawbaker *et al.* (2013) was used. Each ecoregion was subdivided into blocks of 3 × 3 pixels and then one fire cell and one non-fire cell randomly selected from within each block. If a block included only fire or non-fire cells, only that cell type was retained. Using the sampled cells, fire models were fitted and semivariograms of the models' deviance residuals were plotted. If there was strong evidence of spatial autocorrelation, the block sizes were increased, newly sampled observations were generated, and the models were refitted until the semivariograms showed pure nugget effects. A factor was applied to the final equation to correct bias in the proportion of fire and non-fire observations resulting from the sampling scheme. For each ecoregion, the original dataset was randomly partitioned into a training dataset (75% observations), which was used to build and select a model, and a validation dataset (the remaining 25% observations), which was used for model testing.

As in Chapter 4, ROC curves were used to evaluate the accuracy of each model, and model fit was measured as the AUC of the ROC curve. AUCs were calculated for both training (AUC_T) and validation (AUC_V) samples of each ecoregion model. GAM modelling and ROC calculations were carried out using R modules *mgcv* (Wood 2006) and *pROC* (Robin *et al.* 2011), respectively.

5.4 Results

Explanatory variables, deviance explained, and AUCs of each ecoregion model are given in Table 5.2. Different variable types were informative in different ecoregion models. Vegetation variables featured in most models except the TSG model, while vegetation formation was included in the TB & MG model and NDVI contributed to the TG, MF, and DX models. Climate variables (Annual precipitation, July minimum temperature, January maximum temperature) were featured in the TB & MG and TG models; topographic variables appeared in none of the models, whereas the spatial effect term was included in all of them; and anthropogenic variables (Distance to WUI, Distance to road, and Distance to railroad) were featured in the TB & MG, MF, and DX models.

AUC values ranged from 0.70 to 0.88 for training datasets, and from 0.63 to 0.84 for validation datasets (Table 5.2). The TG model (AUC_T=0.85, AUC_V=0.84), DX model (AUC_T=0.88, AUC_V=0.82), and MF model (AUC_T=0.83, AUC_V=0.80) all performed well, with 24.5%, 21.8% and 17% of model deviance respectively explained. In comparison, the TB & MG model (AUC_T=0.76, AUC_V=0.75) and the TSG model (AUC_T=0.70, AUC_V=0.63) performed fairly or poorly, respectively explaining 13.5% and 9.05% of the deviance. Although the predictive powers of some models were not as good, these models are still useful from an explanatory perspective.

Table 5.2 Explanatory variables, deviance explained, and AUCs of all ecoregion models.

Model	Variable	Dev	AUC_T	AUC_V
1. TB & MG	Vegetation formation + Annual precipitation + July minimum Temperature + Distance to WUI + Protected area + Spatial effect	13.5%	0.76	0.75
2. TSG	Spatial effect	9.05%	0.70	0.63
3. TG	NDVI + January maximum temperature + Spatial effect	24.5%	0.85	0.84
4. MF	NDVI + Distance to railroad + Spatial effect	17%	0.83	0.80
5. DX	NDVI + Distance to road + Distance to railroad + Spatial effect	21.8%	0.88	0.82

Note: TB & MG, temperate broadleaf and mixed forests (TB) & montane grasslands and shrublands (MG); TSG, tropical and subtropical grassland, savannas, and shrublands; TG, temperate grasslands, savannas, and shrublands; MF, Mediterranean forests, woodlands, and shrubs; DX, deserts and xeric shrublands. Dev, deviance explained by the model; AUC_T, AUC of the training data; AUC_V, AUC of the validation data.

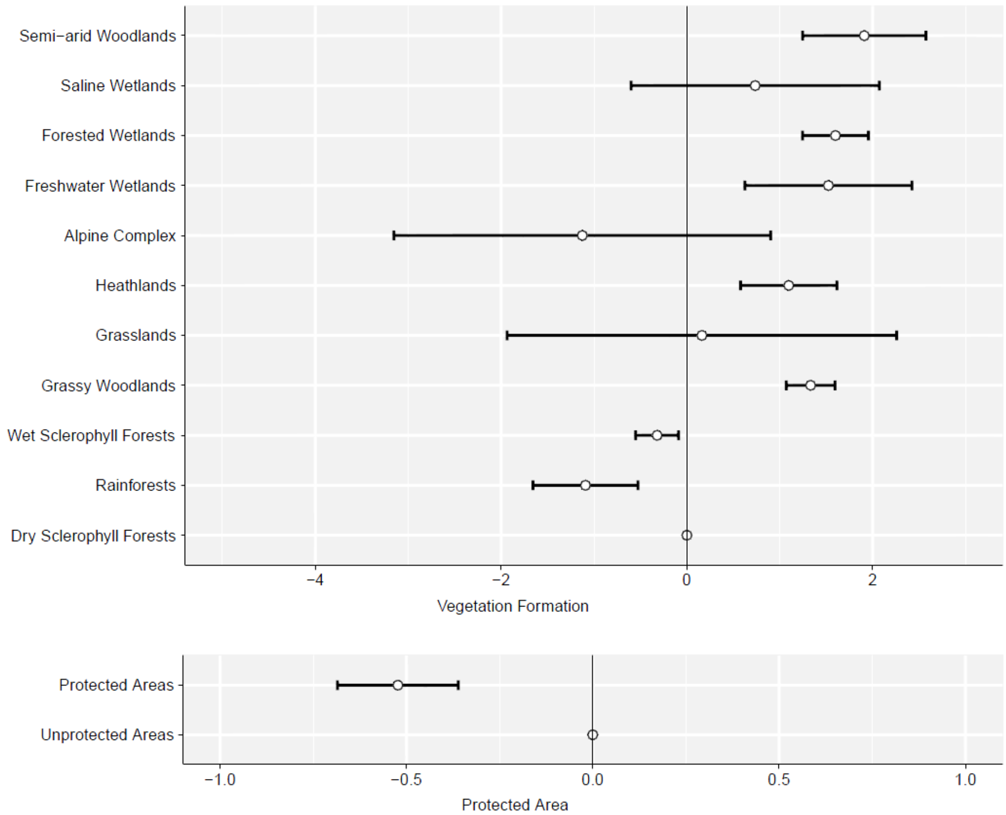

Figure 5.4 Estimated partial effects of two categorical variables in the TB & MG model, with 95% confidence bands. The reference classes are dry sclerophyll forests and unprotected areas, respectively.

The final TB & MG model included six variables (Table 5.2). The partial effects of categorical variables (Figure 5.4), i.e. vegetation formation and protected area, illustrated the difference between estimated classes and the reference classes (dry sclerophyll forests and unprotected areas). As the data filtering process could affect the different effects of forestry, grassy, and other vegetation formations, comparisons were only made between formations treated with the same filtering process. Rainforests and wet sclerophyll forests were found to be significantly less likely to ignite than dry sclerophyll forests ($P < 0.01$), and also less likely than wet sclerophyll forest. There is no evidence of difference between the ignition probabilities of (forested and freshwater) wetlands and some vegetation formations such as semi-arid woodlands and heathlands. Fire occurrence probability was higher in unprotected areas than in protected areas.

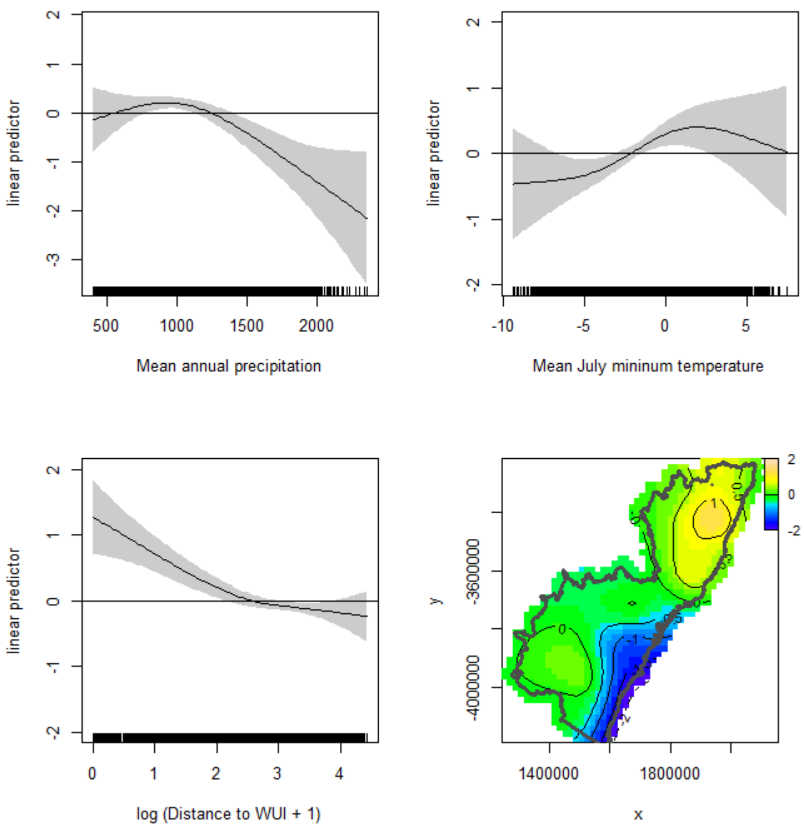

Figure 5.5 Estimated partial effects in the TB & MG model of three non-spatial continuous variables (mean annual precipitation, mean July minimum temperature, and distance to WUI) with 95% confidence bands, and the estimated spatial effect.

The estimated partial effects of continuous significant variables were plotted on a logit scale with 95% confidence bands (Figure 5.5). Probabilities of fire occurrence decreased with mean annual precipitation and the natural logarithm of distance to WUI. When the mean July minimum temperature was between -5 and 0, the relationship between fire occurrence probability and mean July minimum temperature followed an increasing trend. The estimated spatial effect of the model suggests that fire occurrence probability is highest along the north-eastern coast and highlands.

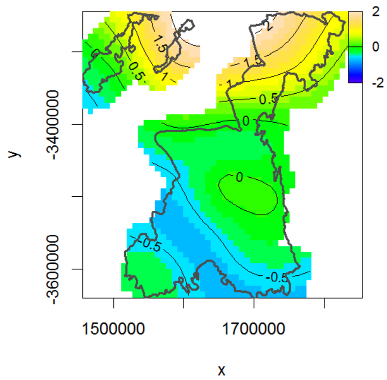

Figure 5.6 Estimated spatial effect in the TSG model.

The final TSG model included only the spatial effect variable (Table 5.2, Figure 5.6), which suggests that probabilities of fire occurrence are higher in the northern part of the region.

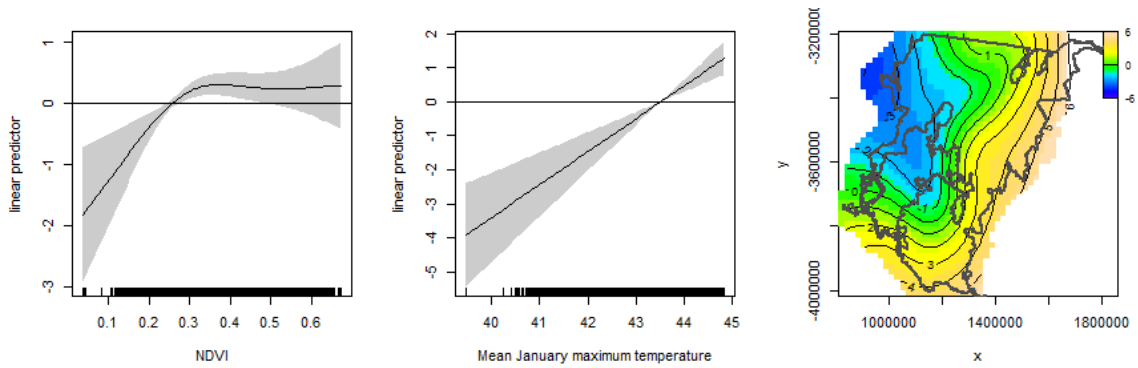

Figure 5.7 Estimated partial effects in the TG model of two non-spatial variables (NDVI and Mean January maximum temperature) with 95% confidence bands, and the estimated spatial effect.

The final TG model included two environmental variables (NDVI and mean January maximum temperature) and the spatial effect variable (Table 5.2, Figure 5.7). Fire occurrence probability increased steadily with mean January maximum temperature. The partial effect of NDVI was non-linear, with positive correlation when the NDVI value was smaller than 0.3 and a near flat trend as the NDVI became larger. The spatial effect showed an obvious positive trend from west to east and north to south, indicating transition from a less fire-prone area to a fire-prone area.

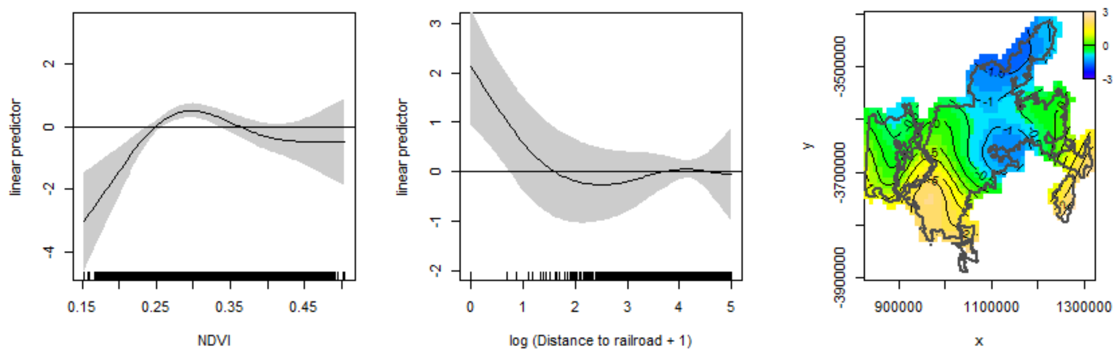

Figure 5.8 Estimated partial effects in the MF model of two non-spatial variables (NDVI and Distance to railroad) with 95% confidence bands, and estimated spatial effect.

The final MF model included one environmental variable (NDVI), one anthropogenic variable (distance to railroad), and the spatial effect variable (Table 5.2, Figure 5.8). The relationship between fire occurrence probability and NDVI was in line with that of the TG model, with probability increasing when the NDVI value was smaller than 0.3 and then near flat/slightly decreasing as NDVI became larger. Fire probability was found to decrease when the log of distance to railroad (in km) was lower than three, and to increase for higher values. This means that fire probability decreases within an approximate 20 kilometres distance buffer around railroads. Spatial effect showed an obvious positive trend from north to south.

The final DX model included one environmental variable (NDVI), two anthropogenic variables (distance to road and distance to railroad), and the spatial effect variable (Table 5.2, Figure 5.9). The probability of fire occurrence increased with NDVI and distance to road, and decreased with distance to railroad. The spatial effect showed a huge drop in probability for the southernmost area.

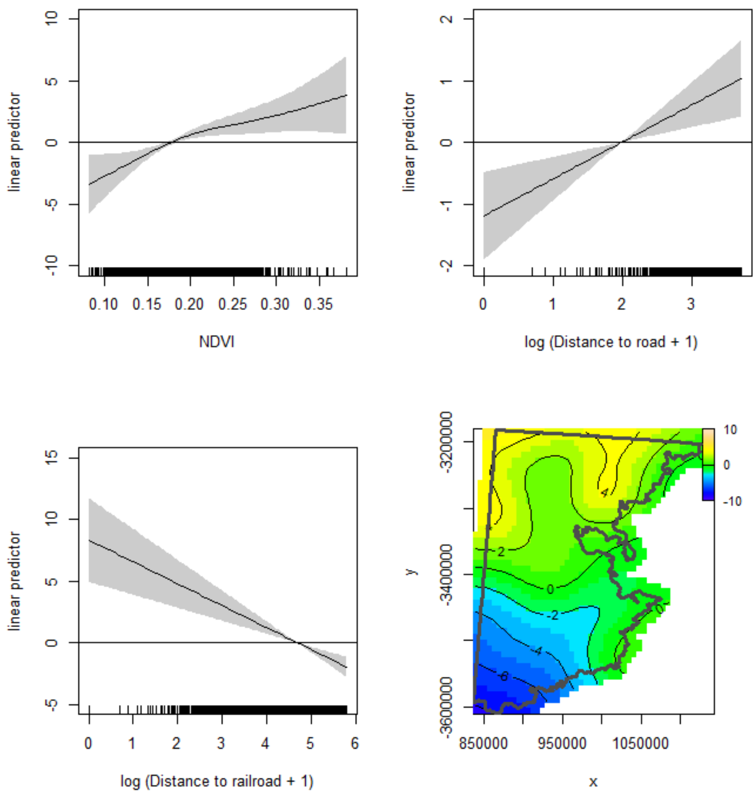

Figure 5.9 Estimated partial effects in the DX model of three non-spatial variables (NDVI, distance to road, and distance to railroad) with 95% confidence bands, and the estimated spatial effect.

5.5 Discussion

5.5.1 Types of Key Driving Factors

It is not surprising that vegetation is one of the main drivers of fire occurrence in most ecoregions, indicating fuel plays an important role in regulating fire patterns at this scale regardless of the ecoregion in question. Of the two vegetation-related factors, vegetation formations were found to contribute to regulating fire patterns in the most fire-prone ecoregion (TB & MG), in which vegetation structure and composition varies significantly across space and NDVI cannot substantially capture the characteristics of the combustible fuels. Climate variables were major drivers of fire occurrence patterns in two ecoregions with broad areas (TB & MG and TG), indicating that climate is an important factor at relatively broad spatial scales, over which top-down processes are dominant. The significance of spatial effect in all presented models indicates the influence of unknown topographic or vegetation variables that were not otherwise included (Preisler *et al.* 2004). The spatial effect term probably suppressed the effects of topographic factors, especially elevation, which were all found to have insignificant effects.

Anthropogenic factors were observed to play important roles in regulating fire occurrence patterns in the most populated ecoregion type (TB & MG) and in two sparsely settled ecoregions (MF and DX). The latter case is probably because fire is a rare event in MF and DX ecoregions; thus, even slight human presence can significantly influence the chance of a fire being ignited.

5.5.2 Effects of Environmental Drivers

Dry sclerophyll forest is an iconic fire-prone vegetation formation, with an open structure that contributes to the drying out of fuels and thus a higher likelihood of fire ignition, especially during periods of higher fire danger. Rainforests are less prone to fire ignition than dry sclerophyll forests because of their high fuel moisture content; rainforests only become easy to ignite under prolonged hot and dry weather. The ignition probability of wet sclerophyll forests is higher than rainforests, but lower than dry sclerophyll forest. Compared with rainforests, the relatively open canopy of wet sclerophyll forests allows for the penetration of additional sunlight, facilitating the growth of understory vegetation and the drying out of fuels (Keith 2004); compared with dry sclerophyll forests, the relatively high fuel moisture content in wet sclerophyll forests dictates that favourable climatic conditions are needed to foster an initial burn. This relative ranking is largely in line with the risk ranking of vegetation categories used for NSW Bush Fire Prone Land Mapping (NSW Rural Fire Service 2015) and with fuel load values assessed and validated by the NSW Rural Fire Service (2006), except that those guidelines treat wet and dry sclerophyll forests as being equally fire-prone. This discrepancy is not surprising since the chance of ignition may not be in line with fire risk, which depends on both ignition and the rate of spread. Therefore, the risk mapping guideline may not be appropriate for ignition probability mapping.

Due to biodiversity conservation concerns, fires are meant to be avoided in some vegetation formations, e.g. rainforests, alpine complex, and saline wetlands (Kenny *et al.* 2004). However, the results of this study showed that there were still a considerable number of fires that burned in and even ignited from these vegetation formations. Another notable fact is the lack of evidence illustrating any difference regarding ease of ignition between (forested and freshwater) wetlands and some fire-prone vegetation formations such as semi-arid woodlands and heathlands. Although the sample size was not sufficient to support a statistically significant effect, this result is somewhat intriguing. Forested and freshwater wetlands can ignite when inundation is punctuated by periods of dryness and their biomass is sufficiently continuous and dry to carry a fire (Keith 2004; Keith and Simpson 2010). From the perspective of environmental sustainability, although the majority of vegetation types in wetlands are fire-adapted (Schneider and Sutherland undated), some include fire-sensitive vegetation such as river red gums (NSW Department of Environment Climate Change and Water [DECCW] 2010), and inappropriate fires can damage the resilience of wetland ecosystems (Allen 2000). Therefore, the impacts of fires on these ecologically-sensitive vegetation formations are worth further exploration (Kenny *et al.* 2004).

As an indicator of live fuel moisture content, NDVI is inversely related to fuel flammability (Caccamo *et al.* 2012) and has a marginal role in fire ignition (Chuvieco *et al.* 2004). It is also closely related to biomass or fuel load, another parameter that influences fire-affected areas (Russell-Smith *et al.* 2007; Turner *et al.* 2011). Without considering the temporal effect, median NDVI may represent the average biomass condition throughout the study period. Although fires have been demonstrated to be more likely to occur in areas with high NDVI values in South-Eastern Australia (Zhang *et al.* 2016), the current study shows that the relationship between biomass and occurrence probability follows a non-linear pattern within most ecoregions. In contrast, the effects of NDVI followed a general trend: when NDVI is smaller than 0.3, fires are more likely to ignite at locations that exhibit higher average biomass, whereas when NDVI is greater than 0.3, it does not exhibit an obvious effect. This is not surprising because the human-caused fires that dominate South-Eastern Australia (Collins *et al.* 2015) normally ignite at places that are easy to access, which are not typically remote areas with dense vegetation cover. At the same time, the environment needs to fulfil the criteria (e.g. sufficient biomass) for a fire to ignite. In desert areas (DX) where NDVI values are generally below 0.3, higher NDVI values also correspond to greater fuel availability, thus fire occurrence may be more strongly regulated by the availability of fuel.

This study included mean values of precipitation and temperature as factors representative of climate gradients, so that temporal variation of climate was not taken into account. In temperate regions (TB & MG and TG), fires tended to occur at places with low annual precipitation because rain raises the dead fuel moisture content above the extinction moisture content (Pickett *et al.* 2010). Fires also tended to ignite at places with high July minimum temperature and high January maximum temperature because higher temperatures lead to low fuel moisture (Sullivan *et al.* 2012).

5.5.3 Effects of Anthropogenic Drivers

In TB & MG ecoregions, fires tended to occur in areas near the WUI, which is consistent with studies conducted in other countries (Syphard *et al.* 2008; Oliveira *et al.* 2012a). The tendency for fires to occur in non-protected areas where human interventions are not restricted also illustrates the association between human activities and fire occurrence. These further indicate the threat of wildfires to human lives and assets, emphasizing the importance of fire management strategies in this region.

In MF and DX ecoregions, the results suggest that fires tend to ignite within a certain distance of railroads, probably because in these sparsely-populated areas, human activities that can trigger fires may be largely concentrated in areas with public transportation. Surprisingly, fires in the DX region, tended to occur at locations away from roads probably because except for those occurring along railroads, most fires in this region are naturally ignited. It is important to note, however, that knowledge of wildfire occurrence is generally lacking for this ecoregion.

5.5.4 Overall Discussion

Model performances were evaluated through the calculation of percentage deviance explained and the AUCs of the training and validation data. Overall performances were good in the relatively less fire-prone inland regions (TG, MF, and DX), indicating that fire occurrence patterns are well-captured by the incorporated factors. Conversely, the merely fair performances of TB & MG and TSG models demonstrate the challenge of assessing long-term fire occurrence probabilities in regions where complex and multiple factors play interactive roles in regulating fire patterns. It is noted that the number of identified ignition points is relatively small in the arid and semi-arid areas and in the TSG ecoregion; therefore, it is possible that alternate patterns might be found as additional MODIS data becomes available.

MODIS data was used because its global accessibility facilitates its use in analysis at broad spatial scales. Additionally, this data does not exhibit the limitations of historical observed data, where some fires in remote areas are not reported to management agencies (Turner *et al.* 2011). A weakness of the MODIS active fire product is that detections representing prescribed and agricultural fires are fully realised. Despite attempts to filter out as many of these detections as possible, some non-wildfire detections may have remained in the modelling data. Other limitations of the MODIS data include its bias towards large fires and the lack of fire cause information. The proposed model would be improved by introducing better-quality occurrence data that contains information on fire causes and has lower omission error.

5.6 Summary

This study identified drivers controlling the spatial patterns of wildfire occurrence over the period of 2003-2013 and across different ecoregions of NSW and the ACT, Australia. Fire occurrence (ignition) points were identified from the MODIS active fire product with the FSR algorithm, and five ecoregion-based GAM models were developed in order to identify the key driving factors regulating wildfire occurrence and to understand the effects of these factors. Findings from this study have the potential to support ecoregion-based fire management and decision making in NSW and the ACT. This study also indicates that the MODIS product is able to be used as an input in wildfire occurrence studies, provided that filtering processes are conducted and the results are carefully interpreted.

This study identified a number of important factors that regulate fire occurrence. Vegetation is important in most ecoregions; vegetation formation affects fire ignition patterns in the most fire-prone areas; climate gradients drive fire ignition in ecoregions with relatively broad areas; spatial effects drive fire ignition patterns in all ecoregions; and anthropogenic factors regulate fire ignition patterns in the most populated areas and in two sparsely-populated areas. In the most fire-prone areas, fires are less likely to ignite within rainforests and wet sclerophyll forests than in dry sclerophyll forests. In most ecoregions, there is a non-linear relationship between NDVI and fire ignition, with small to medium levels of NDVI showing a positive effect on fire ignition. In temperate areas, fires tend to ignite within areas with low precipitation and high temperature. Fires are also likely to ignite near human facilities and at non-protected areas in some ecoregions, but away from roads in one ecoregion.

Chapter 6 Factors Contributing to Fire Ignition in the Semi-arid Inland Riverine Environment

The objective of this chapter is to understand wildfire ignition patterns and their driving factors in inland forested wetlands and the neighbouring dry lands on the NSW side of the Riverina Bioregion. This study aims to address the following questions: (1) What are the spatial and temporal patterns of human-caused and natural wildfire occurrence? (2) What are the effects of weather and fuel on these patterns, and specifically, does the probability of wetland fire ignition and inundation frequency follow a non-linear relationship? (3) What are the relative contributions of fire ignition drivers?

6.1 Study Area

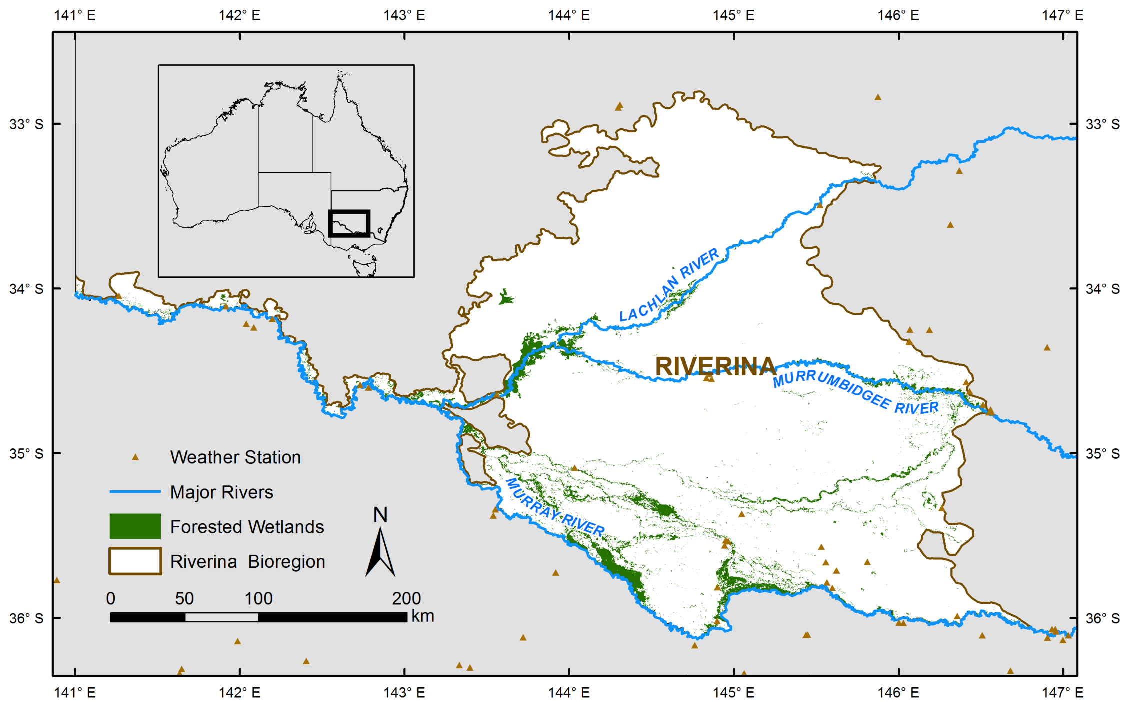

Figure 6.1 Map of Riverina bioregion showing the general location of the study area. The Murray River forms the boundary between the states of New South Wales and Victoria.

The study area (Figure 6.1) is situated approximately between 141.0° E –147.0° E and 33.0° S –36.0° S, covering an area of 70,000 km^2 (Thackway and Cresswell 1995), and comprises the NSW side of the Riverina bioregion (DSEWPaC 2012). The majority of this region experiences a warm and persistently dry semi-arid climate (Stern *et al.* 2000). The average annual rainfall ranges from about 250 mm in the far west to about 600 mm in the south-east, indicating a transition from semi-arid to mesic zones (NSW Natural Resources Commission [NRC] 2009). The topography follows a general trend of increasing elevation from approximately sea level in the far west to 130 m in the east. The Murray, Murrumbidgee, and Lachlan Rivers flow in a westerly direction across the region, forming an area of approximately 9,000 km^2 that experiences periodic inundation (i.e. wetlands). Within the wetland region, an area of 4,000 km^2 is "forested wetlands," a vegetation formation dominated by sclerophyllous trees 5-40 m tall with an understorey of hydrophytic species (Keith 2004, 2010); this accounts for 5.6% of the entire study area. The distribution of vegetation structure and community in forested wetlands varies with topography and flooding regime (Eardley 1999; Keith 2004), ranging from eucalypt open forest with a shrubby understorey in the west of Murray and Lachlan to eucalypt woodland with a tussock grass understorey in the east (DEE 2016). In the majority of the study area, the dominant tree species is *Eucalyptus camaldulensis* (river red gum); *Eucalyptus largiflorens* (black box) predominates in some regions (Eardley 1999; Keith 2004). The understorey vegetation includes a diverse range of perennial, annual, and ephemeral herbaceous/grassy species such as *Centipeda cunninghamii* (common sneezeweed) and Corex appressa (tussock sedge), as well as shrubby species such as *Muehlenbeckia florulenta* (lignum) and *Chenopodium nitrariaceum* (nitre goosefoot). The rest of the Riverina area (non-wetland) is generally upslope from the watercourse and is dominated by cleared lands, chenopod shrublands, samphire shrubs, and forblands with an ephemeral ground layer of grasses and herbs (Keith and Simpson 2010; DEE 2016).

6.2 Data Description

All explanatory variables used in this chapter are listed in Table 6.1. These variables were subdivided into four groups: weather, fuel, topography, and ignition sources

(Section 2.3). Daily maximum and minimum temperatures, wind speed, and relative humidity at 3pm were obtained from 121 weather stations (BOM 2016a) in the Riverina and its neighbouring regions. Specific fire records were assigned to the nearest station having complete records across its entire burning period. A number of variables and indexes – FMI, KBDI, FFDI and days since last rain – were derived from the weather data. Since FMI is highly dynamic (Sharples and McRae 2011), the daily FMI was calculated by averaging the fuel moisture values for the given day. Daily KBDI was calculated according to equations presented by Keetch and Byram (1968), and FFDI was derived following the work of McArthur (1967) and (Noble *et al.* 1980).

The annual rainfall variable was derived from a precipitation map representing the mean values of annual rainfalls for Australia from 2002 to 2016 (BOM, 2016b). This variable was assigned to the fuel group because it synthesises annual weather conditions and is representative of the rate of biomass accumulation (Section 2.3.2). The map distinguishing forested wetlands from other vegetation formations was derived from the NSW vegetation formation map v3.03 (Keith and Simpson 2012). A binary variable (Wetland) was generated to represent whether a sample is located in forested wetland (see also in Table 6.1). Inundation frequency was derived from a water prevalence map created by calculating the proportions of observations with water present in the NSW inundation count dataset (OEH, 2017). The inundation count dataset itself was produced by applying a new water index to each Landsat acquisition from mid-1984 to mid-2016 using the technique developed by Fisher *et al.* (2016). The generation and roles of other variables (e.g. Distance to Drainage Line, Northwestness, Distance to WUI, Protected Area) have been explained in Chapters 4 and 5. Wetland, Water Prevalence, and Distance to Drainage Line were also assigned to the fuel group due to their relationships with fuel load and moisture content.

The wildfire history datasets contain fire records for the state of NSW from 1902 to 2016 (NSW OEH 2016; NSW RFS 2016). Duplicate records and prescribed burning scars were removed. Only records within the Riverina bioregion were used. The positional uncertainty of fire boundaries ranges from 10 to 100 m (Price and Bradstock 2011). Because fire records obtained from NSW RFS have only been consistently captured or updated from the 2001/2002 fire season forward (NSW RFS 2016), those from before 2001 were excluded, resulting in a total of 157 fire records (Table 6.2) that were used in analysis.

Since the actual location where a fire event started is unknown, a given fire could have been ignited anywhere within the fire event polygon. Fires were divided into three categories based upon the degree of event polygon overlap with wetlands: FEW, FPW, and FNW (Section 3.3, Table 6.2). FNW represents fire that neither started from nor spread into forested wetlands. For fires in the FPW category, it is not clear whether they were ignited from or spread into forested wetlands; therefore, this category was used only for descriptive analysis and was not used to build logistic GLMs. Fire observations with unknown causes were subsequently excluded because their presence may mask the effects of important fire drivers in the models. This resulted in a total of 85 fire samples eligible for the quantitative analysis, including 49 natural fires and 36 (suspected) human-caused fires (Table 6.2). The spatial distributions of both types of fires are depicted in Figure 6.2, with fire locations represented by their centroid points.

Table 6.1 Variables analysed in order to explain drivers of wildfire ignition in the semi-arid inland riverine environment.

Variables	Description
Weather	
Maximum Temperature	Daily maximum temperature (°C)
Minimum Temperature	Daily minimum temperature (°C)
Relative Humidity 3pm	Relative humidity at 3 pm (%)
FMI	Daily mean Fuel Moisture Index (Sharples et al., 2009)
KBDI	Daily Keetch-Byram Drought Index (Keetch and Byram, 1968)
FFDI	Daily Forest Fire Danger Index (Noble et al., 1980, McArthur, 1967)
Days Since Rain	Days since last rain day
Fuel	
Annual Rainfall	Mean Annual Rainfall from 2002 to 2016 (mm)
Wetland	Whether site is located in the forested wetland (wetland vs. non-wetland), binary variable
Inundation Frequency	Inundated pixel observations from Landsat acquisitions from mid-1984 to mid-2016
Distance to Drainage Line	Euclidean distance to the nearest drainage line (km).
Topography	
Elevation	Elevation (m)
Slope	Slope (°)
Northwestness (NW)	Aspect relative to the north-west
Ignition Source	
Distance to WUI	Euclidean distance to the nearest WUI (km)
Distance to Road	Euclidean distance to the nearest road (km)
Protected Area	Whether site is located in a protected area (protected vs non-protected), binary variable

Table 6.2 Fire data counts used in this study. All data summarized in the table were used in the descriptive analysis; FPW events and fires with unknown causes were not used to build logistic GLMs.

	FEW	FNW	FPW	$Total_2$	Total
Human-caused Fire	16	20	7	**36**	**43**
Natural Fire	14	35	23	**49**	**72**
Fire with Unknown Cause	12	19	11	**31**	**42**
$Total_1$	**30**	**55**	**30**	**85**	**115**
Total	**42**	**74**	**41**	**133**	**157**

Note: $Total_1$, the total number of human-caused and natural fires; $Total_2$, the total number of FEW and FNW events.

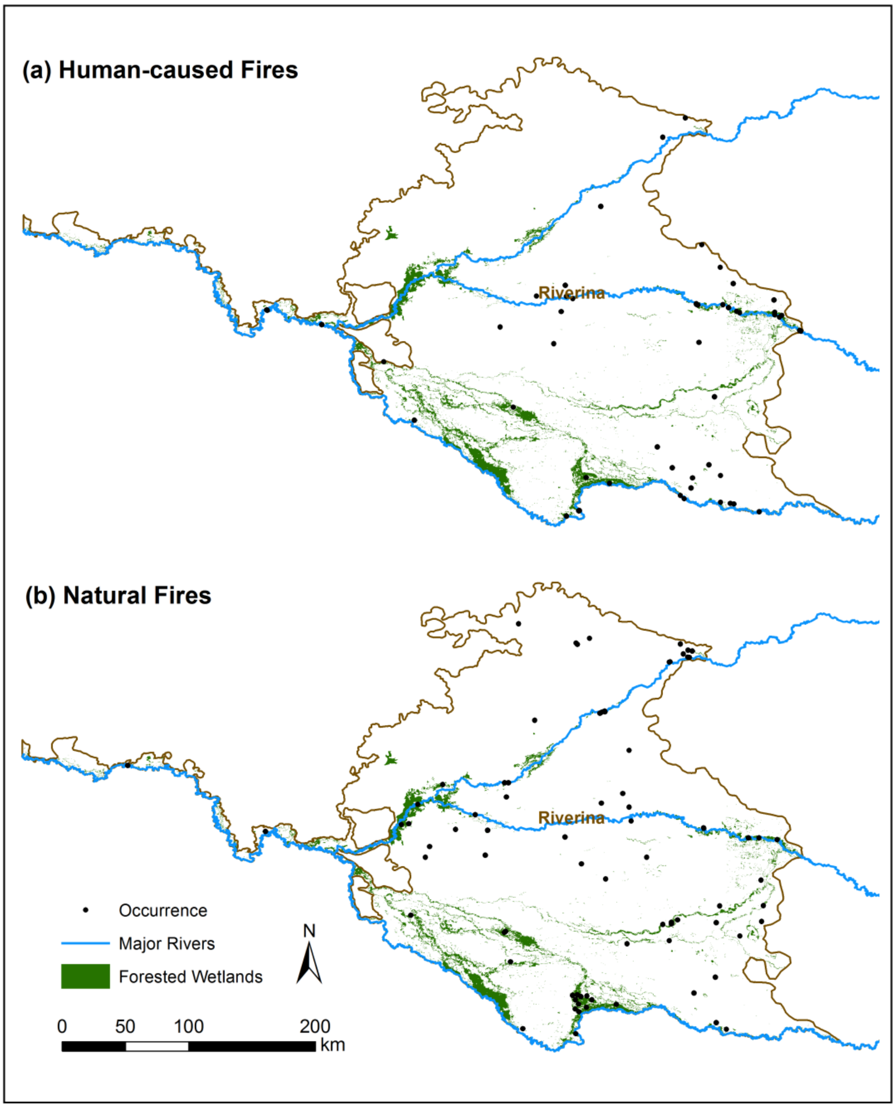

Figure 6.2 Distributions of (a) human-caused and (b) natural fires occurring in 2012-2016 in the Riverina Bioregion (fire polygons are represented by their centroid points).

6.3 Modelling Approach

Descriptive analyses were conducted for each fire cause (i.e. human-caused, natural, and unknown) and category (i.e. FEW, FNW, and FPW) to explore the monthly and seasonal distributions of fire ignition. Pearson's $\chi 2$ tests were conducted to test whether the seasonal distribution of fires was independent of cause or category at the 0.05 significance level. Logistic GLMs were used to compare the probability of ignitions with random points In order to determine whether the variables listed in Table 6.1 affect the ignition of fires differently than what would be expected by chance (Syphard *et al.* 2008), . All ignition points were used; 400 points were allocated to random dates and sites for the regression analysis.

Univariate logistic GLMs were built to quantify relationships between fire probability and its explanatory variables, as well as to find the most appropriate variables for inclusion in the multiple GLMs. According to Vittinghoff and McCulloch (2007), the number of "cases" (fire incidents) per independent variable should range from at least five to nine, therefore the maximum number of independent variables in the multiple logistic GLMs was set to $85/9 \approx 9$ for all fires, $49/9 \approx 5$ for natural fires, and $36/9 \approx 4$ for human-caused fires. The original representation of Inundation Frequency was not significant in either univariate or multiple models; therefore, the square, natural logarithm, and fourth root of the variable were tested. Of these, the fourth root was significant and better fit the data, thus was included in model development. To avoid the influence of multicollinearity, variables with a Spearman's rank correlation of greater than 0.6 (Wintle *et al.* 2005) (e.g. Annual Rainfall and Elevation) or variables that were generated from another (e.g. FFDI was generated from Maximum temperature) were not included in the same model.

As in Chapter 4, the multiple logistic GLMs were built using a backwards stepwise algorithm (Venables and Ripley 1999) based on AIC (Akaike 1998); i.e. explanatory variables were iteratively dropped if the model had smaller AIC without them. All 1st order interactions were tested as well, and none were found to be significant. There was no evidence of spatial autocorrelations according to the plotted semivariograms of the models' deviance residuals. Goodness of fit was measured with the percentage of deviance explained, as well as the AUC of the ROC curve. Three models were explored for each cause of fire: the best model (i.e. the model that explained the most deviance and had the highest AUC) and models that included and excluded Inundation Frequency. The contribution of each variable group to the best model was estimated with a jackknife procedure based on the change in AUC (Bar Massada *et al.* 2013). The effect and contribution of Inundation Frequency on fire ignition probability were examined by graphically plotting the model including Inundation Frequency and comparing the goodness of fit of the latter two.

All statistical analyses were conducted using R version 3.2.3 (R Development Core Team 2016). Modules that were used for data compilation, visualisation, transformation, analysis, and storage included *rgdal* (Bivand *et al.* 2015), *raster* (Hijmans 2016), *pROC* (Robin *et al.* 2011), *ggplot2* (Wickham 2009), *mandate* (Murphy 2013), and *xlsx* (Dragulescu 2014).

6.4 Results

Regardless of their causes and the vegetation types burned, fires mostly occurred in summer, specifically in December and January (Figure 6.3); this also applies to the seasonality of natural fires (Figure 6.3(*a*) and (*b*)). Human-caused fires mostly occurred during spring, followed by summer, with the largest number of fires occurring in October, November, and December. The largest number of FEW and FPW fires were found in summer (especially December and January), while FNW mostly occurred in spring and summer (especially November and December) (Figure 6.3(*c*) and (*d*)). The *P* values from Pearson's $\chi 2$ tests were 0.01 for fire seasonality against fire cause and 0.001 for fire seasonality against fire category. These results indicate that there are significant differences in terms of fire seasonality among different fire categories and causes.

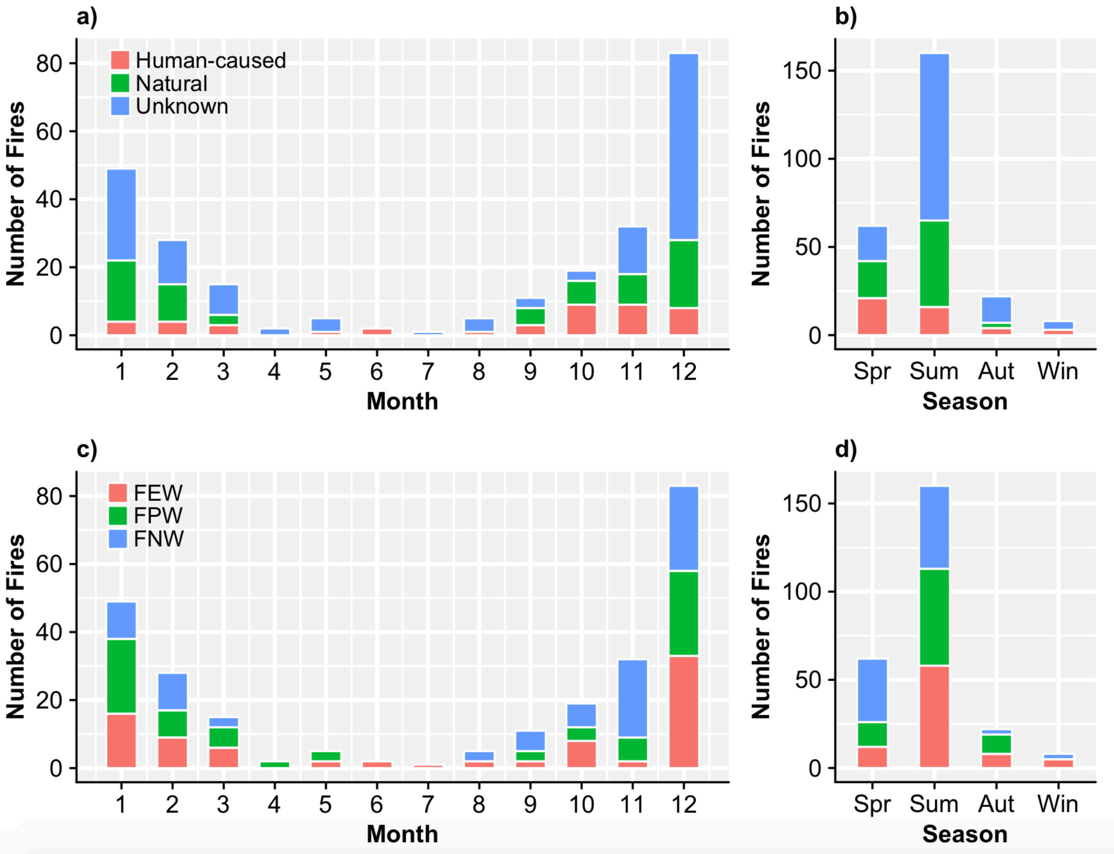

Figure 6.3 Monthly and seasonal distributions of wildfire (a, b) by cause and (c, d) by vegetation type burned. FEW, fires burned entirely in forested wetlands; FPW, fires burned partly in forested wetlands; FNW, fires not in forested wetlands; Spr, Spring; Sum, Summer; Aut, Autumn; Win, Winter.

All variables with significance in univariate models are listed in Table 6.3. Most variables in the groups of weather and fuel were significant at the 0.05 level in explaining the probability of fire ignition, except for Days Since Rain (P = 0.11) and Distance to Drainage (P = 0.39) for human-caused fire, as well as KBDI for both human-caused and natural fires (P = 0.32 and P = 0.79). Elevation was the only significant topographic variable. Some variables in the ignition source group (i.e. Distance to WUI and Distance to Road) were significant in terms of human-caused fire ignition, but did not explain natural fire ignition.

Table 6.3 Results of univariate models for human-caused and natural fires. Only significant variables are listed.

Variable	Human-caused Fire				Natural Fire			
	Estimate	Std. Error	z value	Pr(>|z|)	Estimate	Std. Error	z value	Pr(>|z|)
Weather								
Maximum Temperature	0.08	0.02	3.85	0.00	0.19	0.03	7.25	0.00
Minimum Temperature	0.07	0.02	2.79	0.01	0.18	0.03	6.71	0.00
Relative Humidity 3pm	-0.05	0.01	-4.05	0.00	-0.05	0.01	-4.93	0.00
FMI	-0.08	0.02	-3.11	0.00	-0.16	0.02	-6.28	0.00
FFDI	0.04	0.01	3.72	0.00	0.06	0.01	6.26	0.00
Days Since Rain	0.02	0.02	1.23	0.22	0.03	0.02	2.13	0.03
Fuel								
Annual Rainfall	0.02	0.00	5.74	0.00	0.01	0.00	3.64	0.00
Wetland	-2.25	0.39	-5.84	0.00	-1.71	0.38	-4.48	0.00
Distance to Drainage	-0.02	0.02	-0.85	0.39	-0.06	0.02	-2.34	0.02
Inundation Frequency ^ (1/4)	3.59	1.08	3.32	0.00	3.12	1.02	3.06	0.00
Topography								
Elevation	0.05	0.01	5.06	0.00	0.03	0.01	3.59	0.00
Ignition Source								
Distance to WUI	-0.05	0.01	-5.17	0.00	-0.01	0.01	-1.20	0.23
Distance to Road	-0.23	0.06	-3.93	0.00	-0.02	0.03	-0.75	0.45

Note: The reference class of the binary variable “Wetland” is the class “wetland”.

Among significant variables in the univariate models, positive relationships were found between the probability of fire ignition and variables such as Maximum Temperature, Minimum Temperature, FFDI, Days Since Rain, Annual Rainfall, the fourth root of Inundation Frequency, and Elevation. Negative relationships were found between fire ignition probability and all other variables. The results showed that fires were more likely to occur in wetland than in other vegetation types.

The best-performing model for human-caused fire ignition contained one weather variable (Maximum Temperature), two fuel-related variables (Annual Rainfall and Wetlands) and two ignition source variables (Distance to WUI and Distance to Road), explaining 34% of the deviance with an AUC value of 0.88 (Table 6.4, Table 6.5). The best-performing model for natural fire ignition contained the same weather and fuel-related variables, and had an AUC of 0.89 and explained deviance of 34% (Table 6.4, Table 6.5).

Table 6.4 Performance of multivariate models for human-caused and natural fires. % Dev, percentage of deviance explained; AIC, Akaike information criterion; AUC, Area under the receiver operating characteristics curve.

Models	%Dev	AIC	AUC
Human-caused fire			
Maximum Temperature + Annual Rainfall + Wetland + Distance to WUI + Distance to Road **	34	204.48	0.88
Maximum Temperature + Annual Rainfall + Inundation Frequency ^ (1/4) + Distance to WUI + Distance to Road	29	218.95	0.86
Maximum Temperature + Annual Rainfall + Distance to WUI + Distance to Road	27	223.01	0.84
Natural fire			
Maximum Temperature + Annual Rainfall + Wetland **	34	236.47	0.89
Maximum Temperature + Annual Rainfall + Inundation Frequency ^ (1/4)	33	240.59	0.89
Maximum Temperature + Annual Rainfall	28	253.56	0.87

Note: the best models are marked with **.

Table 6.5 Estimates from the best-performing models for human-caused and natural fires.

Human-caused Fire					**Natural Fire**				
	Estimate	Std. Error	z value	Pr(>|z|)		Estimate	Std. Error	z value	Pr(>|z|)
Intercept	-6.74	1.80	-3.75	0.00	**Intercept**	-12.02	1.76	-6.85	0.00
Weather					**Weather**				
Maximum Temperature	0.10	0.03	3.88	0.00	**Maximum Temperature**	0.21	0.03	7.11	0.00
Fuel					**Fuel**				
Annual Rainfall	0.01	0.00	3.43	0.00	**Annual Rainfall**	0.02	0.00	4.46	0.00
Wetland	-2.25	0.49	-4.55	0.00	**Wetland**	-2.12	0.48	-4.38	0.00
Ignition									
Distance to WUI	-0.02	0.01	-2.21	0.03					
Distance to Road	-0.16	0.07	-2.40	0.02					

The jackknife estimate of variable importance (Figure 6.4) for the best model of human-caused fires showed that each factor group contributes to the final model at approximately the same level; the AUC values of models without weather, fuel, or ignition sources were 0.85, 0.84 and 0.85, respectively. For natural fires, the model without weather variables has an AUC far less than for the model without fuel variables (0.71 vs. 0.84), indicating that weather contributes more than fuel to explaining the ignition of natural fires.

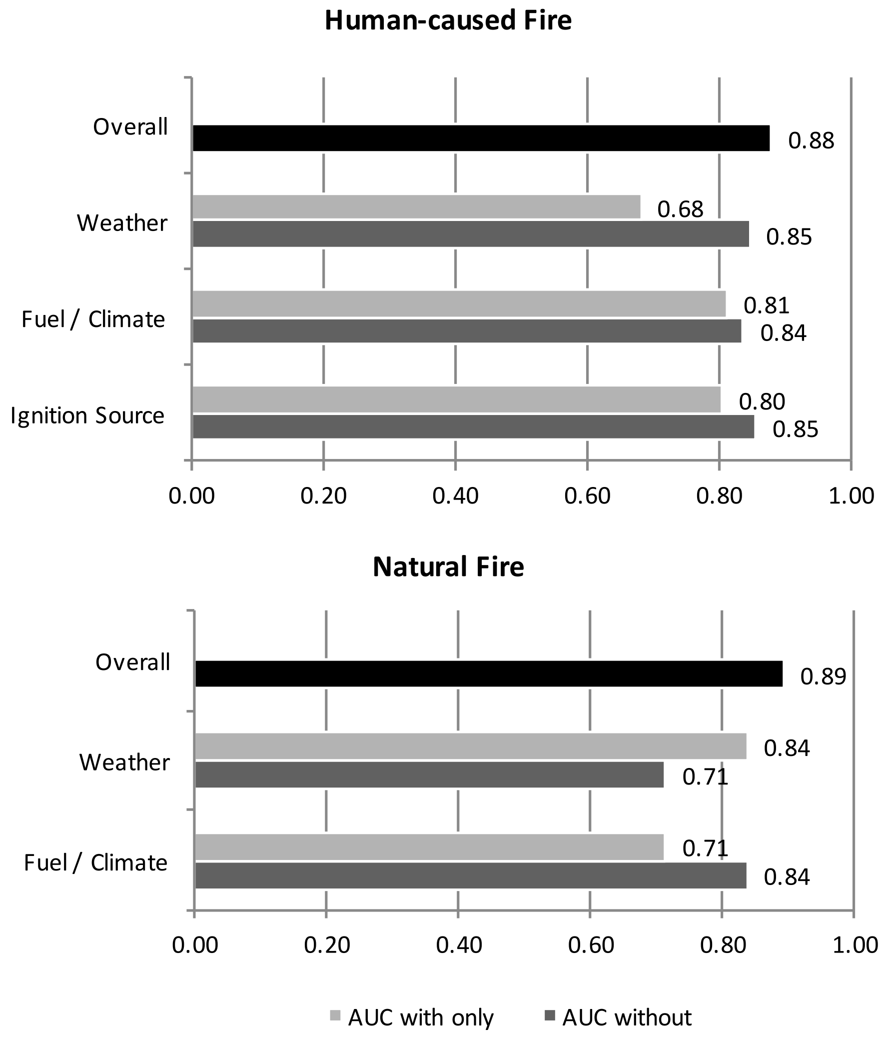

Figure 6.4 Jackknife estimations of variable importance for the final models of human-caused and natural fire. Bars denote the area under the receiver operator characteristic curve (AUC). The black bar represents the full-model AUC, white bars represent the AUCs of univariate models, and grey bars represent the AUCs of models without the corresponding variables.

Models including the fourth root of Inundation Frequency exhibited an AUC of 0.86 for human-caused fires and 0.89 for natural fires, the performances of which are considerably better than models without Inundation Frequency (AUC = 0.84 for human-caused fire and AUC = 0.87 for natural fire, as shown in Table 6.4). Graphs depicting the change of fire probability in relation to selected variables (Figure 6.5) indicate that fire probability increases as Maximum Temperature increases, and that this effect becomes stronger at higher Inundation Frequency values (Figure 6.5 (*a*), (*b*)). Fire probability and Inundation Frequency had a positive and non-linear relationship; the slope was steeper at lower Inundation Frequency than at higher values (Figure 6.5 (*c*), (*d*)).

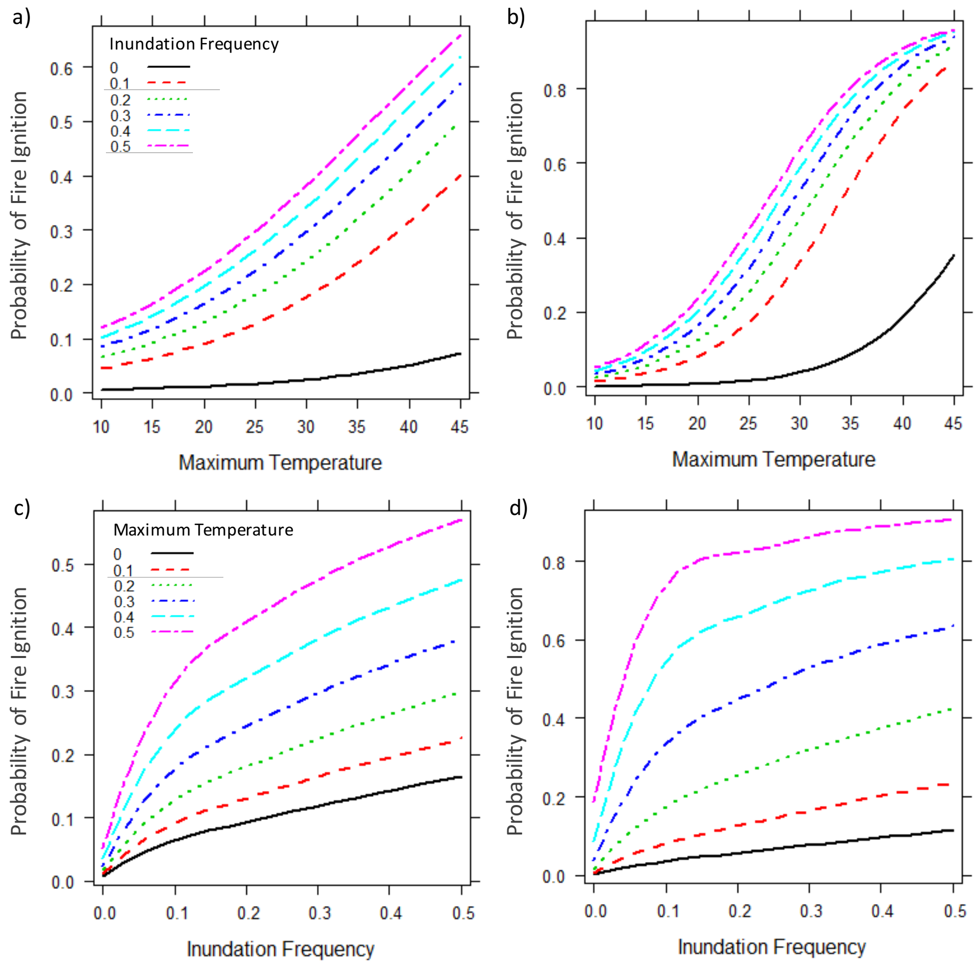

Figure 6.5 Probabilities of (a, c) human-caused and (b, d) natural fire ignition as a function of Maximum Temperature and Inundation Frequency.

6.5 Discussion

6.5.1 Spatial and Temporal Patterns of Wildfire

Most fires in the Riverina bioregion occurred during summer, consistent with the peak fire season of this area (Luke and McArthur 1978). In this bioregion, the conditions most preferable for fire ignition occur during summer when the weather is hot and dry, the average temperature is over 30 °C, and rainfall occurs less reliably (Eardley 1999). Seasonal inundation patterns may also regulate fire seasonality: in the riverine environment, fires are very unlikely to occur during winter inundation phases. However, fires caused by different processes experience different seasonalities. Natural fires are mostly ignited in summer (especially December and January), probably because of lightning strikes associated with summer thunderstorms (Eardley 1999). Human-caused fires have slightly extended seasonality, with fires mostly occurring in spring and summer (especially October, November, and December). This difference in fire seasonality is generally consistent with that observed in the U.S., where lightning fires were clustered in the summer while human-caused fires have extended fire season (Balch *et al.* 2017), although that study also recognized prescribed fires and crop fires as human-caused.

Both FEW and FPW categories tended to ignite in December and January, whereas FNW events mostly ignited in November and December. This reflects the difference between fire activity in temperate eucalypt forests/woodlands and in semi-arid chenopod shrublands; the former is dominated by summer fires and the latter by spring-summer fires (Bradstock 2010; Murphy *et al.* 2013).

Both human-caused and natural fires were found to be more likely to be ignited on days with severe weather conditions (higher temperature and fire danger index, lower relative humidity and fuel moisture content), in areas with higher levels of annual rainfall, in forested wetlands as opposed to the surrounding dry lands, and in areas with intermediate inundation frequencies. Human-caused fires were more likely to occur near urban areas and transportation facilities, consistent with findings in other landscapes (e.g. Pew and Larsen 2001; Romero-Calcerrada *et al.* 2008; Penman *et al.* 2013).

6.5.2 Effects of Weather and Fuel

The observed effects of ambient weather conditions were generally consistent with those found at broader scale (Turner *et al.* 2011) and in other landscapes (Penman *et al.* 2013). The insignificance contribution of KBDI to ignition of both types of fires can be explained by the nature of fuels in Riverina. In this semiarid environment where woody plant cover is inherently sparse, ephemeral and perennial grass is the dominant fuel type (Myers *et al.* 2004; Bradstock *et al.* 2014). Although the drought condition represented by KBDI is expected to be related to the availability to burn litter fuels in forested systems, it lacks the capacity in explaining the ignition of grass fires, the fuels of which are frequently dry enough to burn (Bradstock 2010; Bradstock *et al.* 2014).

Wildfire activity varies with different climatic conditions (Russell-Smith *et al.* 2007; Turner *et al.* 2011). In a semi-arid landscape, the rainfall gradient is an indicator of fuel amount (productivity): the greater the average annual rainfall, the higher the biomass production, and consequently the higher the probability of fire ignition (Bradstock 2010). Accordingly, fire probability was found to be higher in the south-eastern part of Riverina while lower in the far west; this paralleled productivity, and conforms to findings in other semi-arid landscapes (e.g. Pausas and Bradstock 2007).

Results showed that regardless of cause, fires are more likely to start in forested wetlands than in dry lands, which is inconsistent with the fire-vegetation relationship in temperate forests; other studies have documented lower or equal frequency of fire in riparian areas compared with adjacent uplands (Morrison *et al.* 1990; Olson 2000; Dwire and Kauffman 2003; Skinner 2003; Olson and Agee 2005; Pettit and Naiman 2007). This discrepancy is probably determined by the semi-arid climate of Riverina and the larger quantity of fuel in its wetlands. Riparian zones generally have higher fuel loads due to the promotion of high biomass production by better water accessibility, the accumulation of wrack and woody fuels in channels produced by uprooted and redistributed trees, and the harvest of riparian trees (Pettit and Naiman 2007). These factors apply to both dry and wet ecosystems. However, the semi-arid climate in this area accelerates the drying-out of inland riparian forests during the summer drought and non-inundation phase (Briggs 1988), providing favorable conditions for fires to start. This can be partially proved by the fact that wildfire season co-occurs with the drought and non-inundation period. A comparable result has been found in a tropical floodplain system of southern Africa, where fire frequency was higher in wetlands than for dry lands (Heinl *et al.* 2006). The main vegetation formation in that study (savanna) was considerably different from that of the present study (forest); however, it does provide corroboration on the effect of productivity on fire ignition in arid or semi-arid environments. It is notable that, although fires in the Riverina are more likely to occur in forested wetlands than dry lands, these wetland fires appeared to be relatively smaller in size both individually and in total. This is likely due to the low proportion of forested wetlands within the entire study area and the relatively high fuel moisture content associated with both water and forest environments (Zhang *et al.* 2017). A more comprehensive discussion of fire risk in this environment may therefore be needed to support sustainable management and ecological assessment practices.

At inundation frequencies equal to or below 0.5, fires were more likely to occur in areas with higher inundation frequency. This fire-flood relationship can be explained by the fact that higher inundation frequency may lead to higher biomass production and also higher rates of uproot and redistribution of woods, which result in higher fuel load. The relationship between these factors flattened out in areas that were more frequently inundated, i.e. nearer to rivers. This finding reflects the change of balance between biomass amount and its propensity to burn (Bradstock 2010). It also confirms the hypothesis that fire and flood frequency follow a non-linear relationship (Pettit and Naiman 2007).

No fires were recorded on lands with inundation frequencies greater than 0.5, which may mean that fires are very unlikely to occur on these less-inundated lands. It is suspected that at an inundation frequency greater than 0.5, the fire ignition probability will decline with more frequent flooding. as fires are least likely to occur near areas that experience permanent inundation (Camp *et al.* 1997). This suspicion is supported by the finding of Heinl *et al.* (2006) that the highest fire frequencies occur at intermediate flood frequencies, i.e. every second year. However, more data is required to draw a final conclusion.

6.5.3 Overall Discussion

For human-caused fires, weather, fuel, and ignition sources explained fire ignition probability to approximately equal degrees. This means that allocation of suppression resources, fuel management activities, and management of human accessibility are all essential factors for controlling human-caused fires. For natural fires, weather contributed more to the final model than fuel, implying an association between extreme weather and lightning. Weather is therefore more important from the perspective of natural fire risk mitigation.

The present study has some limitations. First, natural fire ignition is expected to be affected by the incidence of lightning strikes (Dowdy and Mills 2012b), hence it may be better modelled by introducing lightning-related factors. Second, the fire history dataset only recorded fires that had been investigated, which means that there might have been minor fires that were not included in the dataset. In addition, the geographical locations of ignition points were unknown; therefore, the factors used in the present study only represent the general conditions of when and where fires get started. Improvements can be made when more precise data regarding ignition points are available.

Using vegetation type as an explanatory variable in these models necessitates that fires ignited from different vegetation types be distinguished, and fires that burned multiple types (i.e. FPW) be discarded. Similarly, fires with unknown causes were excluded to avoid introducing noise to the final models. These filters might have excluded a number of potentially useful samples from analysis. Future studies can look at fire patterns that do not distinguish fires by cause, and build models that do not contain vegetation type.

6.6 Summary

This study investigated the spatial and temporal patterns of wildfire ignition, as well as their driving factors, in the NSW side of the Riverina bioregion. Most fires occured in summer, with human-caused fires primarily in spring and summer and natural fires in summer. In forested wetlands, summer was again the most fire-prone season, while fires in dry lands mostly occured during spring and summer. Fire probabilities were higher under severe weather conditions, in areas with higher annual rainfall, in forested wetlands, and in areas with intermediate inundation frequencies. Human-caused wildfire ignition was strongly associated with human access to the natural landscape, as represented by proximity to urban areas and roads. Weather, fuel, and ignition sources were comparably important in explaining human-caused fire ignition, while weather was more important than fuel in explaining natural fire ignition.

Chapter 7 Effects of Climate on Wildfire Size in *Eucalyptus Camaldulensis* Forests and Dry Lands of the Riverina Bioregion

This chapter aims to investigate the effects of top-down control (climate) on fire size in the NSW portion of the Riverna bioregion, the same study area as in Chapter 6. The study specifically addresses the following questions: (1) What are the properties of wildfires in inland forested wetlands and their adjacent dry lands? (2) How do ambient weather and antecedent rainfall affect the sizes of these fires? (3) Which factor or group of factors provides the best explanatory performance, and how does that performance change as neighbouring lands are included?

7.1 Data Description

In the present study, large fires that burned greater than 1,000 ha (Bradstock *et al.* 2009) and excluded from further analysis. While small- or medium-sized fires are driven by near surface fuels and weather conditions, large fires tend to propagate under a more complex mechanism on account of variable surface conditions, the potential of long-distance spotting, and, more importantly, interaction with upper levels of the atmosphere (McRae and Sharples 2011); therefore, it is inappropriate to investigate sizes of large fires using the same model as for small and medium fires. The study used only records where all relevant explanatory variables were available, resulting in a total dataset of 257 wildfire observations. The dependent variable was the natural log of fire area measured in hectares (ha).

Since fire sizes are driven by severe weather conditions, which influence fire propagation during daytime and the moistening of fuels overnight (Catchpole 2002), the corresponding extreme daily records were assigned to each fire event, comprising seven variables (Table 7.1): maximum daily maximum temperature (MaxTemp), maximum daily minimum temperature (MinTemp), minimum relative humidity at 3pm (RH3pm), minimum daily mean FMI (FMI), maximum daily KBDI (KBDI), maximum daily

FFDI (FFDI), and the number of days since last rain (DaysSinceRain). It should be noted that FMI, KBDI, and FFDI refer to the most extreme values that occurred during the fire event rather than daily/hourly-based values as they were originally defined.

A representation of cumulative rainfall with different phases and lags (PhaseXLagX, Table 7.1) was constructed following the work of Turner *et al.* (2011) by aggregating the maps of monthly rainfall totals (BOM, 2016b). Lag represents the number of the month prior to the month in which a fire event occurred, while phase depicts the number of months being accumulated. For example, Phase1Lag0 denotes the cumulative rainfall of the month immediately preceding the month of the fire event, and Phase13Lag5 denotes the cumulative rainfall of months 6-18 before the fire event month. Lags of 0-24 and phases of 1-24 were considered, resulting in a total of 600 variables. Additional variables representing the cumulative rainfall in each of the preceding four seasons (SeasonalRain, Table 7.1) were also calculated. The daily record variables and the cumulative rainfall within a three-month lag and three-month phase reflect ambient weather conditions, while the remainder represent antecedent rainfall conditions.

Table 7.1 Variables analysed in regression models used to explain wildfire size in the Riverina bioregion.

Variables	Group	Description	Mean	Range	Std.Dev
Dependent variable					
Log (fire size)		Natural log of fire size (ha). Fires are divided into three categories: fires burned entirely in forested wetlands (FEW), fires burned partly in forested wetlands (FPW), and fires not in forested wetlands (FNW)			
Explanatory variable					
MaxTemp	Ambient Weather	Maximum daily maximum temperature during fire event (°C)	33.97	13-46.7	6.77
MinTemp	Ambient Weather	Maximum daily minimum temperature during fire event (°C)	17.54	0.4-30	5.63
RH3pm	Ambient Weather	Minimum relative humidity at 3 pm during fire event (%)	22.58	5-77	13.03
FMI	Ambient Weather	Minimum daily mean Fuel Moisture Index (Sharples *et al.* 2009) during fire event	15.04	5.15-30.58	5.75
KBDI	Ambient Weather	Maximum daily Keetch-Byram Drought Index (Keetch and Byram 1968) during fire event	104.10	8.5-187.1	40.61
FFDI	Ambient Weather	Maximum daily Forest Fire Danger Index (McArthur 1967; Noble *et al.* 1980) during fire event	28.45	0.06-100	19.42
DaysSinceRain	Ambient Weather	Days since last rain	7.42	0-39	7.72
PhaseXLagX	Ambient Weather / Antecedent Rainfall	Cumulative rainfall with different phases and lags (mm) Cumulative rainfall variables within 3 months lag and 3 months phase were assigned to the Ambient Weather group and others were assigned to the Antecedent Rainfall group.	24.37	0-163.77	19.99
SeasonalRain	Antecedent Rainfall	Cumulative rainfall in the preceding four seasons (spring, summer, autumn, winter)	83.67	21.15-309.93	51.49
			110.79	4.51-341.33	77.18
			96.29	6.58-292.11	61.29
			89.92	22.57-231.36	38.15

Note: Statistics (mean, range, and standard deviation) for PhaseXLagX are shown as that of Phase1Lag0; statistics for SeasonalRain are listed in the order of spring, summer, autumn and winter.

7.2 Modelling Approach

Descriptive analysis regarding the distribution of fire sizes was conducted for each fire category. Relationships were quantified using the log-normal model, i.e. a simple linear model with log-transformed fire sizes as the response. This model was used because: (1) fire sizes are non-negative and positively skewed, and (2) the relationship between the response variable and the explanatory variables is close to linear.

Differences in weather conditions for the three fire categories were explored through boxplots and tested with the Wilcoxon signed-rank test, allowing for non-normal distributions. Relationships between fire size and explanatory variables were explored by plotting fire size against selected explanatory variables. Univariate models were first developed to evaluate the independent effect of each variable on fire size and to find the most suitable variables for inclusion in the multiple regression models. Records from FWE, FPW, and FNW fire categories were progressively incorporated into the analysis in that order (Section 3.3); thus models were developed for FEW (Case I), FEW and FPW (Case II), and for FEW, FPW and FNW (Case III). As this study aims to model changes in fire size determinates as the proportion of burned forested wetland decreases from 100% (Case I) to very low (Case III), independent models were not built for FPW or FNW categories.

Multicollinearity was tested via the calculation of Spearman's rank correlation, and variables with a correlation greater than 0.6 (Wintle *et al.* 2005) were not included in the same models. In this study, MaxTemp, MinTemp, RH3pm, FMI, and FFDI were always highly correlated with each other. Model fit was compared on the percentage of deviance explained by each model, and determination of the best model was based on the Akaike information criterion (AIC, Akaike 1998). Models whose AIC values were within two points of the best model were considered meaningful (Burnham and Anderson 2003). The contributions of each variable group (i.e. ambient weather and antecedent rainfall) to the best model were compared using the percentage of deviance explained by each group. The effects of log- and square-transformed explanatory variables, as well as two-way interaction terms, were also tested. Moran's I was used to measure the spatial autocorrelation of model residuals (Legendre 1993).

All statistical analyses were conducted using R version 3.2.3 (R Development Core Team 2016). Log-normal models were fitted using a GLM with family 'gaussian' and a link function of 'identity'. Spatial objects were processed using *rgdal* (Bivand *et al.* 2015) and *raster* (Hijmans 2016). Other modules used in analysis include *ggplot2* (Wickham 2009), *mandate* (Murphy 2013), and *xlsx* (Dragulescu 2014).

7.3 Results

7.3.1 Descriptive Analysis

Some of the size characteristics of FEW, FPW and FNW fires (fire size < 1,000 ha) are depicted in Figure 7.1. The size distributions of all three fire categories and overall area burned are skewed small (Figure 7.1(*a*) and (*c*)). In particular, FEW tended to burn smaller areas both individually (< 200 ha, Figure 7.1(*a*)) and in total (< 1,000 ha, Figure 7.1(*b*)) than the other two fire categories. Case I and Case II datasets had their largest fires burned in January, followed by February (Figure 7.1(*d*)). Case III also had its largest area burned in January, but the next greatest were in December and November (Figure 7.1(*d*)). For all three cases, fires burned the largest area in summer and smallest in winter (Figure 7.1(*e*)).

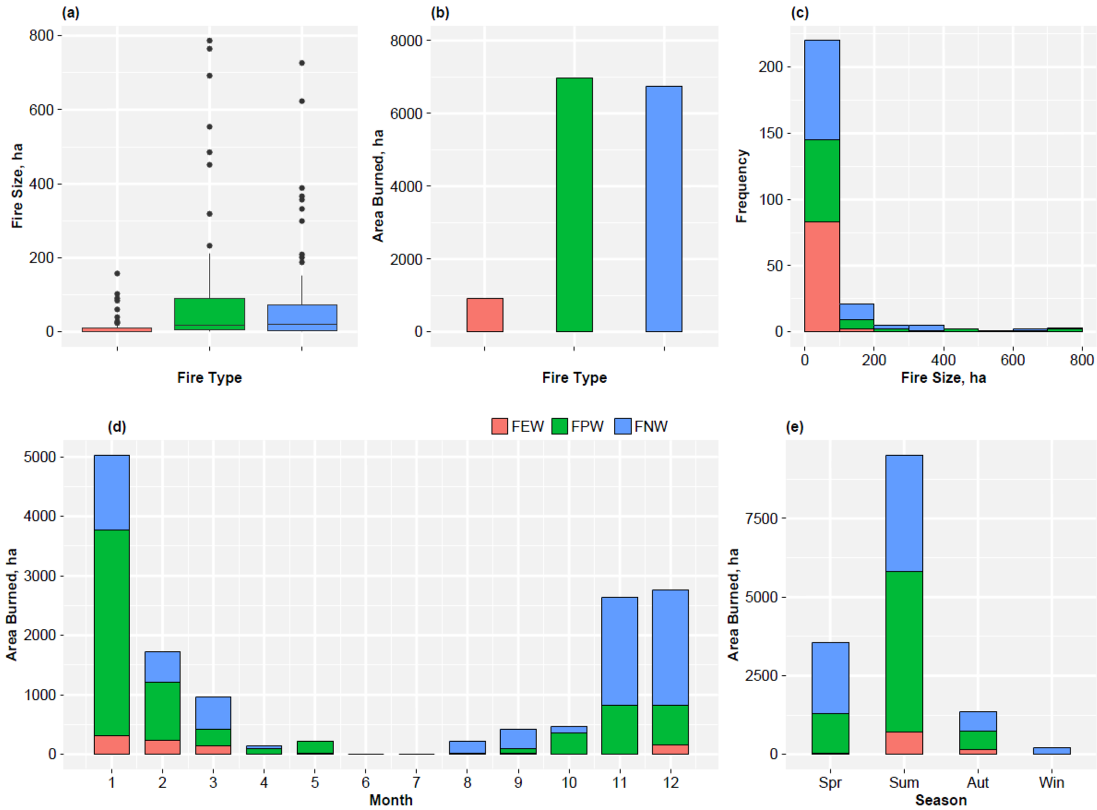

Figure 7.1 (a) Boxplot of fire sizes for different fire categories (FEW, FPW, and FNW); (b) Cumulative area burned by different fire categories; (c) Histogram of fire size; (d) Monthly cumulative area burned; (e) Seasonal cumulative area burned; fire size < 1000 ha; FEW, fires burned entirely in forested wetlands; FPW, fires burned partly in forested wetlands; FNW, fires not burned in forested wetlands; Spr, Spring; Sum, Summer; Aut, Autumn; Win, Winter.

7.3.2 Univariate Models

Weather conditions were not significantly different between the three fire categories except for MaxTemp, which differend between FPW and FNW (Figure 7.2, Table 7.2). Plotting fire size against weather variables showed that the natural-log of fire size and weather conditions have an approximately linear relationship (Figure 7.3).

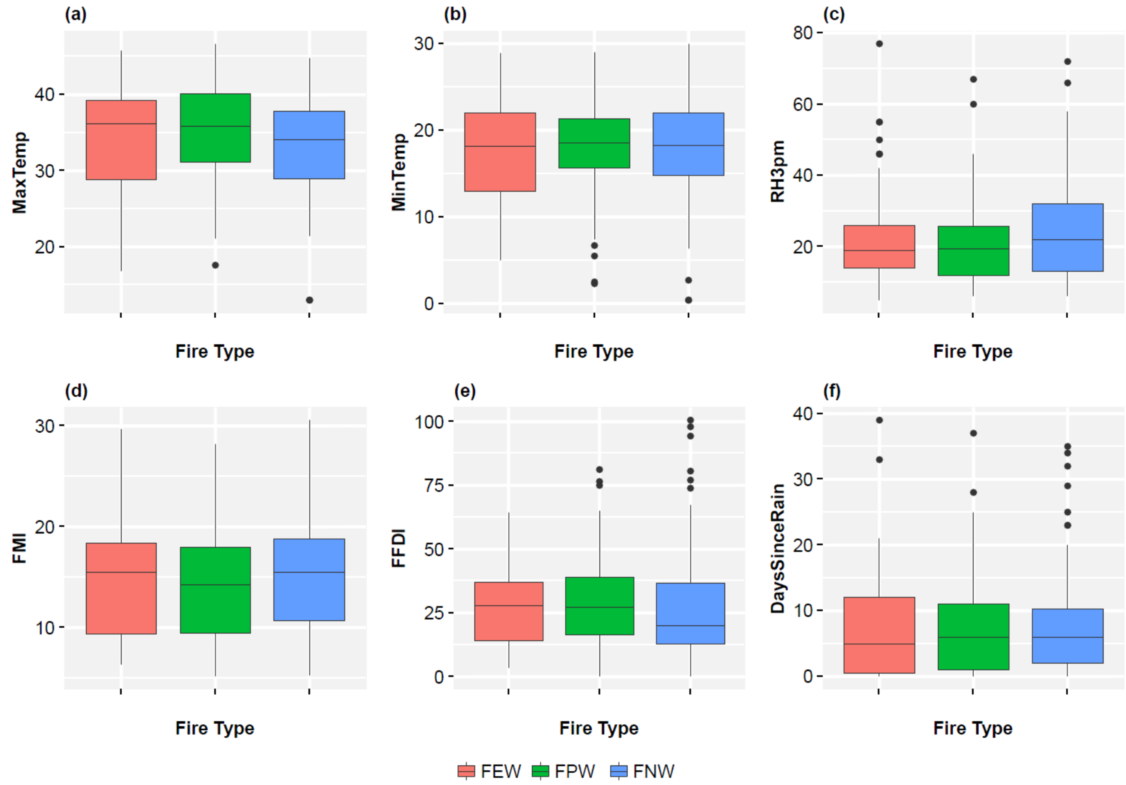

Figure 7.2 Boxplots of ambient weather conditions for the three fire categories. FEW, fires burned entirely in forested wetlands; FPW, fires burned partly in forested wetlands; FNW, fires not burned in forested wetlands.

Table 7.2 Ambient weather differences (mean ± std. error) between paired fire categories.

Comparison	MaxTemp	MinTemp	RH3pm	FMI	FFDI	DaysSinceRain
FEW-FPW	-0.80 ± 2.10	-0.40 ± 1.70	1.00 ± 3.00	0.35 ± 1.75	-1.46 ± 5.36	0.00 ± 2.00
FEW-FNW	1.20 ± 1.80	-0.40 ± 1.60	-3.00 ± 3.00	-1.05 ± 1.45	2.17 ± 5.06	0.00 ± 2.00
FPW-FNW	2.00 ± 2.00 *	0.10 ± 1.40	-3.00 ± 4.00	-1.23 ± 1.72	3.54 ± 5.04	0.00 ± 2.00

* Significant effect (*p*=0.046)

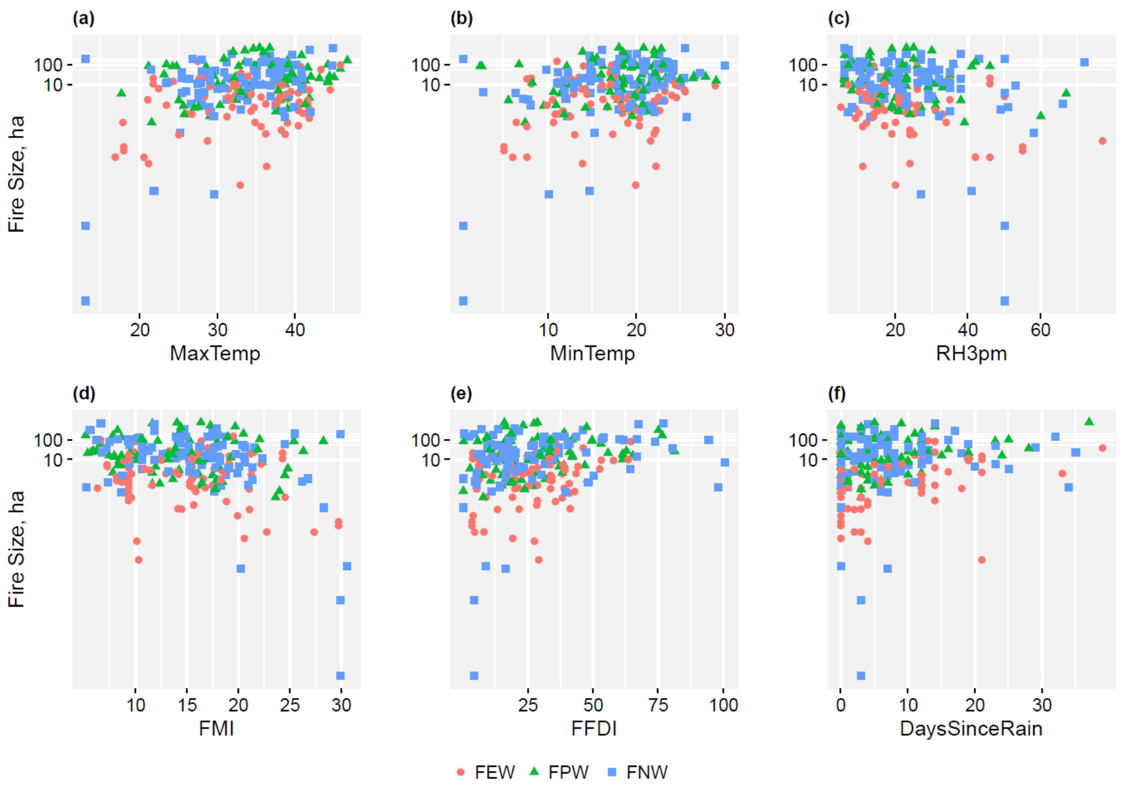

Figure 7.3 Scatterplots of fire size against selected explanatory variables for three fire categories. FEW, fires burned entirely in forested wetlands; FPW, fires burned partly in forested wetlands; FNW, fires not burned in forested wetlands.

Univariate regression results (Table 7.3) show that all ambient weather variables are significant at the 0.95 level across all cases, except for KBDI ($P > 0.05$). In all univariate models, fire extent had positive relationships with MaxTemp, MinTemp, FFDI, and DaysSinceRain, and negative relationships with RH3pm and FMI.

Table 7.3 Univariate regression results for all ambient weather variables and selected antecedent rainfall variables. FEW, fires burned entirely in forested wetlands; FPW, fires burned partly in forested wetlands; FNW, fires not burned in forested wetlands; % Dev, the percentage of deviance explained. Codes for the variables are as given in Table 7.1.

Variable	Coefficient	Std. Error	t value	Pr(>|t|)	%Dev
FEW (Case I)					
MaxTemp	0.112	0.043	2.628	0.010	7.9
MinTemp	0.119	0.056	2.127	0.036	5.3
RH3pm	-0.070	0.025	-2.809	0.006	8.9
FMI	-0.115	0.057	-2.015	0.047	4.8
KBDI	0.014	0.009	1.584	0.117	3.0
FFDI	0.054	0.019	2.821	0.006	8.9

Variable	Coefficient	Std. Error	t value	Pr(>|t|)	%Dev
DaysSinceRain	0.080	0.040	2.014	0.047	4.8
Phase1Lag0	-0.038	0.018	-2.121	0.037	5.3
Phase1Lag5	0.051	0.017	2.995	0.004	10.0
Phase13Lag5	0.007	0.003	2.680	0.009	8.1
Phase2Lag12	0.019	0.007	2.624	0.010	7.8
Phase2Lag16	0.015	0.006	2.405	0.018	6.7
FEW&FPW (Case II)					
MaxTemp	0.104	0.032	3.263	0.001	6.3
MinTemp	0.103	0.041	2.505	0.013	3.8
RH3pm	-0.055	0.018	-3.006	0.003	5.4
FMI	-0.091	0.040	-2.266	0.025	3.1
KBDI	0.002	0.006	0.275	0.784	0.0
FFDI	0.046	0.013	3.571	<0.001	7.4
DaysSinceRain	0.074	0.029	2.531	0.012	3.9
Phase2Lag4	0.023	0.007	3.184	0.002	6.0
FEW&FPW&FNW (Case III)					
MaxTemp	0.172	0.030	5.785	<0.001	11.6
MinTemp	0.190	0.036	5.259	<0.001	9.8
RH3pm	-0.070	0.016	-4.403	<0.001	7.1
FMI	-0.177	0.036	-4.968	<0.001	8.8
KBDI	0.001	0.005	0.137	0.891	0.0
FFDI	0.045	0.011	4.231	<0.001	6.6
DaysSinceRain	0.071	0.027	2.604	0.010	2.6
Phase11Lag7	0.003	0.001	2.463	0.015	2.3

Note: All models were fitted using observations from fires smaller than 1000 ha.

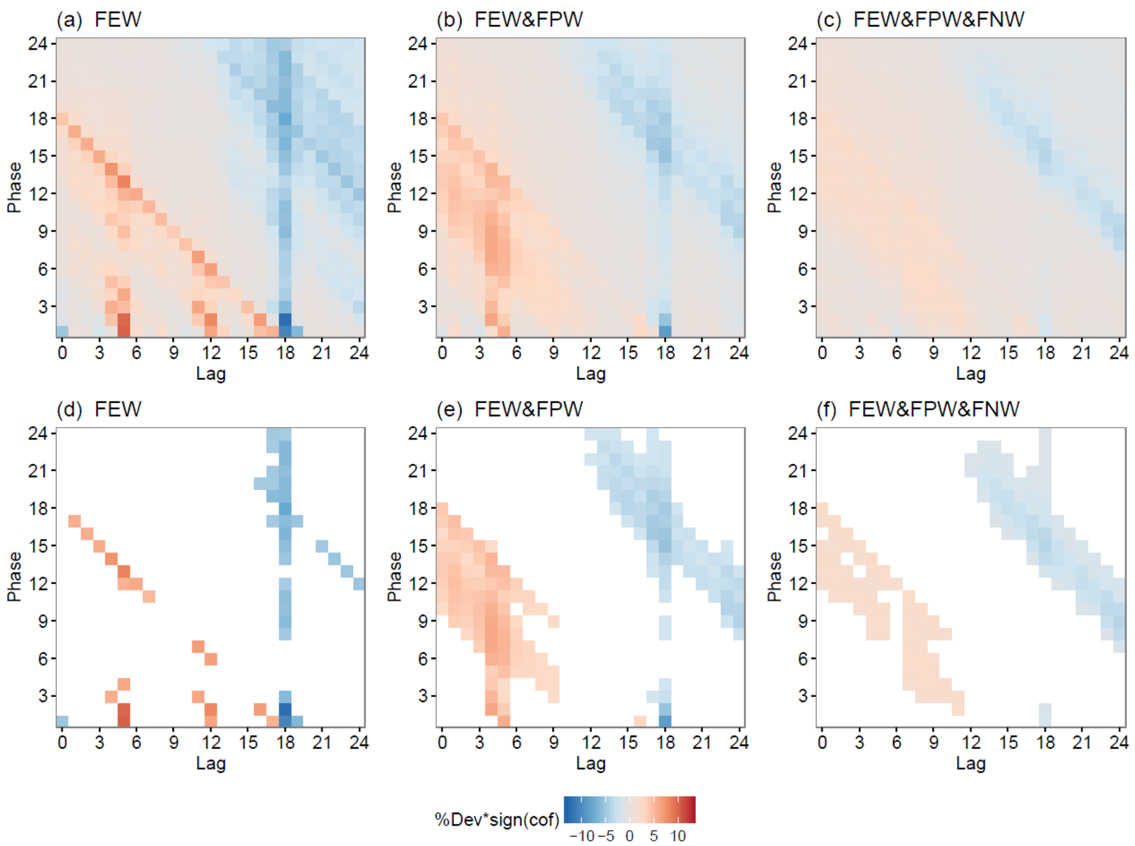

Figure 7.4 Plots of estimated coefficient signs (sign(cof)) times the percentage of deviance explained (%Dev) for (a-c) all antecedent rainfall variables and (d-f) significant antecedent rainfall variables. Axis units are months. FEW = Case I; FEW&FPW = Case II; FEW&FPW&FNW = Case III (see section 7.2 for details). Red colours denote positive relationships and blue colours denote negative relationships, with darker colours representing higher percentage of deviance explained. FEW, fires burned entirely in forested wetlands; FPW, fires burned partly in forested wetlands; FNW, fires not burned in forested wetlands.

Figure 7.4(*a-c*) plots the sign of the estimated coefficients times the percentage of deviance explained against antecedent rainfall variables with lags of 0-24 and phases of 1-24. In Figure 7.4(*d-f*), insignificant variables have been removed. Seasonal rainfall variables did not show significant effects, so they were not plotted.

In Case I models (Figure 7.4(*a*) and (*d*)), antecedent rainfall variables exhibit a 'patchy' pattern of effect; several variables (Phase1Lag5, %Dev = 10.0; Phase13Lag5, %Dev = 8.1; Phase2Lag12, %Dev = 7.8 and Phase2Lag16, %Dev = 6.7) explained a higher percentage of deviance than their adjacent variables (Table 7.3). The only exception is Phase1Lag0 (%Dev = 5.3), which shows a negative relationship with FEW size (Figure 7.4(*a*) and (*d*), Table 7.3).

In Case II models, the effect pattern of antecedent rainfall variables is simpler (Figure 7.4(*b*) and (*e*), Table 7.3). Comparing with the variables highlighted above for Case I models, only Phase1Lag5 is still significant and exhibits a positive relationship with Case II size, and it can be substituted by Phase2Lag4 (%Dev = 6.0), which best explained the extent of Case II. In the Case III models, none of the variables significant in Case I models remained significant (Figure 7.4(*c*) and (*f*), Table 7.3). Phase11Lag7 (%Dev = 2.3) explained the greatest percentage of deviance and shows a positive effect. The above-mentioned variables were introduced into their corresponding multiple regression models.

Additionally, significant negative relationships were found between fire size and some cumulative rainfall variables with lags greater than 18. However, these were not incorporated into the final models as the mechanism behind those relationships is unclear.

7.3.3 Complete Models

For each case, there were a number of models within 2 ΔAIC of the best models: three models for Case I, eight for Case II, and two for Case III. The best three models for each case are listed in Table 7.4. FFDI appears in all selected Case I models and was present in at least one of the Case II models. Temperature variables (MaxTemp and MinTemp) appear in the selected models for Case II and Case III. DaysSinceRain also appears in at least one of the selected models for all model groups.

The best Case I model contained four variables: FFDI, Phase1Lag5, Phase2Lag12, and Phase2Lag16. This indicates an effect for FFDI, as well as for the past one or two months of cumulative rainfall slightly out of phase, with lags of 5, 12, and 16 months. The best Case II model contained MinTemp, DaysSinceRain, and Phase2Lag4, and therefore incorporates the effects of temperature and recent rainfall, as well as two months' rainfall with a lag of four months (Table 7.4). The best Case III model included MaxTemp and Phase7Lag5 (7.5), and demonstrated effects from temperature and seven months' rainfall with a lag of 5. All relationships (positive/negative) were consistent with those determined from the univariate models. The Moran's I values of the three best models ranged from 0.12 to 0.17, which are acceptable according to Gibson *et al.* (2015).

Table 7.4 and Table 7.5 showed that the best Case I model (%Dev = 31.4) exhibited the better overall performance compared with the other two best models (%Dev = 14.6 and 15.6). The contributions of variable groups (ambient weather and antecedent rainfall) to model fits (Table 7.5) showed that in the best Case I model, antecedent rainfall variables explained far more deviance (%Dev = 23.2) than ambient weather variables (%Dev = 8.9), while in Case II and Case III models theyexplained comparable or less deviance (%Dev = 6.0 and 2.3) than ambient weather variables (%Dev = 6.7 and 12.3). Thus, the power of antecedent rainfall dropped significantly from Case I to III, while that of ambient weather stayed the same.

Table 7.4 Selected models within 2 ΔAIC of the best models. FEW, fires burned entirely in forested wetlands; FPW, fires burned partly in forested wetlands; FNW, fires not burned in forested wetlands; AIC, Akaike information criterion. Codes for the variables are as given in Table 7.1.

Model	AIC	ΔAIC	Dev%	Pr(>F)
FEW (Case I)				
FFDI + Phase1Lag5 + Phase2Lag12 + Phase2Lag16	392.320	0.000	31.4	<0.001
FFDI + DaysSinceRain + Phase1Lag5 + Phase2Lag12 + Phase2Lag16	392.924	0.604	32.6	<0.001
FFDI + Phase1Lag5 + Phase2Lag16	394.174	1.854	28.2	<0.001
FEW&FPW (Case II)				
MinTemp + DaysSinceRain + Phase2Lag4	782.950	0.000	14.4	<0.001
MaxTemp + DaysSinceRain + Phase2Lag4	783.657	0.708	14.1	<0.001
FFDI + DaysSinceRain + Phase2Lag4	783.739	0.789	14.0	<0.001
FEW&FPW&FNW (Case III)				
MaxTemp + DaysSinceRain + Phase11Lag7	1327.686	0.000	15.6	<0.001
MaxTemp + Phase11Lag7	1327.909	0.223	14.8	<0.001

Table 7.5 Model estimates and contributions of variable groups to model fits for the three best models. % Dev, deviance explained; FEW, fires burned entirely in forested wetlands; FPW, fires burned partly in forested wetlands; FNW, fires not burned in forested wetlands. Codes for the variables are as given in Table 7.1.

Model	Coefficient	Std. Error	t value	Pr(>|t|)	% Dev
FEW (Case I)					
Intercept	-4.866	0.878	-5.545	<0.001	Overall: 31.4
FFDI	0.055	0.018	3.065	0.003	Ambient Weather: 8.9
Phase1Lag5	0.045	0.015	2.902	0.005	Antecedent Rainfall: 23.2
Phase2Lag12	0.012	0.006	1.926	0.058	
Phase2Lag16	0.019	0.006	3.421	0.001	
FEW&FPW (Case II)					
Intercept	-2.621	0.900	-2.913	0.004	Overall: 14.6
MinTemp	0.117	0.040	2.920	0.004	Ambient Weather: 6.7
DaysSinceRain	0.060	0.028	2.153	0.033	Antecedent Rainfall: 6.0
Phase2Lag4	0.026	0.007	3.776	<0.001	
FEW&FPW&FNW (Case III)					
Intercept	-5.890	1.166	-5.049	<0.001	Overall: 15.6
MaxTemp	0.169	0.030	5.631	<0.001	Ambient Weather: 12.3
DaysSinceRain	0.039	0.026	1.482	0.139	Antecedent Rainfall: 2.3
Phase11Lag7	0.004	0.001	3.105	0.002	

7.4 Discussion

7.4.1 Fire Characteristics and Fuel Types

Smaller fires occurred more frequently than fires of larger sizes, which result is largely in line with those of other studies (e.g. Price and Bradstock 2011). FEW had smaller burned areas, probably because the FEW category is limited to narrow areas alongside the watercourse and also because of the relatively high fuel moisture content associated with water and forest (CFA, 2014). Fires burned the largest area during summer and the smallest in winter; this is regulated by the (summer) drought phases and the (winter) rainfall and possibly inundation phases. This seasonality is consistent with that described in broad-scale studies of Australia (Russell-Smith *et al.* 2007; Turner *et al.* 2008). The monthly distribution of fire size indicates that January is always the most fire danger period, regardless of fuel type. The second-ranked months were February for Case I and December and November for Case III, reflecting a shift in the pattern of seasonal burned area as the proportion of forested wetland declines. This may reflect a change of fire regime from temperate eucalypt forests/woodlands dominated by summer fire to semi-arid chenopod shrublands dominated by spring-summer fire (Bradstock 2010; Murphy *et al.* 2013).

In forested wetlands of the Riverina bioregion, the dominant fuel types (litter or grass) are poorly understood (VEAC 2007, as cited by National Parks Association of NSW Undated). Specifically, litter is the primary surface fuel for eucalypt open forests (30% - 70% foliage cover; Specht, 1970), complemented by shrubs and herbs; in contrast, herb/grass fuel is prominent for eucalypt woodlands (10-30% foliage cover)(Bradstock 2010). Since the structural form of forested wetlands changes from open forest in the west to woodland in the east, an “intermediate” foliage cover (30%) was expected; the contributions of litter and grass fuels may generally be comparable (litter/grass environment), and the balance between them may be significantly altered by additional factors (Bradstock 2010). In other vegetation/land use types, such as lands cleared for cropping and grazing or the poorly flammable chenopod shrublands, both shrubby and grassy fuels predominate, with the dominant fuel type being grass (Myers *et al.* 2004).

7.4.2 Effects of Climatic Factors

Climate influences fire danger through affecting the drying of existing fuels and the spread of fire. In particular, ambient weather directly affects fire size, and biomass accumulation determined by antecedent rainfall indirectly affects fire size (Littell *et al.* 2009; Bradstock 2010; Krawchuk and Moritz 2011). As for forested wetland areas, the dominance of sclerophyllous forest and hydrophytic vegetation, the high moisture contents alongside watercourses and the seasonal rainfall and flooding events complicate the mechanism and distinguish it from that in their surrounding ecosystems.

The effects observed for most ambient weather factors are logical and consistent with those documented for other landscapes (Price and Bradstock 2011). Namely, larger fire extent is associated with higher daily (maximum and minimum) temperatures, higher FFDI, lower relative humidity, and lower fuel moisture index; this is due to the connections of these values with the moisture contained in fuels and with fire danger (McArthur 1967; Catchpole 2002). Notably, daily minimum temperature is not a conventional explanatory variable in fire behaviour modelling; the variables more traditionally used are daily maximum temperature, relative humidity, and FFDI. The minimum temperature normally occurs in the middle of the night, and these higher minimums may disrupt the overnight fuel moistening process, thereby priming the landscape for more severe fire behaviour the next day (i.e. after sunrise). This in turn leads to stretched suppression resources and increased difficulty of initial attack, ultimately resulting in larger fire size. The power of this variable in fire behaviour modelling may be worth exploring further in future studies. The insignificant relationship between KBDI and fire size is likely to be explained by the nature of fuel in this study area. Although KBDI provides information on the dryness of litter fuels and consequently influences forest fire behaviour, it does not necessarily affect grassfire spread; that spread is determined by ambient weather and curing level. This may also be reflected in the relatively better performance of KBDI in models for FEW (litter/grass environment) than for other two cases (shrub/grass environments).

Elapsed days since last rain and the cumulative rainfall within a three-month lag and three-month phase before fire reflects short-term variation in moisture that relates to the availability of fuels to burn, i.e. the dryness of litter and the curing level of herbs/grass (Bradstock 2010; Turner *et al.* 2011). Results indicate that as days since last rain decrease, or the higher the amount of rainfall in the immediately preceding month (Phase1Lag0), the less likely the fuel is to be sufficiently dry or cured to support the propagation of a FEW. This one month phase is far shorter than that determined in Sydney Hinterland dry sclerophyll forests and woodlands, where fire extent was found to be negatively related to past annual rainfall (Price and Bradstock 2011). This is probably because the drying of litter fuels and the curing of herb/grass fuels after rain is faster in inland riparian forest areas where (1) the semi-arid climate is dryer and hotter than mesic, temperate areas, and (2) the taller and less dense trees facilitate greater penetration radiant heat to underground fuels. When fires burning other vegetation types were incorporated, DaysSinceRain became less powerful and the effect of Phase1Lag0 became insignificant, probably because other categories feature areas with higher proportions of shrub/grass fuels, which contain lower moisture and tend to dry out faster after rainfall.

The cumulative rainfall outside three-month lag or three-month phase represents antecedent rainfall related to biomass production (Bradstock 2010; Turner *et al.* 2011). For FEW, greater rainfall in the 6th (Phase1Lag5), 17-18th (Phase2Lag16) and 13-14th (Phase2Lag12) months before fire corresponded with larger area burned by an individual FEW. The former two variables largely coincide with natural late winter and early spring inundation phases, respectively, while the latter term coincides with the summer phase. Rainfall and the inundation that possibly occurs afterwards may promote the growth of highly ephemeral fuels and their drying out in following months (e.g. 6th month) or 1.5 years later (e.g. 17-18th month) (Briggs 1988). The effect of rainfall in the 13-14th month (approximately one year) before FEW can probably be explained by high summer rainfall leading to grassy biomass growth, and possibly by unseasonal summer floods. These effects gradually become insignificant as fires from surrounding landscapes are incorporated, probably because (1) the decreased antecedent rainfall amount and flooding frequency in adjacent dry lands may not be sufficient to stimulate and sustain biomass, and (2) strong human interventions (grazing and cropping) that affect the natural biomass accumulation process in surrounding areas. Nevertheless, a weak connection can still be demonstrated for multiple long-term antecedent rainfall factors less than 18 months (approximately 1.5 years) before fire (Case III). By presenting both the monthly lags/phases and the effect directions (positive/negative) in surfaces (Figure 7.3), the present study provides more precise results and better reveals underlying ecological processed than other studies conducted at larger scales (Russell-Smith *et al.* 2007; Turner *et al.* 2011). This is partially supported by the fact that no relationship has been found between the past seasonal rainfall and fire size in this present study.

All the selected complete models include both ambient weather and antecedent rainfall variables, demonstrating the combined effects of high fuel amount and hot, dry climate in regulating fire size. The presence of FFDI in all selected Case I models and one selected Case II model indicates that it sufficiently explains fire size in forested wetland areas, while direct weather factors such as MaxTemp and MinTemp are more effective when surrounding drylands is incorporated.

The differences in performance of variable groups for the three cases reflect the capacities of the included factors to explain fire sizes for each case. In Case I, ambient weather factors explained far less deviance than antecedent rainfall factors, which is different from that has been found in the temperate Eucalyptus forested ecosystems that weather is more influential in Eucalyptus forest ecosystems than antecedent rainfall (Price and Bradstock 2011). This is probably because in forested wetlands, there is either a natural imbalance between woody litter and grass/herb fuels, or the balance has been altered by grazing activity, which replaces perennial understorey grasses with ephemeral grasses that enhance the sensitivity of fire size to rainfall variation (Noble and Grice 2002; Bradstock 2010). From Case II to III, ambient weather factors are increasingly more important than antecedent rainfall factors, indicating that fire size is less sensitive to biomass accumulation in shrub/grass environments than in litter/grass environments. This difference in relative importance results from decreases in the performance of antecedent rainfall factors; the power of ambient weather factors remained stable throughout all three cases. The weak performance of antecedent rainfall factors in Cases II and III may be explained by the extensive occurrence of less flammable, shrubby fuels in dry lands, where low understorey biomass has limited lateral connectivity (Keith and Simpson 2010).

7.4.3 Limitations

This empirical study is able to give an idea of the driving factors of fire extent in forested wetlands and surrounding vegetation types. There is no denying the fact that significant differences in propagation processes exist among fires with different fuel types, and driving factors may further change throughout the lifetime of a fire. The long-term expansion of a free-burning wildfire is determined by normal spread days punctuated by rare spread events, where major growth occurs. This study's results have the potential to serve as a foundation for the simulation of fire behaviour in riverine areas, which should take these varying factors into consideration.

A limitation of the present study is that other potentially influential factors such as topographic effects, curing, land cover types, and fire management efforts have not been incorporated. For example, while the amount of short-term antecedent rainfall indicates curing level to some extent, the model fit may be further improved by incorporating data that directly reflects vegetation greenness or curing level. Another limitation is that some of the weather variables may not be fully representative of local weather conditions. For instance, wind speed is of paramount importance in non-wetland areas, given their prevailing grassy nature, and relatively distant weather stations may not portray wind speed adequately. This may especially affect the model performances for Cases II and III.

7.4.4 Management Implications

The management of forested wetlands, i.e. river red gum forests and woodlands, has primarily targeted at maintaining ecological function in support of the neighboring communities' environmental and social-economical values, and to minimise the risk of damage from fire (NSW NRC, 2009). Fire risk management plans (including fuel management and the fire suppression) are essential components of the management of forested wetlands (Forests NSW 2008). Similarly, the management of semi-arid shrub/grass environments has primarily focused on maintaining biodiversity value, which is partly affected by fire regimes (Myers *et al.* 2004). The present study provides insights into climatic drivers of fire size, a fundamental component of fire regime in both ecosystems that can potentially be used in support of sustainable management and fire risk reduction.

In forested wetlands, fire suppression resources should be properly allocated according to the level of fire danger, i.e. FFDI (Table 7.5). Fuel management practices such as thinning and prescribed burning may be considered under certain circumstances, e.g. before the greatest fire danger period of summer, specifically January and February (Figure 7.1); or in the year of and year following high levels of winter and/or summer rainfall (Figure 7.2, Table 7.5). Prescribed burning should only be considered in conservation areas, rather than timber production areas, to avoid damaging merchantable timber (NSW NRC, 2009), and its ecological benefits have to be proved before using it as a management tool (Allen 2000).

There should not be any fires burned in chenopod shrublands because their dominant species are unable to regenerate after burning (Myers *et al.* 2004). Although chenopod shrublands are generally less flammable (Keith and Simpson 2010), fuel management activities may be required under exceptional circumstances, e.g. before the greatest fire danger period of spring and summer, specifically January, December, and November (Figure 7.1) in the year after a high level of long-term (e.g. 1.5 years) cumulative rainfall (Figure 7.2, Table 7.5). Daily maximum and minimum temperatures and drought condition (Table 7.5) may be used as indicators for preparation of fire suppression.

After higher levels of antecedent rainfall, fuel management and fire suppression resource allocation may be prioritized for forested wetlands due to their sensitivity to biomass accumulation after long-term rain.

7.5 Summary

This study investigated wildfire characteristics and the effects and relative contributions of climatic factors on fire size in *Eucalyptus camaldulensis* forests and the dry lands of the Riverina bioregion, NSW, Australia. Fire size in forested wetlands and the surrounding areas was found to be driven by ambient weather and antecedent rainfall conditions. The most influential factors and the contribution of each factor group in explaining fire size varied with changes of vegetation type, reflecting differences in the roles and capacities of climatic factors in litter/grass and shrub/grass environments.

The present study provides effective and precise information that better reveals the underlying ecological process in forested wetlands and their surrounding vegetation types. The results have the potential to support forest and fire management and planning in this environment, and the conclusions may be extended to other warm and dry riverine ecosystems around the world.

Chapter 8 Conclusion

The thesis explored patterns of wildfires at two scales in South-Eastern Australia – a broad scale covering NSW, ACT, and VIC, and a small scale covering the NSW side of the Riverina bioregion. Wildfire information was sourced from remotely sensed observations and administrative records. The effects and relative contributions of environmental factors and anthropogenic factors on wildfire patterns were modelled using statistical methods, i.e. GLM and GAM. Spatial and temporal patterns of wildfire occurrence and size were found to be regulated by different factors across different regions and scales, reflecting the complex relationships among components of the biophysical environment. This chapter summarises the main findings of the thesis, discusses its contributions and limitations, and points out potential directions for future work.

8.1 Main Findings

The main findings of the thesis were summarised in the respective sections of Chapters 4 through 7. This section will synthesize these findings to address the four research questions presented in Section 1.2.

(1) What are the broad-scale wildfire activity patterns in South-Eastern Australia; what are the effects and relative contributions of environmental and anthropogenic factors that regulate these patterns; and how can the MODIS active fire product be incorporated into wildfire modelling?

The modelling results reveal that in NSW, ACT, and VIC, wildfires are most likely to occur in mountainous areas, forests, savannas, and lands with high vegetation coverage, and less likely to occur on grasslands and shrublands. Wildfires also tend to occur in areas near human activities. Environmental variables are strong individual predictors of fire activity, while anthropogenic variables contribute more to the final model. The MODIS active fire product can be applied in wildfire modelling, especially for studies that cover broad scales, bearing in mind the limitations of the product and associated requirements in data manipulation and result interpretation.

(2) What are the wildfire ignition patterns across different ecoregions of South-Eastern Australia; are there any non-linear relationships between these patterns and their determinants; and how do the relationships vary spatially?

The modelling results reveal that in NSW and ACT, vegetation is the key factor in most ecoregions: vegetation formations regulate fire occurrence patterns in the most fire-prone area (TB & MG, see Section 5.1 for the definition), where vegetation structure and composition varies significantly across space; climate gradients drive fire occurrence in ecoregions with relatively broad areas (TB & MG and TG), where the top-down process is dominant. Spatial effects influence fire patterns in all ecoregions, while anthropogenic factors regulate fire occurrence patterns in the most populated area (TB & MG) and two sparsely populated areas (MF and DX).

In the TB & MG ecoregion, wet sclerophyll forests are higher in ignition probability than rainforests but lower than dry sclerophyll forest; there is a need for evaluating the impacts of fires on some ecologically-sensitive vegetation formations. In most ecoregions, there is a non-linear relationship between NDVI and fire occurrence, with small to medium levels of NDVI showing a positive effect. Additionally, in temperate regions, fires tend to occur in low precipitation and high temperature areas. Fires also tend to occur near human facilities and at non-protected areas in TB & MG, near railroads in both MF and DX, but away from roads in DX.

(3) What are the spatial and temporal patterns of fires with different causes and different vegetation types in the inland semi-arid riverine environments; how do their determinants affect these patterns; and what are the relative contributions of different factor groups to fire ignition?

The monthly and seasonal distributions of fire occurrence suggest that fires on the NSW side of the Riverina bioregion mostly occur in summer. In particular, natural fires mostly occur in summer, while human-caused fires occur in spring and summer. Summer is the most fire-prone season in forested wetlands, while in dry lands fires mostly occur during both spring and summer.

The results of the regression models reveal that fires are more likely to occur on days with severe weather conditions and in areas with higher annual rainfall. Fires are also more likely to occur in forested wetlands than in dry lands. The relationship between fire occurrence probability and inundation frequency is non-linear, with fire probability being the highest at intermediate inundation frequencies. As in other landscapes, human-caused fire probabilities are higher in areas with better human accessibilities. The relative contributions of weather, fuel, and ignition sources in explaining human-caused fire occurrence are approximately equal, while natural fire occurrence can be better explained by weather than fuel.

(4) What are the properties of wildfires and their sizes in inland forested wetlands and adjacent dry lands; how do ambient weather and antecedent rainfall affect the sizes of these fires; and which are the most important factors that govern fire sizes in these environments?

Smaller fires occur more frequently than fires that are relatively larger in size, as is found in other landscapes. In terms of cumulative area burned by fires smaller than 1,000 ha, forested wetlands and dry lands experience summer and spring-summer fire regimes, respectively. FEW (see Section 6.2 for the definition) burned smaller areas both individually and in total than did fires partially or fully in dry lands.

The regression model results suggest that higher cumulative rainfall conditions in the 6th, 13-14th, and 17-18th months before fire drive larger sizes of FEW, while a number of factors representing cumulative rainfall after the 18th month before fire positively affect fire size for FPW and FNW. Larger fire extents are also driven by more severe ambient weather conditions. FFDI is more powerful in explaining the size of FEW, while daily temperature becomes more effective when FPW and FNW are gradually incorporated; this supports the use of distinct factors as indicators of fire danger in the two diverse ecosystems. Antecedent rainfall factors are more powerful than ambient weather in explaining the size of FEW, while they become less important when surrounding lands are incorporated.

8.2 Contributions and Implications

This thesis systematically studied two types of fire patterns – fire occurrence and size – and their determinants in South-Eastern Australia. The occurrence of fire provides information on when and where fires are most likely to ignite, whereas fire size determines the effects of fire on landscape and ecosystem. The findings from this thesis provide a better understanding of broad-scale and long-term fire activity patterns and their regulators (Chapter 4), the variation of fire ignition patterns and their determinants across ecoregions (Chapter 5) in the states of South-Eastern Australia, as well as patterns in fire occurrence (Chapter 6) and size (Chapter 7) and their driving factors in the semi-arid riverine environment of South-Eastern Australia. This information supplements existing knowledge on the risk and regime of fires in these two Australian landscapes, and can be used to support the planning of sustainable fire management and risk mitigation activities at both strategic and tactical levels.

The broad-scale models of fire activity and ignition (Chapters 4 and 5) are spatially based and temporally irrelevant, and provide information on where fires are most likely to burn or ignite. These models can be used to produce predictive maps (e.g. Figure 4.5) that illustrate areas where conditions related to weather, fuel, topography, and ignition sources produce a higher probability of fire occurrence. Understanding obtained from these models as well as the spatial-based predictive maps is important for making strategic decisions concerning long-term resource management in large regions (Taylor *et al.* 2013). These models may also provide information for the designation of areas with higher fire risk in order to protect new developments from potential fire threats and thus reduce losses from fire (NSW Rural Fire Service 2015).

On the other hand, the spatiotemporal models of fire occurrence (Chapter 6) and size (Chapter 7) provide information on when and where fires are more likely to ignite; they also illustrate how large a fire could be expected in a small region (i.e. the NSW side of Riverina) and during a short period (i.e. one day), given certain environmental and anthropogenic conditions. This information supports the generation of daily-based fire risk maps that inform fire managers of the days and locations of potentially high fire danger. They can also help fire management agencies make tactical decisions on matters such as crew allocation and the planning of fuel management programs within the study area. For example, in forested wetlands of the Riverina, fuel management practices may be emphasized before summer of a year with high levels of winter and/or summer rainfall, and also the year immediately following. After high rainfall and under similar ambient weather conditions, fire risk management priority may be given to forested wetlands since fire size is more sensitive to biomass accumulation in that environment than in the adjacent dry lands. Furthermore, insights obtained from these studies also provide foundational knowledge for the assessment of the ecological impact of fire in fire-sensitive wetland environments, which is out of the scope of this thesis.

In additional to the findings regarding fire patterns and their responses to variation in environmental and anthropogenic processes, knowledge of the relative importance of these processes (Chapters 4, 6, and 7) is also important. The results of the case studies presented in this thesis complement existing knowledge on the relative importance of fire-pattern drivers, which vary regionally with fluctuations in available moisture across different Australian ecosystems (Bradstock 2010). The potential effects of global change as well as future trends in fire patterns can also be assessed or discussed based on these results.

In this thesis, the results from each research theme have been discussed and compared with existing knowledge from landscapes that share more or less comparable characteristics in terms of geographical positions, climatic conditions, vegetation types, etc. Results obtained from this study may be extended and compared with information on fire occurrence and size in other landscapes across the world.

8.3 Limitations and Future Work

For the broad-scale fire occurrence studies (Chapters 4 and 5), fire observations were sourced from the MODIS active fire product. Its merits are that the satellite sensor is capable of capturing fires burning in remote areas, the dataset covers broader areas, and the modelling process can be repeated and extended to other regions. However, there are limitations on this dataset such as the existence of commission error, a bias towards large/natural fires, a lack of information on fire causes, and the existence of detection noise such as prescribed and agricultural fires. Careful data manipulation and result interpretation have been employed to mitigate the influence of these drawbacks.

The limitations discussed in the previous paragraph have been overcome for the studies presented in Chapters 6 and 7, which used administrative fire records that contain information on fire causes and have lower errors or noise. However, these studies have their own limitations. An unavoidable issue is related to the construction of the explanatory variable: station-based weather observations may not fully capture local weather conditions, especially wind speed. Also, there are potentially influential factors other than ambient weather and antecedent rainfall that have not been considered, which may affect model performances. Possible improvements can be made on these models by introducing factors related to curing, land cover types, and fire management activities.

The MODIS fire data are relatively short, and the administrative fire records are few in number. These limitations can potentially be overcome by incorporating datasets that cover larger areas or have longer temporal spans. This thesis did not do so for two reasons. (1) Chapters 6 and 7 had the objective of exploring fire patterns in a particular environment –forested wetlands and their neighbouring drylands (see Chapter 1). Their study area was constrained to the riverine area that experiences a semi-arid climate, roughly corresponding to the NSW side of the Riverina bioregion. Expanding the study to include data from a different bioregion (e.g. a neighbouring bioregion that experiences a mesic climate) is beyond the objective of these case studies; furthermore, doing so can alter the observed fire-environment relationships as well. (2) Both MODIS and administrative fire observations cover brief temporal spans because data availability is limited. The timespan involved cannot be improved until more years of data become available. Despite these limitations, the results of this thesis are valuable and largely consistent with studies conducted in other landscapes across the world (e.g. Penman *et al.* 2013, Syphard *et al.* 2008).

In this thesis, Moran's I and semivariograms were used to test the existence of spatial dependence among model errors. Although these techniques are useful, there are more sophisticated spatial regression models, e.g. simultaneous autoregressive models and conditional autoregressive models, that may provide more information such as a clear picture of the residual spatial pattern and therefore some hints on omitted variables (Wall 2004). These models can be employed in future studies on fire occurrence and size.

The total deviance explained by fire occurrence models in this study ranges from 9% for the TSG model (Chapter 5) to 34% for the best fire ignition models (Chapter 6). The explanatory powers of these models are comparable with or less than those discussed in Penman *et al*. (2013), i.e. 29% for lightning ignition and 57% for arson, but greater than those of Turner (2011), i.e. 1%-5%. The total percentage of deviance explained by fire size models (Chapter 7) ranges from 14.6% for the FEW&FPW model to 31% for the

FEW model, which is comparable with that of Turner (2011), i.e. 4%-32%. Possible reasons for the merely fair performances of some models have been discussed in Sections 5.5.4 and 7.4.3. Although some models do not fit the data as well as others, they remain useful from an explanatory perspective. Nonetheless, possible improvement in terms of model performance can be made by introducing more reliable datasets and explanatory factors.

Studies conducted in other landscapes reveal that the relative contributions of factor groups in regulating fire regime are scale-dependent (McRae and Sharples 2011). For example, the relative role of fire-size drivers varies across scales (Slocum *et al.* 2010; Liu *et al.* 2013; Fang *et al.* 2015; Fernandes *et al.* 2016a). Theoretically, small fires are mainly constrained by bottom-up controls such as the vegetation and topography, while increasingly larger fires are gradually affected more by top-down factors such as weather conditions. Fire likelihood (Parks *et al.* 2011) and area burned (Parisien *et al.* 2011) also have scale-dependent responses to their controlling factors. The effects of scale on the relative contributions of fire-pattern drivers in the study area of this thesis are worth further exploration.

In conclusion, this thesis has shown that fire patterns vary substantially within and between regions and scales due to variations in weather/climate, fuel/vegetation, topography, and factors related to human behaviours. Remotely sensed and administrative fire records as well as statistical methods have been used in understanding fire processes and in predicting fire patterns in the fire-prone states and in the semi-arid riverine environment of South-Eastern Australia. Spatial and temporal variations in fire occurrence and size were explored, and the effects and relative importance of fire-pattern drivers were modelled. Findings from this thesis are expected to inform strategic and tactical decision-making regarding the landscapes of South-Eastern Australia.

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