Faculty of Science and Engineering

Spatial analysis and modelling of fire severity and vegetation recovery on and around Mt Cooke, south-western Australia

Salah Mustafa Dehum

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Declaration

To the best of my knowledge and belief this thesis contains no material previously published by any other person except where due acknowledgment has been made.

This thesis contains no material which has been accepted for the award of any other degree or diploma in any university.

Signature: 

Date: 17th of July , 2015

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ABSTRACT

South Western Australia is one of the world's most fire prone areas and it is also an area of high biodiversity and endemism potentially at risk from changes in fire regime. Granite outcrops in the South Western Australian Floristic Region (SWAFR) are affected by the climate, their topographic structure and the vegetation on and around the outcrops. This study considers that granite outcrops may provide some areas of protection for the localised plant communities from the effects of fire. The climate of the region is in a warming and drying trend and more frequent lightning storm activity increases the risk of lightning ignition in the area. This thesis examines a fire event in 2003 on Mt Cooke, the largest of the granite outcrops on the Darling Escarpment south of Perth to investigate the relationship between topography, fuel age, fire severity and vegetation recovery over a period of ten years.

Remote sensing has been widely used for assessing fire worldwide. A variety of indices have been designed and used for mapping fire scars and fire severity over differing landscapes on local, regional and global scales. This study assessed six common indices (selected after a literature review) and tested their ability to map fire and fire severity over a fire affected granite outcrop. Thus, this thesis determines which of the indices provide the optimal results over the varied topography of Mt Cooke. Two methods of mapping fire scar and assessing fire severity were tested – a single post-fire image and a set composing of a pre-fire image and a post-fire image all derived from Landsat ETM+. At this site three landscape classes of forest, shrubland and bare soil have been chosen to assess the effectiveness of the chosen indices over an area where the vegetation consists of heterogeneous shrubland around granite outcrops, within a generally forested landscape.

Initially, scientific publications involving remote sensing for fire mapping and fire severity from 1990-2012, were reviewed. Based on this review, four commonly used indices and two less frequently used indices were tested. Results from Receiver-Operating Characteristic (ROC) curve statistical analysis revealed that the top four indices produced equivalent area under the curve (AUC) statistics (AUC = 0.85) suggesting that any of the top four indices – Normalised Burn Ratio (NBR), Soil Adjusted Vegetation Index (SAVI), Modified Soil Adjusted Vegetation Index (MSAVI2) and Normalised Difference Vegetation Index (NDVI), could be used to map fire scars with a similar accuracy in this area. Enhanced Vegetation Index (EVI) produced an AUC = 0.72 and proved less reliable. The Normalised Difference Infrared Index (NDII) produced an AUC= 0.80, thus may not perform well on the granite component.

Mapping of fire severity in the short–term, five days post-fire to one year post-fire and then mapping vegetation recovery in the long term, over ten years with the use of Landsat ETM+ imagery was completed with the use of NBR on a single image and with the Differenced Normalised Burn Ratio (dNBR) using two images. The low severity class demonstrated that there was no significance difference between five days post-fire and one year post-fire. However, the moderate and high severity classes showed significant differences, even after one year post-fire. In mapping fire severity, the optimal time for mapping fire severity is between one to four months post fire, to avoid any distortion

of the results caused by early vegetation regeneration. The dNBR provided satisfactory results in mapping fire severity but the Relative Differenced Normalised Burn Ratio (RdNBR) provided improved outcomes and would be the optimal choice for this type of study.

In the assessment of the recovering landscape, the NDVI was used to monitor the regeneration of vegetation over ten years. The dynamics of the regeneration pattern was comparable to other similar fire assessments, but even after ten years some plant communities have not returned to pre-fire status. The fire killed, or at least killed back to lignotuber many of the mature trees in the area. It is expected that if the changing climate trend progresses as forecast, the dominating plant communities may change. The species succession may be impacted by alterations in the wildfire frequency and fire intensity in this region.

The NDVI and Recovery Index (RI) analysis indicated a moderate vegetation recovery to pre-fire patterns, with regeneration to around 40% of the pre-fire levels seven years post-fire. Regression analysis of pre and post-fire mean NDVI exhibited significant re-growth in the first 3 years post-fire with a gradual decrease in the shrubland areas over the following two years. However, the regrowth in the forest areas displayed a slow but continuous increase. The NDVI declined due to post fire effects.

Incorporated in the factors considered in this study was the interrelationship between specific topographic features, fuel age and fire severity. The relationship between fuel age and fire severity was positive – the areas of high fire severity coincided with those having a high fuel age and fuel load – there was a marked decrease in fire severity in areas that had a prescribed burn five years prior to this fire. Fire severity had a positive correlation with the topographic features of elevation and slope. The northern aspects faced a higher fire severity where the vegetation, living and dead, was drier. However, many of the topographic features that were expected to help lessen the fire effects were overridden by the severity and intensity of this particular fire that coincided with a hot dry summer.

Predictive modelling was completed across the study area to predict the fire severity on the granite outcrops and its surrounds. Two models were tested: the Ordinary Least Square (OLS) and Geographically Weighted Regression (GWR), and were compared for predicted fire severity in the area. Nine dependent variables were selected and the final results indicated that the GWR results surpassed those of OLS: Akaike's Information Criterion (AIC) -755 model fit while the GWR was -765. The predictive dNBR map for GWR was similar to the observed map for dNBR but the OLS map displayed significant differences. While there is no fire regime that will prove suitable for every plant community, the results from this study may assist conservation teams in identifying areas that may benefit from fuel load management and may subsequently reduce fire intensity with the aim of conserving ecosystems that house the rare biota in this environment.

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List of Acronyms and Abbreviations

BSC	Biological Soil Crust
AIC	Akaike's Information Criterion
CART	Classification and Regression Tree
CBI	Composite Burn Index
DEM	Digital Elevation Model
dNBR	Differenced Normalised Burn Ratio
dNDVI	differenced Normalised Difference Vegetation Index
dNDII	differenced Normalised Differenced Infrared Index
dNDMI	differenced Normalized Difference Moisture Index
dSAVI	differenced Soil adjusted vegetation index
ENVI	Environment for Visualizing Images
ERR	Elevation Relief Ratio
ETM+	Enhanced Thermatic Mapper
EVI	Enhanced Vegetation Index
FLAASH	Fast Line-of-sight Atmospheric Analysis of Spectral Hypercubes
FPR	False Positive Rate
FPR	False Positive Rate
GIS	Geographic Information System
GOs	Granite Outcrops
GPS	Global Positioning System
GWR	Geographically Weighted Regression
MODIS	Moderate Resolution Imaging Spectroradiometer
MSAVI2	Modified Soil Adjusted Vegetation Index
MSS	Multispectral Scanner
MTEs	Mediterranean Ecosystems
NBR	Normalised Burn Ratio
NDII	Normalised Differenced Infrared Index
NDMI	Normalized Difference Moisture Index
NDVI	Normalised Difference Vegetation Index
NIR	Near Infrared
OLS	Ordinary Least Square Regression
RdNBR	Relative differenced Normalised Burn Ratio
RI	Regeneration Index
R-M ANOVA	Repeated Measurement Analysis of Variance
ROC Curve	Receiver Operating Characteristic
SAVI	Soil Adjusted Vegetation Index
sd	Standard Deviation
SWAFR	South Western Australian Floristic Region
SWIRI	Short Wave Infrared
SWIRII	Short Wave Infrared II
TM	Thermatic Mapper
TOA	Top of Atmosphere
TP	True Positive Result

TPI	Topographic Position Index
TPR	True Positive Rate
TRI	Terrain Ruggedness Index
TRI	Topographic Roughness Index
USGS	United States Geological Survey
VI	Vegetation Index
VIF	Variance Inflation Factor
κ	Kappa

Chapter 1: Introduction

1.1 The issues: Fire

Fire is a natural disturbance that impacts all ecosystems in fire prone regions and is an integral part of the landscape (Levin 1992; Dunlop and Brown 2008; Bradstock *et al*. 2012). A fire regime consists of the intensity at which the fire burns, the type of fire ground or canopy, for example, the intervals between fires (intervals) and the time of year, (or season) in which it occurs (Banks 1982). The intensity with which the fire burns has been categorised by many (e.g. Heinselman 1981; Kilgore 1981; McCarthy *et al*. 1999). Wildfires are unplanned and will vary in both their seasonality and the time of day they occur. On a global scale, the emissions from fire, such as ozone, carbon monoxide and the particulate matter may raise concerns in human health risks from reduced air quality (Bauer 1999) and have a direct impact on the atmosphere (Smith *et al.* 2005). There is also the threat to human life.

Fire affects all aspects of the ecology from individual plants through to plant communities, soil structure, nutrients and soil erosion, water catchment and runoff (Morrison *et al*. 1995; Wan *et al*. 2001; Choromanska and DeLuca 2002; Morrison 2002; Watson and Wardell-Johnson 2004; Russell-Smith *et al*. 2005; Verkaik *et al*. 2013). It directly impacts the complete cycle of plant growth, survival and reproduction. While it may kill mature plants it simultaneously stimulates massive plant regeneration. Fire consumes both live and dead vegetation and in doing so it alters the structure of the plant communities in both local and widespread areas alike (Burrows and Wardell-Johnson 2003; Page *et al*. 2002; Trabaud 2004; Van der Werf *et al*. 2003) however, the role of fire is vital to some types of vegetation as they rely on smoke, heat and the ashbed to regenerate (Gill 1996; Bradstock *et al*. 2006; Burrows 2006; Bradstock 2010).

The effects of large-scale fires across all types of environments, have the potential to change the landscapes in which they occur, not just alter the vegetation growth. It can be dramatic and is visually the main effect observed, but in some ways not so easily identifiable initially. There may be changes to the soil structure and the hydrology (Robichaud *et al*. 2000; Ice *et al*. 2004) and there may also be change to the landscape structure (Morgan *et al*. 2001) and the structure of rock and the surface properties of the rock itself (Shakesby and Doerr 2006). Other factors included in wildfire studies are the size of the fire (Gill 1981) and the heterogeneity, or the variations in the intensity of the burn and its impact within the area affected (Gill *et al*. 1999; Mackey *et al*. 2002). Apart from human intervention as the source of ignition, lightning strikes are common instigators and sparks caused by falling rocks have been known to start a fire. In rarer instances spontaneous combustion can occur (Francisco and Paul 2009).

Fire is a well-recognised natural part of an ecosystem that impacts plant communities in Mediterranean type ecosystems (MTE) such as experienced in South West Western Australia (SWWA), (Di Castri 1981;Naveh 1994; Pausas *et al*. 1999). Globally, there are five MTEs, (Mediterranean Basin, Chile, South Africa, Western North America and Australia), and they are characterised by outstanding floristic diversity and endemism. The SWWA is considered one of the most fire prone areas in the world (Abbott and Burrows 2003) due to extended dry periods and regular hot winds and is at risk of climate change with continued warming and drying. These changes to the climate may impact the unique plant life causing slowing of the growth rates and decreased recovery rates in the vegetation post-fire (Williams *et al.* 2008). Since the 1970s, the decreasing mean rainfall is prolonging the fire season and this, in conjunction with increased tropical cyclone activity in northern WA, brings added storm activity and lightning strikes to the area, (a common cause of the fire starting), which may impact the fire frequency (McCaw and Hanstrum 2003).

Much research over a spectrum of fire prone ecosystems focused at diverse taxonomic levels has recorded the changing species appearances and the diversity in species within the studied areas in response to the time between fires (fire intervals) and time since the most recent fire (Gill 1999; Keith et al. 2002 and Tozer and Bradstock 2002). The intensity of the fire and time frames between fires affects both live and dead vegetation in relation to its structure and composition (Bond and Van Wilgen 1996; Burrows 2008). In addition, soil erosion and changes to the soil nutrient composition comes about through repeated exposure to fire and even to the exclusion of fire, disturbing seed banks and soil structure (Pausas *et al*. 1999; Myronidis *et al*. 2010). Furthermore, the nutrient cycling is also altered by the effects of fire and thus, a diverse fire regime will, as a consequence, influence the composition and formation of the vegetation and promote biodiversity over the landscapes (Gill *et al.* 1981; Whelan 1995; Trabaud and Prodon 2002; Bradstock *et al*. 2002; Abbott and Burrows 2003). However, while wildfire is a natural part of the landscape it is being affected by changes in land use such as grazing by domestic livestock, by harvesting of timbers and the introduction of invasive species (Barrett *et al.* 1991; Ford and McPherson 1999).

The components of fire in the landscape are the fire type, its frequency, the intensity with which it burns (fire severity) and the season in which it occurs (Gill 1975 1981; Thonick *et al.* 2001; Watson and Wardell-Johnson 2004). There is no one combination of fire regime and fire severity that favours all species or ecosystems. Fire response within communities and species is variable, some vegetative assemblages are quite fire resilient and recover quickly to their pre-burned state while others may be sensitive to fire and take many years to recover. Each region has a unique fire interval and a variation of fire intensity and it is this that provides diversity in habitat and an opportunity for flora to recover (Friend and Wayne 2003; Van Heurck and Abbott 2003).

When considering post fire recovery, Bell and Koch (1980); Burrows (1994); Burrows and Wardell-Johnson (2003); Gill *et al*. (1999); Gould *et al.* (2007) concur that the dynamics of vegetation regeneration post-fire tend to have similar patterns. Initially, in the first few years following the fire, plant species richness is greatest before stabilising or decreasing. The understorey vegetation increases in cover and height quickly after a fire due to more space and light, before stabilising for some time. This is then followed by a period of decline in the understorey plant life as the taller shrubs and trees re-establish themselves within the community, reducing the amount of light to the lower levels.

The plant communities that are able to regenerate post-fire take advantage of reduced competition for nutrients, water and light (Yates *et al*. 2003). This demonstrates that the changes in local habitats caused by fire are a powerful and dynamic force influencing the species succession (Pant *et al*. 2002). After bush fires the regenerating vegetation can be affected by a number of factors including, but not limited to, the size of the seedbank, the rate of seed destruction by fire and heat, the predation of the remaining seed in the post-fire period and seedling herbivory (Whelan 1995; Schwilk and Keeley 2006; Cohn *et al*. 2002).

Over the coming century, fire regimes are expected to change as a result of land-use modifications and the warmer dryer climate changes (Pin˜ol *et al*. 1998; Flannigan *et al*. 2000; Houghton *et al*. 2001; Pausas 2004). This lengthening of the fire season will increase the potential for more frequent, intense fires that may impact areas in Western Australia, such as those that are considered to be biodiversity hotspots in the South Western Australian Floristic Region (SWAFR), an area of species richness with high endemism (Williams *et al*. 2008; McCaw and Hanstrum; 2003; Williams *et al.* 2009).

There is an increase in fire risk in Australia with a reduction in the fire intervals predicted and an associated increase in fire intensity with faster fire spread as an outcome of the warmer dryer weather conditions (Tapper 2000; Williams *et al.* 2001). The number of extreme fire danger days is increasing and in south eastern Australia. Hennessey *et al*. (2006) suggests that the increases may escalate by as much as 4-25% by 2020 and 15-70% by 2050. The fire season is predicted to lengthen which leaves only the early spring and autumn and the shortened winter months in which to manage prescribed burning to help control fuel loads.

1.2 Granite outcrops

Granite outcrops (GOs) comprise nearly 15% of the total continental surfaces worldwide (Twidale 1982) and within south western Australia they make up a relatively small proportion of the landscape of approximately 10% of the surface area (Withers 2000; Burrows 2013). The outcrops contain unique features that may offer protective habitats that are not found elsewhere (York Main 1997; Burrows 2013). The outcrops of the mesic south western forested areas have notably high levels of plant endemism (Hopper *et al*. 1997; Myer 2003) and the vegetation may vary widely from that of the surrounding landscape. They hold an estimated 12% of Declared Rare Flora (Hopper *et al.* 1990; Yates *et al*. 2003).

Life forms that were once possibly more widespread have now contracted to the outcrops and their immediate surrounds as a reaction to changing climate and altered fire regimes over thousands of years. There are a range of microhabitats included on the GOs that range from bare rock to cracks and crevices, shallow soil filled depressions, gnammas, winter water flows and a mix of rock and boulder fields and the apron areas surrounding the outcrops (Main 1997). These microhabitats may exhibit varying sensitivity to changing fire regimes. The exposed rock areas experience harsh weather conditions with extremes in heat and cold and differing moisture access (Shure 1999; Yates *et al*. 2003).

The SWAFR contains a region that has been identified as being a "global biodiversity hotspot" (Myers *et al*. 2000), one of 25 such places world-wide, which are considered to be at risk. In the study of hotspots done by Myers (2002, 2003), he states that two-fifths of all species that are under threat of extinction are in just 25 different locales, and these hotspots feature over half of all species considered endangered (Myer 2003). It is thought that GOs do not readily support fire spread due to the nature of the vegetation and the topography of these regions (Hopper 2000). Nonetheless, the GOs on the SWAFR are surrounded by a matrix of vegetation that is seasonally highly flammable and can support intense fires. It is common to find outcrops with evidence of past fires such as residual charcoal and fire scarring on trees. This study examines fire severity and its relationship to topography and vegetation recovery over a ten year period following the 2003 wildfire on Mt Cooke as the basis for the data.

1.3 Research aim, research question and thesis structure.

The overall aim of the thesis is to develop a detailed understanding of the role granite outcrops play during fire and in the recovery of vegetation post-fire. The main research question to be addressed in achieving this aim is:

Does the complex topography of granite outcrops provide more shelter from fire than the surrounding landscape?

I hypothesise that the shelter provided by the topography of the GOs may provide safer havens for plant species during a fire by the effect of natural firebreaks formed within the GOs.

I hypothesise that fire severity may be lessened by the vegetation types that inhabit the GOs due to the sparser vegetation and low growing species, growing on and between the rocks leading to lower fuel loads.

I hypothesise that the Normalised Burn Ratio (NBR), as the fire index, will not change over time.

I hypothesise that the vegetation recovery across this ecosystem may never completely return to the pre-fire state.

Chapter 1 provides an introduction to the issue of fire, changing weather trends and the landform of granite outcrops and the vegetation that exists on and around the outcrops.

Chapter 2 is a literature review of fire, fire regimes, climate change, granite outcrops, remote sensing (vegetation indices and fire indices), vegetation regeneration post-fire on and around GOs and the modelling of fire severity.

Chapter 3 describes the study area on Mt Cooke.

Chapter 4 compares a range of remote sensing-based indices for mapping fire scars. A case study of the 2003 Mt Cooke fire, south western Australia

Question: **Can data from remote sensing provide a reliable information source for mapping fire scars across this Mediterranean type of ecosystem?**

Aim: This chapter aims at mapping the site of the fire, with the use of a variety of vegetation indices and fire indices to decide which offers the optimal results for modelling fire and fire severity on GOs and the surrounding area.

Aim: The second aim for Chapter 4 is to make a comparative study of data results from a single post fire image against the results from a set of images – one pre-fire and one post-fire, to determine if one method provides a significant benefit over the other.

Chapter 5 discusses mapping fire severity and vegetation recovery rates on Mt Cooke and surrounds (2000-2012).

Question: **What is the ideal time post-fire for mapping fire severity?**

Question: **How long does it take for this ecosystem to recover post-fire and will the vegetation return to the pre-fire state?**

Aim: To determine the ideal time at which fire severity should be mapped.
Aim: To assess fire severity and vegetation recovery over time and determine if there is a time frame within which the burned landscape returns to its pre-fire state.

Chapter 6 determines the environmental influence on fire intensity using statistical modelling on Mt Cooke.

Question: **Do topographic influences affect fire severity on the study site and does the topography provide protection from the intensity of the fire?**

Aim: To identify topographic features that may affect fire intensity and spread.
Aim: To compare the relationship between topography and fire severity and the impact these have on vegetation.
Aim: To select a suitable model for fire severity prediction.
Aim: To suggest ways in which fire management plans for similar sites may benefit from this type of research.

Chapter 7 discusses the results from this study and implications for possible fire management plans and suggests areas for further research.

1.4 Thesis Overview

This thesis is composed of seven chapters which begin with a discussion on why granite outcrops and their associated vegetation communities are important and highlights the increasing risk of fire which may impact on the local biodiversity. It investigates the use of remote sensing as a possible means for the assessment of the landscape and in the measurement of fire severity and the recovery of the vegetation across a specific granite outcrops site. The information on the changing weather trends in the area are considered when identifying possible causes for an increased risk of fire in this area. There has been other research done in this topic so initially, in Chapter 2, a review of the literature was completed to determine how other researchers have addressed the topics of fire regimes, climate change and the features of granite outcrops that suggest there may be fire refugia in these areas.

The study area is identified in Chapter 3 and a description of the fire chosen for this study is presented. The vegetation indices chosen for mapping fire scars and fire severity from the literature review are discussed and the test results presented in Chapter 4. A comparison study was made between the results of a one image assessment over the results from a two image assessment to determine if one method is comparably better than the other for mapping fire severity and fire scars.

Chapter 5 discusses the mapping of fire severity and vegetation recovery rates on Mt Cooke. The question of what time frame post-fire provides the optimal result for mapping fire severity and vegetation recovery rates are measured. The topographical features on and around granite outcrops, and the effects these have on fire intensity are explored in Chapter 6. Statistical modelling was implemented to determine if specific topographical features may offer more protection from the fire intensity.

The overall results from every chapter outcome are discussed in Chapter 7 and the implications for possible fire management plans are highlighted and areas for further research within this specific field are suggested.

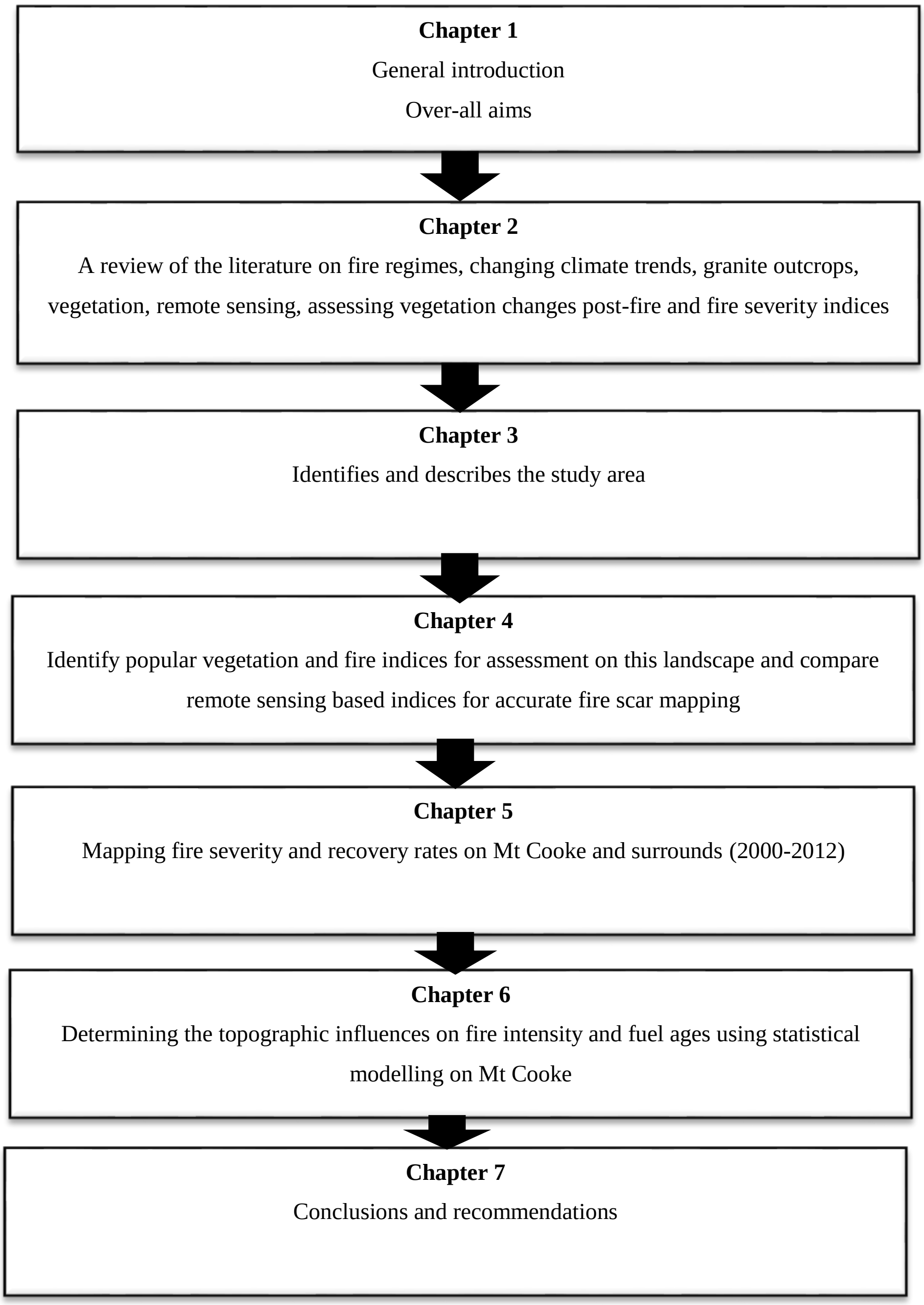

Figure 1.1 Schematic overview of chapter structure of the thesis

Chapter 2: Literature Review

2.1 Introduction

Over time, fire has been an integral part of the environment in Western Australia. There have been indications of fire that have dated back as far as 50ka BP (50 kilo-annum (thousand years) before present) (Dodson and Lu 2000; Turney *et al*. 2001). This suggests that fire has been of great significance in the evolution of the vegetation in this area. Fire has shaped vegetation and it impacts the growth, survival and regeneration of plants. The SWAFR has evolved around fire. Plants have adapted traits to aid in their survival and in an ongoing cycle fire has the ability to kill mature plants but at the same time fire stimulates rapid regeneration (Whelan *et al*. 2002; Bradstock *et al*. 2002; Burrows and Wardell-Johnson 2003).

Fire and fire regimes influence plant communities, both in their structure and their composition (O'Donnell *et al*. 2011; Wardell-Johnson *et al*. 1997). Fire may contribute to the rarity of species, as may environmental and geographical factors, due to the loss of the preferred habitat (Yates 2003). Fire frequency – both high and low, will have ramifications for growth and the maturation cycles of the plants. A long absence of fire can affect a species succession as some require the effects of heat and smoke to release and germinate seed (Van Heurck and Abbott 2003). When fire intensity is high it kills not only the mature plants but may affect succession of species by sterilising the top 5 cm of soil in the seedbeds putting the seeders at higher risk than the resprouters of survival after fire (Keith 1996; Whelan *et al*. 2002).

Weather trend models for the south-western Western Australia theorise that it is likely the number of extreme fire danger days and the frequency in the occurrence of lightning may increase and these factors will promote a rise in fire frequency and intensity (Bradstock 2010). There has been a loss of habitats as land use impinges on specialised environments such as those on and around GOs and in the SWAFR there are areas with high species endemism that are becoming increasingly at risk of fire (Gill 1996; Hopper and Gioia 2004).

2.2 Fire and fire regimes

A "fire regime" is the occurrence of fires that occur in a given ecosystem over an extended period of time. The classification of fire regimes uses a combination of factors including frequency, intensity, size, pattern, season, and severity (Gill 1979). Fires can vary greatly in their severity and the specific effects of an individual fire will be influenced by the fire regime – the fire history of a given area (Taylor and Skinner 2003; Odion *et al*. 2004).

A managed fire regime is one in which fire intervals are based on the juvenile period of a species and aims at conservation of biodiversity while at the same time reducing the severity of wildfires. Prescribed burning is where fires are planned and lit in specific areas under desirable environmental conditions with a specific aim of reducing fuel loads. In a fire maintained ecosystem, the key elements for conserving biodiversity are: (a) seasonal diversity, interval and intensity, (b) patchiness and diversity of burnt patch scale; and (c) seasonal and fire interval limits determined from vital attributes of key fire response in plant species. In prescribed burning, the fuel loads are reduced and while this alone will not prevent wildfires, a reduction in fuel load and fuel age can reduce the intensity of a fire (Fernandez and Botelho 2003).

Terminology used to describe fires in the environment, (as determined by Agee 1993; Dickmann and Cleland 2002; Keeley 2009), use classifications such as:

Ground Fire: This is a fire that combusts the organic matter on the surface. These fires involve a large amount of smouldering combustion and not as much flame as in other classifications. Ground fire has the ability to kill the roots of the upper storey species due to the high temperatures the rooting zones are exposed to.

Surface Fire: The lower vegetation layer, that is mostly comprised of grasses and herbs, moss, lichens and low shrubbery is impacted in the surface fire – these are generally low to moderate in severity and do not impact greatly on the upper storey vegetation.

Understory or Sub-canopy Fire: This category of fire will burn tall shrubs and trees under the main canopy - 80% or more of the dominant vegetation is able to survive the fire as there is little change to the structure of the ecosystem. Depending on the bushland structure, it may also be classed as a Surface Fire.

Crown Fire: Where the upper trees and shrub canopy are burned – generally this is associated with understory fire. A crown fire may or may not be lethal to the dominant vegetation, such as regeneration from sprouting roots, root crowns or stem bases after the tops of the plants have been killed. A crown fire may cover a large area completely, or occur in patches with in areas of a less severe burn.

Stand Replacement Fire: This is where the fire has been severe enough to kill most of the dominant above ground vegetation and has substantially changed the structure of the vegetation. Stand replacement fires may occur in forests, shrublands and grasslands and will involve crown fires or high-severity surface fires or ground fires. In this category, ~80% of the main species type is killed by the fire leaving any remaining above ground vegetation altered.

Mixed-severity Fire: A combination of the above with the variations occurring in space or time. Individual fires vary over time between low intensity surface burns and longer interval stand replacement fires. On other occasions the severity may alter as a result of the landscape complexity or vegetation patterns. This will result in a mosaic of vegetation areas that range from young, older and multiple aged vegetative patches.

Historical data on a particular ecosystem’s fire regime is the key to understanding its resilience, or natural capacity, to recover from fire. Data on the time between fires provides information on how long it takes for a system to recover and it will also indicate how long it takes for fire sensitive species to repopulate a burned area.

In relation to fire behaviour, a greater frequency of high to extreme forest fire danger index (FFDI) days under the predicted warmer and dryer changes is likely to result in longer fire seasons. There may be a potentially elevated risk that fires that are brought under control through firefighting measures will “escape” and be able to propagate through the remaining sparser fuel loads. Added to this, an expected upward shift in average of FFDI and higher night time minima may also allow the fire to burn longer and also reignite under return to high FFDI conditions (Matthews 2009; Sharples *et al.* 2010).

2.2.1 Fire effects on soil

After a fire, there are extensive areas that remain bare on the surface – having no vegetative mantle at all. These areas are said to have a ‘biological soil crust’ or ‘BSC for short, sometimes referred to as ‘cryptogamic’, ‘microbiotic’, and ‘cryptobiotic’ (Waston *et al.*2008). This soil crust provides an insulating factor to the seed beds and while, in intense fires, the top five cm of the soil is left with no seeds having a potential of germination, below there is a wealth of prospects that, when supplemented by moisture and increased mineral wealth caused by the charring of plant material and the carbonisation of the rock itself, will soon support the new generation of plants that will establish themselves post-fire (Burrows & Wardell-Johnson 2003).Temperature readings taken during bushland fires both above ground and below ground are displayed in (Table 2.1).

Table 2.1. Physical changes in some soil properties as temperature increases (after Walker *et al.* 1986)

Temperature(c$^{\circ}$)	Property change
More than 120	Loss of calcium as gas
950	Clay mineral converted to different phases
600	Maximum loss of potassium and phosphorus
540	Little residual nitrogen or carbon
420	Water lost from clay minerals causing change in type
400	Organic matter carbonised

Initially, at the time of the first rains post-fire, there may now be a now highly efficient run-off surface at ground level, where sediment may be driven from the surface by:

- runoff from existing bedrock of the GOs;
- runoff from local areas of thin soil generated by erosion after the fire;
- water repellent soils that may have been generated by high fuel loads such as burning logs; and
- a lower infiltration capacity on post-burned soils which have lost organic matter layers including mosses, lichens and plant litter (Clark 2001).
- a lack of understory vegetation and the protective layer of plant litter contribute to a relatively open landscape where surface water is less effective (Cerdà and Robichaud 2009).

Generally though, the majority of fires do not produce enough heat in the soil to produce any significant alteration to soil properties (Hungerford *et al.* 1991). However, even the smallest changes can impact on an inter-related soil system. Wells *et al.* (1979) implied the scope of the changes on the physical properties within the soil depends mainly on the fire severity, the relative proportions of destruction to the overstorey and understorey, the surface temperatures at the time of the fire and the length of the fire intervals. The main impact involves the amount of organic matter which remains after the fire, which is essential for the maintenance of the structure of the soil (DeBano *et al*. 1998). This is of high importance on GOs where the soils are poor and thin.

In their research, Raison and Walker (1986) determined that the most significant changes occurred when the temperature reached 400°C as depicted in (Table 2.2).

Table 2.2. Soil temperature measured during fires (after Ubeda 1998; actualised by Mataix-Solera 2001).

Vegetation	Depth (cm)	Temperature	Author (Year)
Scrubland	Surface	538	
	3.8	149	Sampson (1944)
Scrubland	Surface	590	
	1	399	Bentley & Fenner (1958)
Eucalyptus	Surface	900	
	5	100	Humphreys Lambert (1965)
Shrubs	Surface	200-400	
	-	-	Smith & Sparling (1966)
Dense forest	2.5	250	
	7.5	105	Beadle (1940)
Various kinds of black ashes	Surface	250	
	2	100	Wells (1979)

2.3 Changing Climate Trends

Wildfire is a global issue and the trends in climate change and how it affects weather, fuel loads, ignition agents and people – will continue to have significant impact on our environment (Flannigan *et al.* 2009). The changing trends of warmer temperatures and a falling rainfall with greater periods that remain dry all combine to increase the risk of fire. Hennessy *et al*. (2007) suggests that the occurrence of high fire danger days will rise markedly over the next century. These changes are expected to increase the size of fire affected areas and an increase in the fire frequency. There may be some regions which will remain relatively unchanged and maybe even with a lesser degree of fire damage, but the length of the fire seasons is expected to increase in temperate and boreal zones. Fire behaviour such as intensity and severity changes are difficult to predict however. Flannigan *et al.* (2009) also agrees that there will be a global rise in fire activity due to the altered climate trends.

These suggested trends in climate change and increasing fire events will impact on fire management planning for controlled burns and the time in which these can be done – in the cooler months – will be relatively shorter. The increasing time spans of warmer weather with little or no rain will affect the ground litter and soil moisture content which can also potentiate the rise in fire severity. As reported in the Steffen *et al*. (2013) Climate Commission as published in “The Critical Decade: Extreme Weather 2013”, it states that climate change is already increasing the intensity and frequency of many extreme weather events. While historical records show that extreme weather events occur naturally, there are new peak highs and lows occurring worldwide. It goes on to say that records of extreme hot days are now happening three times more often than cold events. Over the past 30 years the extreme fire events have increased over much of Australia (Dunlop and Brown 2008).

The SWWA has experienced a 15% drop in rainfall since the 1970s (Indian Ocean Climate Initiative (IOCI), 2012; Water Corporation report 2012. The reduced rainfall pattern means less inflow into Perth dams – the example stated is that "from 1911 to 1974 the average stream flow into the dams was 338 gigalitres (GL) per year; from 1975 to 2000 flows almost halved to 177 GL per year" (Water Corporation report 2012). Inflows more than halved again from 2006 to 2012 to approximately 66 GL per year (Water Corporation report 2012).

The trend towards more drying weather in the SWWA is supported by considerable evidence (Commonwealth Scientific and Industrial Research Organisation (CSIRO) and Bureau of Meteorology (BoM) 2012). The main reason is a move to the south of the winter rain bearing winds coming up from the southern ocean and much of the precipitation is missing the south-west corner. It has been suggested by model-based predictions from the CSIRO and BoM 2007 that the drying trend will continue to intensify with further decreases of up to 10% by 2030 and possibly up to 50% by 2050 (CSIRO and BoM 2007). If this rainfall pattern continues, the South West corner of WA will potentially experience 80% more drought-months by 2070 (Mpelasoka *et al*. 2008). This may increase the opportunity fire has to impact the floristic composition in the landscapes. This area experiences strong afternoon sea breezes, due to deep troughs inland. This can often impact fire behaviour with quick changes of wind strength and direction. The lightning strikes, which are one of the main causes of fire ignition, are moving in from the Indian Ocean from tropical cyclones which originate out to sea (McCaw and Handstrum 2003).

A report by CSIRO (2007) suggested a gradient increase in the mean summer temperatures in South Eastern Australia that may raise the occurrence of very high to extreme fire danger days. They may increase by 4-25% by 2020 and by 15-70% by 2050 (if model predictions are correct) (Hennessy *et al*. 2007). The regions most likely to be affected will be inland and when the usual prescribed burning takes place in spring and autumn, the number of days with ideal conditions to carry out a controlled burn will drop (Hennessy *et al*. 2007).

Habitats such as the riparian zones and wetlands in the SWWA may become increasingly more at risk due to the warming dryer climate. The area, already recognised as one of Australia's 15 hotspots for plant biodiversity, supports a high percentage of plant species that, by the way of reproduction, are at a higher risk of the effects of increasing fire frequency (Steffan *et al.* 2009; Mittermeier *et al.* 2004). Within the SWWA there are greater than 7400 named plant taxa and an estimated 6500 species of vascular flora, of which more than 50% occur nowhere else in the world (Hopper and Gioia 2004).

The changes in the local climate may also impact on a range of perennial plants by slowing growth rates making the time to maturation longer. Decreasing fire intervals will impact this cycle with the predicted long term effect of gradually decreasing populations in resprouter species (Williams *et al.* 2008).

It has been observed by Yates *et al*. (2003) that in south-west ecosystems many rare plants persist only in habitats where fire is infrequent. Hearne *et al*. (2003) reported that "within the south-west forest region, threatened plant species mostly occurred in less flammable niches within the forest landscapes including areas where fuels are sparse or discontinuous – such as on and around GOs, inundated swamps, swamp margins, riparian zones and creek lines". This phenomenon is not well understood, but Burrows *et al.* (2008) showed a firm relationship between the incidence of fire sensitive plants with long juvenile periods and habitat flammability, as estimated by seasonal moisture regime and fuel structure.

In 2015, the SWWA saw a fire that burned for nearly two weeks and burned through 98,000 hectares of bushland. The fire was started by lightning during a dry thunderstorm on a day with strong winds which occurred after a period of hot dry days (DFES 2015). The fire at Mt Cooke in 2003 in this study was also started by lightning after a run of hot dry weather with gusty winds. This weather pattern is common in MTEs and combined with natural highly flammable fuels fire is of great concern for land management and also in relation to the protection of biodiversity.

2.4 The possible role of granite outcrops in the protection of plant species

Granite outcrops are a feature of the SWWA forest region. They make up only approximately 10% of the surface area (Withers 2000; Burrows 2013). In Western Australia the formation of the expansive granite outcrops are not from a uniform age but were actually formed over a period of 2500 million years ago – to more recently, less than 1000 years ago (Myers 1997).

The outcrops often appear as stark islands rising up from the surrounding landscape and the plants found on some of them can reflect "relictual isolation", (Mares 1997), that is referring to a topographic feature that remains after other parts of the feature or structure have been removed or taken away by the passing of time and effects of erosion, or persistent isolated remnants of a once-abundant species (McCaw and Hanstrum 2003).

Features that are common to the outcrops can provide shelter for plants and sources of water (gnammas) that may be permanent or seasonal. Particular habitats can be formed within the rock itself such as depressions, cracks and crevices, flakes and spalls and boulder and block fields (Porembski *et al*. 1997; Byrne & Hopper, 2008).

Understanding and conserving biodiversity may be one goal of scientific research studies. Moreover, these investigations have been based on different biological and ecological scales, such as genes, species, communities, local ecosystems, and landscapes (Comer *et al*. 2003; Joshi *et al*. 2006). Granite outcrops can demonstrate a regional influence on plants, increasing the local species diversity (Mares 1997). There are some habitats on and around granite outcrops that may be moister and cooler than the surrounding environment and may be defined as refugia (Ashcroft 2010). "Refugia are habitats that components of biodiversity retreat to, persist in and can potentially expand from under changing environmental conditions" (Keppel *et al.* 2012).

Hopper *et al*. (1990, 1997) states "outcrops in the mesic south-western Australian forest region in particular display high levels of plant endemism (Hopper *et al.* 1997) and species assemblages that contrast strongly with the surrounding landscape as a result of the strong edaphic, micro-climatic and pyric gradients that exist across the boundaries. In addition to high endemism, a significant proportion (~12%), of all declared rare flora in the south-western region occurs on or around granite outcrops" (Hopper *et al*. 1990, 1997).

As well as providing climactic refugia, granite outcrops may also play a role as biodiversity hotspots. Biodiversity hotspots are regions with a high level of endemic species that are under threat from humans. There are three factors that determine a hotspot: species richness, unique species and the species that are at threat of extinction. These refugia may support localised populations of species that are absent or rare within the surrounding landscape and which could become increasingly isolated and at risk (Decker 2007).

The role that granite outcrops play in forming refugia has been noted in relation to life forms that were once more widespread but have, over the years, retreated to the outcrops in response to changes in the climate, fire regimes and competition from other organisms over the years. They, therefore, form a diverse collection of habitats that are only associated with granite outcrops (Pinder *et al*. 2000; Withers 2000).

All these habitats and the composition of species are likely to be influenced by variable factors such as water availability, soil depth and composition, elevation, gradient and aspect. Post-fire, areas capable of supporting vegetation present a vastly differing appearance. Immediately after the fire there will be areas devoid of above ground growth. The initial indications of regeneration come from the resprouting species while the re-seeders have to wait until there has been adequate moisture accumulation in the soil before their seeds begin to germinate. In the early years post-fire there is a surge in species richness (Posamentier *et al*. 1981; McFarland 1988; Watson and Wardell-Johnson 2004).

How fire interacts with the land is influenced by topography – slope and exposure, fuel loads – litter types: loose, compact or woody, soil depth, presence of rock blocks and large stones, weather conditions and vegetation types (Whelan *et al*. 2006; Schaffhauser *et al*. 2012). Fire moves faster and burns with more intensity as it moves up steep inclines – habitats on and around GO's that are on the fire front are often so badly affected by the heat that the seed banks are destroyed, especially in the shallow soil regions. The habitats on the leeward side are protected and those within valleys and niches will be more likely to protect the vegetation giving the re-seeders and resprouters a much better chance of survival (Watson *et al*. 2008).

Granite outcrops are frequently referred to as "fire refuges" because the landscape on and around the outcrops helps to form a natural firebreak – open and exposed rock sheets (Figure 2.1), boulder and rock fields and sparse vegetation makes the environment less likely to burn or sustain fire (Hopper 2000; Burrows, 2005). Within the forest regions of South-Western Australia, the outcrops are found mainly in a matrix of vegetation that is seasonally highly flammable and can cause a high severity of burn where the fire spreads quickly. The topographic variables will be introduced and discussed in Chapter 6.

Figure 2.1. Rock sheet with sparse vegetation, Monadnocks National Park 2013.

2.5 The Vegetation

The SWWA area is well known for its high plant species diversity and serinoty (Enright *et al.* 2007). Plants, generally, have many adaptive vegetative and reproductive traits that enable them to persist in fire-prone environments (Gill 1981). Two of the major adaptions are based on whether mature plants can endure complete leaf scorch and survive. Gill (1981) classified plants according to their ability to sprout after exposure to severe heat dividing plants into two groups: "sprouters" and "non-sprouters" (Table 2.3).

Fire behaviour on granite outcrops may impact differently on plant communities with seeder or resprouter characteristics which will affect species populations and dynamics over time. However, on a selection of outcrops, this has been attributed to factors other than fire regime, such as edaphic factors (Benwell 2007; Benwell and McCorkell 2011).

Changes in vegetation structure and composition of vegetation after a fire can affect light penetration, soil moisture, and soil nutrient levels. According to Whelan (1995), there are two factors that affect vegetation regeneration after a fire - the first being that a plant survives the direct effects of the fire during the fire but the surviving plants are no longer able to thrive in the altered environment caused by the fire. During the fire, the foliage is exposed to very high temperatures which will affect the nutrient composition and balance within the plant tissues and later, the effects of decomposition or metabolic alteration caused by being exposed to a period of high temperatures may cause dehydration and increase plant mortality (Whelan 1995). In the case where the exposure to the fire was short or of low intensity, this may only be a temporary change to the chemical balance which may be survivable (Whelan 1995).

In relation to the sprouter species, protection of the below-ground buds is a survival mechanism for above ground fires where the heat rises. These plants will survive even 100% leaf burn because of their ability to re-sprout from below ground buds or buds protected in the bark coverings of the plants (Gill 1981).

Table 2.3 A classification of plant species in relation to their response to fire (Burrows and Wardell-Johnson 2003).

Response Class	
Ephemerals	Life span 1-3 years post-fire- seeders.
Seeders	**Seeders** - reproductively mature plants that die following stem girdling or 100% leaf scorch.
	1 - Seed stored on plant (serotinous).
	2 - Seed stored in soil.
	3 - No seed stored in burnt area (depends on dispersal).
Sprouters	**Sprouters -** reproductively mature plants that survive stem girdling or 100% leaf scorch.
	A - Regenerative buds subterranean and present as:
	1 - Root suckers or horizontal rhizomes
	2 - Basal stem sprouts or vertical rhizomes
	B - Regenerative buds aerial and present as:
	1 - Epicormic buds grow out
	2- Undamaged active pre-fire buds (continued outgrowth of active aerial pre-fire buds)

2.5.1 Plant fire response.

Many researchers agree (Bell and Koch 1980; Gill *et al*. 1999; Burrows and Wardell-Johnson 2003; Gould *et al*. 2007) that the dynamics of vegetation regeneration post-fire tend to have similar patterns. Initially, in the first few years following the fire, plant species richness is greatest before stabilising or decreasing. The understorey vegetation increases in cover and height quickly after a fire due to more space and light, before stabilising for some time. This is then followed by a period of decline in the understorey plant life – some of the species are naturally short-lived and as the taller shrubs and trees re-establish themselves within the community, reducing the amount of light to the lower level growth.

According to Gill (1981) the majority of "fire tolerant" species regenerate from shoots post burn (Figure 2.2). Of these resprouters, some can regrow vegetatively after the fire, but there is a subgroup that needs to establish complete new plants to maintain population numbers as the adult plants age and die off (Sugihara *et al*. 2006; Keeley *et al.* 2011). These outcomes indicate that both strategies may be efficient for persistence in Mediterranean fire regimes and that having one of them may reduce the probability of acquiring the other (Pausas and Verdú 2005).

Non-sprouters, or "obligate seeders" are comprised of plants which are easily killed by fire and regenerate from seed banks in the soil or by seeds encased in woody fruits above ground in the plant canopy, (Figure 2.2). Obligate seeder species generally produce more seed (Keeley 1986), and greater numbers of seedlings (Benwell and Mccorkell 2011) than resprouters, and seedling growth rates tend to be faster (Benwell 1998; Atwell *et al*. 1999).

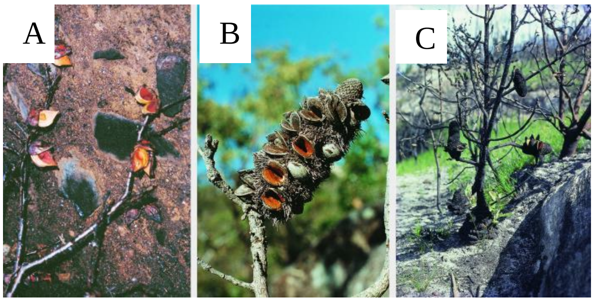

Figure 2.2. (A) and (B) Examples of woody canopy seed storage, (C) showing where intense fire killed the parent plant (after Atwell *et al*. 1999).

Fire intervals are recognized as one of the influencing factors on the persistence of many plant species (Bradstock *et al*. 1997). Fire sensitive species are those which are readily killed by fire even of a low intensity, have a long maturation stage and depend on seed stored on the plant to regenerate "serotinous seeders" (Gill and McCarthy 1998). These fire sensitive species are often associated with rock outcrops (Burrows *et al*. 2008). Interestingly, within the 'fire sensitive' species, many depend on fire at some stage of their life cycle to facilitate rejuvenation (Burrows and Wardell-Johnson, 2003).

Longer intervals between fires are a benefit to some species while others are disadvantaged by the same regime. Abbott and Burrows (2003) suggest an emergent theme of spatial heterogeneity, that is, a mosaic of areas of vegetation at differing post-fire stages which benefits biodiversity by providing diversity in structure and habitat across the landscape of seral stages. Fire can influence plant diversity in two ways. Firstly, species that are able to persist at a particular site are determined by the fire regime, for example – event interval and severity of the fire that will affect regenerative means (e.g. seeds, root suckers, rhizomes). The second factor is the frequency and intensity of fires at a site will influence the heterogeneity of the biodiversity of a region favouring a variety of fire response strategies and hence species.

Often a seeder and resprouter species of the same genus can co-occur an area in about the same proportions and this will provide useful comparisons of how closely related species with contrasting fire responses perform when sharing the same site, climate and exposure to fire. Moreover, since new plantlets to both these populations are probably going to germinate and establish prolifically in the season following a fire, comparisons can be made between them over a number of burn age sites (Atwell *et al*. 1999).

Previous studies that have examined the response of typical sclerophyll vegetation to fire regimes (Cary and Morrison 1995; Toser and Bradstock 2003; Keith *et al*. 2007) show that plants in a particular community and the abundance of the vegetation is sensitive to variations in the length of inter-fire interval. Such effects reflect the regenerative attributes of species and the demographic capacity to deal with the different fire regimes, as well as inter-specific competitive effects (e.g. Keith *et al*. 2007). Pausas *et al*. (2004) revealed that a minimum set of attributes based on the ability of the plant to re-sprout and persistent fire cued seedbanks was enough to account for the response of woody plant diversity to fire regimes. Four distinct types can be defined on this basis. In the (Table 2.4) these are represented as: resprouters with persistent seedbank (Hereafter R+P+), seeders with persistent seedbanks (R-P+); resprouters with transient seedbank (R+P-) and seeders with transient seedbanks (R-P-).

Table 2.4. The functional type scheme used to examine vegetation sensitivity to climate change and fire regimes (after Pausas *et al*. 2004).

Seed Bank Persistence (P)	Resprouting Ability (R)	
	Species that resprout after fire, either from basal or epicormic shoots (may sometimes be killed by fire).	Species that are usually killed by fire causing 100% crown scorch (may sometimes resprout, usually after low intensity fire or incomplete crown scorch).
Species with some carry-over of viable seeds from year to year, including those with a serortinous seed bank (canopy held, released by fire or by drying out) or persistent soil (physical or physiological dormancy broken by heat or other fire – related cue) seedbank.	$R^+ P^+$ Resprouters with persistent seedbank	R^- P+ Seeders with persistent seedbank
Species with short–lived seed usually released soon after maturity. Viable seed persists for no more than one year.	$R^+ P^-$ Resprouters with transient seedbank	$R^- P^-$ Seeders with transient seedbank

2.6 Remote sensing

Fire management teams are aware that satellite based methods for observing fire, fire severity and vegetation assessment is making the future for data collection quicker and easier. In particular, the use of these methods over difficult terrain and inaccessible areas is highly beneficial (Racine *et al*. 2006). With the use of data available from aerial and space imaging, general views of land features in images can be interpreted to understand and improve data records for points of specific interest, such as fire, topography and burn scars (Turner *et al*. 2003). By combining this information with multi spectrum imagery and time-series imagery it can be used in the mapping and monitoring of species distribution and changes within them as they recover from fire (Evans *et al*. 2009; Turner *et al*. 2003).

There have been problems identified with a poor relationship between field measurements and the operational algorithms over wetlands (Hoy *et al*. 2008) and tundra regions when it was tested using a single image for Differenced Normalised Burn Ratio (dNBR), (French *et al*. 2008). These studies encouraged others to develop an improved understanding for the deficiency of the differing spectral indices when compared to field data for fire severity measurements from satellite imagery (Ceccato *et al*. 2001; Henik 2012).

Remote sensing has now been used worldwide to assess burn scars with good results. For example, Koutsias *et al.* (1999) used this data to map fire scars at a local scale in Europe and Chuvieco (1999) applied several indices to measure change in vegetation mosaics following an extensive fire on the Mediterranean coast of Spain. Still others have used remote sensing in Siberia (Bourgeau-Chaves *et al*. 2002), Asia and Indonesia (Siegert and Ruecker 2000). A broad collection of remotely sensed data were used to map varying sizes of fire affected sites at regional scales (Röder *et al.* 2008), continental scales (Masek *et al.* 2008; Pu *et al*. 2007), and global scales (Chuvieco and Martin 1994; 2006; Roy *et al.* 2005). Active fires, fire scars and fire severity assessments have been done using Landsat (Duffy *et al*. 2007; Miller and Thode 2007) and MODIS (Justice *et al*. 2002).

2.6.1 Landsat

Of all the satellite missions, Landsat is the longest-lasting operational satellite mission with a resolution of 30 m. This satellite data has many applications for scientific studies, such as Thematic Mapper (TM) and Enhanced Thematic Mapper plus (ETM+) that were included on Landsat 5, 7 and more recently, 8 (Jensen 2000) (Table 2.5).

It is not a new idea to use remotely sensed data for post-fire assessment, and there have been several sensors assessed to perform the tasks but the most frequently used (as assessed by the review) is Landsat TM (Lentile *et al*. 2006). Fire severity has been assessed from spectral signatures after fire and the maps which delegate burn severities are able to supply vital data on the effects of fire. The Landsat TM and ETM^{+} have proved to be successful in establishing clear patterns of fire severity (Collins *et al*. 2007; Wimberly and Reilly 2007).

Where a single image taken a short time after the fire may be suitable to mapping burn scars, multi-date imagery is proving a better option as it combines data from both pre-fire and post-fire conditions of the vegetation (Wimberly and Reilly 2007). The index commonly chosen to be used with the imagery is the dNBR as it is suitable for a variety of vegetation types and geographical features (Cocke *et al*. 2005; Collins *et al.* 2008).

Table 2.5. Landsat TM and ETM+ band numbers and Corresponding Wavelength Sensitivities, Campbell 2002.

B.n	TM bands	Wavelength	ETM bands	Wavelength
1	Blue	0.45 - 0.52	Blue	0.45 - 0.51
2	Green	0.52 - 0.60	Green	0.52 - 0.60
3	Red	0.63 - 0.69	Red	0.63 - 0.69
4	Near Infrared- (NIR)	0.76 - 0.90	Near Infrared- (NIR)	0.75 - 0.90
5	Short Wave Infrared (SWIR)	1.55 - 1.75	Short Wave Infrared (SWIR)	1.55 - 1.75
6	Thermal Infrared	10.40 - 12.5	Thermal Infrared	10.40 - 12.5
7	Short Wave Infrared (SWIRII)	2.08 - 2.35	Short Wave Infrared II (SWIRII)	2.09 - 2.35

2.6.2 MODIS

The MODIS (Moderate Resolution Imaging Spectroradiometer) sensor and Landsat collect spectral information in similar portions of the electromagnetic spectrum. Where MODIS has the ability to record long-term fire effects and has a high temporal resolution covering the same spot every day, spatially, it has a resolution between 250 meters and 1km. Landsat TM and ETM$^+$, on the other hand, have a resolution of 30 metres and 15 metres for the banchromatic band (Loboda *et al*. 2007).

The main disadvantage of using MODIS imagery in reflectance classifications is in the coarse spatial resolution. The finest pixel size is 250 metres and it is often too coarse for fire analysis, (Clark *et al*. 2003). By comparison, the moderate spatial resolution of Landsat works well in the scale of variability in fire severity assessment. In one test, the lower spatial resolution of MODIS achieved an overall 15% underestimation of an area that was severely burned (Boelman *et al.* 2011). de Klerk *et al*. (2012) found that in some of the MODIS data used in the assessment of fire damage, there were common errors of omission when used on Mediterranean regions so that the areas of fire severity are not correctly identified.

2.6.3 Survey of indices used in fire scar mapping

There is a wide variety of vegetation indices used in the mapping of fire scars and fire severity. To choose the indices that would provide the most accurate data for this study area, a selection of publications were researched from 1990 and 2012, where vegetation indices were used, using the keywords “fire scar mapping”, “remote sensing and fire scar mapping” and “fire severity mapping”. (Only those publications using remote sensing were considered). All were using different resolution and satellite data.

The majority of these studies used Landsat TM / ETM$^+$ (50%) or MODIS (20%) (Figure 2.3). They were performed in many differing landscapes of varying vegetation cover including pine forest, Mediterranean forest and scrubland, steppe, shrublands, grasslands, woodlands, boreal forest and desert spring ecosystems. Most of the studies used Landsat-derived NBR, dNBR and Normalised Difference Vegetation Index (NDVI) to map fire scars and burn severity. From the researched materials, the six most frequently used vegetation indices used for mapping fire were selected for testing in this study. In approximately 90% of these studies, the common bands used were bands Red, NIR, SWIR and SWIRII. The remaining 10% used the Green and the Thermal Infrared bands but as these were in the minority, these bands were not tested for this thesis.

NBR was initially derived by Garcia and Caselles (1991), but in the studies from 1991 to 2000, less than 10% used NBR for fire scar mapping. It was not used for assessing fire severity. From 2003, there has been an increasing interest in its use due to the relationship with dNBR which has offered reliable pre and post-fire image comparisons. There is a standard field measure for burn severity called the Composite Burn Index (CBI) conceived by Key and Benson (2004) which features in research papers, but as it relies on field data it was not a suitable index for testing based on the fact that the fire in this study area occurred in 2003 and no field data was collected at that time. Most studies looking at fire severity around this time noted the link between remotely sensed data, and field sourced data. Of the studies mapping fire severity and fire scars, 89% were using NBR and dNBR as the primary Vegetation Index (VI). Miller and Thode (2007) developed the Relative Differenced Normalised Burn Ratio (RdNBR) for mapping fire severity with comparable results to field collected data and it was used in 70% of the studies.

The Normalised Differenced Vegetation Index (NDVI) is one of the older indices, and has been the commonly used index from the 1970s –for mapping vegetation. Studies have subsequently also included fire assessment. In the past decade 53% of the studies researched used NDVI and difference between the pre and post-fire (dNDVI) as a secondary VI for fire scar mapping and fire severity. Most studies have reported substantial soil noise, which negatively impacted the results (Rouse *et al*. 1974).

Soil Adjusted Vegetation Index (SAVI) was developed by Huete (1988), and is used in the mapping of vegetation. Results are reported to be similar to NDVI, and it has a soil noise reduction factor. It can be used over a variety of vegetation cover and is used for mapping fire as well. From 2003, 35% of the studies used SAVI and Modified Soil Adjusted Vegetation Index (MSAVI2) for fire mapping, fire severity and vegetation assessment. Enhanced Vegetation Index (EVI) was used in 8% of the studies on vegetation stress more than for fire severity and burn scars (Figure 2.3).

Normalised Differenced Infrared Index (NDII) is used widely to remotely sense the alteration in the amount of the green biomass (the chlorophyll content and leaf water content) for foliage and canopies, and can be used in the assessment of vegetation stress (Jackson *et al*. 2004). It has been used in 7% of the studies researched for this paper.

The main method for mapping vast remote fires, according to Key and Benson (2006), is the dNBR – this used the temporal difference across the pre-fire and post-fire NBR and requires the two images. This index provides the separation of vegetation that has been burned from that which remains unburned, and from this the RdNBR, (a variant of dNBR), was created to give improved results in more open types of vegetation (Miller and Thode 2007). These results explain why the dNBR has become widely preferred in mapping of fire severity and fire scars.

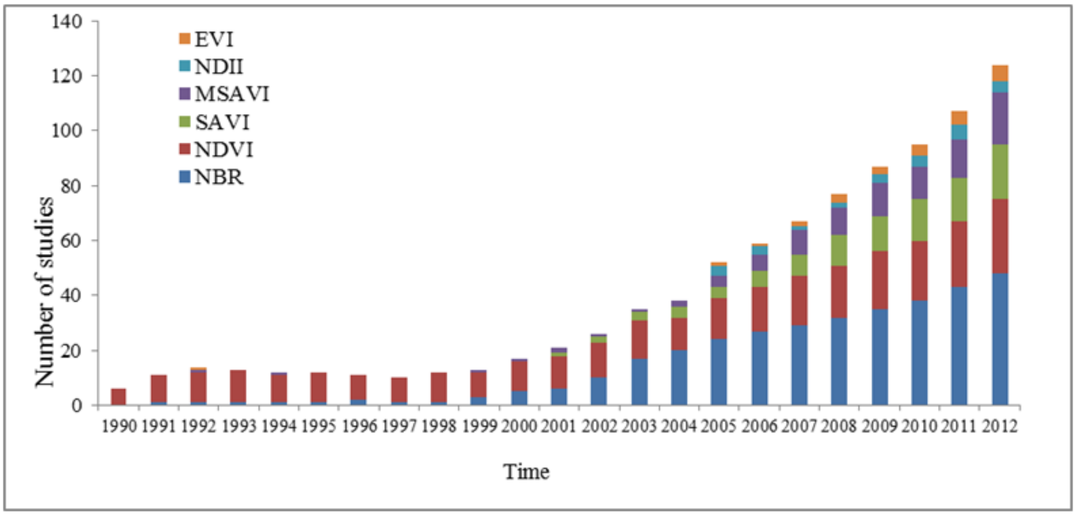

Figure 2.3. Number of publications between 1990 and 2012 referring to "Remote Sensing" and using the key words "fire scar mapping" and "fire severity mapping" that were accessed for this study. Only publications in the Remote Sensing field were researched.

From these results, the four most commonly used vegetation indices and two of the less commonly used (derived from Landsat ETM+ imagery from a single image) have been selected to choose the optimal index for mapping fire severity over the GO ecosystem. These chosen indices are displayed in Table 2.6 with their associated equations. Fire scar maps will be produced for post-fire vegetation assessment using the chosen VIs and it is expected that variations will be evident between the chosen indices. The anticipated outcome is that the data from bands NIR and SWIRII are more likely to give accurate results for mapping fire scars. This is because in band NIR the reflectance decreases after fire due to severe water stress in the plant tissues and the non-vegetative traits that develop as a result of the burning and in band SWIRII; reflectance will increase as a result of the fire. This is linked with the increase in the exposed substrates and charred remains of the fuel loads which band SWIRII registers positively (Key and Benson 2006).

Table 2.6. The four common indices and two less commonly used indices (*) that are tested in this study

Spectral Index	Method of calculation	References
NDVI	(NIR - RED) / (NIR + RED)	Tucker (1979)
SAVI	NIR - RED / NIR + RED + L]* (1 + L)where L = soil adjustment factor 0.5	Huete (1988)
MSAVI 2	(2 * NIR + 1 – sqrt ((2 * NIR + 1) ^{2} - 8 * (NIR - RED) /2)	Qi *et al*.(1994)
*EVI	2.5 * (NIR - RED) / ((NIR + 6*RED - 7.5*BLUE) + 1)	Huete *et al*. (1999)
NBR	(NIR - SWIRII) / (NIR + SWIRII)	García & Caselles(1991)
* NDII	(NIR - SWIRI) / (NIR + SWIRI)	Hardisky *et al*. (1983)

2.6.4 Remote Sensing Assessment of Fire Severity

The skills for the interpretation of imaging are described by many authors (Siegal and Gillespie 1980). The actual interpretation of the images for any particular purpose is dependent on basic characteristics that are identified within the images. These characteristics include grey scale and colour tone, texture, shapes and patterns, landforms, scale and context (Drury 1993). The grey scale and colour tones and the texture within the processed images are all formatted on the spectral reflectance of the surface materials. Their display within the image may be enhanced by the image processing (Lei 1999). It is the interpretation of the images sourced from USGS (US Geological Survey) that form the spectral data for this study.

The remoteness of the locations of fires and the large amount of surface area with varying topography can make fire damage difficult to assess. Data from satellites has provided a good source for these extreme measurements and provides regular updates of the affected areas and this has greatly increased knowledge and the ability to map and assess ecosystems impacted by fire regimes in the landscape (Sukhinin *et al*. 2004; Lentile *et al*. 2006). Methods of mapping burned areas and fire severity have improved over recent years – many of these applications use spectral band ratios and have developed a variety of indices to measure vegetation pre and post-fire and assess soil and vegetation moisture content and are used to quantify fire severity (Lentile *et al*. 2006).

Plant damage and destruction such as charring can be varied across an area of burned landscape. The resulting damage, such as white ash, bare soils and changes in the plant foliage from moist greens to dry browns are evident. The actual structure and composition of the soils can be altered. Spectral results within the imagery are caused by the colour changes of the vegetation, altered soil reflection and changes in the landscape itself such as from fallen trees (Smith *et al*. 2005; Key and Benson, 2006). The techniques to assess these changes remotely have a variety of complexities but all aim to analyse the differences in surface characteristics (Cocke *et al*. 2005; Miller and Thode 2007).

The majority of Landsat mapping research that assesses fire damage and restoration is based on recorded changes in spectral reflectance (Coppin and Bauer 1996). The effects of the fire change the spectral recordings from the vegetation in the area and therefore the complete “signature” of the landscape. This makes remote sensing a valuable tool in the assessment of areas pre and post-fire in relation to recording post-fire regeneration and thus in the prediction of expected outcomes in areas as yet unaffected by fire and those that have remained unburned for long periods.

Remote sensing data can be used to assess forest fuels (Andersen *et al*. 2005); for fire monitoring (Dennison *et al*. 2006), to map the fire scars (Koutsias and Karteris 2000) on a local or global scale (Stroppiana *et al*. 2000) and to assess the effects of the fires (Díaz-Delgado *et al*. 2002). There are still some points of confusion however, when dealing with data on vegetation and its characteristics when choosing the most suitable index to be used.

There are numerous indices, some of them have been widely applied for different purposes and study sites. In the NDVI, (Rouse *et al*. 1973; White *et al*. 1996) green vegetation is separated from other surfaces because the chlorophyll of green vegetation absorbs red light for photosynthesis and reflects near-infrared (NIR) wavelengths due to scattering caused by internal leaf structure (Tucker 1979). More recently, the NBR (van Wagtendonk *et al*. 2004; Smith *et al*. 2005; Cocke *et al*. 2005; Roy *et al*. 2006) is widely used for fire mapping. These indices add vital information in the assessment phase encompassing vegetation features such as health, density and cover and mapping fire severity (Garcia-Haro 2001; Isaev *et al*. 2002).

2.6.5 Spectral Indices

The spectral response is altered when there is a fire – the density of the vegetation is altered, as is the greenness and the amount of water held within the plants. The leaf litter on the ground is removed either in part or totally depending on the severity of the fire. This in turn exposes and changes the appearance of the soil (Chuvieco *et al.* 2006; Lentile *et al.* 2006; Robichaud *et al.* 2007). These alterations in the surface appearance are often easily detected as a drop in the spectral reflectance in the visible near-infrared and shows as an increase in the mid-infrared wavelengths (Epting *et al.* 2005; Lentile *et al.* 2006; Lopez Garcia and Caselles 1991; van Wagtendonk *et al.* 2004).

Of the indices that are now used for mapping fire damage, many were initially used in mapping other types of land disturbances. However, some indices unique to fire monitoring have now been developed – those of particular interest are the differences in the NIR band and SWIR band areas of the spectrum as they are related to vegetation structure and moisture levels in the soils (Trigg and Flasse 2001; Key and Benson, 2006). When using imagery from Landsat TM and ETM+, spectral indices include ratios such as band SWIR divided by band SWIRII, band NIR divided by band SWIRII and band NIR divided by band SWIR. Data on the intensity of the fire was successfully differentiated by Jakubauska *et al.* (1990) using the band SWIRII / SWIR ratio and Epting *et al.* (2005) found band SWIRII / SWIR gave the best correlation. Kushla and Ripple, (1998) preferred band NIR / SWIR as it was highly interpretive of burn canopy cover. Clark (2000), found band SWIRII / NIR to accurately represent field burn severity estimates.

Within the electro-magnetic spectrum, the areas of interest are recordings within the red (0.63 – 0.69 μm) and on through the short wave infrared SWIR 2.08 to 2.35 μm (assessing structure, biomass or moisture content), as these readings indicate foliage that has been impacted by fire (Figure 2.4). This particular range is indicative of vegetation structure and moisture levels which are both signals for fire damage (van Wangtendonk *et al*. 2004; Miller and Thode 2007). There is a direct interrelationship between the reduction in the near infrared wavelength reflectance and the intensity of the fire (Jakubauska *et al*. 1990). This reduction in the reflectance is due to the damage, or total destruction of the leaf surface tissues.

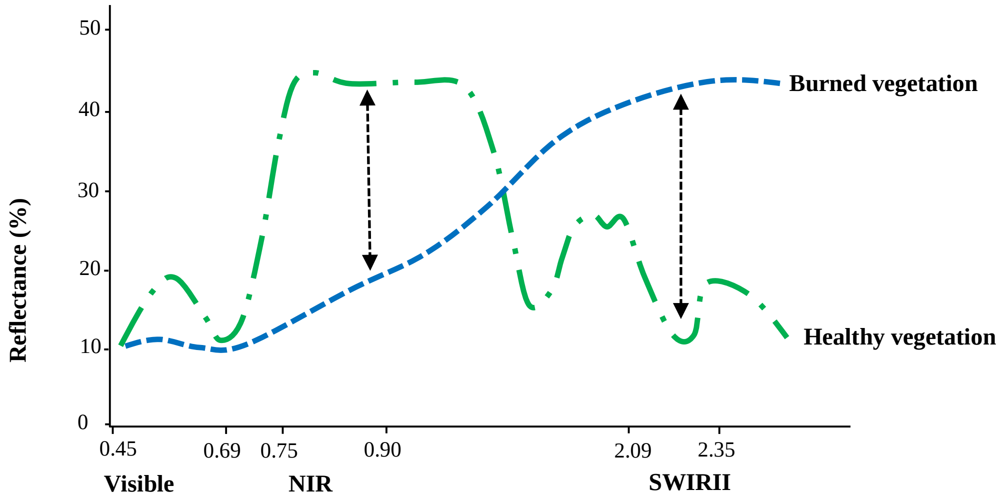

Figure 2.4. Exploiting spectral response curve for healthy and burned vegetation (After Remote Sensing Applications Centre (RSAC), http://www.fs.fed.us/eng/rsac/baer/barc.html)

On the other hand, within Landsat TM7, the spectrum usually rises due to the drop in moisture levels at the site but the readings are affected by plant shadowing (Epting *et al*. 2005; Key and Benson 2006). Because of the impact the shadowing can have on the results, both bands have been used for inclusion in this particular study.

In using Landsat TM and Enhanced Thermatic Mapper (ETM) with band NIR and band SWIRII a significant change in pre-fire and post-fire responses is evident. After a fire the band NIR reflectance decreases, while the band SWIRII wavelengths increase after a fire when compared to readings taken before a fire in the same region (Key and Benson 2006). Decreased moisture levels will also be indicated within Landsat Band SWIR (1.55 - 1.75 µm) as it is also a short wave infrared band. Band SWIR is used in differing band ratios, such as band NIR/ SWIR ratio, band SWIRII / NIR and band SWIRII / SWIR. Blue band (0.45 - 0.52 µm) and Green band (TM: 0.52 - 0.60 µm. ETM^{+}: 0.53 - 0.61 µm) have not been used in this study as there is usually only slight alterations in these spectral wavelengths between pre and post fire images (Miller and Thode 2007). Thermal Infrared band (10.4 - 12.5 µm), due to its lower spatial resolution, has also been ignored. Other research has found measures of Thermal Infrared band which show a fire response in forested ecosystems after fire (Epting *et al*. 2005) but the landscape of the study area was not suited to the use of this.

The preference in using the near infrared bands of Landsat and the short wave infrared Landsat SWIRII band in this study when mapping the damage caused by the fires is because they are paradoxical – highlighting the fire severity in the opposites of reflectance and absorption. De-Santis and Chuvieco (2007) found that the near infrared is more effective in mapping fire severity than short wave infrared band.

Unrelated factors that could impact negatively on the index values that were not always considered in the past have, over time, been included in studies where spectral indices for vegetation mapping are used (Verstraete *et al.* 1996). An example of this is where the NDVI is affected by soil brightness and attempts have been made to reduce the influence (Huete 1988; Qi *et al.* 1994). SAVI is just such an attempt – an experiment was made by Huete in 1988 to compensate for the differences in light and dark coloured soils. When used effectively, this index was designed to have differing soil types provide the same index values through the application of a constant to the red NIR index that was being utilised.

2.6.6 Assessing vegetation changes post-fire

There are many methods that can be applied in the remote sensing of post-fire vegetation recovery. Initially, some of these methods were not intended for use in fire assessment but the methods can be altered for vegetation recovery studies. Image classification is one of the more vital traditional methods applying Vegetation Indices (VIs) (White *et al*. 1996; Patterson and Yool 1998; Isaev *et al*. 2002; Landmann 2003).

Within this research, the Normalised Difference Vegetation Index (NDVI), the soil adjusted vegetation index (SAVI), the Modified Soil Adjusted Vegetation Index (MSAVI2), the Normalised Burn Ratio (NBR), the Differenced Normalised Burn Ratio (dNBR) and Enhanced Vegetation Index (EVI) and Normalised Differenced Infrared Index (NDII) are investigated in respect to alteration of vegetation due to fire (Bobbe *et al*. 2001; Epting and Verbyla 2005; Flasse *et al*. 2004; Miller and Thode 2007; van Wagtendonk *et al.* 2004). The green vegetation is either altered or consumed at differing levels of fire intensity. Fire severity is a measurement of the relative changes brought about by fire. The results in change detection are more accurately assessed using the greatest positive or negative spectral response (van Wagtendonk *et al.* 2004).

The NDVI is the most common ratio used for vegetation studies. It responds to change in the amount of green biomass and chlorophyll content in the vegetation (Eiden *et al.* 1991; Eiden 2000; Jensen 2000). It uses red and near infrared (NIR) segments of the electromagnetic spectrum to exploit the receptiveness of photosynthetically active green vegetation. Reflection in the red and NIR wavelengths are used to calculate the NDVI. The red band records the absorption of chlorophyll, whereas lower values indicate increased chlorophyll content (Sabins 1996).

The NDVI for Landsat TM/ETM$^+$ is calculated using reflectance of Red band (B3) and band 4 in the NIR wavelength (B4). Landsat TM/ETM+ provide index information in spatial resolution of 30 m. Results are unitless and can theoretically vary in the range between –1.0 and 1.0. With increasing vegetation density and thus photosynthetic activity, NDVI values are increasing. Thus, high values are expected to characterise healthy unburned vegetation. Decreased values correlate to lower vegetation density and conversely highly reduced photosynthetic activity. This data is then investigated in respect to changes of vegetation due to fire or similar stress exposure.

The NDVI, while widely used is not approved by all people in the literature review – for example, Pereira (1999) believes it is not the best option for mapping of fire scars in Mediterranean type areas where there may be more bare soil. In the detection of fire severity, the conventional approach is by assessing post-fire images using a Multispectral Scanner (MSS), TM and ETM for vegetation regeneration with the use of NDVI values (Diaz-Delgado *et al.* 2003). The NDVI is more receptive to the vegetation photosynthesis and live biomass than is the NBR and focuses better on vegetation change (White *et al*. 1996). Chafer (2008) preferred dNBR to NDVI for differentiation between the fire severity classes in a study on eucalyptus dry sclerophyll forest, and Escuin *et al*. (2008) was able to replicate similar results in Spain in a study on eucalypt and pine plantations.

When vegetation cover is low – less than 40% exposing the soil surface the amount of reflectance of light from the red to near-red infrared spectrum can impact the vegetation index values. This can be particularly difficult when comparisons are to be made across a range of soil types that may have variable reflectance in the red to near red infrared wavelengths. The Soil Adjusted Vegetation Index (SAVI) evolved as a modification to the NDVI to correct results for the influence of the soil brightness (Huete 1988). There have been mixed results found by researches when using SAVI: In 2008, Boer *et al.* used NBR when assessing vegetation change in Australian Jarrah forests and found this gave the better result than NDVI as the NDVI was more susceptible to seasonal changes. Barati *et al.* (2011) tested 20 spectral indices in areas with sparse vegetation cover and found the results from the SAVI were slightly improved over the others. However, Yang *et al*. (2012) also tested SAVI over sparsely vegetated areas and found that NDVI outperformed SAVI.

MSAVI2 was adapted from SAVI to provide an improved assessment for a variety of soil structures and moisture content (Qi *et al*. 1994). Where SAVI required information of the vegetative cover type and density to develop the correction, MSAVI2 is able to give an optimal performance by self-adjusting the index which allows a broad range for the readings with little interference from the differing soil types (Qi *et al*. 1994). SAVI has been shown to be very sensitive in identifying the amount of vegetation cover especially in very low density areas (Mazuelas Benito and Fernández Torralbo 2012).

EVI was specifically expanded on to improve the sensitivity in areas with high biomass while muting the effects of soil and atmospheric noise (Huete *et al.* 2002). Jiang *et al*. (2008) added to this with two-band EVI to keep the characteristics of EVI without relying on the blue band giving it a wide application (not all satellites sensors have a band in the blue wavelengths).

The Normalised Differenced Infrared Index NDII uses both NIR and SWIR, and it is able to be used by a wider selection of sensors. In other studies, NDII was referred to as the Normalized Difference Moisture Index (NDMI) (Wilson and Sader 2002; Noone *et al*. 2012) and Carreiras *et al*. (2006) referred to it as V17. Veraverbeke *et al*. (2010) found the Differenced (NDMI), (the difference between the pre and post-fire) provided a better outcome than the dNDVI (difference between the pre and post-fire) when assessing fire severity in Greece. When NDII is calculated using TM SWIRII band it uses the same bands as Landsat TM as the NBR when it uses Landsat TM (Lentile *et al*. 2006; Escuin *et al*. 2008) and it was thought to be more sensitive in the mapping of fire scars.

Most studies in Australia use NBR or NDMI in assessment of vegetation change after fire. Australian research has reported that the dNDVI (difference between the pre and post-fire) is highly regarded when mapping fire change on vegetation (Jacobson 2010; Chen *et al.* 2011). Other uses for NDVI include the prediction of fuel loads (Chafer *et al*. 2004). Cash (2012) suggested that more research needed to be directed at the capacity of indices to specifically predict fuel loads in Australian bush. Jacobson (2010) applied both NDVI and NDMI to detect change in vegetation regrowth recovery for the first year after fire and was satisfied that both provided similar results across the seasons. The NDMI outperformed post fire but the variations between these indices relied on the combination of forest layers. NDMI had a greater potential when assessing live fuel loads over the NDVI when he included the under storey layers in his modelling (Jacobson 2010).

2.6.7 Fire severity indices

There have been many remote sensing techniques developed in recent times (since the 1980s) that aim at measuring how much damage is caused to vegetation in a fire at both a local and at a regional level. In other research, scientists have been investigating a more ecological response to the physical changes on the land surface (Jakubauskas *et al*. 1990; White *et al*. 1996).

The use of remote sensing for burned area analysis has increased recently employing a variety of techniques, with a range of resolutions and different sensors (Garcia and Chuvieco 2004). There has been several studies undertaken in forested ecosystems to measure the burn severity within a set area (White *et al*. 1996; van Wagtendonk *et al*. 2004; Epting *et al*. 2005), however, only a minority have been completed focusing specifically on areas with reduced vegetation cover (Smith *et al*. 2005; Roy *et al*. 2006).

Studies that have been made previously have revealed good correlation between the data collected from field work when compared to that of the satellite imagery dNBR results (van Wagtendonk *et al.* 2004; Epting *et al*. 2005). According to results from studies performed by Key and Benson (2006), the dNBR performed better than the dNDVI and other research had similar results (Lentile *et al*. 2006; van Wagtendonk *et al.* 2004).

The normalised burn ratio (NBR) can be defined as a band ratio that was developed in the 1990s (Lopez Garcia and Caselles 1991) and later it was modified and named by Key *et al*. (2002); Brewer *et al.* (2005). It uses near and short wave infrared (NIR and SWIRII) sections of the electromagnetic spectrum to exploit sensitivities of photosynthetically active green vegetation. The NIR band detects high values of reflectance, when vegetation is dense and grows vigorously and thus many leaves reflect NIR wavelengths due to their internal structure (Sabins 1996). The NBR combines the reflectance in the near infra-red and mid infra-red bands.

Further studies done by a range of researchers on fire severity supported the idea that the NBR results that were assessed from satellite imagery worked well across a variety of vegetation types (Rogan and Yool, 2001; Epting *et al*. 2005). Epting *et al*. (2005) in their study on forest and shrubland in Alaska also found that of the 13 spectral indices they assessed, the NBR was a suitable choice. Roy *et al.*

(2006) was critical of the results from NBR, arguing that it was possibly not ideal for assessing fire severity, as it was originally intended to determine burned versus unburned areas. Deficiencies of the dNBR and the Composite Burn Index (CBI) are focused on the fact the results may be affected by user subjectivity when stratified in to the fire severity classes (Lentile *et al*. 2006).

2.6.8 NBR Responses

The burn characteristics and how they relate to the NBR provide the key to understanding the responses of Landsat TM /ETM^{+}. Within the NBR, band NIR amalgamates reflectance (0.76-0.9µm), which reacts positively to the vegetation leaf area and plant activity, and band SWIRII (2.08-2.35 µm) that will react positively to drying vegetation and some non-vegetation area characteristics. Band SWIRII has a minimal reflectance (i.e. it is absorbed) over the green and moist areas, even including areas of soil that are wet or snow covered – this is the opposite of the NIR band readings. As the NBR measures the difference of NIR minus SWIRII it gives a positive value when NIR is greater than SWIRII. This is the common response over most areas where the vegetation is growing normally. When readings from clouds and rock surfaces, bare dry soil or dead vegetation are assessed the readings are near zero – NIR and SWIRII are roughly equal. Readings from areas that have recently been burned will typically display near zero to a strongly negative NBR (Key and Benson 2006).

In a display of a Landsat image of the study area in the bands SWIRII, NIR, Green (RGB) combination, the burned areas appear as bright red or a deeper crimson colour which is distinctly different from the surrounding areas of green or pink which represents the unburned areas. The burned areas can demonstrate a higher return in the SWIRII band from Landsat as a result of reduced canopy moisture content and thus a decrease in the absorption of the wavelength. The burned areas are often low in band NIR reflectance as a result of the overall loss of vegetation (Lutes *et al*. 2006). When Band SWIRII and NIR are set to red and green respectively, the burned areas will have the appearance of bright red due to the high band SWIRII reflectance and demonstrate little or no green at all as a result of using the low band NIR reflectance. Using these bands together makes the burn scars easily apparent from the unburned areas.

2.6.9 Time series

It has been suggested a range of time series parameters be applied based on the progression of post-fire vegetation indices that have not been linked to any pre-fire data (Fiorella and Ripple 1993). Other inclusions suggested are the differenced ratios pre and post-fire (Kushla 1998; Hicke *et al*. 2003); or the application of a regeneration index that uses control plots close to, but untouched by the fire. These inclusions would need to be able to correct external influences such as plant maturity, flowering or seeding variations (Riaño *et al*. 2002; Díaz-Delgado *et al*. 2003). The suggested time frame between the date of the fire’s ignition and the post fire acquisition date should be limited to four months as the measurement of vegetation consumption should be performed before any of the vegetation begins to regenerate (Cawson and Muir 2008). Key and Benson (2006) and Verbyla *et al*. (2008) found that the timing factor was crucial as it significantly impacts the dNBR summation. In a Mediterranean ecosystem (MTE) the time between the pre and post-fire image acquisition is vital as the MTEs with warmer weather recovers faster (Veraverbeke *et al*. 2010).

In the collection of annual image comparisons, NBR and dNBR maps provide valuable data but they fail to provide multi-temporal summary of vegetation dynamics on regional and global scales (Michalek *et al*. 2000) and there is difficulty in obtaining multiple cloud free images on anniversary dates (Song 2002). In this study, the satellite data was sourced from Landsat every 16 days. On some of these days there was cloud cover preventing the use of the images. From April to August all the data images were contaminated with cloud.

2.7 Summary

The topics presented in this chapter include fire, fire regimes, fire severity and the measurement of fire change over a specific ecosystem, the changing climate trends, granite outcrops, plant fire responses and remote sensing as a means of assessing fire on granite outcrops and their surrounds. The literature review results identified the five VIs (NDVI, SAVI, MSAVI2, EVI and NDII), to be tested for this study and the index for measuring fire scar and severity (NBR).

This chapter outlines the purpose of this study to test a variety of vegetation indices and a fire index over an area in SWAFR at high risk of species extinction due to altering fire regimes with recent climactic trends that may increase the occurrence and severity of fire over a topographically varied landscape using remote sensing technology. A literature review has been performed to assess what others working in this field have found.

Chapter 3: Description of the study area on Mt Cooke

3.1 Study Area

The study area for this research is located in the Monadnocks Conservation Reserve, an area of high concentration of granite outcrops, the highest outcrop being Mt Cooke (Figure 3.1a). Mount Cooke's location is at: 32^{o} 25′S, 116^{o} 17′E Altitude 571.05 m. and it is a large granite outcrop which rises from the range on the northern Darling Plateau. It is located 20 Km east of Jarrahdale, 42 Km north east of Dwellingup, 53 Km south of Sawyers Valley and 70 Km west of Brookton in Western Australia. It rises 571 meters above sea level and about 200 meters above the surrounding plateau and as such is the highest granite outcrop in the Darling Plateau (Figure 3.1b shows the contour and elevation of the site). The soils in the area range from bare rock to sandy loams through to red yellow sandy duplex soils and gravel. Soil on the outcrops tends to be thin – ranging from just a few centimetres thick to about a metre in depth (Burrows, 2003).

The granite outcrops are formed through varying geologic times by a range of processes. Over time they have become weathered into a number of landforms that include inselbergs, nubbins (blocks and boulders) and koppies (caused by pronounced weathering of blocks and vertical cracks) (Campbell 1997; Withers 2000). The outcrops form a range of specialised habitats such as rock pools – gnammas, exfoliating rock sheets and a variety of cracks and crevices. The apron areas merge into the surrounding habitats.

The vegetation in the area is a diverse mix of meadow plants (*Borya sp.*), large swathes of moss, heathlands and forest interspersed with Eucalypt forests. On the upper reaches there are clumps of Darling Range Ghost Gums (*Eucalyptus laeliae*), *E. marginata* (jarrah) and *Corymbia calophylla* (marri), and many of the plant forms are specific to this region, such as *Acacia ephedroides*, and *Calothamnus rupestris* (Burrows 2003). These are species groups that are known to favour rock and boulder fields. They are fire sensitive and they rely on seed beds in the soils or canopy storage in woody seed capsules to reproduce. They do, however, also rely on the fires to enable regeneration and rarely regenerate without the effects of fire (Burrows and Wardell-Johnston 2003). To the south–east end of the study area runs a set of high voltage powerlines with an associated cleared land band of approximately 16 metres.

The mean average maximum temperature as recorded at the Karnet weather station (13 km from Mt Cooke), shows a slight increase across the years from 1965 to 2012. The rainfall in the region has been slowly declining since 1970. Data from the Bureau of Meteorology recorded at the weather station at Karnet shows that the average rainfall between 2002 and 2012 has decreased by 12%. Since 2000 there has been six years with below average rainfall, with 2011 being the lowest rainfall recorded since 1965. Conditions that most favour wildfires were major contributing factors in the 2003 fire on Mt Cooke (dry conditions, a high level of fuel on the forest floor, strong winds and lightning strike ignition).

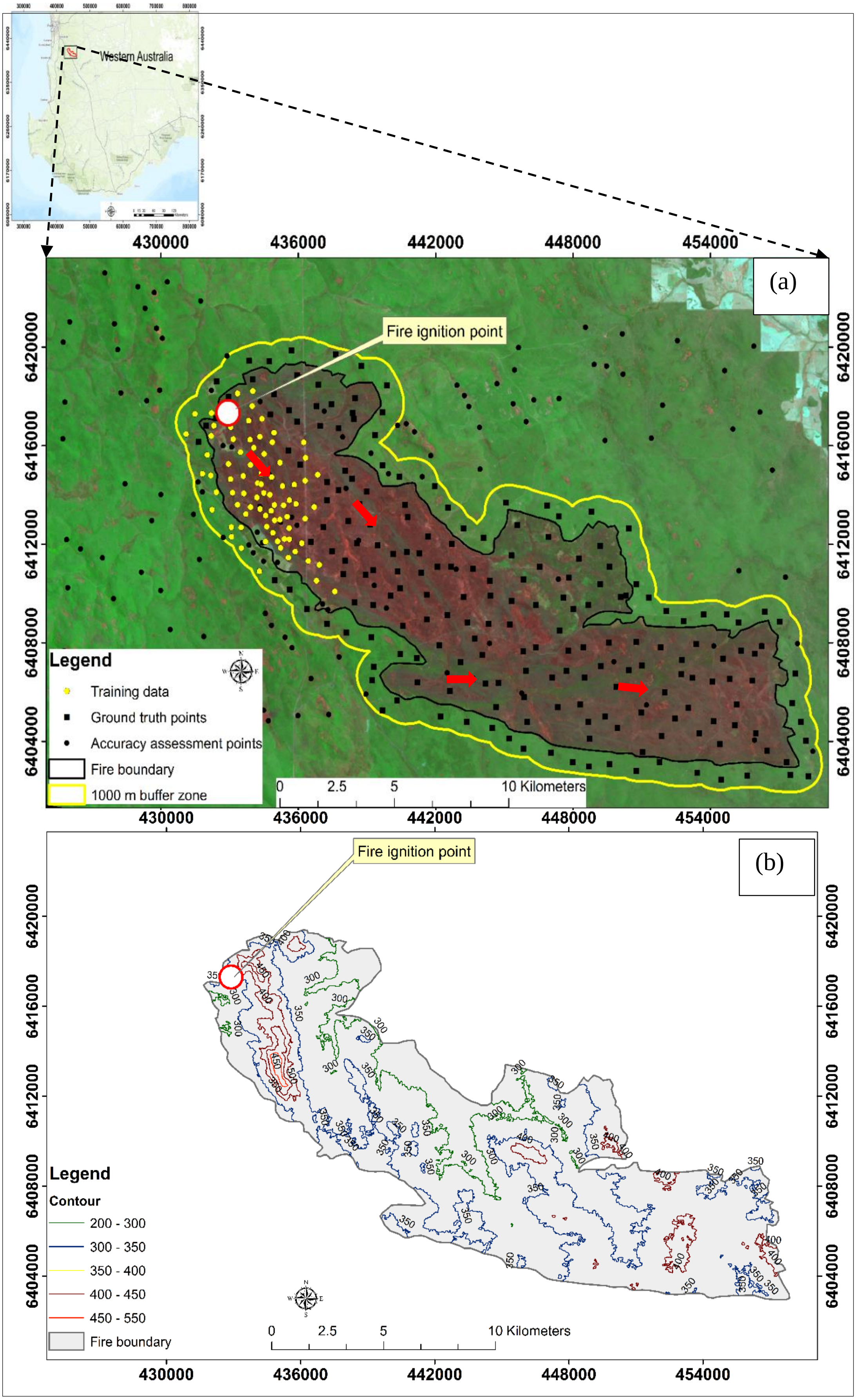

Figure 3.1 a) Location of the study area with a Landsat ETM+ 7 image (R = band SWIRII; G = band NIR and B = band Red. The red pixels show the fire scar. The yellow boundary is a 1 km buffer around the fire scar which is used to provide data on unburnt locations. b) Contour map showing elevation of the study area.

Figure 3.2 Some of the differing habitats across the granite outcrops are displayed in these photographs which were taken in 2012 at Mt Cooke.

3.2 Climate data for the study area

3.2.1 Temperature – This region has a Mediterranean style climate with relatively mild winters and very warm to hot summers. More recently, the warmer weather is extending from November through to March (Bureau of Meteorology, 2003 – making the fire season longer. The mean average maxima as recorded at the Karnet weather station (13 km from Mt Cooke), shows a slight increase across the years from 1965 to 2012 (Figure 3.3).

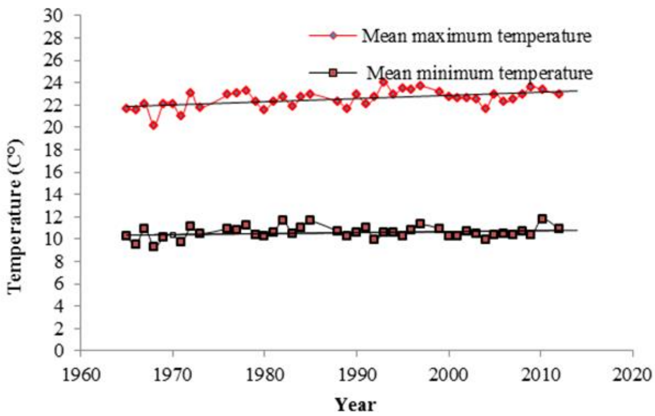

Figure 3.3. Annual mean maximum and minimum temperatures for Karnet weather station, (13 km from the study area) in south-western Australia.

3.2.2 Rainfall - The rainfall in the region has been slowly declining. Data from the Bureau of Meteorology recorded at the Karnet weather station, shows that the average rainfall in the past ten years has decreased by 12% (Figure 3.4). Since 2000 there has been six years with below average rainfall, with 2011 being the lowest rainfall recorded since 1965.

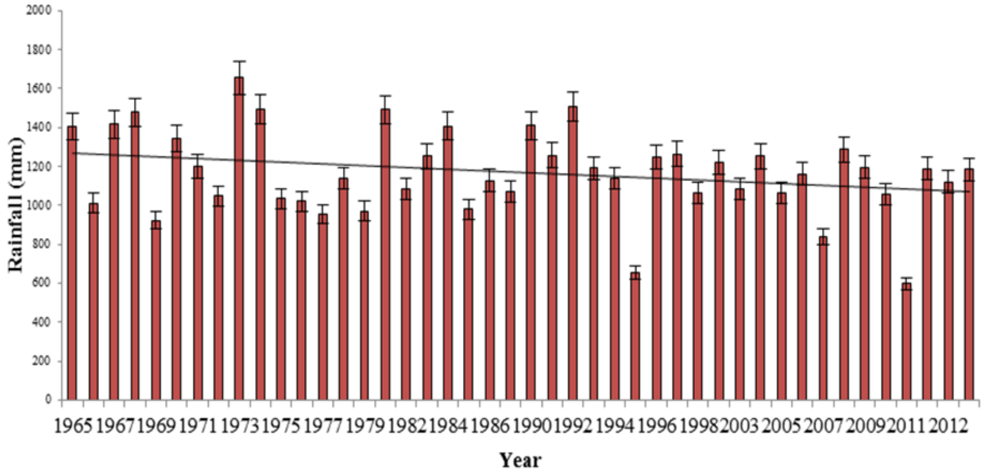

Figure 3.4. Graph depicting the total annual rainfall for Karnet from 1965 - 2013.

3.3 Vegetation

The study area contains a variety of vegetation communities. The area has a matrix of eucalyptus forests and, shrubland, heath and herb fields all in close proximity to each other. The apron area consists of patches of woodlands and forest communities and these have either some grass or shrub understory. Within the forested regions are trees that are estimated to be up to 300 years old (Burrows 2003, 2013). These ecosystems are considered highly flammable due to the rate at which fuel loads accumulate, especially in the Jarrah forest regions (Burrows and Abbott 2003). The shrublands and heath lie in close association with low growing shrubs and herb field formed between rock and boulder fields. On the upper west facing slopes are some communities of Darling Range Ghost Gums. On the outcrops themselves are broad swathes of mosses (e.g. *Grimmia laevigata*.) and lichens. There are species that are restricted to the granite outcrops in this area such as *Calothamnus rupestris* and *Acacia ephedroides (*Clarke 2002*;* Burrows *et al.* 2008). In small rock crevices and rock overhangs are small ferns and there are orchid populations included in the surrounding areas.

3.3.1 Vegetation recovery – After fire, vegetation recovery can appear to be rapid, with a large number of seedlings evident after the first winter rains. These seedlings, from a mix of trees, woody shrubs and herb species take advantage of the open canopy and bare grounds and some areas having an increase in soil nutrients due to runoff of the burned surface of the granite rock. Without the protecting vegetation, both living and dead, areas of topsoil can be completely eroded and washed into waterways after fire. Some soil erosion will leave areas bare and in some places, if the fire is intense, the topsoil is left sterilised with seedbeds destroyed. About half of the species are expected to flower after a full growing season, but other species may not reach maturation for another 2-3 years (Burrows 2006). Photographs depicting the level of vegetation recovery 12 years post fire are included in (Figure 3.7).

A rapid rate of repeat fires in an area may inhibit seeders from restocking seed banks and it may also reduce the bud banks of the resprouters (Zedler *et al.* 1983). However, this pattern of short fire regimes may compliment species with a high resprouting ability (Vila *et al*. 2001). Thus the response to altered fire regimes in MTEs may impact local species communities.

3.4 Mt Cooke Fire – January 2003

In January 2003 a wildfire started that was the result of a lightning strike which hit at the top of the Mt Cooke outcrop. There had been no fire in the area for the previous 17 years and the fire that occurred here burned as a crown fire in a time when the weather had been extreme (Department of Environment and Conservation (DEC), 2003 records). There had been low humidity, a maximum of 36 degrees Celsius and gusty winds from the north-west that ranged between 25-35 km/hr. The origin for this fire was from a lightning strike at approximately 09.50 pm on 9th Jan 2003 on a steep rocky hill-top region (Figure 3.1a). There were around 30 hectares burned in the initial eight hours overnight over inaccessible terrain on the outcrop. The rate of spread was about 80 metres per hour with 3-4 metre high flames. The fire rapidly accelerated after 8.00am driven by hot dry north-westerly winds. The rate of spread ranged from 500-1000 metres per hour. As the fire crossed the power lines (Figure 3.1a) the following day the flames were 15-25 metres high and moving at 2,500 metres per hour and ember spread spotting 1-2 km ahead of the main fire. The weather conditions remained extreme with an air temperature of 35 degrees Celsius with a relative humidity of 20% and fuel moisture of 3%.

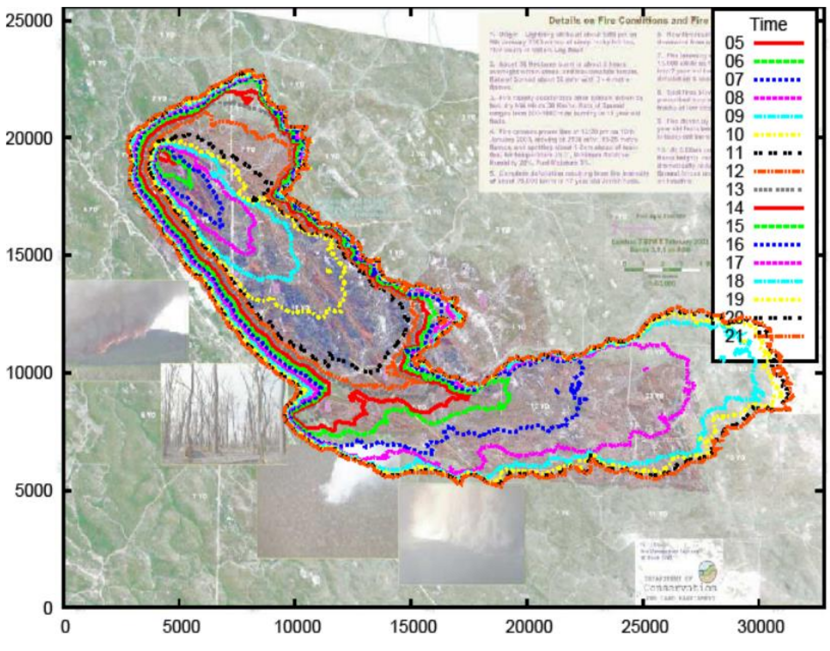

Figure 3.5 Wind spread of 2003 Mt Cooke fire (Reproduced with permission of Milne *et al.* 2007 in Fire behaviour workshop, state of knowledge – Australasian Update Coordinated by Jim Gould and Miguel Cruz; Bushfire Research Group, Ensis – CSIRO,

Complete defoliation of the vegetation resulting from the fire intensity estimated to be of about 75,000 kW/hr in 17 year old jarrah forest fuels. The fire intensity reduced from 75,000 kW to about 15,000 kW/hr as the fire moved out of the area with 17 year old fuels to an area where the fuel was only 7 years old (prescribed burning had taken place earlier). The fire was then driven by westerly winds into an area of 23 year old fuel with a subsequent increase in fire intensity (Figure 3.5). At 5.00 am the head-fire with 10 metre high flames runs into 5 year old fuels and the intensity is dramatically reduced and the ground forces undertake a successful direct attack on the head-fire (G Milne *et al.* 2003).

In the intense heat the granite cracked and whole sheets flaked off. A vast majority of the mature jarrah and marri trees were defoliated and killed by the heat (Burrows 2004). When the fire front reached forest blocks that had been burned in a prescribed burn seven years prior, the intensity reduced and the firefighting teams were able to finally suppress the fire.

3.5 Field Data

Photographic data as provided by Neil Burrows (2003) – scenes photographed after the fire were identified where possible during field trips in 2012-2013. These sites were plotted with GPS and used for visual assessment of fire severity across the study area.

A further 1,700 plots were located randomly within the fire scar and the surrounding area. There plots were assessed for soil cover %, rock cover %, elevation, slope and aspect, valley, ridge and flat, habitat type (forest, shrubland, bare ground), burned or unburned, sheltered or exposed (Table 3.1).“Time since fire” was determined from information sourced from the Department of Environment and Conservation for prescribed burning on and around the study site.

Within the habitat types 298 plots were selected for modelling fire severity within the three classes – a maximum of 100 plots in one class were identified so three classes have nearly the same number. These plots were used in ground thruthing for validation of maximum likelihood classification and fire severity maps.

Table 3.1. Field Data variables

Categories	Statistical variable type	Catagories and measurement units
Soil cover	Categorical ordinal	Percentage %
Rock cover	Quantitative discrete	Percentage %
Shelter/ exposure	Quantitative binary	Yes or No
Time-since-fire TSF	Continuous	1–25
Burnt	Quantitative binary	Yes or No
Valley	Categorical binary	presence-1, absence-0
Ridge	Categorical binary	presence-1, absence-0
Slope	Quantitative continuous	Degrees
Flat	Categorical binary	Yes or No
Aspect	Categorical ordinal	Degrees N, S, E, W
Elevation	Quantitative continuous	Metre
Habitats	Forest, shrub, bare ground	presence-1, absence-0

Figure 3.6 Photos of Mt Cooke (by permission of Neil Burrows) showing: a) typical vegetation, unburned; b) low-moderate burned; c) moderate burned; d) moderate-severe burned; e) severe burned; and f) showing a section of the buffer zone region.

Figure 3.7 These photographs are showing the vegetation 12 years post-fire – the vegetation has still not fully recovered.

3.6 Summary

This chapter has provided a broad description of the study area, the local vegetation and some climate statistics. The data on the 2003 fire from its ignition and spread through the study area is discussed. Some information on the expected post-fire vegetation recovery are presented but this is discussed in depth in Chapter 5. The data collection from field trips made in 2012 and 2013 outlined. More details for specific factors are provided in the following chapters as each subject is highlighted in the research.

Chapter 4: Comparison of remote sensing-based indices for mapping fire scars. A case study of the 2003 Mt Cooke fire, south-western Australia

4.1 Introduction

The South Western Australian Floristic Region (SWAFR) is one of the most fire prone areas of the world (Abbott and Burrows 2003). Since the 1970s, the mean annual rainfall in this Mediterranean-climate region has fallen 15% as presented at the Indian Ocean Climate Initiative conference (IOCI 2012). The mean maximum temperature has increased approximately 0.8° Celsius since 1910 (Bureau of Meteorology 2008; CSRIO and BOM 2007; IOCI 2012). These warmer, drier conditions amplify the flow-on effects of tropical cyclone activity in northern Australia (McCaw and Hanstrum 2003); with lightning being a natural ignition source of dry fuel loads in the area (Tolhurst 2003; Tymstra *et al*. 2007; IOCI 2012).

The climate trend is for longer drier periods and Williams *et al*. (2008) suggest that this may impact the unique plant life of the area and hence alter the level and distribution of biodiversity (McCaw and Hanstrum 2003; Williams *et al*. 2009; IOCI 2012). The associated slowing of growth rates as a response to the longer summer weather season may have a negative effect on the recovery rates of vegetation after fire. It is anticipated that naturally occurring fires will increase in the future as a result of climate trends (Mouillot *et al.* 2002, Littell *et al.* 2009). There is a need to better assess damage from landscape scale fires across areas of granite outcrops that are a feature of the landscape in the SWAFR and which may provide refugia for endangered plant life. The information collected will help formulate risk management plans and ongoing ecological assessments. An aim of this study is to select which vegetation index will provide the most effective measure in the assessment of fire damage to the ecosystem of the Mt Cooke area and provide a gauge to assist in any future measures made in the rehabilitation efforts for the preservation of granite outcrop habitats. The study area consists of three major components - forest, shrublands and bare ground on and around the granite outcrops.

Remote sensing is a means to map fire scars that is cost effective and provides reliable outcomes (White *et al.* 1996, Shen *et al*. 2013, Kontoes *et al*. 2013). Remote sensing is used to map fire scars across a range of vegetation types using indices derived from arithmetic operations on co-registered images (Patterson and Yool 1998, Hudak *et al.* 2007). Prior to 2000, the use of remote sensing for mapping fire was relatively rare.

From the literature review, the index that was most used initially was NDVI as it demonstrated a firm correlation with vegetation over a wide variety of ecosystems but it was found to be an inadequate measure of areas with sparse vegetation (Huete *et al.* 1987, Schowengerdt 1997). Lopez Garcia and Caselles (1991) developed a new measure that was later named NBR by Key and Benson (1999). It highlights the difference between the short wave infrared (2.08-2.35µm) which increases after fire, and the near infrared (0.76-0.9 µm), which decreases and it has become the most widely used index for the mapping of landscape fire and fire severity as it provides a clearer differentiation between burned and unburned vegetation (e.g. Miller and Yool 2002; van Wagtendonk *et al*. 2004; Loboda *et al.* 2007; Lozano *et al*. 2007).

Other indices were also modified from NDVI. SAVI and MSAVI were modified with a soil calibration factor that uses a continuous L function which decreases the background soil effect, and MSAVI has an increased dynamic range over SAVI (Qi *et al*. 1994). In the choice of SAVI in this chapter, the L factor function is based on parameters from Huete 1988 where he assigns 0.1 equals low density, intermediate density 0.5 and high density 0.25 in the vegetation index. These were used primarily for vegetation biomass assessment and only more recently (from around 2003) they have been used for fire mapping. They are better suited to mixed landscape conditions as there is less high reflectance from areas of exposed soil and they have a factor that can be adjusted to suit a variety of biomass types. EVI is a modified version of the NDVI and has the ability to adjust for canopy background and is tolerant to atmospheric interference (Huete *et al*. 2002). It uses blue wavelengths (which rarely provide spectral separation of burned and unburned areas) but it has the ability to be efficient in areas of high vegetation cover and it is more responsive to canopy structure variations than NDVI (Li *et al.* 2008). Rogan and Yool (2001) found that when mapping fire severity SAVI and MSAVI performed better than NDVI.

The Normalised Differenced Infrared Index (NDII) is used to assess changes in the green biomass (the chlorophyll content and leaf water content) for foliage and canopies, and can be used in the assessment of vegetation stress (Cohen 1991; Jackson *et al*. 2004; Davidson *et al*. 2006). The choice of a particular index for this study was based on the four most frequently used from the literature review and two less commonly used indexes – one which used the blue band and the final one which used NIR and SWIR in the logarithms.

This chapter aims to assess the six chosen indices, using Landsat ETM+ imagery to choose the optimal index (looking for which bands best adapt for reflectance) for mapping fire scars across the Mt Cooke landscape which, as stated above, consists of a mixture of components. Fire scar maps will be produced for post fire vegetation assessment using the chosen indices and it is expected that some variations will be evident between the chosen indices. The expected outcome is that there may be a significant difference between the indices across the differing landscape features.

NBR and MSAVI2 may provide the most suitable indices for the forest and shrubland areas. NDVI is expected to give the same results across all classes as it is limited to the identification of vegetation or bare ground only. It is expected that EVI and NDII may produce similar inadequate results, as EVI is limited to blue wavelength and NDII on SWIR band will not give clear differentiation between burned and unburned features, but they are expected to show a variation when compared to the main four indices.

The second aim is to make a comparative study of data results from a single post-fire image against the results from a set of images – one pre-fire and one post-fire, to determine if one method provides a significant benefit over the other. (The results from each method will be tested statistically and with ground truthing comparison to determine which method is more accurate). The two image study results, which can highlight the change detection between the two images, are expected to give accurate results between burned and unburned vegetation, but the more subtle changes, as in the case of only lightly burned vegetation, may prove to be more of a challenge to detect. The various types of vegetation and features that make up this region are expected to impact these results, however, it is anticipated that the two-image method may prove to be the more accurate.

4.2 Methodology

4.2.1 Study site

The study area is located in the Monadnocks Conservation Reserve, a landscape dominated by granite outcrops. The highest outcrop is Mount Cooke, (Figure 4.1), which rises 571 m above sea level and about 200 meters above the surrounding plateau – as described in Chapter 3.

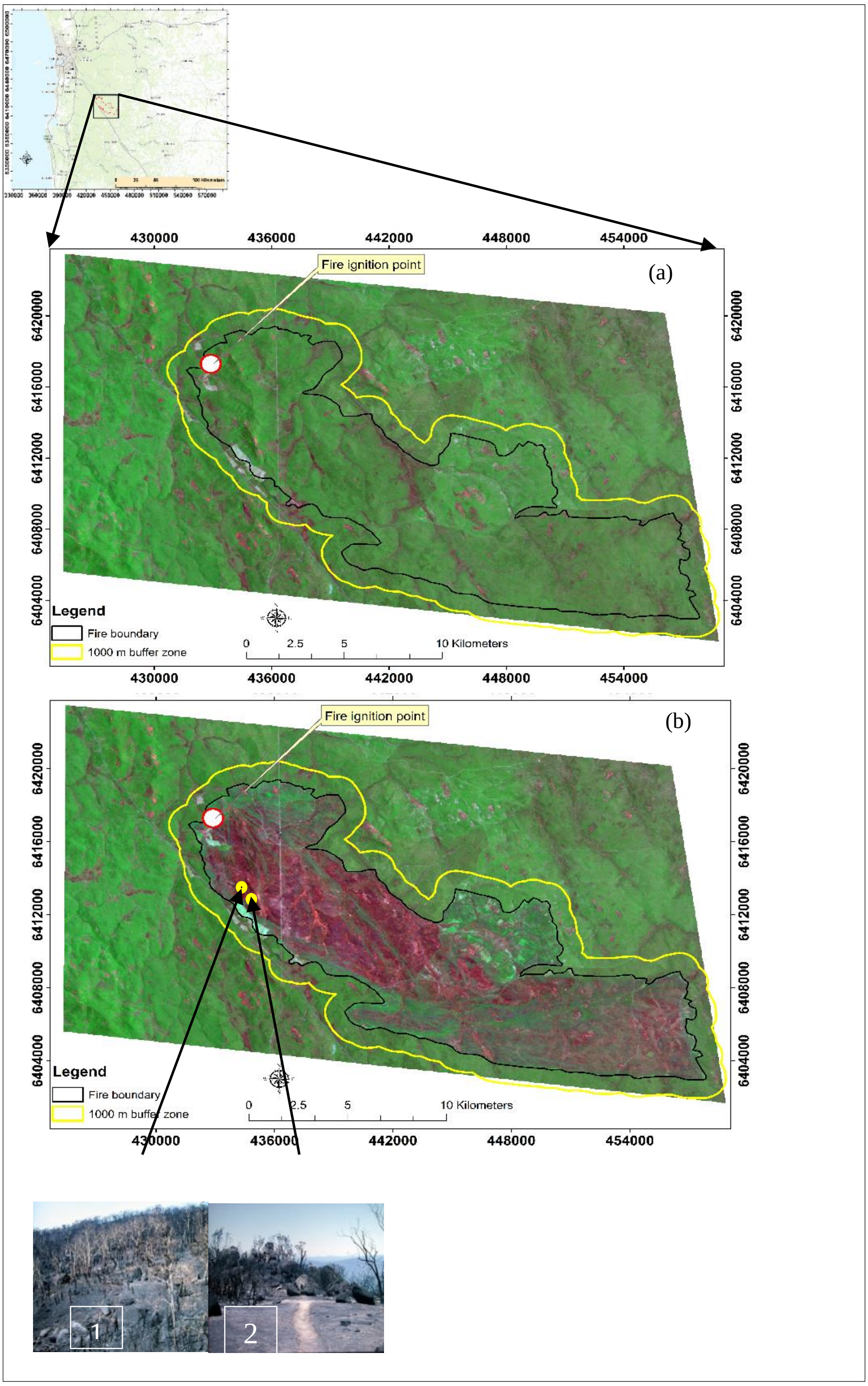

Figure 4.1. Fire scar, 9-11 January 2003 on Mt Cooke, South-western Australia - a) pre fire and b) post-fire image displayed as RGB bands 7, 4, and 2. (Photos 1 and 2 showing post-fire views by permission from Neil Burrows 2003).

4.2.2 Datasets

Landsat ETM$^+$ imagery was chosen because it offered a range of images from both the pre and post fire periods (Table 4.1) and Landsat ETM$^+$ has a spatial resolution from 15-30 m, making it fine enough to register change in local communities, also it has a spectral resolution of seven bands. The choice of bands in fire assessment allows the use of a variety of indices for the mapping of a burn scar. As the satellite orbit recurs every 16 days, repeat images of the affected burn area can be collected to monitor vegetation regeneration.

Table 4.1. Datasets as used in this study.

Pre-Fire			Post-Fire		
Image Date	Path Row	Sensor	Image Date	Path Row	Sensor
17/01/2002	112/82	ETM$^+$	20/01/2003	112/82	ETM$^+$

4.2.2.1 Landsat ETM$^+$ imagery

USGS Earth Explorer Landsat data archive was downloaded from http://earthexplorer.usgs.gov and this forms the data set used in this study. It was taken from Landsat 7 ETM$^+$ at level one systematic and terrain corrected (L1T/G), then two satellite images (ETM$^+$) were selected, the first was taken pre fire on January 17 th, 2002 and the second on January 20th 2003, immediately after the fire. There was no impedance caused by cloud cover in the images used. Reflection and radiance were corrected for the images for each band using Equation (1) below in ENVI (Environment for Visualisation Image) and ERDAS Imagine (Earth Resources Data Analysis System). The images were radiometrically corrected in order to account for the atmospheric and solar illumination factors, Equation (2) below, (Pons and Solé 1994, Chander *et al.* 2009).

4.2.2.2 Radiometric correction

Firstly, the Digital Number (DN) for each band ETM+ was converted to the radiance using equation (1).

$$L_\lambda=[(LMAX- LMIN) / (Qcalmax - Qcalmin)]* (Qcal- Qcalmin) + LMIN\lambda \qquad \text{Equation (1)}$$

Where:

$L\lambda$= Spectral radiance at the sensor's aperture [W/(m^2 sr µm)]

Qcal= Quantized calibrated pixel value (DN)
Qcalmin = Minimum quantized calibrated pixel value corresponding to LMIN (DN)
Qcalmax= Maximum quantized calibrated pixel value corresponding to LMAX (DN)
$LMIN\lambda$= Spectral at-sensor radiance that is scaled to Q calmin (W/(m^2 sr µm))
$LMAX\lambda$= Spectral at-sensor radiance that is scaled to Qcalmax (W/(m^2 sr µm))

The second step involved the calculation of the "top of atmosphere" (TOA) reflectance for each band as per Equation (2). This corrects the sun angle and Earth/sun distance. These corrections were then applied on a pixel to pixel basis for each scene and the output reflectance values were scaled to an 8-bit range.

$$P_{\lambda} = \pi * L_{\lambda} * d^2 \; / \; ESUN_{\lambda} * COS\, \theta s \qquad \text{Equation (2)}$$

Where :

$\rho\lambda$= Planetary TOA reflectance [unitless]
π = Mathematical constant equal to ~3.14159 [unitless]
$L\lambda$= Spectral radiance at the sensor's aperture [W/(m^2 sr µm)]
d = Earth-Sun distance in astronomical units
$ESUN\lambda$ = Mean exoatmospheric solar irradiance [W/(m^2 µm)]
θs = Solar zenith angle in degrees

Once the visual interpretation of the images was performed, the peripheries of the region burned were mapped. The Radiance was initially set on the pre-burned image and then transposed onto the post fire image to produce the signature for each image. The fire scar was digitised manually and finally, the fire perimeter was determined.

4.2.3 Assessment indices

Of the indices that are now used for mapping fire damage, many were initially used in mapping other types of land disturbances. However, some indices unique to fire monitoring have now been developed – those of particular interest are the differences in the NIR and SWIR areas of the spectrum as they are related to vegetation structure and moisture levels in the soils (Trigg and Flasse 2001; Key and Benson 2006).

In this study the various indices that have been assessed are listed in Table 4.2. The value of these indices, (NDVI, SAVI, MSAVI2, EVI, NBR and NDII), range from -1–1. The outcome from each index equation is produced as a map.

Table 4.2. The four common indices and two less commonly used indices (*) that are tested in this study

Spectral Index	Method of calculation	References
NDVI	(NIR - RED) / (NIR + RED)	Tucker (1979)
SAVI	NIR - RED / NIR + RED + L]* (1 + L)where L = soil adjustment factor 0.5	Huete (1988)
MSAVI 2	(2 * NIR + 1 – sqrt ((2 * NIR + 1) ^{2}- 8 * (NIR - RED) /2)	Qi *et al*.(1994)
*EVI	2.5 * (NIR - RED) / ((NIR + 6*RED - 7.5*BLUE) + 1)	Huete *et al*. (1999)
NBR	(NIR - SWIRII) / (NIR + SWIRII)	García & Caselles(1991)
* NDII	(NIR - SWIRI) / (NIR + SWIRI)	Hardisky *et al*. (1983)

* L = 0.5, based on Huete 1988 – intermediate vegetation coverage

4.2.4 Computation of vegetation indices

Two images from the study area of Mt Cooke and its surrounds were sub-set and the chosen indices were calculated (NDVI, SAVI, MSAVI2, EVI, NBR and NDII) and have been used to produce maps. The selected images underwent a filtering process (4 x 4 neighbourhood majority): initially to visually assess for errors and to confirm the file data was not corrupted, and secondly, the image pixels were classified into burned or unburned to create maps. Finally, two polygons were created, one in the burned area and the other in an unburned area. ArcGIS software (Arc Geographic Information System) 2000 points from both the burned (1000 pts) and the unburned (1000 pts) areas were randomly selected. The points were then intersected with data from the maps (NBR, NDVI, SAVI, MSAVI, EVI and NDII maps) and the results were graphed to test them statistically using ROC Curve (Receiver Operating Characteristics Curve) below.

4.2.5 The class boundaries

ROC curves are a popular method to compare between alternative models or tests and are commonly used to display the performance of detectors (such as pixel values) beneath the curve. In this study, it is used to determine the most accurate indices of those assessed (Hosmer *et al*. 2013).

The ROC curve is a graph of the false positive rate (x) versus the true positive rate (y). Some of the pixels will be determined as burned – equalling a True Positive (TP) result or unburned – a True Negative (TN) result, but there are some pixels which will be incorrectly classed as burned, giving a False Positive (FP) result and on the other hand, some incorrectly classed as unburned giving a False Negative (FN) result. The sensitivity is (the areas that have been burned) against the specificity (the areas that have not been burned) False Positive Rate (FPR) = Equations (3) and True Positive Rate (TPR) = Equations (4). To produce the final map for each index the ROC curve is utilised to determine the Sensitivity and Specificity values for the 2000 selected points. From the results of each point, the Sensitivity value has the Specificity value subtracted from it for a higher accuracy result.

The ROC curve is a two dimension illustration of the performance of a ranking scale. To make a comparison of the rankings of data it may be preferable to reduce the ROC execution to a single scale register that represents the expected outcome. A method for doing this is to calculate the Area Under the Curve (AUC), (Bradley 1997). The AUC is a part of the area of the unit square and thus its value will always fall between 0–1. On the other hand, random guessing can produce the diagonal line between 0, 0 and 1, 1 and this has an area of 0.5 and no realistic ranking should have an AUC of less than 0.5. An important statistical property of the AUC is that the classifier will order randomly selected positive instances above randomly selected negative instances.

The nearest point of the ROC curve to the uppermost left corner (AUC = 1) is indicative of a high accuracy result (a true discrimination between true (burned) and false (unburned) outcomes). In the association to the calculated AUC value, Hosmer and Lemeshow (2013) classified a predictive performance as – acceptable (AUC >0.7), excellent (AUC >0.8) and outstanding (AUC >0.9).

A set of cut-points (C) were determined from these values as half the distance between each successive pair. At each cut-point the TPR and FPR; (see below), is calculated. For the NBR, a traverse point that is known to be unburned is a True Positive (TP) if it is greater than, or equal to C. Similarly, a random point that has been burned is considered a false positive if the random point is greater than, or equal to C (Robinson *et al*. 2009). The result giving the highest value from these equations is chosen to produce the map for each index (Ayalew and Yamagishi 2005).

Each of the False Positive rates and the True Positive rates requires a cut point that allows the test result to register as positive or negative, or in this case, burned or unburned. If the AUC is close to 1, this will indicate a strong indicator variable. If the AUC is close to 0.5, this indicates little discrimination power – no better than random. Statistical analysis is made using the AUC in ROC curve to highlight the discrepancies between the indices. The data from the six indices were then compared to each other using cross tabulation to determine the similarities and dissimilarities to produce maps showing the burned and unburned areas. In using the AUC, the ability to differentiate between each index's performance is clear – the best option is that which reduces the false negatives and false positives and shows as the highest AUC (Zweig and Campbell 1993).

4.2.6 ROC values

$$\text{False Positive Rate (FPR)} = 1 - \frac{nTN}{nTN + nFP} \qquad \text{Equation (3)}$$

nTN: Number of true negative decisions

nFP : Number of false positive decisions

$$\text{True Positive Rate (TPR)} = \frac{nTP}{nTP + nFN} \qquad \text{Equation (4)}$$

nTP : Number of true positive decisions

nFN : Number of false negative decisions

The area under the ROC curve

$$A_Z = \frac{1}{n_+ n_-} \sum \{ n_{-=j} * n_{+>j} + \frac{n_{-=j} * n_{+=j}}{2} \} \qquad \text{Equation (5)}$$

n_- =Number of cases with negative actual state

n_+ =Number of cases with positive actual state

$n_{-=j}$ =Number of true negative cases with test result equal to *j*.

$n_{+>j}$ =Number of true positive cases with test result greater than *j*.

$n_{+=j}$ = Number of true positive cases with test result equal to *j*.

4.2.7 Supervised Image Classification

4.2.7.1 Calibration data

A common extraction method used to decipher images that have been remotely sensed is referred to as classification (Vincent 1997, Richards 2013). The use of an algorithm, to assign a pixel to a particular spectral class, is performed to classify the image. Classification techniques, where samples of known information classes referred to as "training sets," are used as a guide to classify pixels of an unknown identity (Lillesand *et al*. 2004). The training regions chosen for testing are selected by the user. This study uses the maximum likelihood classification technique. Two Landsat images were classified and the results were then compared. This involved two steps. Firstly, in the training stage, a sample set of pixels were selected from each of the three land-cover classes that capture the spectral attributes of each class, and secondly, in the classification stage, a comparison is made between the spectral signatures in the training sets with those of remaining pixels in the image and thus, these pixels are automatically categorised to the corresponding land-cover type.

4.2.7.2 Validation

An accuracy assessment has been used to confirm the quality of the information that has been derived from the data analysis after each classification process for the images. The field trips to select GPS points within the study area were conducted in 2012-2013. A confusion matrix and a classification report were generated for each image. The confusion or error matrix was described by Congalton and Green (1991, 2009) as the core of accuracy assessment. Therefore the confusion matrix and accuracy statistics have been established as a reliable method of accuracy assessment, even in times when in-situ data are not available to the user (Congalton 2001).

4.2.7.3 Kappa coefficient

The kappa (κ) analysis is used as another accuracy assessment. It can determine if one error matrix differs significantly from another (Bishop *et al.* 1975, Congalton 1991). The outcome from having performed a Kappa analysis is referred to as a KHAT statistic (actually $K\hat{}$, an estimate of Kappa), which is yet another measurement of accuracy (Cohen, 1960). It can also determine if the values contained within an error matrix represent a result significantly better than random (Jensen 1996). Kappa is computed as Equations (6).

$$\kappa = \frac{N \sum_{i=1}^{r} x_{ii} - \sum_{i=1}^{r} (x_{i+} * x_{+i})}{N^2 \sum_{i=1}^{r} (x_{i+} * x_{+i})} \qquad \text{Equations (6)}$$

Where:

N = the total number of sites in the error matrix; r = the number of rows in the error matrix,

x_{ii} = the number in row (i) and column (i); x_{+i} = the total for row (i); x_{i+} = the total for column (i)

The images used for the accuracy assessment were Landsat ETM^+ images and each was viewed as true colour composites of Bands SWIRII, NIR and Green. Next, a randomised selection of 120 referenced spots was generated through on-field GPS data for each class of the land-cover type. The randomised reference spots were stratified proportionally to the number of pixels in each of these information classes.

4.2.8 Change detection

Classification image data, NDVI, SAVI, MSAVI2, EVI, NBR and NDII from the two Landsat images were compared and the differences (or change) recorded. This evaluation is based on the class of a pixel in the pre fire image being classified as its equivalent class in the post-fire image. Boolean modelling is used in calculating change detection. It is built as a tool in Arc GIS tools. The Boolean model will interpret the input values, where non-zero values are considered true and zero is considered false. It is required that two input values are entered for this value to be determined. The actual order to the inputs is irrelevant for this tool. Each class was masked and coded with colour. Cross tabulation was performed on each image, pre and post-fire. The maps revealing the differences between the images were then produced.

4.2.9 Spectral properties of burned surfaces

The reflected radiation as a function of the wavelength is referred to as the spectral signature. This signature will be influenced by patches of exposed soil and large areas of rock and the amount of moisture in the vegetation and soil. Fire alters vegetation structure, affecting these spectral recordings. Assessment of these changes can be used in the prediction of expected outcomes in areas that have remained unburned for long periods. The level of the fire damage on the landscape is referred to as the burn severity (Epting *et al*. 2005). This damage encompasses decreased moisture content in foliage, changes in soil, the density of species types and their position in the landscape (Avery and Berlin 1992, Miller and Yool 2002, Soverel *et al*. 2010).

In measuring the spectral changes of vegetation that has been burned, using multi-sprectral images, a selection of sample points are taken from a pre-burned image to match the same set of points when overlaid on a post burn image of the same area. From the changes identified between these sample points, using radiometric values for the pixels, the spectral signature is recorded for the burned image. Histogram data plots have then been determined to represent the spectral responses graphically in a comparison to the unburned data.

4.3. Results

4.3.1 The single image results

4.3.1.1 Signature for the burned and unburned areas

Signatures representing the burned and unburned results from the randomly selected points have been graphed below – the (y) axis demonstrates the pixel value and the (x) axis the Landsat bands. The reflectance decreases significantly in band Near Infrared, (NIR), in band Short Wave Infrared (SWIRI) there is a minor decrease, however, in band 7 (SWIRII) there is a significant increase in the burned area results. In the near infrared region the reflectance from the burned surfaces is lower compared to the normal vegetation readings. By contrast, in the mid-range infra-red spectra, an increase in reflectance is noted due to the loss of water content from the vegetation after fire (Figure 4. 2).

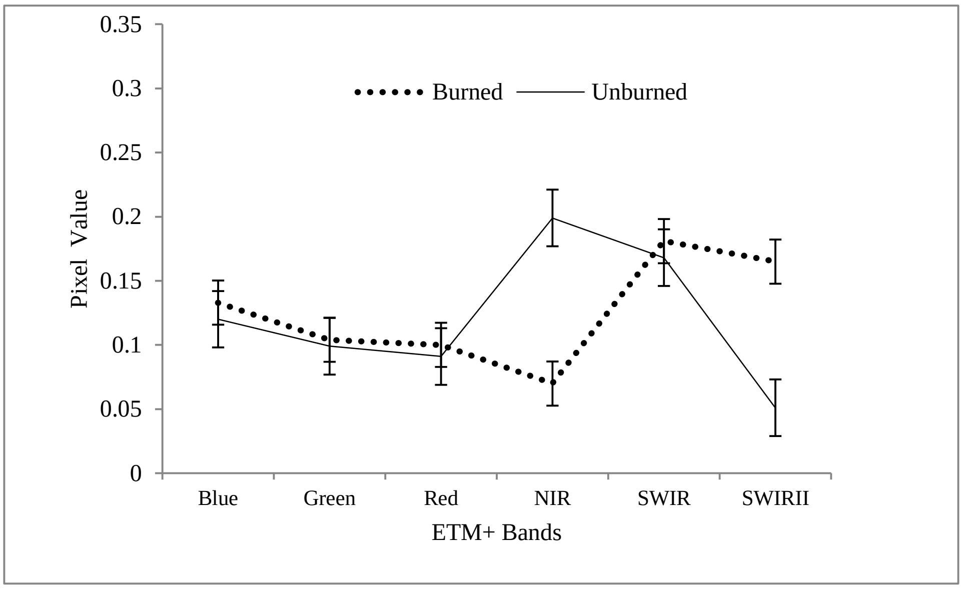

Figure 4.2. Graphed mean spectral separation of the burned and unburned area in the single image

4.3.1.2 ROC curve results

The data has been assessed in terms of a True Positive result and False Positive result. The outcome, according to this analysis is that NBR, NDVI, MSAVI2 and SAVI were very nearly similar. The area under the curve for NBR is 0.85 with standard error of 0.009 and EVI 0.72 with a standard error of 0.01. However, the results for the EVI and NDII are markedly different as displayed on the (Figure 4.3 and Table 4.3 and 4.4).

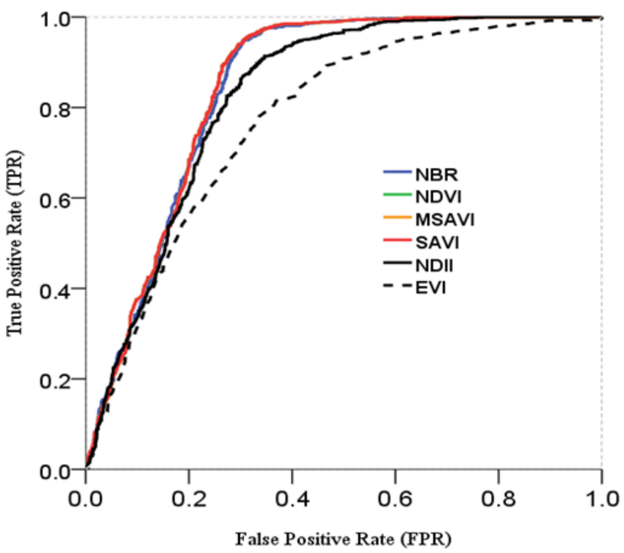

Figure 4.3. Comparison of the results of various indices mapping fire scars

Table 4.3. Area under the curve.

Test Result Variable(s)	AUC	Optimal Cut-Point	Std. Error	Asymptotic Sig.
NDVI	0.848	0.644	0.009	0
SAVI	0.848	0.644	0.009	0
MSAVI2	0.848	0.644	0.009	0
EVI	0.720	0.446	0.011	0
NBR	0.846	0.643	0.009	0
NDII	0.801	0.567	0.01	0

Table 4.4. Summary of the statistics of the AUC for the six chosen indices

Index	N	Minimum	Maximum	Mean	Std. Deviation	AUC mean
NDVI	2000	-0.343	0.270	-0.137	0.152	0.848
SAVI	2000	-0.511	0.403	-0.204	0.227	0.848
MSAVI2	2000	-0.650	0.423	-0.375	0.381	0.848
EVI	2000	-0.680	0.720	-0.167	0.241	0.720
NBR	2000	-0.574	0.474	-0.171	0.252	0.846
NDII	2000	-0.565	0.186	-0.288	0.138	0.801

4.3.1.3 Evaluating different mapping techniques

Six fire scar mapping techniques were evaluated (Figure 4.4). The first involved NBR of Landsat ETM+ bands 4 and 7. Five other techniques involved change detection of ETM+ using bands 1, 3, 4 and 5. The fire scars were discernible in all the indices chosen in the raw data images. However, after Boolean modelling, the results from NBR, NDVI, MSAVI2 and SAVI were similar, while the results using EVI and NDII were markedly different (Figure 4.4 d, e).

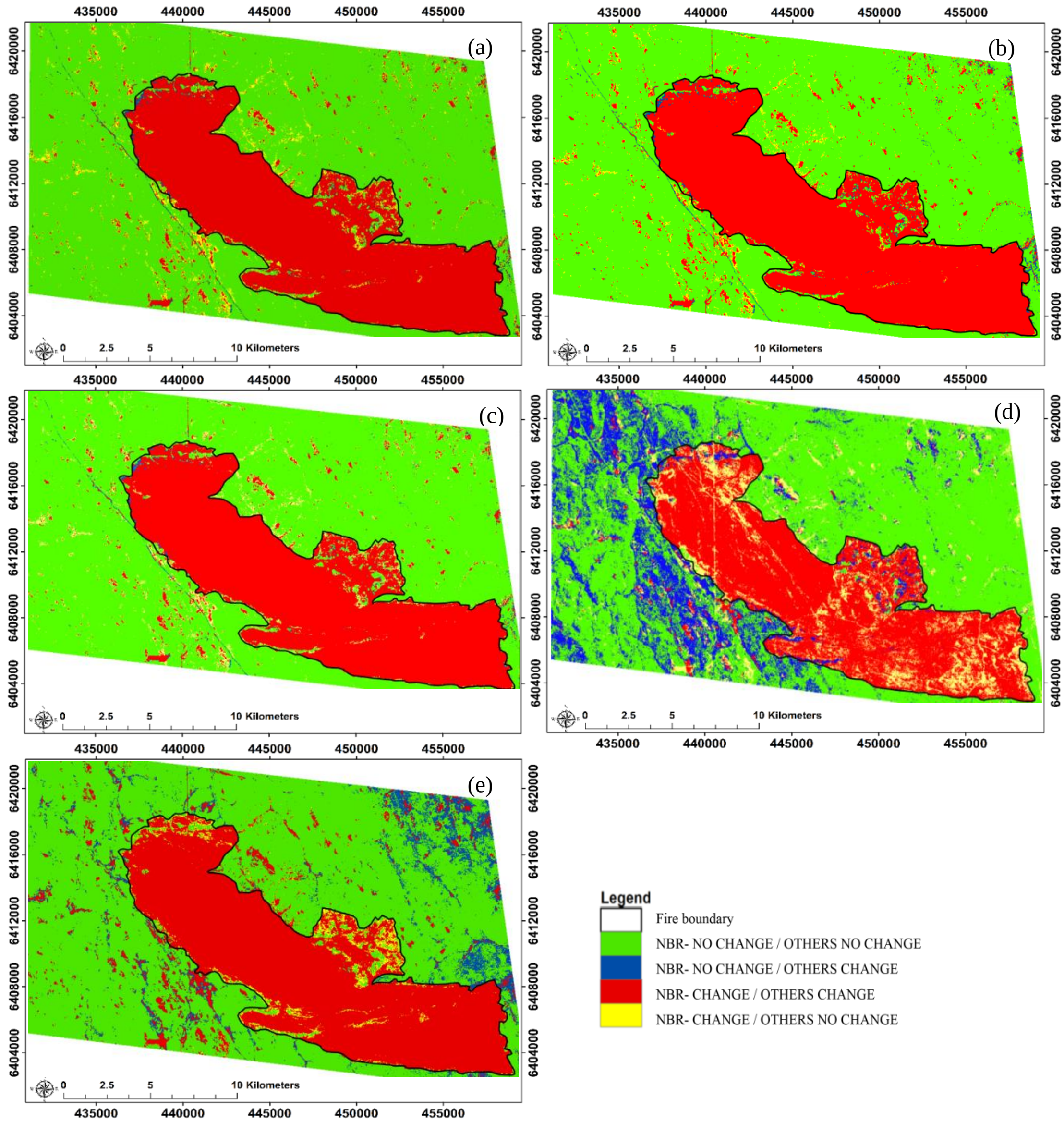

Figure 4.4. The results from cross tabulation between the chosen vegetation indices. (a) NBR verses NDVI; (b) NBR verses SAVI; (c) NBR verses MSAVI2; (d) NBR verses EVI; (e) NBR verses NDII

4.3.1.4 Comparison between the chosen indices

The comparisons between NBR with NDVI, SAVI with MSAVI2, showed no sizeable differences for mapping fire scars. By contrast, NBR, NDVI, SAVI and MSAVI2, with EVI and NDII demonstrate major differences. For example, EVI is showing a large unburned area as ‘burned’(Blue)and a burned area as ‘unburned’ (Yellow) (Figure 4.4 d). NDII demonstrated unburned areas as ‘burned” and some burned areas as ‘unburned’ – i.e., giving false results, but overall a better result than EVI (Figure 4.4e).

4.3.2. Results – The two image result (one pre-fire and one post-fire)

4.3.2.1 Signature for pre-fire and post-fire images

Signatures representing the pre-fire and post fire results from the randomly selected points across the three landscape classes are graphed below – the (y) axis demonstrates the pixel value and the (x) axis the Landsat bands. The forest class - the reflectance in the forest class in band 3 (Red) showed no difference between pre and post fire, but in bands 4, Near Infrared (NIR), and 5, Short Wave Infrared (SWIR), there is a clear decrease in post-fire results and an increase in the reflectance in band 7 (SWIRII). The shrubland class -in the shrubland class, there is a slight difference in bands 1, 2 and 3 across the pre and post fire images. In bands 4 and 5 there is a significant decrease in the post fire image. In band 7 there is a significant increase in reflectance in the post-fire image. The bare ground class **-** in the bare ground class there is a decrease in bands 4 and 5 and an increase in the reflectance from band 7 in the post fire image (Figure 4.5).

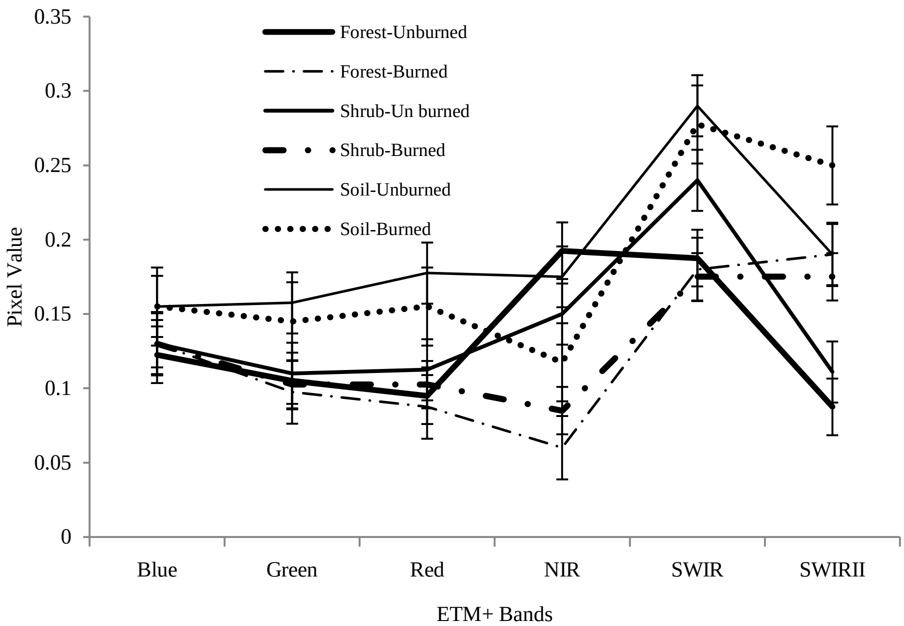

Figure 4.5. The mean spectral separation of the same plots, pre and post fire images.

4.3.2.2 Image classification results

In comparing the results between the pre-burned and post-burned images (Figure 4.6 below) it is clear to see the area was decimated by the fire. The total area of bare ground post fire is 19,861 h compared to the pre-burned area of 1,387 h, an increase of 90%. Table 4.5 and Figure 4.6 below provide the total area from each class shown in hectares.

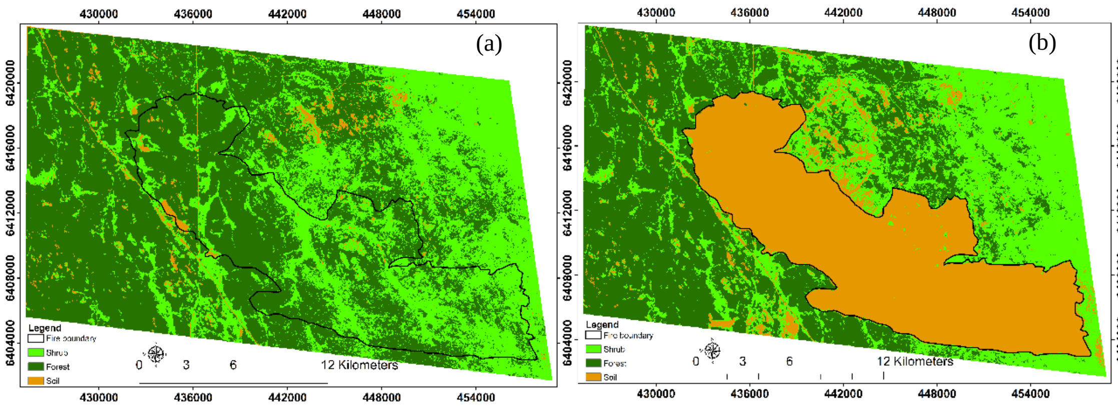

Figure 4.6. Resulting maximum likelihood classification images: a) Pre-fire image and b) Post-fire image

Table 4.5. Classification results for both pre and post fire (area in ha)

Classification	Pre-fire area	%	Post-fire area	%
Bare ground	1387.26	2.39	19861.47	34.30
Shrub	21550.59	37.22	17010.63	29.37
Forest	34961.76	60.38	21027.51	36.31
Total	57899.61	100	57899.61	100

4.3.2.3 Accuracy assessment

Overall accuracy, (Table 4.6) lists users and producer's accuracy and kappa coefficient for ETM+ Landsat image pre and post-fire for the three landscape classes. Overall accuracy was between 80-86% in both images for the three classes and the Kappa was between 0.78-0.79.

Table 4.6. Accuracy assessment results for both images

17-01-2002 image	Bare ground	Shrub	Forest	20-01-2003 image	Bare ground	Shrub	Forest
Producer's Accuracy	70%	89%	92%	Producer's Accuracy	81%	61%	88%
Users Accuracy	94%	74%	93%	Users Accuracy	76%	79%	97%
Over all Accuracy		86%		Over all Accuracy		80%	
Kappa		0.79		Kappa		0.78	

4.3.2.4 Cross comparison of pre and post fire ETM+ images

The cross tabulation was performed on the pre and post fire images for each index and both images were classified:

1-0: The image displayed bare ground in the pre-fire image but not in the post-fire image (Bare – Not bare).

0-1: The image did not display bare ground in the pre-fire image but it did in the post-fire image (Not bare – Bare).

1-1: The images displayed bare ground in both images (Bare –Bare).

0-0: There is no bare ground in either image (Not bare – Not bare).

The bare ground in the post fire image consisted of 15,817 h when NDVI was applied to the data and SAVI demonstrated 15,820 h and NBR showed 15,800 h – no significant difference. However, the result from NDII demonstrated 12,930 h – a large discrepancy of ~ 2,890 h (Table 4.7 and Figure 4.7 and 4.8).

Table 4.7. The differences between pre and post-fire image in bare ground class.

Class	NDVI	SAVI	$MSAVI_2$	EVI	NBR	NDII	Maximum likelihood
BARE – NOT BARE 1-0	341.64	343.26	165.6	531.09	2069.55	1401.84	394.65
NOT BARE –BARE 0-1	15817.14	15820.56	15046.11	15521.13	15800.04	12930.12	18868.86
BARE –BARE 1-1	587.79	590.58	241.29	976.61	7699.5	3190.95	992.61
NOT BARE – NOT BARE 0-0	41153.04	41145.21	42446.61	40869.86	32330.52	40376.61	37643.49
Total	57899.61	57899.61	57899.61	57899.61	57899.61	57899.61	57899.61

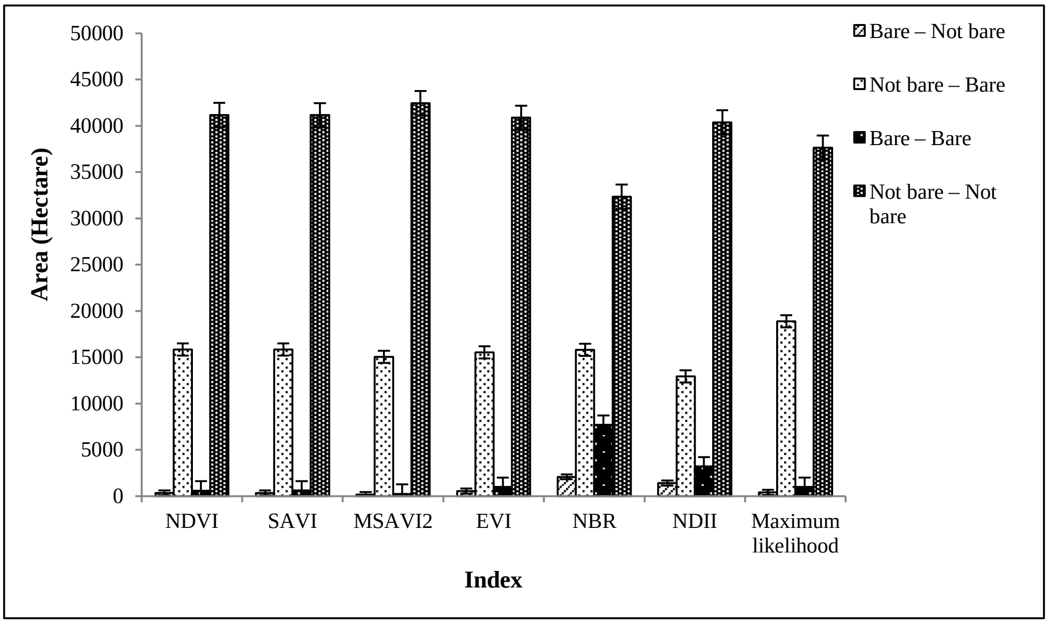

Figure 4.7. The comparison results of the bare ground class from the cross tabulation.

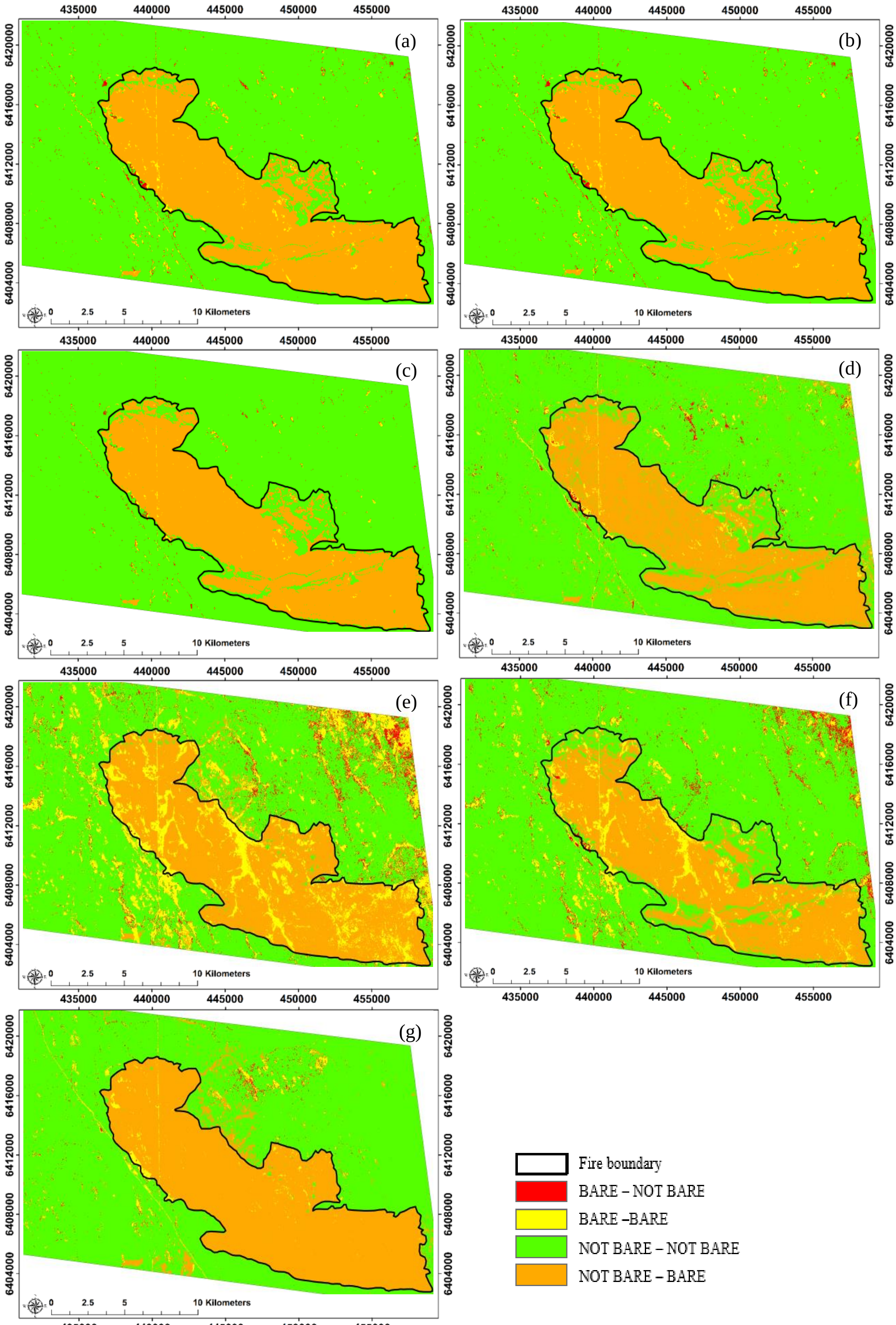

Figure 4. 8 The results from cross tabulation between pre and post fire images: a) NDVI; (b) SAVI; (c) $MSAVI_2$; (d) EVI; (e) NBR; (f) NDII (g) Maximum likelihood

4.4. Discussion

4.4.1 Signature

It is the change in the spectral characteristics of vegetation after fire that enables mapping of fire scars. Damage to plant tissues, with loss of chlorophyll, along with build-up of charred vegetation in the biomass as a result of fire, leads to a drop in reflectance in the near infra-red, and an increase in reflectance in SWIRII. These findings correspond with results reported by Chuviec and Congalton (1989) and White *et al*. (1996). The findings of this study suggest IR and SWIRII are more suitable for mapping burn scars. This result coincides with the majority of studies researched. Thus, NBR is the more commonly chosen index and provides the most accurate results in burn scar mapping and mapping of fire severity (van Wagtendonk *et al.* 2004; Key and Benson 2006; Miller and Thode 2007; Sunderman and Weisberg 2011). In this case study, SAVI, MSAVI2 and NDVI showed similar accuracy to NBR, which use the bands that highlight the greatest change in spectral signature.

4.4.2 Evaluation of vegetation indices

The use of a ROC Curve has been employed as an alternative technique in the comparison of results produced by various indices for mapping fire scars. The results indicate that NBR (0.846), MSAVI2 (0.848), SAVI (0.848) and NDVI (0.848) can give similar results in the mapping of fire scars in this study area. NBR proved to be the most accurate – these findings are in agreement with many other studies that backed up the remotely sensed data with field study proofing (Miller and Yool 2002; Brewer *et al.* 2005; Cocke *et al.* 2005; Epting *et al.* 2005; Key 2006; Parson *et al.* 2010), while MSAVI and SAVI can also provide accurate results as the actual vegetation type can be factored in. In future planned research for the mapping of fire severity in similar topography and vegetation types, NBR with MSAVI2 or SAVI will be used.

Statistics of the AUC summarised over all the indices with the highest potential for discriminating between the burned/unburned area, NBR mean AUC=0.846, SAVI mean AUC=0.848, NDVI mean AUC=0.848, MSAVI2 mean AUC=0.848, making these the most reliable of those tested. The worst performing index was EVI (mean AUC=0.72). The AUC of the four more popular indices tested, showed no significant differences (α=0.05).

4.4.3 Comparison between the chosen indices

Many researchers have used a single-scene image for mapping fire scars using a variety of techniques. The results from this study show that NBR and SAVI/MSAVI2 (AUC 0.848 for all), can be used with reliable outcomes over this landscape type. The majority of studies reviewed suggest NBR as the most reliable (Escuin *et al.*2008; Fox *et al.* 2008; Miller & Thode 2007; Thompson *et al.* 2007). SAVI and MSAVI2 have been used less frequently in previous studies for both fire scar mapping and fire severity assessment, but in this study they were each shown to give similar results to NBR for fire scar mapping. Key and Benson (1999) and Miller and Yool (2002) also found that NBR was more closely related to in-field estimates when assessing burn severity and when mapping fire scars using bi-temporal images.

On testing across a range of landscape types in Alaska, Epting (2004) found that NBR from a single date image provided highest correlations when compared with field data for mapping fire scars but when assessment of fire severity was required, the optimal approach was in the use of bi-temporal NBR values. Epting (2004) went on to suggest that the NBR could become a standard tool for mapping fire.

In this study the results from the NDVI were nearly identical to SAVI and MSAVI2. The NBR uses NIR and SWIR sections of the electromagnetic spectrum to exploit sensitivities of moist, photosynthetically active green vegetation. The NIR band detects high values of reflectance when vegetation is dense and grows vigorously and thus many leaves reflect NIR wavelengths due to their internal structure (Sabins 1996). The reflectance in NIR (which responds to the chlorophyll content in the vegetation) has been demonstrated to be lower after fire, while the SWIR regions that comprise band 7, have been shown to have the largest increase in reflectance after fire (due to the reduction in moisture content), (van Wagtendonk *et al*. 2004, Miller and Thode 2007).

NDVI is chosen as it can correctly use specific bands that are involved in the physiological characteristics of the vegetation such as moisture and chlorophyll content (Pettorelli *et al.* 2005). It relies on the relationship between increased absorption in the visible red range and the increased chlorophyll content of the leaves (Lichtenhaler *et al.* 1998), and this is combined with increased absorption in the near infrared region. Vegetation stress, such as fire affected foliage, decreases the ability of the plant to reflect heat and NDVI demonstrates this (Guerschman *et al.* 2003). Yilmaz *et al*. (2008) revealed that variations occur in the average NDVI values across a variety of landscape types, for example, it is higher in evergreen forest and woodlands and the lowest in shrublands. It does, however, have limitations in that it is affected by soil moisture, making options like SAVI and MSAVI a better choice (Chafer *et al*. 2004; Hammill and Bradstock 2006). Also in agreement with them, when looking at mapping burn severity, Rogan and Yool (2001) indicated that SAVI and MSAVI performed better than NDVI.

The results for the effectiveness of EVI and NDII in assessing fire scars were markedly different from the previous four indices. EVI has its uses when mapping canopy and understory vegetation (Gao *et al*. 2000) but the large amount of bare ground after fire within the landscape in this study area was expected to limit the effectiveness of EVI. In Figure 4.8 d, 4.8 f, it is clear that EVI and NDII, are showing a moderate sized area of burned forest and shrubland as “unburned” when the other indices are registering the area as burned.

4.4.4 Cross tabulation

The expectations from this study were that the bi-temporal approach of using a pre-fire image and a post-fire image would provide the optimal results when applying the indices to the raw data. The use of cross tabulation between the two images is demonstrating that NDVI, SAVI, MSAVI2 and NBR showed no significant difference in the results for mapping of fire scars in this landscape. However, NDII and EVI displayed a marked difference in results across both testing criteria. The refined results, using the bi-temporal imagery, is most probably because of the increased range of the values that assisted the class separation which in return improved the discrimination. The change detection capabilities provided a clearer understanding of the alteration to the landscape, where the single image can only give a picture of what the landscape post fire was like. Thus the two image approach would be better for mapping fire scar and fire severity while the single image method is limited to fire scar mapping.

4.5. Conclusions

Remote sensing as a means of mapping fire scars and fire severity using a range of spectral indices to accurately depict damage to vegetation over vast areas in countries like Australia where the topography makes on-ground assessment expensive, time consuming and labour intensive is a valuable tool in fire risk and damage assessment.

Six indices have been assessed for mapping fire scars on a site in the SWAFA. From the results it is clear that of the vegetation indices, MSAVI2, SAVI and NDVI can provide accurate results along with the fire index NBR. NDII and EVI proved to be less accurate. The performance of each of these indices gives similar outcomes and makes them reliable in the remote sensing of vegetation damage caused by fire in the diverse vegetation classes in and around the Monadnocks Nature Reserve. These results suggest they can be equally effective in the mapping of fire scars and fire severity and support the use of these various indices in fire damage assessment globally. Based on the analysis of the data, NBR, MSAVI2, SAVI and NDVI would be the recommended techniques of choice.

Post fire, the increased area of exposed bare ground increases reflectance in SWIR. The changes to the structure of the vegetation and the vegetation activity will result in a decrease in the near infra-red reflectivity. The majority of indices use the differentiation in the NIR and SWIR reflectance values, firstly to identify the physiologic changes in the vegetation and soil after fire and secondly to quantify them. Classification techniques such as NDVI, SAVI, MSAVI2, and NBR use a variation of band differences (NIR and SWIR) to assess the alteration to reflectance values in images both pre and post fire and as such make them a suitable tool in fire assessment.

Based on the outcomes from this study, the bi-temporal imagery provided the superior data when the indices were tested and fire mapping was complete. While both the single image and the two image techniques provided adequate results for fire scar mapping, the bi-temporal option provided clearer differentiation and would be recommended as the option of choice when mapping fire severity in this landscape.

4.6 Summary

A variety of indices have been designed and used for mapping fire scars and fire severity over differing landscapes globally. Remote sensing has also been widely used for assessing fire. This study looks at which of the indices will provide the optimal results over the varied topography of an area like Mt Cooke, in the south west of Western Australia, in assessing fire damage after the 2003 wild fire that decimated this area. Two methods of mapping the fire scar and assessing the fire severity were tested – a single post-fire image and a set of a pre-fire image and a post-fire image all derived from Landsat

ETM+. At this site three landscape classes of shrubland, forest and bare ground have been chosen to assess the effectiveness of six chosen indices in mapping fire scars and assessing fire severity. The vegetation of the area is heterogeneous, shrubland around granite outcrops, within a generally forested landscape. Initially, scientific publications involving remote sensing for fire mapping and fire severity from 1990-2012, were reviewed. Based on this review, four commonly used indices and two less frequently used indices were tested. Results from ROC curve statistical analysis revealed that the top four indices produced equivalent area under the curve (AUC statistics), (AUC = 0.85) suggesting that any of the top four indices – NBR, SAVI, MSAVI2 and NDVI, could be used to map fire scars with a similar accuracy in this area. EVI produced an AUC = 0.72 and proved less reliable due to the registering of the blue band which in the areas of granite and exposed soil gave unreliable results. NDII produced an AUC= 0.80, thus may not perform well on the granite component. The results from the comparison between the pre-fire and the post-fire image set provided the best results in this study. The maximum likelihood classification technique was performed on the two image set with 120 GPS points from the field and maps were produced for each of the three classes, with an overall accuracy score of 80% and Kappa was 0.79.

Chapter 5:
Mapping fire severity and recovery rates on Mt Cooke and surrounds (2000-2012).

5.1 Introduction

Fire is an intrinsic part of ecosystems around the world (Bowman *et al.* 2009; Koutsias *et al.* 2012). Fire is more widespread than any other natural disruption and inappropriate fire regimes may cause local vegetation community degradation (Ichoku *et al.* 2008; Amraoui *et al.* 2013) with 200-500 million hectares burned annually across the globe (Amraoui *et al.* 2013). Fire regimes influence vegetation distribution patterns and plant structure (Bond *et al.* 2005; Bond and Keeley 2005; Cowling *et al*. 2005). Some species in Mediterranean type ecosystems (MTEs), such as that of the South Western Australian Floristic Region (SWAFR), have developed adaptions to fire (Pausas *et al*. 2004; Pausas and Verdú 2005; Pausas *et al.* 2006; Pausas and Keeley 2009). These adaptions include serotiny, resprouting and the germination of seed stored in soil which is stimulated by fire and/or smoke (Roche *et al*. 1997; Thomas *et al.* 2003; Flematti *et al*. 2004; Enright *et al*. 2007; Dayamba *et al.* 2008; Keeley *et al*. 2011).

The SWAFR is an area of global importance due to high levels of species richness and endemism (Hopper and Gioia 2004). This Mediterranean climate region has nutrient deficient soils and occurs in an ancient, weathered landscape (Hopper and Gioia 2004). This area includes scattered granite outcrops through the region which are surrounded by forest and shrublands, in a patchy mosaic of vegetation (Doronila and Fox 1997; Hunter and Clarke 1998; Watson *et al*. 2008). The risk to these areas from catastrophic fire requires a better understanding of fire severity and how it impacts the successional recovery of areas over time, after such fires. Fire severity rating is an estimation of the damage caused to an ecosystem after it has been burned (De Santis and Chuvieco 2009). Lentile *et al.* (2006) has suggested that fire severity or burn severity have a change in terms to something like "active fire characteristics" and "post- fire effects". The damage impacts not only the vegetation (with plant and tree mortality and a loss of biomass), but it may cause increased soil temperature and consumption of the organic ground materials (French *et al.* 2008). It is difficult to add an empirical measure as the fire intensity is often not able to be assessed at the time, however, Keeley (2009) proposed the amount of loss to organic matter as a better measure of the fire severity. Forest stands are often the regions that are most effected by high severity burns. These effects can be both immediate as well as successional (Jakubauskas *et al*. 1990).

The climate in the SWAFR is experiencing a warming and drying trend (IOCI 2012; Delworth and Zeng 2014). This will have a flow-on effect of rising susceptibility to wild fire due to the increased time that fuels were able to dry out (Whitlock *et al.* 2003). These fire disturbances may become more frequent and of greater intensity and duration as the fire seasons lengthen and extreme weather conditions impact the area (Flannigan *et al.* 2000; Mouillot *et al*. 2002; Westerling *et al.* 2006; Pitman *et al*. 2007). An ongoing challenge in fire management is to adopt a fire regime that is effective in protecting this species rich ecosystem, such as a program of prescribed burns to reduce fuel loads and lessen fire intensity, without impacting the growth cycles of these endangered species.

The high cost of rehabilitation and post-fire stabilisation associated with the damage caused by wildfires in threatened ecosystems urges the study of the initial fire damage on the ecosystem. There is also a need to monitor post-fire regeneration in specific regions to pre-empt many aspects of fire and land management from both decision making aspects as well as the overall costs for helping to protect areas such as this (Gouveia *et al*. 2010; Petropoulos *et al*. 2014). Ecological restoration for this area should focus on the maintenance of biodiversity and protection from invasive species in the newly disturbed areas (Richardson *et al.* 1992; Milberg and Lamont 1995; Keeley 2001).

The Landsat series of satellites provide spatial, spectral and temporal data for vegetation regeneration monitoring, and are now used worldwide across differing ecosystems (Kalivas *et al*. 2013). The use of these systems for the monitoring of post-fire regeneration, however, is a more recent practice. The mapping of fire severity and the regeneration of the vegetation after large scale wildfire using remote sensing may provide an effective option for broad scale monitoring of locations that are remote or difficult to access due to complex topography, such as on granite outcrops. The data collected from such research may assist in predicting ecosystem recovery following future wildfire events and identifying areas susceptible to land degradation as a result of the fire, allowing for the planning of rehabilitation strategies. There has only been a limited body of research that examines the monitoring of long term post fire recovery of vegetation on granite outcrops in the SWAFR that focuses on fire severity and its relationship with post-fire recovery over time.

The Normalised Burn Ratio (NBR) proved to be a reliable method for assessing fire severity in MTEs (see Chapter 4) and will be used to map of the fire severity. The alteration to green vegetation by fire is a visible impact that is a known method in burn severity analysis. The NBR and differenced Normalised Burn Ratio (dNBR) have been used in the mapping of fire severity and vegetation recovery rates in the short term (López-Garcia and Caselles 1991; Key and Benson, 2003).

The Normalised Differenced Vegetation Index (NDVI) has been used more widely in the monitoring of the vegetation recovery rates over the longer term (Hope *et al*. 2007; Roder *et al*. 2008), as it is more specific for measuring the greenness in the recovering vegetation – the burned vegetation containing no chlorophyll and the regenerating vegetation is green with chlorophyll. A less frequently used index is the Regeneration Index (RI) (Riano *et al*. 2002), which is used in the assessment of post-fire vegetation recovery.

A major fire event occurred in the SWAFR in the Monadnocks National Park in 2003, which was started by lightning on the upper reaches north of Mt Cooke. This study aims to 1) assess fire severity and 2) assess rates of vegetation recovery over ten years to identify the period of time required for recovery for differing fire severity classes. It is expected that the level of fire severity may affect the rates of regeneration of the vegetation – the vegetation recovery is not expected to be uniform over the whole study area as the dynamics of regrowth will vary continuously after the fire and be impacted even further by variations in vegetation types on different areas of the outcrop. In measuring the rate of recovery over time, it is hoped that areas with regeneration problems may be quickly identified so that potential high risk areas can have strategies put in place to conserve the biodiversity that makes this particular ecosystem unique

5.2 Study Area and Dataset

5.2.1 Study Area

The study area is located in the Monadnocks Conservation Reserve in Western Australia, (Figure 5.1). For further details please refer to Chapter 3.

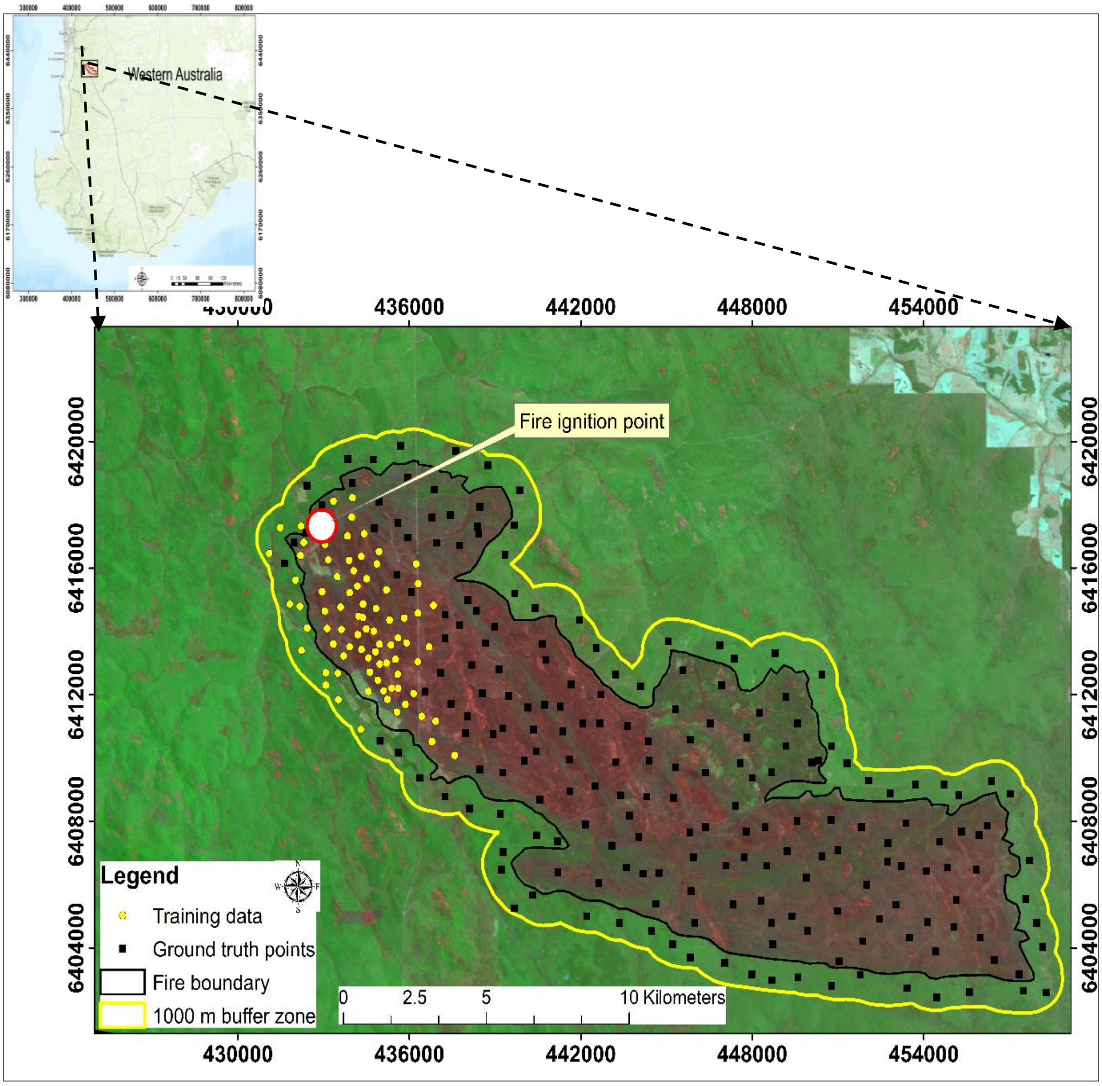

Figure 5.1. Location of the study area with a Landsat ETM+ 7 image (R = band SWIRII; G = band NIR and B = band Red. The red pixels show the fire scar. The yellow boundary is a 1 km buffer around the fire scar which is used to provide data on unburnt locations.

5.2.2 Remote Sensing Data

Moderate resolution imagery from Landsat provided the base data and fire severity assessment was made of both pre-fire and post-fire vegetation with a biennial, comparison (close to anniversary date) to monitor post-fire recovery. USGS Earth Explorer Landsat 5 and Landsat 7 ETM+ archive data images form the data set used. Four data images have been selected – one pre and four post-fire – for the mapping of fire severity during 2003, these image dates were chosen to avoid images that were contaminated with cloud (images from April to August were all excluded due to cloud) (Table 5.1). For vegetation recovery, the images of the study area taken for January from the years 2002 to 2012 were Landsat TM and ETM (and as such this reduced the need for considering the effects of varying solar zenith angles).

Table 5.1. Data set image acquisition dates, platform, sensor and source

Study Aim	Description	Image Date	Path / Row	Sensor
Fire severity	Five days pre- fire	4/01/2003	112/82	ETM+
	Ten days post-fire	20/01/2003	112/82	ETM+
	One month post-fire	22/02/2003	112/82	ETM+
	Eight months post-fire	1/09/2003	112/82	ETM+
	One year post-fire	22/12/2003	112/82	ETM+
Vegetation recovery	One year post-fire	15/01/2004	112/82	TM
	Two years pre- fire	28/01/2000	112/82	ETM+
	Three years post-fire	20/01/2006	112/82	TM
	Five year post-fire	26/01/2008	112/82	TM
	Seven year post-fire	23/01/2010	112/82	ETM+
	Nine year post-fire	29/01/2012	112/82	ETM+

The fire severity assessment data was determined by the total of the entire burned area within the fire scar of the study area, which includes islands of vegetation that survived unburned and an area of unburned vegetation from a 1000 m buffer zone around the perimeter of the fire.

5.2.3 Ground truthing

A collection of photographs taken by Neil Burrows have been used in the ground truthing for this study. He provided photographs taken one week after the fire and at intervals up to six months after the fire on and around the Mt Cooke fire scar. Many of the features photographed were identifiable on field trips made in 2012 - 2014 and plotted on the fire scar with GPS points. From the photos provided, about 100 plots were identified in different classes (unburned, low, moderate and high severity) and have been able to be identified in the field trips for use in this study. Others are used as descriptives for the damage on and around the granite outcrop.

5.3 Methodology

5.3.1 Pre-processing

All satellite imagery was subject to radiometric and atmospheric correction: (absolute atmospheric correction was performed using ENVI's atmospheric correction module FLAASH (Fast Line-of-sight Atmospheric Analysis of Spectral Hypercubes) within ENVI (2015). There was no impedance caused by cloud cover in any of the images used.

5.3.2 Severity analysis

5.3.2.1 Normalised Burn Ratio (NBR)

Chapter 4 concluded that the NBR index can be used effectively for mapping fire severity and vegetation recovery rates in this environment. The NBR was calculated by using Equation (1) for each image comparing the control unburned plots with the burned plots from the same image (López-Garcia and Caselles 1991; Key and Benson 2003; Cocke *et al*. 2005). The NBR value ranges between -1 to +1, where zero corresponds with an absence of vegetation. From photos of the post-fire vegetation, 100 plots were located within each fire severity class. The pixel values for the NBR maps were subtracted using ArcGIS and graphed (Figure 5.3). The 100 plots were used as the base for statistical analysis using two-way ANOVA to determine any significant differences between each of the NBR maps.

(NBR) = (Band 4 – Band 7) / (Band 4 + Band 7) Equation (1)

Where

Band 4 = Near Infrared; Band 7= Short Wave Infrared

5.3.2.2 Differenced Normalised Burn Ratio

The Differenced Normalised Burn Ratio (dNBR) can be defined as the difference between two images – the pre-burn image and the post burn image – Equation (2) (Key and Benson 2003; Cocke *et al.* 2005; Epting *et al*. 2005 Key and Benson 2006). It can also differentiate the levels of fire severity within a specified area (Brewer *et al.* 2005; Cocke *et al.* 2005; Key and Benson 2006; Eidenshink *et al.* 2007; Safford *et al.* 2009). A negative value represents increased vegetation cover for unburned areas while a positive value represents decreased vegetation cover or burned areas.

(dNBR) =NBR-Pre – NBR-Post Equation (2)

Where

NBR-pre = NBR 04/01/2003; NBR- post= NBR 20/01/2003

The pre and post-fire images from five days, ten days, one month, eight months and one year post-fire were processed and the fire severity maps produced were classified into four severity classes: unburned, low, moderate and high severity burn (as per Key and Benson 2006) with the thresholds as described in (Table 5.2). The same threshold was then applied to each of the two pre-determined vegetation classes (shrubland and forest).This data were used to subtract NBR and dNBR values and the data used for statistical pairwise analysis. An analysis of variance for the NBR results for each of the three fire severity classes was undertaken to identify the differences in the NBR value for each class across the first year post-fire.

Table 5.2. dNBR fire severity thresholds, after Key and Benson 2006

dNBR	Burn Severity
-0.2 - 0.1	Unburned/ Recovered
0.1 - 0.27	Low-severity burn
0.27 - 0.44	Moderate-low severity burn
0.44 - 0.66	Moderate-high severity burn
> 0.66	High-severity burn

5.3.2.3 Relative differenced Normalised Burn Ratio (RdNBR)

An alternative to the NBR is the RdNBR (Key and Benson 2006; Miller and Thode 2007). It was developed to enhance performance across open vegetation types – Equation (3), (Miller and Thode 2007). The severity of the fire damage on the ecosystem is determined when the post-fire image is subtracted from the pre-fire image. Once this bi-temporal differencing is completed, the burned area will have high values in the dNBR and the RdNBR maps. The RdNBR will measure the significance of relative change in the pre-fire vegetation by dividing the dNBR by the square root of the absolute value of the pre-fire NBR (Miller and Thode 2007).

$$\textbf{(RdNBR)} = (\text{NBR-pre - NBR-post}) / \sqrt{(\text{abs (NBR} - \text{ pre}))} \qquad \text{Equation (3)}$$

Where

NBR-pre = NBR 04/01/2003; NBR- post= NBR 20/01/2003

5.3.2.4 Composite Burn Index

To integrate post-fire variations, the Composite Burn Index (CBI), as developed by Key and Benson (2005), was applied to photos taken of the study area post-fire as a visual assessment, some were plotted on the study area and can be seen displayed on the map as yellow points (Figure 5.1). The data base photos were located in relation to the GPS points across the study area and from these a visual assessment was made (Key and Benson 2006; Westerling and Bryant 2008; Parsons *et al*. 2010; Harris *et al.* 2011) to determine the threshold points for fire severity classes in the RdNBR maps. The individual results for each photo were later combined to determine an overall fire severity value (van Wagtendonk *et al*. 2004; Cocke *et al*. 2005).

The determination of the threshold levels fall into four classes – unburned, low, moderate and high severity burn with breakpoints for every class having been defined based on CBI data for the photos. A scatterplot of results for RdNBR and CBI was performed and the same threshold was then utilised for all vegetation types. There is no field data for the pre-fire condition of the plots used (other than that they were unburned), thus the CBI assessments were utilised to set the thresholds in this study. The levels of fire severity in the photos used were visually assessed and scored 0 – 3 (0 = unburned, 0.1 – 1 = low severity burn, 1.1 – 2.0 = moderate severity burn and more than 2.0 = high severity burn). As this was a retrospective study, study site photographs were used for ground truthing along with a personal statement from Neil Burrows (Senior Principal Research Scientist, DEC).

5.3.2.5 Validation

An accuracy assessment was performed to confirm the data quality: Photos taken by N Burrows in 2003 immediately post-fire, were located on site with GPS positions and linked with 25 high severity burn results and 25 moderate severity burn results. These sites were then revisited in 2012-2014 for ground truth. Photos by N Burrows from 55 further sites were also located in GPS in areas of low severity burns and unburned areas. A confusion matrix and classification report was then generated for each image. The confusion or error matrix is described by Congalton and Green (1991, 2009). Another accuracy assessment was applied using Kappa coefficient as this can determine if one confusion matrix is significantly different from another and also caters for chance (Congalton 2001; Foody 2010).

5.3.3 Analysis of Variance

To analyse the NBR across different vegetation types, 100 plots were chosen at random in the unburned areas. A further 200 plots were randomly selected from the burned areas in both the class categories of shrubland and forest – 100 plots in each class. To assess short term recovery, an analysis of variance was applied to determine if the results for the NBR values remained the same over time and if not, where the significant differences were occurring.

Repeated Measurement Analysis of Variance **(**R-M ANOVA) was used to assess differences between NBR values over time. In this case, where the measurements are repeated over a set time frame, in each assessment the independent variable is time. The comparisons are produced for five days, ten days, one month, six months and one year time lapses to determine if time does influence the NBR value. The null hypothesis is that there is no significant difference in the NBR value over time.

Mauchly's Test or Sphericity: Sphericity refers to the parity of the variances of the differences between levels of the repeated measures. The differences between each pair of levels of the repeated measures are calculated to determine the differences and then the variances are calculated. The equations, (4 and 5), for Mauchly's test statistic W, given in Huynh and Feldt (1970), are as follows:

$$W = |CSC'| / (\text{trace } CSC' / p)^{p} \qquad \text{Equation (4)}$$

$$X^2 p\left(\frac{p+1)}{2-1}\right) = -(N-g)\left[1 - \frac{2p^2+2+p+2}{6p(N-g)}\right]\ln(W) \qquad \text{Equation (5)}$$

where

g =the number of groups; N = the number of subjects; C = a contrast matrix with p rows suitable for testing a main effect or interaction; S = a k-by-k matrix of the pooled group co-variances. Note that usually, p equals the degrees of freedom of the corresponding term.

Assessing Sphericity: When conducting repeated measurement, ANOVA was used to evaluate the hypothesis that all variances of the differences between the stated conditions are equal. The interpretation of the results is unequivocal – when the significance level, (p value), is less than 0.05 the null hypothesis is rejected. When the significance level is greater than 0.05 the null hypothesis is accepted.

5.3.4. Regeneration analysis

5.3.4.1. Normalised Differenced Vegetation Index (NDVI)

NDVI has been the commonly used index from the 1970s – for mapping vegetation (Rouse *et al.* 1973). It is an expression that corresponds to the amount of photosynthetically active vegetation – Equation (6). NDVI has a confirmed relationship to changes in biomass across a wide variety of ecosystems (Soudani *et al.* 2012).

$$\text{NDVI}=\frac{NIR-RED}{NIR+RED} \qquad \text{Equation (6)}$$

Where

Band 4 = Near Infrared; Band 3= Red

NDVI values range from -1 to +1, where 0 to -1 represents an absence of vegetation (Petorelli *et al.* 2005). Once the NDVI assessment was complete, the analysis of the regeneration was performed by comparing the pre-fire NDVI spatial pattern to the post-fire pattern and these results exposed the extent of the post-fire recovery. From the images, a series of descriptive statistics were refined for the NDVI results from the burned and unburned plots.

In the analysis of vegetation recovery rates, images were taken on alternate years from 2000 to 2012 and are presented in (Table 5.1). An appraisal of the vegetation recovery dynamics was performed based on the NDVI (Band 3 and Band 4) and Regeneration Index (RI). For the vegetation recovery rates, the pre-fire NDVI was compared to the post-fire NDVI – this permitted the rate and the extent of the post-fire recovery to pre-fire levels to be determined. When comparing the images, plots with similar characteristics were chosen across the shrubland and forest classes, 50 plots within the burned regions and 50 plots within the control unburned regions were identified in the same image in each of these vegetation type classes.

5.3.4.2. Post-fire vegetation regeneration based on Regeneration Index (RI)

The post fire regeneration was assessed using the RI. To complete this, the NDVI values between the 50 unburned control plots are compared to the values from the 50 burned plots from the same image across the four burn severity classes within a similar vegetation type (shrubland and forest), (Riano *et al.* 2002). The mean NDVI values of each area is calculated and divided by the mean NDVI values from the control plots (Díaz-Delgado *et al.* 2002; Lhermitte 2007) using Equation (7):

$$\text{RINDVI}=\frac{NDVI\ burned}{NDVI\ unburned} \qquad \text{Equation (7)}$$

Where

NDVI burned means there is fire and unburned represents no fire.

The RI provides a value from 0 – 1 and these values are characteristic of the percentage of recovery.

5.3.5 Change detection

Change detection using remotely sensed images involves the comparison of two or more images from differing dates so that any differences in a variable may be highlighted. The analysis of spectral and spatial attributes of the remotely sensed data is processed to derive the statistics which illustrate any type of change. The process determines if there is a difference in the pixels on two (or more) dates that illustrate either a negative change (such as defoliation), or a positive change indicative of regrowth/revegetation.

The NDVI and NBR indices were produced and change detection (image differencing) was applied. Firstly, the NBR values, five days pre-fire, were subtracted from ten days post-fire, one month post-fire eight months post-fire and one year post-fire to produce a residual image which represented the changes. Secondly, the NDVI value two years pre-fire were subtracted from ten days post-fire, one, three, five, seven and nine years post-fire to produce layers showing the percentage of changes.

5.4 Results

5.4.1 NBR value results

The mean NBR value pre-fire was high (0.25) in the forest and dense shrublands which carried a high biomass prior to the fire. The mean NBR value dropped immediately post-fire in these areas to -0.5 (Figure 5.2). After one month the mean NBR value remains low across the three classes; after eight months it remains low in the moderate and high severity burn areas but in the low severity class it is showing an increase, which by twelve months post-fire is nearly back to its original unburned level. The mean NBR five days pre-fire was 0.14 with a standard deviation of 0.11; on the ten days post-fire the mean NBR was -0.19 with a standard deviation of 0.11; on the one year post-fire the mean NBR was 0.02 with a standard deviation of 0.13, (Appendix1, Table 1).

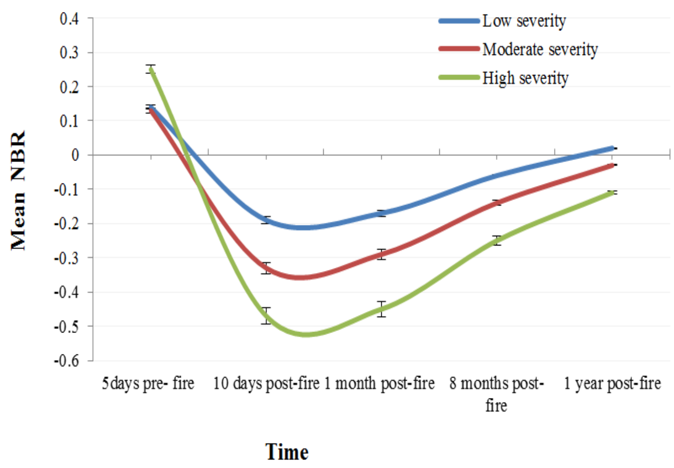

Figure 5.2. Graph of the mean NBR from 100 plots across time

5.4.2 Analysis of Variance for the NBR results between each of the severity classes across four pairs of images

A repeated measures analysis was conducted to evaluate the null hypothesis that there is no significant change in the NBR value over time when measured before and after fire (N=100). The outcome, according to Mauchley's test of Sphericity however, indicates significant differences between those NBR values.

The initial hypothesis was that there would be no significant difference in the post-fire NBR values taken over time in the first year. However, it was found that there were no significant differences in the image comparison results for ten days post-fire with one month post-fire – making this the ideal time to record the NBR for post fire vegetation assessment across all three fire severity classes. The remaining comparison dates were all displaying significant differences.

Follow-up comparisons in the low severity class indicate that the only significant differences, pairwise, ($p < 0.05$), are from five days pre-fire with ten days, one month, and eight months post-fire. There was no significant difference between NBR five days pre-fire with one year post-fire which suggests that the NBR value increases over time as the vegetation regenerates (Table 5.3).

In the moderate severity class, the results show the mean NBR for five days pre-fire was 0.13 and on ten days post-fire was -0.33; both with a standard deviation of 0.08. The mean NBR on the one month post-fire was -0.29 with a standard deviation of 0.08. ANOVA was conducted to evaluate the null hypothesis that there is no significant change in the NBR value over time when measured before and after fire (N=100). The results indicate significant differences between NBR values over time according to Mauchley's test of Sphericity (Table 5.3). Follow-up comparisons for the moderate severity class indicate that the only differences, pairwise, that are significant (where $p < 0.05$), are from five days pre-fire with ten days; one month; eight months and one year post-fire and ten days post-fire with one year post-fire. There was no significant difference between NBR ten days post-fire and one month post-fire. These results also support the initial hypothesis.

Within the high severity class, the results show that the mean NBR on the five days pre-fire was 0.25 with a standard deviation of 0.07; ten days post-fire the mean NBR was -0.50 with a standard deviation of 0.03 and on one year post-fire the mean NBR was -0.11 with a standard deviation of 0.07. R-M ANOVA was conducted to evaluate the null hypothesis that there is no significant change in the NBR value over time when measured before and after fire (N=100). Follow-up comparisons indicate that there are significant differences, pairwise, across all the results, where $p < 0.05$ (Table 5.3) with the exception of ten days post-fire when compared to one month post-fire. The initial hypothesis was that there would be no significant difference between ten days to one month post-fire and this is supported by the result as shown in (Table 5.3). The comparison between the ten days post-fire image and one year post-fire image was expected to show significant differences and this is supported by the data displayed in (Table 5.3).

Table 5.3. The results of pairwise comparisons for NBR across time for the fire severity classes

	Image 1	Image 2	Mean Differenc e	Std. Error	P- value	Within Subjects Effect	Mauchly's W	χ^2	df	P-value
	NBR 5 days pre- fire	NBR 10 days post-fire	0.20	0.01	0.00					
	NBR 5 days pre- fire	NBR 1 month post-fire	-0.20	0.01	0.00					
	NBR 5 days pre- fire	NBR 8 months post-fire	0.20	0.01	0.00					
	NBR 5 days pre- fire	NBR 1 year post-fire	0.01	0.01	0.87					
Low severity	NBR 10 days post-fire	NBR 1 month post-fire	-0.01	0.01	0.99	NBR/ time	0.55	151	9	0.0
	NBR 10 days post-fire	NBR 8 months post-fire	0.12	0.01	0.00					
	NBR 10 days post-fire	NBR 1 year post-fire	-0.08	0.01	0.03					
	NBR 1 month post-fire	NBR 8 months post-fire	0.19	0.01	0.00					
	NBR 8 months post-fire	NBR 1 year post-fire	0.13	0.01	0.00					
	NBR 5 days pre- fire	NBR 10 days post-fire	0.37	0.01	0.00					
	NBR 5 days pre- fire	NBR 1 month post-fire	0.36	0.02	0.00					
	NBR 5 days pre- fire	NBR 8 months post-fire	0.18	0.01	0.00					
	NBR 5 days pre- fire	NBR 1 year post-fire	0.11	0.01	0.00					
Moderate severity	NBR 10 days post-fire	NBR 1 month post-fire	-0.01	0.01	0.46					
	NBR 10 days post-fire	NBR 8 months post-fire	-0.19	0.01	0.00	NBR/ time	0.125	144	9	0.0
	NBR 10 days post-fire	NBR 1 year post-fire	-0.26	0.01	0.00					
	NBR 1 month post-fire	NBR 8 months post-fire	-0.18	0.01	0.00					
	NBR 8 months post-fire	NBR 1 year post-fire	-0.25	0.02	0.00					
	NBR 5 days pre- fire	NBR 10 days post-fire	-0.62	0.01	0.00					
	NBR 5 days pre- fire	NBR 1 month post-fire	0.62	0.01	0.00					
	NBR 5 days pre- fire	NBR 8 months post-fire	-0.34	0.01	0.00					
	NBR 5 days pre- fire	NBR 1 year post-fire	-0.19	0.01	0.00					
High severity	NBR 10 days post-fire	NBR 1 month post-fire	0.00	0.01	0.85					
	NBR 10 days post-fire	NBR 8 months post-fire	0.28	0.02	0.00	NBR/ time	0.25	28	9	0.01
	NBR 10 days post-fire	NBR 1 year post-fire	0.42	0.01	0.00					
	NBR 1 month post-fire	NBR 1 year post-fire	-0.20	0.01	0.00					
	NBR 8 months post-fire	NBR 1 year post-fire	0.15	0.02	0.00					

5.4.3 dNBR value results

Maps for the dNBR were produced and fire severity was classified (Figure 5.3). In the comparison of pre and post-fire data, the 1000 m buffer zone has been removed so only the actual fire scar is being assessed. Of the total, 466 ha (2.6%) remained unburned. In the initial recovery period of 12 months post-fire, this unburned and recovered class has increased to 4,312 ha (~24%), showing that some of the low severity burn class regenerated quickly, causing the NBR value to rise to that of the unburned areas. 2,942 ha (~16%) recorded a low severity burn and after the first 12 months, the area has increased to 7,768 ha (~43%), which indicates recovering vegetation growth across this class. Of the total, 8,572 ha (~47%) sustained a moderate severity burn and after 12 months this has decreased to 4,359 ha (~24%). In the high severity class, 5,886 ha (~32%) sustained a high severity burn but within the first year this has now decreased to 1,427 ha (~8%). These percentage changes can be better understood by reviewing (Table 5.4 and Figure 5.3 a and b).

Table 5.4. The total area in % for the control plots and the three burn severity classes

Fire severity	5 days pre-fire –10 days post-fire	5 days pre fire - 1 year post-fire
Unburned / Recovered	2.61%	24.13%
Low severity burn	16.47%	43.48%
Moderate severity burn	47.98%	24.40%
High severity burn	32.95%	7.99%
Total	100%	100%

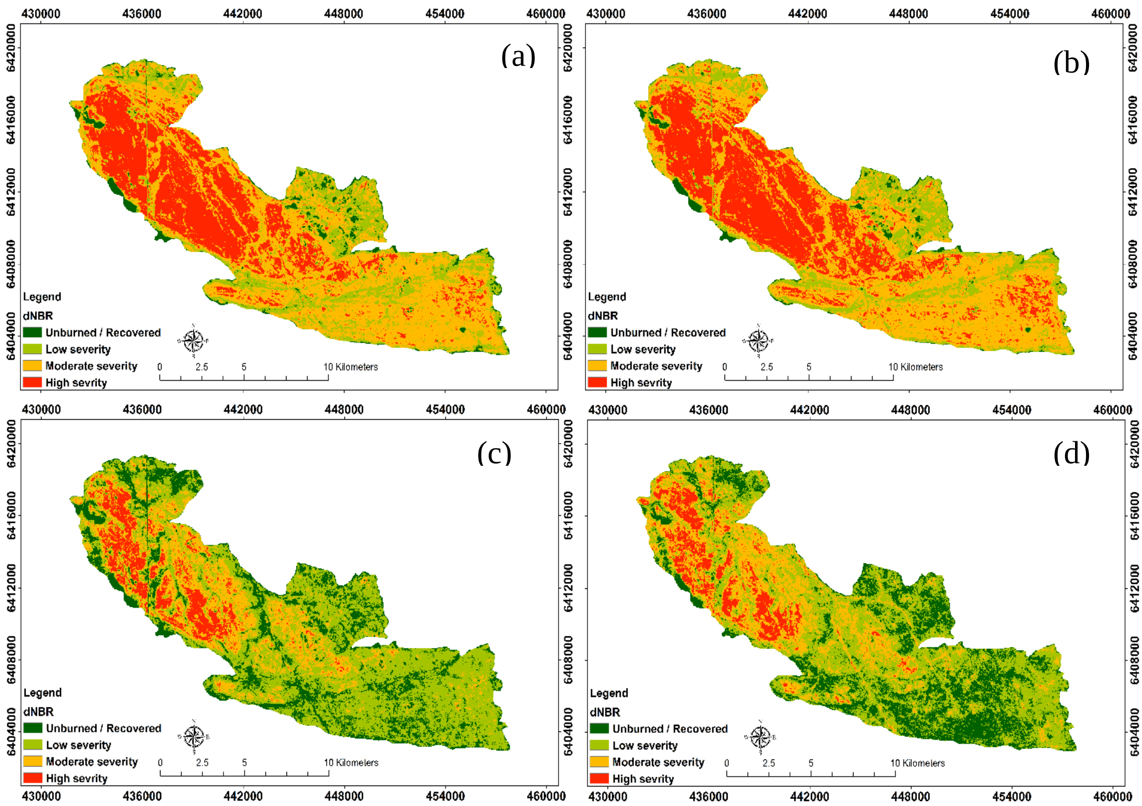

Figure 5.3. The dNBR maps derived using images (a) between the five days pre-fire and ten days post-fire, b) five days pre-fire and one month post-fire, (c) between the five days pre-fire and eight months post-fire, (d) five days pre-fire and one year post-fire.

5.4.4 RdNBR value results

Positive RdNBR values indicate a decrease in the vegetation cover. Whereas, negative results indicate an increase in the vegetation cover, (Miller and Thode 2007). Within the NBR values, a strongly negative result indicates an increase in reflectance from Band seven and a lesser reflectance from Band 4. This can be attributed to the areas that are exposed – the granite and bare soil patches that are particular to this area as they have little to no vegetation cover. The maps of RdNBR (Figure 5.4) show firstly, ten days post-fire and the second is showing the RdNBR results one year post-fire. The areas where there is no vegetation cover – where there is nothing to burn – have resulted in a zero value in the numerator.

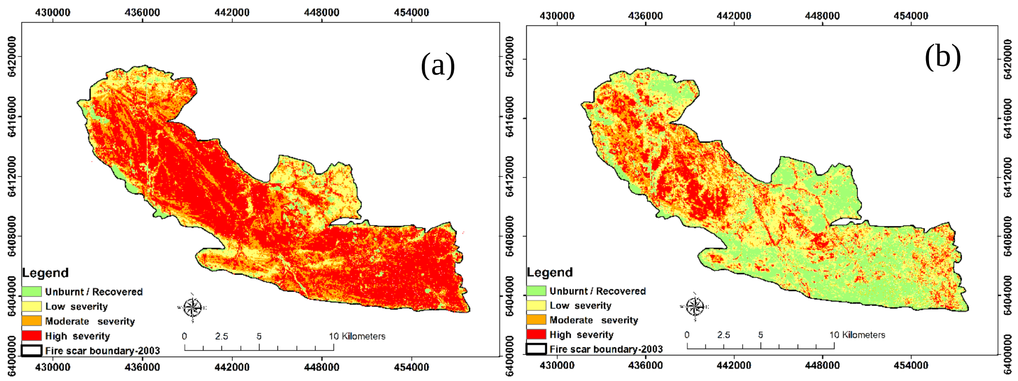

Figure 5.4. RdNBR maps with the results from a) ten days before the fire and b) one year post-fire

5.4.4.1 The relationship between the CBI and the RdNBR values

The RdNBR is strongly correlated with the CBI taken from fire scar photos (R^2 = 0.64, p-value 0.05). The threshold was determined by taking the mean results for both RdNBR and the CBI for each severity class. From the total area of the fire scar on Mt Cooke – 17,870 ha, 4.2% was unburned and 54% of the total burned area which sustained a high severity burn. The threshold points for each class for fire severity were determined by using the mean of the CBI and the RdNBR.

5.4.5 Vegetation and the NBR index

5.4.5.1 Shrubland

The mean and standard deviation of NBR for burned v unburned pixels are displayed in (Appendix1, Table 2). The unburned pixels' NBR values are 0.15 and standard deviation (sd) of 0.14 throughout the year. The Mt Cooke 2003 fire caused a sudden drop in the burned mean NBR values up to -0.17 (sd 0.14). Six to eight months after the fire the NBR has increased to -0.01 with a (sd) of 0.11. At the end of the first year, the burned pixels' mean NBR was -0.05 with a (sd) of 0.1– which was higher than immediately after the fire (Table 5.5).

Table 5.5. The pairwise comparisons for the shrubland and forest classes

	Image-1	Image-2	Std. Error	P-value	Within Subjects Effect	Mauchly's W	χ^2	df	P-value
	NBR 5 days pre- fire	NBR 10 days post-fire	0.00	0.00					
	NBR 5 days pre- fire	NBR 1 month post-fire	0.01	0.00					
	NBR 5 days pre- fire	NBR 8 months post-fire	0.01	0.00					
	NBR 5 days pre- fire	NBR 1 year post-fire	0.01	0.91					
Shrubland class	NBR 10 days post-fire	NBR 1 month post-fire	0.00	0.07	NBR / TIME	0.20	156	9	0
	NBR 10 days post-fire	NBR 8 months post-fire	0.01	0.00					
	NBR 10 days post-fire	NBR 1 year post-fire	0.01	0.05					
	NBR 1 month post-fire	NBR 8 months post-fire	0.01	0.00					
	NBR 1 month post-fire	NBR 1 year post-fire	0.01	0.21					
	NBR 8 months post-fire	NBR 1 year post-fire	0.01	0.00					
	NBR 5 days pre- fire	NBR 10 days post-fire	0.02	0.00					
	NBR 5 days pre- fire	NBR 1 month post-fire	0.02	0.00					
	NBR 5 days pre- fire	NBR 8 months post-fire	0.01	0.00					
	NBR 5 days pre- fire	NBR 1 year post-fire	0.02	0.00					
Forest class	NBR 10 days post-fire	NBR 1 month post-fire	0.00	0.06	NBR / TIME	0.03	328	9	0
	NBR 10 days post-fire	NBR 8 months post-fire	0.01	0.00					
	NBR 10 days post-fire	NBR 1 year post-fire	0.01	0.00					
	NBR 1 month post-fire	NBR 8 months post-fire	0.01	0.00					
	NBR 1 month post-fire	NBR 1 year post-fire	0.01	0.00					
	NBR 8 months post-fire	NBR 1 year post-fire	0.01	0.00					

The NBR value for each image was investigated to determine if there were significant differences between the results from the data collected immediately after the fire when compared to the NBR values up to the anniversary date with the use of repeated measurement analysis. The results indicate significant differences between NBR values over time, according to Mauchley's test of Sphericity (Table 5.5). The only areas where there is no significant difference in the shrubland, ($n = 100$; $p = 0.05$), was when five days compared with one year and ten days compared to one month and one year post-fire (Table 5.5).

5.4.5.2 Forest

The post-fire mean NBR (sd) time series of unburned and burned areas is similar to what was observed in the (Appendix1, Table 2). The unburned pixels' mean NBR was about 0.29 with a (sd) of 0.08 throughout the year. By the ten days post-fire, the burned pixels' mean NBR dropped to -0.32 (sd) 0.13 (Figure 5.5). Immediately post-fire the difference between the unburned and burned pixels' mean NBR values is high. By the one year post-fire, the mean NBR is -0.03 with a (sd) of 0.13. However, this difference diminished as time elapsed due to the regeneration processes.

The NBR value for each image was investigated to determine if there were significant differences between the results from the data collected immediately after the fire when compared to the recovering growth up to the anniversary date with the use of repeated measurement analysis (Two-way ANOVA) as with the shrubland data. The results indicate significant differences between NBR values over time according to Mauchley's test of Sphericity (Table 5.5). There was only one area that was not significant and this was in the comparison of ten days post-fire with one month post-fire indicating that the forested areas take longer to regenerate (Table 5.5).

After mapping the fire severity and the dNBR map was produced, the fire severity was classified into 3 classes: low, moderate and high severity. Of the forest area, 43% had low fire severity, and 41% of the area had moderate fire severity and around 16% demonstrated high fire severity. In the shrubland areas, 49% had low fire severity, 15% had moderate fire severity and around 5% had a high fire severity (Figure 5.6).

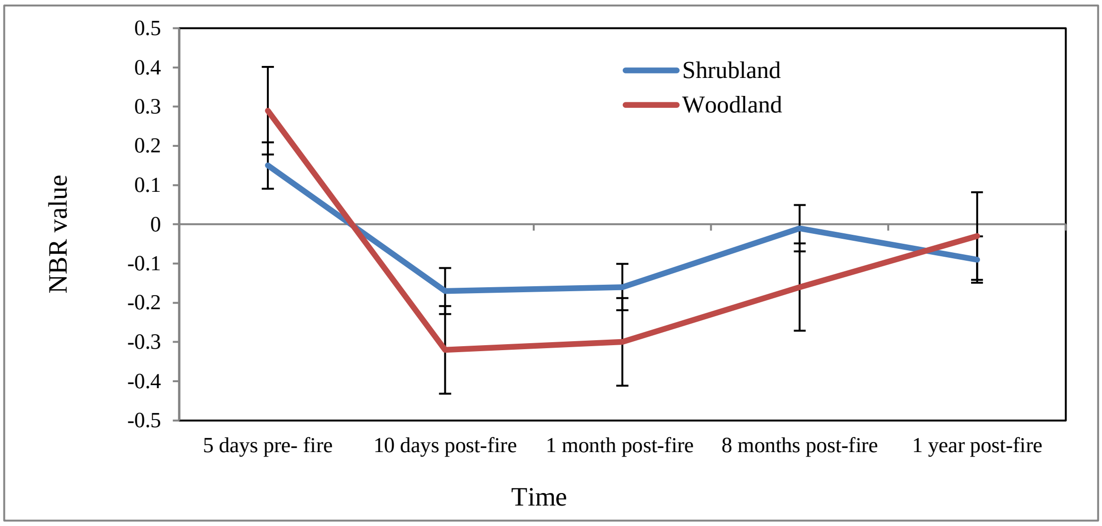

Figure 5.5. The mean NBR value over time in the vegetation classes of shrubland and forest.

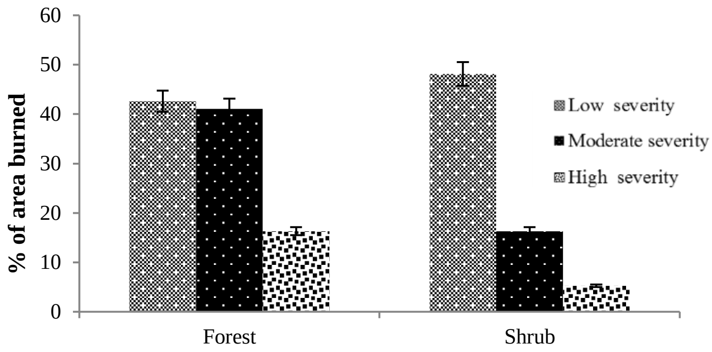

Figure 5.6. Comparison for the percentages of burned area for forest and shrubland classes.

5.4.6 Accuracy Assessment

The results of overall accuracy, user and producer's accuracy and Kappa coefficient for all fire severity classes are demonstrated in (Table 5.6). Overall accuracy for the unburned class was 76% in all images and Kappa was 0.70.

Table 5.6. The mean accuracy assessment results for all images.

	Ground truth							
Predicted	Unburned	Low severity	Moderate severity	High severity	Producer's Accuracy	Users Accuracy	Overall Accuracy	Kappa
Unburned	20	6	0	0	87%	77%		
Low severity	0	18	2	2	62%	82%		
Moderate severity	2	1	22	5	85%	73%	76%	0.70
High severity	1	4	2	20	74%	74%		

5.4.7 Change detection for NBR index maps

The results of the change detection are represented in (Figure 5.8). One to two months after the fire, the change was minimal (Figure 5.7 (a) and (b)) but there is clear differencing between one month versus eight months and one month versus twelve months (Figure 5.8 (c) and (d)).

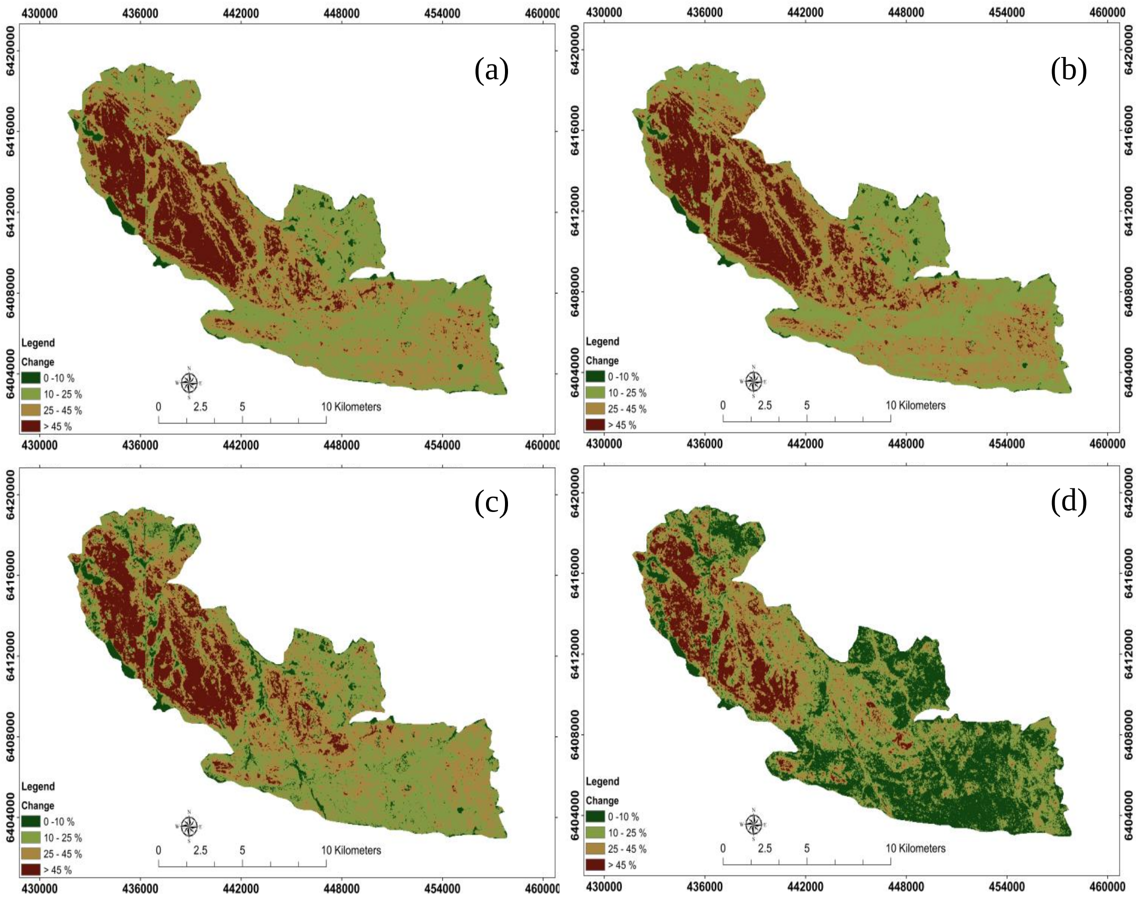

Figure 5.7. Examples of NBR difference maps for the area under the burn scar, (a) between the five days pre-fire and ten days post-fire, b) between the five days pre-fire and one month post-fire, (c) between the five days pre-fire and eight month post-fire, (d) the five days pre-fire and one year post-fire.

5.4.8 NDVI results

Maps for the NDVI values are shown in (Figure 5.8). The comparison results between the pre-fire and post-fire images demonstrate an abrupt drop in the NDVI following the fire and this is followed by an increase in the results from ensuing years. The pre-fire image contained values above ~0.5, which is indicative of heavy green biomass, but in the post-fire images, the preponderance of the values was below ~0.3.

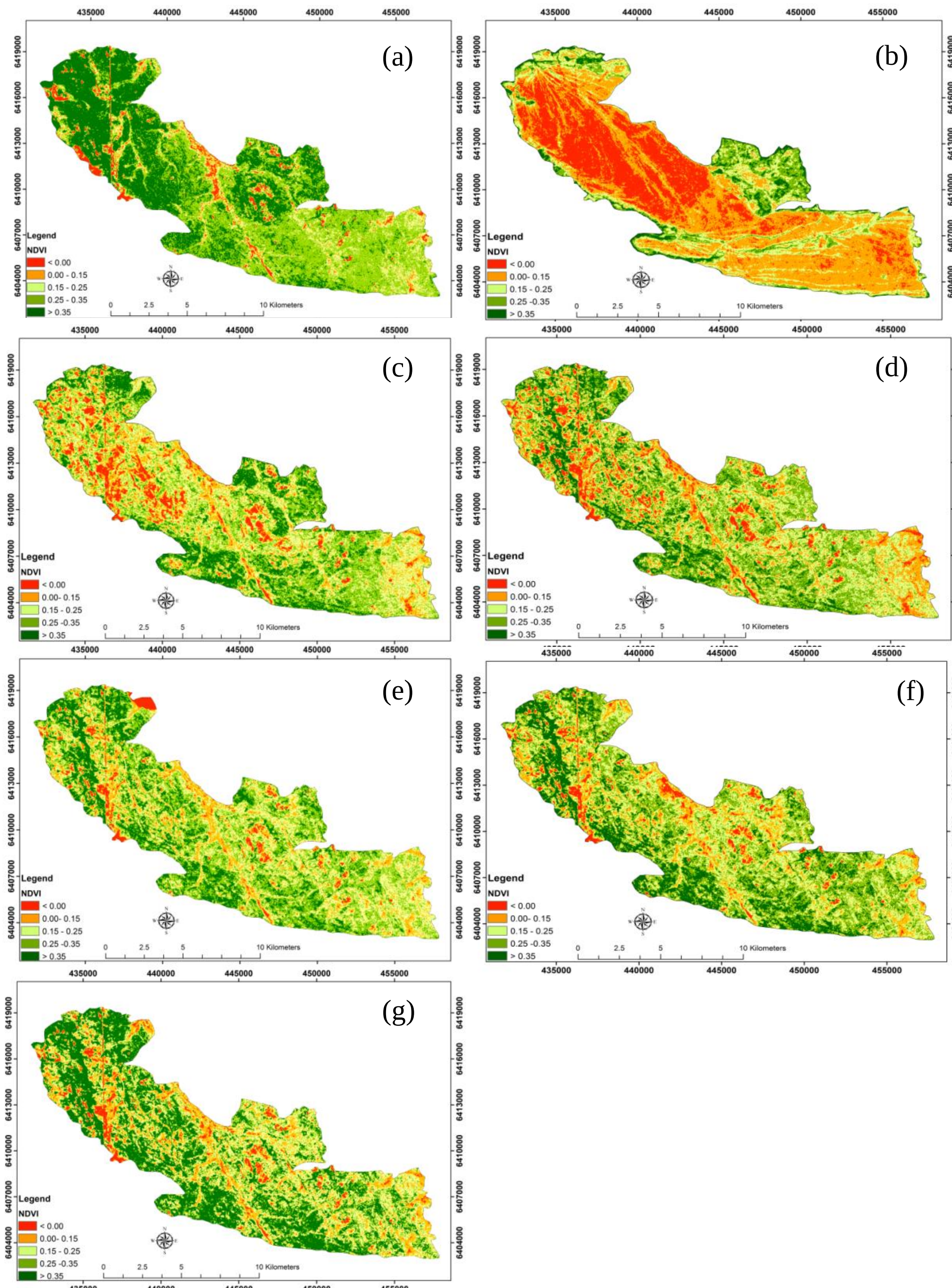

Figure 5.8. NDVI maps produced from Landsat TM and ETM series a) Jan 2000, b) Jan 2003, c) Jan 2004, d) Jan 2006, e) Jan 2008, f) Jan 2010 and g) Jan 2012

5.4.8.1 Analysis of the NDVI values in relation to pre-fire and post-fire images

The correlation between the pre-fire NDVI pixel values and the post-fire pixel values is depicted in this set of scatterplots dated from pre-fire 2003 to post-fire 2012. The positioning of the cloud of points relating to the 1:1 line is representative of the study site return to the pre-fire NDVI conditions (minus the 1000 m buffer zone). The degree of coherence in the pre and post-fire NDVI spatial patterns for each of the depicted years is represented by the scatter of points. The regression model was applied to this data and the adjusted R^2 statistics (coefficient of determination) for the regression line was plotted and it is noted that the adjusted R^2 has increased from 0.07 at one year to 0.39 over seven years (Figure 5.9).

It can be seen that by the end of this series the scatter points are beginning to move into alignment with the axis, indicating a gradual return to the pre-fire NDVI state. To date, these results indicate only a 40% return to the pre-burned state highlighting the fact that it may take over decades for this area to show advanced levels of recovery.

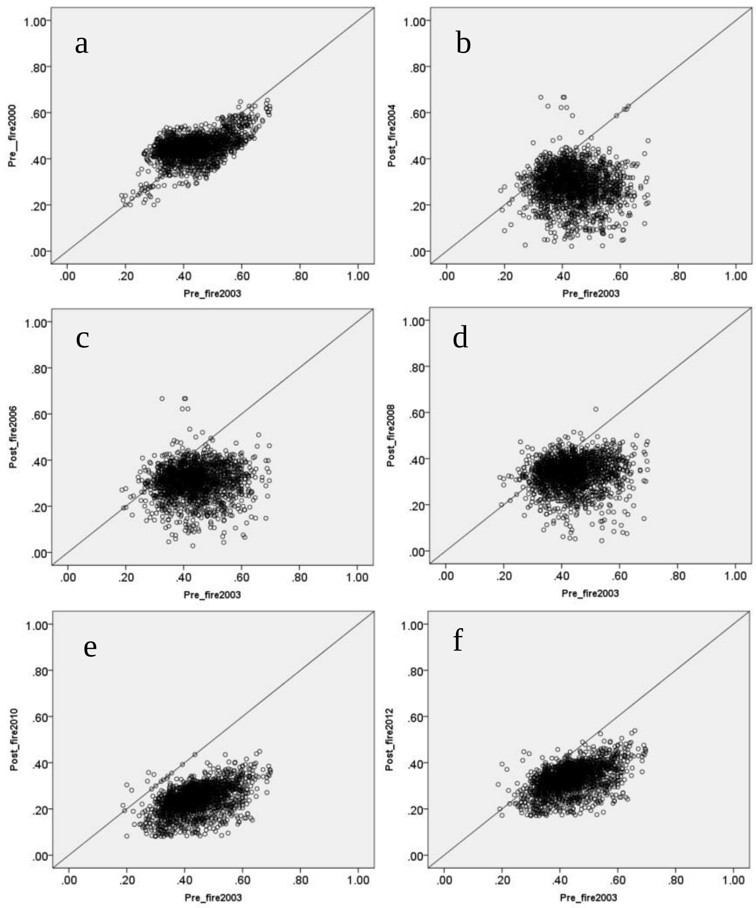

Figure 5.9. Scatterplot a) between the three years pre-fire and five days pre-fire, (b) five days pre-fire and one year post-fire, (c) between five days pre-fire and three years post-fire, d) between five days pre- fire and five year post-fire, e) between the five days pre- fire and seven year post-fire, f) five days pre- fire and nine year post-fire.

5.4.8.2 Change detection for NDVI index maps

The differencing between each pair of images has been calculated and the difference between each two images determined (Figure 5.10). The differencing was calculated between the images from three years pre-fire with ten days, one year, three years, five years, seven years and nine years post-fire. The results of change detection from these maps indicate that the recovery of the vegetation was slow within the initial two years, but in the following seven years the regeneration rate has increased moderately.

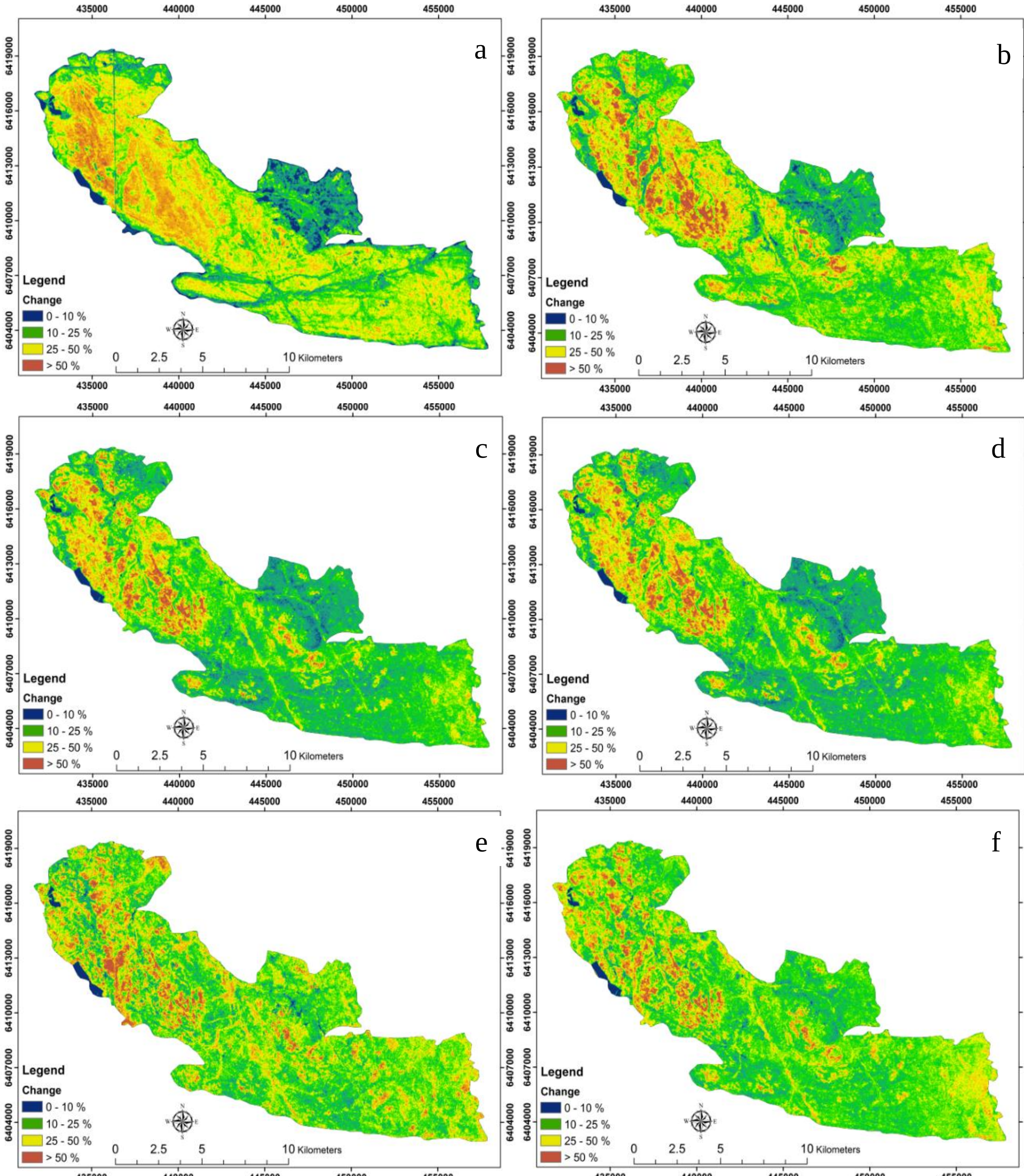

Figure 5.10. Examples of NDVI difference maps for the area under the burn scar, (a) between the three years pre-fire and ten days post-fire, b) between the three years pre pre-fire and one year post-fire, (c) between the three years pre -fire and three years post-fire, (d) between the three years pre-fire and five years post-fire, e) between the three years pre-fire and seven years post-fire, f) between the three years pre-fire and nine years post-fire

5.4.8.3 Recovery Rates

The statistics for the NDVI and RI for anniversary dates in the alternate years: 2002, 2004, 2006, 2008, 2010 and 2012 and the corresponding descriptive classes for the burn scar are displayed in (Appendix 1, Table 3). The comparative maps for the image dates have been produced and are in (Figure 5.10). There is a direct decrease in the NDVI post-fire and this is followed by an increase in the NDVI in the subsequent years as evidenced in the comparison of the maps produced. The comparative change between pre and post-fire mean NDVI images shows the majority of the pre-fire image contained values of or above a mean of 0.49 – demonstrating thick green biomass. There is a large decrease in the NDVI values in the images from the fire date of 09/01/03 (the day of the fire). The images from the following alternate years demonstrate a marked drop in the NDVI value for both the shrubland and forest plots immediately post-fire. Over the first two years post-fire the forest regeneration is slightly more rapid than the shrubland plots and this difference continues to be evident over the next four years.

From the results from the RI (Figure 5.11) in 2006 the regeneration in the forest area declines possibly due to the competition for space causing the weaker plants to die off and then the recovery continues on a more even plane for the following six years. Within the shrubland class, there is a fast regeneration initially over the first two years and then the growth slows until it reaches its peak at 2006 (three years post-fire). From there, there is a slight decline until 2012.

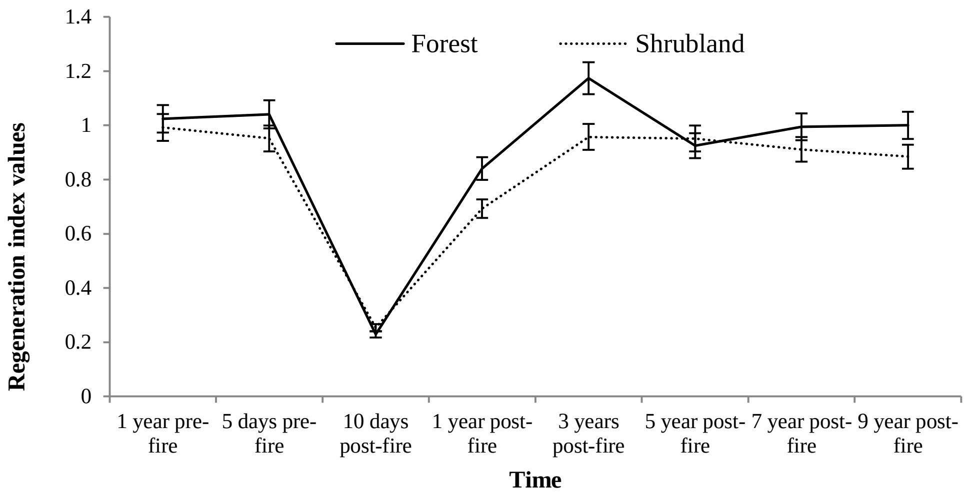

Figure 5.11. The regeneration index values in both shrubland and forest classes across the ten year time frame post-fire.

5.5 Discussion

The climate in Western Australia is experiencing a warming, drying trend over recent years (Westerling *et al*. 2006; Pitman *et al*. 2007; IOCI 2012). This is impacting on the frequency of the fires, changing behaviours within the fires, with areas of increased intensity and the fires are lasting longer and affecting wider areas (van Wagtendonk *et al*. 2004). More recently, fire research has been increasingly focused on detecting trends in fire and fire severity (Miller *et al*. 2008; Verbyla 2008; Karau *et al*. 2014). Discrete classes of unburned, low, moderate and high burn severity are used in describing the level of change to the appearance of the vegetation and the effect on the litter and soil (Miller and Yool 2002).

The use of remote sensing, as well as for mapping the severity of fires, can also be applied to measure the impact the fire has on the environment as a whole (Boer *et al*. 2008) and allow for monitoring its recovery after fire. Comparable studies over time and space for specific fire sites assist in the formation of databases for use in fire management and conservation (Petropoulos *et al*. 2014; Ireland and Petropoulos 2015), especially when the research focuses on areas of specific geographical/ecological importance such as the granite outcrops of the SWAFR, and the possibility of fire refuges for endangered plant species in these areas.

5.5.1 NBR index results

The associations between the historical fire regimes, local weather, area topography, fuel loads and finally the vegetation type all impact on the fire severity. At this particular fire site, prescribed burning three years prior to the fire, in an area to the north-east end of the outcrops resulted in the fire severity being noticeably lower than in the remaining areas where the last burn took place 17 years before. Local weather conditions were particularly hot and dry leading up to the fire, showing that the weather played a significant role in the severity of this fire. Finney *et al.* (2005) also found in their study that severe weather potentiates fire conditions independent of other considerations. The fuel loads in this ecosystem were high and dry over most of the study area adding to the impact on the fire severity.

In Chapter Four, the differing indices for assessing fire severity were researched and tested. The NBR was shown to be a reliable index for the mapping of fire severity over the granite outcrop habitats. The use of dNBR with Landsat imagery has been shown in this study to provide an effective and reliable method of mapping fire severity and is suggested as a good option in the study of fire impact on other similar granite outcrop sites.

At this particular site, the timing of the fire is important to the recovery image results. The fire occurred in the mid to late summer. The new vegetation was able to take advantage of the changes in the environment caused by the fire, such as a decrease in competition between plants to establish new growth – the autumn and winter rains encouraged new plants to flourish. Seed that is activated by exposure to smoke and heat was stimulated to germinate. All these regenerative processes cause the reflection to change, impacting on the NBR values (Key and Benson 2006; Loboda *et al*. 2013). It is recommended that, in this type of ecosystem, when mapping fire severity using images, the ideal time to apply this technique will be within two weeks post-fire to four months after fire. The results taken at this time will avoid any distortion of results that would be caused by the high spring growth season. Changes to the vegetation over time can be seen in pairs of photographs taken from the site – the post-fire photographs show early revegetation in some rock and boulder field areas.

The amount of time that has elapsed between the images can decidedly impact the dNBR values. In a quickly recovering ecosystem, the resprouting and reseeding vegetation may modify the first order fire effects by time. Seasonal timing strongly determines what is actually being assessed. Erroneous seasonal timing may distort growth trends in the recovering vegetation post-fire. A multi-temporal approach is expected to provide more accurate results when assessing the direct effects of the fire as well as the vegetation recovery processes. The time-integrated method has improved potential in the assessment of fire severity comparability across space and time.

After twelve months, the moderate to high severity classes still have a low NBR value suggesting that fire severity assessment can still be performed up to eight-twelve months post-fire across this class over this type of ecosystem and still produce reliable results. Low severity class results however may not be as reliable.

5.5.2 dNBR index results

Several other studies have supported the use of dNBR in mapping fire severity and the results have been verified with ground truthing (van Wagtendonk *et al*. 2004; Cocke *et al*. 2005; Epting *et al.* 2005; Allen and Sorbel 2008; De Santis and Chuvieco 2007). Lentile *et al*. 2006 however, stated that a drawback in the use of dNBR can be that it may be prone to subjectivity when determining the fire severity classes.

This research has identified significant differences across the data in relationship to fire severity and the time elapsed since the fire. Initially, within the unburned area, the comparison between ten days post-fire fire and twelve months post-fire, the percentage of low severity class rose from 2.6% to 24%. This indicates that the early regeneration of the vegetation has impacted on the dNBR results. A further example is that the dNBR values for the low fire severity class between the ten days post-fire and twelve months post-fire images rose from 16% to 43%; this change in the results was significant – suggesting a false result in dNBR as a measure of the low burn severity class if the assessment is made after the initial twelve months have elapsed – this may be due to the fact that these areas recover quickly after rains which re-establish the herbs and grasses over the exposed soil which affect the values. This was the same trend as stated by Shakesby and Doerr (2006), and Veraverbeke *et al.* (2010).

The use of multiple date imagery which merges pre-fire and post-fire data indicates the better option for mapping fire severity in this ecosystem when compared to a single image result supporting the results recorded by Key and Benson 2003, 2006; Zhu *et al*. 2006; Allen and Sorbel 2008.

The results from the moderate and high fire severity areas, on the other hand, show that there are significant differences between the images - the fire intensity has killed many plants or caused major damage to the vegetation that requires a much longer regeneration process. This supports the initial hypothesis that the dNBR can be used to demonstrate the significant differences in the time frame images from one month post-fire and twelve months post-fire, but only in the moderate to severe fire damaged areas in this particular ecosystem.

Miller and Yool, (2002); Lentile *et al.* (2007); and Lee *et al*. (2008) reported the NBR results from Landsat TM and ETM7 were a reliable method for mapping burn scars. Boer *et al*. (2008) in their study of jarrah forest in Western Australia also found the NBR was the most effective index in the mapping of vegetation changes after fire.

5.5.3 RdNBR results

The RdNBR showed positive linear correlation with the CBI photographic data from the study area. In comparison with the dNBR, it was determined that the RdNBR provided for improved comparisons across the spatial and temporal scales, similar to the findings of Miller and Thode in 2007**.** The RdNBR has also been shown to provide accurate results for areas of high fire severity over heterogeneous landscapes (Miller and Thode 2007) which are similar to the Mt Cooke ecosystem**.**

5.5.4 Vegetation

The high resilience of the Mediterranean type plant communities makes the post-fire vegetation appear like the pre-burned vegetation in a relatively short period of time. These regeneration strategies after fire are sometimes referred to as auto succession (Solans Vila and Barbosa 2010). The vegetation that is thought to be making these recovery rates so impressive are the reseeders - seedlings regenerating from a wide range of trees, the woody types of shrubs and the grasses and herbs. The first rains encouraging the germination and rapid growth of the seedlings from seed that was stored in the seed beds (Burrows 2006).

The vegetation in the Monadnocks area is comprised of a diverse assembly of herb and grass fields, shrublands and forests which include areas of eucalyptus forest, all found in close proximity on, around and between the granite outcrops. Many of the plants growing in the area are restricted to granite outcrops within this particular area (Burrows 2006). The granite itself is often covered in lichen and broad patches of moss.

A lot of the species found here are fire sensitive (readily killed by fire) and are only found in association with outcrops, however, they may also be reliant on fire to regenerate – rarely regenerating if there is no fire, but when there is a fire they are prolific in regeneration from the seed banks and canopy seed storage.

In the forest areas the trees were observed to be resprouting from epicormic buds and lignotubers, apart from the areas where the fire was at its most intense; here the tree death and severe damage was dramatic. According to Burrows (2006), up to 50% of the old growth trees had been totally destroyed indicating that this particular fire was one of the most severe this area had experienced as some of these trees had an estimated life of 300 yrs (Burrows 2006).

Landscapes with mixed topographic features and varied vegetation composition, which is typical in areas of GOs, greatly influence the fire and burn severity patterns. Within vegetation type assessment it was found that forest areas sustained moderate to high fire severity burns as opposed to the shrubland areas where reduced levels of severity has been recorded. This is due to the fact that that sclerophyllous trees dominate the forest areas making for high fuel loads. Small pockets of vegetation growing between rock sheets, in cracks and between boulders on the outcrop were left untouched or only mildly affected by the fire which is similar to the findings of Bigler *et al.* (2005); Nunes *et al*. (2005) and Wimberly and Reilly (2007).

Within the areas that were dominated by shrubland, the RdNBR produced higher values than did dNBR – which showed as low to moderate severity. These elevated RdNBR results could possibly be a function of the Landsat Band 7 sensitivities to the particular soil components and only be a factor in areas where the vegetation was sparse pre-fire and the fire of a high severity, which are similar finding to Miller and Thode (2007). The shrubland areas held a lower fuel load and at the time the fire took place the foliage was already thin and dry from the long summer period of low rainfall, extended high temperatures and warm winds. In the recovery phase, it appears that many of the shrub species reached their greatest density two to four years after the fire and that the density reduced after that. The differences in recovery rates for shrubland plants are affected by seasonal differences (Baird 1977), fires occurring after late spring to summer will regenerate with shoots appearing within three to six weeks after the fire once it rains.

5.5.5 Validation

In this fire situation the ability for ground validation was limited. The fire occurred over 10 years prior to this study, however, a common form of validation, the CBI (Key and Benson 2005), used by many researchers was available to the author through the generosity of Neil Burrows. The photographs he took after the fire have been the database for the validation. Smith *et al*. (2007) suggested a validation based on the percentage of live trees after the fire, while Kushla and Ripple (1998) and Isaev *et al*. (2002) worked on the percentage of tree mortality. Combustion completeness was another calibration method used in work by Alleaume *et al.* (2005). None of these methods were available for use ten years after the fire when this study was done.

The CBI has been established as a method of validating data that has been remotely sensed, from which fire severity maps have been produced. An expert assessment of photographic evidence taken at stages following the fire, and the outcome from the assessments tabled, then applied to the whole of the burn scar photographs to achieve a suitable proofing scale. Several characteristics from the photographs form the data, such as a) fuel load consumption, b) surface soil changes, c) understory damage and d) canopy damage (Westerling and Bryant 2008; Harris *et al*. 2011).

According to the data extracted from the photographic data, the overall accuracy was 76% with Kappa 0.7 in all the classes. This provides confirmation that this fire severity class has been validated.

5.5.6 NDVI and RI

The NDVI has been widely used in mapping post fire vegetation recovery (Wittich and Hansing 1995; Gitelson *et al*. 2004; Hope *et al*. 2012). Analysis of NDVI values from a range of dates can highlight changes to the vegetation biomass, such as that caused by fire and is used extensively in the assessment of post-fire recovery (Diaz-Delgado *et al.* 2003).

Fire plays an integral part in the regeneration cycle of vegetation in the SWAFR. The plants have evolved over many years within a regime of fire to the point where plants developed fire sensitive or fire tolerant traits – some requiring the heat and /or the smoke from fires to germinate the seeds for the next generation of plants (Attiwill and Wilson 2003; Jefferson *et al*. 2008; Chou *et al.* 2012). The larger growing trees in the region – some of which were around 300 years of age, had survived fires in the past, only to regenerate and continue to live, until the fire of 2003 where tree mortality was high (Burrows 2006).

The results of this study indicate from the decrease in the NDVI values immediately post-fire that the fire had impacted the vegetation across the study area. From the progressive images post-fire, it is evident that the vegetation will take over a decade to recover and may still not return to its pre-fire state. While it is evident that fires have taken place in this area before (17-20 years before the 2003 fire) the magnitude may not have been as devastating as the mature trees had resprouted and survived, while after this fire there has been a large number of mature trees that died. Younger trees have been able to resprout and these account for the main regeneration in the forest class as evidenced by field trips to the affected areas in 2003 and 2004.

The shrubland areas did not sustain such a high level of burn severity as experienced by the forest areas – the mean NVDI post fire in the shrubland areas had a value of between 0.20-0.35 whereas the forest NDVI mean value was between 0.4-0.56 – the highest regeneration rate within the study area was recorded within the three to five year post-fire period.

From these results, there is a strong relationship between the mean NDVI and the RI. Every care should be taken when selecting plots to assess the RI to choose those with similar characteristics as other factors can impact the fire behaviour and affect such as topography. It has been noted that both of these indices reflected a similar course, which may be indicative of gradual revegetation in the area but that it may take greater than ten years for a full recovery. Arianoutsou *et al.* (2010) suggested that recovery rates in the Mediterranean type of ecosystems, where it is warmer, are generally faster than elsewhere.

Burrows in 2006 described the regeneration at the Mt Cooke site based on four-six weekly visits he made to the site post-fire. He described the dynamic by saying that 68% of the vascular plants regenerated by resprouting and the remainder by prolific germination of seed – he estimated that ~74%

of plants on the site are obligate seeders and after the first rains the seedlings quickly took advantage of the changes in the post-fire environment. While many of the fire sensitive plants regenerated quickly from seed they did not reach flowering stage until up to three years post-fire, and one species – *Calothamnus rupestris*, which reached flowering stage after five years (Burrows 2013). Plant diversity was high initially, apart from some areas where erosion washed the topsoil away – when it was already precariously thin, and in a few areas where the fire was so intense that the soil was left sterile.

5.5.7 Vegetation recovery rates

The regrowth of the vegetation was monitored using NDVI images to observe the trend in revegetation across the study site. The NDVI value dropped immediately post-fire but by the second year post-fire, the regeneration can already be seen. The pattern of regrowth was not even across the site – the open herb and grass fields were the quickest to show some recovery when other areas like the forest regions where the fire severity was high showed little change until the resprouters began to flourish at around three years post-fire. This dynamic is a common phenomenon after fire (Solans Vila and Barbosa 2010). Diaz-Delgardo *et al.* (2003), in a study of MTEs also observed a trend where after the initial five years post-fire, there was a drop in some vegetation types that had survived the fire that then gradually disappeared.

5.5.8 Scatterplots of NDVI, both pre and post-fire

The relationship between the NDVI pre-fire and the values recorded post-fire are displayed in a series of scatterplots (Figure 5.9). The position of the cloud of points and the relationship to the 1:1 line shows the burn scar area NDVI values and the coherence of the points demonstrate the return of the values to pre-fire conditions – it can be seen from the control graph that the points have a trend to line up along the axis line and as is clearly demonstrated in (a). The NDVI pixel placement remains scattered in the one year, three years and five years post-fire. However, after seven years the NDVI values show some improvement and after nine years post-fire there has been further improvement. This indicates recovering vegetation and suggests an extended period to full recovery – possibly over twenty years post-fire for the pre-fire levels to be returned.

5.6 Conclusions

The first aim for Chapter 5 was to assess the fire severity across two vegetation types at the study site. This was achieved by assessment of Landsat ETM+ images using the NBR, dNBR and RdNBR. Personal statements and photographic evidence were provided by another researcher, (Neil Burrows, Senior Principal Research Scientist, DEC), who visited the site five days post-fire and again six months post-fire and while there he took a collection of photographs across the granite outcrops to record the fire severity. The majority of the photographed areas were later matched using geographic features and these were later plotted on the burn scar with GPS markers during field trips that were made in 2012 to 2014 to identify the plots and assess the recovering vegetation.

The performance of the NBR over time provided similar results for the moderate and high severity classes where there were significant differences between the five days post-fire and the one year post-fire images. However, the low severity class results showed no significant change between five days post-fire when compared to the image from one year post-fire.

Within the low and the high fire severity classes the dNBR results performed well but in the moderate class results, when assessing the same areas using the RdNBR, there were some discrepancies noted where some of the previously moderate classed regions were now recording a high severity class rating.

The second aim was to assess the vegetation recovery from one year pre-fire (2002), through to 2012. To achieve this NDVI was calculated and mapped for each image and the RINDVI was calculated from 2002-2012 and graphed. The linear regression model was applied for the NDVI and scatterplots produced and the outcome demonstrated that the NDVI had not returned to the pre-fire state, even after ten years. This means that the vegetation on this area had not fully recovered to the pre-fire state and it may not recover fully to meet those pre-fire criteria.

The topographic variables can affect fire severity patterns and will be studied to assess how these variables affected the fire behaviour. The next chapter will investigate the role the topography played in the fire severity and how it impacts the regrowth, by using the dNBR and modelling of topographic variables from these results across time – up to one year post-fire.

5.7 Summary

This chapter was assessing fire severity on Mt Cooke by comparing the NBR values over time to investigate which is the optimal time for performing a fire severity assessment. The fire severity was mapped and the damage was classified into unburned, low severity, moderate and high severity. From these results, the dNBR and RdNBR were produced and a results comparison performed. The results have demonstrated that the dNBR and RdNBR are good VIs for assessing fire severity on this type of ecosystem.

Vegetation recovery was assessed using RINDVI to investigate the rate of regrowth across the shrubland and the forest classes over a period of ten years. The results indicate that the vegetation recovery in the fire severity classes of moderate and severe have still not returned to the pre-fire state. Field trips to the area in 2012-2014 have shown that there are still large areas that exhibit fire damage, confirming the recovery modelling results.

Chapter 6: Determining the environmental influences on fire intensity using statistical modelling on Mt Cooke

6.1 Introduction

On both a provincial and worldwide scale, fire is a major disturbance that impacts communities with a high cost for prevention, suppression and recovery (Agee 1993; Bowman *et al* 2009; Holden *et al.* 2009). Changing climate trends worldwide are increasing the likelihood of fire, especially in Mediterranean type ecosystems (MTEs) (Mouillot *et al*. 2002), and fires are becoming more severe – in scale, intensity and frequency (Odion *et al*. 2004, Lentile *et al*. 2006; Holden 2009; Amraioui *et al*. 2013).

The SWAFR is recognized as Australia's global biodiversity hotspot (Myers *et al*. 2000; Horwitz *et al*. 2008), with about 70-80% endemic species (Hopper & Gioia 2004; Gole 2006; Horwitz *et al*. 2008). Understanding the impact of fire on the areas that may provide protection for biodiversity in these ecosystems has become increasingly important (Barnosky *et al*. 2008; Midgley *et al.* 2002; Bailey 2009).

Granite outcrops (GOs), as isolated islands in ancient landscapes, house a variety of plants with complex evolution (Byrne and Hopper 2008). The vegetation on outcrops can vary widely from that of the surrounding areas (Wiser *et al*. 1996; Decker 2007). They are topographically complex and include sites that may be more moist and cooler than the surrounding environment and are rich in biodiversity, holding vital remnants for the biota required for landscape regeneration (Wood *et al.* 2011). These areas of assumed protection are frequently referred to as "fire refuges" or refugia (Fuls *et al*. 1992; Clarke 2002; Yates *et al.* 2003; Smith and Sage 2006). The refugial niches on and around GOs may support localised populations of species that are absent or rare within the surrounding landscape and could become increasingly isolated and at risk (Decker 2007; Cary *et al*. 2006; Keppel *et al*. 2011). Supressing fires over difficult terrain can be a major problem and the post-fire effects of accelerated soil erosion and mortality of endemic species (Lloret *et al*. 2002) may alter an area of endangered biodiversity (Savage and Mast 2005; Amraioui *et al*. 2013); especially when fires recur over short intervals (Bond *et al*. 2005).

Features such as aspect, slope and topographic position may influence the spatial distribution of possible fire refugia (Bowman 2000) and influence the distribution of vegetation and biodiversity (Coblentz and Riitters 2004). Open and exposed rock sheets, boulder and rock fields and sparse vegetation growing on thin soils makes the environment less likely to burn or sustain fire (Hopper 2000; Burrows 2005). These topographic features within the GOs, that may affect fire behaviour and may offer protection for plant communities that require relatively long fire intervals to mature or who are especially sensitive to high intensity burns and may also provide some climactic protection in the SWAFR region where there is an increasingly warming and drying trend (Ashcroft 2010; Barnosky *et al.* 2008; Mackey *et al.* 2012). However, in the SWAFR, the outcrops mostly occur in a matrix of seasonally flammable vegetation that is capable of sustaining high-intensity and fast-spreading fire.

Determining the environmental influences of high intensity fires is important for designing suitable management strategies such as reducing fuel loads via prescribed burning in high risk areas (Cary *et al.* 2003; Gill and Bradstock 2012). Linear regression has been widely used for this purpose (Meng and Meentemeye 2011) but is not suitable in situations where the explanatory variables exhibit non-stationarity in their predictive power (Koutsias *et al*. 2010; Martinez-Fernandez *et al*. 2013; Oliveira *et al.* 2014).

Recently, there has been more emphasis on the use of modelling techniques that allow the strength of the relationship to vary through space (Cressie 1993; Jones and Hanham 1995; Matthews and Yang 2013). Geographically weighted regression (GWR) is one such technique, which has been used for fire risk modelling over large areas (Martinez-Fernandez *et al.* 2013; Oliveira *et al.* 2014). It is hypothesised that GWR could also be a suitable model for more local scale heterogeneity. This is tested on Mt Cooke in the SWAFR by comparison to a conventional linear regression.

Aim**:** To investigate the relationship between fire severity in each vegetation class and against the independent variables of fuel load and specific topographic variables to determine if there are areas on the GOs that may offer some protection from the effects of high fire severity.

It is expected that specific topographic features will enhance the effect of the fire while others may offer some amelioration from the intensity of the fire with the possibility of some fire refugia. Assessing where areas of high fire severity are most likely in these environments and highlighting causative factors may assist in better fire management in the future, such as reducing fuel loads with prescribed burning using a regime that allows the slow maturing, local species to recover to their optimal levels between burns.

Secondly, modelling fire severity across the burn scar and include topographic, fuel and vegetation variables with the use of Ordinary Least Square Regression (OLS) and Geographically Weighted Regression (GWR) to determine which predictive model provides the better results when applied to the data for the Mt Cooke fire. It is expected that there may be differences between these two methods of fire severity prediction and the better method will be highlighted when the predictive map and the observed map comparisons are completed.

6.2 Study Area and data set

Mt Cooke is located in the Monadnocks Conservation Reserve in Western Australia, an area of high concentration of granite outcrops on the Darling Escarpment (Figure 6.1), refer to Chapter 3.

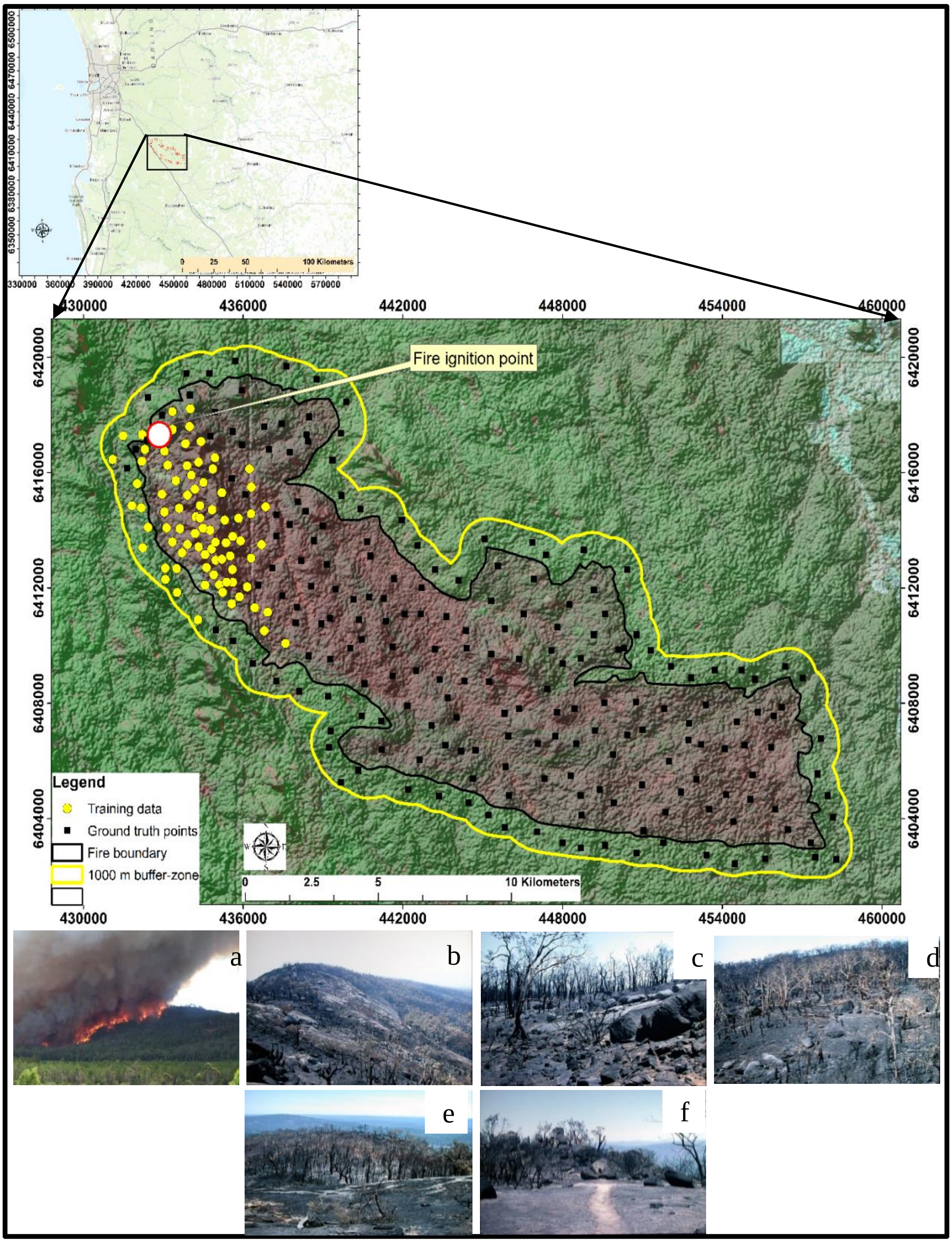

Figure 6.1. Outline of the fire boundary and photographic depictions of the Mt Cooke fire: a) the fire on the NW slope; b, c, d) NW slope after the fire passed through – severe fire class; e, f) at the summit of Mt Cooke the fire severity was moderate-low (Photos used with permission of N Burrows).

6.2.1 Remote Sensing Data

Two data images, one pre-fire and one post fire from the 2003 moderate resolution Landsat imagery, provided the base data, and fire severity maps were derived from the data (Table 6.1). USGS Earth Explorer Landsat 7 ETM+ and DEM archive data images form the data set used. The two images are subtracted to compute the dNBR data. The fire severity assessment was determined by the total of the entire burned area within the fire scar of the study area, which includes islands of vegetation that survived unburned. The Digital Elevation Model with 30 metre resolution was used to derive the topographic variables.

Table 6.1. Data set image acquisition dates, platform, sensor and source.

Study Aim	Description	Image Date	Path / Row	Sensor
Fire severity	Five days pre-fire	4/01/2003	112/82	ETM+
	Ten days post-fire	20/01/2003	112/82	ETM+
Topographic variables	DEM			

6.2.2 Validation data

In compiling the data for this study, regular field trips were conducted in 2012-2013. 1700 randomly selected plots were mapped across a variety of landscapes and vegetation types. For this section of the study, 298 plots were randomly selected for modelling vegetation distribution and fire severity in relation to topography. A collection of photographs taken at intervals from one week to six months post fire by Neil Burrows have been used for matching regions of fire severity on the fire scar. Many of the features photographed were identifiable on field trips and were plotted on the fire scar.

6.3 Methodology

6.3.1 Pre-processing

All satellite imagery was subject to radiometric and atmospheric correction. Absolute atmospheric correction was performed using FLAASH (Fast Line-of-sight Atmospheric Analysis of Spectral Hypercubes) within ENVI (2015). There was no impedance caused by cloud cover in any of the images used.

6.3.2 Severity analysis

The dNBR (see Chapter 5), was used to substract the differences between the two images – the pre-fire image and the post-fire image using Equation (1) (Key and Benson 2003) which was then re-classed into the severity threshold as defined by Key and Benson (2006), (Table 6.2).

Differenced NormalisedBurn Ratio (dNBR) =NBR-Pre – NBR-Post Equation (1)

Where

NBR-pre = NBR 04/01/2003; NBR- post= NBR 20/01/2003

Table 6.2 The dNBR fire severity thresholds, after Key and Benson 2006.

dNBR	Burn Severity
-0.2 - 0.1	Unburned
0.1 - 0.27	Low-severity burn
0.27 - 0.44	Moderate-low severity burn
0.44 - 0.66	Moderate-high severity burn
> 0.66	High-severity burn

6.3.3 Data Analysis

Nine predictor variables were used: seven derived from the DEM (Table 6.3), (USGS Earth Explorer Landsat 7 ETM+ and DEM archive data images (Oct 2011) form the data set used), and one from fuel age and one from habitat, from the field. Two methods were used to assess the fire severity in relationship to the topographic variables across the shrubland and forest. Firstly, the relationship between a single variable and the fire severity class (dNBR) was graphed and secondly, the Classification and Regression Tree (CART – Breiman *et al*. 1984; Dillon *et al*. 2011) method of analysis was applied to examine the relationships between the vegetation type and the topographic variable. The classification regression trees identify change, or splits, within groups of predictor variables that reduce residual error at each split or node (Breiman *et al*. 1984; Holden 2009). This method for analysis is appropriate to both classified and continuous variables, as it requires no assumptions and is vital in relation to the spatial autocorrelation that is fundamental in both the response and predictor variables.

Table 6.3. Summary of the variables used for modelling fire severity and vegetation with topographic variables.

Variable	Source
1- Habitat	
Forest (presence/absence)	Field data (1,0) Independent Variable (IV)
Shrub (presence/absence)	Field data (1,0) IV
2 - Fuel age	DEC map (year) IV
3 - Aspect	DEM- North, East, South, West - IV
4 - Slope	DEM (Flat < 5°, Gentle slope (5–10°), Moderate slope (10–15°), Steep slope (> 15°) IV (Slope parameters after Wood *et al*. 2011).
5 - Elevation	DEM (meters) IV
6 - Northness (cos aspect)	DEM- North or South (-1,1) IV
7 - Topographic Position Index	DEM - position between valley (0) and ridge (1) IV
8 - Topographic roughness	DEM (variance in elevation) IV
9 - Elevation relief ratio	DEM (elevation complexity) IV
10 - Fire severity	dNBR data 7 (low, moderate and high severity) Dependent variable (DV)

6.3.4 Independent variables (Topographic variables and fuel age)

A DEM (30 m resolution) covering the study area, was used to identify seven independent variables. These variables were:

- **Aspect**

The aspect was calculated for each cell from the DEM model (30 m) and divided into North, NE, NW, South, SE, SW, East and West. Aspect determines the effects of air temperature, solar radiation and moisture. In the southern hemisphere, the north facing slopes get a higher percentage of solar heating which can lower the humidity.

- **Elevation**

Elevation was calculated for each cell from the DEM model (30 m) and classified into 4 levels of elevation: 200-300 m; 300-350 m; 350-400 m; and greater than 400 m. (This equal interval classification scheme chosen will divide the range of attribute values into subgroups of that are equal sized. This then allows the operator to determine the number of intervals required and then Arc GIS determines where the breaks should be. This scheme works best when applied to familiar data ranges).

- **Slope**

The slope calculated for each cell from the DEM model (30 m) in degrees. It was then divided in to four levels: 0-5°, 5-10°, 10-15° and greater than 15° (Slope parameters after Wood *et al*. 2011).

- **Fuel age**

The data for fuel age (local prescribed burn areas by date) was supplied by DEC and the data applied over the study area map.

- **Habitat**

Habitat type was determined during field trips to the site and divided into shrubland and forest.

- **Northness Index**

The degree of northness can be calculated as the cosine of the aspect Equation (2, 3) (after Stage 1976). The range extends from minus one to one, with a value of around minus one representing a slope facing directly south and a value of approximately one indicating a slope facing due north. The sine of the aspect calculates the degree of eastness - values ranging from minus one to one, where minus one represent an east-facing slope and one signifying a west-facing slope (Harshburger *et al*. 2010).

Northness Index = $\cos(\text{aspect in degrees} * \pi/180)$ Equation (2)

Eastness **Index** $=\sin(\text{aspect in degrees} * \pi/180)$ Equation (3)

Aspect (°) was calculated from the 30 m DEM. Steep north = - 1, steep south = 1, east and west and flat = 0.

- **Topographic Position Index**

The topographic position index (TPI) (Moore *et al*. 1993; Murphy *et al*. 2010), Equation (4) which is also referred to as the relative topographic position, is an index based on the ruggedness of the terrain combined with the local elevation index (Jenness 2002). The topographic position of every pixel is identified in relation to its locale – its relative position. It is used in identifying patterns in the landscape and the boundaries that may correlate to identifiers such as the main geomorphic process, characteristics of the soil, the vegetation type and drainage. The TPI values reflect the difference between the elevation – in a particular cell and the average elevation of the cells surrounding that cell.

$$\text{T PI} = \frac{\text{DEM}10\times10 - \text{minDEM}}{\text{maxDEM} - \text{minDEM}} \qquad \text{Equation (4)}$$

Where:
DEM 10×10 window = name of smoothed elevation raster cell
minDEM = name of minimum elevation raster cell
maxDEM = name of maximum elevation raster cell

For the purpose of this study, the final output raster is classified into: strongly positive = ridges; strongly negative = valleys.

- **Terrain Ruggedness Index**

Terrain Ruggedness Index (TRI) describe the amount of elevation difference between adjacent cells from a digital elevation grid, Equation (5), **(**Riley *et al.* 1999). Basically, the process calculates the difference in elevation values from a central pixel and the eight surrounding pixels. It then squares the eight elevation difference values to make them positive, and averages the squares. The TRI is then determined by taking the square root of this average, and correlates it with the average elevation change between any point on a grid and the immediate surrounding area. It is an essential variable in predicting which particular habitats are preferred by species and the density of that species across an assortment of habitats is referred to as terrain heterogeneity (Koehler and Hornocker 1989). It is frequently a vital component of a species niche (Whittaker *et al.* 1970). Often, researchers describe the terrain of an area using qualitative words – for example, broken, undulating or rugged.

$$\text{TRI}=\sqrt{\text{Abs}((\text{Square}(3\text{x}3\text{maxDEM}) - \text{Square}(3\text{x}3\text{minDEM}))} \qquad \text{Equation (5)}$$

where:

3x3 window max DEM = name of maximum elevation raster cell
3x3 window min DEM = name of minimum elevation raster cell

Riley *et al*. (1999) suggest the characteristics for the breakdown of the values should be:

0-80 m	Level
81-116 m	Nearly level
117-161 m	Slightly rugged
162-239 m	Intermediate ruggedness
240- 497 m	Moderately rugged
498-958 m	Highly rugged

- **Elevation Relief Ratio**

The Elevation Relief Ratio (ERR) was initially developed as a measure of terrain characteristics which did not involve any particular emphasis from the formation processes from 3 x 3 and 10 x 10 window sizes (Wood and Snell 1960). It has become regarded as a measure to which the topography has been effected by dissection within the landscape (Evans 1972) and from this, Wood and Snell (1960) developed a terrain measure Equation (6). ERR is measured by the differences in elevations between two reference cells divided by the difference between the elevation maximum and the elevation minimum.

The equation for the ERR is:

$$\text{ERR}=\frac{\text{Elevation Mean} - \text{Elevation Minimum}}{\text{Elevation Maximum} - \text{Elevation Minimum}} \qquad \text{Equation (6)}$$

In using this equation, the possible solutions must always be greater than 0 and less than 1, as the mean elevation minus the minimum elevation can approach the relative relief value but never equal it. Pike and Wilson (1971) demonstrated that the elevation-relief ratio is mathematically analogous to the more complex hypsometric integral of Strahler (1952).

The values nearer to 0 are suggestive of sub horizontal terrain with scattered peaks. Conversely, a value nearer to 1 is indicating convexity or sub horizontal terrain with deep incisions. Using an index such as this it is possible to distinguish mathematically between valleys and lowlands and dissected upland plateau which is not possible using simply slope angle or a relative relief (Pike and Wilson, 1971).

All of the topographic variables that were considered probable associations for the three classes of fire severity and were determined and values extracted into tables. All data was then used for modelling vegetation distribution and the relationship between fire severity and topography.

The relationship between each of the individual variables and the high severity burn class are graphed and analysed using conditional probabilities in the Bayesian method (Holden 2009). The conditional probabilities characterise the likelihood of the high severity class fire occurring with the correlation to each variable across the total burned area. The conditional variables were estimated using a binary (high severity vs. other burned) grid of the total burned area as the response (Holden 2009).

6.3.5 Model Building

The best subset of independent variables will be used to regulate the ordinary least square (OLS) regression, and geographically weighted regression (GWR), and these were later evaluated to assess their performance in modelling fire severity. Possible models have been identified with the use of ArcMap 10.1 Explanatory Regression. This was used to identify any potential models with a significant R^2 value. For every model, this tool calculated the Jarque-Bera test for normally distributed residuals. Then a variance inflation factor (VIF) was used to determine collinearity of the explanatory variables. Akaike's Information Criterion (AIC) is commonly used for selecting the best subset of independent variables enabling a multiple regression analysis (Malczewski and Poetz; 2005). Using Exploratory Regression in Arc GIS, AIC value was performed for every individual and potential combination of independent variables. The overall effect was ascertained in assessing the combined effect and the ideal subsets of variables were combined. The best-fit models were chosen using the lowest AICc value for those models with normally distributed residuals, omitting the collinear explanatory variables, including Moran's I (Burnham and Anderson 2002).

6.3.5.1. Pre-processing data for modelling

Visualisation

Nine variables (Table 6.3) were mapped and visualised to identify factors that may potentiate the fire severity. The correlation between both the independent and the dependant variables was calculated to quantify the strength of the relationships. Scatter plot graphs were produced. Transforming of the variables to remove the effect of outliers was conducted using the square root, logarithmic and the Two-Step Transformation of Templeton (2011).

Linearity

Linearity assesses the relationship between dependent and independent variables. The linearity was tested using a scatterplot and if no linear relationship is possible one or both variables are transformed – box-cox, square root, log transformations and the two step method can be used to achieve linearity. Outliers can represent important information between the dependent variable and the independent variable and should not be discarded – the transformation can correct the outliers (Mosteller and Tukey 1977).

Normality

Data normality assessment is required prior to applying statistical analysis as the normality of the data is an underlying assumption in parametric testing. To test if the normality assumption is statistically valid, the Shairo-Wilk test was performed, Equation (7). The Shapiro-Wilk test calculates a W statistic using the following equation (NIST/SEMATECH 2012). If the p value of the Shapiro-Wilk Test is > 0.01, the data is normal. If it is < 0.01, there is a significant deviation from a normal distribution.

$$W = \frac{(\sum_{i=1}^{n} a_i x_{(i)})2}{\sum_{n=i}^{n}(x_i - x_i)} \qquad \text{Equation (7)}$$

Where
x(i) x= Ordered sample values ($x(1)$ is the smallest)
ai = constants generated from the means, variances and covariances of the order statistics of a sample of size n from a normal distribution

Multicollinearity

The variance of inflation factor (VIF) was used to measure the redundancy between each of the independent variables. Generally, the explanatory variables associated with VIF values which are greater than about 7.5 are removed from the regression model. Multicollinearity refers to higher linear inter-correlation among model variables. It highlights the redundancy of model variables and the need to discard variables from the analysis.

Distribution of Residuals

Model bias - the Jarque-Bera statistic demonstrates if the residuals are normally distributed. The null hypothesis for this test is that the residuals are normally distributed. When the p-value for this test is less than 0.05, the residuals are not normally distributed, indicating model bias.

Non-stationarity

Model significance - both the Joint F-Statistic and Joint Wald Statistic are measures of overall model statistical significance. Joint F-Statistic is only reliable where the Koenker (BP) statistic is not statistically significant. Stationarity - the Koenker (BP) Statistic tests whether the independent variables in the model have a consistent relationship to the dependent variable within both the geographic space and data space. The null hypothesis for this test is that the model is stationary. When the p-value is < 0.05 it indicates statistically significant heteroskedasticity and/or nonstationarity. If the results from this test are statistically significant, the robust coefficient standard errors and probabilities have been consulted to determine the effectiveness of each independent variable. Those regression models with statistically significant nonstationarity are frequently better candidates for Geographically Weighted Regression (GWR) analysis (Fotheringham *et al*. 2002).

However, if the Koenker (BP) statistic is significant, it is best to refer to the Joint Wald Statistic to determine overall model significance. The null hypothesis for both tests is that the independent variables in the model are not effective. For a 95% confidence level, a p-value that is less than 0.05 indicates a statistically significant model.

Autocorrelation

Residual spatial autocorrelation - the Spatial Autocorrelation (Moran's I) Equation (8) was applied on the regression residuals to ensure that they are spatially random, (Anselin 2005; Malczewski and Potez 2005). Statistically significant clustering of high and/or low residuals will indicate a key variable is missing from the model (misspecification). OLS results cannot be trusted when the model is misspecified – a distribution value of around 0.0 is preferred (Wang *et al.* 2005).

This Spatial Autocorrelation equation evaluates whether the pattern expressed in the models is clustered, dispersed or random (Equation 8). The Moran’s I Index can be assessed using a z-score and p-value to determine the significance of that index.

$$I = \frac{n}{S_0}\frac{\sum_{i=1}^{n}\sum_{j=1}^{n}\omega i,z_i\, z_j}{\sum_{i=1}^{n} z_i^2} \qquad \text{Equation (8)}$$

Where

Z_i =the deviation of an attribute for feature I from its mean $(x_{\ i} - \chi)$,$\omega_{i,j}$ is the spatial weight between feature I and j; n = the total number of feature

S_0=aggregate of all the spatial weights as Equation (9),

$$S_0=\sum_{i=1}^{n}\ \sum_{j=1}^{n}\ \omega_{i,j} \qquad \text{Equation (9)}$$

The ZI-score for the statistic is computed as Equation (10):

$$ZI = \frac{I - E[I]}{\sqrt{V[I]}} \qquad \text{Equation (10)}$$

$$E[I] = -1/(n-1)$$
$$V[I] = E[I^2] - E[I]^2$$

Where

Z_i =the deviation of an attribute for feature I from its mean $(x_i - \chi)$,$\omega_{i,j}$ is the spatial weight between feature I and j; n = the total number of feature

S_0=aggregate of all the spatial weights as Equation (10),

6.3.5.2 Ordinary Least-Squares Regression

Ordinary least-squares (OLS) regression is a generalized linear modelling technique that may be used to model a single response variable which has been recorded on at least an interval scale, Equation (11). The technique may be applied to single or multiple explanatory variables and also categorical explanatory variables that have been appropriately coded. This model can be extended to include multiple variables by adding variables to the equation. It is the model that is most widely known and is a suitable starting point for any spatial regression analysis (Arc GIS Help 10.2).

$$Y = \beta 0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_n X_n + \varepsilon \qquad \text{Equation (11)}$$

where

Y = the dependent variable

X = the independent variable, β0 and β1, are the parameters to be estimated, and e is a random error term, assumed to be normally distributed. The assumption is that the values of β0 and β1 are constant across the study area.

β = Coefficients values, computed by the regression tool, reflecting the relationship and strength of each independent variable to the dependent variable.

(ε)= residuals or the portion of the dependent variable that isn't explained by the model; the model under and over predictions.

6.3.5.3 Geographically Weighted Regression (GWR)

GWR is one of several spatial regression methods which is popular in geography and similar related fields. It provides a local model of the variable (or the process) which is attempting to be understood, by fitting an equation to each feature in the dataset. If used correctly, this method provides reliable statistics in examining linear relationships (Brunsdon *et al*. 1996; Fotheringham *et al*. 2003). GWR was applied post-OLS modelling to investigate improvements to accuracy by better handling of non-stationarity over the study area (Fotheringham *et al*. 2003), Equation (12). From each model, maps of the residuals were visually examined for clustering. This will potentially identify any spatial variation within the input variables and may also identify any missing variables.

$$Y_i = \beta_o(u_i, v_i) + \sum_{j=1}^{p} X_{ij} \beta_j (u_i, vi) + \varepsilon_i \qquad \text{Equation (12)}$$

Where

$Y_i =$ is the value of the outcome at the coordinate location i where (u_i, v_i) denotes the coordinate of i, β_0 and β_j represents the local estimated intercept and effect of variable j for location i, respectively.

The assessment of model performance: both the Multiple R-Squared and Adjusted R-Squared values are indicators of model performance, with a possible values range from 0.0 to 1.0. The Adjusted R-Squared value is always slightly lower than the Multiple R-Squared value, because it reflects the number of variables, as it relates to the data and thus it is consequently a more accurate measure of model performance.

GWR and OLS is compatible with Geographical Information System, (GIS) tools that facilitate the mapping of the estimated parameters and model statistics spatially which allows in-depth study of variability (Platt 2004; Wang *et al*. 2005).

6.4 Results

6.4.1 dNBR value results

From the 298 points located within the study area, four classes (unburned ~3 %, low ~16%, moderate ~47% and severe ~32%) of fire severity were classified (see Chapters 5), and the dNBR map was produced (Figure 6.2).

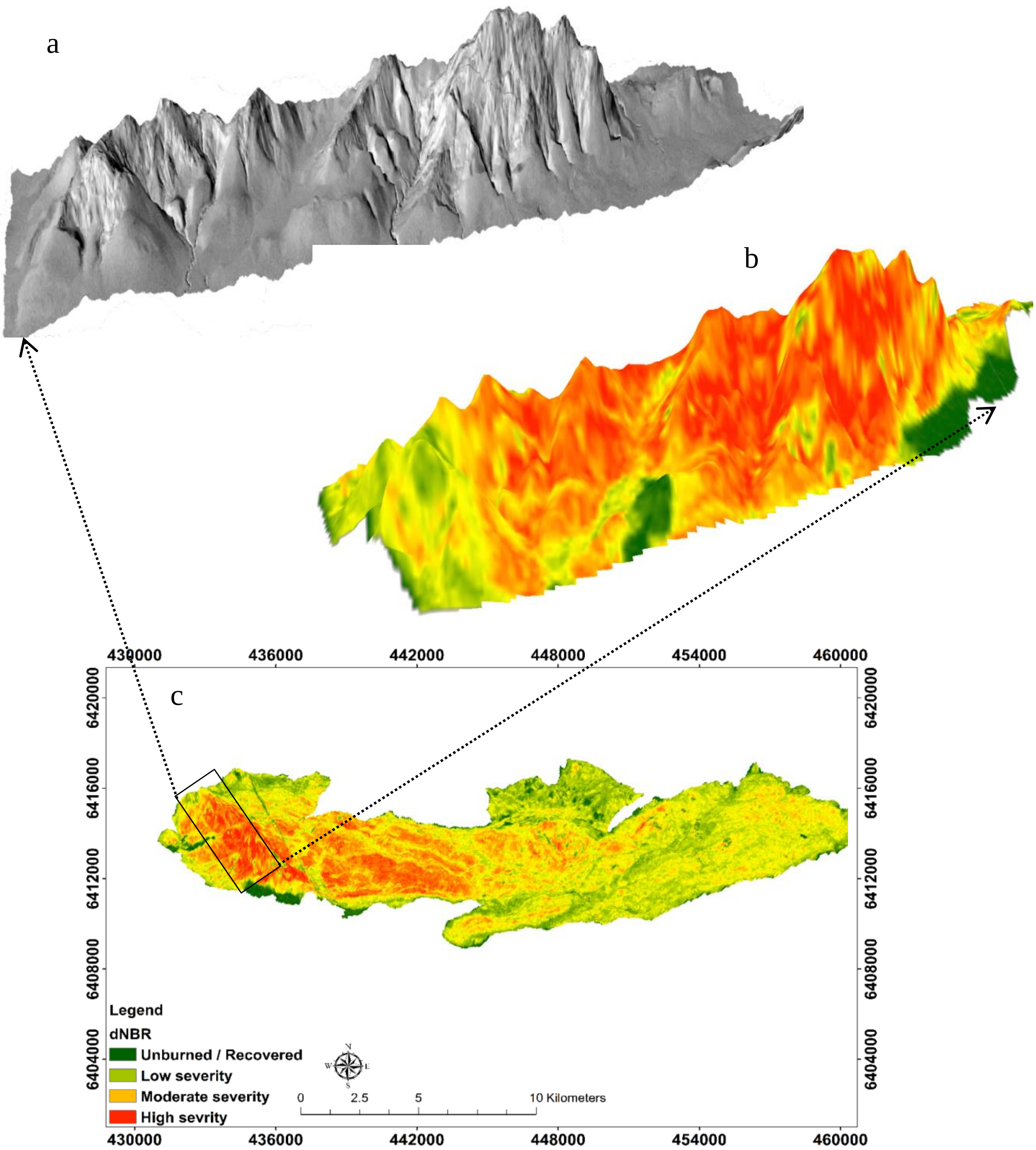

Figure 6.2. Mt Cooke: a) Granite outcrop in 3D; b) fire severity map on the granite outcrop and c) showing the fire severity across the burn scar from dNBR values.

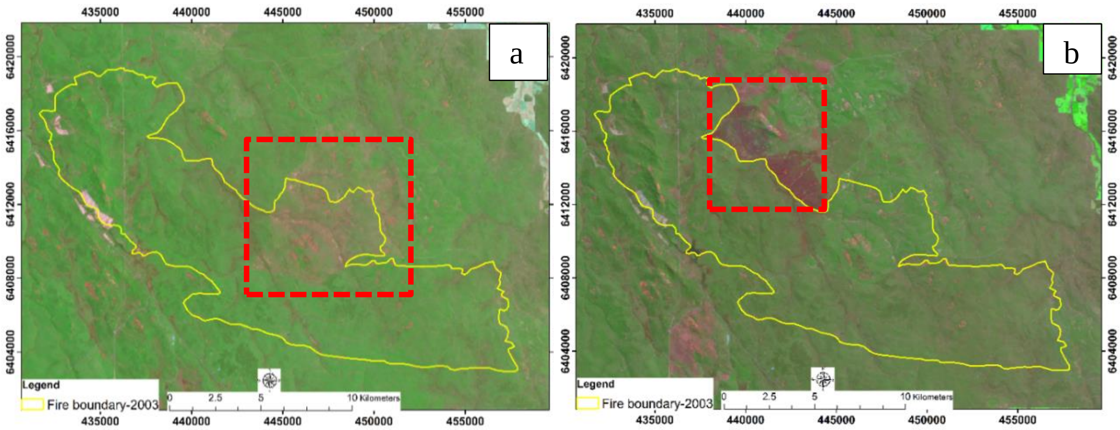

Figure 6.3. Maps showing: a) the area of a prescribed burn 1999 and b) showing the area of a prescribed burn 2002.

6.4.1.1 Fuel age and fire

Within the total area that had a fuel age of one to five years, 13% registers as a low severity burn class; 3.43% recorded a moderate severity burn and only 2.24% registered as a high severity burn. On the other hand – within the total area having a fuel age of greater than 5 years, 40.22% registered as a low severity burn, 30% registered as moderate severity burn and 10% as a high severity burn (Appendix 2; Figure A1). This would suggest that a reduction of the ground litter and fuel reduction with prescribed burning may decrease the level of fire severity. The level of burn severity will also be a function of fire behavior which will vary temporally and spatially. Fire intensity/flame height are a function of a) the amounts of fuel that can burn, and b) how fast it burns (rate of flame spread). Prescribed burning reduces fuel load, so therefore, fire intensity. If the fire intensity is reduced then so will the burn severity reduce. Further studies are required to determine the optimal prescribed burn regimes that will both protect the environment from such high severity burns but also allow time for these specific endangered plants to reach maturity. From the satellite image the areas with differing fuel ages are visible in (Figure 6.3).

6.4.1.2 Elevation and fire

The elevation levels were divided into four groups – 200-300 m; 300-350 m; 350-400 m and >400 m from the DEM. The fire severity for each level was masked, calculated and graphed. The percentages for the three fire severity classes were determined for each level of elevation. From 200-300 m above sea level, 6.01% of the total area at this elevation sustained a low severity burn, 4.7% sustained a moderate severity burn and 3.61% a high severity burn. At 300-350 m 20% of the total area at this elevation sustained a low severity burn, 15% sustained a moderate severity burn and 5.29% sustained a high severity burn. In the regions above 400 m, the low severity burn covered only 2 % of the total area, 3.65% had a moderate severity burn and 3.84% of the total area had a high severity burn, (Appendix 2; Figure A2).

6.4.1.3 Aspect and fire

The results of the fire severity in relation to aspect indicate that the northerly aspects sustained the highest fire severity across all of the study area, (Appendix 2; Figure A3). In the northerly aspects (N, NE, NW), 10% of the total area burned received a low severity burn, compared to the southerly aspects (S, SE, SW), which had 13% in the low severity burn range. In the moderate class it was 12% in the North aspects and 11% in the southerly aspects. The high severity range for the north aspects was 18% compared to 9% in the south and for the high severity burn class.

A decision tree based classification model (Classification Regression Tree, CRT) was produced dividing the data into groups – the dependent variable in this study was the dNBR and the independent variable is the aspect. This was used for exploratory and confirmatory analysis. The high severity burns were recorded in the north, north-east and north-west. In the south, south-east and south-west the classification was low to moderate prediction. For the east a moderate-severe burn was predicted. North facing positions more commonly register a high severity burn than those from the remaining aspects (Figure 6.4).

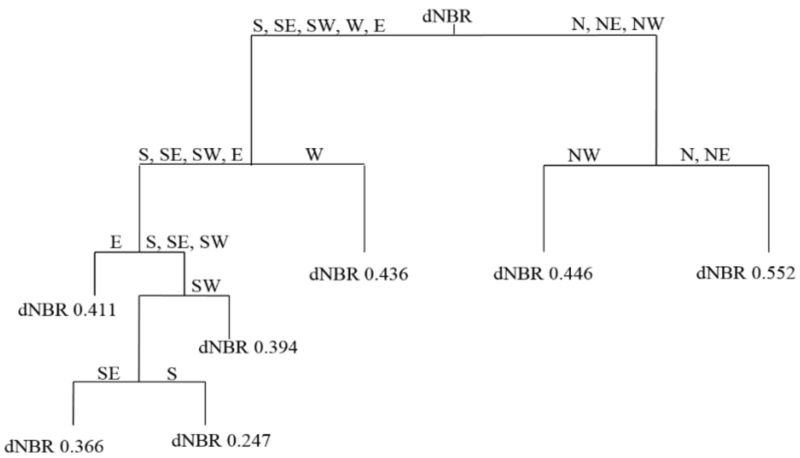

Figure 6.4. Regression tree demonstrating severe fire occurrence within the Mt Cooke fire 2003 on differing aspects.

6.4.1.4 Slope and fire

Of the burn severity recorded on slopes of between 0-5 degrees, 22.8% was a low severity burn, 12.9% was within the moderate severity class and 5.6% was within the high severity burn class. For the area of 5-10 degrees of slope, 19.7% was low severity burn, 12.4% was within the moderate severity class and 4.4% was within the high severity burn class. In the area with >15 degrees of slope, 2.1% was in the low severity class, 3.4% was in the moderate and 3.9% in the severe severity burn class (Appendix 2; Figure A4).

There is photographic evidence of areas on the steeper sections (Figure 6.5) of the outcrop which are close to the summit that exhibit some pockets of vegetation that remained unburned or with only minimal damage. These pockets were preserved by the sparseness of plant growth in the area on which the fire may have taken hold.

Figure 6.5. Micro habitats of isolated vegetation pockets after the fire that remain unburned or only lightly burned, on steep sloping areas towards the summit of Mt Cooke. Photos by courtesy of Neil Burrows.

6.4.1.5 Northness and fire

Of the results from the north facing slope, 9% was a low severity burn, 12% was within the moderate severity class and 20% was within the high severity burn class. Within the south facing aspect, 7% was of a low severity burn, 9% was within the moderate severity class and 12% was within the high severity burn class (Appendix 2; Figure A5).

6.4.1.6 Terrain Ruggedness Index

When calculating the effect of the terrain ruggedness, firstly the percentage for each ruggedness class is determined – level ground makes up 56% of the total study area, nearly level ground was 37%, slightly rugged ground was 3% and 4% intermediate ruggedness in comparison with the fire severity, the results in (Appendix 2; Figure A6) demonstrate that on level ground, 29% was of a low severity burn, 21% was within the moderate severity class and 6% was within the high severity burn class. For the areas of nearly level ground, 21% were low severity burn, 11% was within the moderate severity class and 4% recorded a high severity burn class. Within the slightly rugged ground areas – 4% of the total ground surface area, 2% was rated as a low severity burn, 1.0% was within the moderate severity class and 1.2% was within the high severity burn class. Areas with intermediate ruggedness comprising 3.8% of the total surface area, 1. 5% was a low severity burn, 1.12% was within the moderate severity class and 1.2% was within the high severity burn class. No areas fell within the severely rugged class.

6.4.1.7 Topographic Position Index and fire

From the total study area, 13% is classified as “valley”, 8% of this area sustained a low severity burn, 4.4% was within the moderate severity class and 1.3% was within the high severity burn class. For the areas classed as “flat” – 35% of the total area, 19% sustained a low severity burn, 12% was within the moderate severity class and 4% was within the high severity burn class. Within the areas classed as “slope”, 36% of the total area, 20% sustained a low severity burn, 12% was within the moderate severity class and 4% was within the high severity burn class. In the remaining area, classed as “ridge”, making up 15% of the total ground area, 8% was a low severity burn, 5% was within the moderate severity class and 2% was within the high severity burn class (Appendix 2; Figure A7).

6.4.1.8 Elevation Relief Ratio

The elevation relief ratio (ERR) is considered as either as a measure of the extent the topography has been opened up by erosion (Clarke 1966) or as a measure of the degree of landscape dissection (Evans 1972).

Sub horizontal ground with scattered peaks or horizontal land with deep incisions are labelled “lowlands” made up 52% of the total, with an index of 0.0 – 0.5 and “uplands” made up 47% of the total as 0.51 – 1.0. Of these two variants, within the lowland class, 28% sustained a low severity burn, 17% was within the moderate severity class and 7% was within the high severity burn class. Within the upland class, 25% was low severity burn, 16% was within the moderate severity class and 6% was within the high severity burn class (Appendix 2; Figure A8).

The classification tree analysis cross validation outcomes indicate that the smallest classification tree which could be fitted without increasing the misclassification error rate was one with seven nodes. This tree used four predictors: fuel, elevation, TPI and ERR. The first split was based on fuel at an elevation of <350 m; where fuel was between three to five years old, fire severity was always low, whereas where the elevation was >350m and the fuel was more than ten years of age, a high severity burn was predicted. Below this elevation, fire severity was more often moderate (Figure 6.6).

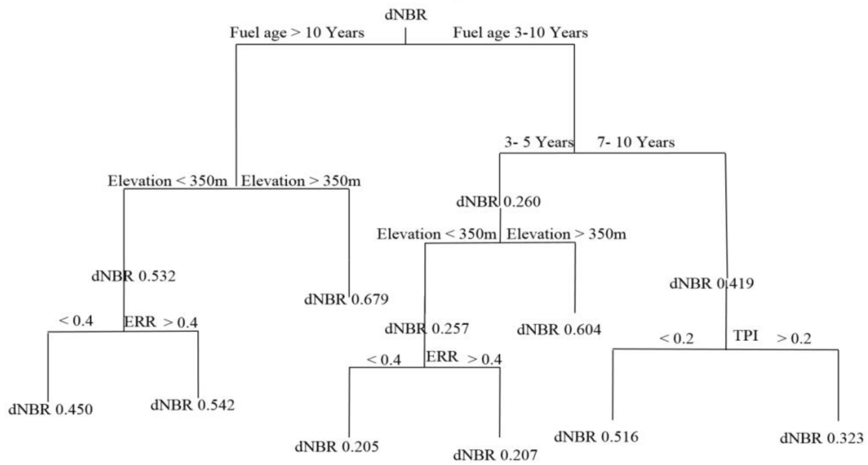

Figure 6.6. Regression tree demonstrating severe fire occurrence within the Mt Cooke fire 2003 on differing variables

6.4.2 Modelling

6.4.2.1 Descriptive Statistics of Model Variables

The statistics of the model variables and descriptive details are shown in (Table 6. 4) and this provides a general overview of the dataset. There was marked variation in the mean values of the various parameters as a result of differences in measurement units.

Table 6.4. Descriptive statistics of the model variables.

Stats	dNBR	Aspect	Elevation	Slope	Northness	Fuel	ERR	TRI	TPI	Habitat
N	298	298	298	298	298	298	298	298	298	298
Mean	0.40	197.09	355.13	7.03	0.01	0.81	0.52	81.09	0.42	0.57
Std. Error of Mean	0.01	2.82	2.41	0.16	0.01	0.02	0.00	1.79	0.01	0.03
Std. Deviation	0.13	48.62	41.64	2.69	0.24	0.39	0.08	30.96	0.25	0.50
Variance	0.02	2363.75	1734.20	7.24	0.06	0.16	0.01	958.34	0.06	0.25

Visualisation – identifying potential factors

Eight maps were produced to identify potential variables which may or may not affect fire severity in the study area (Figure 6.7).

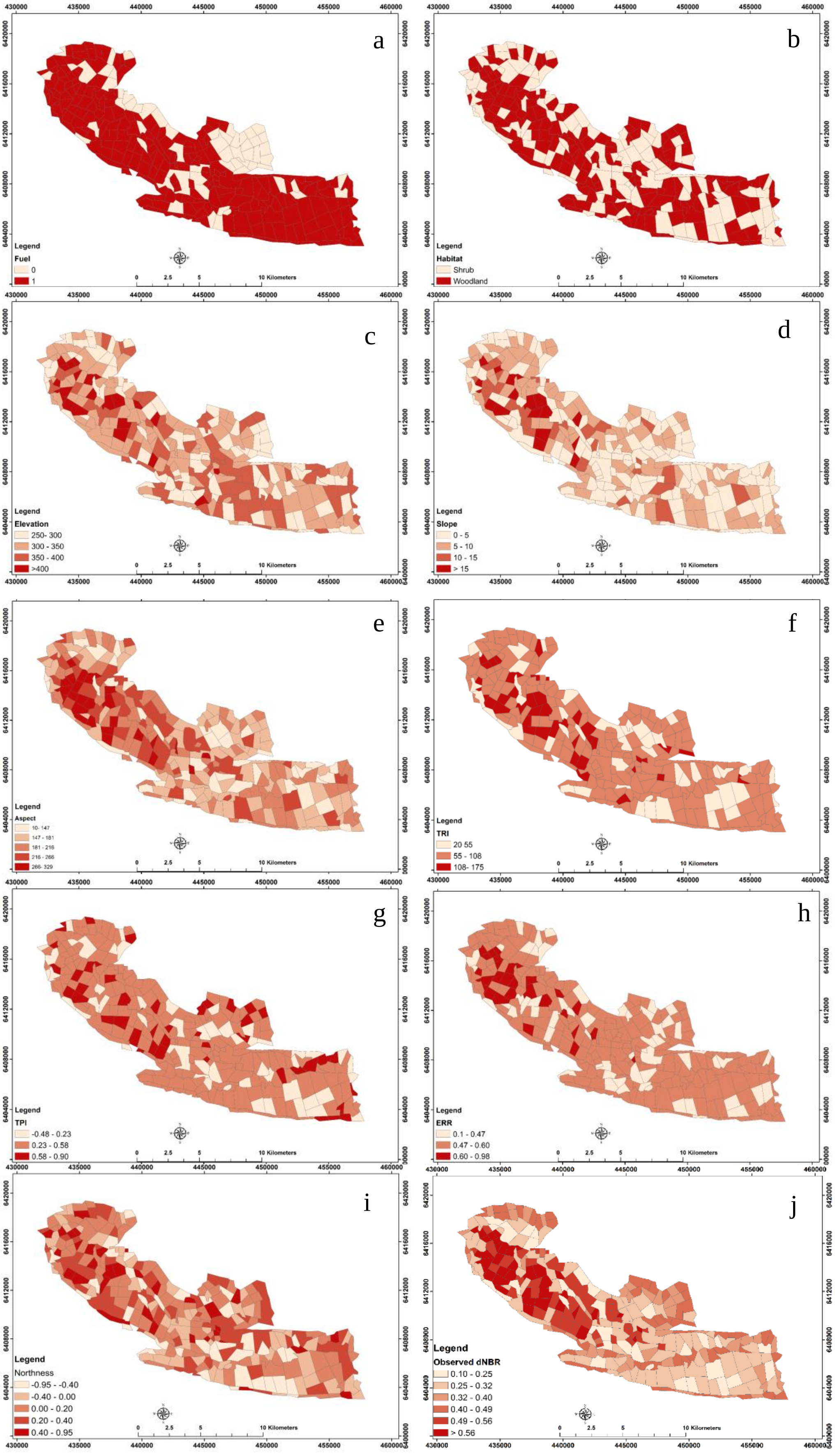

Figure 6.7 Maps showing visualisation of each variable from the raw data – a) Fuel, b) Habitat, c) Elevation, d) Slope, e) Aspect, f) TRI, g) TPI, h) ERR, i) Northness and j) dNBR.

6.4.2.2 Correlation Analysis

This was completed to identify the linear association between the variables to identify if any of the independent variables were linearly related to the dNBR variable. Only the variables which had a significant ($p < 0.05$) with dNBR are chosen for modelling (Table 6.5 and Figure 6.8).

Table 6.5. Table showing the correlation between the dependent variable and independent variables.

		dNBR	Elevation	Slope	Aspect	Northness	ERR	TRI	TPI	Fuel	Habitats
dNBR	P C	1.00	0.58	0.54	0.60	0.53	0.45	0.60	0.50	0.50	0.37
	p-value		0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Elevation	P C	0.58	1.00	0.50	0.52	0.24	0.38	0.40	0.30	0.36	0.27
	p-value	0.00		0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Slope	P C	0.54	0.50	1.00	0.48	0.27	0.32	0.52	0.30	0.24	0.23
	p-value	0.00	0.00		0.00	0.00	0.00	0.00	0.00	0.00	0.00
Aspect	P C	0.60	0.52	0.48	1.00	0.24	0.35	0.38	0.30	0.23	0.21
	p-value	0.00	0.00	0.00		0.00	0.00	0.00	0.00	0.00	0.00
Northness	P C	0.53	0.24	0.27	0.24	1.00	0.30	0.33	0.29	0.23	0.15
	p-value	0.00	0.00	0.00	0.00		0.00	0.00	0.00	0.00	0.01
ERR	P C	0.45	0.38	0.32	0.35	0.30	1.00	0.25	0.29	0.26	0.19
	p-value	0.00	0.00	0.00	0.00	0.00		0.00	0.00	0.00	0.00
TRI	P C	0.60	0.40	0.52	0.38	0.33	0.25	1.00	0.28	0.19	0.21
	p-value	0.00	0.00	0.00	0.00	0.00	0.00		0.00	0.00	0.00
TPI	P C	0.50	0.30	0.30	0.30	0.29	0.29	0.28	1.00	0.36	0.16
	p-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00		0.00	0.01
Fuel	P C	0.50	0.36	0.24	0.23	0.23	0.26	0.19	0.36	1.00	0.35
	p-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00		0.00
Habitats	P C	0.37	0.27	0.23	0.21	0.15	0.19	0.21	0.16	0.35	1.00
	p-value	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.01	0.00	0.00

P C = Pearson correlation, p- value 0.05

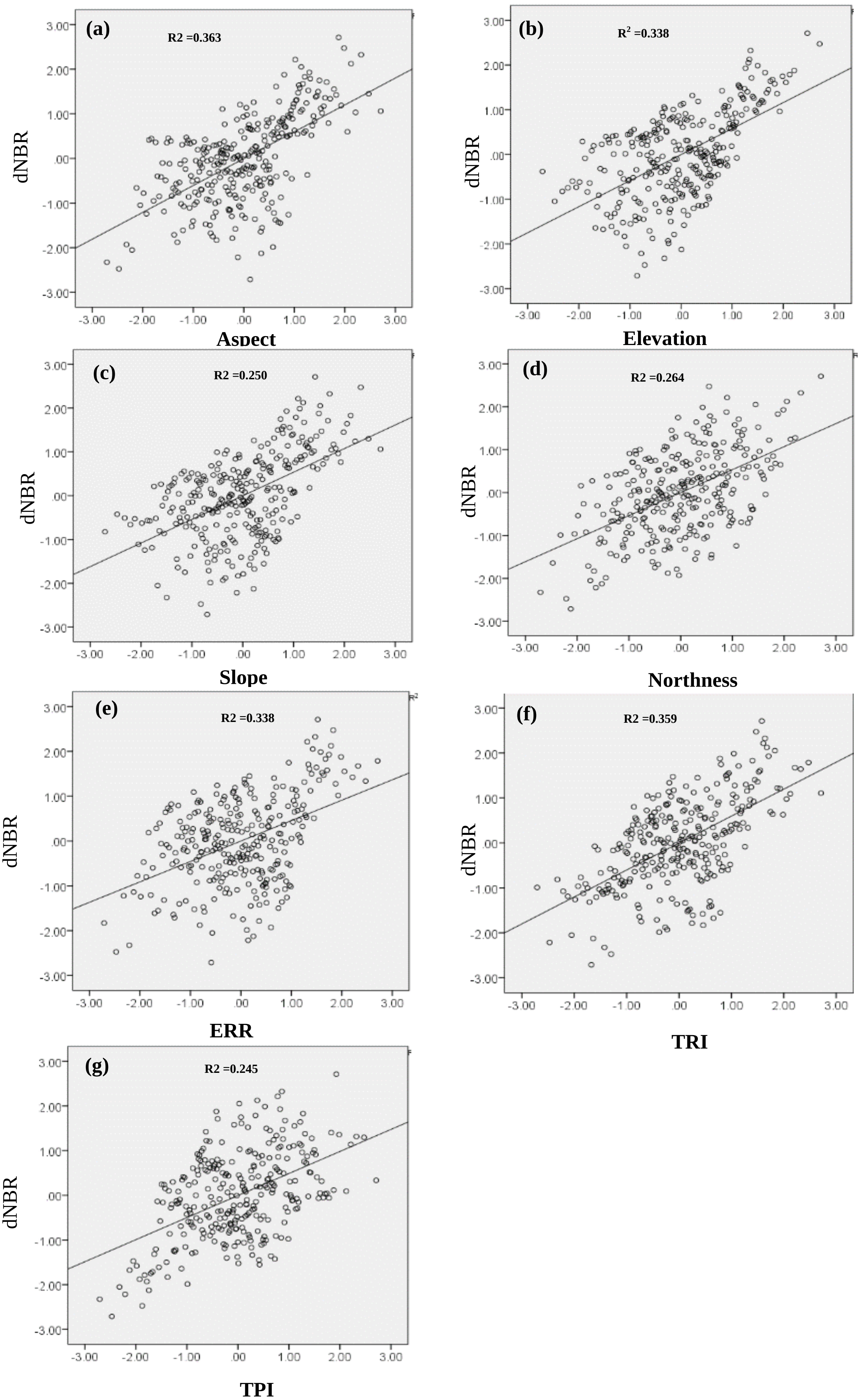

Figure 6.8. Scatterplots showing the relationship between the dependent variable and the independent variables:a) between dNBR and aspect, b) between elevation and dNBR, c) slope and dNBR, d) northness and dNBR, e) ERR and dNBR, f) TRI and dNBR, g) TPI and dNBR.

6.4.2.3 Selection of predictor variables and best model

The statistical results of AIC in the selection of the independent variables which are to be included into multiple regression analysis are shown in (Appendix 3; Table 1). The combination of variables which provides the minimum AIC value is assumed to be the best model.

The combination of these independent variables (Aspect, Elevation, ERR, Fuel age, Habitat, Northness, Slope, TPI and TRI) provided the best subset in which there is the lowest AIC (-765) with nine variables and were statistically significant, apart from the ERR which displayed insignificant results. For the comparative analysis the optimal subset of variables has been calibrated with two models – OLS regression and the GWR.

A model was developed from using ArcGIS Exploratory Regression equation and this was processed to determine the best model. The outcome was that 466 models were produced. Of these, 89% of these models were passed (Min Adjusted R–squared was > 0.5); 460 passed with a maximum coefficient P – value of < 0.05; 466 models were passed with a maximum VIF < 7.5; 303 models were passed with a Min Jarque-Bera P – value >0.1; 174 models were passed with a Min Spatial Auto correlation of > 0.1. From the 460 models – one model was chosen with the lowest Akaike's Information Criterion (AICc) and a high R^2 (Table 6.7 and 6.8).

6.4.2.4 Ordinary least square regression

The value of tolerance and the variation inflation factor (VIF) suggests that there is no problem with multicollinearity in the model specification and stability of the model coefficient. The regression coefficient for eight of the independent variables were statistically significant, (p- value <0.05). All the variables had a positive contribution on the response variable – for example, an increase in the slope lead to an increase in the dNBR value (Table 6.6).

Table 6.6. The OLS results for the model variables in the study area.

Variable	Coefficient	Std Error	t-Statistic	Probability	Robust	SE Robust	t Robust_Pr	VIF
Intercept	0.37	0.01	39.30	0.00	0.01	40.72	0.00	---
Aspect	0.04	0.00	7.19	0.00	0.00	7.24	0.00	1.56
Elevation	0.02	0.01	3.84	0.00	0.01	3.86	0.00	1.67
Slope	0.03	0.01	3.49	0.00	0.00	3.84	0.00	1.68
Northness	0.03	0.00	7.40	0.00	0.00	8.20	0.00	1.25
Fuel age	0.03	0.01	3.25	0.00	0.01	3.27	0.00	1.37
TPI	0.01	0.00	2.76	0.01	0.00	3.14	0.00	1.28
TRI	0.03	0.00	5.32	0.00	0.00	5.88	0.00	1.52
Habitats	0.05	0.02	2.67	0.01	0.02	2.74	0.01	1.19

Using OLS regression ($p < 0.05$) between dNBR and nine variables, there has been a statistically significant positive relationship identified. The Adjusted R-squared value, (as a measure of the model's performance), was 0.71, meaning the model explains 71% of the occurrence of the dependent variable of the dNBR.

All of the model coefficients were statistically significant (except ERR, so this model was run without the ERR variable) and returned Variance Inflation Factor values of < 7.5, indicating that independent variable distributions were not redundant. The model's Jarque-Bera statistic of 0.64 > 0.05, suggests the residuals follow a normal distribution and the results of the model are unbiased (Table 6.7).

Table 6.7. This table shows the statistical results of the OLS models.

	Degree of freedom	Probability	Value
Akaike's Information Criterion	-	-	-755
Multiple R-Squared	-	-	0.72
Adjusted R-Squared	-	-	0.71
Joint F-Statistic	8, 289	0	-
Joint Wald Statistic	8	0	-
Koenker (BP) Statistic	8	0.42	-
Jarque –Bera Statistic	2	0.64	-

The Koenker Statistic is not significant (0.64 > p-value 0.05), showing that the relationships are consistent – there is no stationarity or 110eteroscedasticity (Table 6.7). Throughout the model building process the model adequacy was validated by confirming the model assumptions (Montgomery *et al*. 2001). The histogram of standardised residuals was checked and it indicated that there was no problems with the normality assumption and this was further supported by the statistical test of normality (Jarque-Bera) JB = 0.64, and Shapiro-Wilk (W = 0.99, p-value = 0.05) which did not reject the normality of the residual distribution (Table 6.8).

Table 6.8. Tabled results after applying Shapiro-Wilk test for normality.

		Shapiro-Wilk	
Variable	df	Statistic	Sig.
Aspect	291	0.999	1
Elevation	291	0.998	0.974
Slope	291	0.996	0.685
Northness	291	0.997	0.936
Fuel age	291	0.485	0
ERR	291	0.999	1
TPI	291	0.999	1
TRI	291	0.999	1
Habitats	291	0.631	0

Results of the OLS model were also evaluated for spatial autocorrelation using the ArcGIS Spatial Autocorrelation with a reported a z-score of – 0.30 and reported the model's resulting pattern to be significantly random, concluding that key independent variables were present in the model (Table 6.9). Moran's I was used to test OLS model residuals for spatial autocorrelation the Moran's index -0.01 and p-value 0.75.

Table 6.9. Moran's I results for the residual distribution.

Moran's Index:	Expected Index	Variance	z-score	p-value:
-0.01	0	0	-0.3	0.75

Mapping observed, predicted and residual values across the study area

Maps of the predicted and the standard deviation for the residual dNBR values fitted by OLS models and were created in ArcGIS (Figure 6.9).

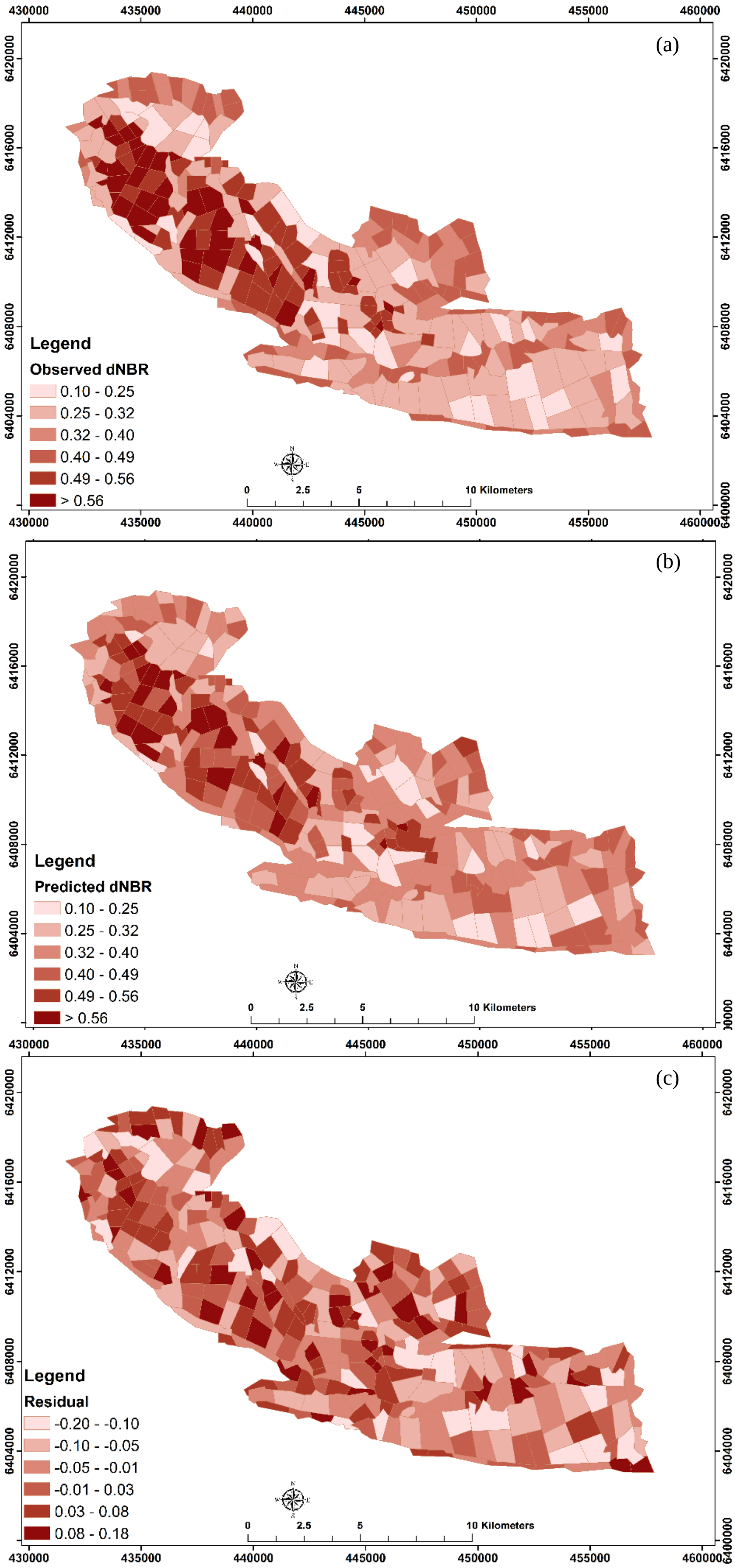

Figure 6.9. Results from the OLS: a) the observed dNBR map, b) the predicted dNBR map and c) the residual map

6.4.2.5 Geographically weighted regression (GWR)

GWR produced a set of parameter estimates and model statistics at each sample point rather than to a set of constant values over the study area. The GWR can often produce a better residual sum of squares which indicates a better model fit (Brunsdon *et al*. 1996; Fotheringham *et al*. 2002; Zhang and Shi 2004).

The results from the GWR model demonstrate no significant presence of multi-collinearity between the independent variables. The AICc statistic for the GWR model was -765. This lower AICc statistic indicates the GWR model is better than the OLS model at explaining the occurrence of the dependent variables (Table 6.7 vs Table 6.10).

Table 6.10. The results of the GWR model for the fire severity

	Adjusted R^2	R^2	Residual Squares	Effective Number	AICc
Low severity	0.74	0.76	1.24	30.77	-765

Mapping Observed, Predicted and Residual Values across the Study Area

Maps of observed, predicted and residual dNBR values fitted by GWR models were created in ArcGIS (Figure 6.10).

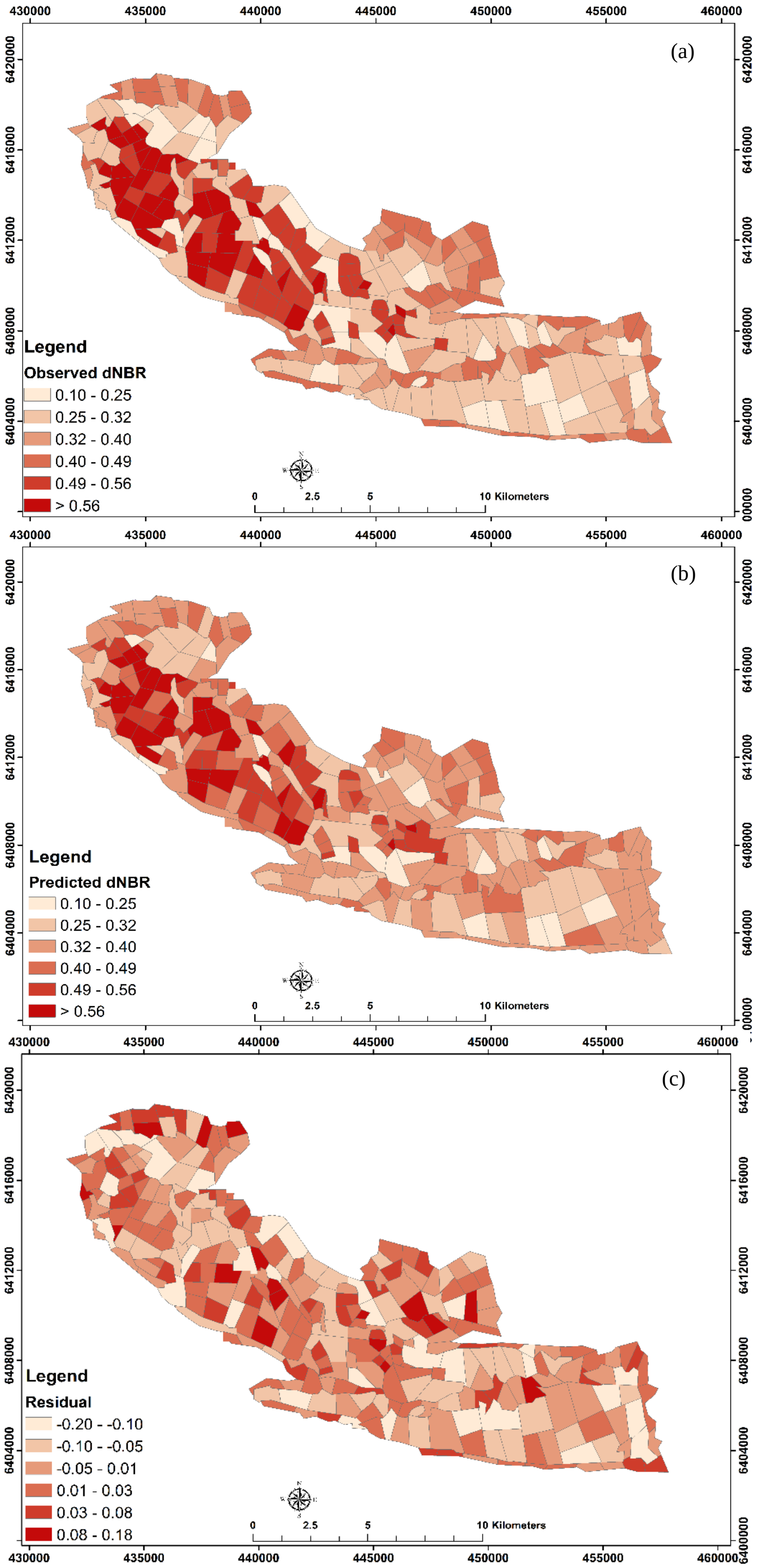

Figure 6.10. Results from the GWR: a) the observed dNBR map, b) the predicted dNBR map and c) the residual map

6.5 Discussion

6.5.1 Topography and vegetation with fire severity

Topography describes the shape of the landscape with the use of factors such as aspect, elevation, slope, slope positioning and ruggedness, among others. These topographic variables impact on fire behaviour as the fire moves across the varying landscape features. Fire behaviour and severity will be influenced by several factors such as vegetation type, recent weather conditions, the topography of the area and the amount of accumulated fuel loads, for example, the spread of the fire will be influenced by slope and wind direction and these factors can affect the intensity of the fire (Whelan 1995; Heyerdahl *et al*. 2001; Román-Cuesta *et al.* 2009; Bradstock *et al*. 2010; Sharples *et al.* 2010).

Vegetation characteristics strongly impact fire ignition and fire behaviour (Hines *et al.* 2010). Not only the type of vegetation, but also the continuity of the vegetation and the plant sizes and structure can impact the likelihood of an ecosystem burning (Hines *et al*. 2010; Watson *et al*. 2012). The dry sclerophyll forest that comprises the study area's vegetation cover is one of the more fire prone types. It forms a highly inflammable fuel in both the living and the dead vegetation (Bradstock *et al*. 2009). The fibrous bark on these tree types and a large amount of eucalyptus leaf litter in these forest areas encourage fire to spread quickly (Bowyer and Danson 2004; Gillen 2005; Keith 2006).

Summer temperatures can exceed 30 degrees and rise to 40 degrees (Bureau of Meteorology 2012). A common phenomenon of warm dry air along with high temperatures can decrease relative humidity to below 20% and the added effect of the wind can cause the fuels to quickly dry out (Pippen 2008). The area was affected over a broad scale by the changing climactic conditions (Whitlock *et al*. 2003; Whitlock 2004; Alexander *et al.* 2006; Matthews 2009), and weather conditions at the time of the fire's ignition were extreme. The winds were gusty NW 25-35 km/hr and temperatures had been high with low humidity and with no recent rains (Burrows 2003; DEC 2011). Lecina-Diaz *et al*. (2014) and others found in their studies of fire and topographic variables that wind assisted fires, spreading with increased speed, can reduce the effect of other variables such as topographic factors, which may at other times ameliorate fire progression (Matthew 2009; Bradstock *et al*. 2010; Price and Bradstock 2012).

In 2008, Boer *et al*. found that in the southern Australian eucalypt forests, the fire frequency distribution was aligned to extreme weather events which led to non-suppressible fire intensity and that this may be a vital factor impacting the area burned and fire regimes in these types of environments.

The fuels on Mt Cooke consisted of accumulated vegetation that incorporated at least 3 seral stages (post-fire habitat stages) from previous fires at this site (Burrows 2006). Heterogeneity in relation to topographic features at fine scale can impact vegetation types and moisture levels leading to particular burn patterns forming – known as a mixed severity fire regime where vegetation mosaics affected by low and high fire severity are positioned randomly side by side (Beaty and Taylor 2001). This study found a similar trend over areas of comparable landscape features and at times some unexpected fire severity levels were recorded.

When discussing the whole picture of topography, weather and vegetation, Wood *et al*. (2011) stated that based on satellite assessed burn scars, the fire patterns were not limited to any topographic features but on the topography in relation to the topographic position as influenced by the weather and wind and these findings coincided with others (Alexander *et al*. 2006; Collins *et* al. 2007; Viedma *et al*. 2009 and Bradstock *et al.* 2010). In assessing fire sensitive forest in South African fires, Geldenhuys (1994) found that the prevailing winds and terrain physiology dictated the fire severity levels.

6.5.2 Fuel age

Fuel accumulation rates are influenced by vegetation types and the elevation, slope and aspect on which they grow (Whitaker and Niering 1975; Holden *et al*. 2009). Moisture content in the fuel and whether the vegetation types are dead or living will greatly affect the fire – flame size and the rate at which a fire spreads is not reliant on a heavy fuel load but the heavier the fuel load, the more heat is released and this makes a fire substantially harder to suppress (Matthews 2009). Agee (1993) and Odion *et al*. (2004) found that sclerophyll types of vegetation burns relatively easily and these fires release high amounts of energy. The rate fuel loads accumulate in jarrah forests is estimated to be 1-2 tonnes/ha each year to a maximum of ~20 tonnes/ha within 20 years, (Parks and Wildlife, 2012). Fuel moisture content has more impact on fire severity in all geographic and topographic variables (Chuvieco *et al*. 2004; Oliveras *et al*. 2009; Dannison and Moritz 2009; Caccamo *et al*. 2012). This study found that the increased fuel load in particular areas had a higher burn severity.

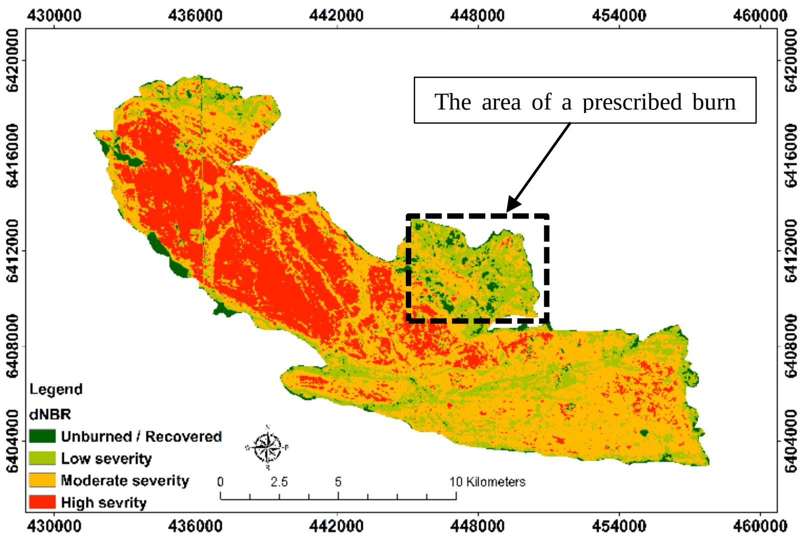

Figure 6.11. The dNBR map indicating the area where a prescribed burn took place in 1999. It correlates with a marked reducation in fire severity in the overall assessment.

Fuel load reduction in some of the study area has greatly reduced the fire severity in these regions. On the eastern aspect are areas which were managed with prescribed burns ranging in time frames from 1-23 years previous to the 2003 fire. The areas where the burn severity is highest are within a region that the most recent prescribed burning was performed between 10-17 years before (Figure 6.11). The fire intensity represents heat released by the fire in relationship to the heat yield from the fuel and the amount of fuel per unit of area in association to the speed of the forward spread of the fire. This relationship is described in Byram's (1959) fire intensity equation: I = Hwr

where,

I is intensity (kW/m)

H is heat yield of fuel (J/g)

W is fuel consumed (kg/m^2)

R is spread (m/sec)

When comparing regions within the study area that had been burned in the one to five years before the 2003 fire, the results clearly demonstrated that the reduced fuel loads greatly impacted the severity of the burn (Figure 6. 6). The percentage of high severity burn class in the region that had been burned three years before was 2.2% and in the region where the prescribed burn had taken place more than five years prior the percentage in the high severity burn class was 10% of the total. This would suggest a key component to good fire management within the granite outcrop regions of the SWAFR is to maintain a regular schedule of prescribed burns to reduce the fuel loads at intervals that protect the slow maturation growth cycles of the local species. In their study on a Sydney fire, Hammill and Bradstock (2006) found a fuel age of less than five years can decrease the chance of crown fires and thus may diminish some adverse ecological effects. They went on to show that fuel discontinuity, such as found in rocky outcrops, can lower fire intensity, even in severe burns.

This research shows that the whole study area sustained burn damage in the 2003 fire. The forest areas sustained the highest fire severity burns – in the forest the fuel loads were high and very dry and these areas were totally defoliated or fully scorched and trees that were estimated to be over 300 years old died in this fire (Burrows 2006) (see Chapter 5).

The shrubs on the slopes, in the rock fields and over the broken grounds, and are seen mostly on granite outcrops, are fire sensitive and they were burned but will regenerate quickly from seedbeds in the soil. Higher up on the granite outcrops the vegetation amounts were lower than that of the surrounding area and this has the potential for a lower severity burn - >400 m high the fire severity was expected to be lower due to the reduced fuels but the fire severity was high. There were some small pockets of vegetation in rock crevasses seemingly untouched though. The heat however, was so intense that it caused large sheets of rock to flake off (Burrows 2003).

The hypothesis was that it is expected that the results will show a variety of fire severities across the GOs which will support the argument that some communities have a degree of topographic protection from fire. This has not been shown in this study – all areas were burned and no particular topographic variable offered more protection than another in this intense fire. The fire intensity was increased by a combination of long unburned forest fuels and dry conditions. The fire danger rating at the time of the fire was Very High. The ember attacks started fires in areas that may have been thought of as refugia.

Miller *et al*. (2009) in their studies in the Sierra Nevada regions on the west coast of America found an increasing trend in severity and scale of wildfires despite human intervention in reducing fuel loads and state the vegetation fragmentation caused by land use adds to the risks for an increase in fire severity. Their findings suggested that the average and maximum fire size has – since the early 1980s – risen to above the values recorded in the years preceding 1940s when there was no national fire suppression program.

6.5.3 Elevation

Elevation may influence temperature and vegetation types within the landscape. It may also affect fire behaviour – for example, to the exposure of prevailing winds and a feature's relationship to the surrounding landscape.Temperatures may be moderately affected by elevation as will the availability of moisture within the fuel load (Whittaker and Niering 1965; Stage 1976; Stephenson 1990). The results from this study reveal that fire severity in areas of higher elevation was higher than that of the low elevation areas, probably due to the fire burning strongly upslope and being encouraged by the gusty winds.

The results of the relationship between fire severity and topographic features have shown that there are a multitude of components that play a role in how the fire behaves over the complete structure and no one topographic feature offers better protection than another. For example, elevation is impacted by the fact that there is less vegetation on the higher reaches of the outcrop and the plants are low growing, on limited soil and occurring between rocks. This would suggest that the fire severity will be lower but from these results the percentage of high severity burn was roughly the same at 300 m as it was at 400 m. (The results from > 400 m are discounted here as this total area is only between 1-4% of the total area).

In studies in the west coast regions of America Miller *et al.* (2009) found the fire in low to middle elevation burned with greater severity that those in areas of a higher elevation and they also concluded that the change in plant size and the continuity of the vegetation being broken up on the high elevation areas caused these findings.

It is evident from this study that fire behaviour may be different from other hill/mountain fires when it occurs on and around GOs. For example, the results from this study indicate that where the fire severity increases as the fire moves up a slope, when it reaches the upper levels of the outcrops the severity remained high despite the fact that there is little or no vegetation or high fuel loads – the radiant heat increased the temperatures in the granite itself causing the rock to split and crack and for large sheets to flake.

6.5.4 Aspect

Aspect has been shown to affect fuel moisture levels (Frank and Lee 1966; Waring and Running 2007).The north facing areas showed a higher burn severity than the south facing areas, probably due to the fact that the north westerly facing areas are dryer and warmer (Whelan 1995; Chafer *et al.*

2004).Greater sun exposure leads to more favourable fuel moisture and vegetation type on north westerly aspects in the southern hemisphere (Whelan 1995).

Wind direction and speed will affect how areas on a particular aspect are more affected than others when a fire is burning across a landscape. The wind will have an increased wind speed if it is blowing up a slope rather than down – the winds on the days the fire was burning was gusty, at 25-35 km/hr (Burrows 2006; DEC 2011). The north-northeast facing areas had a mean dNBR of 0.552 – the highest of the burn severities in relationship to aspect. The more moist fuel loads on the south facing slopes as a result of reduced exposure to solar radiation and may explain the lower burn severity recorded on these aspects – a mean dNBR of only 0.25. In fire studies in the northern hemisphere it was found that the south facing slopes burned with greater intensity (Weatherspoon and Skinner 1996; Taylor and Skinner 1998; Alexander *et al*. 2006), probably due to exposure to greater solar radiation, generally less available moisture, which results in drier fuels and smaller diameter plants and this corresponds with the trend seen at this site on the north facing areas.

6.5.5 Slope

The topographic feature of slope refers to the amount of the incline in a landscape. Fires will burn more rapidly when moving up a slope than when moving downhill (Whelan 1995). The steeper the incline, the faster the fire burns. This is due to the fact that the fuels above the fire are brought into closer contact with the upward moving flames. Convection and radiant heat will assist the fuels to catch fire more quickly. The relationship between the steepness of the slope and fire spread is not fully understood (Oliveras *et al.* 2009), and in their study they found these rules of increasing slope affecting increasing fire spread do not always apply.

The position of the fire in relationship to the topography of a region will be a major contributing factor for the fire behaviour. For example, a fire which is burning across level ground is primarily influenced by the fuels present and the wind driving the flames. A fire which ignites at the bottom of a slope with the usual upslope wind conditions tends to spread faster and has a wider area to spread uphill than if a fire begins closer to the summit of the slope. The ignition point in the Mt Cooke fire was due to a lightning strike on the upper north facing area of the slope (Figure 6.1). The winds were 25-35 km/hr from the North-West. The fire moved quickly up the slope and across the top of the mountain ridge and burned 18,000 hectares in just 24 hrs (Sneeuwjagt DEC 2008).

Slope is known to affect fire spread by raising the efficiency of radiant energy transfer from the fire flame front upslope to the as yet unburned fuels (Rothermel 1983; Agee 1993). The amount of moisture in the live fuels above the flames increases the flammability of the vegetation as the fire spreads upwards (Dimitrakopoulos and Papaioannou 2001). On granite outcrops however, the slope of the areas assessed demonstrated that the high severity burns increased with the slope of the landscape but only to a point – as the higher slopes where the granite rock is exposed was not severely burned. These sloping areas have small pockets that have been protected and some areas isolated from the fire and they generally hold less vegetation than the surrounding areas. These pockets that occur in rugged areas may be considered fire resistant and as such may act as a fire refuge for endemic species, but only for those species that live in these positions on the outcrops and are small low growing varieties.

6.5.6 Northness

From the results of this study, the slopes affected by northness have the highest burn severity of the four categories – 19% has a high burn severity compared with the second highest on the south facing slopes which sustained 12% of the total area with high severity burn. The east and west facing slopes were markedly lower at 6% for the east and 4% for the west facing slopes. These findings are in accordance with other studies in the southern hemisphere and mirror the findings from studies in the northern hemispheres, which found the same results (Heyerdahl *et al*. 2001; Chafer *et al.* 2004; Miller *et al.* 2009; Bradstock 2010; Wood *et al.* 2011).

6.5.7 Terrain Ruggedness Index (TRI)

In regards to the surface ruggedness, it was found that the fire severity decreased as the terrain became more rugged. Holden *et al*. (2009) suggested that the surface roughness may exert subtle influences on fire behaviour by the effects of micro climates and wind pattern changes or provide change in the fuel/fire behaviour. The surface ruggedness may also impact on the soil development and soil moisture holding abilities. The level ground had a higher fuel load and this may explain why the burn severity was higher on the even ground. The refuge effect became more evident as the granite outcrop surfaces became more rugged (such as in areas on the rock and in boulder fields) – the percentage differences across the fire severity classes were negligible the more rugged the terrain. The area is an old weathered landscape – one of the oldest on Earth (Hopper and Gioia 2004) with softer angles and this may have modified some of the factors expected to be highlighted in a younger, more rugged landscape.

6.5.8 Topographic Position Index (TPI)

The results from the topographic position index indicated that the percentages of high severity burn were low in both valley and ridge features and shown in (Appendix; Figure A7). The lower severity damage in the valleys may be explained by a higher level of moisture content in the foliage and soil of these areas that may have reduced the intensity of the fire. The ridges are generally exposed rock surfaces and this would account for decrease in the high severity burn results as there is low biomass present.

Bradstock *et al*. (2010) also found that the topographic position factor that may enhance or reduce the effect of a fire on the vegetation may be minimal if extreme weather conditions pre-empt the fire. They found the fire sensitive plant communities are frequently restricted to valleys and the southern facing slopes where there are higher moisture levels and a degree of protection from wind exposure. Hammill and Bradstock (2006) concluded that the extreme weather was the dominant factor in the Sydney region fire they studied where the fire severity was high in the dry sclerophyll forests and that in more moderate weather conditions terrain was the impacting factor. They found that the valleys and ridges had a lower burn ratio. The findings by Wood *et al*. (2011) in their study in Tasmanian rainforest fire that the lowest risk of fire was down in valleys and on the ridges and that the flat lands were more likely to burn was in conjunction with Bradstock (2006, 2010).

6.5.9 Elevation Relief Ratio (ERR)

Lowland areas comprised 52% of the total area – of this, 28% sustained a low severity burn, 17% a moderate burn and 7% a high severity burn. Upland areas comprised 47% of the total area. The results for the upland areas revealed that 25% sustained a low severity burn, 16% was a moderate severity burn and the high severity burn comprised 6%. These results are insignificant across this variable.

6.5.2 Modelling

6.5.2.1 Ordinary Least Square Regression Model

OLS regression is widely used as the regression technique for estimating structural parameters in ecological applications (Zhang and Shi 2004; Anselin 2005). From the results from the OLS model, (Tables 6.6 and 6.7), the overall regression was highly significant. The model explained 71% of the variance – which is acceptable (Foody 2003). It explained the majority of the variance, there was no problem with multicollinearity with the model. The variables of aspect and Habitats had the largest influence in predicting the dNBR due to the large coefficient. These results were expected as the aspect has a high correlation with the dNBR. All of the regression coefficients were significant except the ERR. When building the model it was important to validate the model adequacy and after transformation the model data was shown to be normally distributed (Table 6.8). Moran's I score of p-value 0.75 supports the residual as randomly distributed. The scatterplots between the observed transformed variable and the dNBR were analysed to be sure the model performed visually (Figure 6.8).

6.5.2.2 Geographic Weighted Regression

Up until more recent years, GWR has not been used in ecological/fire studies (Zhang *et al*. 2005; Shi *et al*. 2006) and for vegetation species analysis (Foody, 2004; Shi *et al*. 2006). Zhang *et al*. 2004 used modeling for spatial variation in tree sizing relationships using both OLS and GWR and determined that GWR performed the better of the two. In this study, GWR was also found to have the better performance (R^2 0.76 and AICc was -765) indicating a more reliable model for mapping fire severity. These results concur with study results achieved by other in mapping fire over a broad scale (Koutsias *et al*. 2010; Sá *et al*. 2011; Oliveira *et al.* 2014).

Comparison of OLS and GWR Models

A method of assessing the model performance is to compare model diagnostics (Anselin 2005).The results demonstrated the comparative analysis of the two models based on the model diagnostics. Once the GWR is applied, the value of R^2 value increases from 0.72 for OLS model to 0.76 for GWR. The comparison using R^2 on its own is not ideal as it can't be compared to the coefficient model from the OLS; therefore another measurement such as AICc is required to completely evaluate model performance (Anselin 2005). From the results, it is clear that GWR, with the lowest AICc (-765) and the highest R^2 of 0.76 has a better model performance. Thus, it is concluded that by allowing for spatial nonstationarity in the modeling process, GWR provided the better result for dNBR modelling than OLS. From Fotheringham *et al*. (2003), it is evidence of an improved model fit.

In studies done by Oliveira *et al. (*2014), they found that GWR showed an improved performance over OLS when applied to the physical and anthropogenic variables. Similar results were stated in the study by Koutsias *et al*. (2010) when the used both OLS and GWR when assessing possible causative variance factors in fire studies in Southern Europe. They stated at the OLS was insufficient, but that GWR overcame problems with non-stationarity.

6.6 Conclusions

The purpose of this study was to assess the impact that topographic variances have had on a wildfire which burned through the area of GOs in the SWAFR in 2003. These regions hold biota that is diverse with local populations that may be rare or absent in the in the surrounding landscape and it is a globally recognised hotspot of biodiversity. Wood *et al.* (2011), states that topographic variability may override the effect of large-scale disturbance such as an intense fire, by either preventing fire spread or greatly reducing its intensity.

There have been suggestions that fire refugia on GOs may act to preserve some of the endemic species by offering areas that are less likely to burn. This research revealed that all of the study area has had a degree of burn severity. There were no outstanding areas that proved the possibility for reliable fire refugia. More studies are required to provide a more balanced perspective as this fire occurred under dry conditions and the weather implications have over-shadowed the topographic and fuel load variables, in this case where there was long unburned dry fuels.

It also aimed at prompting discussion on the best fire regimes and fuel management plans to protect such endangered areas from broad scale high severity fires in an environment that is becoming warmer and dryer. As the management of fuel loads is the sole factor that can be impacted on by land management groups it has been vital to quantify the significance that the fuel loads had on fire severity in such a fire prone landscape.

6.7 Summary

This chapter investigated the relationships between fire severity and a range of variables (topography, fuel age and vegetation type). Fire severity was mapped using the same variables and a set of predictive maps were produced to assist with fire severity over a similar ecosystem for future fire management teams. The aim was to ascertain if there were areas on the outcrop that could be considered as fire refugia where the local plant communities were offered some protection from high fire severity in an area with biota that is at risk from extinction from fire. The results showed that the areas with a fuel age of less than five years sustained only low severity damage. In areas where the fuel age was higher than five years there was moderate to high severity damage. Elevation, slope and aspect factors increased the fire severity.

Modelling of the data was performed to produce predictive maps for fire severity for future fire management over areas of similar topography and vegetation type. The results revealed that the GWR model provided the better predictive map with an AICc of -765 with R^2 0.76 and the predictive map was very similar to the observed map. The predictive map produced using the OLS, however, had an AICc of -755 with R^2 0.72 and the predictive map had differences from the observed map.

Chapter 7: Conclusions and recommendations

7.1 Research Summary

This thesis studied fire in an area of global biodiversity significance on and around a granite outcrop (GO) in the South Western Australian Floristic Region (SWAFR). These regions on and around GOs are species rich areas that face an increasing risk of changing fire regimes. There is little doubt that changes in fire regimes impacts species richness and may cause some species to decline. However, the plant communities adapt to the effects of fire. Because there is a trend towards more frequent fires in Mediterranean type ecosystems (MTE), it is important for both fire management and conservationists to work together to determine a fire regime that will protect both the diversity of the area and at the same time reduce the fuel load to reduce the fire severity.

This study considers the severity of a fire which occurred on a GO and monitored the recovery of the vegetation. It has examined the role of the topography in a severe fire to assess if there was a possibility for fire refugia on and around the GO. The potential of a range of vegetation and fire indices were tested to find those that provided the optimal results over this varied landscape which contained heterogeneous plant communities in a diverse range of ecosystems. To collect data to study all of these factors in synchronicity, a study area was identified in the Monadnocks Conservation Reserve in Western Australia, an area of high concentration of granite outcrops on the Darling Escarpment. This outcrop was chosen because there was an extensive wildfire in the area in 2003, over an area that had remained unburned for more than 17 years. There were Landsat TM and ETM data available for a timeframe to allow the study to include the post-fire regeneration studies over a ten year period and all with the long term goal of adding to fire management databases for managing fuel loads and fire regimes in areas requiring concentrated conservation endeavours.

Although there have been other studies on fire and its effects short term and long term in Australia (Shedley *et al*. 2010; O'Donnell *et al*. 2011; Duff *et al*. 2013; Taylor *et al*. 2013), there is little that looks specifically at fire and fire recovery on granite outcrops with the aim of conserving this specific habitat.

7.2 Wildfire

Wildfires are unplanned and will vary in their seasonality but occur in the SWWA mainly in the summer. The frequencies at which they recur may become more frequent with changing trends in the climate. This particular fire occurred when the fire risk was rated as high, in a dry summer season when there was a large fuel load in most areas of the region studied. The intensity of this fire was such that even after ten years the vegetation has not yet recovered to resemble the pre-fire state.

The effects of large-scale fires across all types of environments have the potential to change the vegetation and in an area of global importance for the biodiversity found here, it is a driving force for many researchers to look for better ways to protect these environments from severe fire and promote vegetation recovery.

Being able to perform these studies in a cost effective and efficient method highlights the importance of remote sensing as a valued tool when working across difficult terrain assessing vast areas.

7.2.1 Fire in the environment

While fire plays an integral part in the regeneration cycle of vegetation in the SWAFR, the frequency and intensity of wildfires have been increasing (Bradstock 2010; IOCI 2012), possibly due to the changing climate trends in the area (IOCI 2012; Prober *et al.* 2012) and prescribed burning to control the build-up of fuels has been decreasing (Burrows and McCaw 2014). The local vegetation has evolved within fire regimes to where plants have developed fire sensitive or fire tolerant traits. Bond (2005) described species fire responses and how these form the basis of community composition in the wild; for example, some requiring the heat and /or the smoke from fires to germinate the seeds for the next generation of plants (Attiwill and Wilson 2003; Jefferson *et al*. 2008; Chou *et al.* 2012).Within the study area, large trees, some of which were around 300 years of age, had survived fires in the past by successfully resprouting (Burrows 2006) but in this fire had died.

7.2.2 Fire effects

The degrees to which post-fire changes may deviate from what is considered usual depends on a variety of components such as the vegetation type, the growth cycle that the vegetation has achieved in a particular season and the intervals between fires (Cocke *et al*. 2005; Hudak *et al*. 2005). Other effects include canopy loss and changes in soil composition (White *et al*. 1996; Keane *et al*. 2001; Lentil *et al*. 2006). The comparison of images and the incorporation of image differencing techniques across time – including pre-fire, post-fire and annual reviews have been recommended in assessment of the effects of fire and change over the complete ecosystem (White *et al*. 1996; Cocke *et al*. 2005; Lentile *et al*. 2006).

At the local level, the after effects of the fire can include the instigation of microbial processes within the soil (Wan *et al*. 2001; Choromanska and DeLuca 2002); it can promote seed germination, the production of seed and sprouting (Perez and Moreno 1998). High severity fires have the potential to affect below ground processes causing changes to the hydrologic, microbial and the biogeochemical actions which all support the health and the sustainability of the local vegetation (Neary *et al*. 1999). On a global scale, the emission from fire such as ozone, carbon monoxide and the particulate matter may raise concerns in human health risks from reduced air quality (Wirth *et al.* 2002) and have a direct impact on the atmosphere (Smith *et al.* 2005).

7.3 Fuel age

Fire consumes fuels consisting of plant materials, and in doing so, is reliant on the plants which produce the fuels. A small percentage of plants make up the greater contributions to the fuel loads which support fire. Reducing fuel loads may not prevent fires but it does reduce the fire severity (Gill 1996). Fire can eliminate a species from local areas and Gill and Bradstock (1995) found that species made locally extinct by fire were mainly seeder species whose adult plants are fire sensitive. The variables of fire intervals and seasonality of the fire may affect the survival of species (Gill 1975).

The dynamics in a MTE for vegetation growth relies on fire regimes – there are many mechanisms involved in a species response to a fire (Lloret *et al*. 2002). The ways in which plants survive a fire range from the shrubs, which themselves are killed by the fire but regenerate from seed, through to the woody types of shrubs and trees which are protected by thick fibrous or cork-type bark that acts as insulation for the live tissues underneath – when the smaller branches and foliage is scorched, dormant buds under the protective layer will activate and re-sprout. Short fire intervals may result in high mortality rates in the seeder populations as the plants do not have the time to mature and set seed for future vegetation while high intensity fires may impact the resprouters by killing bud banks (Lloret and López-Soria 1993). On the other hand, species that have a combination of high resprouting and fast maturation and seedling establishment may persist (Vila *et al*. 2001).

7.4 Granite outcrops and biodiversity

Granite outcrops comprise nearly 15% of the total continental surfaces worldwide (Twidale 1982). Of the GOs, particularly those in the MTEs, there is a need to better understand the effects of fire, as they become increasingly threatened by changing climactic trends with an associated rise in fire disturbances. These GOs house areas of endangered biodiversity in an ecosystem where fire has been an integral part of the vegetation life cycles (Hopper 2003).

Although the areas on and immediately around GOs are not suitable for agriculture, the surrounding landscapes are frequently cleared and the resulting fragmentation of vegetation may also be a threat to these regions. Increasing levels of salinity in the soils and changes to ground water flows can also impact the areas and altered historical timing and extent of fire regimes may impede local species maturation (Covington and Moore 1994; Morgan *et al.* 2001) and influence species succession, allowing the spread of introduced species to the plant populations, adding to the post-fire species modification (Spencer *et al*. 2003; Keighery 2004; Vieira *et al*. 2004).

7.5 Remote sensing and fire

The use of remotely sensed data from satellites in fire management began nearly three decades ago, (Richards and Milne 1983). The study of fire over inaccessible regions on a broad scale is increasing (Hardy *et al*. 1999) and both satellite and airborne sensors are being utilised. The assessment of pre-fire environmental conditions are one focus and another is the assessment of fuel loads (Nelson 2001; Lefsky *et al.* 2002; Falkowski *et al*. 2004) – both important points in fire management. Within the literature reviewed, there are many who have utilised remote sensing for assessing fire (Laris 2005; Koutsias *et al*. 2009; Stroppiana *et al*. 2012; Veraverbeke *et al*. 2012; Loboda *et al*. 2013).

Remote sensing data taken at the time of the fire, can provide valuable information in the areas of detecting active fires and fire spread (Dennison 2006; Dennison *et al*. 2006), and after the fire, in recording and monitoring post-fire change across landscapes (Roy *et al*. 1999; Ichoku *et al.* 2003; Holden *et al.* 2005). It can be used to investigate post-fire vegetation changes (Turner *et al*. 1994; White *et al*. 1996; Díaz-Delgado *et al.* 2003). In the recovery phases, remotely sensed data can be an effective tool in identifying areas where natural recovery post-fire may be difficult (Bobbe *et al*. 2001; Ruiz-Gallardo *et al.* 2004).

The use of multi-temporal remotely sensed data can be cost effective and provide quick access to data where field trips to difficult to reach or remote areas with difficult terrain can be expensive and lengthy (Hardy *et al.* 2009). Studies using moderate to higher resolution remote sensing can provide data for fuel load management pre-fire and on fire suppression techniques post-ignition (Lentile *et al*. 2006). More recent research is investigating change ecologically with fire induced change on and within the landscape both locally and regionally (Jakubauskas *et al*. 1990; White *et al*. 1996).

7.6 Fire scar and indices

In choosing the indices for this study area, a literature review was performed on publications from 1990 and 2012, where vegetation indices were used (Chapter 2). The majority of these studies used Landsat TM/ ETM$^+$ (50%) or MODIS (20%). From the researched materials, the six most frequently used vegetation indices used for mapping fire were selected. In approximately 90% of these studies, the common bands used were Bands 3, 4, 5 and 7. The remaining 10% used Bands 1, 2 and Band 6 but as these were in the minority, bands 2 and 6 were not tested. The indices chosen for assessment were NBR, NDVI, MSAVI2, SAVI, EVI and NDII.

The NBR was derived by Garcia and Caselles (1991). It was not used for assessing fire severity initially. From 2003, there has been an increasing interest in its use due to the relationship with dNBR which has offered reliable pre and post-fire image comparisons. Most studies looking at fire severity around this time noted the link between remotely sensed data, and field sourced data. From this review, 89% of the studies mapping fire severity and fire scars were using NBR and dNBR as the primary VI's.

The RdNBR was used in 70% of the studies reviewed. In the past decade 53% of the studies reviewed used NDVI and dNDVI for fire scar mapping and fire severity. From 2003, 35% of the studies used SAVI and MSAVI2 for fire mapping, fire severity and vegetation assessment. EVI was used in 8% of studies on studying vegetation stress, rather than on fire severity or vegetation assessment. Lastly, NDII is used widely to remotely sense the alteration in the amount of the green biomass for foliage and canopies rather than fire severity. It has been used in 7% of the studies researched for this paper.

7.7 Remote sensing based indices for mapping fire scars

The aims for Chapter 4 were:

1. To determine the optimal index for mapping fire scars.

To achieve this, (in testing using one image), 2000 plots were located within the study area – 1000 for the burned areas and 1000 from the unburned areas. The indices chosen for assessment were NBR, NDVI, MSAVI2, SAVI, EVI and NDII. These indices used a range of bands – SWIRII, SWIR, NIR and the Blue band. The results from the ROC curve in relation to the indices showed that the NBR, NDVI, MSAVI2 and SAVI were nearly similar with the AUC = 0.848. However, EVI at +0.72 and NDII +0.80 showing these two are not as accurate as the others.

In this study the NBR was found to be the optimal fire index while MSAVI2, SAVI and NDVI were found to produce similar results for mapping fire scars. This outcome was in agreement with Cocke *et al*. 2005; Epting *et al.* 2005, Key 2006; Parson *et al.* 2010. However, Roy *et al*. (2006) found that NBR was insensitive to the changes from burning and was therefore not their preferred index for mapping fire severity in studies on fire in South Africa, Australia, Russia and South America and stated their results did not provide evidence that the NBR was the optimal choice when assessing fire shortly after the event. Roy *et al*. (2006) also found that spectral displacements due to the fire occurred in numerous directions in relation to the NBR index isolines that meant the index might not be consistently sensitive to fire severity.

2. To make a comparative study of data results from a single post-fire image against the results from a set of images – one pre-fire and one post-fire, to determine if any of the indices provides a significant benefit over the other.

7.7.1 Image classification

Image classification was applied for both the pre and post-fire images and 18,961 h bare soil from the post-fire image was compared to the pre-burned area of 1,387 h of bare soil, an increase of 90%**.** The results from the accuracy assessment were: overall accuracy 86% and the kappa coefficient were 0.78. Cross tabulation was applied to the images and the results from the post-fire images are: the bare ground in the post-fire image consisted of 15,817 h when NDVI was applied to the data and SAVI demonstrated 15,820 h and NBR showed 15,800 h – no significant difference. However, the result from NDII demonstrated 12,930 h – a discrepancy of approximately 2,890 h (~15%). Therefore, this highlights the fact that the vegetation indices using Bands NIR, SWIR and SWIRII are more accurate than indices using the remaining Bands.

In the comparison of pre and post-fire ETM^+ images signatures, using two images, the signatures representing the pre-fire and post-fire results from the randomly selected points across the three landscape classes of soil, shrubland and forest were graphed. The results showed that reflectance in the forest class on Band NIR and SWIR showed a decrease in reflectance, and in Band SWIRII there was an increase in reflectance. In the shrubland class there was a slight difference in Bands Blue, Green and Red across the pre and post-fire image and in Band NIR and SWIR there is a significant decrease, however, Band SWIRII showed an increase. This study found that of the six bands tested, NIR, SWIR and SWIRII provided clear differentiation in pre and post fire signatures. Bands blue, green and red provided a poor indication of change.

These findings correspond with results reported by Chuviec and Congalton (1989) and White *et al*. (1996). The findings of this study suggest NIR and SWIRII are more suitable for mapping burn scars. This result coincides with the majority of studies researched. Thus, NBR is the more commonly chosen index and provides the most accurate results in burn scar mapping and mapping of fire severity (van Wagtendonk *et al*. 2004; Key and Benson 2006; Miller and Thode 2007; Sunderman and Weisberg 2011). In this case study, SAVI and MSAVI2 showed similar accuracy to NBR. In their recently published studies Pleniou and Koutsias (2013) found that NIR and SWIR were the most important bands in the estimation of the burned areas and this is supports the findings of this study.

7.8 Mapping fire severity

1. The first aim for Chapter 5 was:

To assess fire severity: In the short term, the NBR values from five days before fire, ten days, one month, eight months and one year post fire from Landsat ETM7+ imagery were calculated. The results were tested statistically over time using pairwise comparison to determine if there was a significant difference in NBR values that highlights the optimal time for mapping severity. From the NBR values pre and post-fire, the dNBR values were produced to classify the fire severity levels into three classes – low, moderate and high severity. It was found that the NBR for the low severity class declined with time. There was no significant difference between the five days pre-fire and one year post fire results. In the remaining two classes – moderate and severe, even after one year there were significantly remarkable differences. The RdNBR maps were produced and fire severity classes determined. The threshold points were based on field data collected post-fire (as evidenced by photos and personal observation taken by Neil Burrows 2003). Change detection between the images was completed to calculate the percentage of differences between the images and these were mapped.

The results from Chapter 5 show there is a difference between the dNBR maps one month post-fire, six months post-fire and one year post-fire and a similar result was highlighted in the change detection studies. From analysing the maps, the areas with low severity class damage began decreasing gradually after six months and after one year the low severity class had recovered such that the differences were no longer discernible. There was no significant difference between the low severity class between five days pre-fire and one year post-fire. From this it was concluded that after one full growing season the low severity class damage was fully recovered and this was also the finding of Veraverbeke (2010) in their studies.

The timing of this fire occurrence was important in the recovery results. The fire occurred in mid to late summer and the weather conditions immediately after the fire, with the autumn rains, enabled the new vegetation to thrive – seedlings quickly took advantage of the reduced competition for space and sunlight. These regenerative processes cause the reflection to change and this has impacted the NBR values – these findings were similar to those of Key and Benson (2006) and Loboda *et al*. (2013). Changes to the vegetation caused by reseeding and resprouting in the early recovery phases can modify the first order effects of the fire in a relatively short space of time. Verbyla *et al*. (2008) found that the NBR values decreased after fire through the northern summer months and the dNBR were substantially higher going into autumn.

This highlights the fact that erroneous seasonal timing may distort the re-vegetation patterns post fire. It is recommended that, in this type of ecosystem, when mapping fire severity using images, the ideal time to apply this technique will be between three to four months after fire. The results taken at this time will avoid any distortion of results that would be caused by the high spring growth season.

Other than the low severity class assessment results, these findings are in accordance with findings reported by others: White *et al*. 1996; Cocke *et al*. 2005; Hudak *et al*. 2005 who have all recommended similar differencing time frames in assessing the effect of fire and ecological changes (Lentile *et al*. 2006).

7.8.1 Comparison between the results of dNBR and the RdNBR maps

When comparing the results between the dNBR against the RdNBR: dNBR results that were recording as moderate severity, when compared against the results of the RdNBR, over the same area, the RdNBR was showing as high severity. To clarify these findings, these RdNBR results, when compared with field data, were found to be more accurate (in this study, this is supported by photographic images). It may be difficult to separate between the moderate and the high severity classes in this ecosystem due to the discontinuity of vegetation between the exposed rock areas and the fragmentation of forest and shrublands. Consequently, RdNBR would be the recommended index for mapping fire severity over this ecosystem, but further research should be instigated to support these findings.

Miller and Thode (2007) found in their comparison studies of 14 fires that the RdNBR can produce more accurate results than the dNBR in the high severity burn class when tested from a universal set of thresholds when applied across multiple fires. They go on to say that in the classification of historical fires this is important where precise field data may be lacking and that it will also permit a more direct comparison when assessing across space and time where it is important for landscape level analysis. A second advantage of using the RdNBR as highlighted by Miller and Thode (2007) was that the accuracy should he improved in the high severity classes – especially over heterogeneous pre-fire vegetation – as seen in the Mt Cooke fire. Zhu *et al.* (2006) also found the RdNBR provided an improved estimator within the sparsely vegetated or non-productive vegetation in the South West USA fires in their study.

7.8.2 Vegetation recovery over time

2. The second aim for Chapter 5 was:

To assess recovery rates over a ten year period to observe the time required for this type of ecosystem to return to the pre-fire state after a severe fire assault. It was expected that the recovery patterns would not be uniform and that it would be possible to identify areas where a delayed recovery may take place as a result of the fire damage and that in the future this information may aid in strategies that may assist these regions to conserve the biodiversity that makes this particular ecosystem unique.

This was determined by selecting 50 control plots in an unburned area and compared these with 50 plots in similar vegetation types (shrubland or forest). The mean from the NDVI burned was divided by the mean of the NDVI unburned and the value was between 0-1. Results were graphed and the representation of regeneration over time was produced. In the ten year time review period, the vegetation has been shown not to have returned to the pre-fire condition.

When reviewing the recovery rates between one year post fire and ten years post fire it was found that there is a direct decrease in the NDVI post-fire and this is followed by an increase in the NDVI in the subsequent years as evidenced in the comparison of the maps produced. The images from the following alternate years demonstrate a marked drop in the NDVI value for both the shrubland and forest plots immediately post-fire. Over the first two years post-fire the forest regeneration is slightly more rapid than the shrubland plots and this difference continues to be evident over the next four years.

The pattern of regrowth was not even across the site – generally, the open herb and grass fields are the quickest to show some recovery when other areas like the forest regions where the burn severity was high showed little change until the resprouters began to flourish at around three years post-fire. This dynamic is a common phenomenon after fire (Solans Vila *et al.* 2010). Diaz-Delgardo *et al.* (2003), in a study of MTE also had a trend where, after the initial five years post-fire, there was a drop in some vegetation types that had survived the fire that then gradually disappeared.

In 2006 the regeneration in the forest area declines possibly due to the competition for space causing the weaker plants to die off and then the recovery continues on a more even plane for the following six years. Within the shrubland class, there is a fast regeneration initially over the first two years and then the growth slows until it reaches its peak at 2006 (three years post fire). From there, there is a slight decline until 2012, thought to be related to the growth patterns of the reseeder plants reaching maturity. Rainfall as a possible cause for growth fluctuation was considered and the annual average rainfall is presented in (Figure 3.4).

The results of this study indicate from the decrease in the NDVI values immediately post-fire that the fire had impacted the ongoing vegetation growth across the study area. From the progressive images post-fire, it is evident that the vegetation will take over a decade to recover and may still not return to its pre-fire state. While it is evident that fires have taken place in this area before (17-20 years before the 2003 fire) the magnitude may not have been as devastating as in the past, the mature trees had resprouted and survived, while after this fire there has been a high amount of mature tree mortality. Younger trees have been able to resprout and these account for the main regeneration in the forest class as evidenced by field trips to the affected areas in 2003 and 2004.

Arianoutsou *et al.* (2010) suggested that recovery rates in the MTEs, where it is warmer, are generally faster than elsewhere. Ireland and Petropoulos (2015) found in their study in Canada that vegetation regeneration can potentially take decades to revert to a pre-fire state in such ecosystems. After eight years the burned vegetation as measured by NDVI had achieved only around a 40% return to the pre-fire state.

7.9 Topographic features and fire severity

Chapter 6 investigated the relationships between topographic features and their influence on fire severity. There are presumed patterns of fire behaviour in relation to aspect, elevation, slope, elevation relief ratio, northness, terrain ruggedness index and the topographic position index. Fuel loads and fuel age are also factored in.

The overall aim was to identify if there are areas on GOs that may provide a lower fire severity risk or possible fire refugia. Topographic variables are known to exert particular effects on fire when it moves across a landscape. It is known, for example, that areas with a north western aspect in the southern hemisphere and the steeper slope are more conductive to ignition and potentially a more rapid spread of fire (Chafer *et al*. 2004).This is due to the flames that are moving upslope being angled more toward the ground and add a drying quality and heating effect on the vegetation above the fire front making the vegetation more likely to burn and the vegetation in the north westerly aspects being naturally drier due to more exposure to the sun's radiation and the associated reduced soil moisture levels.

Other examples of topography effecting fire severity include valleys that are expected to have a lower fire severity result due to higher levels of moisture in both the soils and the vegetation itself and a lower exposure to wind. Ridges are generally expected to have high severity fire effects due to exposed positions with associated wind factors (Bradstock *et al*. 2010). Other studies have highlighted the effect elevation has in the moderation of temperature and a benefit in availability to moisture within the fuel load (Stage 1976) (which may reduce the fire severity) are of little impact at this site – the elevation is not extreme and the thin sandy soils are not able to take advantage of a possible small increase in available precipitation.

7.9.1 Assessment of the topographic variables

The main focus in chapter 6 is the relationship between topography and fire severity and the impact these have on vegetation located on and around the Mt Cooke GO. Initially, DEMs were produced. The fire severity classes for each topographic feature are mapped using NBR and dNBR and combined with field data from the study area.

Seven topographic variables were calculated from the DEM and fire severity for each variable was determined. For example, elevation was divided into four levels according to height above sea level; the percentage of area in each level was calculated and then assessed for fire severity (appendix 2, a) 2). These assessments were repeated for each of the seven variables.

7.9.2 Aspect and fire severity

The results for the topographic variable of aspect showed that there was added impact associated with aspect that effected fuel moisture levels. The north facing areas showed a higher burn severity than the south facing areas, probably due to the fact that the north westerly facing areas are drier and warmer (Whelan 1995; Chafer *et al*. 2004). Greater sun exposure leads to less fuel moisture and drier vegetation types on north westerly aspects in the southern hemisphere (Whelan 1995). These results were as expected and coincide with other studies on similar variables (reverse direction for the northern hemisphere study results).

7.9.3 Elevation and fire severity

In relation to elevation, the area from 300-400 m sustained the highest fire severity, up a total of 12% of the total area, 26% was moderate severity and 38% of the total area rated as low severity. Only 10% of the total study area was above 400 m, and of this, 4% sustained a high severity result, 4% a moderate severity result and 2% low severity – there is little vegetation over 400 m and the majority of the vegetation is comprising shrubs and low growth plants that are surviving in shallow soils between the rocks and in the cracks and on the rock surfaces. These findings are dissimilar to those of Miller *et al*. (2009), who found that the low to middle elevation regions burned with a greater fire severity and stated that the reduced plant size on the upper reaches and the discontinuity of vegetation were the cause. Areas of higher elevation had a higher percentage of high fire severity.

7.9.4 Slope and fire severity

The results for the slope variable have shown that the steeper the slope the greater fire severity. In the low to moderate sloping regions, the fire severity ranged from low to moderate severity. On the steeper slopes, the percentages of low, moderate and high showed only a slight variable with an inclination towards moderate – high severity. Holden *et al*. (2009) found the most severe fire occurred on the steeper south facing slopes at the higher elevations (northern hemisphere study), a similar result to this study.

7.9.5 Northness and fire severity

Of the north facing topographic regions, 9% sustained low severity burn, 12% sustained a moderate severity burn and 20% sustained a high severity burn, probably due to the drier fuel loads. The northness factor has been proven to impact the fire severity at this study site.

7.9.6 Terrain ruggedness and fire severity

At this site there was no terrain that fitted the parameters for the highly rugged classification, but within the area of intermediate ruggedness, for low fire severity class 1.5% was in the intermediate ruggedness regions, for moderate fire severity 1.12% was in the intermediate ruggedness regions and in the high fire severity 1.2% occurred in the intermediate ruggedness regions. These results were caused by the low number of plants growing in these regions between the rocks and boulders and what did grow there were low growing sparse grasses and herbs.

7.9.7 Topographic position index and fire severity

In the valley regions the fire severity tended to be low – there was more moisture in the valleys and the fire intensity was lower reducing the effect of the flames. On the flat regions there was a trend towards low to moderate fire severity; only 35% of the total area was classed as flat and some of this area fell in the regions of prescribed burning prior to this fire. The slope classification comprised of 36% of the total area; 16% sustained a moderate to high severity burn and 20% sustained a low severity burn – these figures are influenced by the sloping areas in many places being bare rock or areas of low vegetation.

7.9.8 Elevation relief ratio and fire severity

In the lowland regions comprise 52% of the total and the upland 47% of the total. The fire low fire severity in the lowlands was 28% and the moderate fire severity was 17%. The high fire severity classification was only 7% of the total. The results for the upland regions were nearly the same: low fire severity 25%, moderate 16% and high 6% - indication that this topographic factor had little influence over the fire severity at this site.

Generally, fire behaviour and fire severity will be influenced by factors other than just topography, such as vegetation type, recent weather conditions and the amount of accumulated fuel loads (Heyerdahl *et al*. 2001; Román-Cuesta *et al.* 2009; Bradstock *et al*. 2010; Sharples *et al.* 2010). Several studies on recent extreme fires in Australia and other MTEs have all stated that it was the extreme weather conditions leading up to the time of the fire that made the fire severity so high and that topographic influences were negated in these types of fires (DECCW 2010; Avitabile *et al*. 2013).

Chapter 6 identified the topographic features and compared these with the fire severity recorded for each particular feature across the burn scar. The result was that all the area sustained a level of fire damage – the main findings revealed that there is a variety of fire severities over the study area – for example, the region where the fuel load was less than five years sustained a lower severity burn than the other areas (Figures 6.3 and 6.4).

7.10 Modelling fire severity

The second aim for Chapter 6 was modelling fire severity on the burn scar to include the variables of topography, vegetation type and fuel age to predict fire severity across this type of ecosystem for the future fire management. This was achieved using the OLS and GWR models. Assessment of the temporal and spatial fire severity patterns may show relevant data on the factors that influence fire severity. It is known that topography can influence fire behaviour and in this study topography, fuel age and habitat together predicted OLS 72% and GWR 76% of the variability in the fire severity at this site – before the local effect of weather was included. It would be useful for other GO sites to have predictive maps made to assess severe fire episodes over similar topographic and vegetation type sites. This data may be used by future fire management strategists in decision making for similar environments in the SWAFR.

In modelling, OLS, (a single model that is applied over the burn scar using a single and constant coefficient but does not include spatial variances like vegetation types), and GWR, (a more modern regression method that has the ability to include spatial non-stationarity) were both used in modelling the fire severity to assess which provides the better predictive maps.

This chapter has highlighted the better performance of GWR over OLS for mapping fire severity in this ecosystem. These results are similar to the outcomes from other studies such as those done by Oliveira *et al.* (2014) who reported that when considering model performance on fire occurrence and the physical and anthropogenic variables that GWR showed an improvement over OLS in both regions. Koutsias *et al.* (2010) also used both OLS and GWR in their study of the possible variance of factors causing wildfires in Southern Europe. They found that OLS was not sufficient in providing a complete picture of underlying variables but that GWR did complement the global model in overcoming difficulties with non-stationarity or missing variables. It has been observed that the GWR provided significantly better predictions (AIC = -765 and R^2 = 0.76) as compared to OLS (AIC = -755 and R^2 = 0.72). The ability of GWR to explore spatial non-stationary could provide important local management implications such as mapping fire severity, fuel age and loads and exploring local variations such as weather, topography and fire severity.

7.11 Research Findings

-Fuel age – the areas where prescribed burns had taken place prior to the 2003 fire sustained lower severity burns – recommendation from this study is to maintain a prescribed burning plan to lessen the wildfire effects.

-Remote sensing – provided effective means of assessing this fire scar and fire severity – recommendation from this study to make better use of the satellite technology available in monitoring fuel loads and fires generally.

-Fire indices – In this study NBR was found to be the etter choice of index, while SAVI, MSAVI2 and NDVI also produced good results.

-Image classification – it was determined that the use of two images provided the more detailed results as they highlight the differences clearly between pre and post fire state.

-Fire severity – this research found the best time for mapping fore severity to be three-four months post-fire.

-Comparison between dNBR and RdNBR – the RdNBR proved to be more accurate.

Vegetation recovery – after ten years post fire the vegetation is still recovering from the effects of the fire.

-Topography and fire severity – in this fire, south facing regions had an overall lower fire severity than the north; elevation provided no protection in this fire; the higher fire severity occurred where the slope was steepest across this fire site.The Terrain Ruggedness - had minimal effect on fire severity at this site; topographic positioning – valleys had lower fire severity damage than the other regions.

Elevation Relief Ratio – had little effect on fire severity at this site.

-Modelling fire severity – GWR was shown to provide a better predictive model than OLS at this site.

7.12 Recommendations and Implementations

Prescribed burning has been used extensively in forest landscapes since the 1960s to mitigate the impacts of bushfires on the community and on environmental values including biodiversity. The ecological implications of prescribed burning, however, remain contentious. The main difficulty is that many of the plants endemic to the GOs have differing maturation times and they require a long growing season before reaching maturation. The top five centimeters of soil may be left sterile after a high intensity fire. This opens the way for invasive species to take advantage of the open spaces. Ideally, there should be fully orchestrated information collection from the GO sites in the SWAFR to identify plant communities and their positions on the GO. The data will form the basis of the pre-fire knowledge that can be accessed when and if fire occurs in these areas. Suggested areas for further study include:

1. Pre-fire vegetation assessments on the GOs in the SWAFR including soil assessment (depth and organic material) and fuel load and fuel age. This information can be considered with the post-fire information on topics such as vegetation consumption, vegetation mortality and soil alteration that is available from fires on GOs in the past.
2. In this study, there is a difference between the dNBR and RdNBR. More research is required to better understand the pre-fire condition of the vegetation (such as canopy height, vegetation condition and vegetation communities) for improved fire severity modelling using remote sensing data.
3. Modelling at risk endemic species from the GOs to identify how each species community reacts in relationship to fire.
4. Once the data is collected, resulting prediction maps can be combined with the post-fire data already on record and used to form a management support model that can be integrated into decision making trees for better future fire management.
5. Assess the erosion patterns on this and other burned GOs so that a plan for better management for fire damage in the future can be determined.
6. Install observation plots across a variety of GOs for regular monitoring of weather/climate, to form the basis of an ongoing database for comparisons if fire occurs.
7. The predictive capabilities of landscape and topographic variables are important and good recording of local weather conditions is significant. Using predictive modelling techniques, from the newly formed (suggested) data base, model results can be used to predict the probability of severe fire occurrence on GOs and identify areas at risk.
8. The use of remote sensing capabilities may provide a more comprehensive and efficient method for monitoring fuel states.
9. It would be recommend that further assessment of fire severity-topography-weather interactions across a range of GOs and vegetation types will be necessary to understand how these patterns vary across space and time.
10. Interpreting burn severity from satellite data, for hundreds of fires across a range of environments and climatic conditions will greatly enhance our understanding of why and where fires burn severely.

7.13 Conclusion

It has been found that remotely sensed Landsat data can be used when combined with field data to provide accurate results in assessing fire severity over GO sites. The resultant maps can assist in future fire management planning as they have the ability to provide distinct quantifiable data related to fuels, vegetation communities, succession modelling and habitat information that can also relate to post fire management of effects such as erosion and landscape change. In the future, it is expected that improved higher resolution imagery techniques will make mapping fire effects even more precise and. Also assist with interpreting fire effects and impacts and for mapping fire history.

Two modelling techniques were compared against each other for this study, OLS and GWR. OLS performed reasonably well but GWR proved a better fit with improved outcome with predictive mapping. These results suggest that GWR would provide the best option of the two in modelling fire severity and predicted fire severity across a similar landscape for future studies.

The hot and dry weather conditions that occurred leading up to this fire event affected the expected outcomes in relationship to fire severity. This study has not found that there were fire refugia on this GO at the time of this fire. The hot and dry weather trend combined with the elevated fuel loads and very dry fuels led to the whole site having some degree of fire damage. The topographic features that may, in a fire of less severity, offer some protection were impacted by the intense fire on Mt Cooke.

This study has highlighted the need for better understanding of the role of pre-fire vegetation structure and composition, climate and active fire weather, land use and the effects of topographic features on the prediction of fire severity. These additional datasets should increase the accuracies of fire severity prediction in the future.

7.14 Summary

This thesis studied fire in an area of global biodiversity significance. A range of vegetation indices were tested for mapping fire severity and fire scars and the indices that were shown to work effectively on this type of MTE. Data from remote sensing, such as Landsat data, provided a reliable source of information in this type of study. It proved to be cost efficient and was able to access difficult areas of bushlands in remote regions. The interaction of fire with the topographic variables correlate but the severe weather conditions leading up to this fire event made the severity so high that the protective aspects of the topography were mostly negated. GWR and OLS regression models were tested and can both be used in fire severity prediction, but in this event the GWR performed better with the independent variables.

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Appendix 1: NBR values and vegetation recovery.

TABLE 1: The descriptive statistic for 100 plots in the severity classes.

		N	Mean	Std. Deviation	Std. Error
Low severity	NBR-pre fire 04/01/03	100	0.14	0.11	0.01
	NBR-post fire 20/01/03	100	-0.19	0.11	0.01
	NBR-post fire 22/02/03	100	-0.17	0.10	0.01
	NBR-post fire 1/09/03	100	-0.06	0.09	0.01
	NBR-post fire 22/12/03	100	0.02	0.13	0.01
Moderate severity	NBR-pre fire 04/01/03	100	0.13	0.08	0.01
	NBR-post fire 20/01/03	100	-0.33	0.08	0.01
	NBR-post fire 22/02/03	100	-0.29	0.08	0.01
	NBR-post fire 1/09/03	100	-0.14	0.07	0.01
	NBR-post fire 22/12/03	100	-0.03	0.10	0.01
High severity	NBR-pre fire 04/01/03	100	0.25	0.07	0.01
	NBR-post fire 20/01/03	100	-0.50	0.03	0.00
	NBR-post fire 22/02/03	100	-0.45	0.03	0.00
	NBR-post fire 1/09/03	100	-0.25	0.06	0.01
	NBR-post fire 22/12/03	100	-0.11	0.07	0.01

TABLE 2: The descriptive statistics for the shrubland and forest class pre and post-fire.
(These points differ from the points located in the fire severity classes.)

Habitats	Image	N	Mean	Std. Error of Mean	Std. Deviation
Shrubland	NBR-04-01-03	100	0.15	0.01	0.14
	NBR-20-01-03	100	-0.17	0.01	0.14
	NBR-22-01-03	100	-0.16	0.01	0.14
	NBR-01-09-03	100	-0.01	0.01	0.11
	NBR-22-12-03	100	-0.05	0.01	0.10
Forest	NBR-04-01-03	100	0.29	0.01	0.08
	NBR-20-01-03	100	-0.32	0.01	0.13
	NBR-22-01-03	100	-0.30	0.01	0.13
	NBR-01-09-03	100	-0.16	0.01	0.11
	NBR-22-12-03	100	-0.03	0.01	0.13

TABLE 3: The NDVI statistical analysis of recovery rates across the control plots. The shrubland and forest plots

	Image data	Mean	Std. Error of Mean
Control plots for forest	17/01/2002	0.47	0.01
	04/01/2003	0.49	0.01
	15/01/2004	0.38	00
	20/01/2006	0.35	0.01
	26/01/2008	0.52	0.00
	23/01/2010	0.54	0.01
	29/01/2012	0.56	0.01
Control plots for shrubland	17/01/2002	0.36	0.01
	4/01/2003	0.40	0.01
	15/01/2004	0.23	0.01
	20/01/2006	0.21	0.01
	26/01/2008	0.39	0.01
	23/01/2010	0.37	0.01
	29/01/2012	0.39	0.01
Forest burned	17/01/2002	0.48	0.01
	4/01/2003	0.51	0.02
	15/01/2004	0.32	0.01
	20/01/2006	0.42	0.01
	26/01/2008	0.48	0.01
	23/01/2010	0.54	0.01
	29/01/2012	0.56	0.01
Shrubland burned	17/01/2002	0.35	0.01
	4/01/2003	0.38	0.02
	15/01/2004	0.16	0.01
	20/01/2006	0.20	0.01
	26/01/2008	0.37	0.01
	23/01/2010	0.34	0.10
	29/01/2012	0.35	0.01

Appendix 2: Topographic variables and fuel load and fire severity

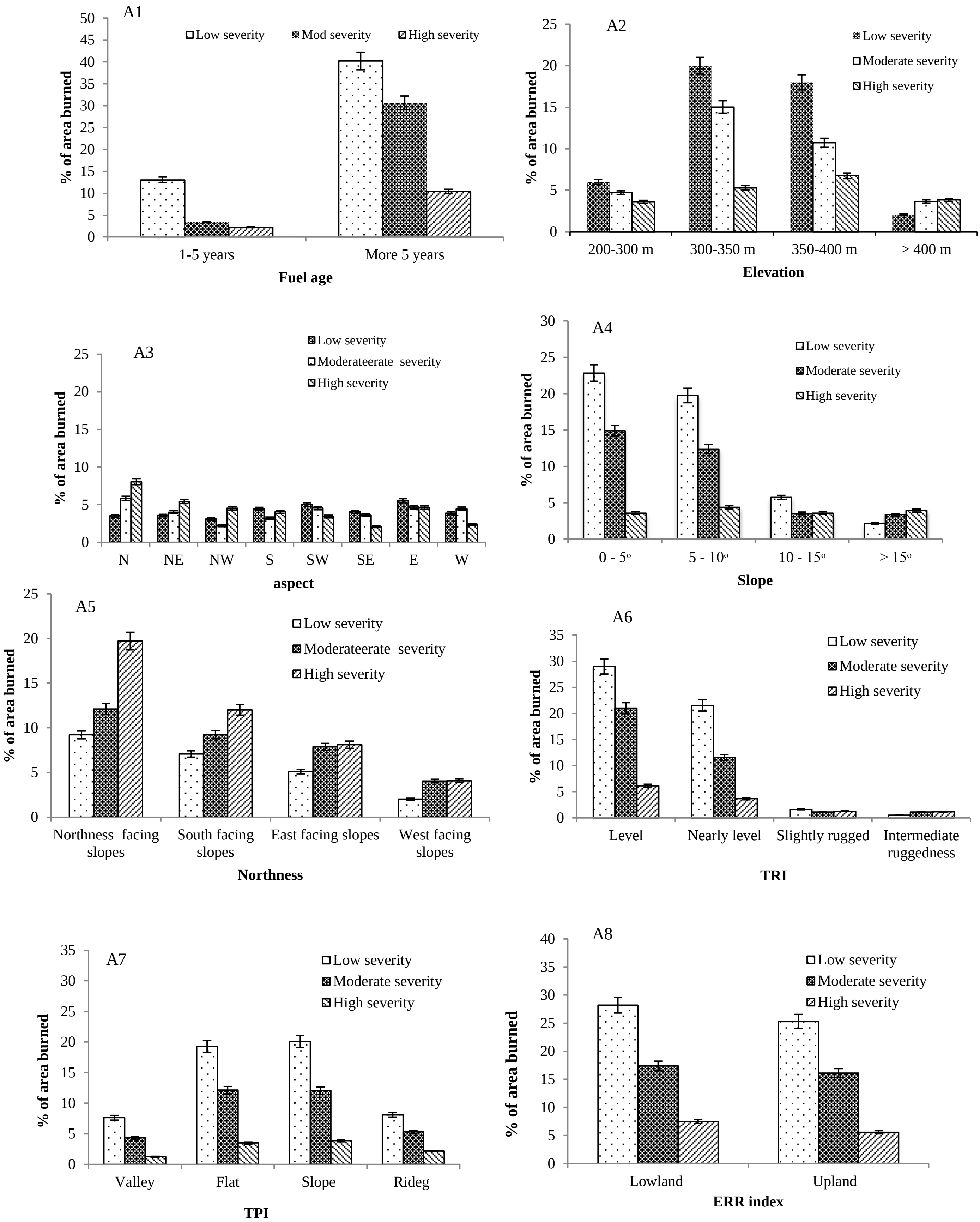

Figure 1. A1: The percentage of the burned area in relation to the fuel ages, A2: The percentage of area burned in relation to elevation, A3: The percentage of area burned in relation to aspect, A4: The percentage burned in relation to slope, A5: The percentage burned in relation to Northness , A6: The percentage of burned area in relation to Terrain Ruggedness Index and , A7: The percentage of area burned in relation to the Topographic Position Index, A8: The percentage of area burned in relation to the ERR

Appendix 3: selection of predictor vaiables and best model

Table showing the descriptive statistics for 100 plots in the severity classes

$AdjR^2$	AICc	JB	K_BP	MaxVIF	X1	X2	X3	X4	X5	X6	X7	X8
0.71	-748.1	0.5	0.26	1.7	Slope	Elevation	Aspect	Northness	ERR	TRI	Fuel	
0.72	-750.8	0.61	0.29	1.67	Slope	Elevation	Aspect	Northness	TRI	TPI	Fuel	
0.67	-709.4	0.26	0.61	1.7	Slope	Elevation	Aspect	ERR	TRI	TPI	Fuel	
0.67	-707.9	0.67	0.54	1.58	Slope	Elevation	Northness	ERR	TRI	TPI	Fuel	
0.71	-740.9	0.6	0.05	1.63	Slope	Aspect	Northness	ERR	TRI	TPI	Fuel	
0.71	-741.9	0.63	0.21	1.64	Elevation	Aspect	Northness	ERR	TRI	TPI	Fuel	
0.72	-752.4	0.56	0.3	1.7	Habitat	Slope	Elevation	Aspect	Northness	ERR	TRI	Fuel
0.72	-755.9	0.64	0.43	1.68	Habitat	Slope	Elevation	Aspect	Northness	TRI	TPI	Fuel
0.68	-712.0	0.28	0.76	1.7	Habitat	Slope	Elevation	Aspect	ERR	TRI	TPI	Fuel
0.68	-713.0	0.77	0.65	1.59	Habitat	Slope	Elevation	Northness	ERR	TRI	TPI	Fuel
0.71	-746.4	0.59	0.12	1.64	Habitat	Slope	Aspect	Northness	ERR	TRI	TPI	Fuel
0.71	-739.7	0.24	0.09	1.68	Habitat	Slope	Elevation	Aspect	Northness	ERR	TRI	
0.71	-747.4	0.47	0.18	1.68	Habitat	Slope	Elevation	Aspect	Northness	TRI	TPI	
0.72	-750.3	0.47	0.52	1.67	Habitat	Slope	Elevation	Aspect	Northness	TRI	Fuel	
0.7	-730.2	0.36	0.4	1.63	Habitat	Slope	Elevation	Aspect	Northness	TPI	Fuel	
0.67	-701.0	0.16	0.36	1.68	Habitat	Slope	Elevation	Aspect	ERR	TRI	TPI	
0.67	-704.2	0.29	0.47	1.7	Habitat	Slope	Elevation	Aspect	ERR	TRI	Fuel	
0.63	-673.6	0.11	0.88	1.67	Habitat	Slope	Elevation	Aspect	ERR	TPI	Fuel	
0.67	-706.4	0.28	0.73	1.67	Habitat	Slope	Elevation	Aspect	TRI	TPI	Fuel	
0.67	-707.4	0.46	0.64	1.58	Habitat	Slope	Elevation	Northness	ERR	TRI	TPI	
0.67	-706.4	0.92	0.68	1.58	Habitat	Slope	Elevation	Northness	ERR	TRI	Fuel	
0.65	-686.1	0.66	0.36	1.52	Habitat	Slope	Elevation	Northness	ERR	TPI	Fuel	
0.67	-709.1	0.78	0.7	1.57	Habitat	Slope	Elevation	Northness	TRI	TPI	Fuel	
0.63	-622.4	0.8	0.98	1.58	Habitat	Slope	Elevation	ERR	TRI	TPI	Fuel	
0.7	-733.6	0.24	0.1	1.63	Habitat	Slope	Aspect	Northness	ERR	TRI	TPI	
0.71	-741.7	0.45	0.12	1.63	Habitat	Slope	Aspect	Northness	ERR	TRI	Fuel	
0.68	-715.7	0.24	0.14	1.45	Habitat	Slope	Aspect	Northness	ERR	TPI	Fuel	
0.71	-743.3	0.4	0.4	1.62	Habitat	Slope	Aspect	Northness	TRI	TPI	Fuel	
0.67	-703.4	0.18	0.58	1.63	Habitat	Slope	Aspect	ERR	TRI	TPI	Fuel	
0.65	-686.7	0.71	0.37	1.48	Habitat	Slope	Northness	ERR	TRI	TPI	Fuel	
0.71	-739.9	0.44	0.13	1.59	Habitat	Elevation	Aspect	Northness	ERR	TRI	TPI	
0.71	-742.2	0.46	0.39	1.65	Habitat	Elevation	Aspect	Northness	ERR	TRI	Fuel	
0.71	-745.8	0.59	0.37	1.61	Habitat	Elevation	Aspect	Northness	TRI	TPI	Fuel	
0.67	-701.1	0.24	0.76	1.65	Habitat	Elevation	Aspect	ERR	TRI	TPI	Fuel	
0.65	-691.6	0.54	0.63	1.45	Habitat	Elevation	Northness	ERR	TRI	TPI	Fuel	
0.7	-732.6	0.44	0.21	1.32	Habitat	Aspect	Northness	ERR	TRI	TPI	Fuel	
0.71	-738.8	0.44	0.06	1.68	Slope	Elevation	Aspect	Northness	ERR	TRI	TPI	

Appendix 4:

Study area photographs reproduced with permission from Neil Burrows.

Figure 3.5 Wind speed on the study area reproduced with permission of G Milne (UWA).