University of the Witwatersrand
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Fire Regimes in Southern Africa - Determinants, Drivers and Feedbacks

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Declaration

I declare that this thesis is my own, unaided work. It is being submitted for the Degree of Doctor of Philosophy in the University of the Witwatersrand, Johannesburg. It has not been submitted before for any degree or examination in any other University.

Signature of candidate

12 day of May 2010

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Abstract

The spatial and temporal patterns of fire in Africa south of the equator are described and investigated to test hypotheses on the main drivers of fire. In particular, the relative importance of climate, vegetation, and human activities are assessed and related to current theory on savanna fire regimes and their response to global change.

This thesis makes use of newly-released burned area and fire radiative power data derived from satellite imagery. This information was integrated with data on climate, vegetation, and human activities, as well as long-term field data on fire, to test hypotheses about savanna fire regimes. Regression tree techniques and mixed effects models were used to determine the main drivers of spatial and temporal variability in fire, and feedbacks between fire and tree cover were explored at a range of spatial scales. New datasets on fire size and fire number were also developed to test theories on the effect of human activities on ignition probability and fire spread.

The results show that fire in these grassy ecosystems is very responsive to climatic factors such as rainfall but there are large areas where human activities play an equally significant role. The effect of people was always to reduce the total area burned, although the number of individual fires increased with population density up to about 10 people per km^2. Areas inhabited by people were also less susceptible to year-to-year fluctuations in annual burned area caused by climatic variability, possibly because of the reduced probability of large, runaway fires in these highly-impacted landscapes. Both of these findings are important for modelling of fire and carbon emissions in Africa.

Evidence of negative feedbacks between tree cover and fire were found. When the percentage tree cover is less than 40% a range of factors control the extent of fire in a system; but above 40% tree cover fire is never a large component of the landscape. On the other hand, tree cover was shown to have a bi-modal distribution, and examples of intermediate tree cover (40-70%) were rare. Over a wide range of mean annual rainfall (1000-2000mm) vegetation can exist either in a "high tree-cover, low fire" or a "high fire, low tree cover" state.

This research challenges some assumptions about how savanna fires will respond to global change, and provides important clues to help disentangle the mechanisms driving fire in Southern Africa. Importantly, it highlights that fire in southern Africa, and in other highly-utilised savanna systems, can not be understood outside the context of human use.

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Then I want to thank my supervisor Bob Scholes, who maintained a delicate balance between letting me do exactly what I want and making suggestions that were impossible for me to ignore. All of his advice improved this dissertation, and the many other ways that he supported and promoted me mean that I come to the end of my PhD with as much enthusiasm and excitement about the activity of science as I had when I started. This is quite an achievement.

The time I have spent with Winston Trollope and William Bond has given me a breadth of understanding on fire that I could not have found anywhere else. William has an amazing ability to interpret half-formed ideas, and helps me to distinguish new concepts from the chaff that tends to float around with them. There is nothing more enjoyable than spending time in the field with him.

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Contents

Chapter 1

Introduction

1.1 Fire management, fire ecology & pyrogeography

Human fascination with nature is equalled by the human desire to manipulate it, and the desire to manipulate fire is no exception. Unlike volcanoes, droughts, or plagues of locusts, vegetation fires seem particularly amenable to control and management, although this belief has sometimes been shown to be misguided. The conspicuous ecological effects of fire also make it an obvious scapegoat for perceived ecological problems, and a first stop when trying to exert control on a system.

Of course, the goals of fire management vary substantially over time and between cultures (Pyne, 1995). Contrasting views of the value of igniting or suppressing vegetation fires have resulted in conflict between different land users in many parts of the globe. This was especially the case in areas colonised by Europeans, who brought a culture of fire suppression into human-vegetation-fire systems where fire was often viewed more as a tool than as an unwanted disturbance (Kull, 2004). This conflict has become more nuanced in recent decades as experimental evidence accumulates which questions the wisdom of trying to exclude fires from most ecosystems. Recent fire legislation has started to incorporate 'traditional' fire-management ideas, which focus on controlled burning for fuel manipulation (Russell-Smith *et al.*, 2003b; Van Wilgen *et al.*, 2008).

The social, political, and environmental concerns around the management of vegetation fires have influenced the way that scientists have approached fire ecology. Fire has often been studied as a disturbance, impacting the vegetation, soils, and biogeochemistry of an ecosystem. There has been far less emphasis on fire as a response variable. Fire research has also generally been aimed at answering particular policy questions in a specific environment. As a result, opportunities to expand understanding across similar ecosystems, and develop a more theoretical, synoptic understanding of fire have been lost.

For example, only when global data on fire became available was it noticed that boreal forests in North America burn more intensely than those in Russia (Wooster & Zhang, 2004). This led to the realisation that the North American fires are largely crown fires, with fundamentally different ecological and biogeochemical consequences than the surface fires of Russian boreal regions. Similarly, due to an unfortunate confusion over terminology, the research into grass-fuelled surface fires in south east Asia has been largely ignored by fire researchers working in other savanna and woodland systems because they are referred to as 'forest fires' (Stott, 1988). Thus, a coherent theoretical framework of fire does not yet exist.

There are a number of reasons why all this is changing. Firstly, data are now available at spatial and temporal scales that allow for global perspectives on fire (eg Van der Werf *et al.* (2008); Carmona-Moreno *et al.* (2005); Krawchuk *et al.* (2009b); Csiszar *et al.* (2005)). Secondly, climate change research and carbon accounting require that global patterns of fire be quantified and explained (Scholes *et al.*, 1996; Korontzi *et al.*, 2003). In particular, there is a growing realisation that the occurrence of large wildfires - damaging to property and threatening to life - is responsive to changes in climate in many parts of the world, and that we understand very little of the processes driving these extreme events (Moreno, 1998; Williams, Richard & Bradstock, 2008; Bowman *et al.*, 2009). Finally, views of fire management and fire suppression have been rapidly changing. There is a move towards tailoring human interventions to act within limits imposed by the environmental characteristics of the ecosystem in question (Van Wilgen *et al.*, 2008; Moritz *et al.*, 2004), and to re-instate evolutionarily-representative fire regimes for the purposes of biodiversity conservation.

Hence the fast-growing field of pyrogeography (Bowman *et al.*, 2009), which hopes to interrogate the climate-vegetation-fire system, test ideas about the limits and controls on this system, and develop predictions of future response of fire to global change. Recent publications now emphasise the fact that particular fire regimes emerge from an interaction between people, the vegetation and the environment, and that the response of fire to climate change and human interventions depends on this context. For example, the efficacy of fire suppression through fuel manipulation is different in Alaska and the Chaparral region in California because of differences in the relative importance of weather conditions and fuels in limiting fire spread (DeWilde & Chapin, 2006; Moritz *et al.*, 2004). Similarly, an extended drought can increase or decrease the extent of fire depending on the fuels in which it burns (Van der Werf *et al.*, 2008).

1.2 Thesis aims and research approach

A global theory of fire requires both a better description of fire regimes in different environments, and an understanding of the processes involved in determining these fire regimes. This is what my dissertation aims to do for southern Africa. My study area covers all of Africa south of the Equator, including Madagascar. Fires in this region occur largely in savanna and grassland vegetation. These environments produce fine fuels which dry out rapidly during the dry season, so savanna and grassland fires are extreme in terms of their frequency and annual extent, although their rate of energy release is orders of magnitude lower than that of crown fires in forested systems. Savannas in Africa are often in areas of highly variable climate and changing human land use and there is no clear understanding on how this feeds back to fire regimes. Currently it is estimated that African fires contribute about 50% of all fire emissions annually (van der Werf *et al.*, 2006) - about half of which come from southern Africa - and there is much interest in manipulating these fire regimes to accumulate carbon (Williams *et al.*, 2008).

In this context there is a strong need to expand our understanding of the drivers of fire in southern African ecosystems. One of the key questions to be asked is how humans interact with fire in Africa - and the extent to which human activities can modify the environmental controls of fire on the continent. Australia, South America, and India all have similar savanna and grassland ecosystems. Africa differs from other continents not only in the extent of the savanna biome (70% of all savanna vegetation occurs in Africa), but also in its long history of human occupation, and current patterns of human land use.

Answering these questions required that I draw on long-term fire records from across the region and on the wealth of data from earth observation platforms designed to record fire occurrence and other fire characteristics. It also required exploring statistical techniques that could identify important processes in a system which is characterised by strong feedbacks and often non-linear relationships. To address questions on fire ignition and spread I developed algorithms which provide new information from the remotely-sensed datasets - in particular, information on fire size and fire number. Ultimately this research would be complemented by a modelling exercise where the understanding developed in the previous analyses is used to ask more process-based questions about the historical role of humans, and the mechanisms by which trees limit grassland fires, for example. However, this modelling component was beyond the scope of this thesis.

The structure of the dissertation emerged from the initial analysis on the limits of fire in southern Africa (**Chapter 2**). In this chapter I developed a conceptual model of the drivers of burnt area in southern Africa, and then explored how the patterns of burnt area change across the sub-continent in relation to these drivers.

Three key questions arose from this initial analysis, which I addressed in the following chapters.

Firstly, Chapter 2 identified a threshold of 40% tree cover above which the extent of fire is substantially reduced. This threshold fits with current understanding of fire as an important mechanism maintaining the forest-savanna boundary. In **Chapter 3** I went on to explore fire's role in the maintenance of these biomes in collaboration with Carla Staver, a PhD student at the Ecology and Evolutionary Biology Department at Princeton.

Second was the question of climatic controls of fire - how responsive fire regimes are to changes in climate drivers. Results from Chapter 2 highlighted the importance of climate but focussed on spatial variability and were drawn from only one year of data. In **Chapters 4 and 5** I assessed the degree to which inter-annual variation in climate feeds back to fire regimes. For this I used field-collected data from six study sites, as well as eight years of remotely sensed data. Some unexpected results emerged, which question assumptions made about how fire will respond to climatic change in Africa and the approaches that are currently used to incorporate fire into dynamic global vegetation models (Thonicke *et al.*, 2001; Venevsky *et al.*, 2002).

The regional analysis in Chapter 2 highlighted the contradictory roles of humans in increasing ignition frequency (i.e. number of fires) but decreasing fuel continuity (i.e. the size of individual fires). In **Chapters 6 and 7** I compare fire size-frequency relationships in different savanna systems and highlight some important departures from current theory on fire spread, fire probability, and the occurrence of large fires. This is particularly important in the context of several recent global-scale analyses: Mouillot & Field (2005) and Van Aardenne *et al.* (2001) both make the assumption that increasing human densities increase the extent of fire but this assumption does not incorporate the negative effects human activities can have on fire spread.

Chapter 7, as well as investigating human impacts on fire, also represents a summary of the current information available in the region. In it I integrate all sources of spatial information on fire to provide the first regional description of African fire regimes (fire frequency, fire seasonality, burned area, fire return periods, fire intensity, and fire spatial patterns: Gill (1975); Bond & Keeley (2005)). This chapter tests how applicable current theory on savanna fire regimes is to Africa, and highlights areas where further research would be helpful.

By focussing on feedbacks from the environment to fire, this dissertation complements the substantial body of work which already exists on fire in southern Africa. What follows is a brief summary of fire research in the region, and the current state of the science.

1.3 Fire research in southern Africa

Southern Africa has a rich scientific history of research into the ecological effects of fire dating back to Bews (1918) and Phillips (1930). These ecologists emerged at a time when the prevailing policy in the colonies was fire suppression, and started giving voice to a growing belief that fire suppression was not only not feasible, but also not beneficial to the ecosystems of southern Africa. One of the ideas promoted by John Phillips was that in the savanna and woodland regions of Africa total fire suppression would result in rapid woody thickening - a belief which was corroborated by several seminal fire exclusion experiments some decades later (Brookman-Amissah *et al.*, 1980; Swaine *et al.*, 1992; Menaut, 1977; Trapnell, 1959). The experimental burn plots in the Kruger National Park follow from this intellectual tradition (Higgins *et al.*, 2007).

In a rangeland context there was much experimental research into the effect of fire on grassland productivity and palatability. Work by West (West, 1965), Morris (Morris & Tainton, 1992), Tainton (Tainton & Mentis, 1984), and later Trollope (Trollope & Tainton, 2007) demonstrated that the effects of fire on grass - while complicated by grazing and species compositional factors - were not always negative.

Bond *et al.* (2005) later drew these lines of research together into a more biogeographical understanding of the importance of fire in C4 grassy systems, and the role of fire in maintaining the savanna biome. Theoretical (Higgins *et al.*, 2000; Hoffmann, 1999) empirical (Gignoux *et al.*, 1997) and correlative data (Sankaran *et al.*, 2005; Bucini & Hanan, 2006) point to the importance of fire and fire-vegetation feedbacks in savanna systems.

This recognition of the essential role that fire played in the maintenance and functioning of African savanna ecosystems did not eradicate the desire to control fire. Rather fire ecologists spent much time and energy determining what was the most appropriate fire regime for a particular system, and even more time and energy trying to implement this fire regime.

Research into 'fire behaviour' and the environmental drivers of fire therefore emerged from a continuing desire to manage fire, together with a growing realisation that this was not as simple as one might think. Trollope (Trollope & Potgieter, 1985) initiated fire behaviour studies in southern Africa, which were aimed at controlling the season, frequency, intensity, and therefore the ecological effect of fire. Brian V Wilgen pioneered the use of fire models such as were used in Australia (McArthur, 1966) and the U.S. (Rothermal & Deeming, 1980) to predict fire behaviour under different weather and fuel conditions in southern Africa.

This approach inevitably resulted in fire being viewed not only as an ecological driver or disturbance, but something that is equally impacted by the environmental context in which it occurs. Van Wilgen *et al.* (2004) was also influential in demonstrating that fire regimes were not wholly malleable - that 'fire management' was always constrained by the vegetation, climate, and soils of particular ecosystem.

While all this was happening in the commercial farming and conservation areas, rural people were still burning their land for their own purposes - these often being quite different from those of the commercial farmer or conservation official. Hall (1984) and Frost (1999) were the first to try to record the practices and motivation for traditional burning in Africa. Gathering data on indigenous fire management is a difficult job, not entirely suited to the methodologies traditionally available to ecologists (Pyne, 1995; Laris, 2002).

However, while anthropological studies of fire in southern Africa are rare, another source of information on burning practices of rural African people has recently become available. Remotely sensed imagery has become frequent enough, and at high enough resolution to record daily fire occurrence across massive tracts of land, and over several years. Thus, in recent years it has been possible to gather information on the timing and spatial extent of fire across a range of land uses and environmental gradients - to expand fire research outside of protected areas and agricultural experimental stations. Although analysing spatial patterns of fire does not provide information on the complexities of the socio-ecological system that created them, it is an opportunity to explore the results of this complexity - and to quantify the effect of humans on fire regimes in a way that was not possible before.

Similarly, in the last few decades the data and methods available to quantify biogeochemical processes affected by fire has increased. The Safari 2000 campaign produced estimates of combustion efficiency and emissions of various gases (Otter *et al.*, 2002) and also started to estimate how these change seasonally and inter-annually (Korontzi *et al.*, 2003; Anyamba *et al.*, 2003). It was also the first study to develop a regional perspective of biomass burning on the sub-continent (see Scholes *et al.* (1996) but also Lehsten *et al.* (2009) and Roberts *et al.* (2005) for more recent estimations). Model-inversion studies have also been useful in constraining our estimates of carbon and trace gases emissions (Scholze *et al.*, 2008)

These multiple sources of data and different methodologies allow us to take fire behaviour studies to a new level, and start to address questions of the drivers of fire in the same way that climatologists have (with the help of data of similar spatial and temporal breadth) been developing regional understanding of rainfall regimes for many years. A 'fire climatology' for Africa is now close to being a reality.

1.4 Thesis structure

The six chapters which form the body of this thesis are each written as stand-alone research papers and several of them are submitted, under revision, or already published. This introductory chapter serves to explain how each paper fits into the larger aim of this thesis, and a preface before each chapter is included to link the papers together and explain the current state of each paper and the roles of the co-authors. The conclusion draws out the key findings from all the chapters and discusses what has been achieved, and how it contributes to improving our understanding of fire in southern Africa. The chapters are presented exactly as they were submitted, except that all the references are to be found at the end of this dissertation in one bibliography section.

Preface: Chapter 2

This chapter was published in Global Change Biology in January 2009. It explores the spatial variation in burned area across the subcontinent and develops an understanding of the factors promoting and limiting fire in these savanna systems.

First I present a conceptual model which describes the direct and indirect determinants of burned area. This framework identifies the various climatic, environmental and human variables that affect fire spread, fire size, ignition frequency, and ultimately burned area. Spatial data on all of these factors are then used to assess how important each variable is in driving burned area in the region.

Because these environmental controls act on different aspects of a fire regime, the same variable can have both positive and negative impacts on burned area. Variables are also often not independent, and are either correlated with each other, or causally related (for example tree cover and rainfall). We decided that a regression tree modelling approach would give the most reliable and interpretable results in this instance.

This paper is my work with the advice and assistance of the various co-authors: Prof David Roy provided early access to the remotely sensed burned area data and spent much time developing the regression tree modelling procedure with me. Dr Bob Scholes, my supervisor, worked on the conceptual model with me and provided guidance on which environmental variables to include and how to access the necessary spatial data. Dr Brian Van Wilgen gave input on the structure of the paper, and substantially improved my writing.

Chapter 2

What limits fire?: an examination of drivers of burnt area in southern Africa

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2.1 Abstract

The factors controlling the extent of fire in Africa south of the equator were investigated using moderate resolution (500 m) satellite-derived burned area maps and spatial data on the environmental factors thought to affect burnt area. A random forest regression tree procedure was used to determine the relative importance of each factor in explaining the burned area fraction and to address hypotheses concerned with human and climatic influences on the drivers of burnt area. The model explained 68 % of the variance in burnt area. Tree cover, rainfall in the previous two years, and rainfall seasonality were the most important predictors. Human activities represented by grazing, roads per unit area, population density, and cultivation fraction were also shown to affect burnt area, but only in parts of the continent with specific climatic conditions, and often in ways counter to the prevailing wisdom that more human activity leads to more fire. The analysis found no indication that ignitions were limiting total burnt area on the continent, and most of the spatial variation was due to variation in fuel load and moisture. Split conditions from the regression tree identified (i) low rainfall regions, where fire is rare; (ii) regions where fire is under human control; and (iii) higher rainfall regions where burnt area is determined by rainfall seasonality. This study provides insights into the physical, climatic and human drivers of fire and their relative importance across southern Africa, and represents the beginnings of a predictive framework for burnt area.

2.2 Introduction

A prolonged annual dry season combined with relatively rapid rates of fuel accumulation create conditions conducive to frequent vegetation fires in southern Africa. Indeed, fire is considered a major determinant of the ecology and distribution of Africa's savanna and grassland vegetation types (Van Wilgen & Scholes, 1997; Higgins *et al.*, 2000; Bond, 2005). The fraction of the landscape that burns varies greatly across the region. Understanding the causes of this variation is not simple because the propensity to burn is influenced by weather conditions, the presence of ignition sources, and the amount, type and arrangement of the available fuel, all of which change across space and through time.

Satellite data products and spatially explicit environmental data are increasingly becoming available, and continental-scale information on many environmental factors, including fire, is now relatively easy to obtain. Quantitative methods can now be applied to address scientific questions that previously relied on anecdotal information or localised studies; in particular, how the various drivers of fire interact to result in characteristic fire regimes. These questions have become increasingly important in the context of global change. Fire is both an important determinant of vegetation community structure

(Bond & Van Wilgen, 1996), and a globally-significant source of greenhouse gas emissions (Williams *et al.*, 2007; Patra *et al.*, 2005). Fire patterns will almost certainly change in response to population, land use, and climatic changes in Africa (Boko *et al.*, 2007), and an understanding of the drivers of such changes will be needed to predict their consequences.

A century of experimental and descriptive research has provided a good understanding of the physical factors controlling the ignition and spread of both grass-fuelled and forest fires (see in particular Viegas (2004); Byram (1959); Luke & McArthur (1978); Trollope *et al.* (2002)). The challenge is to determine which factors dominate under different conditions, and to predict the outcome of the interaction of several, often antagonistic influences. For example, areas of high population density have been shown to be associated with an increase in the number of fires (Keeley *et al.*, 1999), but increased population densities also result in more intensive land use, reduced fuel loads, and fragmentation of landscapes, which act to reduce the spread of fire (Frost, 1999). Similarly, although fuel production generally increases with rainfall, so too do factors with negative effects on fire, such as fuel moisture (Spessa *et al.*, 2005; Scholes *et al.*, 1996). Thus, it is the relative importance of contrasting influences acting under different circumstances that determines the characteristic fire regime of a particular region.

This paper aims to investigate the factors controlling the annual fraction of the landscape that burns across Africa south of the equator. The fire regime of an area is defined by several variables, including the intensity, season, and type of fire (Gill, 1975). The average period between fires, often confusingly referred to as the 'fire frequency' is fundamentally important. In this paper, we analyse the annual burnt area fraction, which is usually regarded as the reciprocal of the fire return time (Frost, 1999). Burned area fraction is also important in its own right. For example, it is necessary for calculating greenhouse gas emissions (Crutzen & Andreae, 1990).

Information on the relative importance of the various environmental factors affecting burnt area in southern Africa is currently lacking. Further, there is little agreement over how much influence people have, relative to abiotic factors such as climate, in controlling fires (see Westerling *et al.* (2006); Heyerdahl *et al.* (2001); Keeley & Fotheringham (2001); Moritz (2003); Dickson *et al.* (2006) for a recent north American discussion on this). Human population data have been incorporated into mechanistic fire models (Venevsky *et al.*, 2002; Thonicke *et al.*, submitted), but in Africa fundamental assumptions on the extent that human activities constrain or promote fire are yet to be tested over large areas. Rather than modelling fire processes mechanistically, we adopt a statistical modelling approach. This research provides new, continental scale insights into the physical, climatic and human drivers of fire and the relative importance of these across southern Africa.

2.3 Hypotheses

The majority of fires in southern Africa are surface fires, fuelled by grass and litter. Given sufficient rainfall this fuel can re-grow rapidly after fire, and can cure and be ready to burn after only a few weeks of dry weather (Stott, 2000). Current theoretical understanding of the drivers of fire in southern Africa is synthesized in Figure 2.1. Rainfall and soil nutrients positively affect grass production, and therefore grass fuels; however, high tree covers and high grazing pressure will reduce grass fuels (Van Wilgen & Scholes, 1997; Trollope, 1984). The duration of the dry season will determine the amount of time that fuel is dry and available to burn and, combined with weather conditions on the day of burning, determine fuel moisture (Spessa *et al.*, 2005; Russell-Smith *et al.*, 2007). Variations in lightning frequencies and human population densities are likely to affect ignition frequencies (Keeley *et al.*, 1999), and land management may affect both the ignition and suppression of fires (Frost, 1999). Fuel continuity is impacted both by the landscape morphology – highly dissected, variable landscapes will prevent the spread of large fires (Dickson *et al.*, 2006; Russell-Smith *et al.*, 2007); and by human activities – building of roads and transformation of land through cultivation and urban expansion may break up the landscape and prevent fire spread. Removal of fuel for building, domestic cooking and heating purposes, may also reduce fire spread (Saunders *et al.*, 1991; Frost, 1999).

All the factors illustrated in Figure 2.1 vary spatially, and burnt area is unlikely to be controlled by the same combination of factors in different parts of the sub-continent. We aim to determine which environmental and human drivers are important in affecting fire regimes in different areas of southern Africa; and specifically, to test whether human population densities have a positive or a negative effect on burnt area. Humans can affect fire regimes directly, by altering the ignition regime, and indirectly, by reducing fuels and fragmenting the landscape, thus reducing fuel continuity. Thus, increasing human densities could be predicted both to increase the incidence of fire, and decrease the extent of fire, and it is unclear which effect would be more important in determining total burnt area.

Similarly, areas with high rainfall have high fuel loads but also would have many perennial rivers, which might act as barriers to fire spread; and shorter dry seasons, which might limit the number of fires that could occur. We aim to find out whether, and under what circumstances, factors that decrease fire ignition and spread outweigh the positive effects of increased grass biomass.

Moreover, there are questions concerning the importance of fire management. Commercial farmers prepare fire breaks, actively suppress unplanned fires, and try to burn at certain times of year with set return periods (Van Wilgen & Scholes, 1997). Fire management in communal land is more varied, fires are lit for a variety of reasons and it

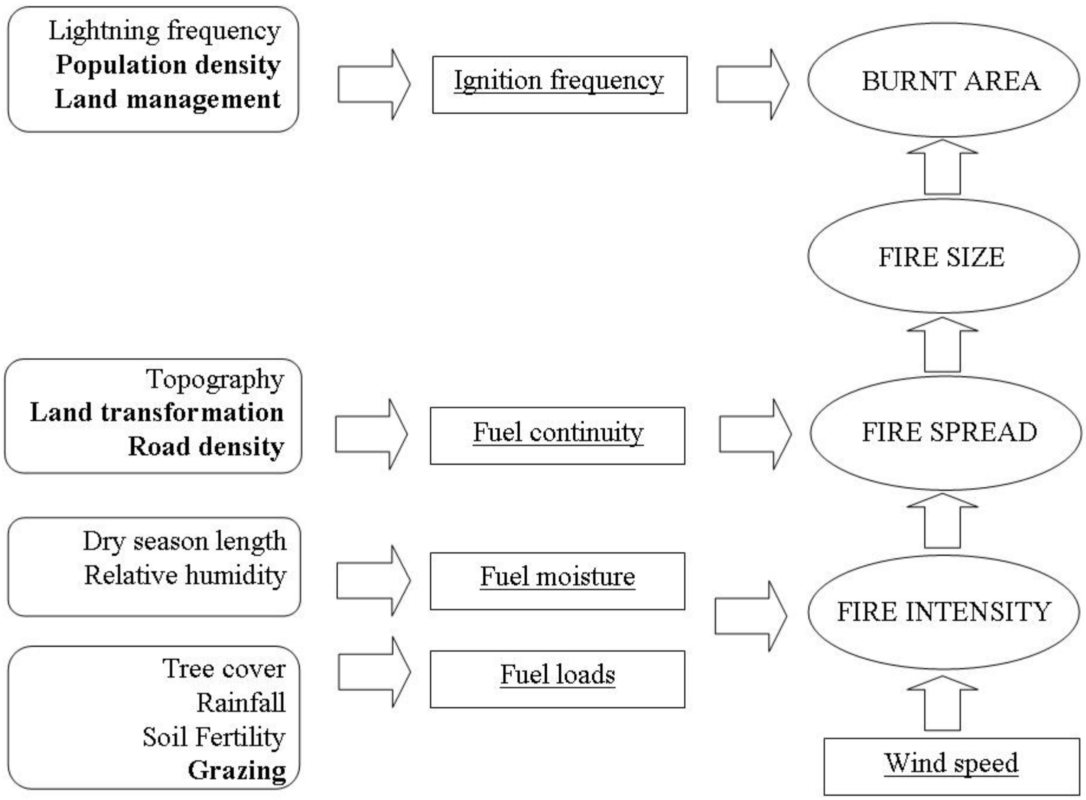

Figure 2.1: Theoretical model of the factors affecting burnt area. Items in upper case are components of a fire regime, items underlined are direct drivers of fire. The rest (list of items on the left) are the indirect drivers of fire, which can be measured. Many of these factors co-vary: rainfall affects tree cover, population density is correlated with grazing density

is not common to suppress actively burning fires (Verlinden & Laamanen, 2006; Mendelsohn, 2002). Early-season burning in communal areas is commonly undertaken, which could break up fuel loads for later fires and reduce total burnt areas (Frost, 1999; Laris, 2005). We aim to investigate whether land tenure differences have any apparent effect on burnt area.

Ultimately, we want to determine whether human or climatic influences are more important in driving fire regimes in southern Africa, so as to gain insights into how global change - both human and climate induced - will affect fire regimes. This study is based on only one year of data, and thus concerns itself largely with variation in space, but insights gained from this analysis will contribute towards predictive models of burnt area for the sub-region.

2.4 Data and methods

2.4.1 Data

Spatially explicit data on burned area and the environmental factors thought to affect burned area were assembled for the 2003 fire season for all of Africa south of the Equator (including Madagascar). Although 2002-2003 was a low rainfall year over much of South Africa, at the time of writing these were the only spatially-explicit data available. Summary statistics of each data set in the Lambert Azimuthal equal area projection were derived with respect to fixed, non-overlapping square windows, defining the mean, median or percentage value within each window across the study area. A 100x100 km window size was adopted as a result of window size sensitivity analysis (described below), resulting in 899 sample points.

Selection of appropriate environmental factors was based on a conceptualization of the direct and indirect drivers of fire in southern Africa (Figure 2.1). Fuel load, fuel moisture, fuel-bed continuity, and wind speed all affect the spatial extent of an individual fire (Stott, 2000; Van Wilgen & Scholes, 1997). These factors, together with ignition frequency, are direct drivers of annual burnt area and are influenced by a number of indirect drivers (Figure 2.1). Eleven datasets describing the indirect drivers were used (on the left side of Figure 2.1), of which four represented controls on fuel load, one on fuel moisture, three on fuel continuity, and three on ignition frequency. Wind speed and relative humidity at the time of burning are important in determining fire size and intensity (McArthur, 1966; Trollope, 1984) but were not included, as these data are not available for the entire study region.

The eleven independent variables are summarized in Table 2.1 and are described below, after description of the burned area data. Most of the independent variables are available as derived data products, and their sources and attributes are noted in Table 2.1. Others, including grazing density, land tenure, extent of transformed land, length of the dry season, topographic roughness, and lightning strikes, were derived from the best available spatial information.

Table 2.1: Spatial data on environmental drivers used as inputs to the regression tree model

Direct driver of burnt area	Indirect driver (input surface)	Name	Units	Summary statistic	Original resolution (km)	Source and attributes	Notes
Fuel load	accumulated rainfall	rainfall	mm/year	mean	28	TRMM 3B43 rainfall product (Huffman *et al.*, 1995)	Rainfall positively affects grass production and there is carry-over of fuel from year to year. The previous two years of rainfall has been shown to be a good predictor of total burnt area Van Wilgen *et al.* (2004).
	soil fertility	sand	%	mean	9	IGBP global soil data product (IGBP, 2000)	Soil fertility positively affects grass production. Soils with a higher sand content were considered less fertile.
	tree cover	treecover	%	mean	0.5	MODIS Vegetation Continuous Fields Hansen *et al.* (2003)	Tree cover has a negative impact on grass biomass (Scholes et al., 1997), especially above about 40% cover (Scholes, 2003)
	grazing	grazing	kg/km^2	median	6	Global Livestock Distributions (FAO, 2005). See text for details on filling these data.	Grazer density affects how much grass will be left in the system to fuel fires.
Fuel moisture	length of the dry season	dryseason	months	mean	28	TRMM 3B43 rainfall product (Huffman *et al.*, 1995)	The longer the dry season, the drier the fuel, and the more time spent in a flammable state. Dry season length is defined as the number of months in which less than 30% of the rain fell.
Fuel continuity	topographic roughness	topography	meters	mean	0.09	Calculated using SRTM digital topographic data Version 2 (SRTM, 2005)	An indication the natural barriers to fire spread. Defined as the standard deviation of a 3x3 block of a 90m resolution DEM (see Russell-Smith et al., 2007)
	road density	kmroads	km/km^2	sum	N/A	2000 road vector from www.mapstudio.co.za.	A measure of human impacts on fuel continuity.
	fraction of transformed land	trans-formed	%	%	1	Global Land Cover 2000 (Mayaux *et al.*, 2004)	A measure of human impacts on fuel continuity Cultivated and settled land were considered transformed.
Ignition frequency	mean lightning strikes over the burn season.	lightning	# hits/km^2 over the fire season	mean	55	GHRC LIS/OTD High Resolution Full Climatology (GHRC, 2003)	Only lightning occurring at the same time as fire can be a source of ignitions. Defined as the average lightning frequency during the fire season (when 90% of the burning occurred).
	population density	popdensity	# people/ km^2	median	5	Ciesin Population of the World Version 3. year 2000 adjusted estimates (Ciesin, 2005).	Increased population densities might result in increased numbers of fires.
	percentage of communal land	communal	%	%	N/A	Data surface created using individual country data (see text for details)	Ignitions might be more frequent on communally managed land - where fire is used freely - compared with land managed for commercial or conservation purposes - which often have strictly controlled fire schedules.

Annual burned area: Data for the main burning season (March-November) of 2003 were used in this study. The dependent variable, annual burned area, was derived from the NASA Moderate Spatial Resolution Spectroradiometer (MODIS) burned area product, that defines the 500 m location and approximate day of burning to a precision of 8 days (Roy *et al.*, 2008, 2005a). The MODIS design includes features specifically for monitoring fires (Kaufman *et al.*, 1998). The MODIS burned area product maps the spatial extent of recent fires and is available as a monthly summary product. It is being generated on a global systematic basis in support of the global change community in conjunction with a number of other NASA funded satellite products (Justice *et al.*, 2002). Southern Africa was selected as the first regional test for the burned area product that has been validated using independent reference data collected by the Southern Africa Fire Network (Roy *et al.*, 2005b) detecting about 85% of the true burned area. At the time of writing only one year of burned area data was available. In addition, the 1 km MODIS active fire product that defines the location of fires observed at the time of satellite overpass (Giglio *et al.*, 2003) was used to study ignition incidence. Interpreting polar-orbiting satellite active fire data is complicated by the fact that only fires actively burning at the time of satellite overpass and under cloud free conditions are detected, but when interpreted with this caveat in mind the active fire product provides qualitatively different information from the burnt area product (see results). Further information and MODIS fire product examples can be found at http://modis-fire.umd.edu/MCD45A1.asp.

Grazing: The grazing intensity data (kg live mass/km^2) were created by summing cattle, sheep, and goat biomass per unit area from the FAO livestock distribution dataset (FAO, 2005). The FAO data do not cover protected areas so the effect of indigenous large mammal grazers was estimated for these regions using wildlife census data from Kruger, Gorongoza, Etosha, and Serengeti National Parks, as well as published carrying capacity information (Fritz & Duncan, 1994).

Land management: Land tenure was used as an easily-derived spatial indication of different land management practices in the region. Three different land management (land tenure) classifications were identified: communal, commercial, protected area. The surface was created by combining available land tenure maps for South Africa, Namibia, Botswana, and Zimbabwe with the World Protected Areas map (UNEP-WCMC, 2006). Each map was interpreted to identify communal, commercial, and protected areas. We assumed that the extent of commercial rangeland in Angola, Zambia, Zaire, Mozambique, and Tanzania was negligible, and that the major land tenure types in those countries were communal and protected area.

Land transformation: The Global Land Cover 2000 Africa product (Mayaux *et al.*, 2004) was simplified into a binary map of 'transformed land' (crops, plantations, or urban use) and 'untransformed land' (all other categories). This was used to as a measure of the extent to which human activities have fragmented the fuel load.

Accumulated Rainfall: The monthly Tropical Rainfall Measuring Mission (TRMM) best-estimate precipitation rate product (Huffman *et al.*, 1995) was summed between July 2001 and June 2003 and divided by two to give the preceding two-year average rainfall (see Van Wilgen *et al.* (2004) for justification of this metric).

Length of the dry season: The dry season length (months) was derived using the monthly TRMM product (Huffman *et al.*, 1995). For each TRMM pixel, 12 monthly rainfall estimates from July 2002 - June 2003 were ranked and summed in descending order until at least 70% of the annual rainfall was reached. The remaining number of months (representing less than 30% of the annual rainfall) was considered as the length of the dry season for that pixel. These values ranged from 3 months in the high-rainfall belt near the equator, to 9 months in the subtropical arid zones in the continental interior. This metric represents an improvement on dry season metrics developed in the literature (Russell-Smith *et al.*, 2007; Spessa *et al.*, 2005) in that it is independent of total annual rainfall or an *ad hoc* identification of the wet season. These are strongly seasonal climate systems, and a sensitivity analysis showed that the data were not sensitive to the choice of the 70% cut-off.

Topography: Topographic roughness was derived from Shuttle Radar Topography Mission (SRTM) elevation data (STRM, 2005) as the standard deviation of the SRTM elevation values in 3x3 90 m pixel windows (following Russell-Smith *et al.* (2007) and resampled to 500 m using the nearest neighbour method). At the scale of this analysis (values summarised over 100km windows), topographic effects are likely to be manifest in terms of the negative effect that a highly dissected landscape has on fire spread (Russell-Smith *et al.*, 2007; Frost, 1999). At finer scales the topographic position of individual fires affects rate of spread (Viegas, 2004) and fuel moisture (Heyerdahl *et al.*, 2001), but we expect that these effects would not be apparent in our analysis.

Lightning frequency: Most lightning in these systems occurs in the rainy summer months when there is very little fire (Figure 2.2). To extract a metric for lightning ignitions we included only the lightning strikes that could have been ignition sources for the fires in the system. Data from the Global Hydrology Resource Centre (GHRC, 2003) were used to compute the mean frequency of lightning strikes per km^2 during the fire season (defined as those months in which 90of the fires occurred). No correction was made for cloud to cloud strikes, because, lacking any data to the contrary, it was assumed that the proportion of these strikes was relatively constant across the study region.

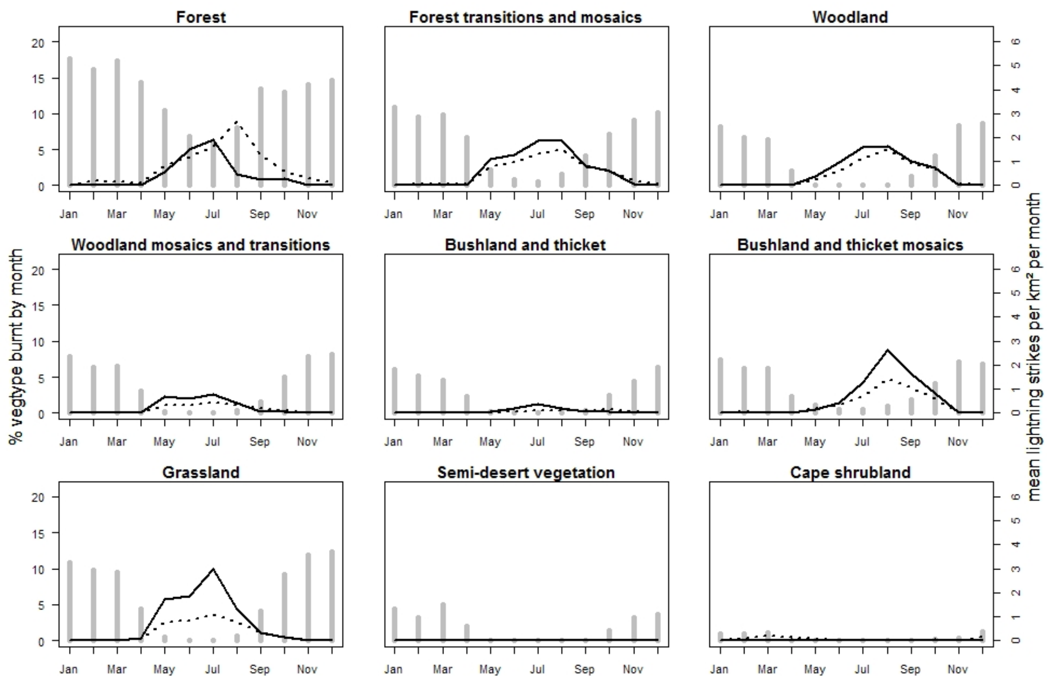

Figure 2.2: Seasonal distribution of lightning strikes and burnt area in the twelve major vegetation types identified by (White, 1983). Grey bars show mean monthly lightning strike frequency; solid lines show the percentage of the area burnt defined by the MODIS burned area product (Roy et al., 2005b); dotted lines show the percentage of fire-affected area defined by the 1km MODIS active fire product (Giglio *et al.*, 2003)

Data pre-processing

Considerable effort was taken to ensure that these data were precisely co-registered, and projected in a way that preserved the data integrity. All the data were re-projected into the same Lambert Azimuthal equal area projection with an African projection (centre of latitude -25°, centre of longitude, 15°; sphere radius 6370997m). The raster data products were re-projected with nearest neighbour resampling to maintain the pixel values, and resampled with 1km or 500m output pixel dimensions to reduce nearest-neighbour resampling pixel shifts (i.e., position errors). Similarly, the vector data were converted into raster thematic layers with 1km output pixel dimensions.

Summary statistics of each data set in the Lambert Azimuthal equal area projection were derived with respect to fixed, non-overlapping square windows, defining the mean, median or percentage value within each window across the study area. A 100x100 km window size was adopted as a result of window size sensitivity analysis (described below). Road density (km) was derived by summing the length of roads in the 100x100 km window. Mean values were used for the other independent data sets (Table 2.1), except for grazing and human population density. Median values were used to summarize these latter data to reduce the skewness introduced by high human populations confined to relatively small urban areas, and similarly to reduce the influence of some unrealistic outliers in the FAO cattle data (W. Wint, pers. comm. 2006). The annual percentage burned was found by summing within each window the number of 500m pixels that were labelled as burned in the period March-November 2003. The proportion of non-land (i.e. coastal and inland water bodies) and invalid (i.e. missing, cloud contaminated, unavailable, unmapped) data within each window were computed. Windows for which any of the data sets listed in Table 2.1 had greater than one third non-land and invalid pixels were excluded from the analysis.

2.4.2 Analysis

Conventional statistical models such as General Linear Models are inappropriate for investigating the drivers of burnt area in the context of this study because many of the relationships are likely to be non-linear, with non-additive predictor-response interactions, and several of the independent variables are highly correlated (see Table 2.2). Decision trees (regression trees) are hierarchical classifiers that predict class membership by recursively partitioning data into more homogeneous subsets, referred to as nodes (Breiman *et al.*, 1984). They accommodate abrupt and non-monotonic relationships between the independent and dependent variables and make no assumptions concerning the statistical distribution of the data. When run using continuous data a sum of squares criterion is used to split the data into successively less varying subsets. This splitting procedure is followed until a perfect tree is created or until preset conditions are met for terminating the tree's growth. It is then possible to identify the variables and the split conditions that result in the final prediction. For our purposes, it is this latter property that make trees particularly advantageous; the tree structure enables interpretation of the explanatory nature of the independent variables.

A random forest regression tree procedure was used. Like other bootstrapping procedures, random forests improve the predictive ability of regression tree models and reduce over-fitting (Breiman, 2001; Prasad *et al.*, 2006). A large number of regression trees are grown, each time using a different random subset of predictor variables, and keeping a certain percentage of data aside ('reserved'). In our case we grew 1000 trees, using three of the 11 variables at each split, and using 66 % of the data each time. The default minimum node size of five (Breiman, 2001) was used, meaning no node with fewer than five cases was split. Predictions were run on the reserved data each time a tree was grown, and the final prediction for each data point was the mean of the predicted values. The analysis was undertaken using R software (http://www.r-project.org/), using the randomForest package.

Table 2.2: Correlations between the 11 independent environmental variables used in the analysis

treecover										
0.75	*rainfall*									
-0.50	**-0.53**	*dryseason*								
-0.25	-0.08	0.00	*grazing*							
0.05	0.17	-0.15	0.48	*popdensity*						
-0.38	-0.29	-0.07	0.28	0.13	*kmroads*					
0.28	0.41	-0.40	0.07	0.32	0.09	*topography*				
-0.04	-0.01	0.02	**0.50**	0.35	0.27	0.08	*transformed*			
0.47	**0.54**	-0.04	-0.03	0.22	**-0.51**	0.11	-0.02	*communal*		
0.62	0.35	**-0.55**	-0.15	-0.02	-0.11	0.17	-0.05	0.06	*lightning*	
-0.23	-0.22	0.10	-0.19	-0.26	0.00	-0.32	-0.20	-0.14	-0.1	*sand*

Importance of independent environmental variables

There are several metrics for determining how important different variables are to the final prediction (Breiman, 2001). We used a method which takes the difference in mean square error (MSE) between a test sample, and the test sample when that variable is randomly permuted, calculated using the reserve data for each tree, for each variable (Breiman, 2001). The differences are averaged over all 1000 trees, and then normalised by the standard error. This value therefore provides a measure of how much the predictive ability of the model is reduced when the effect of a certain variable is excluded. When looking more specifically at the effect of individual drivers on burnt area, a piecewise quantile linear regression method (Koenker, 2005; Sankaran *et al.*, 2005) was used to fit the upper boundary of burnt area and to identify breakpoints. This was done using Quantreg in R statistical software. The 99^{th} quantile was used to identify the upper limits of burnt area under different drivers.

Split conditions

In the random forest procedure many different trees are grown and the average result taken, so one can not explore the explicit split conditions for classifying data into different groups. As the particular conditions resulting in high and low burnt areas were of interest to us, we took this approach a step further and ran one more regression tree using the predicted data from the random forest permutation as an input. We pruned this tree using a complexity parameter of 0.01 (see R documentation 'rpart.control' for an explanation of this parameter). This tree was stable and explained 85% of the variance in the input data which was significantly ($p < 0.001$) more than a random tree (see Rejwan *et al.* (1999) for significance-testing methods for regression trees). The original observed burnt area data were then classified using this regression tree, and the splits and nodes analysed to determine the combinations of environmental conditions that result in high and low burned area proportions across the sub-continent.

Spatial Autocorrelation

Spatial autocorrelation in the burned area data (Lynch *et al.*, 2006) and the predictor variables may result from various causal mechanisms (e.g., physical and biological processes), acting both simultaneously and additively, and from variables and processes not quantified in this study. The scale of the analysis and the summary units used to aggregate the data into 100x100 km windows also imposes a spatial structure on the data. It is established that auto-correlated data violate the assumption of independence of many statistical procedures (Cliff & Ord, 1981; Legendre & Legendre, 1998). Approaches to resolve this issue have been to manipulate the sampling scheme to avoid auto-correlated observations or to attempt explicitly to incorporate spatial dependence into the model.

To date, no technique to incorporate spatial dependence into decision trees has been reliably demonstrated, and this remains an area of active research (Miller *et al.*, 2007). In this analysis rainfall, tree cover, and topography are all explicitly included as predictor variables which accounts for the major geographical gradients. We also sub-sample the data in the random forest procedure (using 66% of the data each time) which will further reduce the spatial dependency of the data. However, we admit to a degree of uncertainty related to the statistical tests that may result due to inclusion of spurious explanatory variables (Lennon, 2000); for these reasons only the most important splits in the regression tree results are considered in the subsequent results section.

Window size sensitivity analysis

Geographical analyses of this kind are sensitive to the scale of the analysis; both with respect to the size and location of the windows and to the nature of the summary units used to aggregate the data (Openshaw, 1984; Unwin, 1996). Rather than select an arbitrary window size, a sensitivity analysis was undertaken to evaluate an appropriate size for the analysis. This was undertaken by applying the random forest regression tree procedure to the data several times, each time using a progressively larger window size and recalculating the summary statistics (fraction, percentage, mean or median). Window side dimensions varying from 30x30 km, approximately equivalent to the coarsest available input data (0.5° lightning data, Table 2.1), to an order of magnitude greater, 300x300 km, were considered, providing 10,876 to 114 windows across the study area respectively.

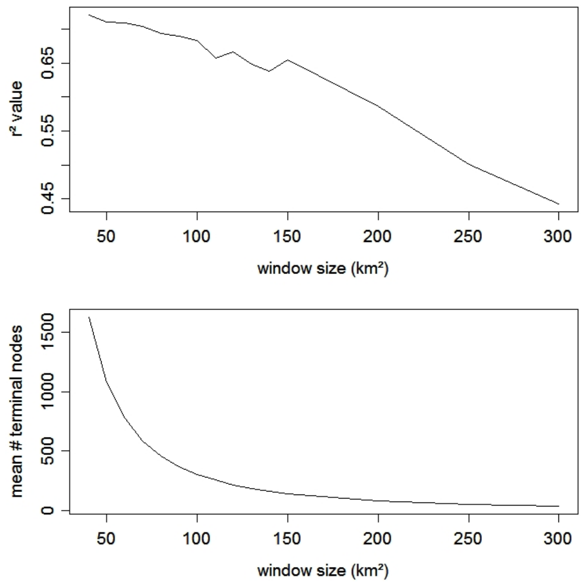

Figure 2.3: Sensitivity analysis of the effect of increasing window size on A) the predictive ability (R^2 of predicted vs. observed burnt area) and B) the number of terminal nodes, in the random forest regression tree model.

2.5 Results

2.5.1 Window size analysis

The number of nodes in the final tree declined steeply with increasing window size, and the predictive ability (R^2) of the random forest model declined less steeply (Figure 2.3). The R^2 values are calculated for each window size from the linear relationship between the burnt area values predicted by the statistical model and the observed percent burnt area. Window dimensions between 100x100 km and 150x150 km show some variability in R^2, perhaps related to the original resolution of some of the input data relative to the window sizes and locations. The 100x100 km window was chosen as an acceptable trade off between over-fitting the model (too many split conditions), and reducing the predictive ability (by averaging the data too much).

2.5.2 Spatial patterns of burnt area

The MODIS 500m burned area product identified 18 % of the observable study area as burnt in 2003. Some 26 % of the region could not be classified as burned or unburnt due to persistent cloud and missing MODIS observations (Roy et al. 2005a), so the actual burnt area statistic for Africa south of the equator could range from 13-39% (from all unclassified pixels unburnt or all burnt respectively). The majority of the unclassified pixels occurred over the equatorial parts of Gabon, Congo, and the Democratic Republic

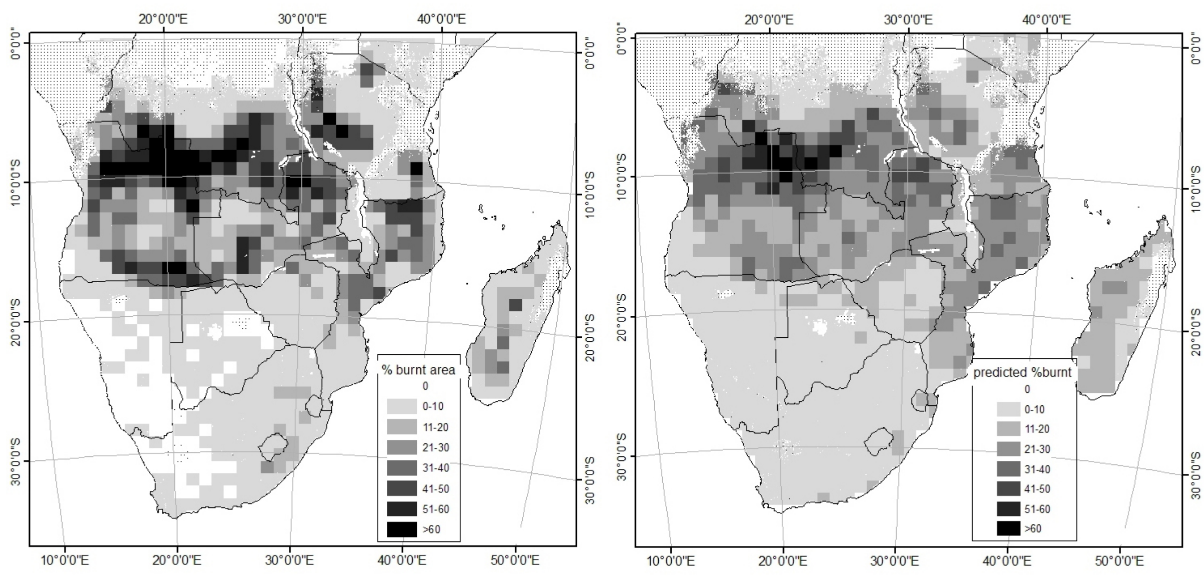

Figure 2.4: Observed (left) and predicted (right) percent burnt areas for 100x100 km windows across southern Africa. Predictions are mean values for the reserve samples in the random forest (see methods). Dark stipples represent areas where cloud or missing MODIS data preclude burned area mapping for more than five months of the year.

of Congo (DRC) and are associated with persistent cloud at the time of MODIS overpass. The DRC and Angola had the highest burnt areas: 56 % and 41 % respectively of the valid pixels in these countries were burnt in 2003. Although we were unable to determine the state of burning in the invalid pixels, it is likely that the high burn percentages are representative of the country totals (pers comm. Bahananga Muhigwa, University of Bukava, DRC). In contrast, 2.5 % and 1.7 % of South Africa and Namibia, respectively, burnt. These results are consistent with other burned area estimates for the region: total burned area derived from the SPOT vegetation product for 1990 for the same area was calculated at 17% (Silva *et al.*, 2003), and the spatial distribution of burning reflects that of independently detected MODIS active fires (Roy *et al.*, 2005b). The annual fraction burned data are shown in Figure 2.4A, summarised for the 100x100 km window size adopted for the analysis.

A linear regression between predicted values from the random forest and observed burnt areas had an R^2 of 0.68 (Figure 2.5), and the model captures the spatial distribution of burning well (Figure 2.4). The model under-predicts the high burnt areas and over-predicts the low burnt areas, as would be expected from a procedure that groups data into homogeneous classes.

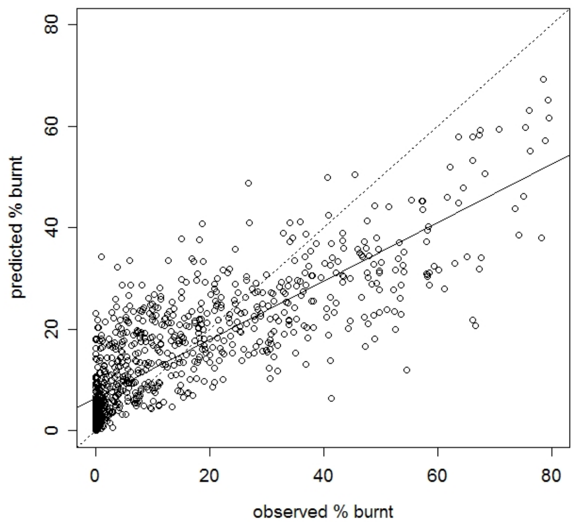

Figure 2.5: Predicted burnt area calculated from a random forest regression tree run on 2003 burnt area data using 11 independent variables (see Table 2.1). The dotted line represents an exact 1:1 relationship, the solid line shows a linear regression of these data. The explained variance (R^2 of regression line) is 68% but the model over predicts at low burnt areas and under-predicts at high burnt areas. One thousand trees were run, excluding 33% of the data each run ('reserve' sample). The predicted value is calculated as the mean value predicted each time a data point was included in the reserve sample (see methods).

2.5.3 Relative importance of environmental variables

The analysis identified tree cover, rainfall, and dry season length as the most important predictors of burnt area across the study region (Figure 2.6). Human activity also appears to influence burnt area, with grazing, population density, and road density all identified as moderately important - increasing the MSE by between 35 and 40 % (see methods for definition of importance). Sand percentage - an inverse measure of soil fertility - was the least important variable, probably because grazing density is a better indicator of the effects of soil fertility. Lightning density was also less important. As can be seen from Figure 2.2, fires occur at very different times of year from the peak density of lightning strikes in all vegetation types. This supports commonly-held perceptions that humans are the main sources of ignition in Africa (Frost, 1999; Sheuyange *et al.*, 2005). However, it does not totally exclude lighting as an important source of ignitions at certain times of year (such as the early wet season), or in places where there are few people (Edwards, 1984).

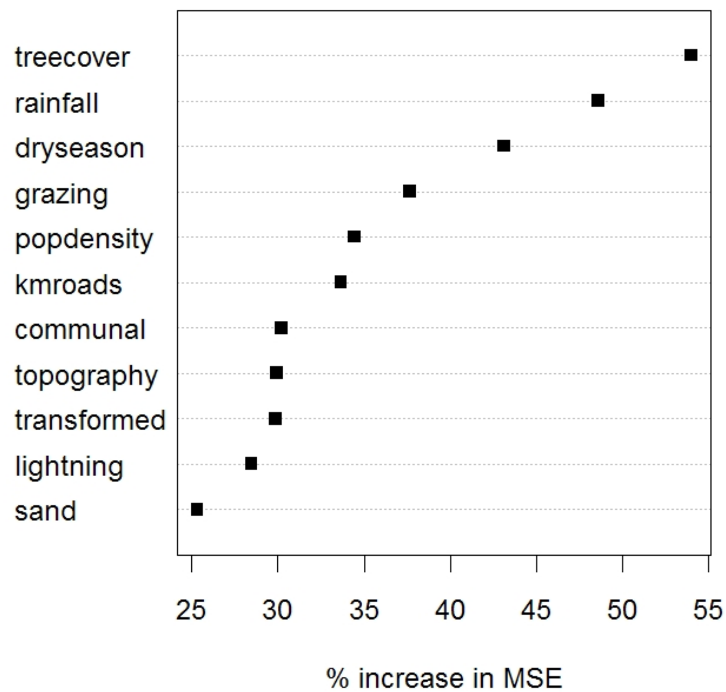

Figure 2.6: The relative importance of each independent variable in determining burnt area for Africa south of the equator. Importance is measured by testing how the accuracy of the results is affected if the input variable is randomly permuted. It is calculated as the increase in mean squared error (MSE) that occurs in the predicted values when each variable is randomly permuted in the test set. Importance is calculated for each variable, for each tree, then averaged, and normalised by the standard error. See Table 2.1 for a definition of variables

2.5.4 Split conditions

The conditions that result in high or low burnt areas on the continent were identified by cascading the observed burnt data through the final regression tree created from the random forest predictions (Table 2.3). The reliability of this prediction is slightly decreased from the original random forest predictions, ($R^2 = 0.57$, $p < 0.001$) but because the split conditions are available, these results give an indication of the mechanisms driving fire on the continent, and how these drivers change over space.

Two different sets of conditions can result in very low burnt areas (nodes 1 and 5, Table 2.3). Areas with low tree cover have a mean predicted burnt area of less than one percent. These areas coincide with areas of very low rainfall (mean rainfall 288 mm), and it is likely that low rainfall, rather than low tree cover, is the cause of this. The low rainfall does not permit the accumulation of sufficient fuel to sustain extensive fires. The second condition resulting in low burnt area is that the length of the dry season is less than six months. Figure 2.7A shows the parts of Africa where these two sets of conditions hold true; covering approximately 31 % of the study area.

Table 2.3: Split conditions identified by a regression tree run on the random forest predictions

Split conditions								Mean percent burnt	Node #
treecover < 21	treecover < 5							0	1
	treecover ≥ 5	kmroads ≥ 355						3	2
		kmroads < 355	grazing ≥ 5					14	3
			grazing < 5					35	4
treecover ≥ 21	dryseason < 6							0	5
	dryseason ≥ 6	grazing ≥ 6	kmroads ≥ 333					9	6
			kmroads < 333					20	7
		grazing < 6	rainfall < 1150					20	8
			rainfall ≥ 1150	popdensity ≥ 15				27	9
				popdensity < 15	treecover ≥ 38			20	10
					treecover < 38	topography ≥ 0.4		47	11
						topography < 0.4	rainfall < 1300	50	12
							rainfall ≥ 1300	71	13

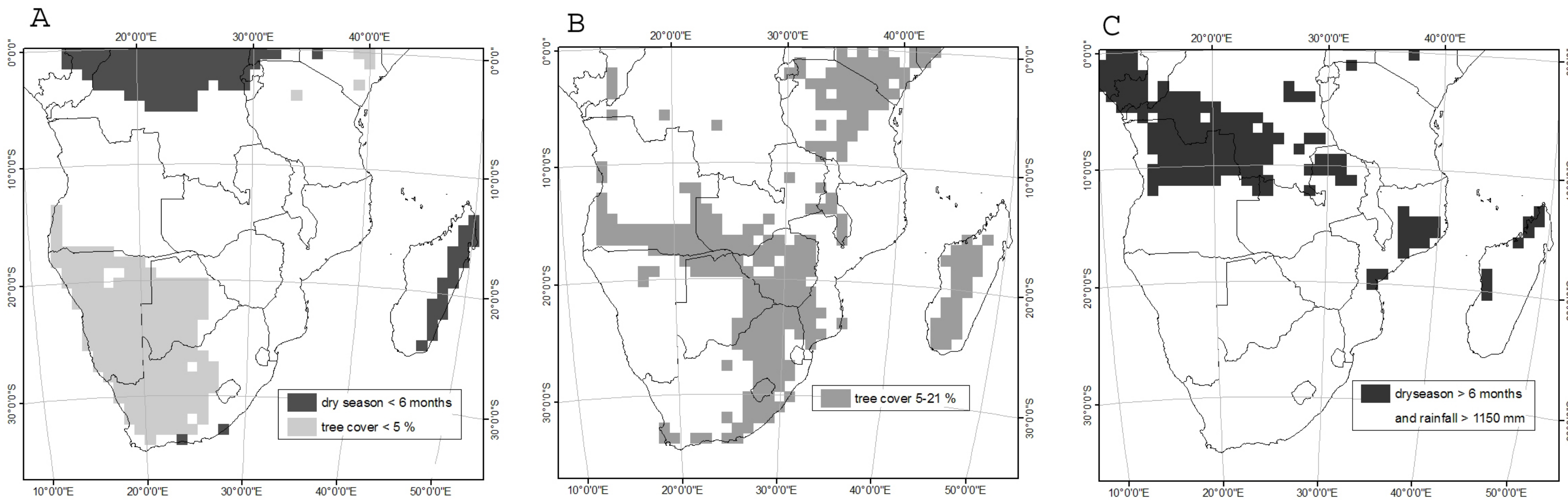

Figure 2.7: Areas where the fire regime is under varying degrees of climatic control. A) areas of very low tree cover (and rainfall) always have low burnt areas (grey), as do areas with short dry seasons (black). B) areas where the burnt area is most under human control: depending on population density, grazing, road density, and the percentage of transformed land these areas can range from 3 to 35 percent burnt. C) areas where significant percentages of the landscape burn, and human activities reduce, but can not eliminate, fire. Here dry season is measured as the number of months with less than 30 % of the annual rainfall. These maps were created by plotting spatially the areas in Africa which fulfilled particular environmental conditions identified in Table 2.3.

Extremely low burnt areas therefore seem to be correlated with a certain set of climatic factors. However, human activities can *decrease* burnt areas in circumstances that otherwise would result in intermediate to high burnt areas. For example, when tree covers are between 5 and 21 % a large range in burnt areas is possible (3 to 35 %). The percentage of the landscape that actually burns in these areas depends on grazing density, and the density of the road network (nodes 2,3 and 4, Table 2.3). Fire regimes in these parts of Africa, which cover around 28 % of the total area (Figure 2.7 B), are therefore highly spatially variable, and can be modified by human activities.

Where annual rainfall exceeds 1150 mm a year and the dry season is longer than six months (node 9), annual burnt area exceeds 20 %. Although high population densities, variable terrain, and high tree covers can reduce burnt area, regular surface fires are an inevitable consequence of climate in these parts, which cover 17 % of the sub-continent (Figure 2.7 C).

2.5.5 The effect of people

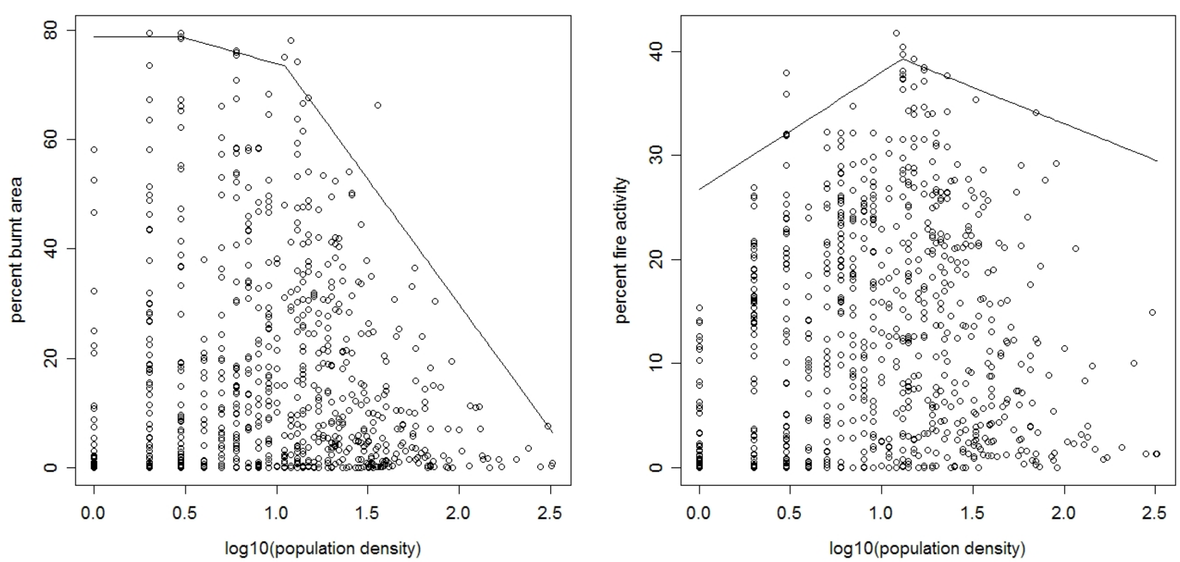

Figure 2.8: Burned area (% of 100x100 km window) plotted against log population for the MODIS burned area product (left) showing the negative effect of people on burnt area at densities over about 10 people per km2; and for the MODIS active fire product (right) showing a different pattern, where decreasing densities of people appear to decrease fire activity. A piecewise quantile linear regression (Koenker (2005) 99th percent quantile, run using quantreg in R) of these data is superimposed.

Population density always had a negative effect on burnt area in the regression tree model. Figure 2.8a, and a piecewise quantile linear regression model (Koenker (2005)

99th percent quantile, run using quantreg in R) indicate that the negative effect of people on burnt area holds for population densities greater than 10 people/km^2. Below this population density, the slope of the quantile regression is not significantly different from 0.

The relationship between population density and *number* (rather than area) of fires appears to be quite different however (Figure 2.8b). The results suggest that increasing human population densities up to around 10 people/km^2 are associated with more fires, but that densities higher than 10 people/km^2 are associated with fewer fires (Figure 2.8b). The difference between Figure 2.8a and Figure 2.8b implies that as population density decreases, the size of individual fires must increase, we suggest due to less fragmented fuel beds.

2.6 Discussion

2.6.1 Drivers of fire: Fuel and weather

In order for a fire to start and spread three conditions must be met: there must be an ignition event, there must be flammable fuel, and the weather conditions must be suitable (Stott, 2000; Van Wilgen & Scholes, 1997). Moreover, the fuel bed must be adequately continuous, or the fire will not spread. At a sub-continental scale our analysis suggests that annual burnt area is controlled mainly by the second condition: the fuel. The four most important variables identified by the random forest procedure (Figure 2.6) either affected fuel loads (rainfall, tree cover, grazing) or fuel moisture (length of the dry season). The continuity of the fuel bed was also shown to be important, as high road densities and variable topography both limit burnt area.

We were unable to include weather conditions in our statistical model - the daily data necessary to produce daily fire danger indices were not available at the scale of Africa south of the equator. However, it has been shown in several fire-prone systems that a small number of large fires account for the majority of the area burnt (Yates *et al.*, 2008; Dickson *et al.*, 2006). These very large fires are thought to be caused by extreme weather conditions (McArthur, 1966; Bessie & Johnson, 1995; Moritz, 2003), in particular, periods of several days of hot, dry winds following a good rainy season. Including daily-resolution fire weather would undoubtedly improve the predictive power of the model.

Where tree cover exceeds 40 % the maximum possible percent burnt area declines rapidly (Figure 2.9a). This threshold presumably results from a reduction in grass fuels as tree density increases, and was also identified by the regression tree procedure (Table 2.3 node 10). There is much evidence for a non-linear interaction between fire and vegetation structure in these systems - and forest and fire-maintained grasslands are

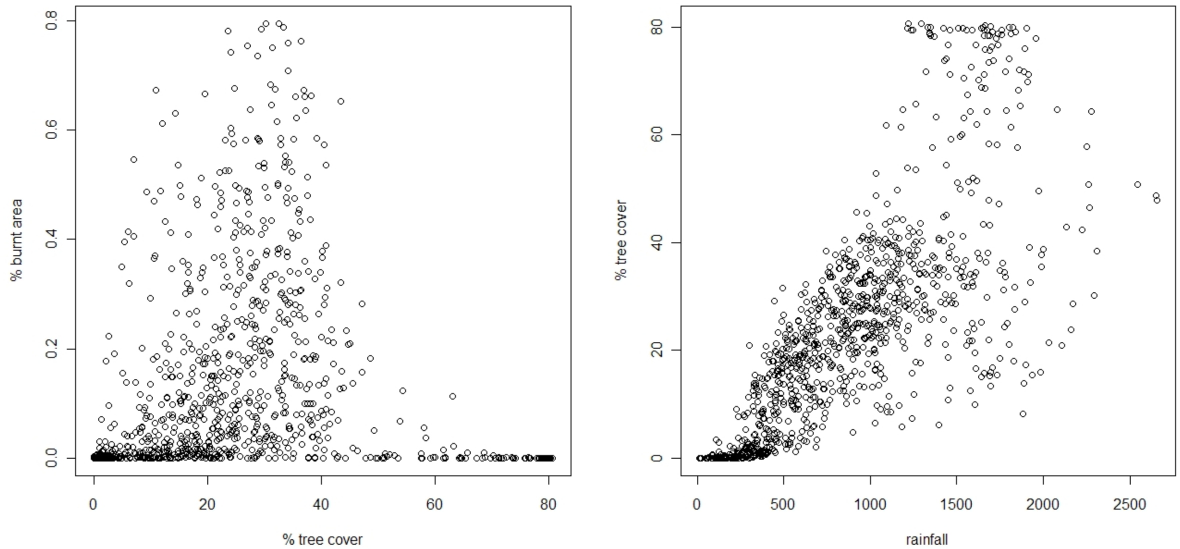

Figure 2.9: Burned area (% of 100x100 km window) plotted against a) rainfall and b) percent tree cover. The maximum possible percent burnt area declines rapidly at tree covers greater than 40 %.

identified as alternate stable states (Bond, 2005). If the sudden drop in burnt area that we found is valid, and not an artefact of the remotely-sensed data used, then it appears that 40% tree cover is the threshold at which such a system switch might occur, fires might be kept out, and a tendency to canopy closure would proceed. Empirical data supports this - identifying a non-linear response of grass productivity to tree cover with an inflection point around 35 and 40% cover (Scholes, 2003), and a switch in the under-storey species composition to more forbs (Malaise, 1978). Our data show that tree cover can only exceed 40 % in systems with more than about 800 mm of rainfall (Figure 2.9b). Thus, these results corroborate Sankaran *et al.* (2005), who found that a rainfall threshold of 784 mm was dividing point between stable (rainfall-maintained) and unstable (fire/disturbance-maintained) savannas.

2.6.2 Drivers of fire: Ignitions

We found no indication that the frequency of ignition limited or promoted burnt area in the region. Lightning frequency over the fire season came out as one of the least important predictors, as did land tenure (there is a perception, unsupported by our data, that fires are more commonly ignited on communal land than on privately-held land). Moreover, low human population densities, which should be associated with fewer ignitions (Keeley *et al.*, 1999; Stott, 2000), do not appear to reduce burnt area (Figure 2.8a). The opposite was true; high human densities (greater than 10 people/km^2) resulted in less area being burnt, probably because of the effect that people have in fragmenting the landscape (Saunders *et al.*, 1991) through cultivation, grazing livestock, fuel-wood collection, roads, or possibly by suppressing fires.

Theoretically, there must be a point at which a lack of ignition sources should limit the total area burnt, but our analysis did not reveal any set of circumstances where this might be the case. Low population densities were associated with a reduction in the number of fires identified by the MODIS active fire product but there was no concomitant reduction in burnt area (Figure 2.8a and b). These results have two implications. Firstly, in sparsely populated regions, reduced ignition occurrence seems to be adequately compensated for by less-fragmented fuel beds, resulting in more extensive individual fires. Secondly, it takes very few people to provide sufficient ignition opportunities, and lightning can provide sufficient sources of ignition in areas where even this minimum population density is not reached. It is not possible to test this hypothesis without data on individual fire size, but Frost (1999) indicates that increased human densities are associated with smaller fires, and that the proportion of lightning-caused fires increases in drier, less-populated areas.

2.6.3 Potential for change: where do people matter?

The analysis makes some clear predictions on the conditions under which people can affect annual burnt area, and the conditions where climatic factors overwhelm the effect of people. Once the very dry (<300 mm) and very wet (>1000 mm) areas have been excluded, there remain large parts of Africa (Figure 2.7b) where the burned area is responsive to influence by non-climatic factors. In these regions the burnt area fraction can range from 3 to 35 % of the total area. Running a separate random forest procedure on this data identified road density, grazing, fraction of transformed land (cultivated/urban), and population density as the four most important predictors of burnt area.

Given that major demographic and economic changes are predicted in 21st century Africa (Kirk, 1999; UNEP, 2002), it is likely that fire regimes, particularly in this intermediate-rainfall area, will also change.

2.6.4 Potential for change: climatic limits to fire

Importantly, this research also shows that there are large parts of southern Africa where human activities have little effect on fire regimes - and climatic factors either limit, or promote widespread fires. The analysis identified a tree density of <5 % (corresponding to a mean rainfall of around 288 mm) as a threshold below which very little fire activity occurs. The assumption that it is rainfall, not tree cover, that is causing the reduced burnt area is corroborated by field data on fire spread. Annual rainfall of 288 mm produces grass fuels of around 1000-1500 kg/ha (Scholes, 2003), and Trollope's fire behaviour equations for southern African savannas estimate a zero rate of spread at just under 1000 kg/ha (Trollope *et al.*, 2002).

The other condition resulting in low burnt areas was a dry season of less than six months (i.e. for more than half of the year monthly rainfall is significantly contributing to the total annual precipitation). Stott (2000) suggests that dry seasons of as little as 2.5 months are sufficient to provide dry grass fuels for burning. The fact that this analysis identifies six months of dry weather implies that it is not only the presence of dry, flammable fuels, but the proportion of the time that these flammable fuels are available that is important for determining burnt area. It also hints at a potentially interesting interaction between length of the dry season and ignition probability which should be further investigated. Ignitions might prove to be limiting in areas with very short dry seasons.

About 17 % of the study region has the high rainfall and long dry seasons necessary for widespread fire (Figure 2.7c). This relatively small area accounted for 37 % of the area burnt in 2003. In these regions (core Miombo woodlands, covering northern Angola, southern Congo, and Northern Mozambique) human activities were still shown to reduce burnt areas, but never to very low levels (Table 2.3). These parts of Africa are the focus of current projects aiming to store carbon by reducing fire (peaceparks annual review: http://www.peaceparks.org/) so it is important to know the extent to which fire can be managed in these systems. Our results suggest that climatic and environmental conditions are likely to over-ride human attempts to prevent fire - unless tree covers can be increased to 40 % or more.

2.6.5 Potential for change: climatic variability

Much of southern Africa is characterised by high inter-annual variability in rainfall. Because all other the factors influencing burnt area on the continent change slowly, at decadal time scales, inter-annual variability in burnt area is likely to be driven largely by variation in rainfall and dry season length. Published analyses of long-term fire datasets support this hypothesis (Balfour & Howison, 2001; Van Wilgen *et al.*, 2004; Mulqueeny, 2005; Russell-Smith *et al.*, 2007). Thus the limits of the fire-prone and non-fire prone systems shown in Figure 2.7 are strongly dependent on the rainfall preceding the year of study (2003), and could change quite dramatically during periods of extremely high or low rainfall. As more years of burnt area data become available, it will be possible to test whether the relationships between rainfall and burnt area identified at local sites also hold true over large areas. This, together with improved weather inputs, will be the next stage of the research.

2.7 Acknowledgments

We thank Dr John Mendelsohn, Dr Pauline Dube, Kolethi Gumbo, and Heidi van Deventer for providing the land tenure data, Minnie Wong for help obtaining the MODIS active fire product, Drs Jeremy Russell-Smith and Mike Wimberly for their useful comments. The research was completed with funds from the CSIR SRP Global Change project, the EU CarboAfrica project, and NASA grant NNG04HZ18C.

Preface: Chapter 3

This chapter is under review in Ecology Letters.

The paper follows up on the intriguing finding in Chapter 1 that tree cover is the most important determinant of burned area - and that there is a threshold tree cover (40%) above which very little fire occurs. It investigates the applicability of the theory of alternative stable states in explaining how the forest biome and the savanna biome co-occur across a very large rainfall gradient. In particular it investigates whether fire is involved in stabilising feedbacks which help to maintain separate forest and savanna states.

The co-authors on this paper are Carla Staver, a PhD student at Princeton University, and her supervisor and my mentor Prof Simon Levin from the Ecology and Evolutionary Biology Department. The manuscript arose from a collaboration that I developed with Carla when I was visiting Princeton as a graduate student research collaborator. I was wanting to explore the mechanism behind the 40% tree cover threshold, and had decided that for this it was necessary to address the interaction between rainfall, tree cover and fire at multiple spatial scales. Carla's PhD is investigating the mechanisms by which the forest-savanna boundary is maintained and she was frustrated that no one had satisfactorily demonstrated whether these were in fact alternative stable states. The data and analytical approach which I had was a perfect starting point for her work.

It was truly a collaborative exercise but by mutual agreement Carla is the first author on this paper. I produced the data, developed the analysis and ran the statistical tests, but Carla wrote the text, and we designed the analyses to fit the structure she had in mind. Simon Levin provided ideas on how processes operating at the forest-savanna boundary compare with other examples of alternative stable states and pushed us towards an analytical model of this system.

Chapter 3

Are forest and savanna alternative stable states in sub-Saharan Africa?

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3.1 Abstract

Alternative stable state concepts have been used to explain the processes leading to the existence of different ecological states in a range of aquatic, marine and terrestrial systems. The boundary between forest and savanna vegetation has often been discussed in context of this theory but without conclusive evidence that these two biomes are alternative stable states. Here we present a continental-scale analysis of tree cover, rainfall, and fire which demonstrates that two key characteristics of alternative stable state systems are apparent across the forest-savanna boundary in Africa. First we show that tree cover does not vary uniformly over a rainfall gradient - it shows a bimodal distribution related to a low tree cover 'savanna' state, and a high tree cover 'forest state'. These two states overlap: areas with rainfalls between 1000 mm and 2000 mm can exist in either state. Second we show that feedbacks between fire and grassy vegetation might be a stabilising feedback in this system: over the 1000-2000 mm rainfall range the presence of fire is highly associated with the savanna state and areas with high tree cover do not burn. Although there are many possible mechanisms which could operate to create the bimodal distribution of tree cover there is much theory to support the idea that these are alternative stable states and that positive feedbacks from fire to savanna and negative feedbacks from forest to fire are key to the maintenance of these states.

3.2 Introduction

Systems displaying alternative stable states can exist in more than one state or regime for a given set of environmental conditions (Scheffer *et al.*, 2001). Savanna and forest have often been thought of as alternative stable states (Favier *et al.*, 2004a; Sternberg, 2001; Warman & Moles, 2009), although the relevance of alternative equilibria to forest and savanna and, more broadly, to biome distributions is very much up for debate (Woodward & Lomas, 2004; Breckle, 1999; Whittaker, 1975). Biome distributions are often treated as though they are rigidly determined by climate (Woodward & Lomas, 2004; Breckle, 1999). However, modeling and experimental work have shown that mesic savannas can certainly exist where climate, soils, and topography suggest that forest should dominate (Higgins *et al.*, 2007; Moreira, 2000; Russell-Smith *et al.*, 2003a; Swaine *et al.*, 1992). In Africa, climate defines the maximum woody cover (Sankaran *et al.*, 2005), but disturbances play a major role in decreasing woody cover below that 'climate potential' (Sankaran *et al.*, 2008; Bond, 2008; Bucini & Hanan, 2006).

These results suggest that the forest-savanna boundary is not solely defined by climate, but they do not necessarily imply alternative stable state dynamics. Ecosystems subject to multiple stable states have distinct configurations under the same set of environmental conditions (May, 1977). These configurations are locally stable, but when state changes occur, transitions among states are often rapid and are not reversible on short time scales (Scheffer *et al.*, 2001; Scheffer & Carpenter, 2003). These transitions can be either endogenous to the system, when they result from interactions between fast and slow processes (Ludwig *et al.*, 1978), or exogenous to the system, when some disturbance results in the breakdown of feedbacks that maintain distinctions among states (van de Koppel *et al.*, 1997; Sinclair & Fryxell, 1985; Scheffer *et al.*, 1993; Carpenter *et al.*, 1987, 1985).

What evidence is there that forests and savannas represent alternative stable states? Variability in vegetation structure alone is not sufficient, because it can equally be explained by non-equilibrium dynamics (Scholes & Archer, 1997) wherein disturbances or environmental stochasticity never allow an ecosystem to reach an equilibrium. Paleo-ecological studies of patterns of changes in tree-grass ratio over time provide tantalizing evidence that rapid changes between tree-dominated and grass-dominated systems are common (Gillson, 2004), but these studies are inconclusive because these changes happen over time scales at which climate has varied substantially.

Thus, we are left with the fundamental question of whether forest and savanna represent alternative stable states. If they do, the regional distribution of tree cover should be discontinuous, with some tree covers occurring rarely (Scheffer *et al.*, 2001). Sudden discontinuities in tree cover along climate gradients are not the norm (Woodward & Lomas, 2004) but are to be expected if savanna and forest exist as alternative states.

Crucially, there may also be evidence of stabilizing feedbacks that function within a state to maintain it (Sternberg, 2001; Scheffer *et al.*, 2001). A number of factors are likely important, but fire is known to suppress tree cover (Higgins *et al.*, 2007; Moreira, 2000), probably via demographic controls on tree populations (Higgins *et al.*, 2000; Hoffmann, 1999). Similarly, there seems to be a threshold of tree cover above which fire is suppressed (Chapter 2, Archibald *et al.* (2009)).

To address these questions, we analyzed spatial patterns of woody cover with respect to rainfall and fire frequency using datasets derived from satellite data that provide complete spatial coverage of sub-Saharan Africa. These spatially-explicit data allow for analyses that were not possible in previous continental-scale analyses of woody cover, which were limited by the restricted availability and spatial extent of field data (no data above 1200mm rainfall: Sankaran *et al.* (2005)).

These processes are likely to be strongly scale-dependent. Climatic determinants of biome distribution are often discussed at continental to regional scales (Sankaran *et al.*, 2005; Williams *et al.*, 1996), while disturbances that reduce tree cover below its 'climate potential' are usually considered local processes (Sankaran *et al.*, 2005). We have included explicit considerations of scale in order to discriminate among potential determinants of the savanna-forest boundary at different scales.

3.3 Methods

We analyzed patterns of woody cover with respect to rainfall and fire frequency using satellite data. We used satellite-derived data on fire frequency and tree cover from the MODIS sensor, which is available at 500m resolution. We used the Tropical Rainfall Measuring Mission best-estimate precipitation product (Huffman *et al.*, 1995), which has a resolution of 0.25 degrees (approx. 28km x 28km at the equator and 28km x 20km at the southern tip of Africa).

Tree cover: Percentage tree cover was calculated from the MOD44B Collection 3 product (Hansen *et al.*, 2003). These 500m resolution data have been shown to have a mean square error of 9.1 % compared with IKONOS-derived validation data, (Hansen *et al.*, 2003). This error decreases substantially when data are averaged over slightly larger scales (Hansen *et al.*, 2003), and they describe continental-scale patterns well.

Fire frequency: To derive an estimate of fire frequency we used the monthly MCD45A1 burnt area product (Roy *et al.*, 2008), which uses BRDF-based change detection procedures to identify burned areas in the landscape and identifies burnt areas in Africa with over 70% accuracy (Roy *et al.*, 2008), although it does not identify small fires (< 500m diameter). Resolution (500m up from 1km) and quality of flag information are a major improvement over previous burnt area products. For this analysis, monthly data layers from April 2000 to March 2008 were combined to calculate the number of times a pixel burned in eight years (fire frequency). Pixels with invalid data more than two times a year on average were excluded based on quality flags. This yielded a 500m resolution map of number of burns in eight years (ranging from zero to 13). Savanna fires are grass-fuelled with average return times ranging from two to six years; while an eight year dataset is short, the dataset does span the range of fire frequencies expected to occur in the system.

Rainfall: The TRMM combines satellite-data, rain gauge data, and precipitation models to produce a best-estimate of global precipitation at hourly to annual scales. In this analysis, monthly precipitation rates were used to estimate annual rainfall for each year for which there were data (1998-2007). This was averaged to create spatially-explicit mean annual rainfall data that compares favorably to other measurements of MAR.

These data were clipped at 15 degrees north to include only sub-Saharan Africa, re-projected to an Albers equal area projection. Fire and tree data were resampled to align with the larger-scale TRMM data. They were then progressively degraded to produce maps of average tree cover and average fire frequency at 500m, 1km, 2.5km, 5km, 10km, 25km, 50km, and 100km resolution. Rainfall data were not available for fine scales (resolution less than about 25km), but rainfall is known to vary over regional to continental scales.

The centroid of each TRMM pixel was used to create a regular grid of sampling points (yielding 22,726 sites) over sub-Saharan Africa. Rainfall, average percent tree cover, and average fire frequency were extracted at each point for each scale of analysis. At resolutions of 50km and 100km, which are larger than a TRMM pixel (25km resolution), the number of unique data points available was reduced to 6982 and 1751, respectively, but at smaller scales, all of the available sampling points were used.

All analyses were run at all scales, but for the purposes of reporting two representative scales were chosen, the 1km scale to represent patterns at local scales and the 50km pixels to represent regional-continental scale patterns. Data were extracted in ERDAS 9.3 and ArcGIS 2.8.1 and analyzed in R 2.8.1.

3.4 Results and discussion

3.4.1 Are savanna and forest alternative stable states?

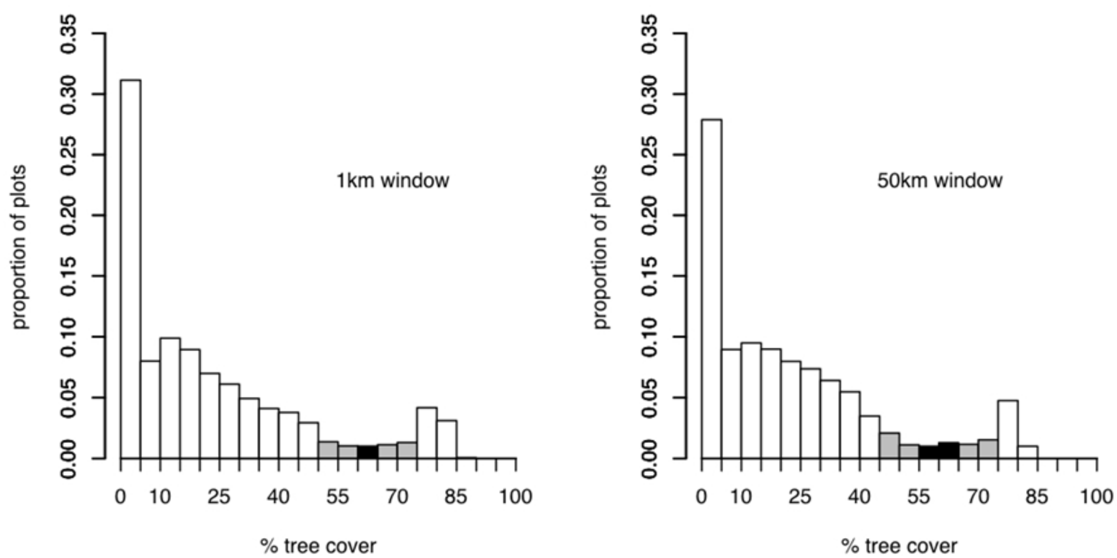

Figure 3.1: Histograms of percent tree cover at 1km and 50km scales. Grey bars denote categories with proportion of plots of <2.5%; black bars denote the midpoint of the range of grey bars, designated as the threshold between low (savanna) and high tree cover (forest). Tree cover from 0% to 50% and from 75% to 85% is abundant, but tree cover between 50% and 75% is scarce

Frequency distributions of woody cover across sub-Saharan Africa showed two clear maxima, one at low woody cover and another at high woody cover, separated by a minimum (see Figure 3.1). These two peaks can be understood to represent a savanna state at low woody cover and a forest state at high woody cover. Sites with intermediate woody cover (between 50% and 75%) were rare (density less than 5%), although the corresponding range of rainfall did occur. The data were split into low (hereafter called savanna) and high (hereafter called forest) tree covers based on the mid-point of the minimum values. This mid-point was remarkably consistent across scales, ranging between 60% to 62.5% tree cover.

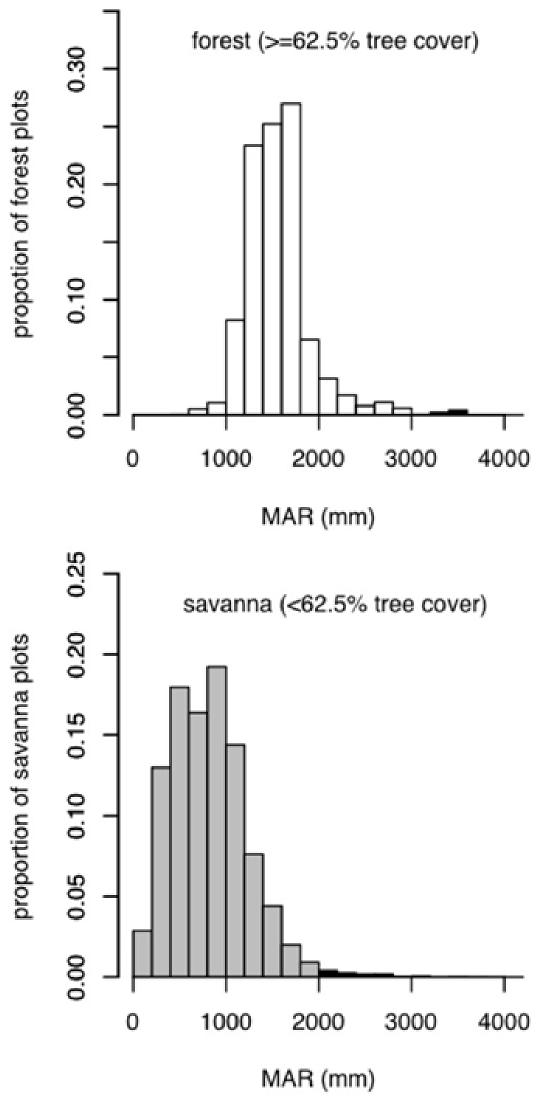

Figure 3.2: Histograms of savanna (top) and forest (bottom) sites versus mean annual rainfall at the 1km scale. Black bars denote proportion of plots of less than 1%. Savanna predominates below 1000mm mean annual rainfall and forest predominates above 2000mm or rainfall. Savanna and forest both occur with abundance between 1000mm and 2000mm mean annual rainfall

Analysis of the frequency of savanna and forest along a rainfall gradient at 1km scale indicates that savannas can occur at MAR of up to 2000mm per year and that forests occur frequently at MAR as low as 800mm per year (see Figure 3.2). Thresholds were defined at the point at which the proportion of plots in the class fell below 1%. Thresholds were remarkably constant across scales from 500m to 100km; the upper rainfall limit of savanna was 1800mm annual rainfall at all scales, while the lower rainfall limit of forest ranged from 800mm to 1000mm annual rainfall. To further evaluate the range of rainfall at which two alternative states were present, we divided sites into 200mm rainfall classes. Tree cover is distinctly bimodal between MAR 1000mm and 2000mm at all scales (see Figure 3.3 for categorized tree cover at the 1km scale). Plotting modes to a plot of woody cover versus rainfall (see Figure 3.4) shows that woody cover was strongly related to rainfall only at low rainfall (<1000mm) and at high rainfall (>2000mm). At intermediate rainfall, forest was the climate maximum woody cover, but savanna persisted over large areas. This suggests that some stabilizing feedback mechanism promoted savanna vegetation at the expense of forest. High tree cover (forest) represented the climate potential in this range, but a distinct low tree cover state (savanna) was also possible. Intermediate woody cover (between 50% and 75%) appeared to be unstable.

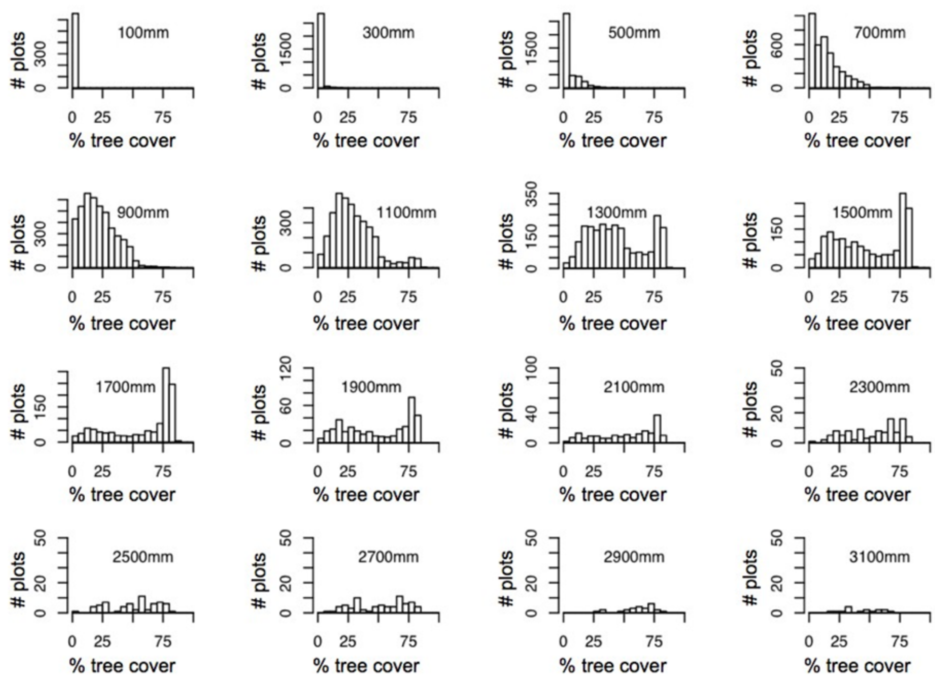

Figure 3.3: Histograms of percent tree cover categorized by rainfall at the 1km scale. Each plot includes data from a 200mm range in rainfall and is named with the midpoint of that range. Tree cover appears unimodal from 0mm to 1000mm and from 2000mm to 3000mm MAR; tree cover appears bimodal between 1000mm and 2000mm MAR.

These thresholds for the minimum rainfall that can support forest (900mm ± 100mm MAP) and the maximum rainfall at which savannas occur (2000mm MAP) differ somewhat from previous estimates calculated from field data, which put the lower limit of forest at 650mm 125mm MAP and did not define a maximum rainfall for savannas (Sankaran *et al.*, 2005). However, the estimate of 900mm 100mm annual rainfall as

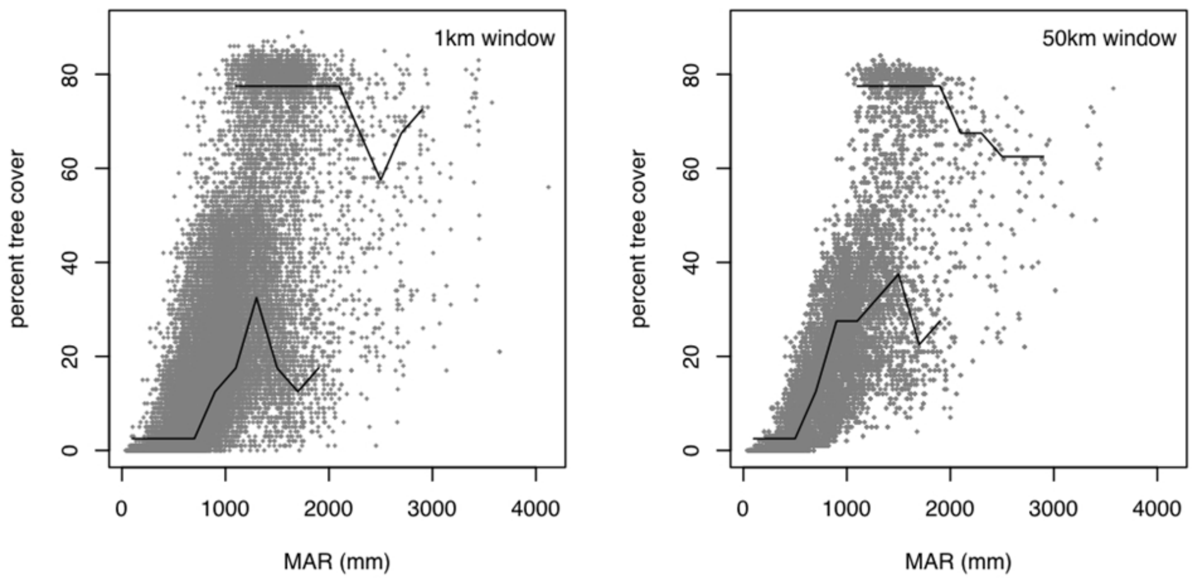

Figure 3.4: Percent tree cover v. mean annual rainfall at 1km and 50km scales. Lines represent the mode (or multiple modes) of tree cover at each rainfall, derived from rainfall classes used in Figure 3.3. Tree cover is unimodal from 0mm to 1000mm and from 2000mm to 3000mm MAR; tree cover is bimodal between 1000mm and 2000mm MAR.

the threshold where canopy closure (forest) is possible is consistent with data from fire exclusion experiments on the continent (see Bond et al. (2005) for a review of these). Below 1000mm annual rainfall, fire exclusion resulted in woody thickening but not in a transition to forest, while above 1000mm annual rainfall, fire exclusion resulted in a transition to from savanna to forest (Bond *et al.*, 2005).

3.4.2 Evidence of stabilizing feedbacks

Analyzing the distribution of woody cover with respect to fire as well as rainfall indicated that fire was probably one important stabilizing feedback operating within savannas (see Figure 3.5). Fire had a clear impact on woody cover. Below 1000mm rainfall, only savannas occurred, regardless of fire frequency; fire actually slightly increased mean tree cover at both the 1km (mean tree cover, no fire = 8.2; mean tree cover, fire = 17.0; W = 8,124,242; $p < 0.001$) and 50km scale (mean tree cover, no fire = 5.8; mean tree cover, fire = 18.0; W = 8,288,570; $p < 0.001$). Between 1000mm and 2000mm rainfall, savannas occurred in areas with fire, while forests occurred in areas that never or rarely burned; fire decreased mean tree cover at both the 1km (mean tree cover, no fire = 44.3; mean tree cover, fire = 28.0; W = 12,297,180; $p < 0.001$) and the 50km scale (mean tree cover, no fire = 46.6; mean tree cover, fire = 29.9; W = 9,173,365; $p < 0.001$). Above 2000mm of rainfall, fires were rare. Including the presence/absence of fire as a categorical variable into linear models of tree cover on mean annual rainfall improved model fit significantly across all scales (see Table 3.1). At all scales, a model including categorical fire presence and a cubic function of rainfall was the best predictor of tree cover among all the models tested. In fact, at the largest scales, this model explained as much as 71% of the variation in tree cover. This again suggests that fire is an important feature of savannas that differentiates savanna systems from forest systems.

Fire certainly does not fully explain variation in tree cover with rainfall. In part, this is undoubtedly because the available satellite fire record only spans the last 8 years. However, other feedbacks and drivers, like herbivory, nutrient cycling, hydrology and human activity, which are more difficult to quantify remotely, probably also contribute. In addition, determining whether fire results in savanna or whether savanna results in fire is impossible from this analysis, and in fact both are probably true. We know from fire exclusion experiments around the world that fire actively reduces tree cover (Higgins *et al.*, 2007; Russell-Smith *et al.*, 2003a; Moreira, 2000; Swaine *et al.*, 1992).

We also know that grass fires can only spread in systems with grass cover of at least 55% (Chapter 2, Archibald *et al.* (2009)). This mechanism provides a strong stabilizing feedback that has the potential to contribute to maintaining savanna and forest as alternative stable states at intermediate rainfall.

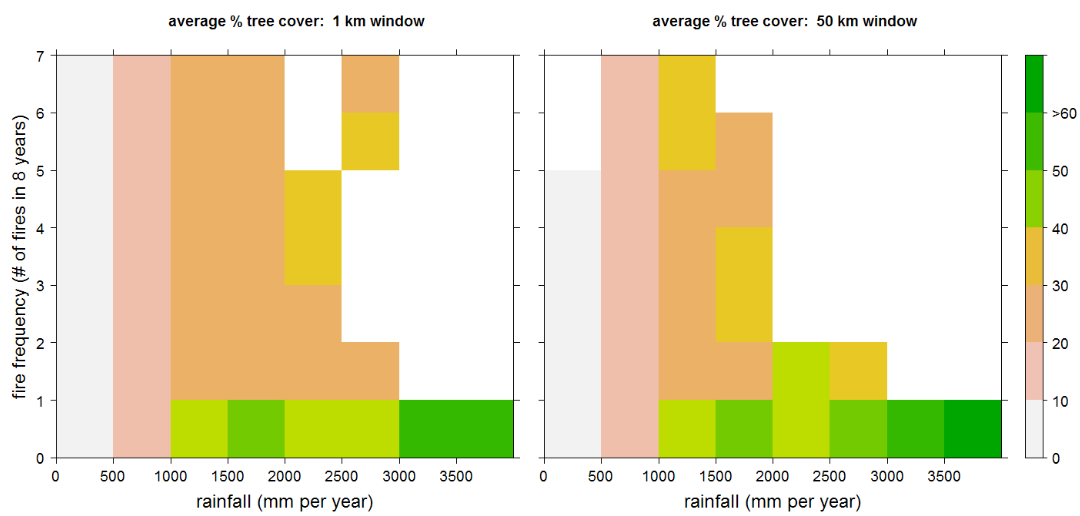

Figure 3.5: Mean percent woody cover at different rainfall and fire frequencies across sub-Saharan Africa. Savanna occurred below 1000mm rainfall (first two rows), regardless of fire, and forest occurred above 2500mm rainfall. Between 1000mm and 2500mm rainfall, areas that burned had savanna tree covers and areas that did not burn had forest tree covers. Fire did not burn in any sites with tree covers >40%.

3.4.3 Interactions among scale-dependent processes

Surprisingly, patterns were relatively consistent across scales. Fire is clearly a local landscape process, but one with the clear potential to influence continental patterns of woody cover. If anything, fire and rainfall were even better predictors of woody cover at larger scales than they were at smaller scales (see Table 3.1). Again, this may be more indicative of the quality and resolution of tree cover and fire data, which was available over only an 8 year time period, than it is of any difference in processes at different scales. However, it is distinctly possible that other factors besides fire and rainfall determine more local scale heterogeneity in savanna structure but do not play a major role in shaping continental patterns in tree cover.

3.5 Conclusions

These results show convincing evidence that savanna and forest exist as alternative states, and that multiple state dynamics may be applicable to the ecology of mesic savannas. Interactions between rainfall at a continental scale and fire at a local scale produce discontinuities in tree cover with alternative savanna and forest states at intermediate rainfall (between 1000mm and 2000mm). This mechanism for alternative equilibria may be analogous to the classic example from shallow lakes, wherein concentrations of algae can be either high or low over a wide range of intermediate nutrient concentrations, depending on food web structure (Scheffer *et al.*, 1993; Carpenter *et al.*, 1987, 1985). Modeling work examining a) whether a fire-rainfall interaction can produce alternative stable equilibria, b) the mechanistic processes responsible for these alternative forest and savanna states, and c) transitions between states, is forthcoming. The consistence of patterns and determinants of tree cover across scales suggests that although fire undoubtedly is a local landscape process, it nonetheless has the capacity to affect woody cover at much larger scales. In fact, fire and rainfall explain patterns in tree cover at a large scale even better than at a small scale. Although this finding is by no means conclusive, it does suggest that while local heterogeneity is an important feature of savannas, savanna and forest are relatively well constrained as alternative states at larger scales. For mesic savannas, several authors have discussed the idea that local heterogeneity in savanna structure aggregates at large scales to produce a 'meta-stable' biome - a biome that is heterogeneous and dynamic at small scales but exhibits some characteristics of equilibrium at larger scales

Fire exclusion experiments (Higgins *et al.*, 2007; Russell-Smith *et al.*, 2003a; Moreira, 2000; Swaine *et al.*, 1992) and documentation of forest encroachment from around the world (Goetze *et al.*, 2006; Favier *et al.*, 2004b; Bowman *et al.*, 2001; Loehle *et al.*, 1996) provide an idea of the patterns and mechanisms involved in transitions from savanna to forest. Changing burning practices and patterns through landscape fragmentation and management policy have resulted in widespread encroachment of forest into savanna. Periods of increased rainfall on the decadal scale have also played a role.

Theories about what results in transitions from forest to savanna in the absence of major anthropogenic disturbance (i.e. deforestation) are much less well developed. Paleo-ecological work has suggested that contemporary savannas may have established in areas that are now wet enough to support forest during a period with drier climatic conditions (Desjardins *et al.*, 1996; Schwartz *et al.*, 1996; Mariotti & Peterschmitt, 1994). This hypothesis fits well with the alternative stable state framework presented here. This analysis shows that in order for forest to be converted to a savanna state, a decrease in rainfall to below 1000mm (as defined here) would be necessary. Once this transition has occurred, savanna would be stable even if rainfall increased, due largely to stabilizing feedbacks such as fire, which acts to prevent forest encroachment. In fact, C4 grass evolution and the global expansion of the savanna biome occurred during the Miocene, a period marked not only by aridity but also by increased rainfall seasonality (Keeley & Rundel, 2005).

Global projections indicate that rainfall and fire frequency will change in coming decades due to increasing atmospheric CO2 and associated climate change. These changes may result in major biome shifts in favor of savanna over forest. Recent work has suggested that the Amazon rainforest may be at risk of severe drying (Phillips et al. 2009), putting large areas that are currently forest at risk of a transition to savanna. These results, showing that savanna and forest are alternative stable states at annual rainfalls between 1000mmm and 2000mm, imply that changes in biome distribution with response to climate change will not result in smooth transitions from savanna to forest or back. We can expect potential responses to climate change to be sudden and swift.

3.6 Acknowledgements

We would like to thank Duncan Menge and Lars Hedin for helpful comments on earlier versions of this manuscript.

Table 3.1: Results of regression and ANCOVA model fitting tree cover to an interaction between rainfall and fire frequency

scale	model		R^2	p-val	AIC	△ AIC
500m	tree cover	MAR	0.483	<0.001	219470	33278
	tree cover	MAR + MAR^2	0.501	<0.001	218588	32396
	tree cover	MAR + MAR^2 + MAR^3	0.511	<0.001	218040	31848
	tree cover	MAR*fire	0.472	<0.001	187812	1620
	tree cover	MAR*fire + MAR^2*fire	0.495	<0.001	186841	649
	tree cover	MAR + MAR^2*fire + MAR^3*fire	0.509	<0.001	186192	0
1km	tree cover	MAR	0.511	<0.001	216713	30934
	tree cover	MAR + MAR^2	0.530	<0.001	215733	29954
	tree cover	MAR + MAR^2 + MAR^3	0.541	<0.001	215125	29346
	tree cover	MAR*fire	0.508	<0.001	187810	2031
	tree cover	MAR*fire + MAR^2*fire	0.533	<0.001	186626	847
	tree cover	MAR + MAR^2*fire + MAR^3*fire	0.550	<0.001	185779	0
2.5km	tree cover	MAR	0.532	<0.001	214590	32505
	tree cover	MAR + MAR^2	0.550	<0.001	213575	31490
	tree cover	MAR + MAR^2 + MAR^3	0.561	<0.001	212916	30831
	tree cover	MAR*fire	0.536	<0.001	184789	2704
	tree cover	MAR*fire + MAR^2*fire	0.564	<0.001	183344	1259
	tree cover	MAR + MAR^2*fire + MAR^3*fire	0.588	<0.001	182085	0
5km	tree cover	MAR	0.545	<0.001	213190	33198
	tree cover	MAR + MAR^2	0.563	<0.001	212146	32154
	tree cover	MAR + MAR^2 + MAR^3	0.574	<0.001	211469	31477
	tree cover	MAR*fire	0.553	<0.001	183397	3405
	tree cover	MAR*fire + MAR^2*fire	0.587	<0.001	181586	1594
	tree cover	MAR + MAR^2*fire + MAR^3*fire	0.615	<0.001	179992	0
10km	tree cover	MAR	0.557	<0.001	211773	33946
	tree cover	MAR + MAR^2	0.575	<0.001	210682	32855
	tree cover	MAR + MAR^2 + MAR^3	0.587	<0.001	209964	32137
	tree cover	MAR*fire	0.569	<0.001	181734	3907
	tree cover	MAR*fire + MAR^2*fire	0.608	<0.001	179587	1760
	tree cover	MAR + MAR^2*fire + MAR^3*fire	0.637	<0.001	177827	0
25km	tree cover	MAR	0.575	<0.001	209420	34266
	tree cover	MAR + MAR^2	0.595	<0.001	208228	33074
	tree cover	MAR + MAR^2 + MAR^3	0.608	<0.001	207396	32242
	tree cover	MAR*fire	0.596	<0.001	179475	4321
	tree cover	MAR*fire + MAR^2*fire	0.638	<0.001	176976	1822
	tree cover	MAR + MAR^2*fire + MAR^3*fire	0.666	<0.001	175154	0
50km	tree cover	MAR	0.591	<0.001	207028	34026
	tree cover	MAR + MAR^2	0.609	<0.001	205871	32869
	tree cover	MAR + MAR^2 + MAR^3	0.624	<0.001	204923	31921
	tree cover	MAR*fire	0.612	<0.001	177566	4564
	tree cover	MAR*fire + MAR^2*fire	0.659	<0.001	174619	1617
	tree cover	MAR + MAR^2*fire + MAR^3*fire	0.683	<0.001	173002	0
100km	tree cover	MAR	0.608	<0.001	204006	34853
	tree cover	MAR + MAR^2	0.627	<0.001	202716	33563
	tree cover	MAR + MAR^2 + MAR^3	0.644	<0.001	201553	32400
	tree cover	MAR*fire	0.650	<0.001	173394	4241
	tree cover	MAR*fire + MAR^2*fire	0.688	<0.001	170812	1659
	tree cover	MAR + MAR^2*fire + MAR^3*fire	0.710	<0.001	169153	0

Preface: Chapter 4

This chapter is in press in the International Journal of Wildland Fire.

This is a methods chapter, the purpose of which is to test different measures of accumulated rainfall, and different models for describing inter-annual variability in burned area. In Chapter 4 I test theories on how climate influences fire in southern African savannas, but to do this I needed to identify a climate variable that best described the influence of rainfall on fuel loads.

Co-authors on this paper are Alecia Kirton and Bob Scholes from my research group, and Prof Roland Schulze from the university of Kwa-Zulu Natal. Alecia Kirton helped me to run the linear and probit regression models, Bob Scholes gave input on the writing, and Roland Schulze provided filled weather data.

Chapter 4

Defining an appropriate measure of accumulated rainfall to estimate fuel loads and derive burnt area

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4.1 Abstract

In southern African savannas grass production - and therefore the extent of fire - is highly dependent on rainfall, and variation in annual rainfall has been found to explain up to 70% of the variance in burnt area between years. Although this response has been repeatedly noted in the literature, authors have used different rainfall indices and regression techniques which means their results are not comparable. This paper tests alternative methods for determining the relationship between rainfall and burnt area and describes a methodology that can be used regionally to compare patterns in different savanna systems. The type of rainfall accumulator, the period over which to calculate annual burnt area, and the regression model were all investigated using long-term data from six national parks.

Although a probit regression model is theoretically more appropriate to this analysis we found that linear and probit models produced results of similar accuracy. Contrary to some suggestions in the literature the importance of accumulating rainfall over more than one growing season was highlighted in all parks - improving the accuracy of the models by up to 30% compared with indices that only used the previous year's rainfall. A rainfall accumulator of 18 months starting in June of the year of burning is suggested as a universally-applicable index. This can be used to compare fire management approaches in different savanna systems and to test theories of the effect of climate on fire regimes.

4.2 Introduction

Fires are frequent in systems where grass is a major component of the available fuel. After burning, the grassy fuels can re-grow rapidly and are often able to carry a fire again within one season. Moreover, grass production is very responsive to rainfall, and the amount of grass biomass available to burn depends on the amount of rainfall the system has experienced in the past few seasons. Nutrient availability, tree cover, and grazing intensity all affect the standing biomass of available grass fuel, but these do not generally vary between years to the same extent that rainfall does. As a result it has been found in several different studies in southern Africa that a measure of accumulated rainfall is strongly associated with the extent of burning in a particular year (Mulqueeny, 2005; Van Wilgen *et al.*, 2004; Balfour & Howison, 2001; Gandiwa & Kativu, 2009; Norton-Griffiths, 1979).

If this relationship were found to be generalisable across different savanna systems it would be useful as a tool for guiding fire management policy (eg Van Wilgen *et al.* (2008)). It could also indicate the degree to which the extent of fire might vary with changing rainfall patterns (Chapter 5,Patra *et al.* (2005)). However, currently in the literature there is no agreement on the best rainfall index or regression model to describe this relationship.

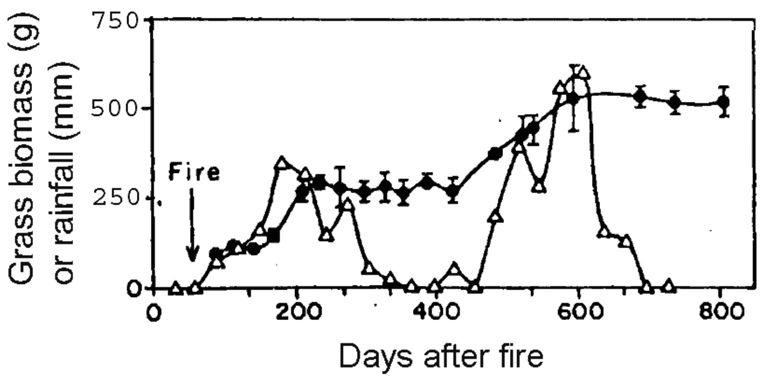

Figure 4.1: Grass biomass accumulation over two years in a savanna in northern South America. Graph reproduced from Medina & Silva (1990). Solid circles are grass biomass in g/m^2. Open triangles are rainfall in mm.

If there is adequate rainfall grass biomass can rapidly increase after a fire. It has also been shown that unburned biomass is carried over from one year to the next (Medina & Silva (1990), Figure 4.1). Growth rates of unburned perennial grass decrease with time as old dead plant material slows the growth of new shoots from the base of the plant (Johnson & Parsons, 1985; Schwinning & Parsons, 1999). Both of these facts imply that the influence of rainfall in determining landscape-level values of fuel will be relatively short-lived; the effect of periods of very high or very low rainfall are likely to last only a season or two.

Van Wilgen *et al.* (2000) found a lagged response of burnt area to rainfall in the Kruger Park, and later tested various accumulators of rainfall, and found the best relationship with current year's burnt area and the mean of the previous two years (Van Wilgen *et al.*, 2004). They also found that management activities had no significant effect on this relationship. This was corroborated by Balfour & Howison (2001) who found a better relationship with mean annual rainfall of the previous two years than with last year's rain. Norton-Griffiths (1979) and Mulqueeny (2005) looked only at wet-season rainfall of the previous year and found a significant positive relationship, but they did not test whether a 2-year accumulator would have worked better. Gandiwa & Kativu (2009) similarly found a significant relationship with previous year's rainfall. Midgley *et al.* (2006), on the other hand, argue that the amount of carry-over in grass biomass from one season to the next is negligible, especially in systems with heavy grazing. See Table 4.1 for a summary of these analyses.

The measures of annual burned area were also not equivalent in these different studies. In southern Africa the wet season occurs from November to April and annual rainfall is usually reported by hydrological year (sum of all rainfall from July of one year to June of the next). Burnt area is generally summarised by calendar year as the majority of burning occurs from May to October. However, some authors used a fire-year running from April-March for summarising burnt area (an approach that has recently been validated by an analysis done on satellite-derived fire phenology for the region (Boschetti & Roy, 2008)). Thus the relationships found in different parks are seldom comparable.

Moreover, the analytical approach used by previous authors might be flawed. All previous reports used simple linear regressions to test for an association between rainfall and burnt area, although Norton-Griffiths (1979) de-trended the data before running the analysis. Because burnt area is always recorded as a proportion of the total landscape it would be more appropriate to use a probit regression, where the response variable is restricted between 0 and 1. Results for the probit regression are likely to be more reasonable - for example, it would never predict a negative burnt area. On the other hand, simple linear regressions are easier to interpret. Given that total burnt areas seldom get close to the limits of 0 or 100 percent, it might in fact be reasonable to use a linear regression, especially if the data were centered on the mean value (Snee & Marquardt, 1984).

Table 4.1: Summary of relationships between rainfall and burnt area found in the literature - and the different methods used to derive them. Rainfall was either accumulated for the previous hydrological year (July to June), or for the previous wet season (November:March). Either the previous year's rain (one year), or else the mean of the previous two years' rain (two years) was used. Burnt area was summarised either by fire year (April:March) or by calendar year. All reported relationships were significant and R^2 values are shown. In order that the co-efficients could be comparable across parks the regression equations reported in the literature were standardised by recalculating the burnt area measure as a percentage, and the mean rainfall measure as a mean monthly rainfall

Park	rainfall measure	rainfall accumulation	burnt area measure	R^2	int	slope	other tests
Kruger NP [1]	Jul-Jun	two years	Apr-Mar	0.70	-20	0.82	Compared four different management periods
Hluhluwe- iMfolozi GR [2]	Jul-Jun	two years	Jan-Dec	0.54	-45	0.86	Also tested a one year accumulator
Hluhluwe- iMfolozi GR [2]	Jul-Jun	one year	Jan-Dec	0.41	md	md	
Mkuze GR [3]	wet-season	one year	Jan-Dec	0.40	-7	0.53	Tested whether residuals were related to dry season rainfall
Serengeti NP [4]	wet-season	one year	Jan-Dec	md	md	md	De-trended to extract effect of changing grazer numbers
Gonarezhou NP [5]	Jul-Jun	one year	Jan-Dec	0.31	0	0.13	Identified a downward trend over time

[1]: Van Wilgen *et al.* (2000), [2]: Balfour & Howison (2001), [3]: Mulqueeny (2005), [4]: Norton-Griffiths (1979), [5]:Gandiwa & Kativu (2009)

There is unlikely to be one perfect solution as the rainfall index is only one of the many factors that might affect how much of a landscape burns. However, given that accumulated rainfall has been found to explain up to 70% of the variance in burnt area between years there would be great value in developing a rainfall index that can confidently be applied at different sites.

We used long-term fire data collected in six protected areas in southern Africa, together with monthly rainfall data, and tested a range of different rainfall accumulators and starting months to determine the effect of different accumulators on the burnt area-rainfall relationship. We also tested whether summarising annual burned area by fire year (April-March) or by calendar year (Jan-Dec) has an impact on the results. Finally we tested whether there was any reason to apply a probit model to the data - or whether it produced better relationships than a linear regression model. This information was used to develop a standard method for assessing the effect of rainfall on burnt area, which can be applied in all savanna systems.

4.3 Methods

4.3.1 Fire data

Field-derived fire maps were collected from six national parks and game reserves in southern Africa: Kruger National Park (KNP), Hluhluwe iMfolozi Park (HIP), Pilanesberg Game Reserve (PGR), Mkuze Game Reserve (MGR), Etosha National Park (ENP) and Hwange National Park (HWG) (Table 4.2). These data were recorded in the field by rangers who would draw the burn extent onto hard-copy maps which were subsequently digitised. Sometimes auxiliary information on date, intensity, and cause of the fire were also recorded, but these data were not always available. For the Kruger Park the earliest records were not spatially explicit: proportion area burned was estimated per fire block. For details of how these data were produced see Van Wilgen *et al.* (2000); Balfour & Howison (2001); Brockett *et al.* (2001); Mulqueeny (2005); Du Plessis (1997).

The parks vary in terms of size, grazer stocking density, mean annual rainfall, and topography. They also differ in the extent of burning recorded in the park (Table 4.2). However, each had at least 20 years of fire records (n ranged from 21 to 50 years). Most parks only recorded data by calendar year but some of the Kruger Park fire data recorded the dates of individual fires. We used these data to test the difference between annual sums by calendar year and by fire year (April-March). All other analysis were performed by summarising by calendar year because this was the only information that was available for many parks.

Using a geographic information system and an equal area projection the total area of each fire was determined and annual totals calculated. If a patch of land burned twice

Table 4.2: Summary of the environmental characteristics of each protected area used in the analysis. ENP = Etosha National Park, KNP = Kruger National Park, PGR = Pilanesberg Game Reserve, HWG = Hwange National Park, MGR = Mkuze Game Reserve, HIP = Hluhluwe iMfolozi Park.

park	n	mean annual rainfall	median area burnt	area	altitude	grazing intensity	tree cover	road density
	years	mm/year	%	km^2	m	kg/km^2	%	km/100km^2
ENP	32	380	11	33941	1000-1200	25	0-10	3
KNP	49	512	22	18989	200-300	19	5-25	12
PGR	25	576	37	481	1400-1500	60	5-25	8
HWG	21	608	5	14600	900-1000	6	10-40	2
MGR	38	649	10	340	90-120	68	20-40	2
HIP	50	802	20	897	140-250	94	15-60	6

it was only counted once so that the total area burnt could never exceed the area of the park. The area of each park was similarly calculated from a GIS and a measure of percentage burnt area was calculated for each year. Percentage burnt area was used for ease of comparison between parks of different sizes.

4.3.2 Rainfall data

Daily rainfall data for all weather stations within or close to the parks were acquired from the South African Weather Services for parks in South Africa, and from park officials in parks outside South Africa. If these records had gaps they were filled with data from the Quaternary Catchment Hydrological Database (Schulze & Maharaj, 2007), and then summarised by month. Some parks spanned a large rainfall gradient, either due to their size (KNP, HWG) or their topography (HIP). For these parks 3-4 rainfall stations were selected to span the entire rainfall gradient, and the average monthly value of all rainfall records were used in the analysis

The various accumulated rainfall indexes were derived by summing the monthly rainfall over a certain number of months (N). Accumulations from 1 month to 48 months (4 years) were tested. We also tested which month of the year was the most appropriate for starting the accumulation (i.e. which month best represented the fuel available for burning in that particular fire year). For example, an accumulation starting in June of the year of burning and accumulated for 12 months would represent the average rainfall over a hydrological year (July-June). If it were accumulated for 24 months it would represent the mean of two hydrological years.

This resulted in 48*12 = 576 different rainfall indices on which to regress annual burned area. These indices were reported as the average monthly rainfall over the N months so that different accumulators could be compared with each other.

4.3.3 Data analysis

Both a linear regression and a probit regression (which limits the response variable to be between 0 and 1) were used to test for an association between accumulated rainfall and percentage burnt area. MAE values were compared for these different methods to determine which model predicted the data better.

The MAE is defined as

$$1/n \sum_{i=1}^{n} |y_i - \widehat{y_i}| \tag{4.1}$$

where y_i and $\widehat{y_i}$ represent an observed and predicted value pair, respectively, and n is the total number of observations.

The linear regression model can be represented by the following equation:

$$y = \beta_o + \beta_1 x + \varepsilon \tag{4.2}$$

where β_o is the intercept and β_1 is the slope, x is the vector of accumulated rainfall and ε is the vector of random errors which is assumed to be independent and normally distributed with zero mean and constant variance (σ^2) (Gross, 2003).

The probit regression model is essentially a regression model with a probit or inverse normal link function, and can be defined as:

$$\Phi^{-1}(y) = \beta_o + \beta_1 x + \varepsilon \tag{4.3}$$

where $\Phi^{-1}(y)$ is the inverse of the normal distribution applied to y (McCullagh & Nelder, 1989). The advantage of this model is that the response is expected to lie between 0 and 1, which is appropriate when the response is a proportion. It has the additional advantage that it does not assume a constant variance for the proportion, but rather allows the variance to change systematically as a function of the expected value of the proportion (McCullagh & Nelder, 1989).

All analyses were performed in R statistical software (http://www.R-project.org). Proportion burned area was used in the analysis, but results are reported as a percentage for easy reference.

4.4 Results

4.4.1 Choosing an appropriate regression model

The difference in MAE between the probit and the linear regression models was very small in all instances. Over all accumulations and all parks the maximum difference between the two models was less than 1 percent (Table 4.3). In the Kruger Park and Mkuze Game Reserve the linear model actually produced a better prediction (smaller MAE) over all accumulations than the probit. The different in MAE between parks ranged from 6.35 % to 18.01 % but the difference between the two models for the same park was always less than 0.25 % (Table 4.3). Therefore it appears that the linear regression model can be substituted for the probit regression model, as it predicts the data as well if not better than the probit regression model. This model was used for the rest of the analyses.

Table 4.3: Comparing the mean absolute error (MAE) in % burnt area from probit and linear regression models. The table reports the MAE for a two year accumulation starting in June, as well as the maximum difference found between models over all accumulations. The % of model comparisons when the probit model produced a better prediction (had a lower MAE) is also reported.

Park	**MAE (%) two year accumulation**			**maximum diff in MAE**	**probit better than linear**
	linear	probit	diff (L-P)		% of models
KNP	6.35	6.59	-0.24	0.36	9
HIP	18.42	18.01	0.41	0.41	66
MGR	8.31	8.30	0.01	0.38	30
PGR	16.53	16.54	-0.01	0.29	64

4.4.2 Summarising burnt area by calendar year vs fire year

There were twelve years in which all of the recorded fires in the Kruger park were associated with dates and for seven of these twelve years the difference between a calendar year and a fire year summary was less than 2000 ha (0.1 % of the park). However, in two of these years the difference between the two summary methods came to 73544 and 94490 ha respectively (corresponding to 3.9 and 5% of the park) - so the type of summary measure used to calculate burnt area could occasionally make a big difference to the annual sum.

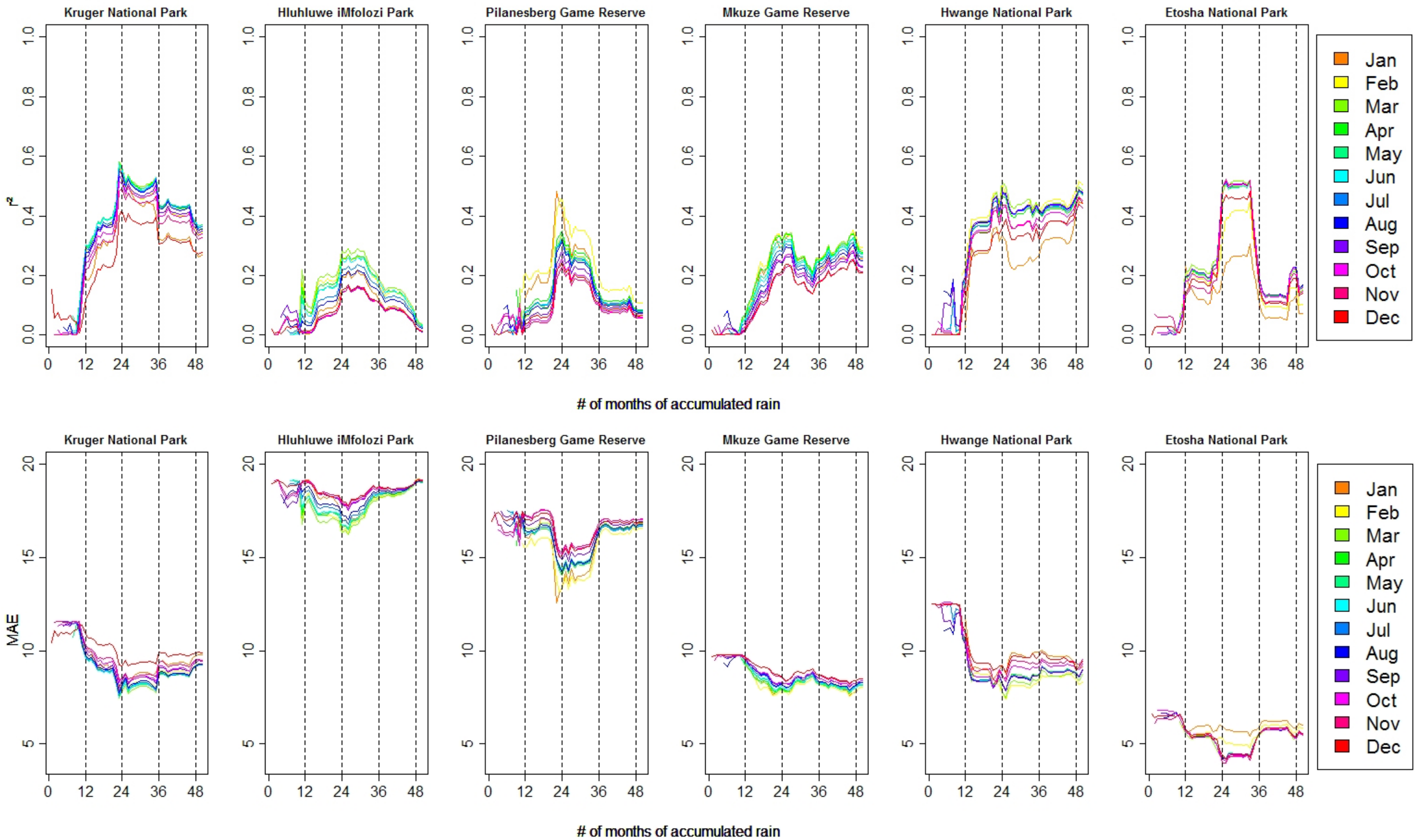

Figure 4.2: Comparing different rainfall accumulations and different start months for all parks. x-axis represents different rainfall accumulations starting from 1:48 months. Each line represents a different starting month (from January to December of the burn year). Top graph: R^2, Bottom graph: Mean absolute error (percentage burnt area)

4.4.3 Finding an appropriate rainfall accumulator

For all parks the predictive power of the rainfall-burned area relationship improved as rainfall was accumulated from 1 month to 12 months (Figure 4.2) - indicating that the previous season's rainfall is an important driver of total area burned in these grass-fuelled systems. However, contrary to Midgley (2006) who believes only the previous year of grass growth drives burned area, the R^2 values continued to increase with rainfall accumulations > 1 year, indicating that carry-over of fuels is indeed important.

Maximum R^2 values usually occurred when rainfall was accumulated over 1.5-2.0 seasons (Figure 4.2), after which the strength of the relationship leveled off and started decreasing again for accumulations longer than 3 years. The five parks studied were similar in their pattern of response, but different in terms of the amount of variance in burned area that was explained by rainfall (the variance explained was lowest for HIP, and highest for KNP). Similar patterns were found when MAE was used as a measure of model fit - although the differences between parks were more apparent.

Table 4.4: Testing which is the best month to start accumulating rainfall

park	**months in order of decreasing R^2**												**R^2: best-Jun**	**R^2: best-Dec**
KNP	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Feb	Nov	Jan	Dec	0.01	0.13
HIP	Mar	Apr	May	Feb	Jun	Jul	Aug	Jan	Dec	Oct	Sep	Nov	0.03	0.12
PGR	Feb	Jan	Apr	Mar	Jun	Jul	May	Aug	Sep	Oct	Dec	Nov	0.10	0.16
MGR	Mar	Apr	Jan	Feb	May	Jun	Jul	Aug	Oct	Sep	Dec	Nov	0.02	0.09
HWG	Mar	Sep	Feb	Aug	May	Jul	Jun	Apr	Oct	Nov	Dec	Jan	0.02	0.11
ENP	Mar	Oct	Nov	Sep	Jul	Jun	Aug	Apr	May	Dec	Feb	Jan	0.01	0.06

As expected, accumulations starting during the dry season (from March to October) performed better than accumulations starting in the middle of the wet season (Figure 4.2, Table 4.4). March was most commonly the best month to start accumulating rainfall but there was little difference between accumulations starting in March, April, May, June or July (Figure 4.2), which would be expected as these are dry months. Pilanesberg Game Reserve was the exception here, as accumulations starting in January and February were observed to perform better. Overall, however, the R^2 between a hydrological year accumulation (accumulating backwards from June) and the best month fit usually differed by as little as 1 percent (Table 4.4). This suggests that summing rainfall over a hydrological year gives as good a relationship as summing over the wet season.

A smaller model set of two start months (July and March) and five accumulated rainfall indices (6, 12, 18, 24, 30 months) was used to illustrate how the choice of this index changes the regression model parameters (Figure 4.3). For all parameters the difference between start dates is always much smaller than the difference in the length of the accumulation. The patterns for all six parks are similar: the R^2 value peaks at an 18 month rainfall accumulation, the slope parameter tends to increase with longer rainfall accumulations and the intercept parameter tends to decrease. At the 18 month accumulation the mean intercept is -18 and the mean slope is 0.7 with standard deviations of 12 and 0.7, respectively.

For a more detailed analysis of differences between parks see Archibald *et al.* (in pressa) where the importance of climate in driving inter-annual variability in burned area is discussed further.

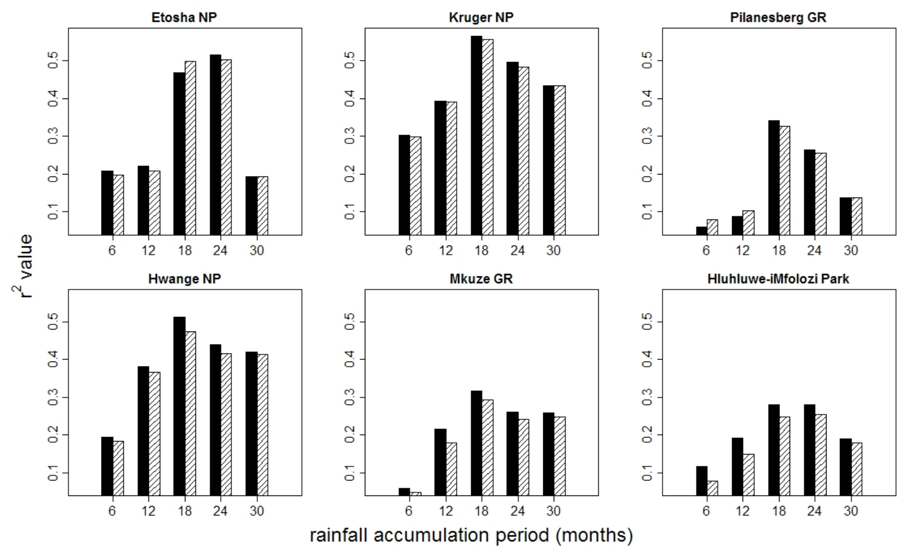

Figure 4.3: Change in model fit when rainfall is accumulated over 12, 18, 24, and 30 months. Solid bars represent an accumulation starting in March (the end of the dry season), hatched bars represent accumulations starting in June (a hydrological year).

Discussion

The analysis performed here comfirms previous research showing a significant relationship between accumulated rainfall (as an index of fuel loads) and annual burned area. Our analysis rigorously tested different indices of accumulated rainfall, different summary values of burned area, as well as two different regression model equations to determine a method that can be used to explore patterns of across different regions and management regimes.

We showed that there was very little difference between using a the more appropriate probit regression and a linear regression model. We also showed that the majority of the time there is very little difference between summarising burned area by calendar year or fire year (i.e. there are very few fires from January to March in these systems).

It was also possible to demonstrate that by accumulating rainfall over more than one growing season we produced a stronger relationship with annual burned area - for all five parks the highest R^2 and lowest MAE occurred using 18 months of accumulated rainfall (Figure 4.3). It is surprising that an 18 month (1.5 year) accumulation performs better than a 24 month (2 year) accumulation, but might be explained by the fact that early-season grass growth is generally consumed quickly by herbivores and that only late-season grass growth is carried over to the next year. The model was fairly insensitive to the starting month for accumulating rainfall - as long as the accumulation started during the dry season. Given that the exact end of the wet season might vary in different areas across the region we suggest that starting the accumulation at the end of the conventional hydrological year used in these systems (June) would probably give the most generalisable results.

In all five parks, burned area shows similar responses to rainfall, which implies that accumulated rainfall could be a useful index for estimating inter-annual variability in burned area. The most noticeable difference was the strength of the relationship which explained nearly 60% of the variance in burned area in KNP, but only 29 % in HIP (corresponding to mean absolute errors of 4 to 16.2 percent burned area).

Table 4.5: Showing the parameters of a linear regression (Equation 4.2) between accumulated rainfall and burned area for six national parks in southern Africa. The index of accumulated rainfall used was the average rainfall in the 18 months preceding June of the year of burning.

Park	Intercept (β_o)	Slope (β_1)	R^2 value	Mean Absolute Error (%)
KNP	-24	0.88	0.50	4
HIP	-20	0.88	0.56	8
PGR	-2	0.92	0.33	14
MGR	-33	0.89	0.47	8
HWG	-17	0.43	0.29	8
ENP	-21	0.72	0.25	17

Conclusions

Given that there appear to be a number of acceptable ways of representing this relationship we recommend running a linear model, accumulating rainfall over 18 months starting in June of the year of burning, and using a calendar year for summarising burned area. This standard method would allow for inter-park and inter-region comparison resulting in an acceptable response function for a range of different parks.

In Chapter 5 we used this rainfall index to investigate the role of climatic variables in driving inter-annual variation of burned area across southern Africa and found that the strength of the rainfall-burned area relationship depends on the mean annual rainfall of the system, but that the slope of this relationship can be considered constant across a range of environmental conditions.

One other useful application would be to compare the effect of different management approaches on annual burned area. This is a subject which is still up for debate: Van Wilgen *et al.* (2004) demonstrated that changing fire management had little impact on annual burned area in KNP, but Mulqueeny (2005) and Balfour & Howison (2001) found differently. Once the effect of varying fuel loads can be accounted for using the rainfall index presented here, it would allow for a more informed comparison of whether and how managers can impact annual burned area. Similarly, it would be possible to differentiate between the effect of other variables which affect fuels or burned area: for example changing grazer numbers have been suggested as important in driving trends in annual burned area in the Serengeti.

The method presented here only applies to systems where grass is the dominant fuel load, and rainfall is more important in driving fuel availability than in determining fuel moisture. At inter-biome and global scales other methods need to be developed which can assess how rainfall influences different aspects of a fire regime (Van der Werf *et al.*, 2008).

4.5 Acknowledgements

We thank all researchers and managers who contributed fire and rainfall data: Navashni Govender and Sanparks, Ezemvelo KZN Wildlife (Sue Van Rensberg and Craig Mulqueeney), Bruce Brocket and North-West Parks Board, Johan Le Roux and the Etosha Ecological Institute, Peter Frost and Simon Chamaille. Thanks to Brian van Wilgen, whose original research inspired most of this work.

Preface: Chapter 5

This chapter is in press in Global Ecology and Biogeography. It addresses the second major question that arose from Chapter 1: Inter-annual variability in fire and the role of climate.

In Chapter 1 climatic variables were highlighted as important drivers of spatial patterns of fire: rainfall appeared to set the limits within which vegetation and human factors acted to limit or promote fire. However, climate also varies substantially from year to year in southern African savannas, whereas other drivers of fire change over decades to centuries.

This chapter develops a better understanding of how responsive fire regimes are to inter-annual variability in three key climatic variables, each of which affect different aspects of fire: accumulated rainfall (fuel loads), length of the dry season (fuel flammability), and fire weather conditions (fire intensity). For this I used long-term fire records collected from six national parks, as well as 8-years of MODIS burned area data which had recently become available.

I developed hypotheses on how the effect of the climatic drivers might change across environmental gradients and tested these hypotheses using mixed effects models. The results were surprising; they corroborate the tentative findings of Chapter 1 that a better understanding of the relationship between human activities, fire size and fire number is necessary. They also indicate that current predictions of the effect of changing climates on fire regimes in Africa are unlikely to be accurate.

The co-authors on this paper are Alecia Kirton and Dr Bob Scholes from my research unit at the CSIR, Navashni Govender from SANPARKS, and Dr Veiko Lehsten from Lund University. Alecia Kirton introduced me to mixed effects modelling, ran all the initial analyses and helped write the methods and results section. Bob Scholes gave input on how to discuss variability and improved the writing. Navashni Govender contributed ideas and information from Kruger National Park's long-term fire research and contributed towards the management section in the discussion. Veiko Lehsten gave much-needed input into the complexities of the analysis and shared ideas on human drivers of fire in southern Africa.

Chapter 5

Climate and the inter-annual variability of fire in southern Africa: a meta-analysis using long-term field data and satellite-derived burned area data.

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5.1 Abstract

Aim: This study investigates inter-annual variability in burnt area in southern Africa and the extent to which climate is responsible for this variation. We compare data from long-term field sites across the region with remotely-sensed burned area data to test whether it is possible to develop a general model.
Location: Africa south of the equator
Methods: Linear mixed effects models were used to determine the effect of rainfall, seasonality, and fire weather in driving variation in fire extent between years, and to test whether the effect of these variables changes across the sub-continent, and in areas more and less impacted by human activities.
Results: A simple model including rainfall and seasonality explained 40% of the variance in burnt area between years across 10 different protected areas on the sub-continent, but this model, when applied regionally, indicated that climate had less impact on year-to-year variation in burnt area than would be expected. It was possible to demonstrate that the relative importance of rainfall and seasonality changed as one moved from dry to wetter systems, but most noticeable was the reduction in climatically-driven variability of fire outside protected areas. It was shown that inter-annual variability is associated with the occurrence of large fires, and large fires are only found in areas with low human impact.
Main conclusions: This research gives the first data-driven analysis of fire-climate interactions in southern Africa The regional analysis shows that human impact on fire regimes is substantial and acts to limit the effect of climate in driving variation between years. This is in contrast to patterns in protected areas, where variation in accumulated rainfall and the length of the dry season influence the annual area burned. Global models which assume strong links between fire and climate need to be re-assessed in systems with high human impact.

5.2 Introduction

Inter-annual variability in wildfire extent has been identified as one of the most important factors behind variations in global atmospheric carbon dioxide and aerosols (Patra *et al.*, 2005; Schultz *et al.*, 2008). This is likely to be particularly important in Africa, which shows extensive burning every year and is characterised by variable climates. Long-term field studies in African savannas record that the area burnt by wild fires can range from 0 to 80 percent of the landscape from year to year (Balfour & Howison, 2001; Van Wilgen *et al.*, 2004; Mendelsohn, 2002), and this is generally attributed to variation in the amount of grass fuel available, driven by variable rainfall patterns.

Recently, continental-scale modelling exercises have aimed to characterise this inter-annual variability by relating it to variability in the environmental drivers of fire (Williams *et al.*, 2007; Lehsten *et al.*, 2009). These results give the first estimates of the extent and variability of fire and fire emissions, but the assumptions underlying them - which link vegetation and climate to fire regime - have not been rigorously tested in Africa. Africa has a remarkable richness of long-term fire experiments and fire records, but this research has often been constrained within protected areas, and the degree to which these results can be extrapolated to non-protected land is not known. Similarly, fire-vegetation-climate relationships found in other savanna systems such as Australia (Spessa *et al.*, 2005) might not easily be transferable to Africa, where much higher rural population densities and different land use practices become important in affecting regional patterns of burning (Frost, 1999; Laris, 2002; Hudak *et al.*, 2004).

A range of human, environmental, and climatic factors affect the amount of burning in southern African savanna and grassland ecosystems (Phillips, 1930; Trollope, 1984; Van Wilgen & Scholes, 1997; Archibald *et al.*, 2009). Of these, only climatic factors vary substantially from year to year. It is reasonable to assume that much of the inter-annual variability in fire is driven by these climatic factors. Three climate indices that have been shown to affect the extent of fire in savanna and grassland systems are the amount of rainfall (fuel loads), the seasonality of the rainfall (availability of dry fuels), and the occurrence of high fire danger weather conditions.

Although all three of these variables can vary substantially from one year to the next in southern Africa the amount of rainfall is generally perceived to be the most limiting factor, and the factor driving inter-annual variation in fire regimes. Indeed several studies have shown an index of accumulated rainfall to explain up to 60 percent of the variance in burnt area between years (Norton-Griffiths, 1979; Balfour & Howison, 2001; Mendelsohn, 2002; Van Wilgen *et al.*, 2004; Mulqueeny, 2005). Similarly, preliminary studies using remotely sensed data have found relationships with fire and the El Nino/Southern Oscillation (ENSO) - where increased fire incidence is associated with above average rainfall periods (Anyamba *et al.*, 2003; Riano *et al.*, 2007; Van der Werf *et al.*, 2008).

Nevertheless it is possible that the less well studied climatic variables (seasonality and fire weather) could impact the annual extent of burning in these environments. Despite the fact that grass fuels can become flammable after only a few weeks of dry weather (Stott, 2000), the length and intensity of the dry season have been shown to be important in promoting fire in both Australia and Africa (Spessa *et al.*, 2005; Russell-Smith *et al.*, 2007; Archibald *et al.*, 2009) - presumably because of increased opportunity for successful ignition. Similarly, large fires associated with periods of extreme fire weather are responsible for a disproportionate amount of the total area burnt in Australian savannas (Yates *et al.*, 2008), and high fire danger indices result in more fires in the Brazilian

Cerrado (Hoffmann *et al.*, 2002). It is possible that variability in the occurrence of these high fire danger days also drives variability in fire in southern Africa.

The relative importance of these three climatic drivers - accumulated rainfall, the length of the dry season, and the occurrence of dangerous fire weather - might also change across the sub-continent. For example, in very wet areas in the Democratic Republic of Congo rainfall is almost always sufficient to produce a grass sward of over 4000 kg/ha and the amount of time the fuels are dry and flammable might be the major constraint to fire. On the other hand, fires in the dry Kalahari only spread in years when there is enough rain to create a continuous grass sward (Heinl *et al.*, 2007).

The effect of climatic drivers on fuel loads, fuel moisture, and fire weather must also be seen in a larger context. Where human/landscape interactions act to reduce fire spread, fuel continuity might become the limiting factor for fire, and the link between climatic variability and variability in fire might be broken.

Here we present an analysis using two different regional-scale records of annual burnt area - one derived from long-term field data collected in various protected areas, and the other from a moderate-resolution satellite-derived burned area product. The aim is to derive simple relationships between climate drivers and annual burned area, and test how these relationships hold across different landscapes in southern Africa.

Previous assessments have been limited to identifying a relationship between annual burned area and an index of accumulated rainfall for a particular site (Balfour & Howison, 2001; Van Wilgen *et al.*, 2004; Mulqueeny, 2005). In this paper we expand on these analyses in two ways: by testing how generalisable these relationships are between parks and across the region, and by including other climatic variables as potential drivers of variability.

We use the field data to test (Question 1) whether the slope and intercept of the relationship between accumulated rainfall and annual burned area change across different sites and (Question 2) whether including other possible drivers of variability (rainfall seasonality and fire danger index) can improve this model. Using both the field data and the regional data we explore (Question 3) whether the relative importance of these three climatic drivers might change across the sub-continent as one moves from drier to wetter systems. We compare models developed on each data set to test (Question 4) whether climate-fire relationships found with long-term fire records (collected in areas of low human impact) are consistent with trends in the 8-year satellite data (which are more representative of the current patterns of fire in the region).

Ultimately the aim of this research is to determine how well climate explains patterns of variability in fire in Africa.

Rigorous testing of fire-vegetation-climate feedbacks in Africa is essential. Relationships between fire and climate are being incorporated into global vegetation models and used to predict the long-term consequences of global climate change (Thonicke *et al.*, 2001; Notaro, 2008). Incorrect assumptions could have far-reaching policy implications. Secondly, interest in managing fire to promote carbon sequestration in Africa is increasing, and large-scale projects to alter fire regimes are fast becoming a reality. Any project of such scale must be able to assess the risks and limits associated with climate-induced variability. Finally, there is increasing evidence that the dynamics of these ecosystems depend on variable patterns of fire: tree recruitment events and grass compositional switches can be linked to periods of below or above average fire occurrence (Trollope, 1984; Staver *et al.*, 2007). Attempts to control or reduce this variability must take into account the ecological consequences.

5.3 Methods

5.3.1 Study area

Africa south of the equator is largely covered by savanna/woodland vegetation - transitioning to forest or arid shrublands at the wet and dry end of the rainfall range respectively. Fire occurs across a large part of southern Africa (34% of the region burned at least once in the last 8 years) but the extent and frequency of burning varies depends on tree cover, rainfall seasonality and amount, and human land use activities (Van Wilgen & Scholes, 1997; Archibald *et al.*, 2009). Climates in southern Africa are very variable, and both the amount and the seasonal distribution of rainfall varies substantially between years (Nicholson, 2000). Year-to-year changes in annual burned area fraction are therefore likely to be largely controlled by this climatic variation.

Protected land covers about 10 % of this region and cultivated land covers about 9 %. The rest consists of uncultivated land which is used for grazing and fuel wood, with rural population densities that vary but can be very high (> 10 people per km^2). Archibald *et al.* (in pressc) have shown that human population densities and land use (grazing, roads and cultivation) can negatively impact both the size of individual fires and total burned area, so it is likely that in this analysis too there would be marked differences relating to human activities.

Field data were available from six different protected areas in southern Africa (Fig. 5.1): Kruger National Park (KNP), Hluhluwe iMfolozi Park (HIP), Pilanesberg game reserve (PGR), and Mkuze game reserve (MGR) in South Africa, Hwange National Park in Zimbabwe, and Etosha National Park in Namibia. The parks are all located predominantly in savanna/woodland vegetation but they vary in terms of size, tree cover, grazer numbers, altitude and road densities (Table 5.1).

Hwange National Park had the shortest fire records (21 years) and the longest fire record was from HIP (50 years) (Table 5.1). The Kruger National Park and Hluhluwe iMfolozi Park both span a very large rainfall gradient (from 420-730 mm and 680-950 mm respectively). Because rainfall is known to be such an important driver of burnt area, these parks were divided into sections according to their mean annual rainfall. Kruger was split into southern, central, northern and far northern sections (centred on Skukuza, Satara, Letaba, and Shingwedzi respectively), and HIP was split into the Hluhluwe section (high altitude, high rainfall) and the iMfolozi section (lower altitude, lower rainfall) (Fig. 5.1). This approach provided 10 different samples with which to assess inter-annual variation in burnt area (Table 5.1, Fig. 5.2).

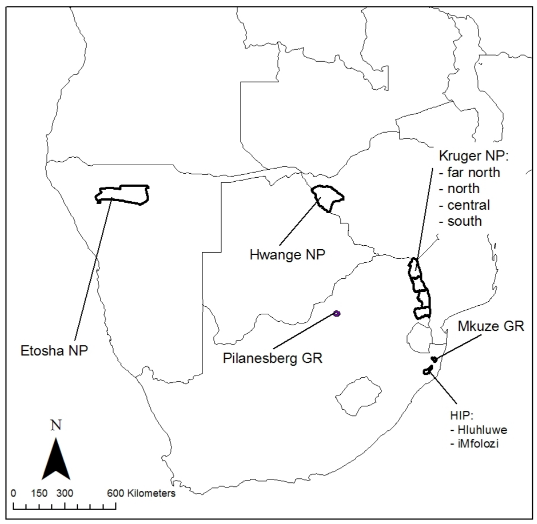

Figure 5.1: Showing the location of the six protected areas for which long term burnt area data were available. The Kruger National Park and Hluhluwe iMfolozi park were split into regions of homogeneous rainfall, resulting in 10 separate sets of fire records.

5.3.2 Data

Burnt area data

Field data: The occurrence and location of all fires have been mapped for at least 20 years in the 10 parks and protected areas used in the analysis (Van Wilgen *et al.*, 2000; Balfour & Howison, 2001; Brockett *et al.*, 2001; Mulqueeny, 2005). Originally the mapping was done by section rangers on field maps - and in the best cases they recorded the start date, end date, cause (arson, management burn, lightning), and type (clean burn, patchy burn), as well as the spatial extent of each fire. In some cases (Hwange, Etosha) only the spatial extent and year of burning was recorded. These field maps were then digitised into a GIS. Small patches of unburned vegetation within a burned landscape are unlikely to be mapped by this method, as the rangers only walk the

Table 5.1: Summary of the environmental characteristics of each protected area used in the analysis (in order of increasing rainfall). ENP = Etosha National Park; north, farnorth, central and south = the four regions of the Kruger National Park; PGR = Pilanesberg Game Reserve; HWG = Hwange National Park; MGR = Mkuze Game Reserve; umf, hlu = the two regions of Hluhluwe iMfolozi Park.

park	n	mean annual rainfall	mean(sd) burnt area	size	mean(sd) altitude	mean(sd) tree cover	road density	grazing density
	years	mm/year	%	km^2	m	%	km/ $100km^2$	kg/km^2
ENP	32	380	12 (8)	33941	1157 (60)	1 (1)	4	25
north	49	425	15 (13)	5364	318 (52)	12 (4)	9	19
farnorth	49	494	25 (19)	4482	347 (58)	13 (7)	9	19
central	49	533	20 (17)	4948	297 (40)	13 (7)	12	19
PGR	25	576	41 (21)	481	1240 (140)	12 (6)	7	60
HWG	21	608	13 (15)	14600	1005 (49)	20 (8)	2	6
south	49	609	26 (16)	4194	334 (137)	16 (8)	17	19
MGR	38	649	14 (12)	340	101 (39)	28 (12)	3	68
umf	50	686	27 (27)	627	154 (40)	19 (9)	3	94
hlu	50	952	33 (23)	269	149 (47)	31 (15)	13	94

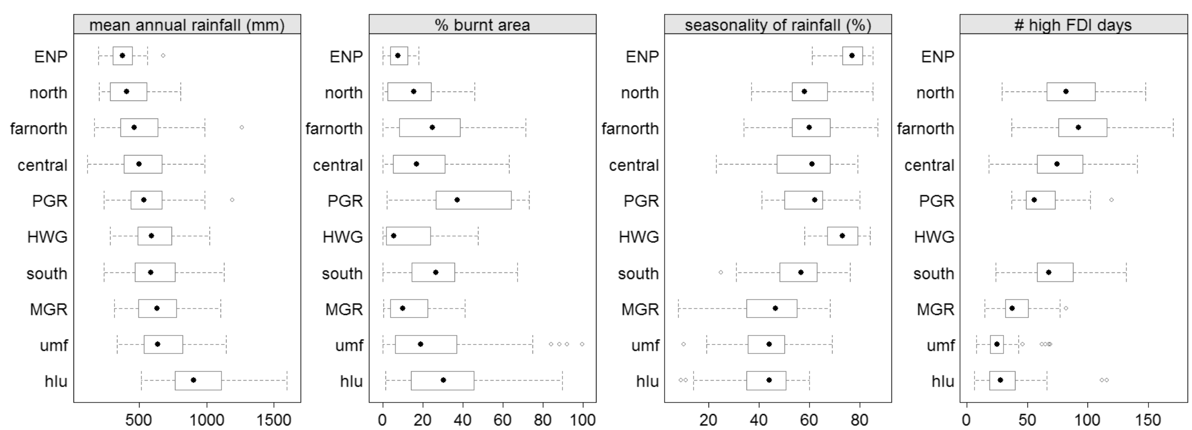

Figure 5.2: The median, 25% (box) and 95% (whisker) confidence intervals of the climatic and burnt area data for each set of fire records used in the analysis. The variability between years within parks is in the same order as the variability between different parks. Parks are ordered in terms of increasing rainfall: Etosha National Park = ENP; The four regions of the Kruger National Park = north, farnorth, central and south; Pilanesberg Game Reserve = PGR; Hwange National Park = HWG; Mkuze Game Reserve = MGR; The two regions of Hluhluwe iMfolozi Park = umf, hlu. FDI data were not available for the parks outside South Africa.

boundaries of the fires. More recently some of the parks have started using remotely-sensed burned area data to inform their fire mapping, but the burn scars are still mapped by hand by field rangers with personal experience of the fires, and the satellite data are used during the digitisation process to adjust the exact boundaries of each fire.

With the exception of a small winter-rainfall region in the south-west most fires in southern Africa occur between April and November. Therefore fire data were summarised by calendar year to produce estimates of annual burnt area. Annual burned area was divided by the total area of each reserve to produce a percentage area burnt for each year for each sample.

Satellite data: The collection 5 MODIS global burnt area product (MODB45) (Roy *et al.*, submitted) was used as a regional representation of fire extent. This burnt area product was developed in southern Africa, has been extensively tested in the region (Roy *et al.*, 2008; Roy & Boschetti, 2009). It is produced at 500m resolution giving an approximate day of burning and an indication of the confidence of the detection for each pixel. Quality flag information identifies pixels where the algorithm could not be implemented due to excessive cloud cover or sensor problems ('invalid' pixels). Data were summarised annually to produce a burnt/unburnt layer for each fire year (January to December). Data from June 2001 were missing due to technical problems, and were filled using information on the rest of the year (see Appendix S1 in Supporting Information and Archibald *et al.* (in pressc) for a description of the filling method.). Pixels with more than five months of invalid data each year were excluded from the analysis, as it was not possible to say with any certainty whether they had burnt or not. At the time of writing the product runs from April 2000 to March 2008, which provides eight full years from which to calculate burnt area.

Climate data

Field climate data: Monthly rainfall data were available for all parks from databases held by the conservation institutions. However, calculating a fire danger index (FDI) requires daily rainfall, temperature, relative humidity and wind speed data. For South African parks these data were available from the SA Weather Services. Gaps in these records were filled using the Schultz hydrological database (Schulze & Maharaj, 2007), and a 45 year wind speed re-analysis dataset from the European Centre for Medium-Range Weather Forecasts (ECMWF) (http://www.ecmwf.int/). The few ($< 6\%$) gaps that remained were filled with the mean value over the entire time period for that day.

Regional climate data: Spatially-explicit meteorological data for Africa are difficult to obtain. The Tropical Rainfall Measuring Mission (TRMM) provides relatively high-resolution (0.25 degree) monthly rainfall data for the region, but temperature, relative humidity and wind data are best derived from data-assimilation weather models, and this is only available at fairly course resolution. We used climate data derived for the model inter-comparison study of Africa's ecosystem productivity (Weber *et al.*, 2008) at 1 degree resolution for calculating fire danger indices, and the TRMM3B43 rainfall product (Huffman *et al.*, 2007) for calculating rainfall indices.

Defining the input variables

Accumulated rainfall (rain): There is a certain degree of carry-over of grass fuels from year to year, and the standing grass biomass is a function not only of the current year's rainfall, but also of previous rainfall events (Medina & Silva, 1990). A recent review and re-analysis of fire-rainfall data showed that the effect of rainfall was best demonstrated using an 18 month accumulation of rainfall ending in June of the year of burning - i.e. accumulating over one and a half hydrological years (Archibald *et al.*, in pressb) (see Appendix S2 for details of the calculation).

Length of the dry season (season): There are various measures that could be used to represent the length of time for which fuels are dry and flammable. The simplest would be the coefficient of variation (CV) of monthly rainfall. We used a 'rainfall concentration' index developed by Markham (1970) which assesses the degree to which rainfall is equally dispersed over a 12 month period. The index ranges from 0 (all months contribute equally to total annual rainfall) to 100 (all rainfall fell in one month) and is entirely independent of the total amount of rainfall that falls in a year (see Appendix S2 for details of the calculation).

Number of high Fire Danger Index days (FDIdays): A number of different Fire Danger Indices have been tested and applied to southern African systems. The most widely used are the McArthur Forest FDI (McArthur, 1966), and the Lowveld index (Meikle & Heine, 1987). We used the McArthur Forest FDI which, despite its name, is effective when applied to grassy systems because it includes a term (calculated from climatic inputs) for the dryness of the fuel (the McArthur Grassland FDI requires a user-defined assessment of grass curing, which is not possible in retrospective analyses). In order to summarise this daily measure to an annual time scale we counted the number of days when the FDI went above a threshold value of 24 (5=low,12=moderate,24=high,50=very high,100=extreme: McArthur (1966)).

Other possible drivers of inter-annual variation in burnt area: Several authors found trends in burnt area data over time - Norton-Griffiths (1979) found an increasing trend in burnt area in the Serengeti which he attributed to a decrease in grazer numbers and a consequential increase in available fuel. Frost (unpublished) noted a sudden increase in burning in Hwange Game Reserve in the 1974-1979 civil war in Zimbabwe and attributed it to changing fire management practices during the conflict. Similarly, it is possible that there could be a carry-over effect - where the extent of burning in a previous year affects how much fuel is available to burn in the following year. All of these possibilities would result in temporal trends or temporal autocorrelation in the data that would not be accounted for by climatic variables. Three alternative approaches were used to test for the importance of these non-climatic drivers of variability in the data. Firstly, the previous year's burnt area was added as an additional factor (test of how important recent fire history is to the current year). Then the year of burning was added as an additional factor (to test for long-term trends in the data). Finally, an auto-regressive covariance structure was added. This explicitly includes a parameter (φ) estimating the degree to which records close together in time are related to each other.

Analysis

It is possible that the response of burned area to accumulated rainfall, seasonality, and FDI is not linear, and that it levels off at high values. However an analysis of various fitting methods (Archibald *et al.*, in pressb) gives no indication that within one site there is a saturating response to rainfall, even though the range of rainfall values at one site can span 800 mm. Linear models were therefore used throughout the analysis.

Unimodal regressions of burned area against rainfall, seasonality, high FDI days and previous year's burned area were run for both the field data and regional data. The strength of these relationships was explored in relation to the hypothesis (Question 3 in the introduction) that variation in rainfall would have more effect on burned area in dry systems (where fuel amount limits fire extent) and length of the dry season and FDI would have more impact in wetter systems (where availability of dry fuels limits fire extent). For the spatially-explicit data correlation coefficients were compared between regions of high and low mean annual rainfall (MAR) using chi-square tests. For the field data the R^2 values were plotted against MAR.

Mixed Effects Modelling

Mixed effects models are useful when one wants to determine the general effect of a process on a group of individuals, as well as investigate the degree to which each individual differs from the general response. A linear mixed effects model can therefore be seen as a simple regression model (applied to all individuals), with an extra parameter (defined for each individual) indicating the individual's deviance from this general model. In its most general form a linear mixed effects (LME) model with one predictor would be defined as:

$$\mathrm{y}_{ij} = (\beta_0 + b_{0i}) + (\beta_1 + b_{1i})\mathrm{x}_{ij} + \varepsilon_{ij} \tag{5.1}$$

Where $i = 1...\mathrm{N}$ represents the individuals, $j = 1...\mathrm{t}$ is an index for records for a particular individual, and ε_{ij} represents the error. Both the intercept (β_0) and the slope (β_1) are modified by the terms b_{0i} and b_{1i}.

When the same individual is sampled repeatedly (as in this instance where we have repeated measures of annual burned area for the same site) it is not reasonable to assume that the covariances between observations on the same individual are zero. There are various ways of defining the covariance between these repeated measures. One widely used covariance structure is the autoregressive structure (AR(1) where 1 refers to the lag) which assumes that the correlation between observations from the same individual one unit apart in time is φ, two units apart is φ^2, and n units apart is φ^n. As $|\varphi|$ is < 1 the size of the covariance between observations decreases with time.

We centered the data on the X-axis: i.e we used the anomaly (difference from the park mean) of rainfall as the predictor variable. This meant that we were not extrapolating beyond the bounds of the data to calculate the Y-intercept (which in mean-centered data represents the mean value of the dependent variable). Mean centering has traditionally been used to avoid collinearity problems (Snee & Marquardt, 1984), although its efficacy in this regard is up for debate (Kromrey & Foster-Johnson, 1998). For our purposes the mean centered data were useful because we were able independently to determine the intercept terms for each grid cell in the regional data, and to apply the model developed on the field data to the regional data.

To test whether the slopes and amount of variance explained by the rainfall-burnt area relationship are the same across parks (Question 1) we compared all possible LME model formulations which included rainfall as a single predictor - i.e. models with random slopes (b_{1i}), random intercepts (b_{0i}), and temporal autocorrelation (AR(1)). To test whether predictive power could be improved by also considering other variables that vary between years (Question 2) we compared LME models with the same formulation but different combinations of predictor terms (rainfall, seasonality and fire danger index). Residual analysis and outlier diagnostics were performed - the residuals were corrected using the Cholesky decomposition (Houseman *et al.* (2004)).

The Bayesian Information Criterion (BIC) was used to assess the relative strengths of evidence for different models. The more common Akaike Information Criterion (AIC) can be biased in favour of including additional parameters (Fitzmaurice *et al.*, 2004; Burnham & Anderson, 2004) and in this instance sometimes favoured models with parameters that were not significant. AIC values were reported in the Appendix S3 for comparison.

The model with the highest explanatory power (lowest BIC value) was then implemented on the regional climate data to produce a predicted burned area anomaly (difference from the mean burned area) for each 1-degree grid cell in southern Africa for each of the 8 years for which satellite-derived burned area data were available. This was possible because we had mean-centered the data, so the intercept term (mean burned area) could be independently calculated for each grid cell. The prediction was performed over the whole region but results were only reported over the range of environmental data represented by the field data. Observed and predicted anomalies were compared and mapped to explore how well the climate relationships developed on the long-term data related to patterns seen across the region (Question 4).

A separate LME analysis was also run on the spatial data. Mixed effects models require independent sample data so a random sub-sample of 33% of the 828 valid grid points (276 points) was extracted to avoid spatial autocorrelation. To test whether the samples were in fact independent the burnt area in the closest grid cell to each grid cell was included as an input in the LME analysis (closest). The LME model was run 50 times with a different random sample each time and the model identified most frequently as the best model was reported. First the LME model was run only for regions which represent the environmental conditions of the field data. Subsequently separate LME models were run for regions of low (< 1000 mm) and high (> 1000 mm) mean annual rainfall to see whether different model formulations were selected over this environmental gradient.

Comparing the two sources of data

Two analyses were run to test how comparable the two different sources of data were. First the area of each park recorded as burnt by the MODIS data was extracted and compared with estimates of burnt area from the field data that overlapped the satellite record (44 data points). Secondly, to test how informative the eight year satellite data product was compared with a longer dataset, the long-term park data were sub-sampled so that each park only had 8 consecutive years of fire and climate data. Then the same LME analysis was run on this reduced data set to see if it gave similar results.

5.4 Results

5.4.1 Comparing the two sources of data

The environmental characteristics of the field data represent about half of the environmental range of all the areas that burn in southern Africa (Fig. 5.3). The mean annual rainfall (MAR) of the parks ranged from 380-950 mm (mean 590 mm), the mean seasonality ranged from 41-76%, and the mean FDI days ranged from 1-93. Regionally the MAR in areas that burn ranges from 300-1700 mm, seasonality from 30-75% and FDI days from 0-150. Thus the long term data represent the lower half of the rainfall range, and are a slight under-representation of the extremely seasonal and high FDI parts of the region. Fig. 5.3 maps the mean and standard deviation of the climate inputs, and indicates the parts of southern Africa for which the field data are representative.

The satellite-derived data consistently detect about 70% of the burned area identified

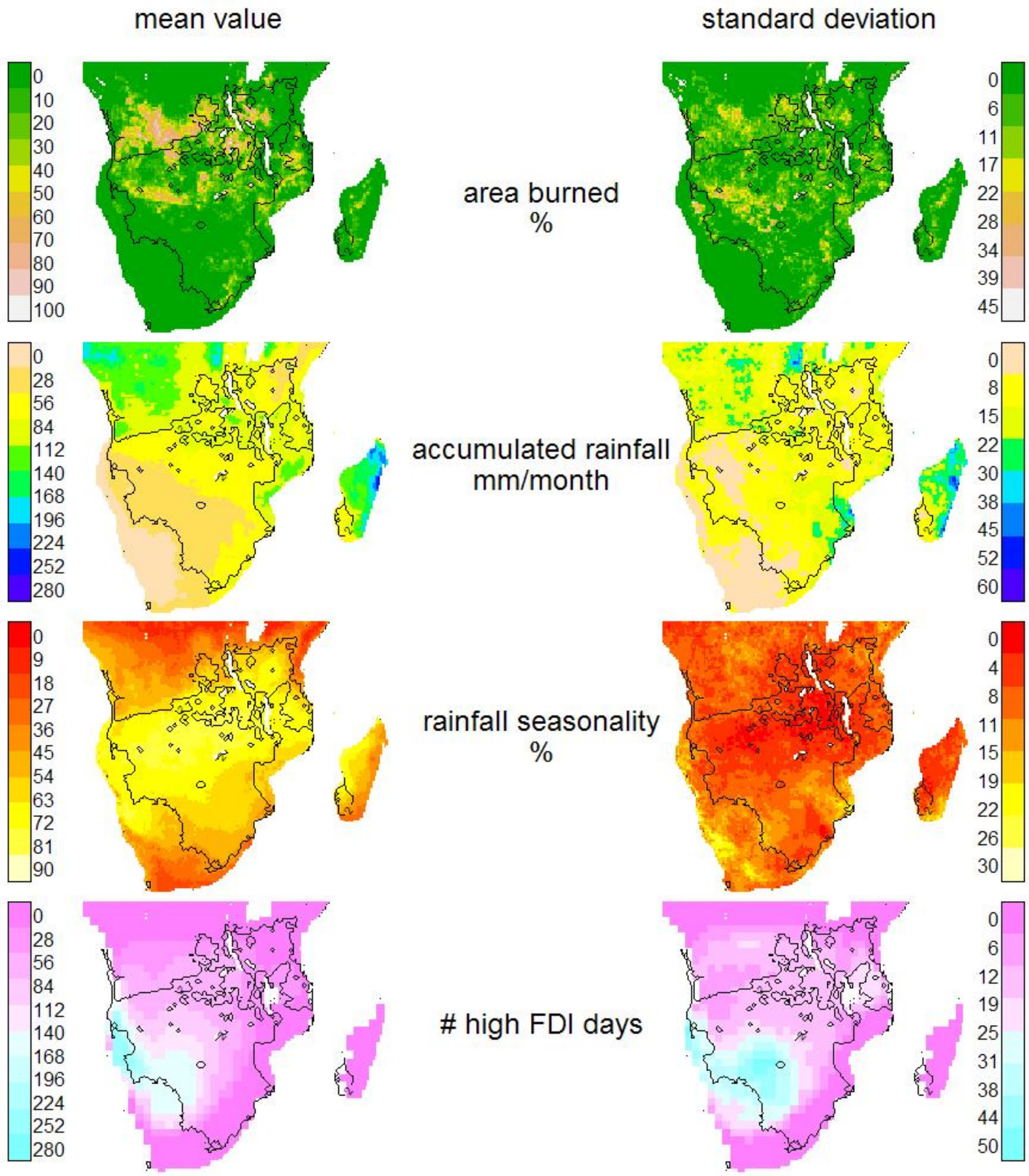

Figure 5.3: Maps of southern Africa showing the mean (column 1) and standard deviation (column 2) of burnt area, and the three environmental drivers of burnt area that vary from year to year. The region for which the field data are representative is marked in black: it characterises the seasonality range and range of FDI days fairly well, but does not give a good representation of the higher-rainfall savannas.

from the field data (linear regression: y = 0.8x-2, $R^2 = 0.7$, Appendix S1). This is is similar to what has been found in other accuracy assessments of the MODIS data (Roy *et al.*, 2008) as the MODIS data do not identify very small (< about 2000 ha) fires. Interestingly, the two different data sources did not differ significantly in the variability between years recorded for each park (Two sample t-test: df = 16, p = 0.16), indicating that the satellite data successfully detects changes in burnt area from year to year when they are present.

Similarly, when the length of the park-level data was reduced to eight years (randomly sampled from the available years for each park), the variability in burnt area was not significantly different from that of the entire dataset (t.test: $t = -0.83$, $p = 0.69$) and an LME model gave similar results (Appendix S3). Thus the variability shown at the park scale is entirely consistent with what would be expected at the regional scale if the driving variables were the same.

5.4.2 Field data analysis

A unimodal analysis on the field data showed that accumulated rainfall had by far the most significant effect on annual burnt area (Table 5.2, Fig. 5.4). Correlations with accumulated rainfall were significant for all parks, and correlation coefficients ranged from 0.37 to 0.75 (Table 5.2). Correlations with length of the dry season were all positive, but seldom significant on their own. There also appeared to be a weak relationship with previous year's burnt area which indicated that the covariance structure of the mixed effects model needed to account for this. Surprisingly, the relationship with number of high fire danger days was largely negative, but seldom significant.

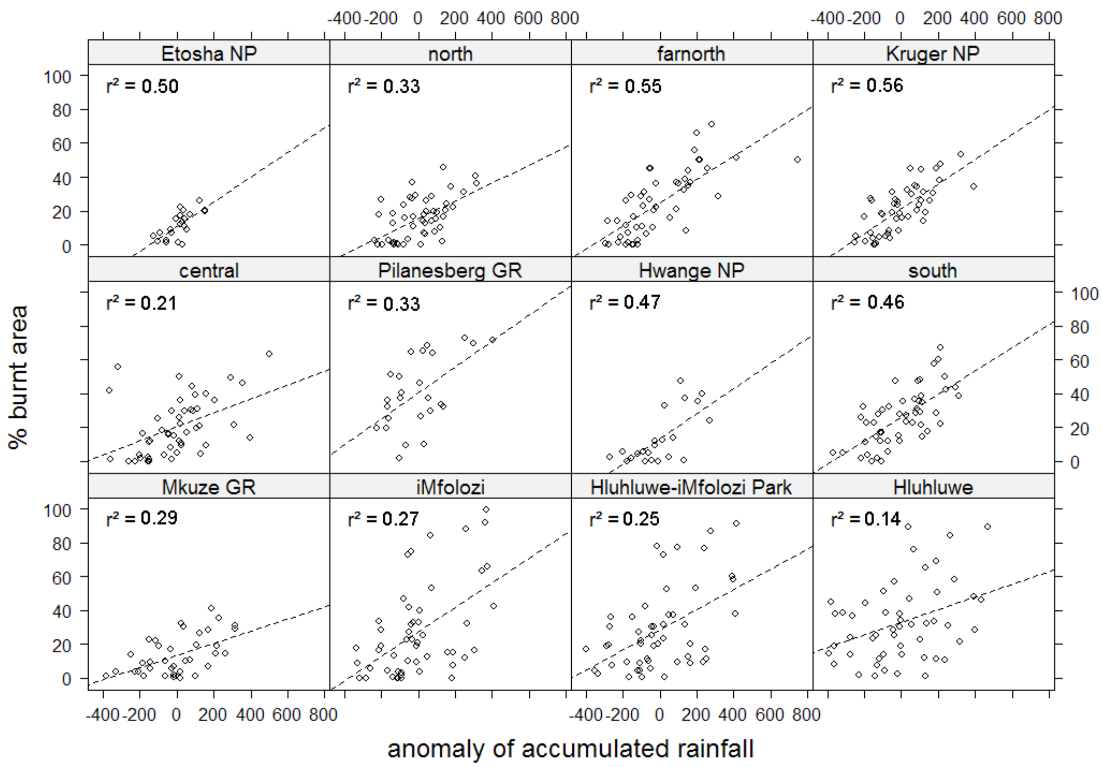

Figure 5.4: Relationship between the annual percentage burnt area and the rainfall anomaly for each protected area in southern Africa. Parks are presented in order of increasing mean annual rainfall: the explanatory power of the relationship (R^2) appears to decrease as rainfall increases. A mixed effects analysis (Table 5.3) indicates no difference in the slopes of the relationship between parks. Relationships for the entire Kruger National Park and Hluhluwe iMfolozi Park are also shown, but were not used in the analysis.

Table 5.2: Pearson's correlation coefficients of burnt area against accumulated rainfall, extent of the dry season (rainfall concentration index), number of high FDI (fire danger index) days, and previous burnt area.

		accumulated rainfall			extent of dry season			FDIdays			previous area burnt		
park	n	R	conf.int	pval	R	conf.int	pval	R	conf.int	pval	R	conf.int	pval
ENP	22	0.71	(0.41, 0.87)	0.000*	0.36	(-0.07, 0.68)	0.100	NA	(NA, NA)	NA	0.43	(-0.08, 0.76)	0.095
north	50	0.57	(0.35, 0.73)	0.000*	0.29	(0.01, 0.52)	0.043*	-0.32	(-0.55,-0.05)	0.022*	0.11	(-0.18, 0.38)	0.452
farnorth	49	0.74	(0.58, 0.84)	0.000*	0.15	(-0.14, 0.41)	0.303	-0.29	(-0.54, 0.00)	0.047*	0.08	(-0.21, 0.36)	0.573
central	49	0.45	(0.20, 0.65)	0.001*	0.06	(-0.22, 0.34)	0.669	-0.13	(-0.40, 0.15)	0.356	0.09	(-0.20, 0.36)	0.549
PGR	25	0.57	(0.23, 0.79)	0.003*	0.33	(-0.07, 0.64)	0.105	-0.25	(-0.59, 0.16)	0.232	-0.28	(-0.61, 0.14)	0.188
HWG	22	0.69	(0.38, 0.86)	0.000*	0.13	(-0.31, 0.52)	0.563	NA	(NA, NA)	NA	0.25	(-0.21, 0.61)	0.284
south	50	0.68	(0.50, 0.81)	0.000*	0.23	(-0.05, 0.48)	0.110	-0.19	(-0.44, 0.10)	0.191	0.05	(-0.24, 0.32)	0.754
MGR	38	0.54	(0.27, 0.73)	0.000*	0.25	(-0.08, 0.53)	0.132	-0.03	(-0.34, 0.30)	0.878	0.07	(-0.26, 0.39)	0.669
umf	51	0.52	(0.29, 0.70)	0.000*	0.21	(-0.07, 0.46)	0.147	-0.16	(-0.42, 0.12)	0.270	0.39	(0.13, 0.60)	0.005*
hlu	51	0.37	(0.10, 0.59)	0.008*	0.24	(-0.04, 0.48)	0.091	0.05	(-0.23, 0.32)	0.722	0.33	(0.05, 0.55)	0.021*

* denotes significance at the 5% level.

Mixed effects model

The linear mixed effect analysis gave no indication that the slope of the rainfall response was different across the 10 parks studied (Question 1). The most probable formulation of the model had annual % burnt area as a function of accumulated rainfall with a mean burnt area that varied between parks (variable intercept) but a constant response (slope) across all parks (Table 5.3 A). It also included an AR(1) covariance structure. This model structure was given a weighting of 0.976 out of the models considered, and was used to test whether including additional factors could improve it further.

Table 5.3: Results of mixed effects models run on long-term burnt area data from 10 protected areas in southern Africa. A: Testing model structure (only accumulated rainfall included as a factor). B: Testing whether additional factors can improve on the best model identified in A. Models are listed from most likely (lowest Baysian Information Criterion: BIC) to least likely.

model	random effects	covariance	k	$\triangle BIC$	w_i	df
A						
rain	int	AR1	4	0	0.976	396
rain	int	none	3	8	0.016	396
rain	int, slope	AR1	6	10	0.008	396
rain	int, slope	none	5	18	0.000	396
rain	none	none	2	66	0.000	405
B						
rain + season	int	AR1	5	0	0.716	350
rain	int	AR1	4	2	0.277	351
rain + season + FDI	int	AR1	6	10	0.005	349
rain + FDI	int	AR1	5	12	0.002	350
season	int	AR1	4	98	0.000	351
season + FDI	int	AR1	5	98	0.000	350
FDI	int	AR1	4	104	0.000	351
null	int	AR1	3	105	0.000	352

The $\triangle BIC$ is the difference in the BIC between each model and the most likely model (values less than 4 indicate that the models are equally probable), k = number of model parameters, w_i = BIC weighting, rain = accumulated rainfall, season = extent of the dry season (rainfall concentration), FDI = number of high Fire Danger Index days, AR1 = model includes an autoregressive covariance structure, int = model includes different intercept estimates for each park, slope = model includes different slope estimates for each park.

Including length of the dry season as a predictor improved the rainfall model (Question 2), but there was no indication that the number of high fire danger days should be included in a predictive model of burnt area. A model with seasonality and accumulated rainfall had a weighting of 0.7 compared with 0.3 with accumulated rainfall alone (Table 5.3 B), but none of the models with FDI had BIC weightings > 0.005. The AR(1) covariance structure was retained which indicates that not all temporal trends are explained by the climate variables. We subsequently tested whether including variable slopes terms for seasonality of rainfall improved the model and this was not the case (see Appendix S3 for the full set of models tested).

The final predictive model was a function of accumulated rainfall and length of the dry season:

$$\text{burnt}_{ij} = \beta_0 + b_{0i} + \beta_1 \text{rain}_{ij} + \beta_2 \text{season}_{ij} + \varepsilon_{ij} \tag{5.2}$$

The error term (ε_{ij}) had an auto-regressive covariance structure ($\varphi = 0.25$), and the coefficients (with 95% confidence intervals in brackets) were:

$\beta_0 = 23$ (18-28)
$\beta_1 = 0.69$ (0.59-0.78)
$\beta_2 = 0.24$ (0.13-0.36)

This model had an R^2 of 0.40 and a Mean Absolute Error (MAE) of 11.9%. This MAE value is equivalent to the median burned area in some parks, but is much smaller than the range reported between years in individual parks (which was 60% on average). Residuals were normally distributed with constant variance.

We expected (Question 3) that the importance of accumulated rainfall in influencing burnt area would be reduced in wetter parks (because there would always be sufficient fuel), and that the importance of seasonality and FDI would be greater, but the mixed effects modelling gave no indication of this. When mean annual rainfall (MAR) was included as a park-level fixed effect it was not significant, and when a categorical variable classifying the parks into low (<550 mm) and high (>550mm) rainfalls was included as a higher-level random effect it was also not significant (not shown - see Appendix S3).

Thus the LME did not support including a higher-level rainfall effect but a closer examination of the accumulated rainfall - burned area regression did indicate that mean annual rainfall was affecting the strength of the relationship. Figure 5.4 shows that in wetter parks rainfall explains less of the variance in burnt area between years, and this was supported by a t-test (one-sided: p-val = 0.04, n = 10, low rainfall = < 550 mm). These results would probably be more convincing if field data from parks with higher mean annual rainfall could be included in the analysis. At 1000 mm MAR grassy fuels are still probably quite strongly rainfall-limited; we expect that switches in the relative importance of rainfall and seasonality in driving fire might be more apparent at higher rainfalls. There was also a potentially-confounding positive relationship between the size of the park and the strength of the relationship (bigger parks tended to have lower rainfall) so it is not possible to distinguish between the two effects).

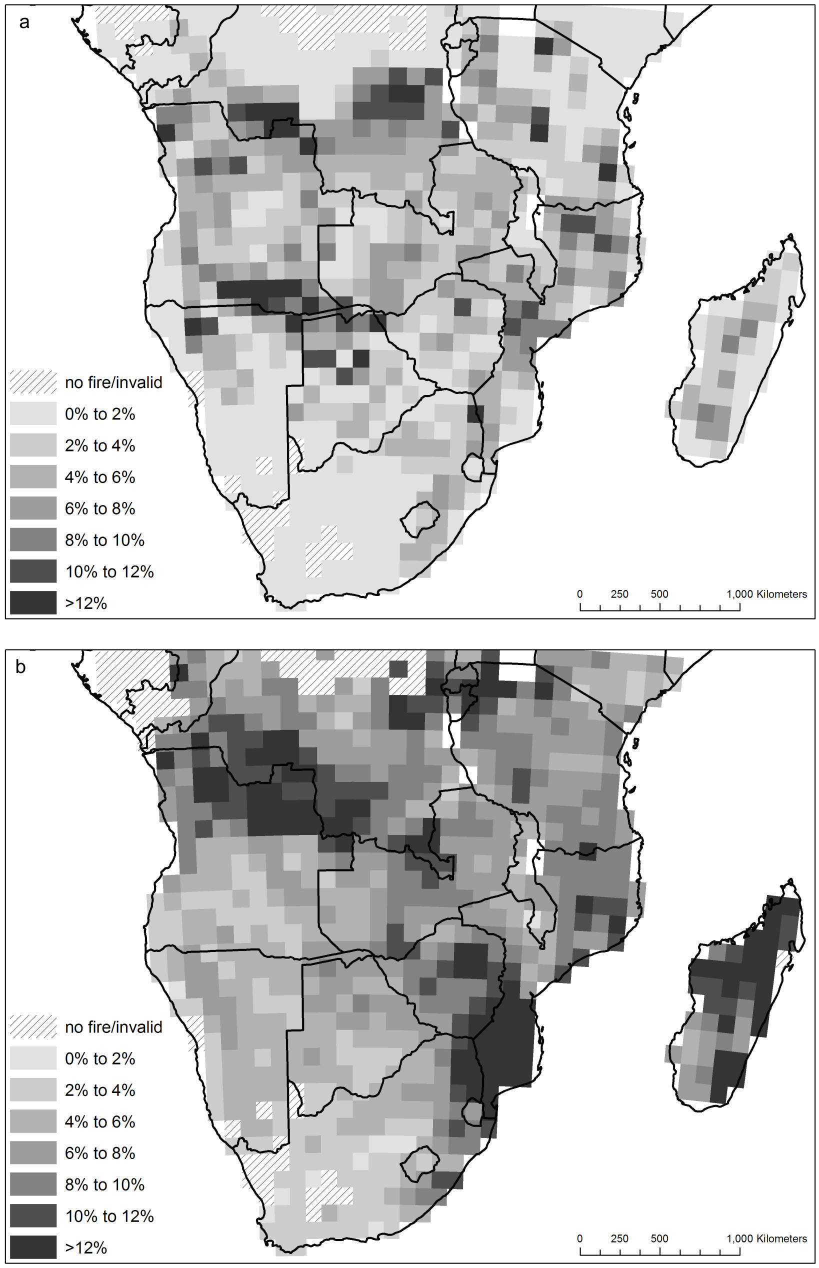

Figure 5.5: Maps of the standard deviation in burnt area A) observed in an 8 year satellite-derived burnt area product and B) predicted from variation in climate data over the same 8 year period. If burnt area were as responsive to climate drivers as the protected area data predict then we would see very different patterns across the region

5.4.3 Spatially-explicit analysis

The model developed from the field data implies that areas in southern Africa which have high variability in rainfall and the length of the dry season should be associated with more variable fire regimes. An initial glance at patterns of temporal variability across southern Africa suggests that this is not the case (Fig. 5.3): Areas in southern Mozambique, northern Angola and the DRC that have the highest rainfall variability (linked to the movement of the inter-tropical convergence zone (Nicholson, 2000)), and regions in south-west Africa and southern Mozambique have the highest variability in the length of the dry season. These regions show remarkably little variation in burned area (with the exception of a small part of the southern DRC which shows a degree of variability in both rainfall and burned area).

Indeed, when the regional data was fed into Equation 5.2 the predicted patterns were very different from what is observed (Fig. 5.5). Even for regions which fall within the climate envelope in which the model was developed (MAR 380-950 mm, mean seasonality 41-76%, mean FDI days 1-93, mean % burnt area 11-40), observed and predicted values show very poor relationship ($R^2 < 0.01$). The model also predicts a much higher anomaly from the mean burned area than was actually seen in the data (Fig. 5.6).

It appears that the climatic influence on burnt area which was so apparent in the field data is substantially reduced over much of the southern African region (Question 4). However the patterns that do exist are consistent with the expectations from Question 3. In low rainfall areas (MAR $<$ 1000 mm) accumulated rainfall showed positive correlations with burnt area more often than would be expected from a null model (chisq = 22.69, p $<$ 0.001), as did seasonality (chisq = 26.96, p $<$ 0.001). FDI did not seem to be correlated with burnt area at low rainfalls (chisq = 1.81, p = 0.178). In high rainfall areas (MAR $>$ 1000 mm: northern Angola, the DRC, Madagascar and northern Mozambique) correlations with accumulated rainfall showed no patterns (chisq = 0.745, p =0.388), but correlations with seasonality and FDI were positive more often than expected (chisq = 90.1, p $<$ 0.001 and 63.4, p $<$ 0.001 respectively).

A mixed effects analysis run on the satellite data supported the inference that climate drivers were not good at explaining variability in burned area regionally (Table 5.4). When run on grid cells with the same environmental characteristics as the field data the null model (no climate drivers) was the most likely model 74 percent of the time, although seasonality was shown to be important in 28% of the model runs. The same pattern was shown in low rainfall (<1000mm) regions, but in high rainfall regions seasonality and number of high FDI days were both shown to improve the null model. Accumulated rainfall was never a significant factor in any of the models considered, which is a remarkable departure from the results of the protected areas analysis.

5.4.4 Other possible drivers of inter-annual variation

In all instances there was evidence for temporal trends in the burned area data due to factors other than the climatic variables considered. As mentioned, these could be related to changes in grazer numbers, tree cover, or fire suppression activities, and might be quite particular to the history of individual locations. One area could show an increasing trend in fire associated with reduced grazer numbers while another park would

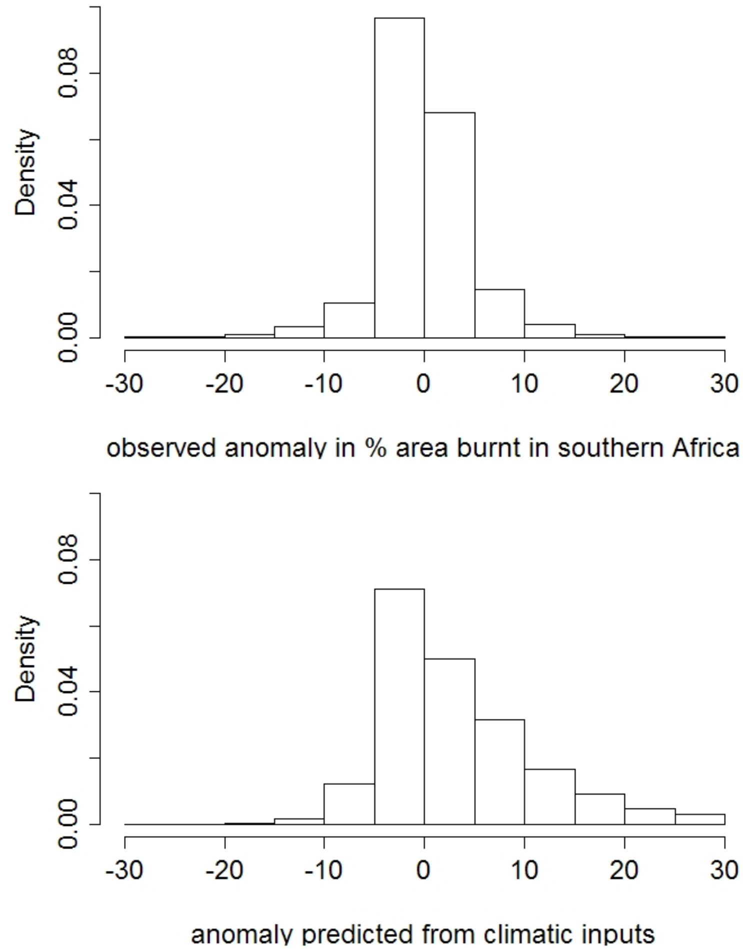

Figure 5.6: Comparing the variability predicted from climate data with the actual variability observed in an 8 year satellite-derived burnt area product. Data are reported as the anomaly from the mean burnt area for each year for each 1 degree grid square across southern Africa. Only grid cells within the environmental limits of the field data (see Figure 5.3) were included. The range of values is similar, but the observed values are more concentrated around zero, which implies that the variability in the climatic drivers of fire between years is greater than is reflected in the burnt area data

show less fire due to woody encroachment. This is probably why the very general auto-regressive covariance structure accounted for these better than including the previous year's burned area or the fire year as terms in the model.

Table 5.4: Mixed effects models run on 1-degree grid cells across southern Africa using the 8 year MODIS satellite product. Results are a summary of 50 replicates each using 33% of the grid cells each time. Separate analyses were run for low and high rainfall regions to test whether the importance of the input variables changes over a rainfall gradient. A third analysis was run on pixels within the environmental limits of the field data. Accumulated rainfall was never a significant factor in any of the models considered, which is a remarkable departure from the results of the protected areas analysis.

	best model (%)	within 2 of best model (%)	average BIC weight	coef1	% sig	coef2	% sig	coef3	% sig
LOW RAINFALL REGIONS									
null	22	74	0.20	-	-	-	-	-	-
season	6	46	0.11	0.11	61	-	-	-	-
FDI	0	2	0.01	-0.05	25	-	-	-	-
season + FDI	0	2	0.01	0.11	58	-0.04	19	-	-
closest	2	0	0.02	0.04	6	-	-	-	-
rain	0	0	0	-	3	-	-	-	-
rain + closest	0	0	0	0.01	3	0.04	5	-	-
rain + FDI	0	0	0	-	1	-0.04	23	-	-
rain + season	0	0	0	-0.01	1	0.12	63	-	-
rain + season + FDI	0	0	0	-0.02	3	0.11	60	-0.04	19
HIGH RAINFALL REGIONS									
season	60	72	0.16	0.18	68	-	-	-	-
closest	28	32	0.23	0.18	76	-	-	-	-
season + FDI	14	28	0.05	0.19	69	-0.21	58	-	-
null	4	24	0.03	-	-	-	-	-	-
FDI	4	8	0.01	-0.2	49	-	-	-	-
rain	0	0	0	-	3	-	-	-	-
rain + closest	0	0	0	-	4	0.18	54	-	-
rain + FDI	0	0	0	-	3	-0.2	49	-	-
rain + season	0	0	0	-	4	0.18	68	-	-
rain + season + FDI	0	0	0	-0.01	4	0.19	69	-0.22	58
FIELD DATA CONDITIONS									
null	74	86	0.62	-	-	-	-	-	-
season	14	28	0.18	0.13	70	-	-	-	-
closest	14	18	0.14	0.09	34	-	-	-	-
FDI	0	2	0.02	0.05	6	-	-	-	-
rain	0	2	0.01	-0.02	16	-	-	-	-
rain + closest	2	2	0.01	-0.02	14	0.09	34	-	-
rain + FDI	0	0	0	-0.02	16	0.04	6	-	-
rain + season	0	0	0.01	-0.03	22	0.14	78	-	-
rain + season + FDI	0	0	0	-0.03	18	0.14	80	0.04	6
season + FDI	0	0	0	0.13	68	0.04	6	-	-

BIC = Bayesian Information Criterion, rain = accumulated rainfall, season = extent of the dry season (rainfall concentration), FDI = number of high FDI days, closest = annual burnt area of the closest grid cell, coef and %sig are the average coefficients of each term in the model and the percentage of the runs in which these coefficients were significant.

5.5 Discussion

Scaling up from field studies to regional patterns is notoriously difficult (Turner, 1991; Heyerdahl *et al.*, 2001; Falk *et al.*, 2007). A range of factors come into play when attempting to apply rules developed in local studies to regional patterns. Solving this problem is going to become more and more important as we try to apply ecological understanding developed under a localised set of conditions to answer questions about the earth system (Bowman *et al.*, 2009).

In this paper field-based studies in protected areas across southern Africa indicated that climatic factors were largely responsible for variation in burnt area from year to year. The general model (Equation 5.2) predicts a change of 6.9 % in the area burned for every 10 mm change in the monthly accumulated rainfall index (equivalent to a change of around 120mm rain a year). Similarly, if the seasonality of this rainfall increased by 10 percentage points, annual burned area would increase by 2.3%.

This relationship was shown to hold across 10 different parks representing rainfall from 380 mm to 950 mm, and a variety of management histories, altitudes, grazing densities, and tree covers. The model explained 40% of the variance in area burned, and compares favourably to models developed in chaparral systems - known to be highly weather-driven - which explain less than 10% of the variance (Keeley, 2004).

However when the model developed from individual locations was applied regionally it did a remarkably poor job of predicting the variation in annual burnt area which was observed in the remotely sensed data set. Both the amount of variability found between years, and the spatial distribution of this variability across the region did not seem to be associated with variation in the climatic drivers of fire (Figs 5.5 and 5.6).

In particular, it was the effect of accumulated rainfall on fuel loads that showed the greatest reduction outside protected areas. In a mixed effects analysis on the regional data the coefficient of the seasonality response was 0.13, which is only slightly lower than the 0.23 for the field data analysis, whereas the coefficient for accumulated rainfall was close to zero (compared with 0.69 for the field data - see Table 5.4 and Equation 5.2).

High numbers of domestic grazers in much of the region, together with a more fragmented landscape where fires can not spread, might explain this. Outside protected areas fires are much smaller (Archibald *et al.*, in pressc) and it is the number of fires, rather than the size of individual fires, that affects how much of the landscape burns. Under these conditions the relationship between fire and rainfall would be less apparent. Seasonality (the amount of time during which fuels are flammable) affects how many fires can occur in a year and might still be relevant in human-impacted systems.

If a system had many small fires, rather than a few large ones, then overall one would expect a reduction in variability between years. Initial analysis supports this hypothesis.

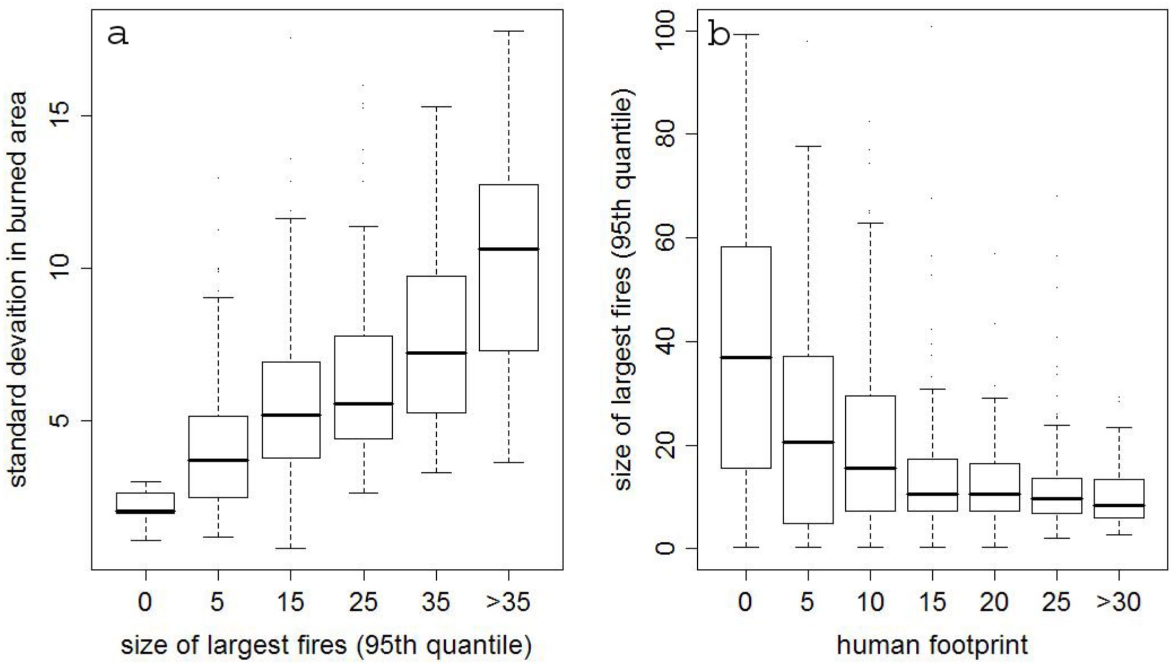

Figure 5.7: A: The importance of large fires in driving variability in burnt area, B: The effect of humans on the occurrence of large fires. These data suggest that humans limit the responsiveness of fire to climatic variability by preventing the spread of large fires. The human footprint score was derived from the last of the wild project (Sanderson *et al.*, 2002) and is an index ranging from 0-100 representing the degree of influence that humans have on an ecosystem

Areas characterised by large wildfires had the highest variation in burnt area between years (Fig. 5.7(a)). Similarly, only areas with a limited human impact (< 10 on the human footprint score) still had large wildfires (Fig. 5.7(b)). Thus it appears that one of the main effects of humans on fire regimes is in reducing the extent of large wildfires, and consequently reducing the impact that climatic variables - and in particular rainfall - have on fire regimes in the region.

This does not mean that fire is entirely uncoupled from climatic drivers in southern Africa however. The regional data did provide evidence that accumulated rainfall, seasonality, and FDI days were correlated with variation in burnt area between years, and that the relative importance of these three climatic drivers changes as one moves from dry to wetter parts of the region. In southern Africa, unlike many other savanna systems which are strongly associated with monsoonal weather patterns (Yadava, 1990; Bowman, 2002), seasonality decreases as rainfall increases. This means that the positive effect of increasing rainfall on the grassy fuels is at some point outweighed by the negative effect of a reduced dry season for burning. It will be important to identify the threshold where seasonality takes over from rainfall in becoming the dominant driver of fire, as it impacts on predictions of future fire patterns in the region.

These results must be interpreted with an understanding of the limitations of the data used. Eight years of burnt area records are adequate for describing fire regimes in systems with fire return periods of 2-3 years, but for drier parts of southern Africa, where fire return periods are more in the order of 5-10 years, the eight year satellite data product might not provide reliable indications of the true variability in the system. It is reassuring, however, that results from a reduced 8-year subset of the long-term fire data were not significantly different from results using the entire time series (Appendix S3), indicating that 8 years of data represents a sufficient range of climatic and fire conditions.

The implication from these analyses is that the human impact on fire regimes in Africa is substantial, and acts to limit the responsiveness of fires to climatic events. As longer satellite data products become available, and our understanding of regional-scale drivers of fire improves, it should be possible to produce maps of potential, and actual variability in fire, and to identify parts of Africa most susceptible to climatic regulation.

5.5.1 Management implications

For managers of national parks, these results indicate that "adaptive" fire management is possible: that burning targets can be planned to incorporate year-to-year changes in the fuel and weather conditions which affect fire. Such burning programs are already being implemented in the Kruger National Park - where rangers are given monthly burn targets based on the rainfall of the preceding two growing seasons (Van Wilgen *et al.*, 2008). In years of high rainfall managers ignite more early-season management burns, to prevent the dangerous large wildfires that might occur later in the season. In years of lower rainfall these burn targets are reduced, which prevents frustration for managers asked to burn fuel that isn't there. This approach represents a compromise between trying to take control over a process which is strongly environmentally driven, but still having some flexibility in applying fire to implement management goals (in savannas fire is used extensively as a management tool to influence vegetation structure (Higgins *et al.*, 2007), control grazing (Fuhlendorf & Engle, 2004), and maintain biodiversity (Parr & Anderson, 2006), among other things).

At a regional scale, and outside protected areas, where fire management is being promoted as a method for altering carbon stocks on the continent (Peace Parks Climate change programme: http:// www.peaceparks.org/, N'hambita Community Carbon Project: http:// www.miombo.org.uk/), the link between climatic drivers and fire is less obvious. This analysis shows that not only the extent of fire, but the variability between years, is substantially reduced from what would be expected based on climate in large parts of the region. This supports the idea that humans are able to intervene to alter savanna fire regimes, but plans to reduce the incidence of fire might have to take into account the fact that it has already been constrained in many areas. The current understanding is that climate change will increase the incidence of extreme fire events in many parts of the globe (IPCC2007). We are not yet able to make such predictions for Africa. To do so would require including human variables into analyses of fire size, fire frequencies, climate, and vegetation across the region.

5.6 Acknowledgments

The authors would like to acknowledge all people and organisations who helped with the collation of the field data: South African National Parks; Ezemvelo Wildlife, in particular Sue van Rensberg and Craig Mulqueeny; North West Parks and Tourism Board and Bruce Brockett; The Zimbabwe Parks and Wildlife Management Authority, especially Patience Zisadza and Elsabe van der Westhuizen; and Peter Frost and Simon Chamaille. Thank you to Brian Van Wilgen who improved the manuscript with his comments. Ulrich Weber helped by providing the regional climate data and David Roy and Luigi Boschetti were enormously helpful with the MODIS burned area data. This work was completed with funding from the EU CarboAfrica project 037132_GOCE and CSIR Strategic Research Funding.

5.7 Appendix

5.7.1 Defining the climate indices

The rainfall concentration index (Markham, 1970) is calculated by treating the monthly rainfall values as vector quantities, the magnitude being the amount of rain, and direction being the month of the year expressed in units of arc (15° for January, 44° for February etc). These 12 monthly vectors are then added, and the vector resultant is a measure of the seasonality of precipitation: the magnitude represents the degree of seasonality and the direction represents the time of year when rainfall is most concentrated. The ratio between the magnitude of the resultant and the total mean annual rainfall (expressed as a percentage) gives the rainfall concentration index: a value ranging from 0 to 100 (Figure 5.8). A value of 100 represents the extreme case where all rainfall fell in one month, and a value of 0 would indicate that equal amounts of rain fell in each month.

The accumulated rainfall index is calculated as the summed rainfall from June of the year of burning back to January of the previous year (an 18 month accumulation representing one and a half growing seasons (Chapter 4). This value is divided by the

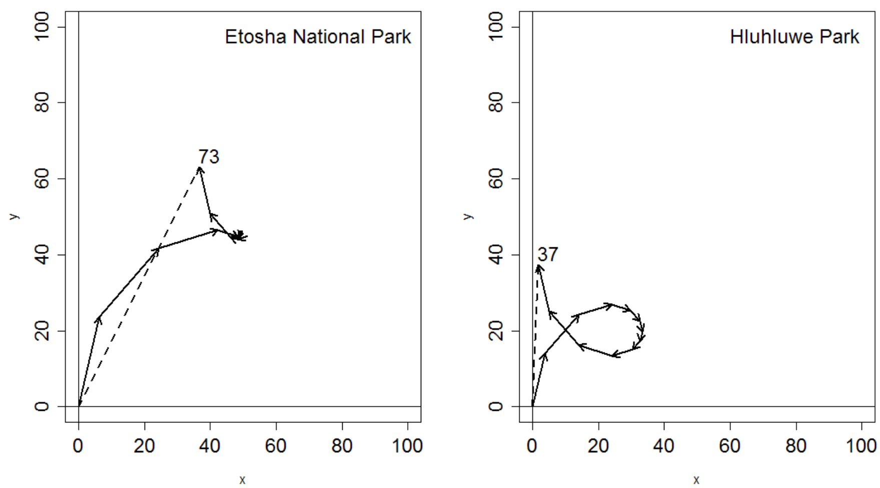

Figure 5.8: **Demonstrating how the rainfall concentration index is calculated through the vector sum of monthly rainfall.** Vectors represent mean monthly rainfall as a percentage of total annual rainfall with slopes representing the month of the year. Data for Etosha National Park (average rainfall concentration index of 73), and Hluhluwe Park (average index of 37) are shown.

number of months to create the accumulated rainfall index in mm/month.

5.7.2 Filling and testing the MODIS data

Due to technical problems on the satellite there were no burnt area data for June 2001. To fill these data in the annual sums the following method was used: for each year the area burnt in June and the area burnt in the rest of the year were calculated. The 2001 burnt area (no June) was divided by the average burnt area (no June) over all other years to give a ratio indicating the degree to which the 2001 burn year was above or below the mean. The average area burnt in June in all other years was then multiplied by this ratio to give an estimation of the 2001 June burnt area.

This filling algorithm was computed separately for each geographic unit used in the analysis (country, vegetation, land use category and 1 degree grid) to accommodate differences in patterns of variability in different parts of the sub-continent. To test the effect of this filling algorithm the July data were systematically removed from each of the remaining years (2002:2007), and filled using the same methods. The algorithm produced a predicted annual burnt area that was more than 96% accurate ($R^2 > 0.96$, mean absolute error $< 1\%$) for all six years.

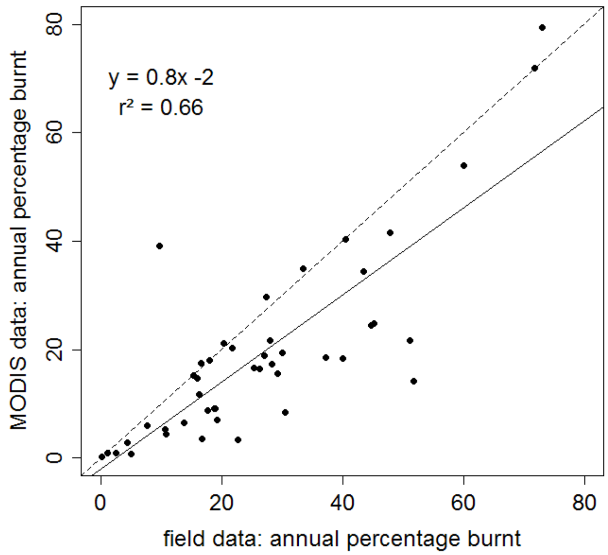

Figure 5.9: **Comparing annual burnt area recorded from field records in protected areas and from the MODIS burnt area product.** Dashed line represents a 1:1 relationship, solid line a linear regression (equation shown above). The MODIS product is consistently lower than the field data, probably because it can not identify small fires (< 500 m) and also because the field data do not account for patchy burns.

5.7.3 Auxiliary information on the mixed effects modelling

Here three tables are presented which give the results of all mixed effects analyses performed. The first summarises the field data mixed effects analysis, the second shows the results of the same analysis when only 8 years of data are used for each park. The final table gives results for three different regional analyses run on different subsets of the data: low rainfall areas only, high rainfall areas only, and areas with she same environmental attributes as the field data.

Table 5.5: Comparing all models from the mixed effects modelling on the long-term data from 10 protected areas in southern Africa. Including a term for the mean annual rainfall (rainfac) does not improve explanatory power, and including the previous years burnt area (pvsBA) as a factor is only significant when the autoregressive (AR(1)) covariance structure is not used.

model	df	k	int	coef1	coef2	coef3	covariance	random effects	$\triangle BIC$	w_i	$\triangle AICc$	w_i
rain + season	435	5	24.98 ***	0.69 ***	0.23 ***		AR(1)	int	0	0.866	0	0.633
rain	436	4	24.98 ***	0.71 ***			AR(1)	int	4	0.104	8	0.010
rain + season + FDI	434	6	24.98 ***	0.69 ***	0.23 ***	0.02 ns	AR(1)	int	8	0.014	4	0.077
rain + season	435	7	25.02 ***	0.70 ***	0.23 ***		AR(1)	int+slope	10	0.005	2	0.203
rain * rainfac	435	6	20.42 ***	0.77 ***	7.63 ns	-0.10 ns	AR(1)	int	11	0.004	7	0.021
rain + pvsBA	435	4	20.52 ***	0.67 ***	0.18 ***		Indep	int	11	0.003	15	0.000
rain + FDI	435	5	24.97 ***	0.71 ***	0.04 ns		AR(1)	int	12	0.002	12	0.001
rain + pvsBA	435	5	24.31 ***	0.70 ***	0.03 ns		AR(1)	int	15	0.001	15	0.000
rain + pvsBA	435	7	26.00 ***	0.72 ***	-0.03 ns		AR(1)	int+slope	15	0.000	7	0.019
rain	436	6	25.01 ***	0.72 ***			AR(1)	int+slope	15	0.000	11	0.003
rain + season + FDI	434	8	25.02 ***	0.70 ***	0.23 ***	0.01 ns	AR(1)	int + slope	19	0.000	7	0.024
rain + season	435	4	24.97 ***	0.67 ***	0.21 **		Indep	int	19	0.000	23	0.000
rain	436	3	24.95 ***	0.69 ***			Indep	int	20	0.000	28	0.000
rain * rainfac	435	8	20.46 ***	0.76 ***	7.66 ns	-0.07 ns	AR(1)	int + slope	21	0.000	9	0.008
rain + FDI	435	7	25.01 ***	0.72 ***	0.04 ns		AR(1)	int+slope	23	0.000	15	0.000
rain + pvsBA	435	7	25.07 ***	0.72 ***	ns		AR(1)	int+slope	26	0.000	18	0.000
rain * rainfac	435	5	20.25 ***	0.75 ***	7.85 ns	-0.10 ns	Indep	int	27	0.000	27	0.000
rain + season + FDI	434	5	24.97 ***	0.67 ***	0.21 **	ns	Indep	int	28	0.000	28	0.000
rain + FDI	435	4	24.95 ***	0.69 ***	ns		Indep	int	29	0.000	33	0.000
rain + pvsBA	444	3	18.17 ***	0.65 ***	0.26 ***		Indep	none	31	0.000	40	0.000
rain	436	6	24.39 ***	0.70 ***			Indep	int+rainfac	38	0.000	33	0.000
rain * rainfac	443	4	20.19 ***	0.75 ***	7.45 ***	-0.10 ns	Indep	none	53	0.000	57	0.000
rain	445	2	24.45 ***	0.68 ***			Indep	none	63	0.000	75	0.000
rain	444	5	23.93 ***	0.70 ***			Indep	rainfac	64	0.000	64	0.000
rain + season	444	3	24.47 ***	0.66 ***	0.20 **		Indep	none	64	0.000	72	0.000
rain + FDI	444	3	24.45 ***	0.68 ***	0.01 ns		Indep	none	71	0.000	79	0.000
rain + season + FDI	443	4	24.47 ***	0.66 ***	0.20 **	0.01 ns	Indep	none	72	0.000	76	0.000
season	436	4	24.73 ***	0.31 ***			AR(1)	int	135	0.000	139	0.000
season + FDI	435	5	24.74 ***	0.31 ***	-0.12 ns		AR(1)	int	142	0.000	142	0.000
null	437	3	24.72 ***				AR(1)	int	143	0.000	151	0.000
FDI	436	4	24.73 ***	-0.09 ns			AR(1)	int	151	0.000	155	0.000
season + FDI	435	7	24.74 ***	0.31 ***	-0.12 ns		AR(1)	int+slope	154	0.000	146	0.000
season	436	3	24.72 ***	0.31 ***			Indep	int	156	0.000	164	0.000
FDI	436	6	24.73 ***	-0.09 ns			AR(1)	int+slope	163	0.000	159	0.000
null	437	2	24.68 ***				Indep	int	163	0.000	175	0.000
season + FDI	435	4	24.73 ***	0.31 ***	-0.09 ns		Indep	int	164	0.000	168	0.000
FDI	436	3	24.69 ***	-0.09 ns			Indep	int	170	0.000	179	0.000
season	445	2	24.26 ***	0.30 ***			Indep	none	180	0.000	192	0.000
null	446	1	24.23 ***				Indep	none	184	0.000	200	0.000
season + FDI	444	3	24.27 ***	0.30 ***	-0.08 ns		Indep	none	187	0.000	196	0.000
FDI	445	2	24.24 ***	-0.09 ns			Indep	none	192	0.000	204	0.000

df = degrees of freedom, k = number of model parameters, int = intercept, coef 1,2,3 = coefficients of the different terms in the model, The $\triangle BIC$ and the $\triangle AIC$ are the difference in the Bayesian Information Criterion and Akaike Information Criterion between each model and the most likely model (values less than 4 indicate that the models are equally probable). w_i = BIC and AIC weighting respectively, rain = accumulated rainfall, season = extent of the dry season (rainfall concentration), FDI = number of high FDI days.

Table 5.6: Results of an LME analysis run using only 8 years of data for each protected area for comparison with the MODIS dataset. The results are comparable - although a model with only rainfall rather than rainfall and seasonality has a slightly higher BIC weighting in this analysis. The coefficients are very similar to a model run on all the data.

model	df	k	int	coef1	coef2	coef3	covariance	random effects	$\triangle BIC$	w_i	$\triangle AICc$	w_i
rain	86	3	17.25 ***	0.60 ***			Indep	int	0	0.419	2	0.090
rain + season	85	4	17.49 ***	0.58 ***	0.28 *		Indep	int	0	0.339	0	0.237
rain	86	4	17.13 ***	0.59 ***			AR(1)	int	2	0.128	2	0.092
rain * rainfac	85	5	16.95 ***	0.68 ***	0.82 ns	-0.15 ns	Indep	int	5	0.042	2	0.093
rain + season	85	5	17.41 ***	0.58 ***	0.25 *		AR(1)	int	5	0.042	2	0.095
rain	86	6	17.75 ***	0.65 ***			AR(1)	int+slope	7	0.013	2	0.095
rain * rainfac	85	6	16.78 ***	0.64 ***	0.81 ns	-0.08 ns	AR(1)	int	7	0.011	2	0.074
rain + season	85	7	18.20 ***	0.65 ***	0.25 *		AR(1)	int+slope	9	0.004	2	0.100
rain * rainfac	85	8	18.14 ***	0.78 **	-0.53 ns	-0.22 ns	AR(1)	int + slope	11	0.002	1	0.120
rain	86	6	17.25 ***	0.60 ***			Indep	int+rainfac	14	0.000	9	0.003
rain	98	2	17.10 ***	0.46 ***			Indep	none	16	0.000	20	0.000
rain + season	97	3	17.38 ***	0.45 ***	0.30 *		Indep	none	16	0.000	18	0.000
rain * rainfac	96	4	17.09 ***	0.64 ***	0.62 ns	-0.32 ns	Indep	none	20	0.000	19	0.000
null	87	2	16.07 ***				Indep	int	20	0.000	24	0.000
season	86	3	16.40 ***	0.33 *			Indep	int	20	0.000	22	0.000
null	87	3	15.94 ***				AR(1)	int	23	0.000	25	0.000
null	99	1	16.11 ***				Indep	none	24	0.000	30	0.000
season	86	4	16.35 ***	0.31 *			AR(1)	int	24	0.000	24	0.000
season	98	2	16.43 ***	0.32 *			Indep	none	25	0.000	29	0.000
rain	97	5	17.29 ***	0.47 *			Indep	rainfac	29	0.000	26	0.000
rain + season	85	7	24.53 ***	1.02 ***	0.11 ns		AR(1)	int+slope	63	0.000	56	0.000
season	86	6	25.12 ***	0.27 ns			AR(1)	int+slope	107	0.000	102	0.000

Headings are the same as in Table 5.5

Preface: Chapter 6

This chapter was published in the proceedings of the 2009 International Geosciences and Remote Sensing Symposium (IGARSS)

It is a methods chapter, which documents an algorithm for identifying individual fires from burned area maps. The MODIS burned area product identifies burnt pixels and their approximate date of burning. In order to derive fire size information from these data it is necessary to allocate each burned pixel to a particular fire. To do this some assumptions need to be made about how fires spread in a landscape.

Information on the frequency and size distribution of fires is useful for a number of different reasons, but I was particularly interested in using it to explore the effects of people on fire regimes in southern Africa. This chapter describes the algorithm used and tests it against other spatial data on fires. It then briefly demonstrates some patterns of fire-size and frequency in southern Africa.

Prof David Roy, who developed the MODIS burned area product, is a co-author on this paper. He provided ideas on the algorithm development and helped me with the sensitivity analysis.

Chapter 6

Identifying individual fires from satellite-derived burned area data

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6.1 Abstract

An algorithm for identifying individual fires from the Modis burned area data product is introduced for southern Africa. This algorithm gives the date of burning, size of fire, and location of the centroid for all fires identified over 8 years in Africa south of the equator. The results are compared with other available spatial information on fires, and tested to see whether they give reasonable results in a range of different fire systems in the region. Initial results indicate that humans can have massive impacts on fire size distributions and on the area burned by large fires. This information on fire number and fire size can be used to ask important questions on the effect of increasing human ignitions, and the barriers to fire spread in savanna systems.

6.2 Introduction

One of the many ways in which moderate-resolution satellite imagery has expanded our view of the earth system is the information that it has been able to provide on fire. Mapping fire over large regions is complicated because the occurrence of fire at a single point in space and time is a stochastic process which depends upon many interacting factors. In Africa until daily remotely sensed information became available information on regional fire regimes was limited to anecdotal accounts supported by some localised field records (Frost, 1999; Trollope, 1984; Phillips, 1930).

In the last few years, however, satellite information has been used successfully to explore the spatial and temporal patterns of burning on the continent (Barbosa *et al.*, 1999; Cahoon *et al.*, 1992; Giglio *et al.*, 2006; Silva *et al.*, 2003; Verlinden & Laamanen, 2006; Archibald *et al.*, 2009). However, one key piece of information still missing is information on ignition frequency, fire size and fire number. Active fires provide data on the temporal patterns of fire, fire intensity and fuel loads. Burn scar data record area burnt and fire return period. However, it has not been possible to identify individual fires, so it has not been possible to ask questions about human effects on ignition frequency, and about the barriers to fire spread.

Here we introduce a method for identifying individual fires from the MODIS burnt area (MODB45) product, and describe some ways that it can be used to describe the different fire regimes in the southern African region and to test hypotheses about ignition frequency and fire spread. These data help us to understand the patterns of fire in southern Africa - and in particular the effect that human activity has on fires.

6.3 Methods

An evaluation version of the MODIS MOD45B burnt area product (Roy *et al.*, 2008) is available from 2000 to 2008. This product gives the location and approximate day of burning of burn scars at 500m resolution. It is accompanied by quality flag information on the confidence of the detection as well as a monthly data product indicating which pixels were 'invalid' i.e. unable to be classified as either burned or unburned.

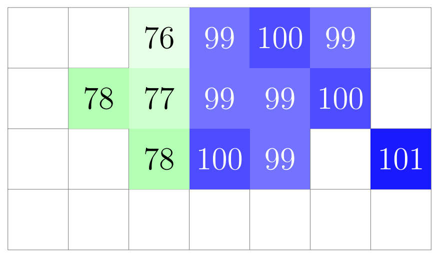

Figure 6.1: Demonstrating the algorithm for identifying individual fires. Pixel shade and pixel number indicate the day of burning. Neighbouring pixels which burned within 8 days of each other are classified as the same fire. Diagonal pixels are included as neighbours. In this instance two separate fires were identified - one with mean burn date on day 77 and one on day 99.

Table 6.1: Sensitivity analysis on the effect of using diagonals and changing the time period on the fire size statistics. Total number of fires as well as the percentage of fires in each of 6 size classes are reported for one fire year (2003). Including diagonals and using an 8-day cut-off results a smaller proportion of very small fires.

	# fires	<1 km	1-5 km	5-10 km	10-50 km	50-100 km	100-500 km	>500 km
8-day with diagonal	261×10^3	51	34	8	6	0.62	0.39	0.07
8-day no diagonal	343×10^3	57	31	6	5	0.46	0.27	0.04
4-day with diagonal	525×10^3	66	26	4	3	0.27	0.16	0.02
4-day no diagonal	703×10^3	73	22	3	2	0.18	0.11	0.01

These data were used to identify individual fires using a modified flood-fill algorithm (Figure 6.1). All burnt pixels start off as unclassified, and are then allocated individual fireID's based on the following rules: the first burnt pixel is given a fireID of 1. All burnt pixels neighbouring this pixel, including diagonals (8 possible neighbours), are then identified. If any of these pixels is recorded as burned within 8 days of the centre pixel, it is given the same fireID. The neighbours of these pixels are then identified, and tested to see whether they had burned within 8 days of their centre pixel, in which case they are given the same fireID.

This process continues until no more neighbouring pixels can be found that have burned within 8 days. The next unclassified burnt pixel is then identified and given a fireID of 2. The same flood-fill process is repeated until all pixels have been allocated an individual fireID.

Eight days was used as a cut-off because that is the temporal accuracy of the original MODIS data (Roy *et al.*, 2008). Sensitivity analyses were run to investigate the effect of different cut-off times and of including or excluding diagonal neighbours on the fire size statistics.

The individual fires identified were then compared with annual fire maps created by the Kruger National Park. These fire maps are produced with information from the field rangers on the date and location of individual fires and corroborated using satellite data (Figure 6.2). The total number of fires identified by each method each year was compared over a range of size classes (from 2000-2006). The estimated area burned by fires of different size classes was also compared.

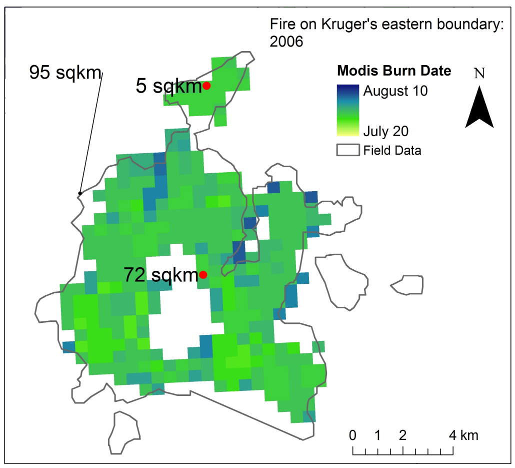

Figure 6.2: Comparing fires identified by field data and from the Modis burn scar data. Colours represent day of burning (ranging from July 20 to August 10). Where the field data identified one fire of 95 km^2, the Modis algorithm identifies two fires of 72 and 5 km^2 each.

The Modis fire size data were then used to look at fire size distributions in different savanna systems in southern Africa. Information on rainfall, tree cover, human population density and burnt area were collated at 1-degree resolution over southern Africa (see Archibald *et al.* (2009) for information on data collection). Three representative grid squares were selected in each of four different regions, representing a range of rainfall, population densities, and tree covers. The Kalahari has low rainfall, tree cover and people, Northern Angola has high rainfall and tree cover, but relatively few people. Zambia represents median rainfall, tree cover and human densities, and Malawi has similar rainfall and tree cover to Zambia, but very high human population densities. Fire size class distributions were computed for each 1-degree grid and compared across these regions. Because large fires are known to contribute disproportionately to the total area burned

Yates *et al.* (2008), the percentage area burned by each size class was also calculated for each pixel.

6.4 Results

6.4.1 Sensitivity Analysis

As would be expected, including diagonal pixels in the fire algorithm resulted in fewer fires being identified overall, and a smaller proportion of them being small fires ($< 1\text{km}^2$, Table 6.1). On the other hand, if 4-days instead of 8-days was used as the cut-off (i.e. neighbouring pixels had to have burned within 4 days of each other to be identified as the same fire) then more fires were identified, and more of these fires were small fires.

6.4.2 Comparison with field data

The fire size distributions from the two different data products were similar over the 6 year comparison period (Figure 6.3a). The Modis method identified more small fires than the field data (paired t.test, $p = 0.002$, $n = 6$), but the number of fires larger than 1km that were identified by both methods were similar (paired t.test $p = 0.62$, $n = 6$). The difference in small fires is unlikely to be important as the area burnt by these very small fires is negligible ($\approx 1\%$: Figure 6.3b).

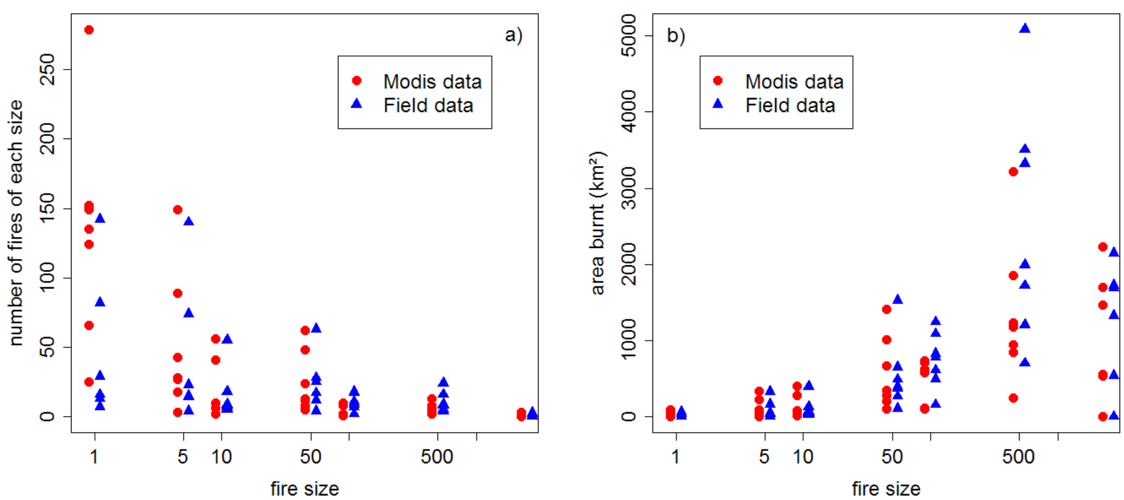

Figure 6.3: Comparing a) the fire size distributions and b) area burnt by fires of different sizes identified by two different methods over a six year period in the Kruger National Park, South Africa

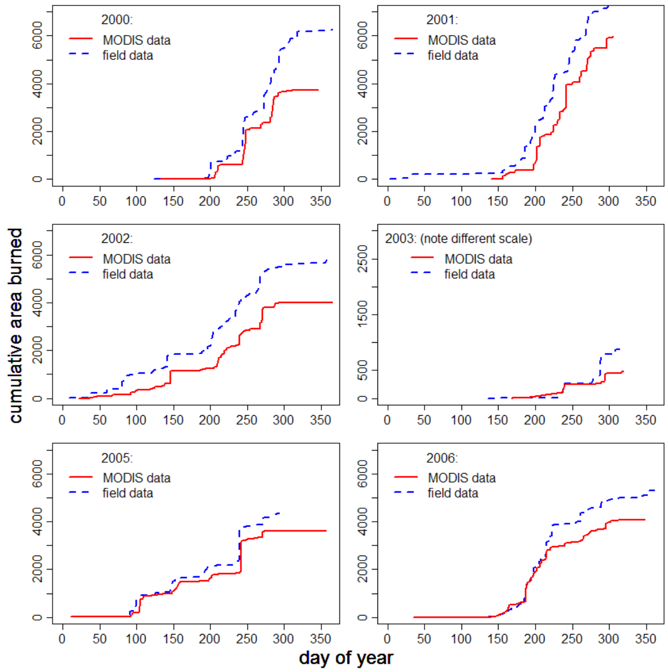

Figure 6.4: Cumulative area burnt by individual fires identified by two different methods in the Kruger National Park, South Africa. Fire areas were accumulated over the year after being sorted by start date. Six different fire years are shown.

Figure 6.4 shows how the area burnt accumulates over the year for the six years. The occurrence of large fires is represented by steps in the curve. Both data sources identified the same fires, but because fire size estimated from the field data is usually higher than that estimated from Modis data the total area burnt each year is higher. The true accumulation curve is likely to be somewhere between these two lines: Modis data does not pick up all the burn scars, but field data does not pick up the patchiness of many of the fires (Figure 6.2).

6.4.3 Fire size distributions in different parts of southern Africa

There are substantial differences in fire size distributions in the four different regions. In the Kalahari and Angola 13% and 9% of the fires were larger than 10 km^2, compared with 4% and 1% in Zambia and Malawi respectively. This translates to massive differences in the area burned by large fires (Figure 6.5): in Malawi most of the area is burned by fires 1-10 km^2 in area, in Zambia, most of the area is burned by fires of 10-100 km^2, whereas in Angola and the Kalahari over 40% of the area is burned by fires > 500 km^2.

A full investigation of the drivers of these patterns is beyond the scope of this paper, but the pattern does not appear to be related to rainfall or the total area that burns. The strongest relationship found was with human population density: areas with more people have fire-size distributions skewed towards the lower fire sizes.

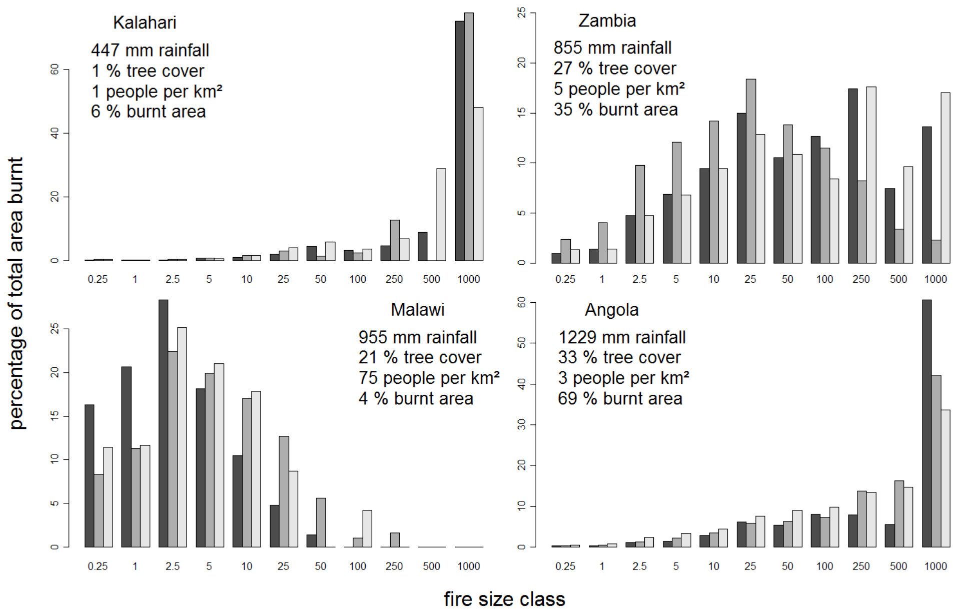

Figure 6.5: The percentage of the total area burned by fires of different sizes in four different parts of southern Africa. Data from three representative 1-degree grid squares are reported for each region. The mean (average of the three grid squares) environmental characteristics for each region are also shown. In areas with fewer people substantially more of the landscape is burned in large fires. This pattern seems to hold across the rainfall gradient

6.5 Conclusions

The flood-fill algorithm developed here identifies individual fires and calculates the area burnt, the date of burning, and the centroid of each fire. Many of the fires identified by the algorithm are very small: 1-4 pixels (0.25-1 km^2). Despite this, these data can successfully differentiate between systems with many small fires, and systems with a few large fires. The differences in fire size distributions shown between areas with low and high human population density are striking, and point to some intriguing relationships between human ignitions and fire spread.

One of the biggest questions remaining in African savannas concerns the effect that humans have had on fire regimes since they first began to manipulate fire several hundred thousand years ago. Information on fire size and fire number can be used to test hypotheses on the current human impact on ignition frequency, timing, and fire spread.

These data and the spatial fire data recorded by the Kruger National Park give comparable results. The field data have their own potential sources of error so any differences between the two data sets can not be attributed to error in either method. The flood-fill method is very sensitive to changes in the cut-off date for neighbouring pixels to be considered one fire, and to the use of diagonals as neighbours. The parameters chosen here are considered the most appropriate for the spatial resolution and temporal accuracy of the MODB45 data (500 m and 8-days respectively).

Preface: Chapter 7

This chapter is in press in the International Journal of Wildland Fire. It provides a regional description of fire regimes in southern Africa based on a range of remotely-sensed information. The paper integrates findings from the previous four chapters to give a best-available view of fire on the sub-continent and highlight areas of further research. In particular, this chapter aims to demonstrate when fires in southern Africa fit with theory of savanna fire regimes, and when they depart from current thinking.

One theory tested in this paper is whether '1 % of the fires burn 99 % of the area' in southern Africa. This is a finding that applies across a range of systems from boreal forests to grasslands, and a substantial body of work has developed around fire size-frequency distributions and the mechanisms which create power-law distributions for fires. We show that much of this theory breaks down in southern African situations.

Similarly we test whether fires at the end of the dry season are hotter and larger than early-season burns, as has been shown elsewhere. This has important implications for fire management. Southern Africa - where most of the fires are still ignited by rural people - is a useful contrast to Northern Australia, where managers are trying to institute a seasonal pattern of fire more similar to that created by aboriginal burning practices which have now fallen away.

Finally this paper serves the practical purpose of documenting information on burned area, fire season, and fire return period in a way that can be used by managers and policy makers - particularly to fulfill IPCC requirements when calculating greenhouse gas emissions from wildfire.

Co-authors on this paper are Dr Bob Scholes, Prof David Roy, Dr Gareth Roberts and Dr Luigi Boschetti. This chapter was written at the suggestion of Bob Scholes and he gave vital input into what information needed to be presented, and helped to clarify my thinking about fire intensity and fire return period. David Roy and Luigi Boschetti both worked on the burned area data and analysis. Gareth Roberts provided the fire radiative power information and spent a lot of time giving input on how to present and interpret these data.

Chapter 7

Southern African fire regimes as revealed by remote sensing

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7.1 Abstract

Fire regimes in southern Africa are described using a range of remotely-sensed products. Fire characteristics such as annual burnt area, fire frequency, fire seasonality, fire radiative power, and fire size distributions are compared across different countries, vegetation types and land use categories, and regional patterns are explored.

The fire regime differs across a gradient of human land use intensity. The pattern can be explained by the differential effect of humans on ignition frequencies and fire spread: ignition frequency shows a unimodal distribution against population density, peaking at around 10-20 people per km^2. The mean size of the fires declines steeply as human densities increase above 1 person per km^2.

Contrary to findings in the savannas of Australia there is no obvious increase in fire size or fire intensity from the early to the late fire season in southern Africa, presumably because patterns of fire ignition are very different. Similarly, the importance of very large fires in driving the total annual area burnt is not obvious in southern Africa - fire density is a better predictor of burnt area than fire size.

These results point to the substantial effect that human activities can have on fire in a system with high rural population densities and active fire management. Not all aspects of a fire regime are equally impacted by people: the overall pattern is strongly influenced by climate and vegetation controls on fuel availability, particularly dry grass. The diversifying and improving set of remotely sensed fire products is invaluable in providing a comprehensive view of the patterns of fire ignition and spread in different southern African landscapes.

7.2 Introduction

When the first satellite-derived information on fires became available in the 1990s one of the most striking features was the sheer number of fires in Africa. Global maps of fire occurrence were dominated by a mass of burn points centred on Africa, which caused it to be dubbed 'The Fire Continent' (Goldammer, 2001).

Of course, these data only confirmed the observations of ecologists and African pastoralists that fire was an important part of these ecosystems. Savanna and grassland environments produce fine fuels which dry out rapidly when there is no rain. The seasonal rainfall over much of the region means that fuels can develop and cure over just one year, resulting in some of the most frequent fire return intervals on earth. Moreover, human ignition and fire management is pervasive throughout Africa, where much of the population is not yet urbanised, and communal land management is common.

Africa has been a source of seminal research into the ecological effects of fire intensity, frequency, and season in savanna, grassland and fynbos systems (Phillips, 1930; Belsky, 1992; Bond *et al.*, 2003; Gignoux *et al.*, 1997; Pellew, 1983; Trollope & Tainton, 2007), and the continent boasts a suite of long-term fire exclusion and fire application experiments (Menaut, 1977; Brookman-Amissah *et al.*, 1980; Swaine *et al.*, 1992; Govender *et al.*, 2006; Higgins *et al.*, 2007; Booysen & Tainton, 1984).

What the satellite data provide, which had not been available before, is a spatially-explicit and comprehensive view of the distribution of fire in Africa. Thus, for the first time, it is possible to describe fire regimes not only at localities, but across the whole continent. This makes it easier to expand our view of fire from a disturbance acting almost randomly on the system, to a process which is affected by the climate, topography, vegetation and social context in which it occurs. At the same time the need to characterise and quantify patterns of fire has increased, prompted by greenhouse gas accounting efforts and climate change research (Scholes *et al.*, 1996; Schultz *et al.*, 2008), as well as by the desire of conservation managers to provide a more natural fire regime (Brockett *et al.*, 2001).

The frequency, seasonality, intensity, severity, fuel consumption and spread patterns of fires that prevail are referred to as the fire regime (Gill, 1975; Bond & Keeley, 2005). How fire regimes will change as human population, their land use practices, and the climate change is unclear (Bowman *et al.*, 2009). Good descriptions of fire regimes at regional scale are needed to better understand these processes. In the past, fire regime data have only been available for relatively small areas in Africa, almost all of which were protected areas where the fire regime was substantially different from the general, inhabited landscape. Furthermore, the sample did not include representatives of all the climate and vegetation combinations on the subcontinent.

The data available from remotely sensed data on fire in Africa have improved substantially in the last few decades. The first satellite fire products identified the date and time of actively burning fires ('hot spots'), but had biases introduced by the time of satellite overpass (Giglio, 2007). The radiometer sensors that provide these data are now more sensitive and resolved, and can also be used to provide an indication of the rate of energy release of the fires - Fire Radiative Power (Giglio *et al.*, 2006; Wooster *et al.*, 2003). Fire radiative power (FRP) gives an indication both of the biomass consumption rate and the fireline intensity (Roberts *et al.*, 2005, 2009; Smith & Wooster, 2005). These data are available over nearly a decade - sampled four times daily at 1km resolution (from the MODIS sensor on the Terra and Aqua polar-orbiting platforms), and every 15 minutes at 5km resolution (from the SEVERI sensor on the Meteosat geostationary satellite). Thus it is possible to characterise the daily and seasonal patterns of burning. Moreover, several algorithms to identify and map burned areas have been developed (Barbosa *et al.*, 1999; Plummer *et al.*, 2006; Giglio *et al.*, 2009; Roy *et al.*, 2005b; Tansey *et al.*, 2004), which give an indication of the total area burned by fire, and can be used to derive the season and frequency of fire. The most complete of these burnt area data span nearly a decade, and can therefore give reliable estimates of fire frequency in places where the average return time is only a few years. Finally, because the burned area data provide information on the spatial extent of burning they can be used to identify individual fires. This provides a route to the most elusive information of all: ignition frequency and fire size distributions.

The wide range of data sources now available allows for a more nuanced view of fires on this continent. The initial assessment of Africa as the fire hot-spot of the globe was based only on active fire data i.e. the number of actively burning pixels recorded at certain times of day. If these fires were all very small - for example, crop fires or small management burns - then initial estimations of the extent and importance of African wildfires might be inflated. In fact, recent models suggest that the fires from C4 systems and in Africa contribute much less to global emissions of greenhouse gases and aerosols than initially expected (Randerson *et al.*, 2005).

By combining all sources of remotely-sensed information it should now be possible to provide a full description of the fire regime of any point across the continent. How will these data be useful? For land managers and policy makers it provides information on which to base regulatory decisions. Control and management of fire has always been an important focus of national land strategies in southern Africa. In the future the attention given to fire management is likely to increase as countries attempt to understand and reduce vulnerability to climatic change, and as incentives to manipulate fire regimes to store carbon increase. Baseline data on the extent, season and intensity of fire are required before decisions can be made on what fire regimes are appropriate, and also for testing whether management interventions are effective.

Fire-management strategies all operate from the assumption that it is feasible to manage fire in southern African ecosystems, but many questions still remain on the limits of human control of fire, and which aspects of a fire regime can be manipulated. Indeed, recent work in southern African savannas suggests that anthropogenic fire management has little impact, and the extent of fire is controlled by rainfall (Van Wilgen *et al.*, 2004). For scientists who aim to understand the role of humans in the fire-vegetation-climate system (Archibald *et al.*, 2009) and the importance of fire in determining biome distributions (Bond, 2005) these remotely-sensed products provide the data to test their theories. Correlative studies at regional scales can now be used to supplement experimental and plot-level data.

This paper provides quantitative data on annual burnt area, fire frequency, fire season, fire intensity and fire size distributions derived from remotely-sensed data sources for southern Africa. Data are summarised by country, by vegetation type and by land use. They are mapped at quarter degree and 1-degree resolution to demonstrate regional patterns and the limits of fire on the sub-continent. The data are available continent-wide but in order to focus on regions with which we had some personal ecological experience this study is limited to southern Africa. This paper is a summary of our current knowledge, and a springboard for future research: it aims to expand fire research out of the national parks and protected areas of the region and to highlight the importance of humans in affecting fire in Africa.

7.3 Methods

7.3.1 Data

Satellite fire data

Burnt area: Eight years of burnt area data from the MODIS (MCD45A1) product were used. These data are produced at 500m resolution using a view direction-corrected change detection procedure to identify pixels that burned and the approximate day of burning (accurate to within 8 days) (Roy *et al.*, 2005b). When insufficient input data are available to run the algorithm due to excessive cloud cover or sensor problems pixels are flagged as 'no data'. A southern African accuracy assessment indicates that the product can identify about 75% of the burnt area (Roy & Boschetti, 2009). This accuracy is expected to decrease with increasing tree cover (Roy *et al.*, 2008). Improved spatial resolution (500m instead of 1km) and the availability of quality flag information are a major improvement over previous burnt area products.

Annual burnt area: The monthly burned area data were summarised annually to produce a burnt/unburnt layer for each fire year (January to December). Boschetti & Roy (2008) suggest summarising the data using a fire year from April to March for southern African savannas. However, it is more common to use a calendar year, and very little (<0.6%) of the burning occurs from January-March.

Due to technical problems on the satellite there were no burnt area data for June 2001. To fill these data in the annual sums the following method was used: for each year the area burnt in June and the area burnt in the rest of the year were calculated. The 2001 burnt area (no June) was divided by the average burnt area (no June) over all other years to give a ratio indicating the degree to which the 2001 burn year was above or below the mean. The average area burnt in June in all other years was then multiplied by this ratio to give an estimation of the 2001 June burnt area. This filling algorithm was computed separately for each geographic unit used in the analysis (country, vegetation, land use category and 1 degree grid) to accommodate differences in patterns of variability in different parts of the sub-continent. To test the effect of this filling algorithm the July data were systematically removed from each of the remaining years (2002:2007), and filled using the same methods. The algorithm produced a predicted annual burnt area that was more than 96% accurate ($R^2 > 0.96$, mean absolute error $< 1\%$) for all six years.

Fire frequency: Monthly burned area data layers from April 2000 to March 2008 were combined to calculate the number of times a pixel burned in eight years (fire frequency). Pixels which had invalid data more than two times a year on average were excluded. Savanna fires are grass-fuelled, with average return periods ranging from two to six years, so the eight year MODIS dataset can capture a great deal of the variation in fire frequency on the subcontinent. The result was a map at 500m resolution of the number of burns a pixel experienced in eight years (ranging from zero to 13).

Fire return period: Calculating fire return period from fire occurrence data involves fitting a distribution (usually the Weibull distribution) to a set of individual fire return records, and accounting for the censoring which occurs at the beginning and end of the record period (Moritz *et al.*, 2009; McCarthy *et al.*, 2001; Polakow & Dunne, 1999). Although methods for estimating fire return from fire count data are well developed they require an a-priori identification of landscape units within which to estimate parameters, and they make the assumption that the landscape being considered has a uniform fire regime (Polakow & Dunne, 1999). This is likely to be problematic at different spatial scales and particularly in mixed forest-grassland systems, or landscapes of mixed cropland and natural vegetation where different parts of the landscape burn at different frequencies.

Despite this caveat we used the Weibull distribution to estimate a fire return period for different geographic units (country, land use and vegetation classes). The fire return was estimated by randomly selecting 100 500m pixels in each class and fitting a Weibull distribution to the return periods (right-censored data was included, following Moritz *et al.* (2009) and Polakow & Dunne (1999)). The Weibull shape and scale parameters and their confidence intervals were estimated using all data, and also using only data from pixels that burnt at least once in the 8 year period. The difference between these two distributions provides an indication of the impact of having patches that never burn within a fire landscape. The median fire interval (MEI) was then estimated from these parameters following Moritz *et al.* (2009):

$$MEI = b(ln2)^{(1/c)}$$

where b is the scale parameter and c is the shape parameter.

These fire return data allowed for an initial comparison of return periods across geographic units, but a rigorous assessment of fire return periods across Africa is beyond the scope of this paper. For this reason we used raw fire frequency data in many of our analyses.

Fire size and fire number: Individual fires were identified from the MODIS burnt area data using the algorithm described in Chapter 6. This produces a list of points with the size, location of the centroid, the start date, mid-date and end date of each fire across southern Africa. A number of different methods were used to create summary statistics from these data. Firstly, the number of fires in each 1-degree grid point was calculated and converted to a fire density (# of fires per km^2). Then the fires were divided into 12 size classes: <0.25 km^2 (the resolution of the original data), 1, 2.5, 5, 10, 25, 50, 100, 250, 500, 1000, and 2500 km^2. It has been shown in many systems that the majority of the area is burned by the very largest fires: the top 1% of fires burn 99% of the area - (Strauss *et al.*, 1989). To test this in southern Africa we calculated both the number of fires and the area burned by fires in each size class for each 1-degree grid. We also calculated the 95th percentile of fire size for each 1 degree grid cell as a measure of the size of the largest fires experienced in different parts of the sub-continent.

Fire Radiative Power as an index of fireline intensity: Fireline intensity is a measure of the rate of energy released from a fire per unit length of the burning front. It has traditionally been calculated as the product of the dry weight of biomass burned, the energy content of the fuel and the rate of spread of the fire (Byram, 1959). Fireline intensity is a good predictor of the effort required to control a fire. Ecologically, fireline intensity is related to flame length and has effects on the size class of trees which are top-killed (Williams *et al.*, 1999) and on the patchiness of a burn (Hely *et al.*, 2003) (but see Keeley (2009) for a discussion of the limitations of using fire intensity as an index ecosystem response to fire). Fires with higher fireline intensities might also burn for longer, and burn larger parts of the landscape, as they are less likely to be extinguished by night-time weather conditions, moist fuels, or topographic barriers.

Satellite middle-infrared wavelength measurements sensed over actively burning fires can be used to calculate the rate of radiant energy release: the fire radiative power (FRP) (Kaufman *et al.*, 1996). This is measured in units of megawatts per pixel. Given that the energy content of grass fuels is fairly constant, it can also be used to quantify the amount of biomass burned by fires in Africa (Roberts *et al.*, 2005; Wooster *et al.*, 2003). It could also theoretically be related to used as a spatially and temporally continuous measure of the fireline intensity (Smith & Wooster, 2005).

The SEVIRI sensor provides fire radiative power measurements every 15 minutes. It is placed on the Meteosat platform, which flies in a geostationary orbit about 36 000km above the earth centred on the equator. The pixel sizes are of the order of 4.8 x 4.8 km at the sub-satellite point, and somewhat larger in southern Africa. SEVIRI data were processed to FRP using the algorithm of Roberts and Wooster (2008) and used to identify high-intensity fire pixels in a one year period from February 2004 to January 2005. The energy released by individual fires varies greatly over the duration of the fire:

for example, grassland fire FRP has been observed to change by an order of magnitude with the wind direction relative to the unburned fuel bed (Smith & Wooster, 2005), and at night the fire intensity is typically much lower. In our case we were most interested in the maximum fireline intensity - as this affects vegetation processes like grass and tree response to fires (Trollope & Tainton, 2007). Therefore the maximum FRP recorded in each SEVIRI pixel was isolated as an indication of the maximum rate of energy release. At present this index cannot be directly related to the conventional measure of fireline intensity(kW/m) because the length of the flame front is not known. There is ambiguity introduced since a very small, very intense fire could have the same FRP value as a very large, less intense fire.

Seasonal patterns of fire: The average and standard deviation in area burnt each month was quantified by country, vegetation type, land use and 1-degree grid. The month of peak fire activity, as well as the 'seasonality' of fire (how long the fire season is) was calculated for each geographic unit. The median and 95th quantiles of fire size and FRP were also plotted over time to test whether fire size and fireline intensity increase over the dry season.

Geographic stratification and environmental explanatory data

Country boundaries: The current geographic boundaries of the 16 countries south of the equator (including Madagascar) were used to quantify fire regimes for politically-distinct regions. Countries which straddled the equator were clipped, and totals calculated only for the southern hemisphere portion. A one degree grid square was also used to summarise and map data.

Vegetation classes: The 19 major vegetation classes in White's vegetation map of Africa (White, 1983) were reclassified into 7 classes: forest, forest transitions, thicket, savanna (including woodland), grassland, arid shrubland (including desert), and fynbos. Edaphic grassland mosaics were included in the grassland category, woodland mosaics were included in savannas, but forest transitions were maintained as a separate class. These are generally grassy systems with clumps of forest trees. The grass component burns extensively and this vegetation class can be seen to represent the edge of the forest-savanna boundary. All other vegetation (altimontaine, azonal, anthropic) were classed as 'other' and not included in the analysis as their geographic extent was very limited.

Land Use The land use categories were identified by lumping the GLC2000 land cover map (Mayaux *et al.*, 2004) into three broad classes: settlements, cultivated land, and uncultivated land (mostly used for grazing). The World Protected Areas (UNEP-WCMC, 2006) map was overlaid on this to produce a map with four categories: settlements, cultivated, uncultivated and protected areas which represent a gradient of decreasing intensity of human impact.

Other Data: Spatial information on human population density (Ciesin, 2005) was also used to investigate the effect of people on fire in southern Africa. These data were summarised (using the median) by 1-degree grid cell. Spatially explicit datasets on tree cover (Hansen *et al.*, 2003), rainfall (Huffman *et al.*, 2007), grazing density (FAO, 2005) and soil texture (IGBP, 2000) were also used to explore the environmental limits of fire (see Archibald *et al.* (2009) and Chapter 2 for detailed information on these data).

7.3.2 Analysis

The environmental characteristics of pixels which burnt at least once in the 8 year data period were used to characterise the environmental limits of fire on the sub-continent. In Chapter 2 (Archibald *et al.*, 2009) we identified rainfall, tree cover, length of the dry season, grazing density, population density, and soil fertility as potential drivers of burnt area. The median, 75th, 95th, and 99th quantiles of these variables were calculated for burnt pixels and for all pixels in the region and compared.

Annual burnt area, monthly burnt area, fire frequency, and fire radiative power data were summarised by country, land use and vegetation type, as well as by 1-degree grid cell. These data were used to describe fire regimes across environmental, geographic, and human impact gradients in the region.

The proportion and probability of extremely large fires were summarised in a number of ways. First the size of the 95th quantile of all fires in a 1-degree grid was calculated, and these data were mapped and plotted against information on fire number and burnt area to explore how important large fires are in determining annual area burned. Then the median and 95th quantiles of fire size and FRP were plotted over time to test whether fire size and fireline intensity increase over the dry season as has been shown in northern Australia. Finally, human population density was plotted against fire size and fire number to test theories of how human patterns of ignition and land use alter fire-size distributions.

7.4 Results

7.4.1 The environmental limits of fire

On average 11.2 % (sd 0.81) of southern Africa was identified as burned each year by the MODIS burned area product, which is thought to detect about 75% of the burned area mapped using high-resolution images in southern Africa (Roy & Boschetti, 2009). Therefore the mean percentage burned area could be as high as 15%. Invalid pixels (usually due to cloud cover) made up about 3% of the landmass and this area was not included in the calculation.

Fire affected pixels were considered pixels which burned at least once in the 8 year period for which there were data, and 35% of the landmass is classified as fire-affected (Figure 7.1). Most of this area burnt only once or twice, but almost 4% of it burnt every year over the 8 years.

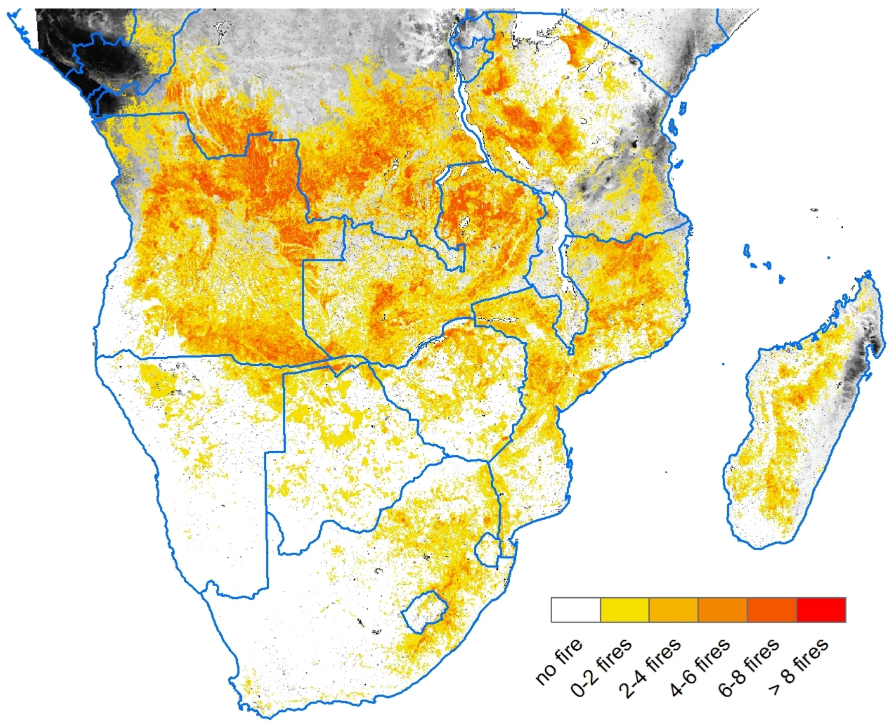

Figure 7.1: The area affected by fire determined from an 8 year satellite burnt area product. Colours indicate the number of times pixels were classified as burned. Grey areas represent pixels which were classified as invalid over the time period: darker grey = more invalid data.

The environmental characteristics of 'fire-affected' pixels give an indication of the environmental limits of fire in southern African savannas (Figure 7.2). Fire does not occur in pixels with tree cover greater than about 55%, human population densities greater than 150 people per km^2, or grazing densities higher than 400 kg/km^2. Fire also does not occur in regions with rainfall less than 320 mm or seasonality less than about 25% (a seasonality score of 0% would occur if an equal amount of rainfall fell in each month of the year, if all the rainfall fell in one month the seasonality would be 100%. See Markham (1970) and Chapter 5 for a complete definition of rainfall seasonality).

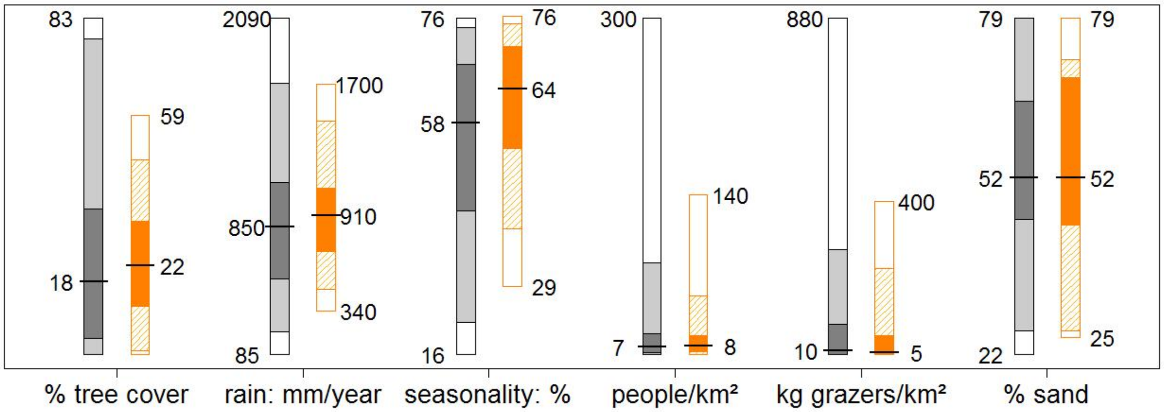

Figure 7.2: The environmental limits of areas that burn in southern Africa (orange, hatched) compared with the environmental limits of the entire region (grey, unhatched). The horizontal line represents the median (50th quantile), dark bars represent the 25 and 75th quantiles, light bars represent the 5th and 95th quantiles, and open boxes represent the 1st and 99th quantiles. Fire-affected areas have higher mean rainfall and tree cover than the entire region, but are also limited in the upper values of rainfall and tree covers in which fire occurs. Fire also occurs more in areas with strongly seasonal rainfall. Fire appears to be limited by very high human densities and grazer numbers.

7.4.2 Fire regimes by country, vegetation, and land use

The countries that show the most fire activity are Angola, Zambia and Mozambique (Figure 7.3). Over 50% of the land area of these countries is affected by fire, and much of this area burned more than four times in the eight year period (return period of approximately two years). Except for the fynbos region in the Western Cape, fires in southern Africa are largely grass-fuelled surface fires, so it is not surprising that vegetation types with a dominant grass layer (savannas, grassland, and forest transitions) burned more extensively, and more frequently, than vegetation types with little grass, such as forest, arid shrubland and thicket (Figure 7.3). Fires in the fynbos are crown fires, consuming dense sclerophyllous shrubs and small trees, with fire return periods in the order of 10-30 years. This eight year dataset is unlikely to characterise their fire frequency accurately (median fire intervals fitted using the Weibull distribution either didn't converge or gave unrealistically high values - Table 7.1).

Median fire return intervals (MEI) for grassland and savanna systems in the region range from 1.7 to about 10 years, depending on the rainfall and degree of human impact (Table 7.1). In Malawi, for example, which has a very high human population density, very little (<5%) of the landscape outside protected areas burns, which means that estimated MEI's are over 100 years. Those parts of the landscape that do burn, however, burn with characteristic return periods of 3-10 years (Table 7.1). A similar pattern is seen in most cultivated areas, where very small percentages of the area burn frequently

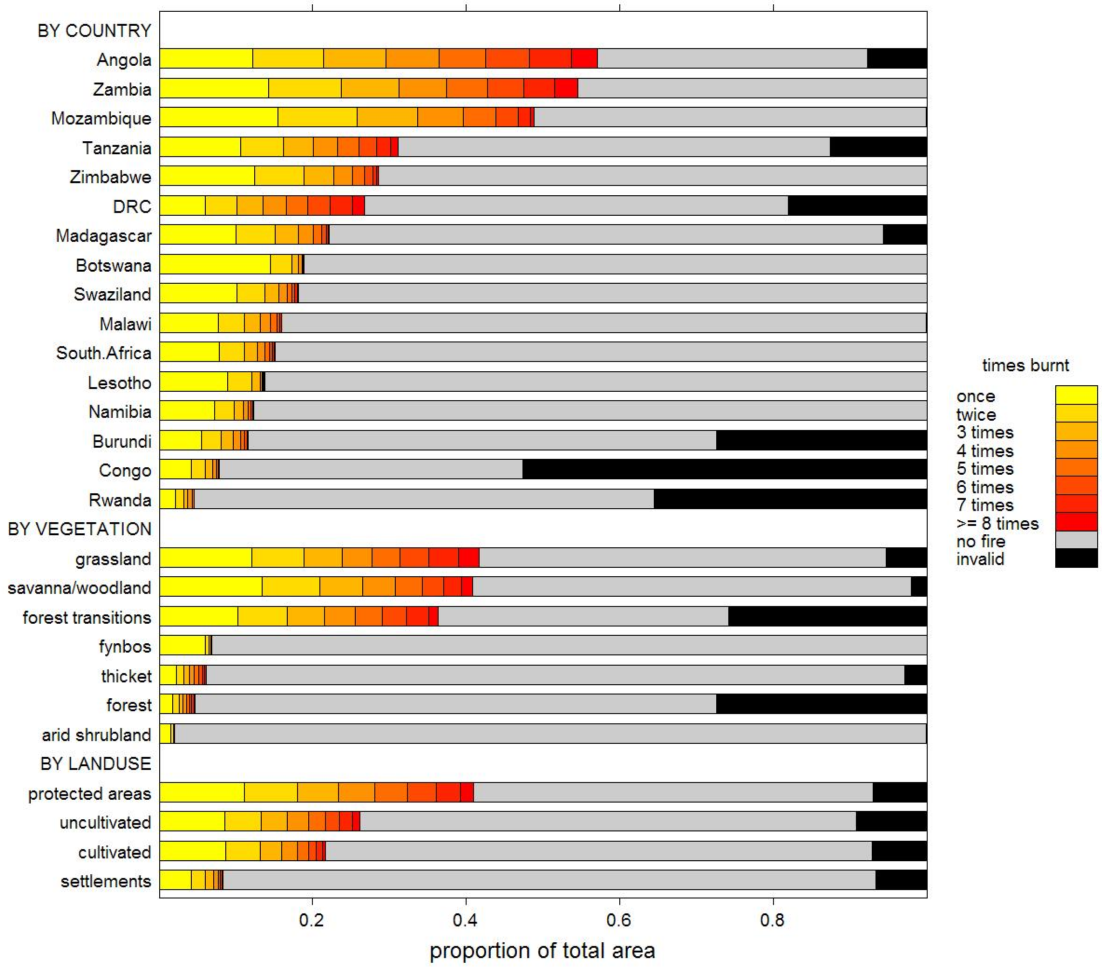

Figure 7.3: The frequency of fire (expressed as the proportion of the total area which burned 0-8 times over 8 years). Data are summarised by country, vegetation type and land use category in southern Africa. Grassy systems (grasslands, savanna/woodland and forest transisions) have substantially more fire than non-grassy systems, and the area affected by fire decreases as human land use intensifies (from grazing, to cultivation to settlements).

(Table 7.1). This highlights the importance of choosing the correct landscape units to calculate fire return intervals.

The seasonal pattern of burning is remarkably similar across the region (Figure 7.5). July, August, and September are the dominant months for burning. Fires start slightly earlier in countries that are closer to the equator, and only the southern-most countries show much burning into October. This supports previous satellite-based studies which noted a progression of fire from northwest to southeast through the dry season (Cahoon *et al.*, 1992; Kendall *et al.*, 1997; Dwyer *et al.*, 2000; Roy *et al.*, 2005b). The winter-rainfall fynbos region clearly has a different seasonal burning pattern. Arid shrubland vegetation in the south-western part of the subcontinent straddles both winter and summer rainfall regimes, and although it burns very little, it shows some fire throughout

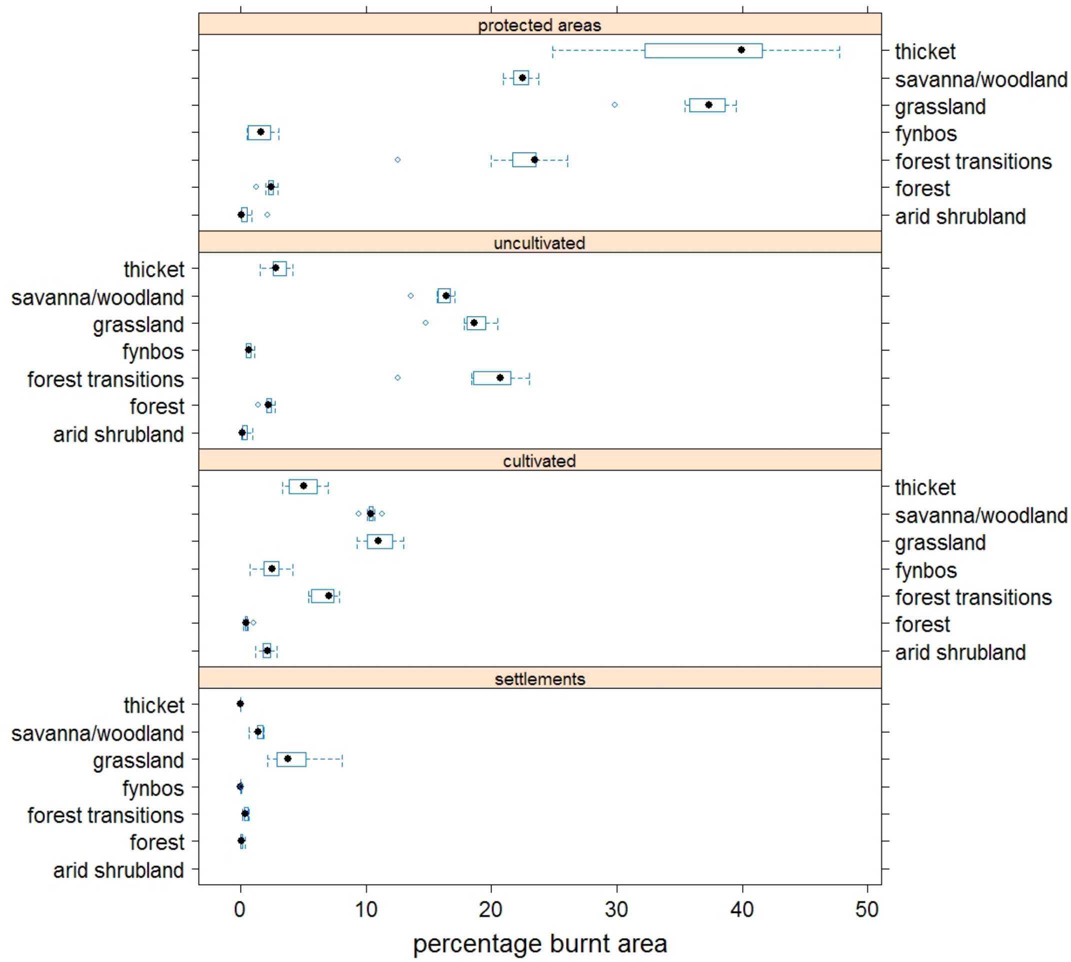

Figure 7.4: The median and 75% confidence intervals of total area burnt each year in different vegetation types under different land uses. Land uses are ordered from least impacted by humans (protected areas) to most impacted (settlements). The high value and large range of values for the thicket protected areas class is due to the fact that the vegetation map classified the Serengeti, which shows extensive burning and is actually a savanna/woodland, as thicket. In general, thicket vegetation classes do not burn (Figure 7.3)

the year. Settled land has a markedly greater proportion of early season burning than other land uses, and more than 80% of the area is burnt by the end of July.

When summarised by vegetation and by land use it appears that certain fire characteristics are more easily influenced by human activities than others (Figure 7.6). Annual burned area is greatly reduced outside protected areas in areas which are utilised by humans and their cattle, and further reduced in areas of cultivation and settlement. Maximum fire size shows the same pattern. In contrast, the season of burning does not change across land use types, and nor does the mean fire return time (except in settlements which generally have much longer return times). Fire radiative power generally decreases as human land use increases, except for the arid shrublands where it is the cultivated areas that have high fire intensities (presumably because these areas are also irrigated), and in Fynbos where FRP remains high across all land uses. Except for the fynbos, which has a markedly different season of burning, return time, and fire radiative power, all vegetation types display variations on a grass-fuelled fire regime (Figure 7.6). This is because areas classified as forest, thicket or arid shrubland inevitably contain some grassy vegetation and it is this which generally burns.

7.4.3 Regional and seasonal patterns

When one maps information on the size of the largest fires and the number of fires per unit area against mean annual burnt area it is clear that areas that burn the most tend to have many fires, but not necessarily the largest fires (Figure 7.7). Flat, arid systems

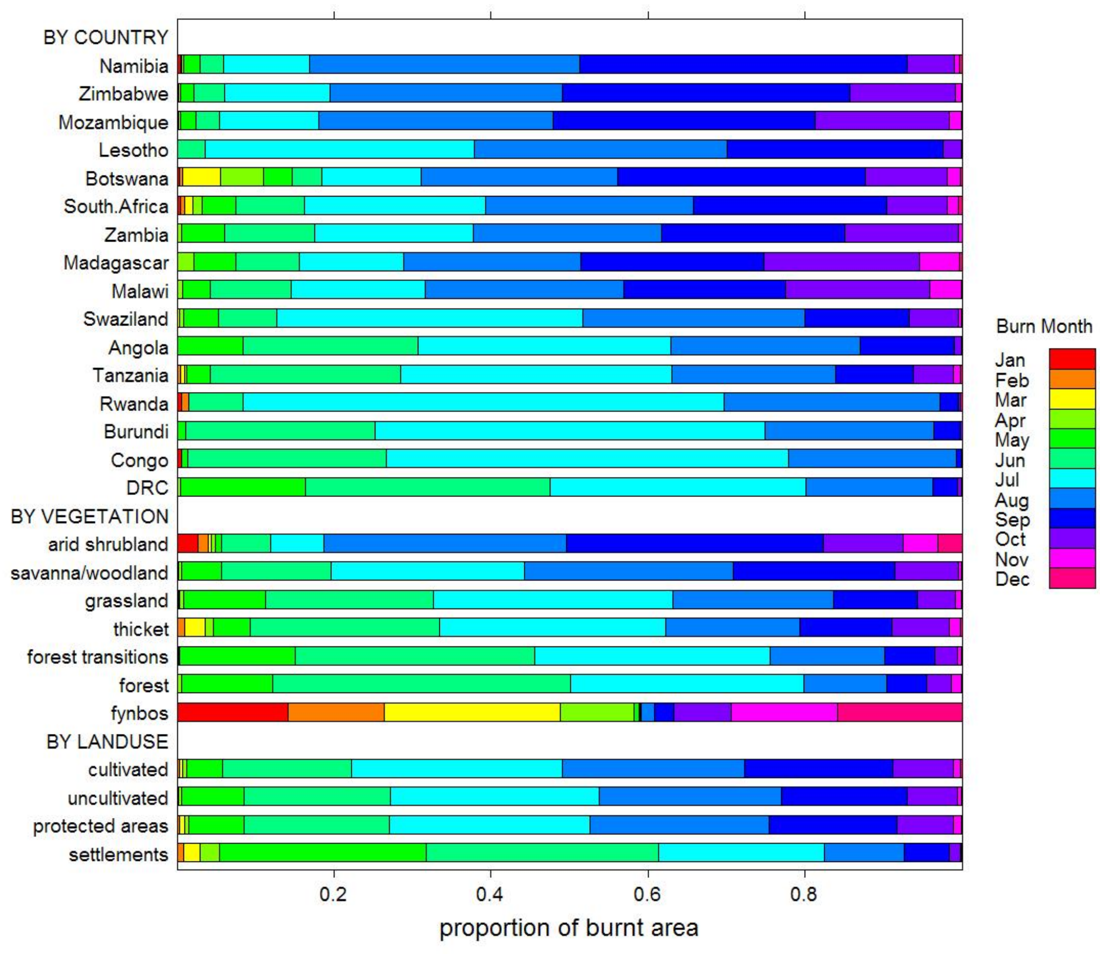

Figure 7.5: Proportion of total area burned each month in the different countries, vegetation types and land use categories in southern Africa. Most areas have very similar seasonal fire patterns (burning from July to October), but the winter rainfall fynbos region burns from November to March, and settlement areas - with very high human densities - burn earlier in the season.

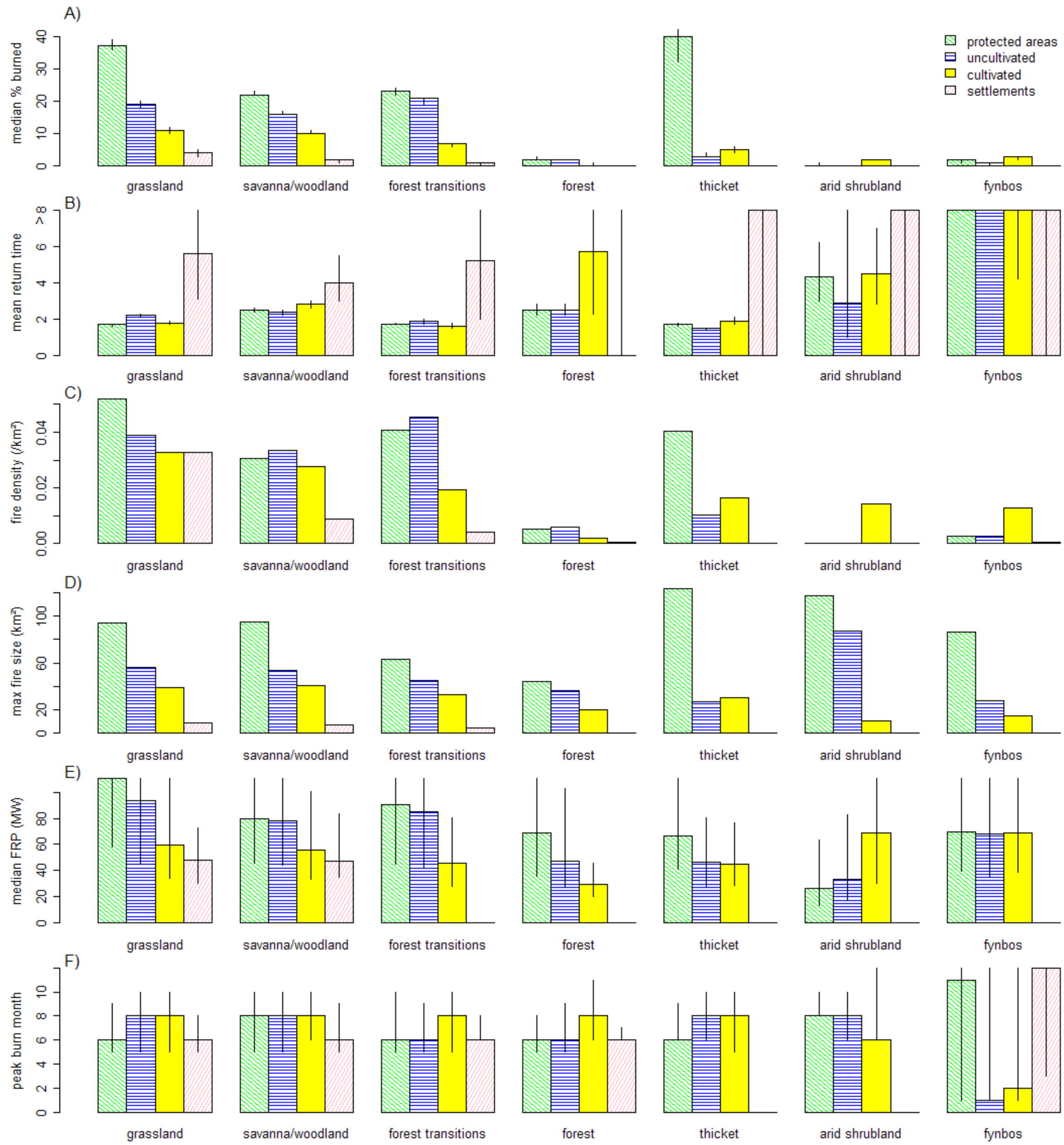

Figure 7.6: Aspects of the fire regime stratified by vegetation types over a gradient of human land use. For more detailed, country-specific data see Table 7.1. A) Median % burned area (+- 25 quartiles) summarised over 8 years. B) Mean fire return periods (years with 25% confidence limits) calculated using only pixels which burned: > 8 means that the Weibull estimation either did not converge or gave values greater than the length of the fire dataset. C) Fire density: the number of fires per km^2 per year. D) The size of the top 1% of fires in each landscape type. E) the median (+- 25 percentiles) Fire Radiative Power (in MW per 5 km x 5 km pixel). F) The month when the greatest area burned (lines represent start and end of season calculated using a threshold of 5% of the total).

such as the Kalahari can have very large fires, but the annual area burnt is often less than 10% of the landscape. In contrast, parts of central Zambia where over 50% of the area burns annually seldom have fires larger than 30 km^2 (3000 ha).

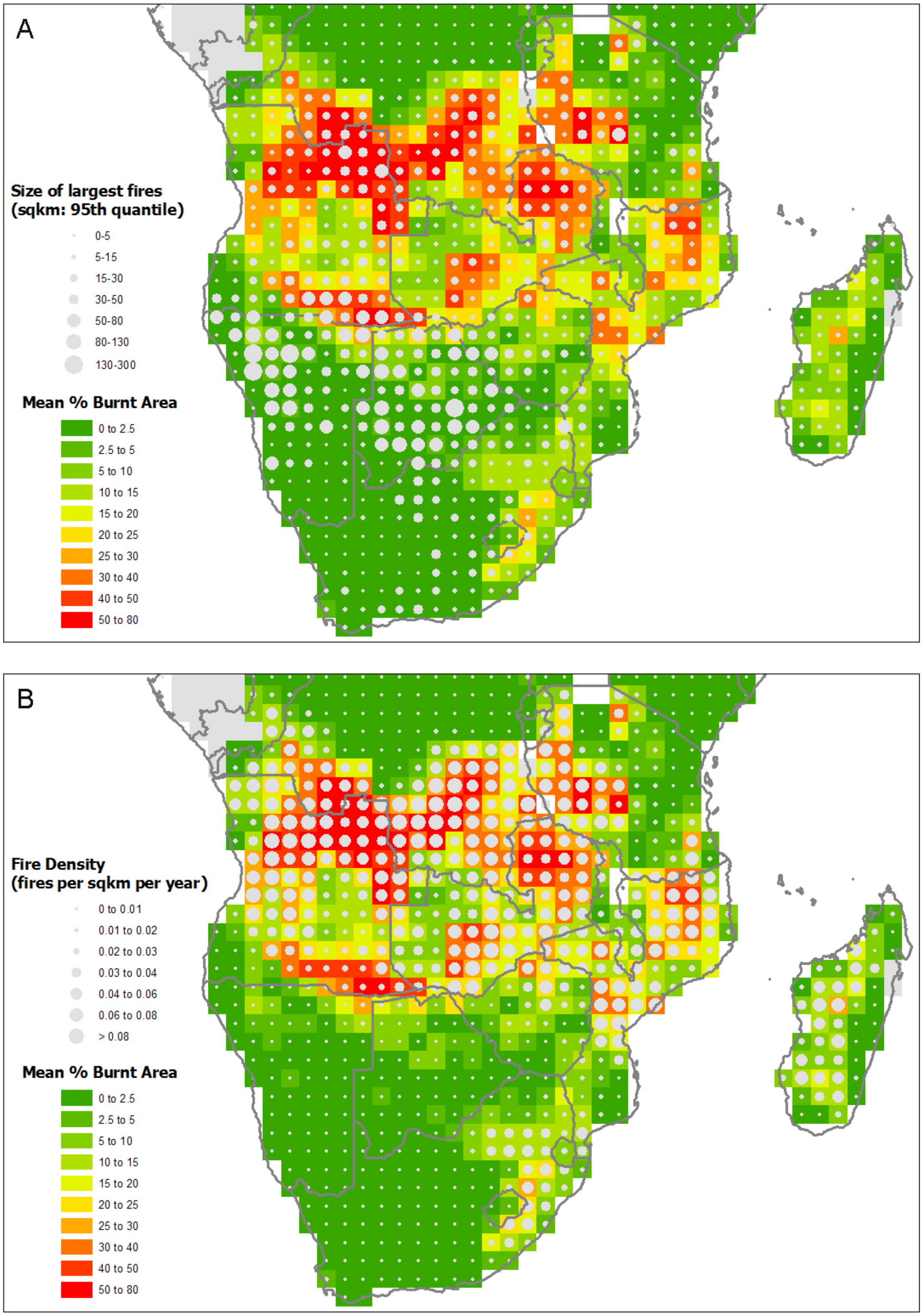

Figure 7.7: Maximum fire size (A) and density of fires per km^2 (B) - both plotted over the mean percentage burnt area for southern Africa. Areas that have the largest fires do not correspond to areas with higher total burned areas, but fire density and burned area seem to be related.

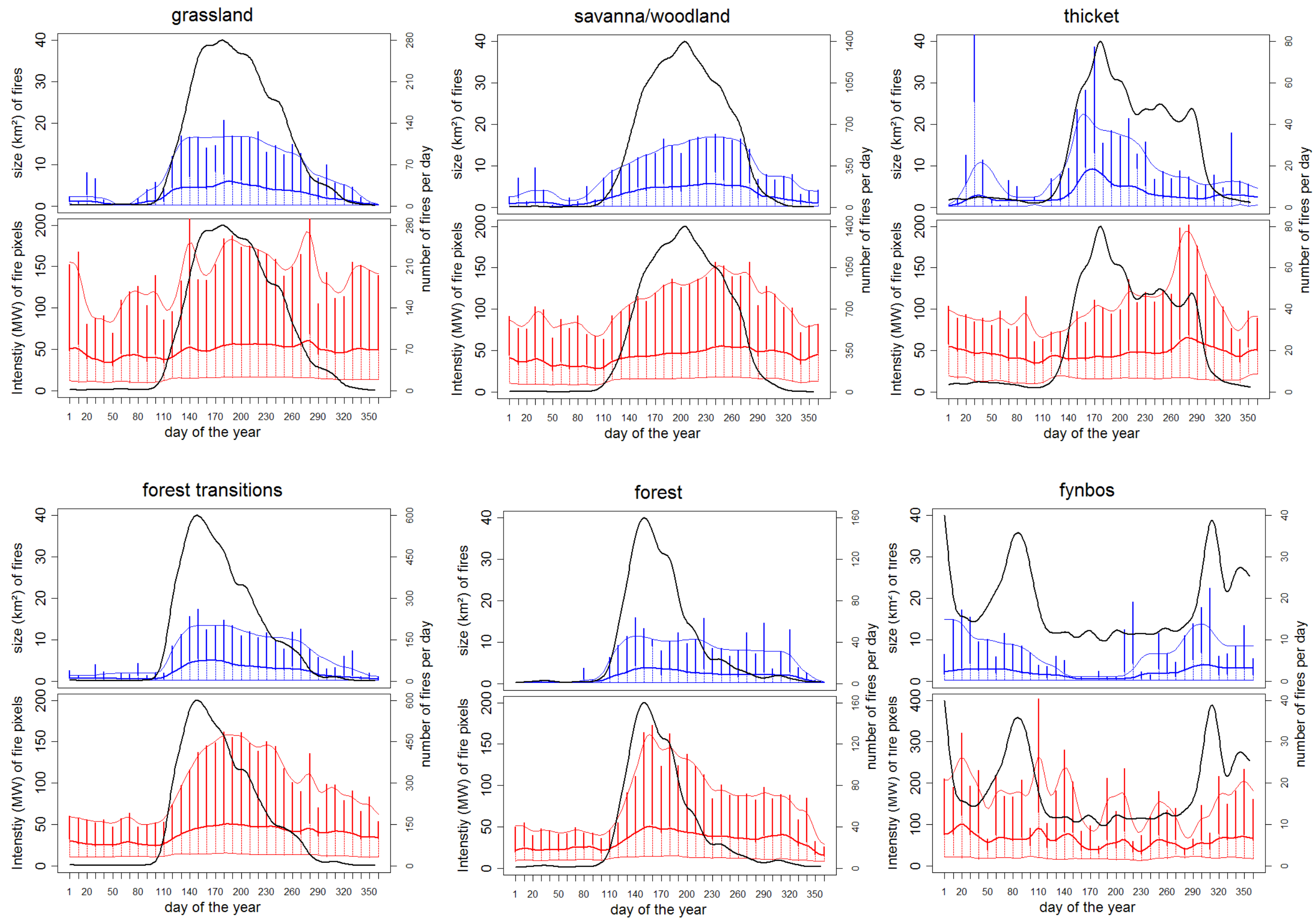

Figure 7.8: Seasonal patterns of fire size and fire intensity (FRP) across six different vegetation types in southern Africa. Coloured bars represent the 5th, 50th and 95th percentiles of fire size (blue) and FRP (red) for each 10 day timestep in the year 2004. The black line represents the number of fires each day of the year and can be used to identify the start and end of the fire season. Savannas show a slight increasing trend in fire size and fire radiative power over the fire season, forests show a slight decreasing trend. Grasslands have more uniformly high FRP values throughout the year. The Fynbos region burns from October-March and at much higher FRP's (note the difference in scale). Only the thicket region shows the expected pattern of larger fires early in the fire season, and more intense fires later in the fire season.

Because more dry fuel is available at the end of the dry season, and because hot windy weather conditions are conducive to fire spread it would be expected that fires at the end of the season would be both larger and have a higher intensity than early-season burns (Frost, 1999; Roy *et al.*, 2005b). This has certainly been found in savanna systems in northern Australia, and in protected areas in Africa (Russell-Smith *et al.*, 2007; Yates *et al.*, 2008; Govender *et al.*, 2006). Regionally, however, only the thicket vegetation type shows a marked increase in fire radiative power later in the dry season (Figure 7.8). In most other vegetation types fire size and intensity increase at the beginning of the season and stay high until the number of fires drops off again at the end of the season (Figure 7.8).

Fires can go out when there is not enough fuel to sustain them, when weather conditions are not appropriate for burning, or when they run into topographic or anthropogenic barriers or previously-burned areas (Trollope & Potgieter, 1985; Stambaugh & Guyette, 2008). If fuel and weather conditions were the main factors driving the occurrence of large fires then one would expect to see a stronger association between high energy fires and large fires. Similarly, the fact that the largest fires appear to be in unpopulated areas, with very flat landscapes (Figure 7.7) also suggests that barriers to fire spread are limiting the maximum fire size in many parts of the sub-continent.

Frequent fires in southern Africa occur within clearly defined environmental limits (Figure 7.2) and different parts of the sub-region show different characteristic fire regimes. We quantified some of this variability by classifying the landscape according to country, major vegetation type, and land use.

Most noticeable from this analysis is the way that the fire characteristics change across a gradient of intensity of human impact (which is assumed to increase from protected areas; uncultivated but grazed land; cultivated land; and settlements). While annual mean burnt area fraction (Figure 7.6A), maximum fire size (Figure 7.6D), Fire Radiative Power (Figure 7.6E), and cumulative fire-affected area (Figure 7.3) decrease as human impact increases, the effect on the seasonality of fire (Figures 7.5 & 7.6F), number of individual fires (Figure 7.6C), and the frequency of fire in the places that do burn (Figure 7.6B) is much less obvious. This implies that the ignition regimes in these different areas are quite similar, and that it is fire spread and fuel continuity that are most affected by intensifying human use of the landscape.

It is important to remember that while the four land use classes represent a gradient of increasing human impact there is no 'without humans' land use category in this analysis. Many protected areas in southern Africa still have people living in them, and even in those like the Kruger National Park which do not have resident communities except for tourists and park staff, the overwhelming majority of fires are still lit by humans (whether by managers, poachers, tourists, or cross-border migrants). What is different about the national parks is that they generally have fewer roads, less cultivation, and a lower biomass of grazing mammals than areas outside parks, and we suggest that this is what accounts for the differences in annual burnt area and fire size.

Since people light most of the fires in all land use and vegetation classes, it is not surprising that the seasonal pattern of fire is similar across categories (Figure 7.5). Only the fynbos vegetation type associated with the small winter-rainfall region on the south-west coast of Africa has a different seasonal pattern of fire. In all other vegetation and land use classes the majority of fires occur in the middle of the dry season: in July, August and September. As there are very few lightning strikes in these months a lightning-driven fire regime in southern Africa would probably show very different seasonal patterns. However, such a fire regime is unlikely to have existed in the region for at least the last 400 000 years (Karkanas *et al.*, 2007).

Space for time substitution is often used to infer fire return periods in instances where long term data are not available (Scholes *et al.*, 1996). Our results indicate that this could give a very skewed picture of fire patterns in Africa - or in any part of the globe where a relatively small percentage of the landscape burns with high frequency, while other parts of the landscape do not burn. For example, 5.3% of the uncultivated savanna land in Malawi burns each year and a space for time substitution would suggest that the average fire return time in this vegetation type is 19 years. In fact, the satellite data show that the patches of the landscape that do burn will burn frequently, and fitting the Weibull distribution to these patches gives a fire return time of 5.9 years (c.i. 2.9-11.8) which is a more reasonable estimate for this system (Table 7.1). Similarly, Figure 7.6A shows that the spatial extent of fire in forest vegetation is very low (less than 3 %). These small areas, which are presumably patches of grassland within the forest, have fire return periods very similar to the return times shown by grassy fuels in the region (3 to 4 years: Figure 7.6B). A space for time substitution would estimate a uniformly low fire return time of 33 years for African tropical forests, whereas in fact there are small patches that burn frequently, and large areas that never burn. This problem can be accommodated by ensuring that homogenous areas are selected on which to perform space-for-time substitution, but when summarising by quarter-degree grid square for climate modelling, for example, this is not possible.

Yates *et al.* (2008) and Williams *et al.* (1998) have shown in northern Australia that fires lit in the early dry season are smaller and less intense than fires which occur late in the dry season. A southern African analysis does not support this pattern (Figure 7.8). In most vegetation types fire size distributions and fire intensities remain fairly stable throughout the fire season, and forests even show a decreasing trend in fire intensity. One explanation for this divergence is that these two savanna systems have very different seasonal patterns of burning. All of southern Africa is characterised by relatively early-season burning, and the ‘Aboriginal burning regime’ that is being promoted in Australia is already in operation in Africa. Therefore, except in the thicket vegetation type, there is no evidence of the large, late-season fires that so characterise the current fire patterns of the northern territories of Australia. A finer-scale analysis of the southern African data may reveal more intense and larger fires during the late dry season in some individual landscapes (eg, Govender *et al.* (2006)).

Fires can go out when there is not enough fuel to sustain them, when weather conditions are not appropriate for burning, or when they run into topographic or anthropogenic barriers or previously-burned areas (Trollope & Potgieter, 1985; Stambaugh & Guyette, 2008). If fuel and weather conditions were the main factors driving the occurrence of large fires then one would expect to see a stronger association between high energy fires and large fires. Similarly, the fact that the largest fires appear to be in unpopulated areas, with very flat landscapes (Figure 7.7) also suggests that barriers to fire spread are limiting the maximum fire size in many parts of the sub-continent.

Fire size distributions

The frequency distribution of fires of different sizes contains ecological information: it should change depending on the ignition rate and pattern, the rate of regrowth of fuels, and the density of barriers to fire spread in the landscape. It is a useful metric for protected area managers striving to optimise ‘pyrodiversity’, the variety of fire regimes (Brockett *et al.*, 2001).

Like many other natural phenomena fires have a skewed distribution, with a large majority of small fires and a few large fires. It has been shown in systems ranging from boreal forests (Strauss *et al.*, 1989) to Australian savannas (Yates *et al.*, 2008), that the few largest fires burn the majority of the area, and that the many small fires do not contribute significantly to burnt area. Thus it is the probability of large infrequent fire events that has been the focus of much fire research (Williams, Richard & Bradstock, 2008)

The fire-size distributions in southern Africa break some of these rules (Figure 7.7). Here, it appears that it is the number of fires, rather than the area burned by large fires, that is a better indication of the annual area burned - i.e. most of the area burned in southern Africa is due to the accumulation of many small- to medium-sized fires, rather than to the occasional extreme fire event.

To test how different fire sizes contribute to the total burned area we regressed mean annual burnt area against the average number of fires in different size classes (the number of fires greater than 0, 0.25, 1, 5, etc km^2). The explanatory power improves from an r^2 of 0.57 ($p < 0.001$) when all fires are included, to an r^2 of 0.91 ($p < 0.001$) when only fires bigger than 25 km^2 were counted, and then decreases (Figure 7.9). There appears to be a trade-off between fire size and fire number in controlling total burned area which is related to the frequency distribution of fire sizes. It would be productive to compare fire size distributions between different savanna ecosystems, and across different biomes (see Archibald & Roy (2009) for some examples of this within African savannas).

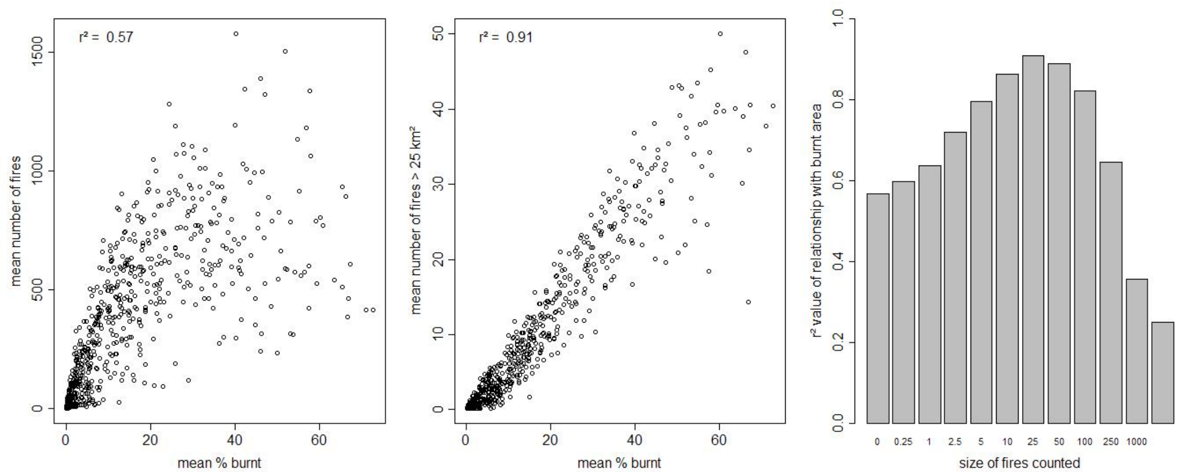

Figure 7.9: Demonstrating the relationship between the number of fires and the area burned. Better relationships are found when one considers only the number of large fires (>25 km^2), this relationship decreases again when only very large > 100 km^2 fires are included.

7.4.4 Conclusions

All of these lines of evidence point to a very strong human control on fire regimes in southern Africa. The frequency with which people in Africa light fires, and their proactive approach to using fire as a management tool is well known (Laris, 2006; Kull, 2004; Frost, 1999), and is often cited as explanations for why Africa is such a "fiery continent" (Crutzen & Andreae, 1990). Our research highlights other more complicated relationships between human land use and fire regimes. In particular, human activities appear to decrease the area burned by individual fires. The number of ignitions increases with human population density (up to a certain extent; Figure 7.10A) but this does not completely compensate for the simultaneous reduction in mean and maximum fire size (Figure 7.10B). Thus the total burned area fraction decreases in areas of high human use intensity. However, because ignitions remain high, areas in human-impacted landscapes that *do* burn have a similar fire frequency, seasonality and intensity as is found in less-impacted areas.

There is no evidence that any parts of southern Africa are following a lightning-driven ignition regime (Figure 7.5). These results support previous assertions that people are the main causes of fire in the region, and they also suggest that paucity of ignitions

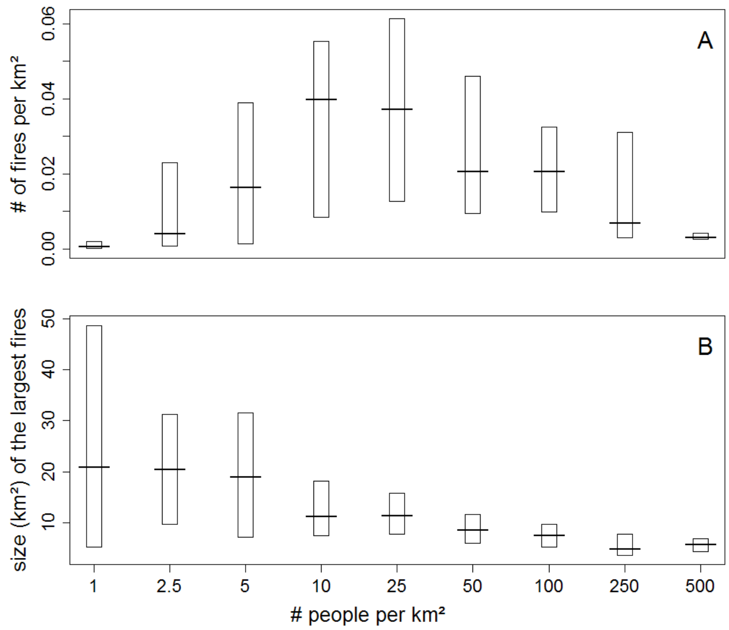

Figure 7.10: Showing how population density affects A: the density of fires and B: the size of the largest fires. Large fires are defined as the 95th quantile of all sizes and the graph gives the median (horizontal line) and ±25 percentiles (box). The number of individual fires increases as population densities increase, peaking at around 25 people per km^2 and then dropping off. However, the size of large fires decreases steadily with increasing human population densities - and areas with more than 10 people per km^2 seldom have fires larger than 20 km^2 (2000 ha).

are generally not a key factor limiting the area burned in southern Africa. Because very large fires contribute a relatively small fraction of the total burnt area in southern Africa we would expect that area affected by fire would be less variable between years than systems such as boreal forests - where large fires dominate the area burned, and climatic factors control the probability of these large fires (Fauria *et al.*, 2008; Balshi *et al.*, 2009). This hypothesis is confirmed by research into the inter-annual variability of fire in southern Africa (van der Werf *et al.*, 2004; Archibald *et al.*, in pressa): burned area is not as strongly linked to climate variability in this region as it is in other parts of the globe.

The sharp disjunction between the extent of fire in the 'grassy' vegetation types of Africa, and the 'non-grassy' vegetation types (Figure 7.3) supports the theory that fire is involved in creating and maintaining these vegetation types and their distribution on the sub-continent (Bond, 2005). C4 grasses promote frequent fire, which prevents recruitment of forest species (Hoffmann, 1999). Low-light forested environments on the other hand prevent the development of a flammable grassy understory (Hennenberg *et al.*, 2006).

Figure 7.6 shows that forest systems have very little fire but when fire does occur it occurs with the same frequency, FRP, and fire size as the grassy systems. This is most easily explained as fires occurring in patches of grassy vegetation within the forest matrix. Having said this, we did not specifically search for evidence of fire-induced transformation of forest, such as is prevalent in South America (Cochrane *et al.*, 1999).

We have previously published findings (Archibald *et al.*, 2009) that assess the relative importance of climate, vegetation, and human drivers in affecting annual burned area. We have also shown that within one landscape, the presence and land use activities of people can dampen patterns of inter-annual variability in fire (Archibald *et al.*, in pressa). This paper complements these findings by using newly-developed datasets on fire size, fire number, and fire intensity to explore the mechanisms by which these regional and inter-annual patterns emerge.

7.5 Acknowledgments

Regional-scale research is of little value without input from people with local knowledge and the authors thank all southern African fire ecologists who have contributed ideas and information to this study. In particular we would like to acknowledge the contributions of Winston Trollope, Patience Zisadza, Peter Frost, Brian van Wilgen, Navashni Govender, and the members of the GOFC-GOLD Southern African Fire Network. The exemplary work on savanna fire regimes by Australian fire ecologists helped to contextualise and give meaning to the analyses presented here. This work was supported by CSIR Parliametary Grant funding, and NERC Grant NE/F001584/1.

Table 7.1: Fire statistics of different vegetation types and land use categories for each country in southern Africa. Columns represent the total area evaluated, median percentage burnt area, the fire return period (MEI) calculated over all pixels (all), and only the pixels that burnt (burnt), the month of peak fire, and the seasonality of fire (ranging from 0: fire all year round, to 1: all fire occurred in one month). The ˜ indicates that the Wiebull parametrisation did not converge so median fire return could not be calculated. 'c.i.' indicates 25% confidence intervals

Vegetation	Land use	km^2(x1000)	%burnt	c.i.	MEI all	c.i.	MEI burnt	c.i.	peak month	seasonality
Angola										
arid shrubland	protected areas	21	0	(0:0)	˜	˜	˜	˜	Aug	0.5
arid shrubland	uncultivated	43	0	(0:0)	99	(0.2:>5000)	0.5	(0.3:0.8)	Aug	0.6
arid shrubland	cultivated	1	0	(0:0)	2.7	(2.5:3)	˜	˜	Aug	0.8
forest	uncultivated	7	33	(31:36)	2.9	(2.4:3.5)	1.7	(1.5:2)	Jun	0.9
forest	cultivated	1	5	(0:10)	˜	˜	˜	˜	May	1
forest transitions	uncultivated	220	33	(30:37)	1.8	(1.6:2.1)	1.2	(1.1:1.3)	Jun	0.9
forest transitions	cultivated	2	51	(45:58)	0.9	(0.8:1)	0.8	(0.8:0.9)	May	0.9
grassland	protected areas	16	67	(65:67)	1.1	(1:1.2)	1	(0.9:1)	Jun	0.9
grassland	uncultivated	79	51	(50:52)	1.5	(1.3:1.6)	1.1	(1:1.2)	Jun	0.9
grassland	cultivated	1	61	(52:63)	1.6	(1.4:1.7)	1.1	(1:1.2)	Jun	0.9
savanna/woodland	protected areas	47	34	(30:36)	2.3	(2:2.6)	1.5	(1.4:1.7)	Aug	0.9
savanna/woodland	uncultivated	767	26	(24:27)	3.3	(2.8:3.9)	1.4	(1.3:1.6)	Aug	0.8
savanna/woodland	cultivated	41	17	(15:19)	7.3	(5.4:9.9)	2.1	(1.8:2.6)	Aug	0.8
savanna/woodland	settlements	1	0	(0:0)	˜	˜	˜	˜	˜	˜
Botswana										
arid shrubland	protected areas	14	0	(0:0)	˜	˜	˜	˜	˜	˜
arid shrubland	uncultivated	9	0	(0:0)	˜	˜	˜	˜	˜	˜
savanna/woodland	protected areas	83	1	(1:5)	4.6	(1.7:12)	0.4	(0.3:0.5)	Aug	0.8
savanna/woodland	uncultivated	389	2	(1:5)	2.3	(2.1:2.5)	˜	˜	Aug	0.7
savanna/woodland	cultivated	38	3	(0:4)	70	(4.9:986)	6.5	(2.7:16)	Aug	0.7
savanna/woodland	settlements	1	0	(0:1)	˜	˜	˜	˜	Aug	0.5
Burundi										
forest	uncultivated	1	1	(0:1)	˜	˜	˜	˜	Aug	0.8
grassland	protected areas	1	0	(0:0)	˜	˜	˜	˜	˜	˜

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Table 7.1 – continued from previous page

Vegetation	Land use	km^2(x1000)	%burnt	c.i.	MEI all	c.i.	MEI burnt	c.i.	peak month	seasonality
grassland	uncultivated	6	1	(0:2)	~	~	~	~	Aug	0.9
grassland	cultivated	4	0	(0:1)	~	~	~	~	Aug	0.9
savanna/woodland	protected areas	1	30	(22:33)	4.8	(3.8:6)	2.6	(2.2:3)	Jun	0.9
savanna/woodland	uncultivated	9	4	(2:6)	33	(10:106)	2.9	(1.9:4.4)	Aug	0.9
savanna/woodland	cultivated	5	3	(1:5)	53	(13:221)	3.3	(2.1:5.2)	Aug	0.9
Congo										
forest	protected areas	14	0	(0:0)	~	~	~	~	~	~
forest	uncultivated	178	0	(0:0)	~	~	~	~	Aug	0.9
forest	cultivated	14	1	(0:1)	~	~	~	~	Aug	0.9
forest transitions	protected areas	8	11	(7:13)	~	~	~	~	Jun	0.9
forest transitions	uncultivated	83	9	(8:9)	~	~	~	~	Jun	0.9
forest transitions	cultivated	3	9	(7:13)	~	~	~	~	Jun	0.9
DRC										
forest	protected areas	56	3	(2:3)	134	(13:1360)	2.9	(1.5:5.7)	Jun	0.9
forest	uncultivated	943	2	(2:2)	57	(13:252)	1.2	(0.9:1.7)	Jun	0.9
forest	cultivated	65	0	(0:0)	~	~	~	~	Jun	0.9
forest	settlements	1	0	(0:0)	~	~	~	~	~	~
forest transitions	protected areas	20	29	(25:33)	2.1	(1.8:2.4)	1.6	(1.4:1.8)	Jun	0.8
forest transitions	uncultivated	362	21	(18:24)	2.5	(2:3.1)	1.2	(1.1:1.4)	Jun	0.9
forest transitions	cultivated	12	2	(2:2)	1042	(0.6:>5000)	5.3	(1:27)	Jun	0.9
grassland	protected areas	10	37	(31:37)	1.6	(1.4:1.8)	0.8	(0.7:0.8)	May	0.8
grassland	uncultivated	91	34	(31:36)	1.7	(1.5:1.9)	1.1	(1:1.2)	Jun	0.8
grassland	cultivated	8	4	(3:5)	41	(11:151)	1.3	(1:1.8)	Jun	0.8
savanna/woodland	protected areas	21	32	(28:34)	2.9	(2.5:3.4)	1.6	(1.4:1.8)	Jun	0.8
savanna/woodland	uncultivated	374	32	(28:34)	2.4	(2.1:2.8)	1.2	(1.1:1.3)	Jun	0.8
savanna/woodland	cultivated	3	18	(16:20)	4.5	(3.6:5.8)	1.9	(1.6:2.3)	Jun	0.7
thicket	uncultivated	1	58	(51:63)	1.5	(1.3:1.6)	1.2	(1.1:1.2)	Aug	0.9
Lesotho										
grassland	uncultivated	21	2	(1:4)	5.5	(4.7:6.3)	~	~	Aug	0.9
grassland	cultivated	4	1	(1:2)	203	(5.3:>5000)	4.1	(2:8.3)	Aug	0.9

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Table 7.1 – continued from previous page

Vegetation	Land use	km^2(x1000)	%burnt	c.i.	MEI all	c.i.	MEI burnt	c.i.	peak month	seasonality
Madagascar										
forest	protected areas	13	2	(2:2)	72	(12:451)	3	(1.9:4.8)	Aug	0.6
forest	uncultivated	99	3	(3:4)	279	(16:4970)	6.4	(2.6:16)	Aug	0.6
forest	cultivated	47	1	(1:1)	496	(5.4:>5000)	3.7	(1.5:9.6)	Sep	0.8
forest transitions	protected areas	1	0	(0:4)	106	(0.2:>5000)	8.5	(1.3:54)	Oct	0.9
forest transitions	uncultivated	12	1	(1:2)	3465	(2.2:>5000)	16	(1.9:133)	Oct	0.8
forest transitions	cultivated	9	0	(0:0)	24	(15:39)	3.3	(1.1:10)	Oct	0.9
grassland	protected areas	1	6	(5:8)	38	(14:105)	5.9	(3.7:9.3)	Sep	0.7
grassland	uncultivated	126	11	(8:15)	8.2	(6:11)	2.3	(2:2.8)	Aug	0.8
grassland	cultivated	2	8	(6:8)	21	(11:38)	3	(2.2:3.9)	Sep	0.8
savanna/woodland	protected areas	6	6	(5:7)	36	(14:98)	4.1	(2.8:5.8)	Aug	0.7
savanna/woodland	uncultivated	210	8	(7:10)	21	(12:39)	2.9	(2.3:3.7)	Aug	0.6
savanna/woodland	cultivated	8	4	(3:6)	111	(19:656)	10	(4.6:23)	Sep	0.8
thicket	protected areas	1	1	(0:3)	117	(14:952)	2.1	(1.5:3)	Oct	0.9
thicket	uncultivated	54	2	(1:2)	1783	(5.6:>5000)	9.6	(2.1:44)	Sep	0.7
Malawi										
grassland	protected areas	3	31	(26:34)	3.1	(2.6:3.6)	1.8	(1.6:2)	Aug	0.7
grassland	uncultivated	7	4	(4:4)	147	(11:1877)	11	(3.9:31)	Sep	0.8
grassland	cultivated	3	2	(1:2)	139	(18:1055)	3	(1.9:4.8)	Sep	0.8
savanna/woodland	protected areas	8	13	(12:14)	12	(7.8:17)	3.6	(2.9:4.6)	Aug	0.8
savanna/woodland	uncultivated	43	5	(5:6)	109	(11:1111)	5.9	(2.9:12)	Aug	0.7
savanna/woodland	cultivated	28	2	(2:2)	200	(10:3929)	8.2	(3.1:21)	Aug	0.8
Mozambique										
forest transitions	protected areas	6	32	(27:40)	3.4	(2.9:4)	2	(1.7:2.2)	Sep	0.8
forest transitions	uncultivated	213	17	(16:18)	6.6	(5.1:8.6)	2	(1.7:2.3)	Aug	0.8
forest transitions	cultivated	9	16	(13:19)	5.5	(4.4:6.9)	2	(1.7:2.3)	Aug	0.8
grassland	uncultivated	2	13	(11:14)	15	(9.5:25)	3	(2.3:3.9)	Aug	0.8
grassland	cultivated	1	3	(3:4)	138	(9.4:2024)	7.4	(3.1:18)	Aug	0.8
savanna/woodland	protected areas	38	17	(15:22)	5.6	(4.5:7.1)	2.7	(2.3:3.2)	Aug	0.8
savanna/woodland	uncultivated	433	20	(19:21)	3.2	(2.8:3.8)	1.9	(1.7:2.1)	Aug	0.8

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Table 7.1 – continued from previous page

Vegetation	Land use	km^2(x1000)	%burnt	c.i.	MEI all	c.i.	MEI burnt	c.i.	peak month	seasonality
savanna/woodland	cultivated	54	15	(14:17)	7.5	(5.7:10)	3.2	(2.7:3.8)	Aug	0.8
Namibia										
arid shrubland	protected areas	82	0	(0:1)	8	(6.5:9.7)	2.9	(1.2:7.2)	Aug	0.9
arid shrubland	uncultivated	364	0	(0:1)	1.9	(1.7:2)	~	~	Aug	0.8
arid shrubland	cultivated	2	1	(0:1)	0.4	(0.4:0.5)	~	~	Sep	0.6
grassland	uncultivated	1	5	(4:13)	16	(9.3:26)	4.4	(3.3:5.8)	Oct	0.6
savanna/woodland	protected areas	26	15	(12:18)	6.7	(5.1:8.9)	2.8	(2.3:3.4)	Aug	0.9
savanna/woodland	uncultivated	323	5	(4:5)	57	(13:257)	4.9	(3:8)	Aug	0.9
savanna/woodland	cultivated	16	0	(0:1)	124	(1.3:>5000)	3.6	(1.7:7.8)	Aug	0.8
savanna/woodland	settlements	1	2	(2:5)	34	(13:86)	2.8	(2.1:3.7)	Jun	0.7
Rwanda										
grassland	protected areas	2	0	(0:0)	~	~	~	~	Aug	1
grassland	uncultivated	3	0	(0:0)	~	~	~	~	Aug	0.9
grassland	cultivated	5	0	(0:0)	~	~	~	~	Aug	0.8
savanna/woodland	protected areas	2	23	(9:30)	3.9	(3.2:4.7)	2.1	(1.9:2.4)	Aug	0.9
savanna/woodland	uncultivated	7	0	(0:1)	~	~	~	~	Aug	0.8
savanna/woodland	cultivated	8	0	(0:0)	1340	(0:>5000)	3.6	(0.8:17)	Aug	0.9
South.Africa										
arid shrubland	protected areas	19	0	(0:0)	~	~	~	~	Nov	0.6
arid shrubland	uncultivated	444	0	(0:0)	~	~	~	~	Sep	0.4
arid shrubland	cultivated	3	5	(2:5)	73	(20:262)	2.8	(1.9:4.1)	Jun	0.6
forest transitions	protected areas	3	5	(4:5)	55	(15:201)	5.6	(3.4:9.3)	Aug	0.7
forest transitions	uncultivated	35	4	(3:5)	118	(13:1103)	7.6	(3.5:16)	Aug	0.8
forest transitions	cultivated	15	3	(2:4)	64	(10:396)	4.2	(2.6:6.8)	Aug	0.8
forest transitions	settlements	1	1	(0:1)	809	(9.4:>5000)	5.2	(2:14)	Jun	0.9
fynbos	protected areas	9	2	(1:2)	~	~	~	~	Nov	0.7
fynbos	uncultivated	53	1	(0:1)	~	~	~	~	Jan	0.5
fynbos	cultivated	10	3	(2:3)	189	(19:1898)	10	(4.2:26)	Feb	0.6
fynbos	settlements	1	0	(0:0)	~	~	~	~	Dec	0.3
grassland	protected areas	8	17	(16:18)	8.3	(6.1:11)	3.2	(2.6:3.8)	Aug	0.7
grassland	uncultivated	187	9	(8:9)	14	(8.8:21)	2.5	(2:3.1)	Aug	0.8

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Table 7.1 – continued from previous page

Vegetation	Land use	km^2(x1000)	%burnt	c.i.	MEI all	c.i.	MEI burnt	c.i.	peak month	seasonality
grassland	cultivated	63	11	(9:12)	23	(11:47)	6.4	(4.2:9.5)	Aug	0.8
grassland	settlements	4	4	(3:5)	113	(20:626)	5.6	(3.1:10)	Jun	0.8
savanna/woodland	protected areas	33	16	(12:16)	7.6	(5.7:10)	3.8	(3.1:4.6)	Aug	0.7
savanna/woodland	uncultivated	234	5	(3:5)	60	(18:201)	3.4	(2.3:4.9)	Aug	0.7
savanna/woodland	cultivated	66	6	(4:8)	62	(17:224)	3.8	(2.5:5.6)	Aug	0.8
savanna/woodland	settlements	2	3	(2:3)	109	(3.1:3807)	4.9	(2.2:11)	Jun	0.8
thicket	protected areas	2	0	(0:1)	3.9	(3.5:4.3)	~	~	Jan	0.5
thicket	uncultivated	24	1	(1:2)	3.7	(3.3:4.1)	0	(0:>5000)	Aug	0.8
thicket	cultivated	2	2	(2:3)	94	(5.1:1733)	11	(3.4:33)	Aug	0.8
Swaziland										
grassland	protected areas	1	36	(33:38)	2.2	(2:2.5)	1.9	(1.7:2.1)	Aug	0.8
grassland	uncultivated	2	11	(9:12)	18	(11:32)	3.7	(2.8:4.8)	Aug	0.9
savanna/woodland	protected areas	1	8	(6:9)	153	(17:1366)	10	(4.2:25)	Aug	0.7
savanna/woodland	uncultivated	15	3	(2:5)	130	(16:1025)	6	(3.1:11)	Aug	0.8
Tanzania										
arid shrubland	uncultivated	1	0	(0:0)	~	~	~	~	Aug	0.8
forest	uncultivated	1	10	(3:17)	~	~	~	~	Aug	0.9
forest transitions	protected areas	11	13	(4:17)	~	~	~	~	Jun	0.9
forest transitions	uncultivated	84	4	(4:4)	26	(8.4:80)	3.4	(2.1:5.4)	Aug	0.8
forest transitions	cultivated	9	9	(7:9)	19	(8.6:42)	2.6	(1.9:3.5)	Aug	0.8
grassland	protected areas	14	39	(36:41)	1.9	(1.7:2.1)	1.4	(1.2:1.5)	Aug	0.8
grassland	uncultivated	64	9	(8:10)	20	(10:41)	2.1	(1.6:2.9)	Aug	0.7
grassland	cultivated	11	9	(8:10)	15	(9.1:25)	2.7	(2.1:3.5)	Aug	0.8
savanna/woodland	protected areas	82	30	(25:31)	1.6	(1.4:1.8)	1.2	(1.1:1.4)	Aug	0.8
savanna/woodland	uncultivated	291	12	(11:14)	9.9	(6.3:15)	2.6	(2:3.3)	Aug	0.8
savanna/woodland	cultivated	95	18	(17:19)	4.9	(3.9:6.3)	1.9	(1.6:2.2)	Jun	0.8
thicket	protected areas	33	42	(33:45)	2.1	(1.9:2.4)	1.3	(1.2:1.4)	Jun	0.7
thicket	uncultivated	111	3	(3:4)	151	(23:991)	5.9	(3.1:11)	Aug	0.7
thicket	cultivated	68	5	(4:6)	168	(20:1433)	7.6	(3.5:16)	Aug	0.7
Zambia										
forest	protected areas	6	7	(7:8)	12	(7.7:17)	2.4	(2:3)	Jun	0.8

Continued on next page

Table 7.1 – continued from previous page

Vegetation	Land use	km^2(x1000)	%burnt	c.i.	MEI all	c.i.	MEI burnt	c.i.	peak month	seasonality
forest	uncultivated	31	8	(7:9)	26	(12:56)	3.8	(2.8:5.1)	Aug	0.8
grassland	protected areas	46	31	(30:35)	3.8	(3.1:4.5)	1.7	(1.5:1.9)	Aug	0.8
grassland	uncultivated	39	26	(24:26)	4	(3.3:4.8)	1.8	(1.6:2)	Aug	0.8
grassland	cultivated	6	53	(51:55)	1.7	(1.5:1.8)	1.2	(1.1:1.3)	Aug	0.8
savanna/woodland	protected areas	143	33	(32:34)	2.6	(2.3:3)	1.8	(1.6:2.1)	Aug	0.8
savanna/woodland	uncultivated	408	22	(21:23)	7	(5.2:9.3)	2.2	(1.9:2.7)	Aug	0.8
savanna/woodland	cultivated	43	20	(18:21)	5.5	(4.4:7)	2.1	(1.8:2.4)	Aug	0.8
savanna/woodland	settlements	1	0	(0:1)	~	~	~	~	Aug	0.7
thicket	protected areas	4	37	(33:44)	2.3	(2:2.6)	1.8	(1.6:2)	Jun	0.8
thicket	uncultivated	1	44	(43:57)	1.5	(1.4:1.6)	1.3	(1.2:1.4)	Aug	0.9
Zimbabwe										
forest transitions	uncultivated	2	2	(2:3)	76	(15:375)	3.3	(2.1:5.1)	Aug	0.8
grassland	protected areas	1	18	(13:25)	4.4	(3.6:5.3)	2.1	(1.9:2.4)	Aug	0.8
grassland	uncultivated	6	4	(3:5)	63	(16:245)	4.6	(2.9:7.2)	Aug	0.9
grassland	cultivated	1	0	(0:1)	2.8	(2.5:3)	~	~	Aug	0.8
savanna/woodland	protected areas	48	16	(15:17)	13	(8.2:20)	2.4	(2:3)	Aug	0.8
savanna/woodland	uncultivated	228	10	(7:10)	21	(12:39)	4.3	(3.2:5.8)	Aug	0.8
savanna/woodland	cultivated	102	4	(4:5)	36	(16:82)	2.8	(2:3.8)	Aug	0.8
savanna/woodland	settlements	2	1	(1:1)	>5000	(0:>5000)	49	(0.2:>5000)	Aug	0.8

Chapter 8

Conclusion

In the time that it has taken to complete this thesis the field of pyrogeography has become far more established. The publication in January 2009 of the review article 'Fire in the Earth System' (Bowman *et al.*, 2009) gave my PhD a context that was only beginning to become evident when I started it four years ago. What makes this aspect of fire ecology so exciting is that it is concerned with answering questions that have been important to ecologists for years, but that we have never had the data or the statistical tools to explore. The spatial and temporal frequency of data from satellite imagery, combined with recent meta-analyses of charcoal records allow us to replace anecdotal accounts and speculation with rigorous scientific methods to answer questions about fire's role in the earth system and the impact of humans on fire regimes.

Scientists around the world are taking advantage of this wealth of new information and every month there are more publications contributing data and ideas towards a globally-applicable theory of fire. (see Balshi *et al.* (2009), Krawchuk *et al.* (2009a), and in particular Bradstock (in press) for some recent examples of these.) The challenge with this abundance of data is to distill insights that are useful, generalisable, and applicable. I started this dissertation asserting that fire ecology has been constrained by its affiliation with fire management, but unless fire ecologists are able to provide answers to the people who want to live and prosper in ecosystems influenced by fire they will have failed in their responsibility. As fire ecologists we should be aiming to provide answers both to the question 'What sort of fire regime would we like to impose?' and 'Is it possible to impose this fire regime?'. This dissertation and the broader field of pyrogeography bring the second question into much-needed focus.

This dissertation is concerned with a particular fire-vegetation-climate system in southern Africa that humans have been actively manipulating for at least 100 000 years. In it I describe this system, test some theories about the importance of various drivers, and provide information on the extent to which fire regimes in southern Africa can be manipulated by climate- and human-induced global change. I also compare these findings with patterns found in other savanna systems, to determine why and how they differ.

One key finding from my thesis concerned the threshold effect of tree cover on fire: that the occurrence and area burned by fire reduces substantially once tree cover reaches 40%. This finding fits with empirical data showing convex relationships with trees and grasses (Scholes, 2003), and a rapid decline in C4 grass biomass as tree canopies reach 35-40% (Hennenberg *et al.*, 2006; Malaise, 1978). The effect of fires in reducing tree cover and maintaining savanna vegetation has frequently been demonstrated in the literature (Williams *et al.*, 1999; Gardner, 2006; Hoffmann, 1999; Higgins *et al.*, 2007) but processes which prevent savanna expansion into forest systems are less well described. Results presented in Chapters 2 and 3 suggest that the negative effect of tree cover on grassy fuels, combined with the positive effect of grassy fuels on fire can result in a clear switch between high fire, low tree-cover; and low fire, high tree-cover vegetation, and that these patterns are apparent at continental scales.

A second important finding concerned the relationship between human population density, ignition frequency, and fire size. Using data on individual fires it was possible to demonstrate that the number of successful ignitions in a landscape increases with population density up to about 10 people per km^2 and then decreases. The probability of large fires, on the other hand, decreases strongly with increasing population densities (Chapter 7). At a landscape scale the reduction in large fires appears to have a far larger effect than the increased ignition frequency, and annual area burned always decreases with increasing human impact (Chapter 2). Ignitions were never shown to be limiting the annual area burned.

These results are important for two reasons. Firstly, it is finally possible to provide empirical data to scientists wishing to model fire in Africa. Attempts to include fire in regional and global models of vegetation have struggled because they are often implemented at scales larger than the scale at which ignition and fire spread occur (Prentice *et al.*, 2007). Data in this thesis provide functional relationships which can be used to parameterise models of ignition and fire spread. They also give an indication of how these processes manifest at larger scales.

Secondly, these results need to be contrasted with ecological theory on fire-size distributions and the importance of large fires. Theoretical models of forest fires demonstrate that the distribution of fire sizes in a landscape is 'fat tailed': that large fires occur relatively more often than would be expected. A substantial body of theory exists around why forest fires show these sorts of power-law distributions (Bak *et al.*, 1990; Malamud *et al.*, 1998; Moritz *et al.*, 2005). On a more practical note, empirical data across the globe have demonstrated the importance of these large fires in driving total area burned (Strauss *et al.*, 1989; Yates *et al.*, 2008) and in affecting human lives and livelihoods Williams, Richard & Bradstock (2008).

The data for southern Africa presented in this dissertation affirm that the probability of large fires is an important characteristic of a fire regime in savanna systems. In Chapter 5 it is shown that the responsiveness of annual area burned to variability in climatic drivers depends on the probability of large fires, and in Chapter 7 it is shown that the total area burned in a landscape correlates with the number of fires $> 25\text{km}^2$. However, these results also suggest that many savanna landscapes do not show the expected power-law distribution of fire sizes (Chapter 6). Similarly, contrary to expectations developed in protected areas (Govender *et al.*, 2006) and in Northern Territory Australia (Russell-Smith *et al.*, 2007), in southern Africa fire size and fire intensity do not appear to increase later in the fire season (Chapter 7).

Unlike in Mediterranean shrublands, where increasing human densities are associated with higher fire return periods (Syphard *et al.*, 2009), in southern African savannas the fire return periods across a gradient of human impact are similar, and it is the spatial extent of this burning that is affected (Chapter 7).

If southern Africa diverges from the expected patterns of fire it is unlikely to be the exception - many other savanna systems in India, South America and Indonesia are likely to show similar dynamics. Understanding these savanna fire regimes, and being able to predict future responses to climatic change require that new theories be developed which explicitly include the effects of humans on land fragmentation (Meyn *et al.*, 2007).

What can this thesis add to the fire management debate? As is the case in many other parts of the world the national fire laws, and the activities of the people who end up lighting and manipulating fires are often at odds in southern Africa. Research that is purely descriptive and does not interrogate the socio-political context in which fire occurs can never hope to resolve this contention. However, my dissertation does provide insights that might be useful when trying to determine what fire regimes are desirable in different circumstances, and whether it is possible to impose these fire regimes. Some results that I found important in relation to fire management were:

a) Attempting to control the annual area burned and the fire return period by manipulating ignition frequency is likely to be futile. In areas with few humans there are still plenty of ignition sources - but much of the area burns in large, perhaps-unplanned fires. In areas with high human population densities (and many ignitions) the annual area burned is the result of an accumulation of many small fires.

b) It follows that modifying fire regimes in Africa to alter GHG emissions will be difficult. As fire number increases, fire size decreases, with no net change in annual burned area. Ultimately the amount of available fuel and fuel continuity appear to be more important than ignition regime. Altering the season of burning might be possible, however, which could influence the chemical composition of the fuel and therefore fire-related emissions.

c) Across a range of vegetation types there is evidence that lighting many fires early in the season results in smaller fires, and prevents large, intense fires later in the season (Chapter 7). Therefore, if the aim of fire management is to prevent the types of fires that are dangerous to human lives and property, then it makes no sense to try to prevent people from lighting fires.

d) A very large number of small, early-season fires are required to burn the equivalent area that burns in late-season wildfires. Therefore this early-season, patchy burning is only really feasible in places with high human population densities: attempting to implement early-season burning regimes in protected areas, or underpopulated areas might be logistically difficult.

e) Finally there appears to be a threshold of around 40% tree cover where the system switches from a C4-dominated grassy environment to a woody-dominated no-fire environment. In systems where tree cover is close to this threshold small management interventions might have long-lasting effects on the system. Closed-canopy woody systems might be desirable from a carbon accounting perspective. However, once a system has switched beyond the 40% threshold it might be difficult to reverse because fire, which acts to prevent canopy-closure has been excluded.

As with most research ventures, this thesis leaves many more questions than it started with. In particular, the need to expand these ideas to a global context is evident throughout this work. The impact of climate and humans varies across the globe - to the extent that the same input can have exactly opposite effects on fire. Chapter 3 hints at how feedbacks between vegetation and fire might operate to create distinct biomes and fire regimes, but there are larger-scale limits imposed by abiotic factors such as climate and topography that remain to be explored.

Results from Chapters 7, 6, and 5 point to the need for a more systematic investigation into the impact of humans on fire regimes. This thesis is largely descriptive and infers the mechanisms by which humans influence ignition frequency and fire spread. With this information one can parameterise models and recreate the fire regimes that might have occurred under different patterns of human occupation and land use. This will allow us to ask fundamental questions on the paleohistory of fire in Africa, the extent to which ignitions limit burned area in savanna systems, and the uniformity of fire size-frequency distributions in systems that burn.

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