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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Running head: fire-climate interactions

Key words: southern Africa, fire, climate, inter-annual variation, savanna, seasonality, fuel dryness

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.

Biosketch: Sally Archibald is a South African ecologist with interests in fire ecology, savanna vegetation dynamics, and the behaviour of complex systems. She works at the CSIR

in a research group which uses systems theory, modelling and advanced earth observation techniques to understand the dynamics of southern African ecosystems under human use.

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.

METHODS

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.* (submitted) 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. 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 1).

Hwange National Park had the shortest fire records (21 years) and the longest fire record was from HIP (50 years) (Table 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. 1). This approach provided 10 different samples with which to assess inter-annual variation in burnt area (Table 1, Fig. 2).

<insert Fig. 1 around here>

<insert Table 1 around here>

<insert Fig. 2 around here>

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 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.* (submitted) 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 reanalysis 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 press) (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 press) 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:

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

Where i = 1...N represents the individuals, j = 1...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.

RESULTS

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. 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. 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 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.

<insert Fig. 3 around here>

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 2, Fig. 4). Correlations with accumulated rainfall were significant for all parks, and correlation coefficients ranged from 0.37 to 0.75 (Table 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.

<insert Fig. 4 around here>

<insert Table 2 around here>

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 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.

<insert Table 3 around here>

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 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:

$$\text{burnt}_{ij} = \beta_0 + b_{0i} + \beta_1 \text{rain}_{ij} + \beta_2 \text{season}_{ij} + \varepsilon_{ij} \tag{2}$$

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 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.

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. 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 2 the predicted patterns were very different from what is observed (Fig. 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. 6).

<insert Fig. 5 around here>

<insert Fig. 6 around here>

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 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.

<insert Table 4 around here>

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 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.

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 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 and 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 4 and Equation 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.*, submitted) 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. Areas characterised by large wildfires had the highest variation in burnt area between years (Fig. 7(a)). Similarly, only areas with a limited human impact (< 10 on the human footprint score) still had large wildfires (Fig. 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.

<insert Fig. 7 around here>

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.

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.

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FIGURE HEADINGS

Figure 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.

Figure 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. Fire Danger Index (FDI) data were not available for the parks outside South Africa.

Figure 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 high Fire Danger Index (FDI) days fairly well, but does not give a good representation of the higher-rainfall savannas. Data are presented at 0.25x0.25 degree resolution except for FDI days which is at 1 degree resolution.

Figure 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 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.

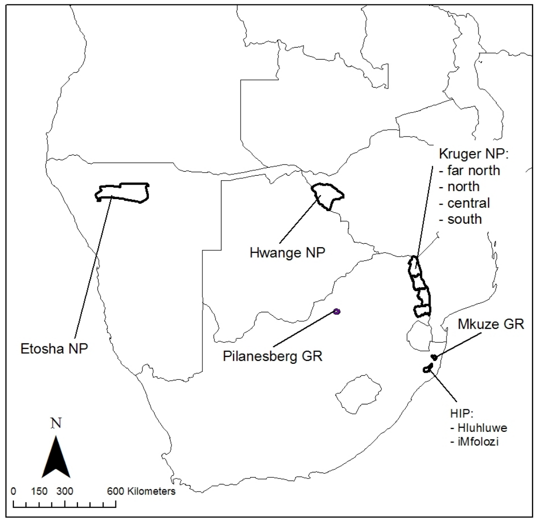
Figure 5: Maps of the standard deviation in burnt area a) observed in an 8 year satellite-derived burnt area product and b) predicted from variation in climate data over the same 8 year period. If burnt area were as responsive to climate drivers as the protected area data predict then we would see very different patterns across the region. The data are presented at 1-degree resolution (the original burned area data were produced at 500m resolution).

Figure 6: Comparing the variability predicted from climate data with the actual variability observed in an 8 year satellite-derived burnt area product. Only grid cells within the environmental limits of the field data (Figure 3) were included. Data are reported as the absolute anomaly (mean annual burned area minus the annual burned area) for each year for each 1 degree grid square across southern Africa. The range of values is similar, but the observed values are more concentrated around zero. This implies that the variability in annual burned area between years is less than expected: if climate were the main driver of fire at regional scales, burned area should vary more than is observed in the satellite data

Figure 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

FIGURES



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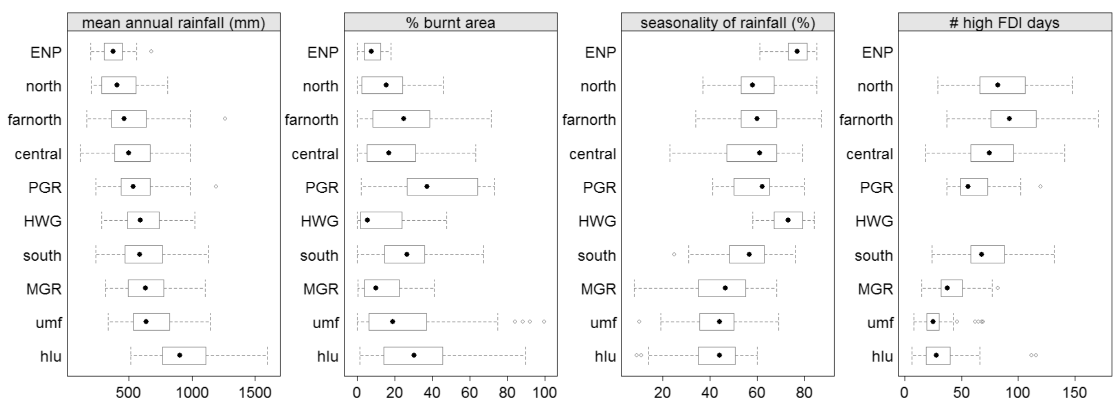

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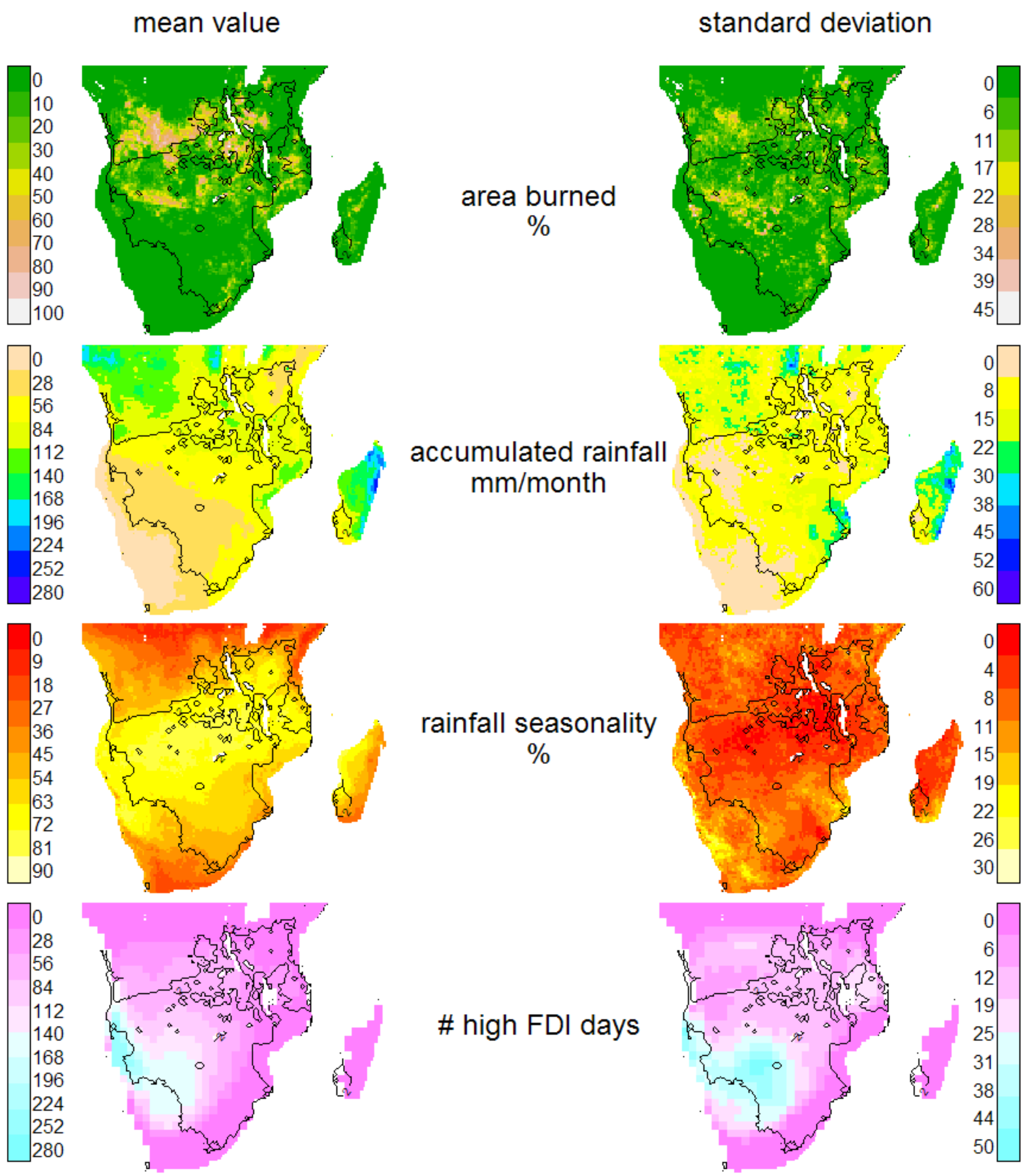

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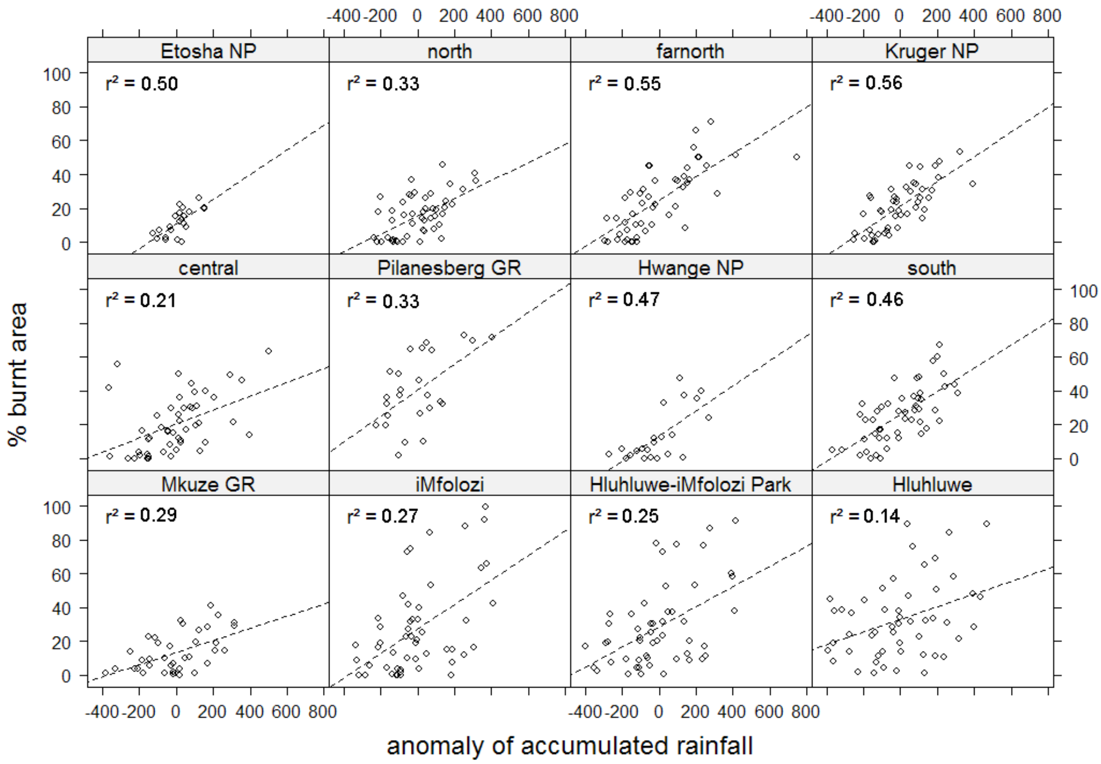

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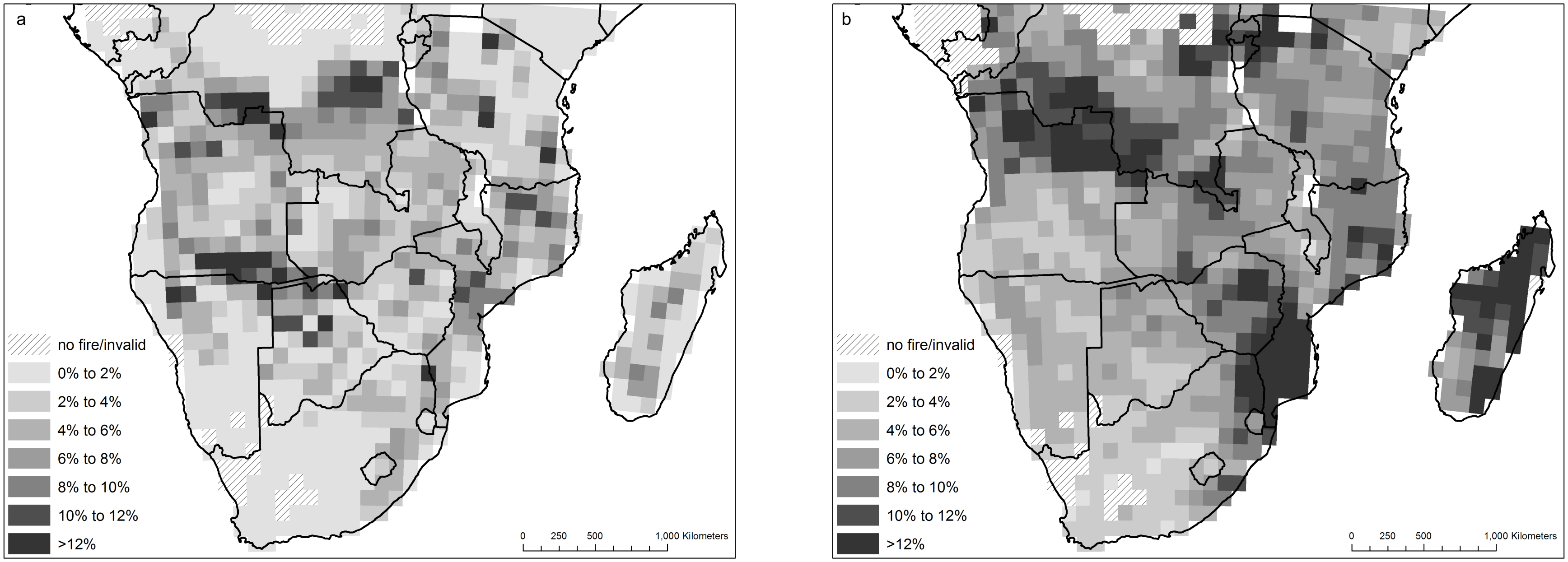

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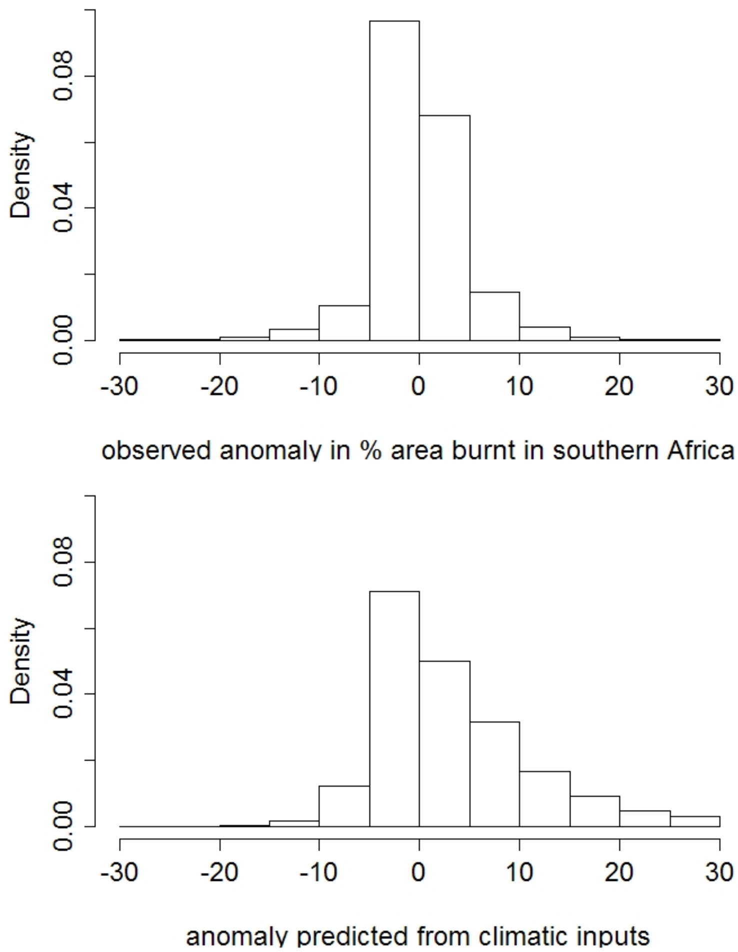

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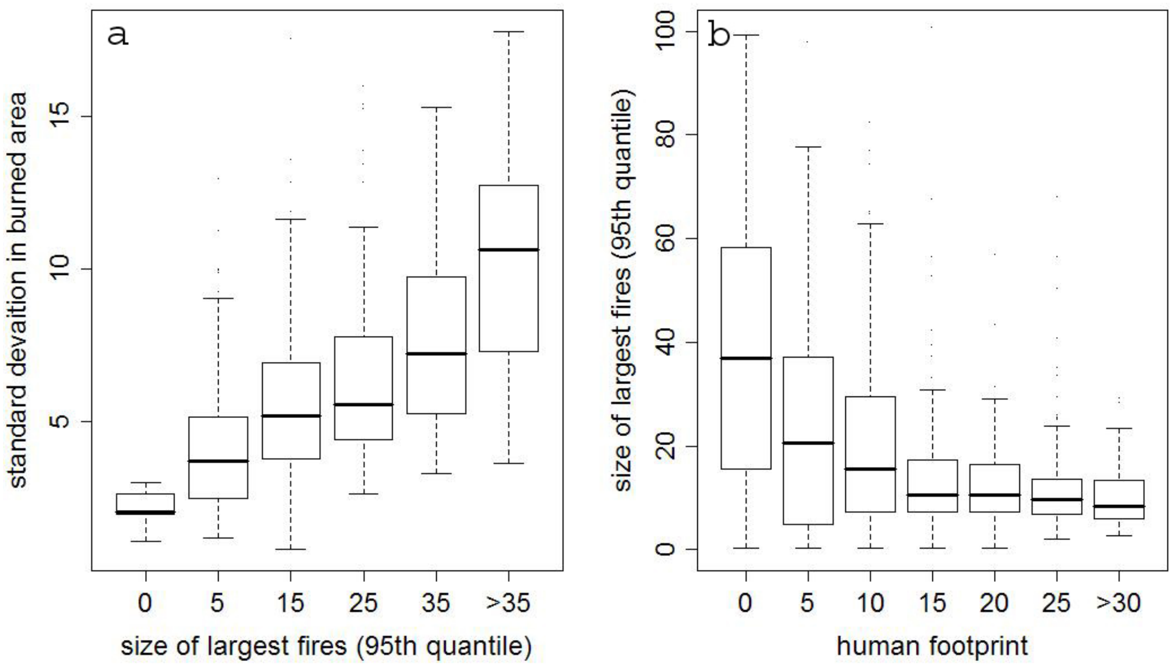

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TABLES

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

Table 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.

Table 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.

park	n	accumulated rainfall			extent of dry season			FDIdays			previous area burnt		
		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.

Table 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.

Table 4: Results of mixed effects models run on 1-degree grid cells across southern Africa using the 8 year MODIS satellite product. Spatial autocorrelation is tested for by including the value of the closest grid cell as a factor in the models. Two different LME models were run for low and high rainfall regions to test whether the importance of the input variables changes over a rainfall gradient. A third model was run using only the environmental conditions represented in the field data. In low rainfall regions the null model was consistently preferred over other models, but a model with seasonality (the extent of the dry season) was equally important 46% of the time. In high rainfall regions a model including seasonality was the best, but because this region is quite small a spatial correlation term was important 32 % of the time. The field data conditions results were very similar to the low rainfall conditions. 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. Results are a summary of 50 replicates each using 33% of the grid cells each time.

	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 = Baysian 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.

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SUPPLEMENTARY MATERIAL

Additional Supporting Information may be found in the online version of this article:

Appendix S1 Filling the MODIS data and testing it against the field data

Appendix S2 Defining the rainfall concentration index and the accumulated rainfall index

Appendix S3 Auxiliary information on the mixed effects modelling

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