Fire Hazard Modelling in Southern Africa

ICSPIE'15

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***Abstract*— In this study, we analysed fire occurrences in Southern Africa using point pattern analysis methods. The intensity of events varied vary across the region, events interacted across the region. The intensity plot showed that events are more concentrated at latitude -12.00 and longitude 35.00. Ripley's k-function revealed that events are clustered up to a distance of 14 km. We tested hypothesis that Higher amounts of dry mass productivity (DMP) and the normalised difference vegetation index (NDVI) result in more fire occurrences and more biomass burning, we also hypothesised that dry woodlands in savannah ecosystems result in more fire occurrences as compared to other land cover types in MaxEnt. Results showed DMP, NDVI and land cover types can be used to model fire occurrences with an ACU of 0,760.It also showed that as DMP and NDVI increased fire occurrence probability also increased. More fires are concentrated (0.79) in crop land with woody vegetation and closed grass land cover types. All the countries in Southern Africa have a high fire risky**

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***Index Terms*—fire harzad, DMP, NDVI, Prediction**

I. Introduction

Introduction

Even though fires are known to occur on the African savannah by accident and by natural causes(Fujisaka, Bell et al. 1996), by far the majority of fires are mainly caused by human pressure on the environment (San-Miguel-Ayanz, Ravail et al. 2005) and occur as part of natural resource management systems (Goldammer 1993).Fire is used for hunting, clearing land for agriculture(Nepstad, Klink et al. 1997), maintaining grasslands, controlling pests, and removing dry vegetation and crop residues to promote agricultural productivity and facilitate displacements (Bruzon 1994). It can also be used as a tool for forest cover conversion (Nelson and Irma˜o 1998)or can affect moist forests under exceptionally dry weather conditions or after selective logging has been undertaken (Holdsworth and Uhl 1997) leading to forest degradation. Fires also maintain savannah ecosystems by preventing the invasion of woody species, especially in forest/savannah transition zones (King, Moutsinga et al. 1997). Rangeland management may also include prescribed burning to reduce devastating run-away *fires* (Hough 1993)

Fires have been taking place throughout tropical savannahs and forests for millennia(Schmitz 1996). In a Savannah, the main short term impact of fires is to prevent the replacement of herbaceous strata by woody biomass and to enhance the production of some graminaceous species(Guerra, Puig et al. 1998). Fire is an important factor in the ecology of savanna, tundra and boreal forests ecosystems(Swaine 1992). Forest fires were once a natural phenomenon that played a very critical role in shaping species distribution and contributed to the persistence of fire dependent species, and helped the natural evolution of species.(San-Miguel-Ayanz, Ravail et al. 2005).

Late fires are actually damaging to ecosystems(Furley, Proctor et al. 1992), particularly to economically and culturally important trees. Early fires thus have both preventative and protective roles (Laris 2002). Land managers can encourage their farmers to clear and burn their fields early in the fire season.

In the present study, fires fire will be modelled as a function of land-cover, dry mass productivity and the Normalised Difference Vegetation Index using data using maps of burnt areas rather than maps of active fires to characterize biomass burning.(Eva and Lambin 1998) have shown that burnt scars carry a 'memory' of previous burning events, remaining detectable for up to three weeks following a fire. They also have a good spectral separability on remotely sensed images. Burnt areas can therefore be reliably mapped by satellite sensors with a high temporal frequency of

Manuscript received June XX, 20XX; revised July 29, 2015.

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acquisition. Maps of burnt areas are much more representative of actual burning events than are maps of active fires, and allow for a detailed representation of the spatial pattern of burning. This can thus be related to spatially explicit data on NDVI, DMP and land-cover, at a fine level of aggregation.

Problem statement states that, fire causes irreversible damage to fragile natural ecosystems and greatly affects the socio-economic systems of many nations especially in the tropics where forest fires are more prevalent ,these impacts have potential to constrain sustainable development.. According to Kitchen and Reid (1999), the common problem that is faced by ecologist when trying to access trends in burned area distribution is the lack of spatially accurate fire data. In Southern Africa the existing fire monitoring approaches are limited. There is little adequate data in the spatial distribution or trends in burned areas and locations. Satellite remote sensing provides the only practical means to monitor and identify fire locations over areas as extensive as Southern Africa(Roy, Frost et al. 2005). There is however a gap in knowledge concerning the application of remote sensing and GIS in veld fire mapping, analysis and modelling.th Most research has focused on the impacts and consequences of fire on ecosystems, Crutzen and Andreane (1990) .The relationship between land cover and biomass burning has not been fully investigated (Buchini and Lambin, 2001). Limited studies have been done in Africa on fire hazard prediction as a function of biomass, thus the modelling of fire hazard based on the wet season accumulated biomass (provides fuel for burning when it dries) is therefore vital as this can represent a pro-active approach to fire management that can be utilized by land use planners and policy makers in Africa.

Therefore we hypothesise that; Higher amounts amounts of dry mass productivity(DMP) and the normalised difference vegetation index(NDVI) result in more fire occurrences and more biomass burning. We also hypothesise that dry woodlands in savannah ecosystems result in more fire occurrences as compared to other land cover types

The objective of this study are focused on mapping and describing fire incidences, this includes plotting the intensity and Ripley’s k-function so as to understand the spatial trends ad patterning of fire. We also intend to explain fire incidences through fire hazard modelling, that is explaining fire as a function of dry mass productivity, NDVI and land cover; fire=f(DMP,NDVI,LC).We also want to establish which countries in Southern Africa have a high fire occurrence risk.

The research is justified because the prediction fire hazard is in Southern Africa is currently based on forecast temperatures. Fire hazard prediction based on wet season accumulated biomass and land cover is there for vital. Data on spatial trends of fire is also limited in Southern Africa, thus it is also vital to study the spatial distribution of burned areas and analyse them using point pattern analysis methods so as to give a good description of the fire. There is therefore need for the application of geographic information systems and remote sensing in monitoring the spatial distribution and modelling fire in Southern Africa. Justification also lies in the increase in the outbreak of fires globally, this has great negative impacts on the environment and socio-economic systems of many nations. Groot, (2007) noted that forest fires can have a wide range of negative impacts on human safety, health, regional economies, global climate change and fire sensitive ecosystems. It is estimated that around 2500 Mt of biomass are burnt every year over Africa, that is around half of the biomass which burn per year in the whole world(Arino and Melinotte 1998). This highlights the need to model and control the fires as possible so as to reduce their impacts on the environment.

Chapter 2: MATERIALS AND METHODS

Study area

The study area extends between latitudes 5 degrees 54 minutes and 32 degrees 3 munities north of the equator and between longitudes 10 degrees and 42 degrees east of the Greenwich meridian. The rainy season ranges from November to March. A pronounced dry season occurs from May to October, this coincides with the fire season.

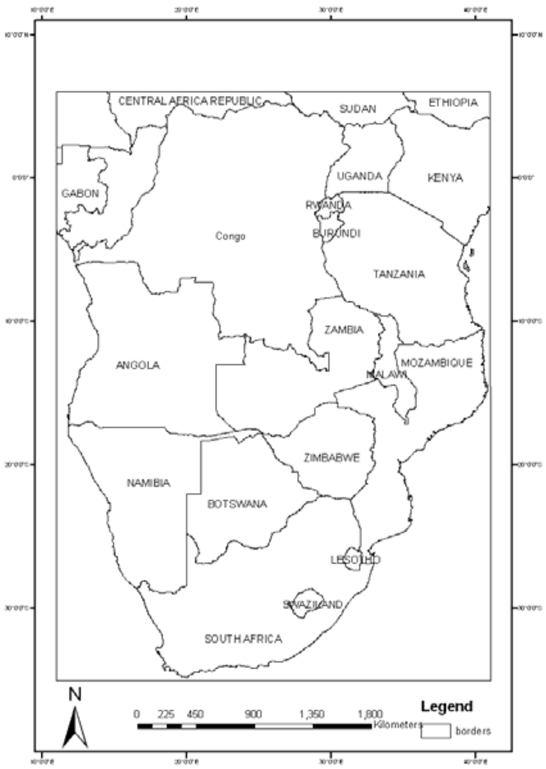

Figure 1.The study area (southern Africa)

Data

Data was gathered using the, Moderate resolution imaging spectroradiometer (MODIS) . The MODIS sensor is located on both the Terra and Aqua satellite, it is an advanced narrow bandwidth sensor with a wide spectral range (from 0,4µm to 14,4µm) and a wide spatial coverage. MODIS outputs geometrically corrected satellite imagery at a 250m spatial resolution, this was used to derive the burned area locations in Southern Africa for 2011.The data was acquire for the whole month of October because this period coincides with the end of the fie season for most countries in Southern Africa .The assumption being that the data is representative of the burning that occurred during the fire season from May to October before the on set of the rain season. The fire data was decoded in text format at the University of Zimbabwe Earth Observation centre. The data was converted to points in ArcView GIS. (www.ESRI.com) Fire occurrences were mapped as below.

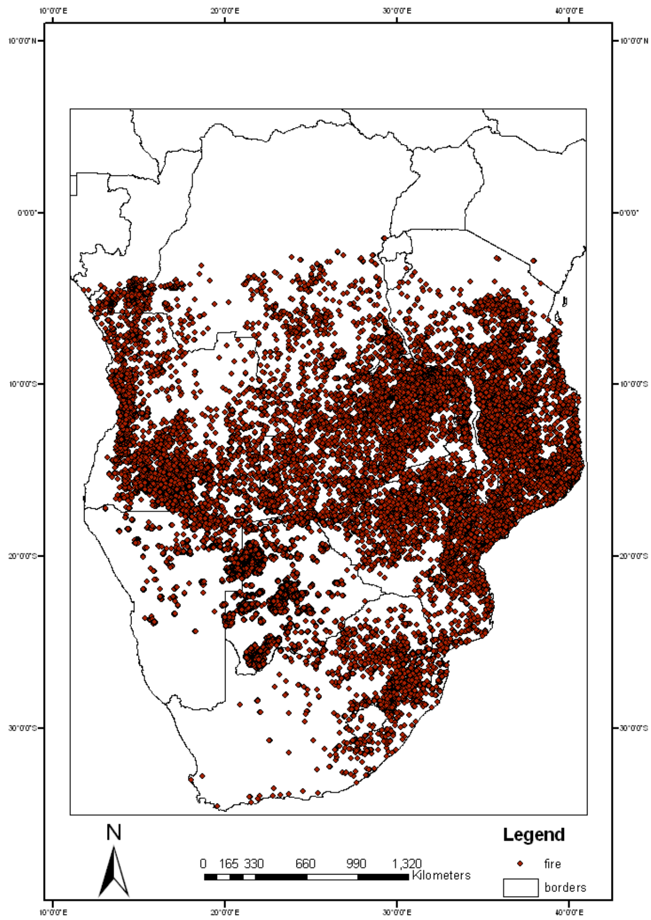

Figure 2. Fire occurrences for the month of 0ctober 2011

Fires are more clustered in the central region area of Southern Africa .Fire is more dispersed in the south - western and northern parts of Southern Africa.

MODIS imagery used for modelling was acquired at the end of the rainy season (end of March) before senescence. The imagery was used to derive the wet season accumulated biomass, approximated by the Normalised Difference Vegetation index (NDVI) and Dry Mass Productivity(DMP).The imagery was extracted using VGTExtract. The data was then exported to ILWIS were it was mapped as below in figure 3 and 4 respectively.

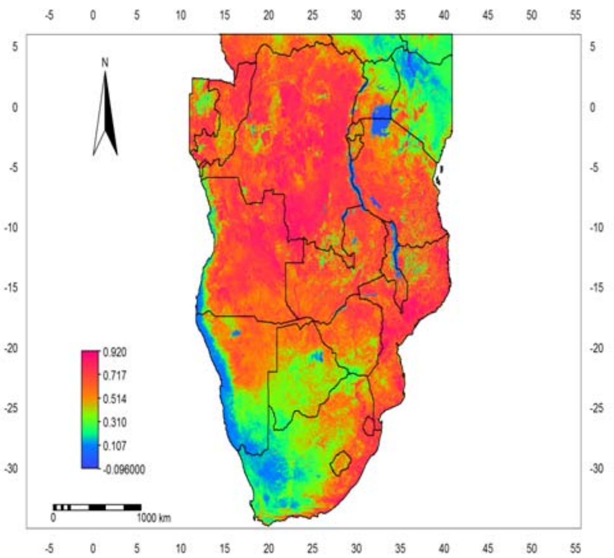

Figure 3.The NDVI distribution

NDVI is quite high throughout the region except in the north-eastern and the south -western corners of Southern Africa .It was derived from broadband measurements in the visible and infrared portions of the electromagnetic spectrum made by the MODIS instrument;

NDVI = (NIR-R)/ (NIR+R)

Where R and NIR are the surface reflectance in the Red (620-670nm) and the Near Infra-red (841-876nm) bands respectively. Generally higher NDVI values indicate greater vigour and amounts of vegetation.

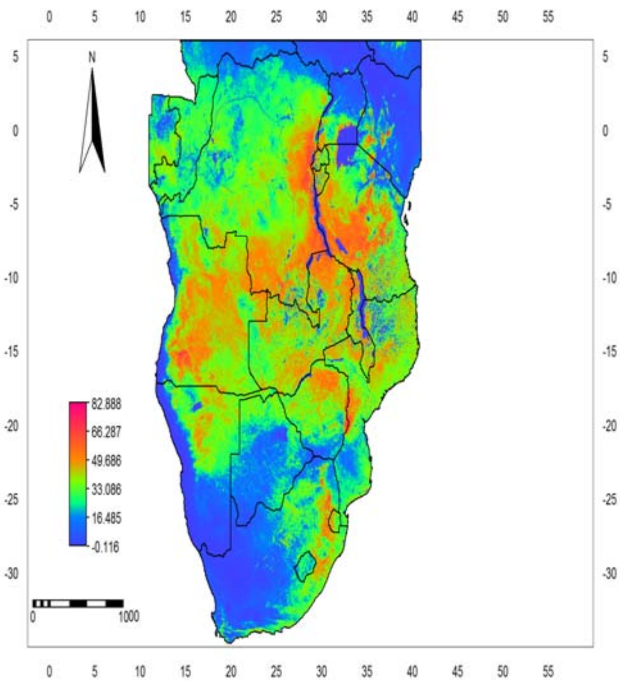

Figure 4.Distribution of DMP

The map above shows the dry mass that has accumulated at the end of the rain season (24 March 2012) measured in tonnes per hectare. Higher amounts were produced in the central region of Southern Africa and are represented by the colour red, whilst relatively little dry mass was produced in the northern and south-western parts of Southern Africa ranging from blue to green..

Land cover data was downloaded from the global land cover facility. It was in Grid format thus it was first converted to shape-file and then exported to ILWIS were it was mapped as below.

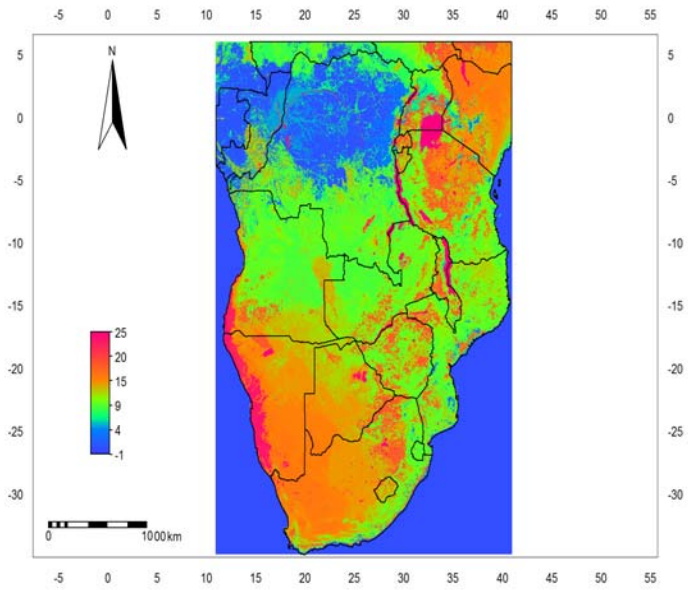

Figure 5.The distribution of Land cover classes

The land cover map used in the MaxEnt model as an environmental variable affecting the distribution of fire.it has classes ranging from 1 to 27. The negative 1 (in the legend) represents the background. Classes 1 to 27 range from range form bare rock to tree crops land cover types (more classes representation are shown in figure 9).

Analysis

In attaining the first objective of describing fire occurrences we used point pattern analysis methods. The intensity plot was used to get an accurate description of the number of points per unit area, fire data in excel spread-sheet format was imported into S-plus were intensity was plotted. The Ripley's k-function was used to describe spatial trends in relation to location, fire data in comma separated value (CSV) format, was imported into SpPack were univariate

Ripley's K-function was done to test for clustering or repulsion against a completely spatially random process (CSR) Ripley's *K* function is useful for identifying differences in spatial patterns through space. SpPack is a menu-driven add-in for Excel written in Visual Basic for Applications (VBA) that provides a range of statistical analyses for spatial point data. Fire predictions were done using MaxEnt, it is a statistical model used for making predictions or inferences from presence only information (Steven, Phillips et al. 2006).The pixels of the study were used as the space on which the MaxEnt probability distribution was defined. The pixels with known fire occurrence records constituted the sample points and the NDVI, DMP and land cover were the environmental variables that constrains the distribution of fire. Fire risk for individual countries was done in ILWIS, the MaxEnt output ASCII file was imported into ILWIS were it was crossed with the Southern Africa countries raster map. The output was converted into a graph.

CHAPTER 3: RESULTS AND DISCUSSION

Results

The intensity plot

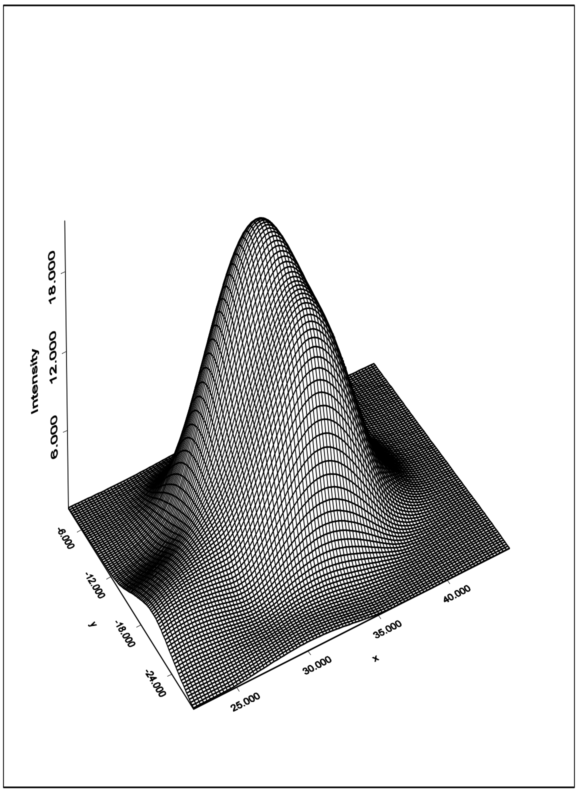

Figure 6.Intensity

The graph above shows the number of events(fire) per unit area. The area is bound by geographic coordinates (Lat-Lon) in the y and x directions respectively .Events are more concentrated at latitude -(Goldammer 1993; Bruzon 1994)12.00 and longtitude35.00. Intensity increases as one moves towards the centre of the study area, mostly in Zambia

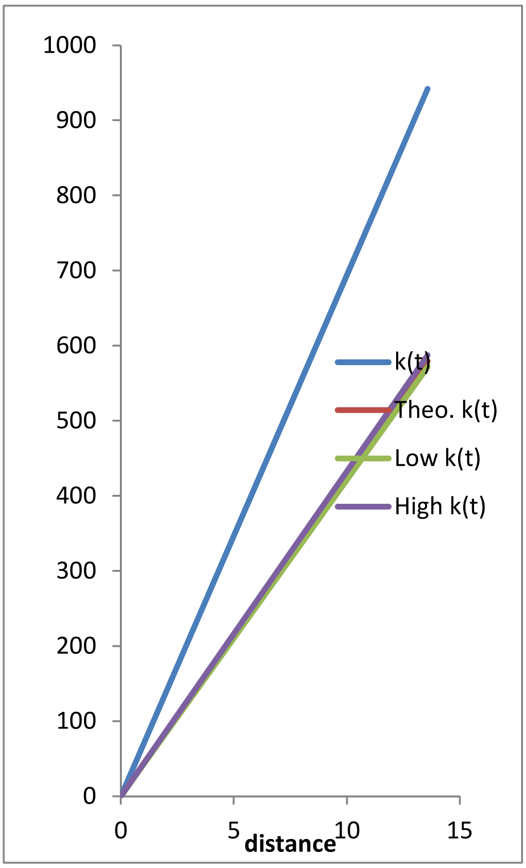

Figure 7. Ripley's k-function

There is clustering at up to a distance of 14 km as indicated by the k(t) line which is above the theoretical (CSR) as represented by the Theo. k(t) line.Number of events clustering increases as distance increases. CIs were at the 99% level based on 499 randomizations.

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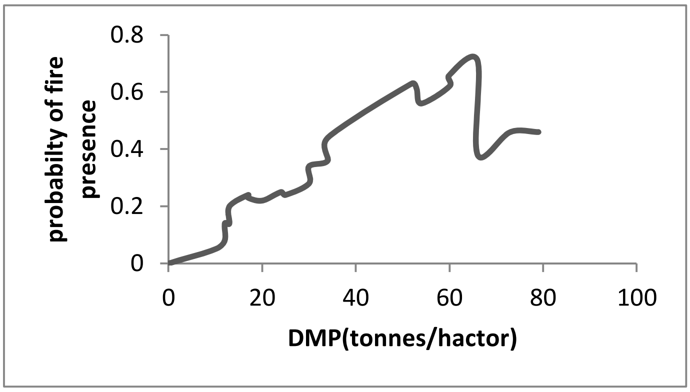

Figure 7.Fire, DMP response curve.

The graph summarises the relationship between fire hazard and DMP.As DMP increases the probability of fire occurrence also increases. DMP over 60 tonnes per hector is associated with a decrease in fire occurrence.

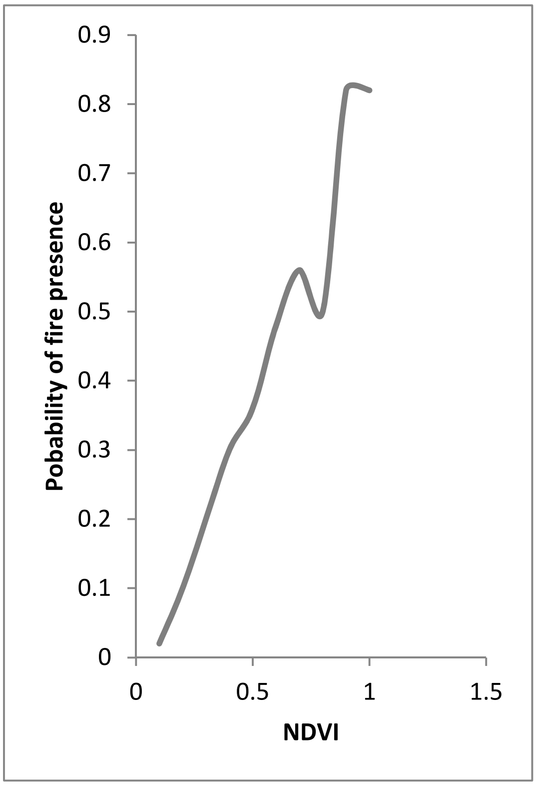

Figure 8. Fire, NDVI response curve.

The above graph shows the predictive relationship between fire and NDVI. Fire risk generally increases with increasing NDVI.

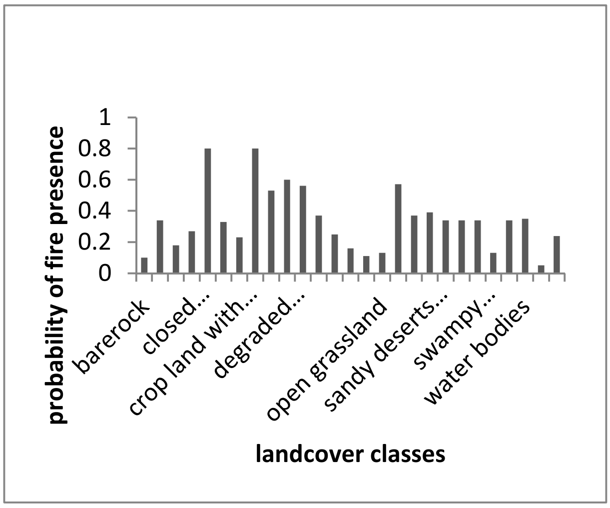

Figure 9.Reponse curve of fire against land cover

Fire risk is higher for the closed grass land and cropland with woody vegetation land cover types. It is lower particularly for bare rocks, open deciduous scrublands and water bodies land cover surfaces.

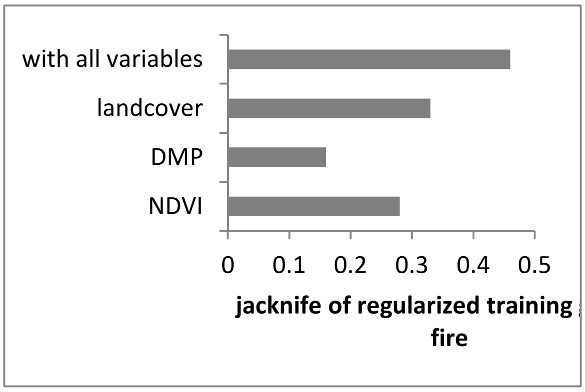

Figure 10. Jack-knife

The above graph shows the jack-knife result, which is a measure of variable importance. Here land cover was the most important variable in modelling fire hazard with a training gain above 0.3.When all the other variables were combined, NDVI was the most important environmental dependent.

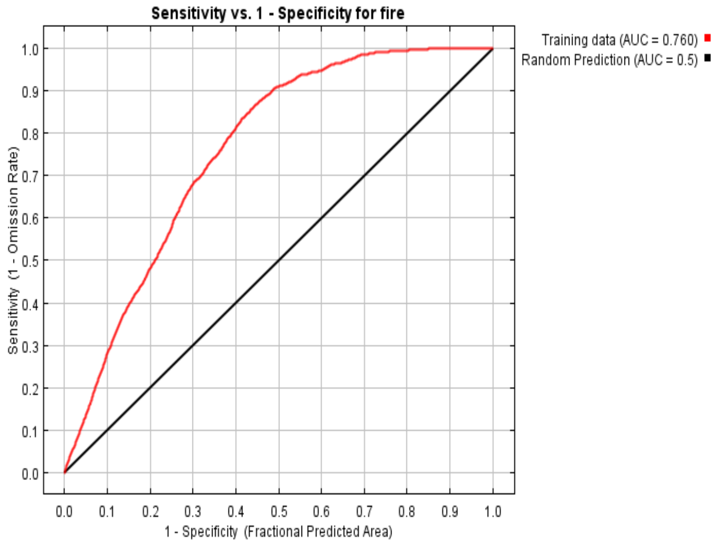

Figure 11 .AUC

Showing the results of the MaxEnt model Area under Curve (AUC)= 0.760. The AUC shows the strength of the model, in this case the value is closer to 1(maximum achievable value).the training data covers a larger proportion of the area thus the model is quite strong for predicting fire risk

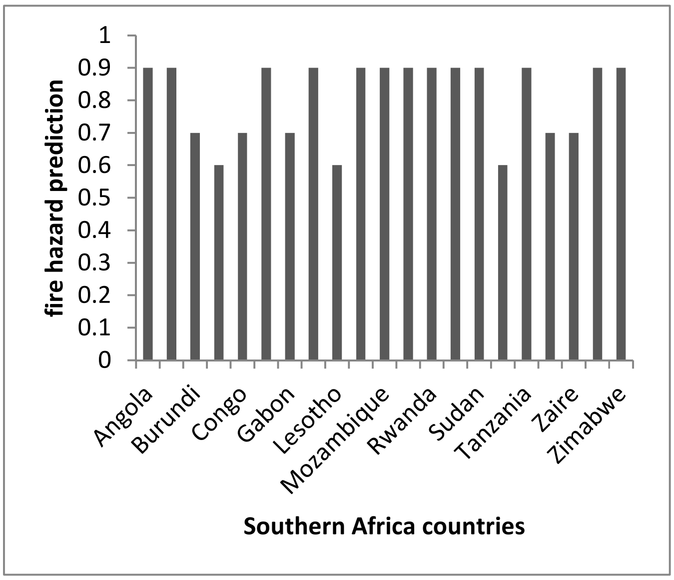

Figure12 .Fire risk for individual countries.

The graph the shows the average fire risk for individual countries in Southern Africa .Zimbabwe, Zambia, Uganda, Tanzania, Rwanda , south Africa, Namibia , Mozambique, Malawi Ethiopia, Botswana and Malawi have an extremely high fire risk.

Discussion

The fist objective of explaining fire incidences was achieved. The intensity of events varied vary across the region, events interacted across the region. The intensity plot showed the amount of the number of events per unity area. More events were clustered in central Southern Africa especially in Zambia; here there are Savannah climatic conditions which produce relatively higher dry biomass for burning. Intensity generally increases as one moves towards the centre of the study area.Riley's K-function revealed that there is clustering at up to a distance of 14 km as indicated by the k(t) line which is above the theoretical (CSR) as represented by the Theo. k(t) line. Number of events clustering increases as distance increases. Continued clustering for the whole region might have been highly influenced by countries such as Zambia with more fuel for burning, thus for individual countries the result might not be the same

Fire incidences follows an environmental gradient, increasing with net primary net primary productivity and standing biomass (Anyaba, Justice et al. 2003). Concentrations of NDVI and DMP in the central regions of Southern Africa can be attributed to the high levels of fire occurrence. In the Northern and South-western corner fewer fires were recorded due primarily to the wet equatorial and dry arid conditions respectively, these conditions are not conducive for dry biomass production (dry biomass provides fuel for burning provided there is an ignition). As NDVI and DMP increased, fire occurrence probability also increased. An excessive increase in DMP also results in a reduction of fire risk, this is evident in the Northern parts of Southern Africa, and this was revealed in the DMP response curves. A high fire risk of 0.79 was shown in the crop land with woody vegetation and closed grass land cover types. Maxent probability distribution is interpreted as an index of environmental suitability (Steven, Phillips et al. 2006) of fire occurrence. Higher probability values indicate higher environmental suitability for burning. This is largely influenced by human activities as in these land cover types there is forest clearing for Agricultural land creation. Land cover was the most important variable in determining fire predictions There is a general high fire risk for individual countries, all of the countries have a fire prediction risk above 0.5

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CHAPTER 4: CONCLUSION

Wet season accumulated biomass provides fuel for burning, provided there is ignition.. As a landscape disturbance, fires result in partial or complete destruction of vegetation cover (Guerra, Puig et al. 1998), the impact of biomass burning largely depending on ecosystem type(Eva and Lambin 1998). In dense humid forests, the presence of fires is usually associated with forest clearing, while savannah vegetation is resilient to fires, thanks to well-adapted species. The research results could be used for land management and conservation in the coming fire season

Fire prediction as a function of wet season accumulated biomass can be applied as apart of pre-season suppression strategies. fire managers can thus take proactive action towards areas that are most likely to be affected by fire, thus remote sensing and geographic information systems have the potential of to improve fire management in Southern Africa there is however need for further studies to model fire occurrences as a function of biomass and other environmental variables such as temperature rainfall, slope and human factors (crutzen 1990).

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