A two-decade analysis of the spatial and temporal variations in burnt areas across ecosystems of Zimbabwe

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Abstract

Understanding wildfire dynamics in space and over time is critical for wildfire control and management. In this study, fire data from MODIS (ESA/CCI/FireCCI/5_1) with ≥ 70% confidence level was used to characterise spatial and temporal variation in fire frequency in Zimbabwe between 2001 and 2020. Results showed that burnt area increased by 16% from 3,689 km^2 in 2001 to 61,330km^2 2011 and decreased in subsequent years reaching its lowest in 2020 (1161km^2). Over, the 20-year period, an average of 40,086.56 km^2 (11%) of land was burnt annually across the country. In addition, results of the regression analysis based on Generalised Linear Model illustrated that soil moisture, wind speed and temperature significantly explained variation in burnt area. Moreover, the four-year lagged annual rainfall was positively related with burnt area suggesting that some parts in the country (southern and western) are characterised by limited herbaceous production thereby increasing the time required for the accumulation of sufficient fuel load. The study identified major fire hotspots in Zimbabwe thorough the integration of remotely sensed fire data within a spatially analytical framework. This can provide useful insights into fire evolution that which can be used to guide wildfire control and management in fire prone ecosystems. Moreover, resource allocation for fire management and mitigation can be optimised through targeting areas most affected by wildfires especially during the dry season where wildfire activity is at its peak.

Key words: MODIS burnt area, climatic drivers, wildfire hotspots, lagged response

1. Introduction

In savanna ecosystems, fires are an important determinant for the co-existence of woody and herbaceous plants as they influence ecological processes such as tree-grass competition, grass productivity and tree recruitment (Scholes and Archer, 1997). Moreover, wildfires are critical in enabling nutrient cycling, seed germination and regulation of species composition and plant reproduction (Richards *et al*., 1999; Magadzire, 2013; Kosoe *et al.*, 2015; Shekede *et al*., 2019). In fact, previous studies have shown that a greater part of African savannas could transition into closed woodlands under the current climate in the absence of fire (Govender et al., 2006). Wildfires also significantly contribute to greenhouse gas emissions and aerosols thereby making them an important driver of atmospheric radiative forcing and air quality (Lasslop *et al*., 2019). Despite the importance of fires in controlling structure and function of ecosystems, uncontrolled wildfires can result in biodiversity loss through destruction of plants and animals, reduction of soil fertility and increased soil erosion rates and decreased infiltration (WWF, 2001; Nyamadzawo *et al.*, 2013). In Zimbabwe, recurrent wildfires are mostly driven by the long dry season coupled with abundant biomass fuel (Anyamba *et al.*, 2003; Maponga, et al., 2018). As a result of wildfires there has been extensive destruction to agricultural land, indigenous forests, national parks, rangelands, commercial timber plantations and communal grazing areas (Nyamadzawo *et al.*, 2013). For example, according to Chinamatira *et al*., (2016), more than 1 million hectares of land are burnt by wildfires every year during the fire season which starts in June and ends in November. Thus, improving our understanding of the spatial and temporal variations of wildfires is critical for guiding wildfire control and management.

In recent years, the availability of satellite data has improved due to the increase in satellite missions in space which has enabled scholars to characterize wildfires at various spatial and temporal scales (Anyamba *et al.*, 2003; Magadzire, 2013; Zhang, *et al*., 2016; Masocha *et al.*, 2018). Such sensors include Advanced Very High-Resolution Radiometer (AVHRR), Moderate Resolution Imaging Spectroradiometer (MODIS) and Landsat. For example, Bond, *et al*., (2002) mapped and assessed the global impacts of fire on ecosystems around the world. Furthermore, various global fire products that are now freely available have been applied to study numerous aspects of wildfires such as frequency and severity. These include the MODIS Burnt Area Products MCD45A1 and MCD64A1, Medium Resolution Imaging Spectrometer (MERIS) Fire CCI Products, Copernicus Burnt Area Products and the GLOBCARBON product (Humber *et al.*, 2019). Before the advent of satellites, it was difficult and, time consuming to characterize wildfires with accuracy especially at larger scales such as the national or even global scales (Roy and Boschetti, 2008).

Wildfires are driven by factors such as human population increase, vegetation biomass production, temperature, humidity, wind speed and slope (Anyamba *et al.*, 2003; Levin and Heimowitz, 2012; Shekede, *et al*., 2019). For example, population increase in resettlement areas and communal lands due to the Fast Track Land Reform Program (FTLRP) led to an increase in burnt areas in Zimbabwe (Maponga, 2012). In savanna ecosystems, high vegetation production during the rainy season provides abundant fuel load for fires to occur and high temperatures during the dry season facilitate the spread of wildfires (Magadzire, 2013). According to Nyamadzawo *et al.*, (2013) wildfires in Zimbabwe are largely caused by anthropogenic activities which include hunting, using fire to improve grazing land, burning of crop residues, land preparation for farming and smoking out bees. Other causes of wildfires are waste dumps, arson, cigarette stubs and natural factors such as lightning (Chinamatira, Mtetwa and Nyamadzawo, 2016). A deeper understanding of the causes of wildfires in Zimbabwe can play a crucial role in planning mitigation and control measures which can reduce wildfire ignition and spread.

Several studies have been carried out on wildfires in Zimbabwe (Maponga, 2012; Magadzire, 2013; Kusangaya and Sithole, 2015; Chinamatira, Mtetwa and Nyamadzawo, 2016; Mpakairi *et al.*, 2019). Some of these studies focussed on drivers of wildfires, fire trends, fire frequency, burnt area and fire hazard zones in different districts of Zimbabwe. In addition, these studies have shown that wildfires in different parts of the country are mainly driven by human activities such as hunting, bee harvesting, land preparation, burning of crop residues, and deliberate arson (Nyamadzawo *et al.*, 2013; Chinamatira, *et al*., 2016). In general, these studies showed that there was a significant increase in burnt areas and coverage from 2000 to 2010, and that wildfires occur regularly in the country. However, all these studies were carried out at smaller spatial scales such as the district level and at comparatively short period of time which limits our understanding of wildfire patterns at large spatial and temporal scales (Maponga, 2012; Magadzire, 2013; Maponga, Ahmed and Mushore, 2018; Mpakairi *et al.*, 2019). Furthermore, these short time scales limit our ability to make conclusive statements about wildfire patterns including trends (Magadzire, 2013). Therefore, studies characterizing spatial and temporal wildfire patterns at large spatial and temporal scales could increase knowledge of wildfires thereby assisting responsible authorities to target wildfire hotspots and optimise distribution of limited resources efficiently across the country.

To improve our understanding of wildfire patterns in Zimbabwe, this study used MODIS remotely sensed fire data from 2001 to 2020. The objectives of this study were to (1) model spatial variation in frequency of occurrence of burnt areas over a twenty-year period, and (2) determine the drivers of spatial and temporal variations in burnt areas in across Zimbabwe. It is anticipated that the results of this study will be useful in identifying spatial trends in fires, identify repeat or incidental fire areas and provide quantitative information for targeted fire management.

2. Materials and Methods

2.1 Study area

The study was carried out in Zimbabwe, which is a landlocked country in southern Africa with a total area of 390,757 km^2. It is bordered by South Africa, Mozambique, Botswana and Zambia (Figure 1). The country is located between latitudes 15°30″ and 22°30″S and longitudes 25°00″ and 33°10″E. Altitude across the country varies from under 300m in the south-east to more than 2500m above mean sea level in the eastern parts. Annual rainfall varies from less than 400 mm in the southern and north-western parts of the country to above 1000 mm in the eastern mountainous areas (Crop *et al.*, 2012; Gwitira *et al.*, 2015). The mean annual rainfall in the country is 675 mm. There are two distinct seasons: wet and dry seasons. The wet season starts in November and ends in March, while the dry season begins in April and terminates in October. The mean monthly temperatures vary from 15°C in the winter months (June-July) to 24°C in the month of November, while average annual temperature ranges from 18°C in the eastern highlands of the country to 23°C in the Limpopo Valley (Crop *et al.*, 2012). These weather conditions support high biomass production in the central, northern, western and eastern parts of the country which provides fuel load for wildfire ignition and spread (Anyamba *et al.*, 2003). In Zimbabwe, the savanna ecosystem is characterized by a mixture of trees and tall grass which ensures abundant biomass fuel for fires particularly during the dry season. The country is under forests and woodlands, the savanna woodlands are made up of five woodland types which are: miombo, *Acacia*, mopane, teak (*Baikiae plurijuga*), and *Terminalia-combretaceae* (Nyamadzawo *et al.*, 2013). These woodlands consist of both grasses and woody plants which provides high biomass fuel that is required for fire ignition.

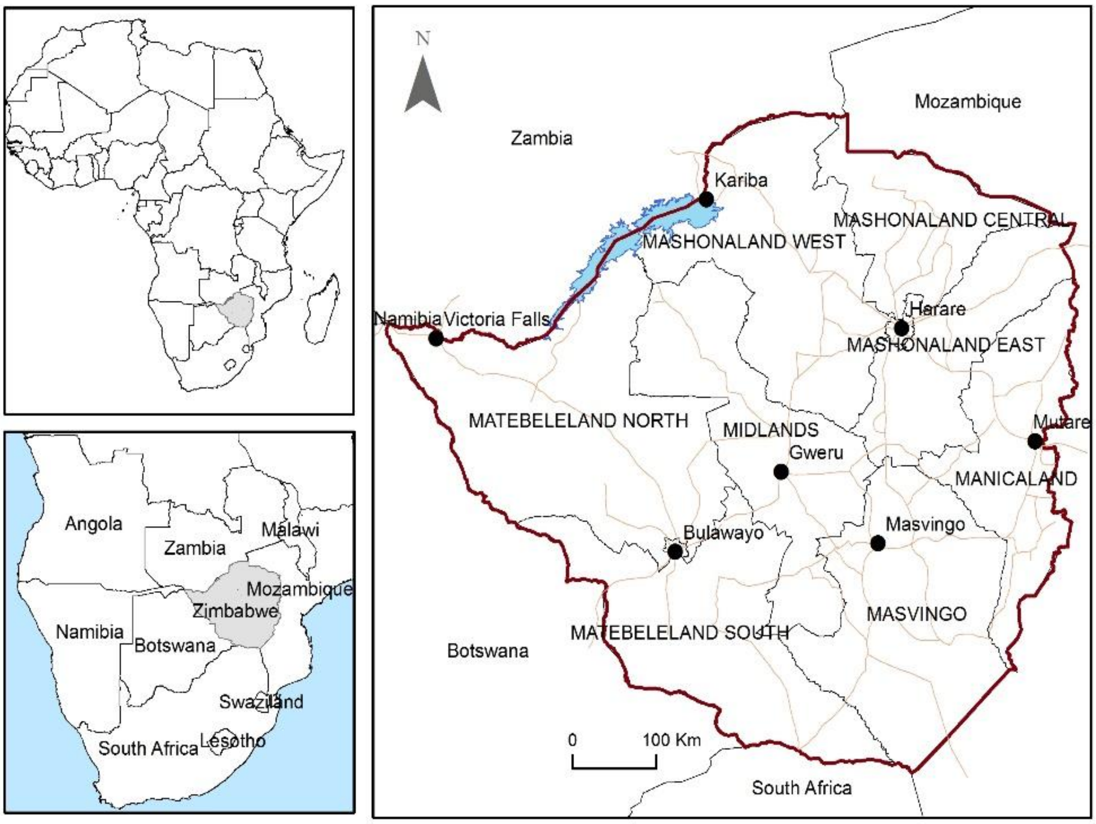

Figure 1: Location of the study area. *The top insert shows the location of Zimbabwe in Africa, and the bottom insert shows the neighbouring countries of Zimbabwe in Southern Africa*.

2.2 Data

The fire data were derived from the Moderate Resolution Imaging Spectrometer (MODIS) Fire Climate Change Initiative Burned Area pixel product version 5.1. The portal was accessed via Google Earth Engine as an image collection (ESA/CCI/FireCCI/5_1). The product is available at global scale with a spatial resolution of 250m. The data considered in this study spanned from1st of January 2001 to the 1st of December 2020. Only burned pixels with a confidence level of ≥70% were selected to ensure reliable fire data products (Roy and Boschetti, 2008; Oliveras et al., 22014; Giglio *et al.*, 2016). The bidirectional reflectance model-based change detection algorithm was applied in the detection of fire pixels (Roy and Boschetti, 2008). The algorithm uses spectral, temporal, and structural changes to detect burned areas at 250m grid cells. Burned pixels are characterised by deposits of charcoal and ash, removal of vegetation and alteration of the vegetation structure (Roy and Boschetti, 2008; Giglio *et al.*, 2016). The images are a series of pixels defined by a specific set of values i.e., Julian day of burning, water, unburned, snow and invalid data (Giglio *et al.*, 2016). The pixels with values ranging from 1-366 which represented the Julian day burning and with other values such as 0 (the pixel is not burned), -1 (pixel is not observed in the month) and -2 (pixels that are not burnable: water bodies, bare areas, urban areas, permanent snow and ice) were considered in this study. The data uses the Julian dating system which is the continuous count of days from the beginning of the year to the end of the year.

Sentinel Landcover data at 20m resolution was acquired from the following website: *http://2016africalandcover20m.esrin.esa.int/ and was used for* determining the fire frequency and return intervals across landcover types of Zimbabwe. From the ESA landcover classification with 19 vegetation cover classes, we reclassified these into the following nine landcover types for Zimbabwe, namely: bare areas, bushland, cultivation, grassland, riverine vegetation, urban, water, wooded grassland, woodland, Figure 2 and Table 1). These nine classes are the ones commonly used by the Forestry Commission of Zimbabwe in landcover classification. The general descriptions of the different landcover classes are as given in Table 2 below:

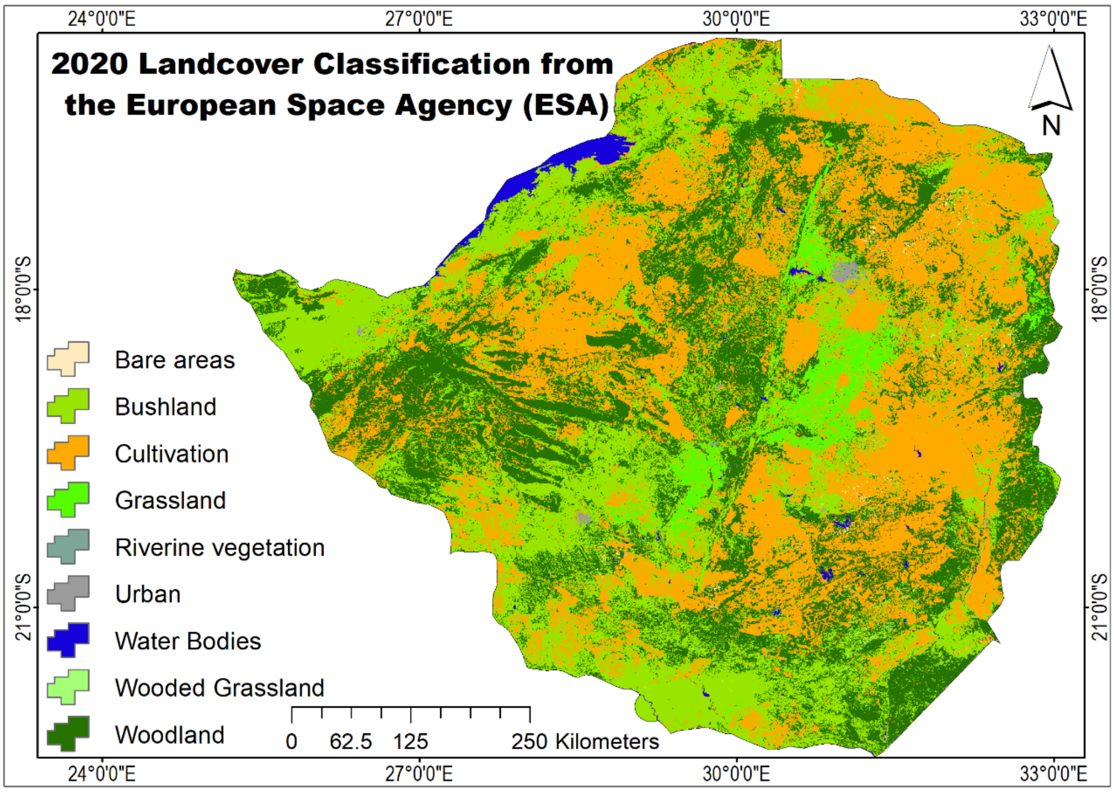

Figure 1:The 2020 European Landcover Classification for Zimbabwe

Table 1: Reclassification of the ESA Vegetation classes into classes used in this paper

Value	ESA Vegetation Classes	Reclassified Vegetation Classes
1	cropland rainfed	Cultivation
2	cropland rainfed herbaceous cover	Cultivation
3	cropland rainfed tree or shrub cover	Cultivation
4	cropland irrigated	Cultivation
5	mosaic cropland	Cultivation
6	mosaic natural vegetation	Woodland
7	tree broadleaved evergreen closed to open	Woodland
8	tree broadleaved deciduous closed to open	Woodland
9	tree broadleaved deciduous closed	Woodland
10	tree broadleaved deciduous open	Woodland
11	mosaic tree and shrub	Bushland
12	mosaic herbaceous	Bushland
13	shrubland	Bushland
14	shrubland deciduous	Wooded Grassland
15	grassland	Grassland
16	sparse vegetation	Bushland
17	tree cover flooded fresh or brackish water	Riverine vegetation
18	tree cover flooded saline water	Riverine vegetation
19	shrub or herbaceous cover flooded	Riverine vegetation
20	urban	Urban / Built-up

21	bare areas	Bare areas
22	water	Water

Table 2: General Description of the different vegetation types in Zimbabwe

Value	Class	Description
1	Woodland	Opened to closed woodlands with a minimum surface coverage of 10%
2	Wooded Grassland	Opened to closed shrubs and bushes; proportion of trees must not exceed the proportion of the shrubs
3	Grassland	Dominance of grasses; the proportion of woody plants must be negligible
4	Cultivated areas	Comprising cultivated as well as uncultivated, irrigated as well as fallow fields / cropland areas
5	Riverine Vegetation	Regularly flooded areas which can be covered by grasses, shrubs and trees
6	Bushland	Sparsely vegetated areas, lichens or mosses
7	Bare areas	Areas without vegetation or almost no vegetation such as rocks, and barren soil
8	Built up areas /Urban	Artificial surfaces, settlements and industrial areas; excluding streets
9	Water bodies	Areas that are covered with water all-season

Climate data used for determining key climatic drivers of wildfire in different vegetation types were downloaded from https://power.larc.nasa.gov/data-access-viewer/. The data included the following variables measured at 2m above the ground: temperature, specific humidity, wind speed, maximum and minimum wind speed, precipitation and root zone soil wetness. The climate data are available at a spatial resolution of 0.5 * 0.625 degrees of latitude and longitude, respectively. The Vegetation Condition Index was calculated from MODIS NDVI data available at https://appeears.earthdatacloud.nasa.gov. The data are available as 16-day NDVI composites at a spatial resolution of 250m.

2.4 Data processing and analysis

Burnt areas extracted from raw images were reclassified into 2 classes: burnt areas (1) and unburnt areas (0) through using conditional statements in ArcGIS software. From the binary map, overall monthly fire frequency was derived by summing all the images with fire in that month from the first to the last year. For example, to get fire frequency for the month of December, all fire images for the month of December from 2001 to 2020 were summed using the raster calculator function in ArcGIS. Similarly, to get the yearly fire frequency map all classified burnt area images of each year from January to December were summed. The frequency indicated the number of times each pixel was burnt over the respective months and years for the ~20-year period. The final fire frequency maps were produced using ArcGIS software. To determine the fire frequency per landcover class, an overlay analysis was performed using the Sentinel 2016 landcover map (European Space Agency Climate Change Initiative - Land Cover project 2017) over the 20-year period. Kruskal Wallis statistic was applied in RStudio to test whether frequency of burnt areas significantly differed across different landcover types in Zimbabwe. In addition, piecewise regression was implemented in RStudio to determine changes in burnt area trends at 95% confidence interval.

2.5 Modelling the drivers of burnt areas

In this study, Generalised Linear Model was used to predict burnt area as a function of climatic variables. To achieve this, variables were first tested for collinearity using a Variance Inflection Factor of 10 based on thresholds suggested in literature (Sulaiman et al., 2021; Shekede et al., 2018). The uncorrelated variables were incorporated in a model using the stepAIC function in R studio. This process yielded a set of models arranged by AIC. Based on the AIC results, the model with the least AIC was selected as the best model that predicted burnt area in the country. The resultant model contained precipitation, vegetation condition index, temperature at 2m, specific humidity at 2 meters (QV2M), wind speed at 2 meters (WS2M), maximum wind speed at 2 meters (WS2M_MAX) and minimum wind speed at 2 meters (WS2M_MIN).

2.6 Validation of burnt area data

Data used for validating the model was obtained from the Environmental Management Agency of Zimbabwe. The data was collected by district officers of the agency as part of the environmental data they gather in their routine work. Once a fire is detected, district officers collect information that include coordinates where fire occurred and an estimate of areal extent of burnt areas. The point data collected in the field was overlaid with the burnt area derived from the satellite imagery. The field data was characterised by lack of consistency hence only points for the year 2019 which were proportionately higher (n=34) were considered. The overall accuracy (True Positive + True Negative) / (Positive + Negative) and F1 score (2*True Positive / (2*True Postive + False Positive + False Negative) were calculated by dividing the number of times when there was agreement between satellite derived burnt area and ground data over the total number of attempts. True positive is when data on the satellites predict a fire that was observed on the ground while the True Negative is when the satellite detects absence of fire when no fire was present on the ground. False positive and False negative occur when the satellite detects a fire that is absent and fails to detect a fire that is actually on the ground, respectively. The approach was necessitated by the fact that fire data was available as presence only data. The MODIS burnt area data had an overall accuracy of 0.69 and F1 Score of 0.81 suggesting a relatively high fire detection of fire by the MODIS Sensor.

3. RESULTS

3.1 Dynamics of Burnt areas across Zimbabwe from 2000 to 2019

Figure 2 illustrates the spatial variations burnt areas across the country from the year 2001 to 2020. Burnt area markedly increased every year for 10 years and declined yearly thereafter. The largest burnt areas were recorded in 2010 and 2011 and 2009 (Figure 1) during which a total of 58,081km^2 (15%) and 61,330km^2 (16%) of land was burnt in different parts of the country, respectively. Over, the 20-year period, an average of 40,086.56 km^2 (11%) of land was burnt annually in the country. Burnt area increased from 3689 km^2 in 2001 to 61,330km^2 in 2011 and decreased thereafter reaching its lowest extent in 2011 (1161km^2).

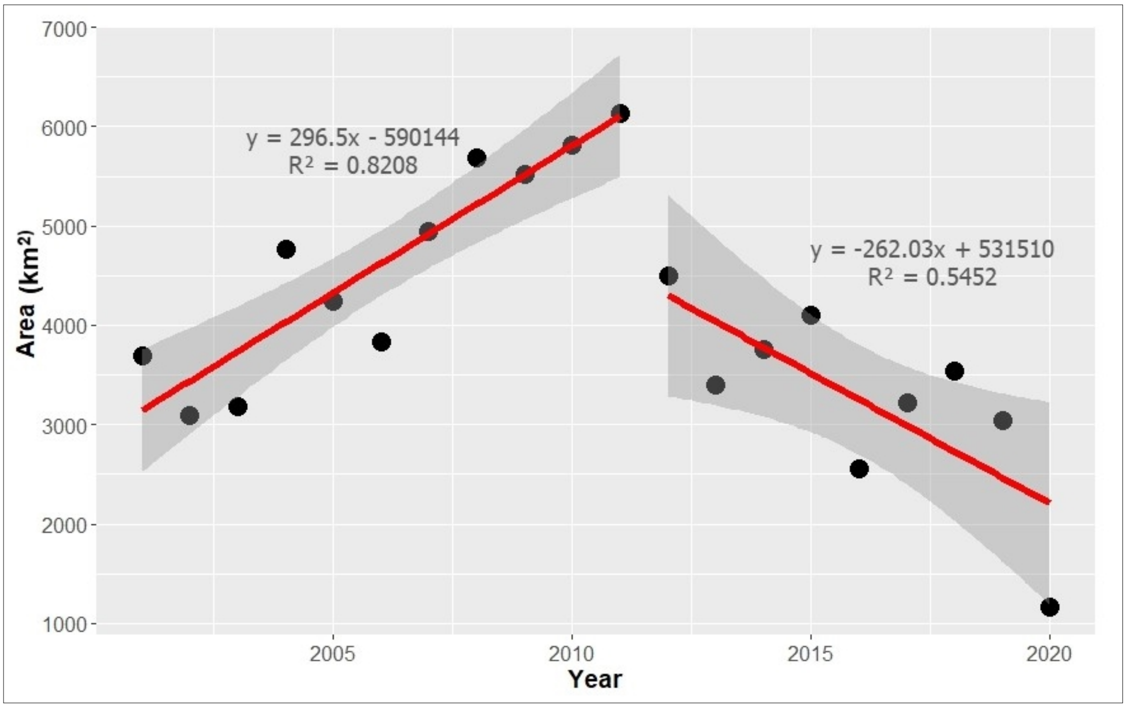

Figure 2: Temporal changes in burnt areas across Zimbabwe from the year 2001 to 2020. A positive trend in burnt area is observed from 2001 up to 2011 while a negative trend is observed thereafter.

An analysis of burnt area data at monthly scale shows that rainfall months had the least burnt area particularly November to April (Figure 3). During this period a minimum average of 7 km^2 and a maximum average of 1,074 km^2 in burnt area were recorded.

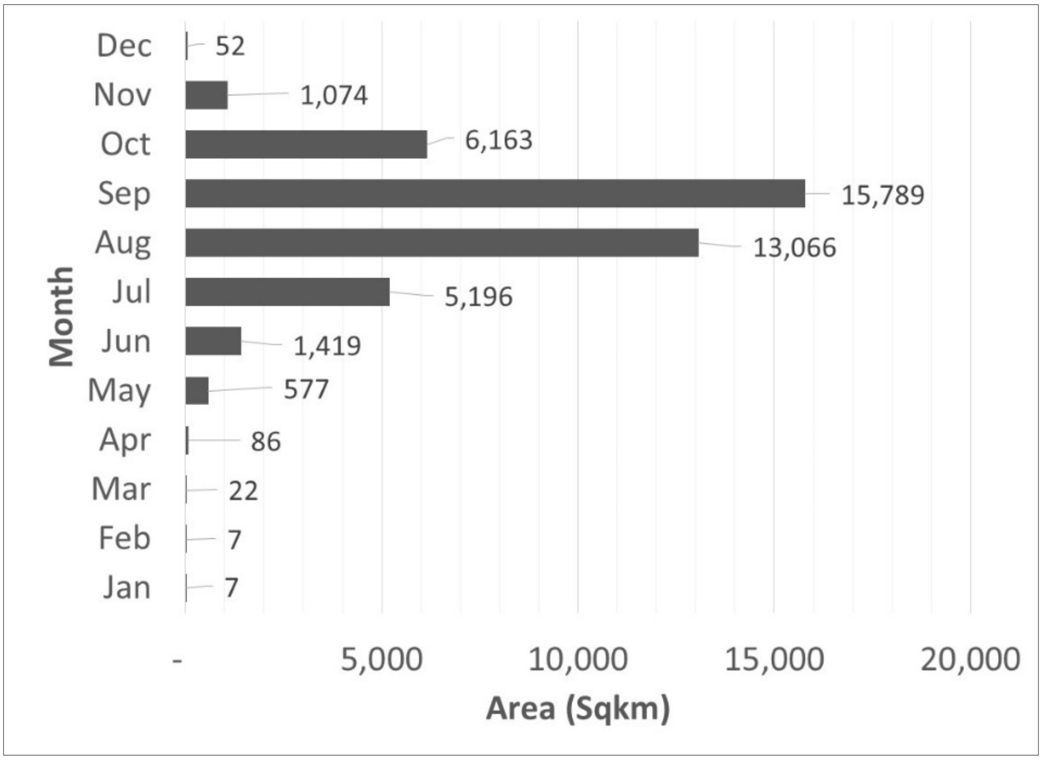

Figure 3: Changes in average burnt area in Zimbabwe between 2001 and 2020

Burnt area increased considerably towards the end of the rainfall season (May) with the maximum burnt area recorded in the driest of months of the year i.e., June to October. This relatively dry period coincides with the fire season in the country.

3.2 Spatial variations in wildfire frequency

Fire frequency i.e., the number of times a pixel burned, varied markedly across the country over the 20-year period (Figure 3). Most of the fire activity was concentrated in the central, northern, and north-western parts of Zimbabwe. Notable areas that experienced persistent and frequent fires include areas around Chinhoyi, Banket, Mhangura, Kariba, Hwange, Shamnva and around Chivhu. The greater parts of these areas recorded fire frequency of greater than 7 suggesting that these pixels burnt more than 7 times over the 20-year period. In contrast, the eastern, southern, and western parts of the country experienced the least fire frequency with either no burnt area recorded, or having burned only once.

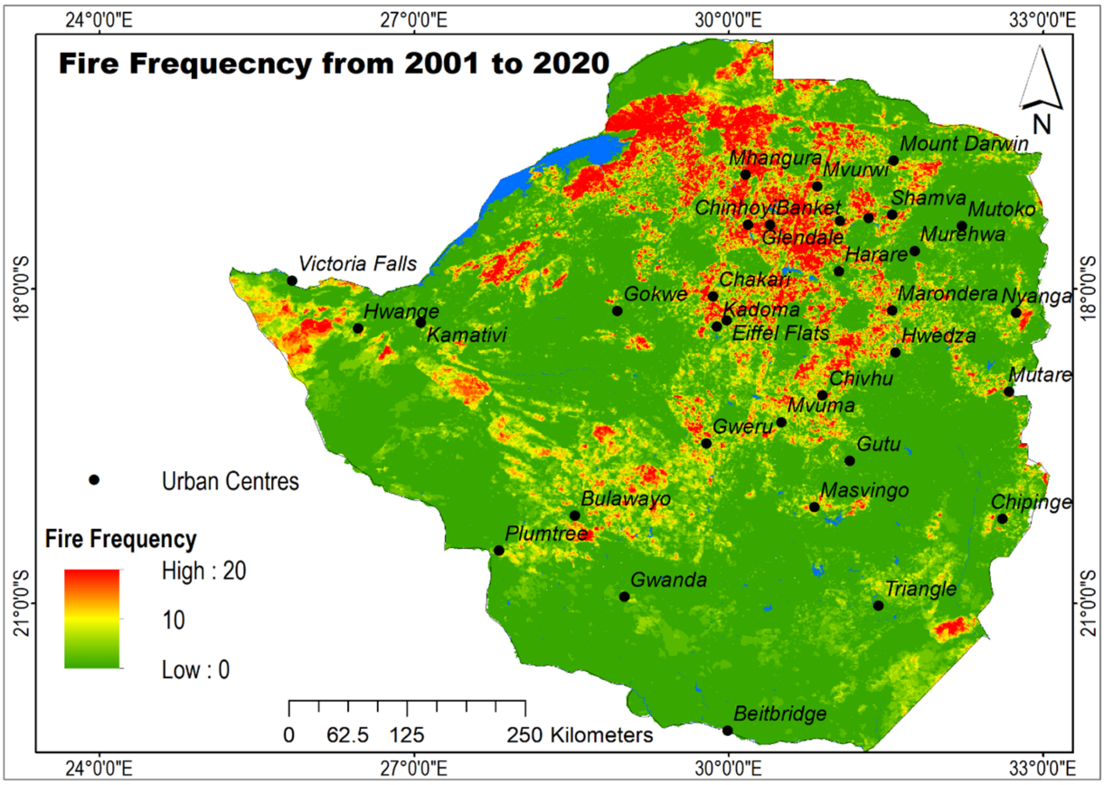

Figure 4: Spatial and temporal variation in wildfire frequency from January 2001 to December 2020.

3.3 Fire Frequency by vegetation type based on Sentinel vegetation classification

Fire frequency significantly (Kruskal-Wallis $\chi^2 = 7346.3$, df = 7, p-value =0.000) varied across vegetation types with the highest frequency of burned pixels observed in sparsely vegetated areas with an average of 2.8 events over 20 years (Table 1). Grassland and tree cover area had the second and third most frequency of burned areas. Shrubland and croplands had the least frequency of burnt areas. In all vegetation types, fire frequency ranged from zero to 20 suggesting that some areas never burned at all while others burn nearly every year (Figure 4).

Table 3: Reclassified 2020 Sentinel vegetation map and the respective fire frequency

Landcover Type	Area SQKM	% of Area	Fire Frequency				
			Min	Max	Range	Mean	Std
Riverine Vegetation	475	0.12%	0	9	9	0.7	1.0
Bare areas	159	0.04%	0	12	12	1.0	2.2
Built up areas	631	0.16%	0	12	12	0.7	1.7
Cultivated areas	104063	26.63%	0	19	19	**1.6**	3.2
Woodland	86648	22.17%	0	20	20	**2.3**	3.5
Grassland	68539	17.54%	0	20	20	**2.6**	4.0
Wooded Grassland	126539	32.38%	0	20	20	**1.7**	2.9
Bushland	381	0.10%	0	18	18	**2.8**	4.1
Open Water	3321	0.85%	0	18	18	0.4	1.5

In terms of extent, bushland had the highest mean burnt area (2.8) all the vegetation type while riverine vegetation were the least burnt area (0.7). Within the cultivated areas, woodland, grassland, wooded grassland, and bushland had the highest fire frequency ranging from 18 to 20, meaning that some areas within this vegetation types burned almost every year in the 20 years under analysis.

3.4 Climatic drivers of spatial and temporal variations in burnt areas between 2000 and 2020

Results of the relationship between burnt areas and changes in climate variables show that temperature, windspeed and root zone soil wetness significantly influenced the extent of burnt areas in Zimbabwe over the 20 years period. Specifically, temperature and windspeed positively influenced burnt areas while Root zone soil wetness had the opposite effect. Of these climate variables, root zone soil wetness had the greatest effect.

Table 2: Climatic variables explaining variations in burnt area

Variable	Standard Error	T-value	P-value
Intercept	**255513.4**	**4.370**	**0.001**
Precipitation	15.9	-1.327	0.211
Vegetation Condition	303.0	1.494	0.163
Temperature (2m)	**9316.5**	**3.857**	**0.002**
QV2M	11881.6	1.546	0.150
WS2M	**24458.9**	**3.338**	**0.007**
GWETROOT	**216265.8**	**-4.066**	**0.002**

WS2M_MAX	4308.4	1.972	0.074
WS2M_MIN	108709.5	1.089	0.299

Figure 5 illustrates the four-year lagged response of wildfires to rainfall across Zimbabwe. It can be observed that burnt area positively responds to preceding four-year rainfall with a 1mm increase resulting in a thirty-eighty-fold increase in burnt area. The annual average rainfall received between 2001 and 2020 ranged from 430 recorded in 2006 to and 876 observed in 2004. On the other hand, minimum burnt area (11,610,000ha) was recorded in 2020 after the second lowest rainfall amount recorded in 2019.

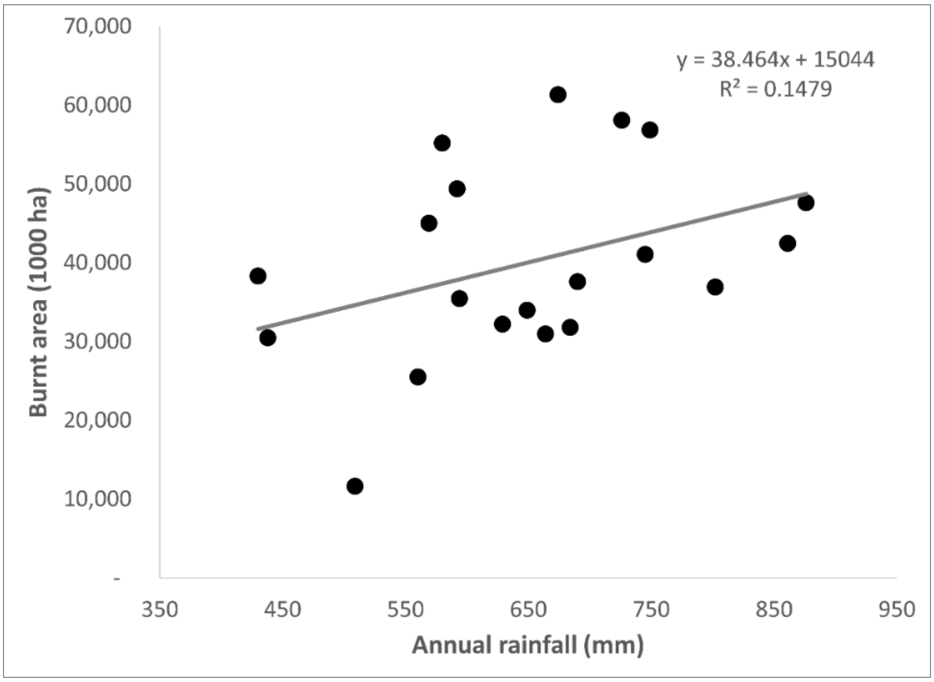

Figure 5: Relationship between mean annual rainfall over the preceding four years and total burnt area across Zimbabwe between 2001 and 2020

4 Discussion

The main objective of this study was to analyse spatial and temporal trends in the distribution of wildfires in Zimbabwe. The results indicate significant spatial and temporal variation in burnt areas across savanna ecosystems of Zimbabwe over the past twenty years. There is a noteworthy increase in the frequency and coverage of burnt areas from June to October in the northern, central, western, and south-eastern parts of the country. This period coincides with the dry season and therefore biomass that would have accumulated during the wet season will have dried up thereby providing fuel load for fire ignition. The result is not surprising as previous studies in southern Africa identified the predominance of wildfire during this prolonged dry period. High temperatures and dry matter which can be easily ignited are the major factors leading to an increase in fire incidence during the dry season (Roy, *et al*., 2002; EMA, 2016). However, as the rain season starts, the occurrence and spatial extent of wildfires decreases drastically across the country with limited fire activity observed in the western and southern parts of the country. Changes in weather conditions are the main drivers of decline in fire activity particularly high moisture content in vegetation and soil, and high humidity which reduce ignition and extent of fires in the ecosystem (Chen *et al.*, 2013). The identification of temporal windows during which fires dominate provides rangeland managers with accurate timeframes during which allocation of resources for managing wildfires could be prioritised.

An important result from this study is that over the 20-year period fire hotspots were concentrated in specific districts and vegetation types in the northern and western regions of the country i.e., Hurungwe, Makonde, Kariba, Hwange, Zvimba, Mazowe, and Chegutu. In terms of vegetation, the largest burnt areas were observed in shrublands and croplands while the least burnt area was recorded in sparsely vegetated areas. These areas burned approximately 14 times during the period under study suggesting that these areas are constantly and persistently burning with a fire return period of close to one year. Recent studies have shown that agricultural activities such as burning of crop residues and land clearing through logging and burning felled trees are the main causes of wildfires in these districts which are predominantly resettlement or communal lands where agricultural activities are dominant (EMA, 2015; Chinamatira *et al*., 2016; Mpakairi *et al.*, 2019). In addition, high atmospheric temperatures, slope, humidity, fuel load and other anthropogenic activities are also key drivers of fires in these districts (Chingono and Mbohwa, 2015). In contrast, districts in the southern and eastern parts of the country experienced the least wildfires over the study period. Although the mechanisms explaining low fire frequency during the study period were not tested, low biomass or sparse vegetation could explain this observation. The southern parts of the country receive the least amount of rainfall and support less biomass production thereby limiting fuel load resulting in fewer fires compared to the rest of the country (Anyamba *et al.*, 2003; Chingono and Mbohwa, 2015). The spatially varying nature of fires in the country could guide fire management by focusing limited resources in areas that are in greatest need i.e., districts with high frequency than elsewhere.

This study has shown that burnt areas increased from 2001 to 2011 before decreasing thereafter. Noteworthy is that the increasing trend in fires during the first decade post the year 2000 coincides with the Fast Track Land Reform Programme (FTLRP) (Maponga, 2012). The FTLRP led to population increase, land clearing and hunting using fires by resettled farmers which increased not only fire ignition but spread as well (Maponga, 2012; Nyamadzawo *et al.*, 2013). Results of this study have shown a general decreasing trend in burnt areas after 2011. The decline in burnt areas from 2012 onwards could be explained by the introduction of fire control measures by the Enviromental Management Agency of Zimbabwe. The control measures include awareness campaigns, formation of fire teams, implementation of wide firebreaks and annual fire awareness promotions in the whole country (Maponga, 2012; EMA, 2016;). The decreasing trend in burnt area identified in this study aligns with previous studies that have reported this phenomenon at various spatial scales such as global and continental scale Africa (Andela et al., 2017; Earl and Simmonds, 2018). Therefore, the approach adopted here could be used to assess the effectiveness of interventions on wildfires such as legislation and wildfire management systems.

Results of this study indicated that root zone soil wetness (Soil moisture) was the most important variable that negatively influenced variations in burnt areas. The negative effect of soil moisture on burnt areas suggests a decrease in burnt areas with increase in soil moisture content. The result is not surprising as soil moisture has been previously identified as an important determinant of wildfire hazard on ecosystems and landscapes across the globe (Krueger, et al., 2015; Hou and Orth., 2020; Kavhu and Ndaimani., 2021). In the context of wildfires, soil moisture does not only influence fuel load through controls on primary productivity but also through determining fuel load moisture content and subsequent flammability (Kreye et al., 2020, . In fact, high rainfall years are associated with elevated soil moisture availability thereby promoting primary productivity, a key ingredient for fires (van Wilgen et al. 2004, Archibald et al. 2009). Ultimately, soil moisture mediates preheating and ignition of unburned fuels, rate of fire spread as well as radiative power of fires (Msweli et al., 2020). However, the influence of soil moisture on wildfire has been shown to be a function of climate. For example, Zubkova et al., 2020 report that above average soil moisture supports high biomass accumulation capable of supporting large fires while in humid regions dry soil moisture conditions precedes wildfires through creating conducive environment for fire ignition and flammability. In Zimbabwe, the southern and western parts of the country receive the least amounts of rainfall, thereby limiting the amount of fuel load to support meaningful fire activity. In contrast, the eastern parts of the country are the most humid (>1000mm annual rainfall) and support the highest woody primary productivity in the country. Rainfall in the eastern highlands is spread across almost all months of the year implying that the region could be too humid to burn, and the regular rainfall episodes experienced in the region rewets the fuel load. However, the predominantly humid conditions, low herbaceous understory alongside low temperatures retard fire ignition and flammability. The northern parts of the country receive intermediate annual rainfall, high temperatures and relatively high herbaceous primary productivity thereby supporting high wildfire activity. Thus, our results are in line with the classical hump shaped fire-aridity aridity relationship (Krawchuk and Moritz 2011; Pausas and Paula 2012; Duane *et al.,* 2021) in which fuel load limits fire activity in very arid conditions while dry and hot conditions limit fire activity in wet regions with well-developed vegetation.

Of the variables considered in this study, temperature and wind speed emerged as the second and third most important variables explaining burnt area variability, respectively. The two variables are critical determinants of ignition conditions with wind considered as the most critical as it desiccates fuel load as well as determining the trajectory of the fire front. Together with relative humidity (inferred from the soil moisture), these variables have been widely incorporated in prescribed fire management (Nieman et al., 2021).

A key observation from this study is the positive but lagged response of burnt area to preceding four-year annual rainfall with a 1mm increase inducing close to a forty-fold increase in burnt area. Although the relationship between antecedent rainfall and total area burnt in any given year is well established (van Wilgen et al. 2004; Archibald et al. 2010), results from this study are surprising in terms of the time scale. Unlike previous studies that have reported lagged responses of between one and two years, this study demonstrated that a four-year time lag in preceding annual rainfall better predicts burnt area in Zimbabwe than other time scales. While the mechanism explaining this observation was not tested, the four-year time lag suggests that the greater part of the country does not have sufficient fuel to support fire ignition and spread at shorter time scales, thus a four-year time scale provide optimal period for fuelwood accumulation.

Fire size and occurrence has been evaluated previously by various scholars, although they focused on smaller spatial scales for example a single district which confines understanding of fire occurrence at a larger scale. This study is among the first to characterise spatial and temporal wildfire patterns at the national scale and at relatively longer temporal window (2 decades) thereby providing wildfire managers with an opportunity to prioritise resource allocation aimed in the control of fire. Furthermore, key drivers of burnt area dynamics were determined thereby providing ecological basis for wildfire management in predominantly savanna landscapes of Zimbabwe. Thus, this study has not only generated new insights into wildfire evolution in the country but has also demonstrated dynamics in the spatial configuration of burnt patches in the landscape. These results further amplify the importance of freely available remotely sensed data and accompanying geo-technologies in wildfire monitoring and management.

Although, the MODIS fire data used in this study is freely available, regularly updated and provide repetitive coverage of fire prone landscapes (Maponga, 2012; Magadzire, 2013), it has some limitations. For example, MODIS fire data only starts from 2000 onwards which inhibits an extended analysis of burnt areas before the year 2000 (Roy and Boschetti, 2008; Giglio *et al.*, 2016). In addition, unlike other sensor such as Synthetic Aperture Radar which can detect burnt areas on cloudy days, the detection of burnt areas by MODIS in different parts of the world can be affected by cloud cover and aerosols (Roy *et al.*, 2008; Lasko, 2019). Nevertheless, a recent comparison of four publicly available global burned area products revealed that MODIS Burnt Area products and Fire CCI Burnt Area Products from Medium Resolution Imaging Spectrometer (MERIS) perform better even in challenging conditions compared to other burnt area products such as the Copernicus Burnt Area Products (Humber *et al.*, 2019). Therefore, MODIS fire products can be relied on for the analysis of wildfire trends, spatial distribution and temporal distribution.

5 Conclusion

This study used burnt area MODIS data to characterise wildfire frequency as well as spatial configuration of burnt areas over a 20-year period across savanna ecosystems of Zimbabwe.

Results indicated that there is high frequency of wildfires in Zimbabwe with some parts recording as high as 20 fire incidences over the two decades. In addition, the study showed that soil moisture, temperature and wind speed are the key drivers of wildfire in savanna landscapes of Zimbabwe. The study has shown that the integration of remotely sensed fire data within a spatially analytical framework can provide useful insights into fire evolution that can be used to guide wildfire control and management in fire prone ecosystems. Moreover, resource allocation for fire management and mitigation can be optimised through targeting areas most affected by wildfires especially during the dry season where wildfire activity is at its peak.

Data availability statement

- ✓ The European Space Agency Fire Data is openly available at https://developers.google.com/earth-engine/datasets/catalog/ESA_CCI_FireCCI_5_1.
- ✓ MODIS NDVI data is available at :https://appeears.earthdatacloud.nasa.gov.
- ✓ Climate data used for determining key climatic drivers of wildfire in different vegetation types were downloaded from https://power.larc.nasa.gov/data-access-viewer/.
- ✓ Yield data used in the study is available on request from the authors

Conflict Of Interests

The authors declare no conflict of interests.

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