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Article *in* The South African geographical journal, being a record of the proceedings of the South African Geographical Society · June 2021

DOI: 10.1080/03736245.2021.1941219

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South African Geographical Journal

ISSN: (Print) (Online) Journal homepage: https://www.tandfonline.com/loi/rsag20

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To cite this article: Blessing Kavhu & Henry Ndaimani (2021): Analysing factors influencing fire frequency in Hwange National Park, South African Geographical Journal, DOI: 10.1080/03736245.2021.1941219

To link to this article: https://doi.org/10.1080/03736245.2021.1941219

Published online: 18 Jun 2021.

SOUTH AFRICAN GEOGRAPHICAL JOURNAL
https://doi.org/10.1080/03736245.2021.1941219

Analysing factors influencing fire frequency in Hwange National Park

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ABSTRACT

Detection of key factors driving fire frequency, especially in protected areas, is important for effective management of ecosystems. In this study, we used Generalized Linear Models to test the contribution of natural (NDVI, wind speed, dry matter productivity, soil moisture, percentage tree cover, elevation and temperature) and anthropogenic (distance from settlements) factors as predictors of fire frequency in Hwange National Park and adjacent areas. We used the Akaike Information Criterion (AIC) to evaluate the variable contribution to fire frequency. The model results indicated that all the variables that were used contributed significantly to fire recurrence ($p < 0.05$). Distance from settlements contributed the most to the model whilst dry matter productivity and annual average temperature were second and third respectively. Removal of distance from settlements from the model increased the AIC value to 1411.2 while removal of dry matter productivity and temperature resulted in AICs of 1269.9 and 1265.8 respectively. Results showed that settlements which are found in the vicinity of the protected area influence the recurrence of fires. Findings from this study can be used for strategic fire management and for the development of effective measures to minimize fire recurrence in a protected area.

ARTICLE HISTORY
Received 20 October 2020
Accepted 7 June 2021

KEYWORDS
Fire frequency; remote sensing; generalized linear modelling; protected areas; savanna

Introduction

Protected areas in savanna ecosystems are endowed with biodiversity and a unique tree grass co-existence which is maintained largely by fires (Capozzelli et al., 2020; Scholes & Archer, 1997; Tedim & De Paula Herrmann, 2007). However, recurring fires continue to pose threats to biodiversity within the protected areas (Bradstock, 2009; Moretti et al., 2004; Vasconcelos et al., 2020). Thus, it is necessary to understand the key factors driving fire regimes in these ecosystems. The recurrence of fires which is also known as fire frequency is an essential characteristic of a fire regime which affects various aspects of ecosystem functions. The commonly affected functions include nutrient cycling, grass productivity to tree recruitment (Gandiwa & Kativu, 2009). Evidence from existing literature suggests that the frequent burning of the savanna ecosystem subsequently

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result in land degradation and loss of biodiversity for example, through facilitating invasion by alien invasive species (Gaertner et al., 2014; Masocha et al., 2011; Reilly et al., 2020).

The fires tend to burn large areas of vegetation annually leading to direct loss of forests markedly in Sub-Saharan Africa (Almsatar, 2020; Le Page et al., 2008). They consume vegetation and act as a top-down control on ecosystem structure (De Castro & Kauffman, 1998). Depending on recurrence and severity, fires reduce plant biomass and can replace trees with shrublands or grasslands (Bond, 2008; Kganyago & Shikwambana, 2019; Schimmel & Granstrom, 1996). Although there are numerous negative effects associated with burning, fires also play a critical role in facilitating relevant ecosystem functions such as offsetting plants and grass regeneration through providing ideal germination and growth conditions (Augustine et al., 2014; Banda et al., 2006; Durigan, 2020; Gawryszewski et al., 2020)

Burning is a major management issue in most protected areas and to management authorities particularly the Zimbabwe Parks and Wildlife Management Authority (Ribeiro et al., 2018). Devastating effects are usually noted in wildlife areas that are associated with recurring wildfires (Mapaure, 2001). For example, in Hwange National Park fires have been considered a major disturbance factor which frequently occurs in the dry season months of the year (Mpakairi et al., 2019; Tafangenyasha, 1997). However, knowledge of the mechanisms and factors driving the wildfire frequencies in most protected areas of savannalandscapes remains largely limited. Yet understanding the factors that drive the recurrence of fires is a critical first step towards mitigation of wildfires in most ecosystems (Finney, 2005).

Remote sensing techniques have been widely used to map burnt areas, assess characteristics of active fires, and characterize post-fire ecological effects (Lentile et al., 2006). Fire products from Moderate Resolution Imaging Spectroradiometer (MODIS), Advanced Very High-Resolution Radiometer (AVHRR), and Landsat have been offering repetitive mapping abilities of burnt area sites which claimed their wide use in fire ecology (Kaufman et al., 1998; Sukhinin et al., 2004; Verlinden & Laamanen, 2006). Studies have shown that the use of remote sensing products in the mapping of fire frequency is possible in various parts of the world (Mouillot et al., 2002; Mpakairi et al., 2020; Ngadze et al., 2020). Given that, understanding the fire frequency of sensitive ecosystems particularly protected areas is plausible.

The availability of historical spatial and temporal datasets of fire ignition enable the development of models that enhance the understanding of fire regimes across space (Archibald & Roy, 2009; Frantz et al., 2017). Studies have used varying natural and anthropogenic variables to model fire occurrences (Bui et al., 2019; Shekede et al., 2019; Syphard et al., 2009; Valdez et al., 2017). Several methods and models have been applied to model wildfire occurrence using statistical and machine learning algorithms (Chuvieco et al., 2014; Massada et al., 2013; Mpakairi et al., 2019). Most of the studies have mapped the frequency of wildfires in protected areas such as Hwange National Park (Kusangaya & Sithole, 2015) and KwaZulu Natal grasslands (Buthelezi et al., 2016). While studies have provided spatially explicit information on variation in wildfire occurrence, little is known about the factors driving variation in wildfire frequency in most protected areas of savannah ecosystems. Yet understanding these factors play an important role in reducing the recurrence of wildfires. This is an important gap that needs to be filled as a strategy to reduce the continual recurrence of wildfires in protected area systems.

This study aims to understand the key factors influencing the distribution of wildfire frequency in Hwange National Park, Zimbabwe. Specific objectives of this study were to map the spatial distribution of wildfire frequency in Hwange National Park and test whether NDVI, annual average temperature (hereafter temperature), distance from settlements, wind speed, elevation, dry matter productivity, soil moisture and percentage tree cover (PTC) influence the distribution of fire frequency. Findings from this study will facilitate reliable wildfire control strategies in protected areas which are characterized by the continuous recurrence of wildfires.

Study Area

Hwange National Park is located in the North-West of Zimbabwe at 19° 07′ 26″ South 26° 35′ 33″ East (Figure 1). It covers ~14,651 km2 making it the largest National Park in Zimbabwe. The park borders with Deka and Matetsi Safari areas in the North, Botswana in the West, Sikumi forest reserve and Dete village in the East and Tsholotsho communal land in the South. The vegetation which is found in the park comprises mixed woodlands and shrublands of *Bairkiea plurijuga, Combretum species, Vachellia species* and *Termina liasericea* (Valeix et al., 2007). The north and north-western of the park is dominated by mopane woodlands (Charmaille-Jammes et al., 2009). Generally, the woodland vegetation of the park is dominated by *Baikaiea plurijuga, Baphiam assaiensis* and *Bauhinia petersiana* on

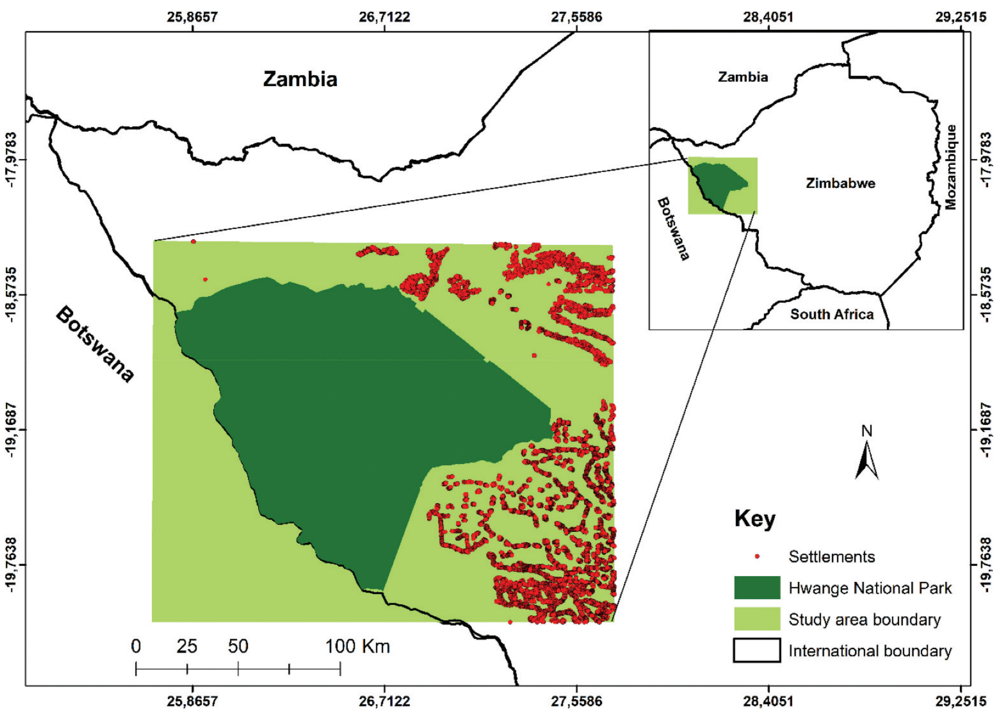

Figure 1. Study area map of Hwange National Park and settlements around the park.

Kalahari sands (Childes & Walker, 1987). However, the north and north-western parts of the park are dominated by, *Colophospermum mopane* and *Guibortiacoleosperm* (Rogers, 1993). The mean annual rainfall of the park is approximately 600 mm and the temperature ranges from 6°C to 33°C. The area has two seasons which comprise the dry season and the wet season. The latter starts from April to October where temperatures will be high with no rainfall and the former stretches from November to March.

Fire Scars

In this study, we used MODIS (MCD64AIV6) monthly fire scars data. We downloaded the images of the fire season for the period 2007 to 2016 from the USGS earth explorer website (www.usgs.gov). These images were selected because of their improved spatial resolution of 500 m and their wide use in fire studies (Justice et al., 2002; Li et al., 2004). Fire data were categorized into management fires and wildfire basing on burn date. We considered fires which were burnt during the period January to July to be management fires and those of the period August to December as uncontrolled fires. We clipped the images to the study area extent and re-projected them from the sinusoidal coordinate system to the Universal Transverse Mercator (UTM) Zone 35 South coordinate system. We merged illegal fire scars for each year and rasterized them in ArcMap 9.1 (Press, 2005). We then calculated the fire frequency by adding the rasterized yearly burnt area maps for the 10 years. We resampled the output map to 30 m using the nearest neighbour method to match with other datasets and masked it to study area extent.

Distance from Settlements

To indicate the human imprint, we digitized the settlements which are close to the park from the Zimbabwean side in QGIS (www.qgis.org) using the Google earth imagery zoomed to a 100 m resolution. We used the digitized settlements to calculate the Euclidean distance from settlements in metres using ESRI ArcMap version 9.1. We re-projected the output from a geographic coordinate system (WGS 84) to a projected coordinate system (WGS84/UTM 35S). We then resampled the output layer to a spatial resolution of 30 m to match the spatial resolution of other variables which were used for analysis (Figure 2).

Elevation and soil moisture

Elevation was used to represent the influence of terrain on the distribution of fire frequency following Syphard et al. (2007). The Shuttle Radar Topography Mission (SRTM) Digital Elevation Model (DEM) with a spatial resolution of 90 m was downloaded from http://www.usgs.gov. Soil moisture from TerraClimate which was downloaded from Google Earth Engine was used to represent the influence of fuel moisture content in the distribution of fires following recommendations by Krueger et al. (2015). Soil moisture has been observed to be linked to fuel moisture content which affects the distribution fire (Bartsch et al., 2009). We clipped the elevation and soil moisture layers to study area extent and reprojected them from a geographic coordinate (WGS 84) system

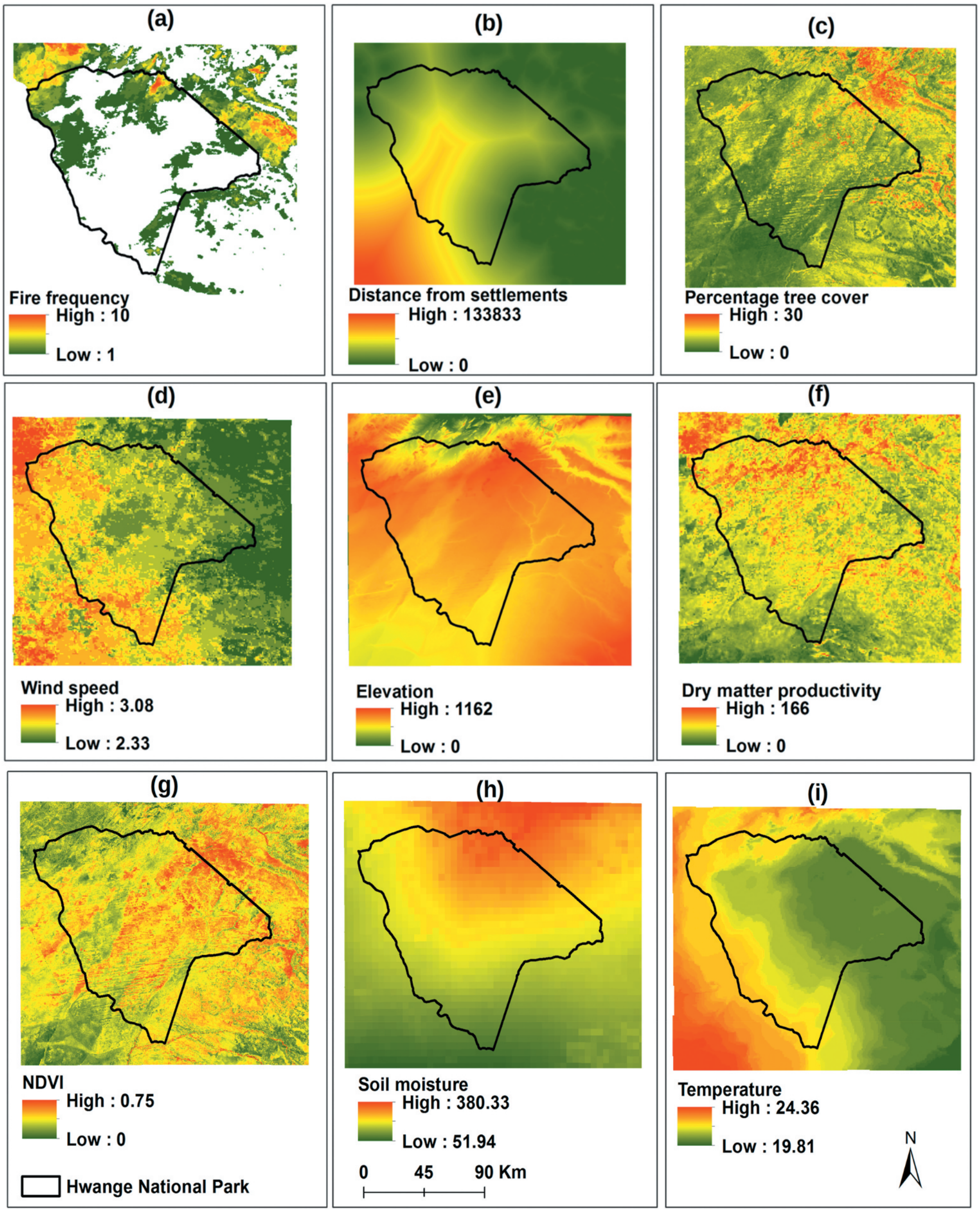

Figure 2. Maps of the variables used in modelling (a) fire frequency, (b) distance from settlements, (c) percentage tree cover, (d) wind speed (e) elevation, (f) dry matter productivity, (g) NDVI, (h) soil moisture, (i) temperature.

to a projected coordinate system. We then resampled the output layer to a spatial resolution of 30 m resolution to match with the spatial resolution of other variables.

Normalized Difference Vegetation Index, percentage tree cover and dry matter productivity

We downloaded MODIS (MOD13A3) NDVI, PTC (MOD44B.006) and SPOT DMP (Dry Matter Productivity) of the fire season for the period 2007–2016. NDVI and PTC were downloaded from Google Earth Engine (GEE) and DMP was made available through the Vito website http://free.vgt.vito.be/. Percentage tree cover (PTC) was used as a representation of vegetation cover, NDVI was used as a proxy for vegetation condition (Mpakairi et al., 2019) and DMP was used as a proxy for fuel load (Shekede et al., 2019). Previous studies have recommended the incorporation of vegetation cover and fuel load when modelling fire distribution (Chifodya, 2014; Matin et al., 2017) In this study, we used MODIS NDVI and PTC products because of their high temporal and spectral resolution (Huete et al., 2002). From the combined vegetation indices of these products, we extracted and saved NDVI and PTC as separate indices and calculated annual averages for the fire season as well as the overall averages for the 10 years. We clipped the overall average NDVI, PTC and DMP to our study area extent and re-projected the layers from a sinusoidal and geographic coordinate system to WGS84 UTM Zone 35S. The NDVI values were multiplied by a scaling factor of 0.00001 to normalize the values from the high NDVI values which are found on the image after downloading for file transferability (Didan, 2015). We resampled the images from their native spatial resolutions to a spatial resolution of 30 m using the nearest neighbour method. We resampled the image to establish consistency in the spatial resolution of all the covariates which were used for modelling (Figure 2).

Temperature and Wind Speed

To analyse the effect of climatic variables on fire frequency, we downloaded long-term temperature and wind speed data which has a spatial resolution of 1 km from the WorldClim database (www.worldclim.org). Studies reported that fire distribution is influenced by temperature and wind speed (Tiwari et al., 2021; Xu et al., 2021). We re-projected the coordinate system from a geographic coordinate system (WGS 84) to a projected coordinate system (WGS 84/UTM35S). We then resampled the images to a spatial resolution of 30 m to match the spatial resolution with that of distance from settlements. We clipped the images for temperature and wind speed to our study area extent (Figure 2). We did not use wind direction as a predictor variable because there is no historical record of wind direction which matches the study period for our study area.

To deal with the collinearity of variables, a pairwise correlation between predictor variables were calculated in *R* statistical package (Team, 2013). The 'folk lore' thresholds of between predictor variables of $r > 0.7$ was used to eliminate correlated variables and create a parsimonious model (Dormann et al., 2013). All variables listed in (Table 1) were used for modelling since they were not correlated ($r < 0.7$).

Modelling and Model Validation

Using the variables; distance from settlements, elevation, soil moisture, DMP, PTC, NDVI, temperature and wind speed we modelled the distribution of fire frequency

Table 1. Shows a list of variables used for predicting fire frequency variability.

Variables	Source	Resolution	Unit of measurement
Fire scars	MODIS MCD64AIV6	500 m	Years
Distance from settlements	Digitized from Google Earth	Reprojected to 30 m	Euclidean distance (m)
NDVI	MODIS MOD13A3	1 km	Monthly estimates
Temperature	WorldClim	1 km	Degrees Celsius
Percentage tree cover	MODIS MOD B4	250 m	Percentage
Soil moisture	TerraClimate	2.5 arc minutes	cubic metres
Elevation	Shuttle Radar Topography Mission(SRTM)	90 m	metres
Wind speed	WorldClim	1 km	metres per sec

using the Generalized Linear Model (GLM) in R-Software (Team, 2013) with fire frequency as the response variable. GLMs have been widely used in other studies and they are found to be more flexible in analysing ecological relationships (Guisan & Hofer, 2003). We used the Akaike Information Criterion (AIC) to measure model goodness of fit. The AIC is an estimator of the relative quality of statistical models and it penalizes a model for increasing the number of parameters (Bolker et al., 2009). Stepwise AIC was performed and the least important variables were removed. We dropped the variables that did not lower the AIC value by more than one point therefore the least adequate model was left with six variables. The variables were ranked according to their importance using the AIC values (Table 3).

RESULTS

Predictor Relevance

Results from linear modelling show that a combined set of predictors namely temperature, soil moisture, NDVI, PTC, DMP, elevation, wind speed and distance from settlements significantly explained variation in fire frequency (F6,737 = 40.15, $p < 0.005$). All predictors combined explained variability in fire frequency (adjusted R2 = 0.240). Results from individual predictors showed that all variables significantly explained fire frequency ($p < 0.05$) (Table 2).

Relative Variable Importance

The results show that distance from settlements and DMP were the most important predictors ranked 1 and 2 respectively whilst temperature is the least important predictor (Table 3). Excluding elevation and wind speed from the model improved model performance as shown by a drop in the AIC value from 1269,31 to 1260,43. The minimum

Table 2. Least minimum adequate model without wind speed and elevation.

Variable	B	T-value	P-value
Distance from settlements	−0.23	−3.053	0.000002
Dry matter productivity	3.60	2.300	0.021732
Annual average temperature	0.48	3.672	0.000258
NDVI	−4.61	−2.390	0.017084
Soil moisture	−0.91	−1.997	0.046188
Percentage tree cover	−2.14	−3.052	0.002353

Table 3. Relative model importance.

Variable	Deviance	AIC	ΔAIC	Rank
Distance from settlements	96.13	1411.2	152.77	1
Dry matter productivity	72.51	1269.9	11.47	2
Annual average temperature	50.09	1265.8	7.36	3
NDVI	30.72	1262.2	3.76	4
Soil moisture	28.44	1261.8	3.36	5
Percentage tree cover	21.44	1260.5	2.06	6

adequate model therefore comprised of distance from settlements, DMP, soil moisture, NDVI, PTC and temperature (Table 2).

Analysis results show that elevation, temperature and DMP were positively related to fire frequency see Figure 3. The relationships between fire frequency and distance from settlements, NDVI, PTC, soil moisture and wind speed were found to be negative. The nature of relationships between fire frequency and the predictors is shown by the plots in Figure 3.

DISCUSSION

We found that the six predictors: NDVI, soil moisture, distance from settlements, DMP, temperature and PTC significantly explained variability in fire frequency. The model with these six main effects exhibited the lowest AIC value (Table 3). We also found that distance from settlements is the major predictor of fire frequency. This is indicated by a remarkably high AIC value for the model that excludes the main effect of distance from settlements. These results possibly imply that most fires are started by humans, close to national parks and spread into the park without being extinguished. The finding that human settlements better explain variability in fire frequency is not surprising. For instance, it has been reported in Pennsylvania, Colorado Font, Tanzania and California (Brose et al., 2001; Syphard et al., 2007; Tarimo et al., 2015; Veblen et al., 2000) that fire occurrence seemed to be influenced by human settlements. Although these studies reported the influence of human settlements on fire occurrence, their influence on fire frequency (which is an indicator of fire recurrence) was not known. As such, this study is amongst the first few to provide evidence for the influence of human settlements on the variability in fire frequency.

We also found that elevation and wind speed were the least important predictors from the step AIC results. We expected wind speed to play a major role in explaining fire frequency variability since stronger winds are associated with rapid the spread of veld fires (Maponga et al., 2018). Our findings are in tandem with those by Himoto (2019), who also found that the effect of wind on fire regime is negligible. The poor contribution by elevation could be as a result of relatively low variation in the elevation of our study area (Figure 2). DMP was found to be the second important predictor of fire frequency. Our findings are supported by previous literature which also reported a strong positive association between DMP and fires (Chingono & Mbohwa, 2015; Shekede et al., 2019). High DMP values are known to be associated with high fuel load for combustion hence frequent fires (Scholes & Archer, 1997; Stott, 2000; Zhang et al., 2016). Literature is replete with evidence for the influence of fuel load on fire frequency (Fiorucci et al., 2008; Hernandez-Leal et al., 2006; Liu et al., 2010).

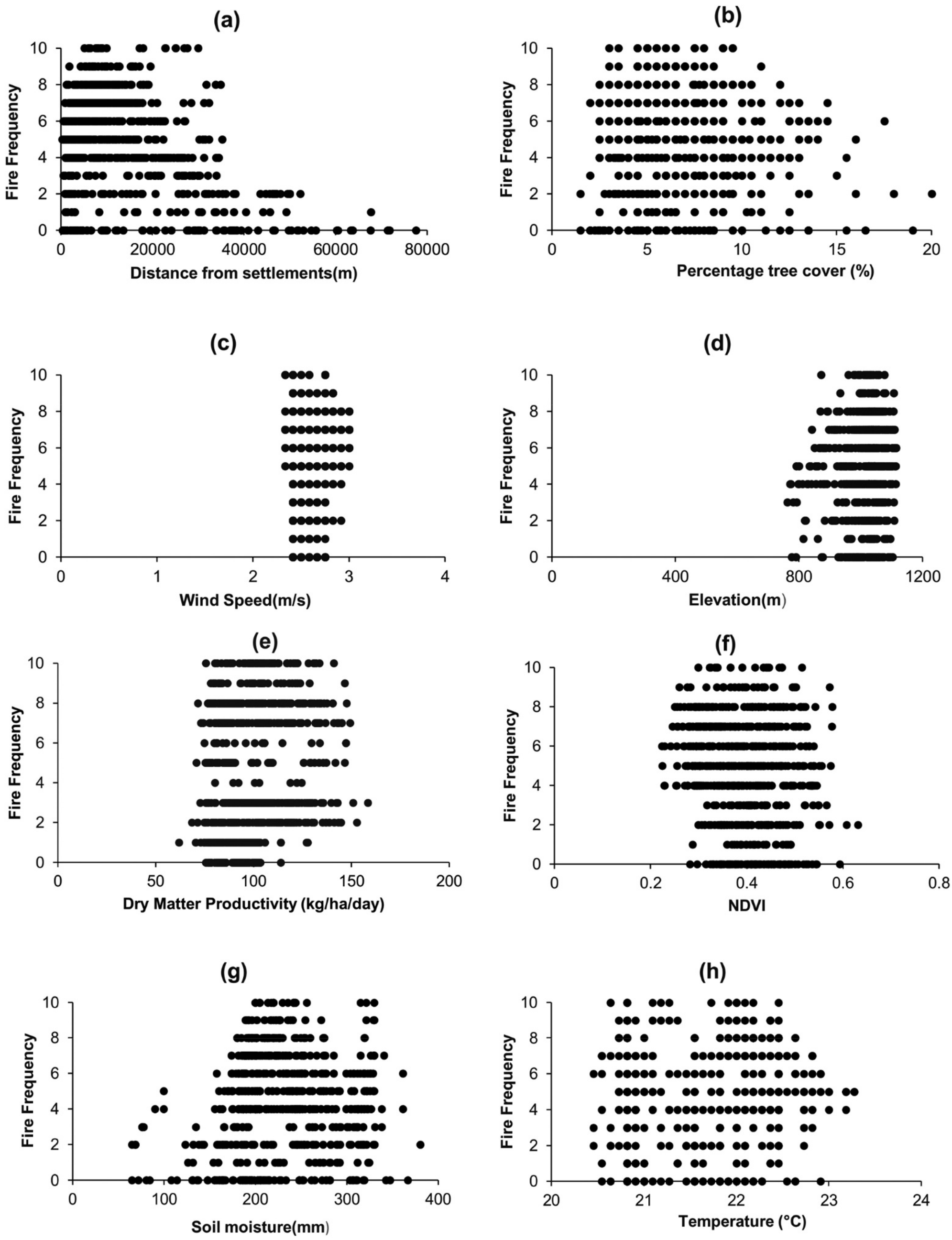

Figure 3. Relationship between fire frequency (years) and eight selected predictor variables in modelling (a) distance from settlements, (b) percentage tree cover, (c) wind speed (d) elevation, (e) dry matter productivity, (f) NDVI, (g) soil moisture, (h) temperature.

Distance from settlements had a negative relationship with fire frequency meaning that fire frequency is relatively higher in areas associated with increased human settlements which can be attributed to various anthropogenic factors that influence fire occurrence such as poaching, land clearing for agricultural activities, hunting and even park management purposes. Fire is considered to be important because it helps in the functioning of the ecosystem therefore in most protected areas, fire is used as a control mechanism. More so, villagers use fires when hunting (Gambiza et al., 2008) and these fires are largely left unattended and they end up spreading into protected areas. The fire season in Zimbabwe (August–November) is usually characterized by land clearing in preparation for the farming season and the majority of people in the rural areas burn the fields to clear, in so doing the fire gets out of control and spreads to the park. Findings from the study indicated that anthropogenic factors are key in mapping fire frequency. Previous studies showed that high human densities (>10 people km-2) were associated with more area being burnt, probably because of the effect that people have in landscape fragmentation through cultivation, grazing livestock, fuel-wood collection, or possibly by suppressing fires (Mpakairi et al., 2019; Saunders et al., 1991). The probability of wildfire occurrence was found to be higher near roads and settlements and drops dramatically with the distance which is also noticed in our study (Valdez et al., 2017). While previous studies were relevant in showing these appropriate findings, the detection of factors driving fire recurrence in protected areas remains an important aspect in wildfire management.

In this study, we used eight predictor variables, which included both the biophysical and human variables. A general linear model (GLM) was used to capture the linear and statistical relationship between our variables hence making it easy to understand fire dynamics. Our study captures the effect of distance from human settlements on fire frequency which is barely investigated in previous studies. Studies have been commonly using two common models (Maximum entropy and Random forest) in explaining factors driving fire regimes (Massada et al., 2013). Nevertheless, future studies could use a combination of several modelling techniques which include machine learning algorithms that provide faster and more accurate models (Elith* et al., 2006). More so, our hypothesis was tested on one site only therefore we cannot conclude that it is the best model.

Fire management and mitigation within the park are guided by the main fire policy of the Parks and Wildlife Authority of Zimbabwe, Parks and Wildlife Act, 1991 (Kusangaya & Sithole, 2015). Fire management strategies such as controlled burning have been implemented in protected areas to safeguard wildlife habitats as well as the different species. Other strategies such as construction and maintenance of fire breaks could be intensified in areas in the vicinity of human settlements to prevent prolonged burning of these areas. Education and awareness campaigns by local authorities and other stakeholders such as the Environmental Management Agency (EMA) could also be enhanced in communities adjacent to protected areas. The use of fire teams which involve the communities drawn from settlements in areas adjacent to protected areas could be put in place.

Using Generalized Linear Models, we modelled fire frequency distribution and results showed a linear relationship between fire frequency and the eight predictor variables namely distance from settlements, elevation, soil moisture, PTC, DMP, NDVI, temperature and wind speed. After a step AIC, we were able to get the minimum adequate model for fire frequency with distance from settlements being the best predictor and wind speed as the least important predictor. Supported by other studies, we observed that distance from settlements influences fire frequency in protected areas. Therefore, management strategies should focus on educating communities adjacent to protected areas on the effects of fires and strategies to rheostat uncontrolled burning. Future studies testing the effect of selected predictor variables on fire frequency could include more variables such as wind direction at a larger scale for better model results.

Acknowledgments

We would like to thank the Zimbabwe Parks and Wildlife Management Authority in Hwange National Park for access to the park.

Data Availability Statement

Data on settlements locations are available upon request.

Disclosure of potential conflicts of interest

The authors declare that there exists no competing financial interests or personal relationship that could have appeared to influence the work reported in this study.

Funding

The authors received no specific funding for this research.

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