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Modelling wildfire risk using GIS and Analytical Hierarchy Process (AHP) in Aberdare afromontane forest ranges, Kenya

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Abstract: The knowledge of wildfire risk is crucial to sensitize and create awareness on fire prevention strategies and mobilization of resources to counter the spread after detection. This study was undertaken to determine the most important environmental and anthropogenic factors associated with wildfire risk in Aberdares ranges. An integrated participatory decisions and geospatial analysis was used. A pair wise comparative analysis of seven factors namely: proximity to roads, proximity to farming areas within the forest, mean precipitation, elevation, slope, land cover and NDVI was undertaken to attribute weight of each factor in relative to the other though Analytical Hierarchy Process (AHP). A wildfire risk equation was developed using the criteria weights of respective factors and risk map developed using QGIS version 3.16. Results indicated that land cover (0.39) and NDVI (0.23) were the most important factors in developing wildfire risk maps while proximity to roads (0.04) was the least. Wildfire risk maps shows that Aberdare ranges is within low (43%) and moderate (30%) risk zone and the area occupied by high and very high zones is 13% and 4 % respectively. The study recommends testing the applicability of developed method in other areas with different climatic and land cover characteristics.

Key words: Geographical Information System (GIS), Analytical Hierarchy Process (AHP), risk maps, wildfires, protected areas, Aberdare ranges

1. Introduction

The use of seasonal fire cycles in rangeland and forest landscape management has been recognized in the studies of Poletti et al., (2019). However, recent changes in the climate and accelerated human activities has resulted to transformation of traditional fire regimes (Bar et al., 2021). According to Chen et al., (2020), over 30% of the world's land surface area is experiencing substantial fire incidences with the tropics and sub-tropics having high fire occurrences (Andela et al., 2016). Although fire occurrences have decreased over the last few decades in many regions, In Kenya, high wildfire incidences have been reported mostly due to illegal activities within protected areas of Kenya (Poletti et al., 2019. Furthermore, studies of Maukonen et al., (2016), identified fire and poor fire management as a major cause of forest unproductivity in Kenya due to destruction of productive stages of vegetation such as young and vulnerable seedlings and saplings.

The knowledge of pre-fire occurrence is crucial to sensitize and create awareness to the local stakeholders and mobilize resources to counter the spread after early detection. The cyclic occurrence of wildfires reflects a complex connection between weather, climate conditions and ecosystem processes. For example, studies of Fasullo et al. (2018) shows close relationship of fire frequency and spatial extent to climate variability of seasonal and decadal time series. Although many approaches have been used in predicting wildfire risk, Geographical Information Systems (GIS) and remote sensing techniques have been widely used through integration of social and environmental factors (Vallejo-Villalta et al., 2019). Some the key factors which contribute to fire risk include topography (elevation, slope and aspect), vegetation (fuel load, fuel moisture, vegetation structure and age), weather (precipitation, wind speed, relative humidity) and human related factors such as distance from road or settlement and human population density (Costafreda-Aumedes et al., 2017). In addition, some studies have utilized vegetation cover metrics and indices such as normalized difference vegetation index (NDVI), enhanced vegetation index (EVI); climate parameters such as land surface temperature, precipitation, and wind speed and fire weather index (FWI) (Vallejo-Villalta et al., 2019) as potential for mapping and modelling wildfire risk.

The increasing wildfires has triggered more studies on mapping and prediction to guide integrated fire management in many countries. However, a review of Costafreda-Aumedes et al. (2017) on modelling fire risk found only few studies had focused on the areas with high wildfire occurrence especially Sub-Saharan Africa as opposed to many research studies focusing on North America and Europe. Some fire risk studies in Africa have mainly focused on protected savanna ecosystems (Molaudzi and Adelabu, 2019) and little research in East African protected mountain areas which is the focus of this study within the Aberdare ranges located in central highlands of Kenya. Aberdare ranges is one of the five main water catchments in Kenya. Others include Mt. Kenya, Mt. Elgon, Mau and Chereng'ani Hills. It provides water that feed into four out of Kenya's six major drainage basins namely; Ewaso Nyiro, Lake Naivasha, Athi and Tana River basins. The Tana and Athi catchment area supplies all the water to Nairobi, the capital City of Kenya with over 5 million people through Sasumua and Ndakaini dam. Together with Mt Kenya, they contribute 70% of the country's hydropower produced by Tana River (Kenya

Forest Service, 2010). Beside the enormous contribution to the economy of the country, Aberdare ranges has been faced with frequent forest fires which has had negative impacts not only to the ecosystem functions but also the livelihoods of the local community living adjacent to the forest (Kenya Forest Service, 2010)

Several methods have been used in generating and validating wildfire risk maps. This includes Multi Criteria Decision Analysis (MCDA) in combination with GIS (Akay and Erdoan, 2017), logistic regression (Milanovi´c et al., 2020), fuzzy logic and machine learning techniques (Kim et al., 2019). Studies in Afromontane forests within southern Africa have not been addressed despite environmental damages due to wildfires. The choice of particular method depends with availability of data, application of outputs by the stakeholders and the skills of developing the fire risk maps and models. Most of the complex machine learning and logistic regression methods require bulk database to run effectively and give a robust fire risk map. In the absence of comprehensive database in Kenya, this study used Analytical Hierarchy Process (AHP) in combination with GIS, which is an advanced Multi-Criteria Decision Analysis (MCDA) technique in mapping fire risk. The most important aspect of AHP is the active involvement of specialist practitioners and stakeholders in ranking and discussion of various factors through an organized order (Van Hoang et al., 2020). The study objectives included (1) to determine the most important factors associated with wildfire risk based on integrated participatory decisions and spatial analysis within GIS environment in Aberdare ranges and (2) to develop wildfire risks map to assist stakeholders in prevention and management of wildfires in Aberdares ranges.

2. Materials and Methods

2.1 Study Area

The study was done in Aberdares Ranges located in the central highland within four Counties of Kenya; namely Kiambu, Murang'a, Nyeri and Nyandarua. The area comprises of ranges covered mainly by forests, grassland and moorland. Administratively it's managed as forest reserves (149,822 ha) by KFS and a National Park (76,700 ha) by KWS (KFS 2010). (Figure 1). The surrounding land use is mainly annual and perennial crop production. It's located along the equator between 36°30' E, 0° 05' S and 36° 55'E, 0° 45'S. The altitude ranges from 2000 m to its highest peak of 4000 m above sea level. The major vegetation categories in Aberdare forest, are primarily described through variation in structure and composition along climatic and altitudinal gradients.

The four broad vegetation zones already documented by Kenya Forest Service (2010) include: (i) Montane humid forest mostly found at lower altitudes east side of the forest mainly dominated by the pioneer species (ii) Sub-montane forest is found at mid elevations (iii) Xeromorphic evergreen forest, which is located in the dry north and north-western slopes of the Aberdares forest and (iv) sub-alpine vegetation mostly found at the moorlands at an altitude of 3,300 m and above. Furthermore, Aberdare ranges is a designated world heritage site with a rich diversity of fauna and flora. Recent estimates suggest that the range is a habit of over 50 species of mammals, 270 bird's species (Massey et al., 2014) and more than 1260 higher plants species (Kipkoech et al., 2020).

2.2 Data sets and processing to develop wildfire risk maps

Based on literature and local landscape characteristics as applied by Akay and Erdoan, (2017), various factors were used to develop fire risk maps within Aberdare ranges. This included anthropogenic factors, topography, meteorological data and vegetation variables. The data was sourced from various sources as shown in Table 1.

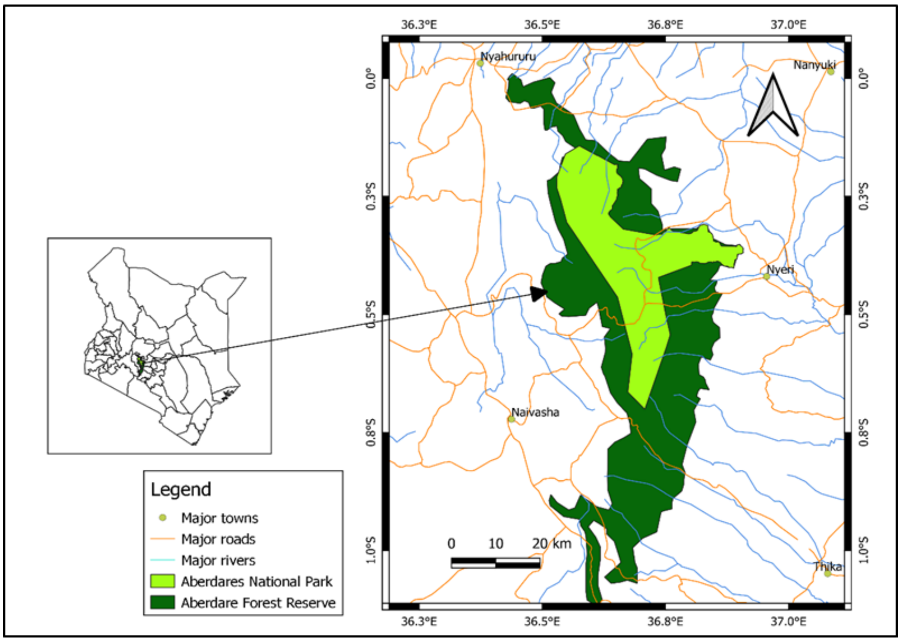

Figure 1. Location of Aberdare forest ranges in Kenya

Table 1. Data set formats and sources used in this study

Product	Format	Remarks
Socio-economics		
PELIS data from 2012 to 2021	Shapefile	Buffered by distance
Roads and nature trails network	Shapefile	Used road network from KFS and Kenya Rural Roads Authority (KeRRA), merged and buffered
Fire occurrence data (Validation of predicted maps)		
VIIRS active fire data (January (2012 – December 2021)	Shapefile/points	Acquired from Fire Information Resources Management; Was used for validation
Forest fire records	Hard copies/digital	Digitized then processed and used to select satellite data
Meteorological data		
Precipitation	Raster	Rainfall data Interpolated from ten forest stations
Topography		
Elevation	Raster	Extracted from Shuttle Radar Topography Mission (SRTM) and clipped to study area
Slope	Raster	Processed from Digital Elevation Model (SRTM)
Vegetation		
Land cover 2016	Raster	Reclassified from the national land cover maps used in reporting forest reference level under REDD+ schemes.
Mean NDVI (2012-2021)	Raster	Mean NDVI Processed using Google Earth Engine (GEE) platform

2.2.1 Anthropogenic factors

Various studies have shown that anthropogenic factors are important in predicting wildfire risk. For example, proximity to roads, rivers and settlement areas have been considered according to Van Hoang et al., (2020); Adaktylou et al., (2020). The roads and nature trails provide easy access for tourists and timber operations within the national park and forest reserves respectively. This can potentially influence the risk of wildfires.

The local community surrounding Aberdares are mostly farmers. Although cultivation within the forested areas has been practiced for many decades, Plantation Establishment and Livelihood Improvement Scheme (PELIS) scheme was introduced by the government to help increase forest cover and restore degraded forests in the country. Consequently, the livelihood of Forest neighbouring communities (FAC) is improved since they are allocated small pieces of land upon which they plant seedlings in consultation with technical officers, while they practice subsistence farming. The planted seedlings are supposed to be maintained while the farmer is tending to the crops until the seedlings are tall enough forming closed crown which makes cultivation impossible. Whereas this has been practiced in many forest stations, it can potentially be a source of ignition during preparation of farms and harvesting crops. In this study, only proximity to roads and PELIS were considered in their contribution to wildfire risk.

The road network used in this study was downloaded from open street map (OSM) and a shapefile of Aberdare ranges used to clip the roads within the study area. Google earth was used to digitize natural trails and undertaking ground truthing of the roads network. Using QGIS version 3.16, vector data of the roads network and nature trails were loaded and a buffer created at 100m, 200m, 250m 500m and 1000m using a buffer tool (Figure 2).

In preparing PELIS layers, a handheld GPS was used and all forest stations within Aberdare ranges were visited and sub-compartments which have had PELIS since 2012 were identified and coordinates taken around the areas. The coordinates were then transferred to QGIS and polygons created to depict PELIS areas. Polygons within 200 m were merged for ease of buffering. Buffers was created below 200m, 200-400m, 400-600m, 600-800m and above 800m.

2.2.2 Topography

Elevation and slope influences fire behavior and response (Van Hoang et al., 2020). Some studies have shown that within high mountains, upper elevations are generally cold accompanied by low oxygen and relatively high wind speed (Adaktylou et al., 2020). Whereas, other studies have shown that higher elevations are more remote and have difficult terrain for early detection of wildfires (Abdi et al., 2018). In this regard, elevation can be either proportional or inversely proportional to fire risk depending with local conditions. On the other hand, in steep slopes areas fire tend to spread faster than in gentle slopes (Abdi et al., 2018).

The Shuttle Radar Topography Mission (SRTM) digital elevation model at a resolution of 30m corresponding to Aberdare ranges was downloaded with SRTM downloader plugins in QGIS 3.16 environment and processing of slope and elevation was undertaken by profile tool plugin. The resulting product of elevation and slope was categorized into five classes based on the Aberdares ranges terrain (Figure 2)

2.2.3 Meteolorogical data

Precipitation and temperature are the major weather and climatic factors affecting ignition and spread of fires due to their influence on growth of vegetation, soil moisture and humidity (Guo et al., 2016). However, studies of Kim et al., (2019) indicated that temperature fluctuation in the tropics is rather small compared to other regions for any significant influence. Hence, temperature was not considered in this study. Monthly rainfall data and the GPS coordinates of the rain gauge was collected from Kenya Meteorological Department (KMD) stations and rain gauge records within Aberdare ranges from January 2012 to December 2021. Mean annual rainfall from all the stations was calculated. An MS-Excel file of the data was created and converted to csv file which was later converted to shapefile using QGIS 3.16 platform. The mean annual rainfall was interpolated using inverse weighted interpolation method in System for Automated Geoscientific Analysis (SAGA) GIS software and raster maps was created using QGIS. The final product was categorized into five classes based on the potential fire risk levels (Figure 2)

2.2.4 Vegetation variables

The main factors for evaluating fire fuels at a landscape scale include land cover and vegetation indices according to studies of Abdi et al., (2018). The land cover maps were obtained from the national land cover maps used in reporting forest reference level under REDD+ schemes. The land cover/ use maps have been developed every 2 years from 1990 to 2022 using Landsat imageries and other auxiliary data. The land cover maps have 10 classes namely dense forest, moderate forest, open forest, wooded grassland, open grassland, perennial cropland, annual cropland, vegetated wetland, open water and otherland. Using QGIS version 3.6, the land cover data set for 2016 that is approximately at the middle of the fire duration under study was reclassified into five classes namely dense forest, open forest, wooded grassland, open grassland and cropland taking into consideration of the possibility of fire ignition in the respective land cover types. The reclassified map was clipped to the area of interest using Aberdare ranges shapefile (Figure 2)

Concerning the vegetation condition, Normalized Difference Vegetation Index (NDVI) has been used widely to depict vegetation vigour and flowering patterns (Van Hoang et al., 2020). It's a measure of vegetation greenness with values ranging from -1.0 to 1.0. The negative values tending to 0 mean drying or possibly lack of healthy floral parts. Values close to 1 indicate the highest possibility of healthy and green canopy vegetation (Adaktylou et al., 2020). In this study, NDVI was computed using Landsat imagery that has a 30-m spatial resolution using equation 1 and classified into five classes in Google Earth Engine (GEE) platform (Figure 2)

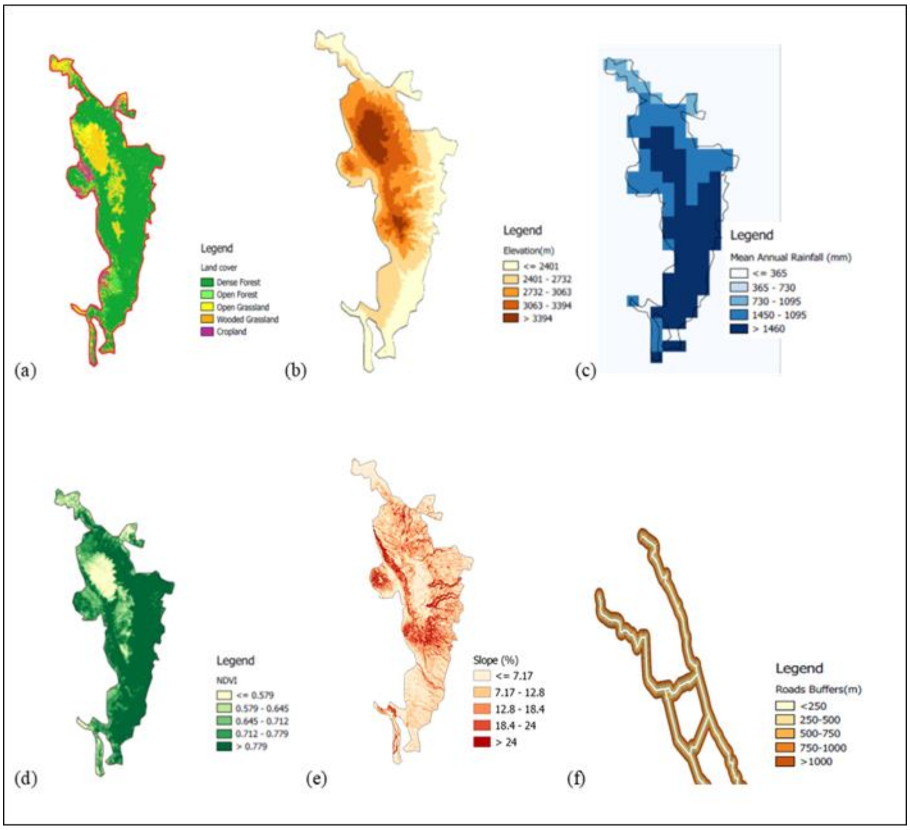

Figure 2. Some of the GIS processed layers of independent factors used in generating wildfire risk maps. This include (a) land cover (b) elevation (c) mean annual rainfall (d) NDVI (e) slope and (f) section of buffered road network within Aberdare ranges

Landsat images were processed within the dry months of the years normally from January to March and before major fire events guided by local fire records to depict true condition of the vegetation for the years between January 2012 and December 2021. The mean value of the NDVI products was used in modeling as proposed by Adaktylou et al. (2020).

The GIS layers used in generating wildfire risk maps were processed before the analysis of AHP as shown in Figure 2.

$$NDVI = \frac{NearInfrared - RED}{NearInfrared + RED} \qquad \text{Eq- 1}$$

2.3 Determining the weights of factors contributing to wildfire risk in Aberdare Ranges

A pair wise comparative analysis of all the seven factors namely proximity to roads/nature trails, proximity to PELIS, mean precipitation, elevation, slope, land cover and NDVI was examined to attribute weight of each factor in relative to the other factors. Experts and relevant stakeholders within the study area were involved through informal discussions in assigning a weight to each factor according to its weight in fire initiation and spread. This was accomplished by providing stakeholders with all the seven factors and requesting them to list and rank the main causes of wildfires within their locality in the order of importance. A method proposed by Saaty, (1977) and applied in the studies of Lamat et al., (2021) was used to compare all factors against each other based on their importance in a scale of 1 to 9. The value 1 representing equal importance between two factors being compared while value 9 representing extreme importance for the values being compared. Afterwards the final qualitative weights were derived by combining the outputs from stakeholders to a harmonized list. While assigning the weight of each factor, literature reviews and researcher's knowledge of the study site was also taken into consideration. The standardized relative weight was calculated by dividing each element of the pairwise matrix by the total summation of each column. The higher the weights, the more was the influence of the parameters on the wildfire risk based on its relative importance. Then each element within the matrix was divided by its total row to generate a standardized pairwise comparison matrix. The criteria weight for each factor was determined by mean of normalized values for each factor. Using QGIS software, the raster layers of all the factors combined with estimated weights were loaded and the wildfire risk developed (Van Hoang et al., 2020) using equation 2

$$FR = \sum_{i=1}^{n} (w_i x_i) \qquad \text{Eq- 2}$$

where

FR is the risk of wildfire; w_i is the weight of factor (i); xi is the factor (i) while n represent the number of factors (from 1 to n).

A consistency ratio (CR) was evaluated using Equations (3) and (4) in order to assess the reliability of the process with the overall aim of minimizing the bias of the model.

$$CR = \frac{CI}{RI} \qquad \text{Eq- 3}$$

$$CI = \frac{\lambda\max - n}{n-1} \qquad \text{Eq- 4}$$

where CR represents the consistency ratio. This is derived by dividing CI (consistency index) and RI (random index) in Equation (3) while in Equation 4, λmax represents maximum value achieved by the mean of dividing the sum of the weights, and n is the number of criteria. After calculation, the CR values of 0.10 and lower was considered as acceptable limits (Lamat et al., 2021).

2.4 Validation of wildfire risk maps

Moderate-Resolution Imaging Spectroradiometer (MODIS) near active fire data (Parajuli et al., 2020) and burnt area products (Henry et al., 2019) have been used in validating fire risk maps. However, this study utilized Visible Infrared Imaging Radiometer Suite (VIIRS) active fire data to evaluate the predictive power of the fire risk maps produced using seven independent variables. The VIIRS is superior to MODIS in detection of small fires which are common in Kenyan forest ecosystems, since the thermal band of VIIRS which has a 375 meters resolution per pixel compared to MODIS which has 1,000 metres resolution per pixel (Strydom & Savage, 2016). The VIIRS data has information on latitude, longitude, date, time, Fire Radiative Power (FRP) and confidence level (Giglio, 2018). The VIIRS reference fire data was accessed freely from NASA Fire Information for Resource Management System (FIRMS) at https://firms.modaps.eosdis.nasa.gov/download/. From the website, the date request was created by drawing a polygon within a representative area of Aberdare ranges in the base map. The data request was limited from January 2012 to December 2021 while the data format was comma-separated text (.csv). Figure 3 and 4 shows the monthly and yearly total fire incidences recorded by VIIRS satellite sensors. The derived fire points were overlaid on the final risk zone map and the degree of concurrence of the observed fire occurences with the predicted risk levels from our results was calculated as percentages.

After validation, the respective area of the various wildfire risk levels was evaluated using spatial analyst tool within QGIS version 3.16. The respective areas were further imported to Microsoft Excel and used in the calculation of the risk zone percentage using Equation 5.

$$Percentage\ of\ risk\ area(\%) = \frac{Estimated\ area}{Total\ area} * 100 \qquad \text{Eq- 5}$$

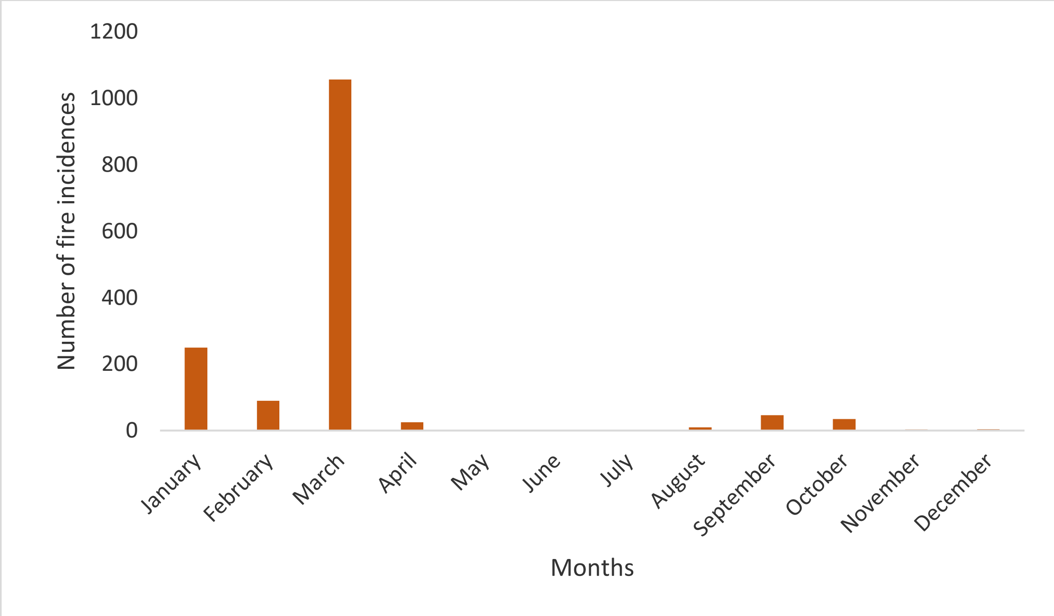

Figure 3. Total number of monthly fire incidences from 2012 to 2021 derived from VIIRS satellite fire data

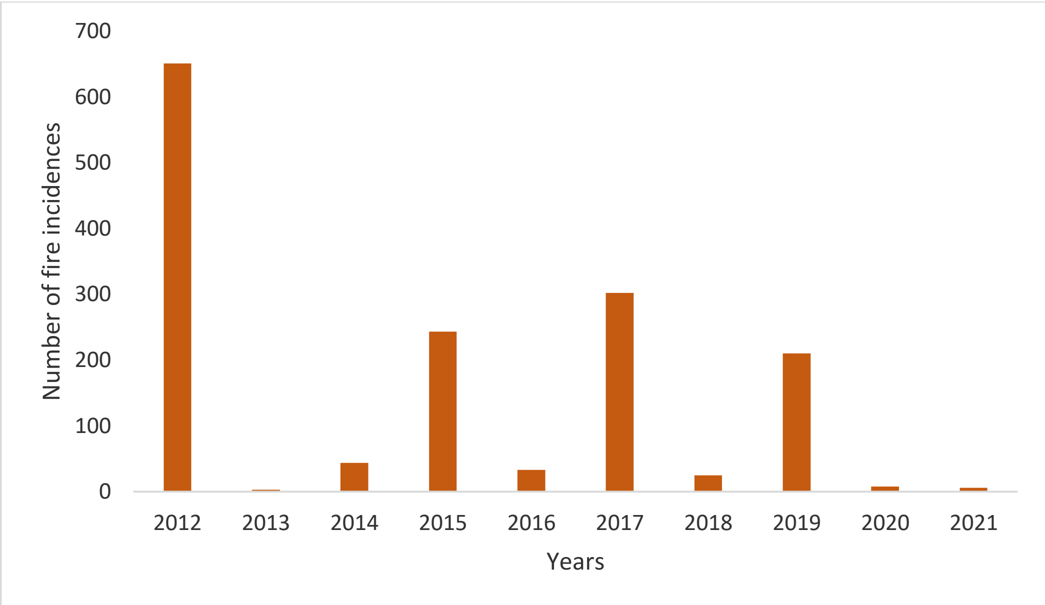

Figure 4. Total number of cumulative yearly fire incidences from 2012 to 2021 derived from VIIRS satellite fire data

3. Results

Table 2 shows a pairwise comparison matrix of potential independent variables contributing to wildfire occurrences based on their importance on a scale of 1-9. The Analytical Hierarchy Process indicated that vegetation-based factors namely land cover (0.39) and NDVI (0.23) were highly rated in causing wildfires whereas anthropogenic factors namely proximity to PELIS (0.05) and roads (0.04) were least (Table 3). The consistency ratio was calculated as 0.06 indicating a consistency of decision-making process of various weights attributed to the independent factors. The weight derived from normalized pairwise matrix was used to generate a wildfire risk prediction model. The wildfire prediction model shown in Equation 7 was used to generate wildfire risk map with five classes (Figure 5). Above 70% of Aberdare ranges area is within low (43%) and moderate (30%) risk zone. Whereas less than 20% of the area is within the high (13%) and very high (4%) areas (Table 4). The Wildfire risk prediction model (FR) is estimated as

$$FR = 0.39 * LC + 0.23 * NDVI + 0.12 * \Pr + 0.10 * Elev + 0.07 * Slope + 0.05 * PELIS + 0.04 * Rd \quad \text{eq-6}$$

where, LC is Land cover, Pr is precipitation, elev is elevation, PELIS is Proximity to PELIS and Rd is proximity to roads.

Table 2. Pairwise comparison matrix of potential factors contributing to fire occurrences

Factor	Land cover	NDVI	Precipitation	Elevation	Slope	Proximity to PELIS	Proximity to Roads
Land cover	1	3	4	5	5	7	7
NDVI	0.33	1	3	4	3	5	6
Precipitation	0.25	0.33	1	3	3	2	2
Elevation	0.20	0.25	0.33	1	3	3	2
Slope	0.20	0.33	0.33	0.33	1	2	2
Proximity to PELIS	0.14	0.20	0.50	0.33	0.50	1	2
Proximity to Roads	0.14	0.17	0.50	0.50	0.50	0.50	1
Sum	**2.27**	**5.28**	**9.67**	**14.17**	**16.00**	**20.50**	**22.00**

Table 3. Normalized pairwise matrix using Analytic Hierarchy Process (AHP)

Factor	Land cover	NDVI	Precipitation	Elevation	Slope	Proximity to PELIS	Proximity to Roads	Criteria weights
Land cover	0.44	0.57	0.41	0.35	0.31	0.34	0.32	0.39
NDVI	0.15	0.19	0.31	0.28	0.19	0.24	0.27	0.23
Precipitation	0.11	0.06	0.10	0.21	0.19	0.10	0.09	0.12
Elevation	0.09	0.05	0.03	0.07	0.19	0.15	0.09	0.10
Slope	0.09	0.06	0.03	0.02	0.06	0.10	0.09	0.07
Proximity to PELIS	0.06	0.04	0.05	0.02	0.03	0.05	0.09	0.05
Proximity to Roads	0.06	0.03	0.05	0.04	0.03	0.02	0.05	0.04

Table 4. Wildfire risk classes showing area and respective percentages

Wildfire risk class	Area (Ha)	Percentage (%)
Very low	20,891.96	8.9
Low	102,132.07	43.4
Moderate	70,851.23	30.1
High	30,905.57	13.1
Very High	10,330.91	4.4
Total	235,111.74	100

Validation of the developed wildfire risk map using (VIIRS) active fire data indicated that 60% of the fire points overlaid fell on the high and very wildfire risk zones, 21% in the moderate zone and below 20% were in the low and very low zone (Figure 6)

4. Discussion

In this study, prediction of wildfire risk in relation to environmental and anthropogenic factors was undertaken using a case of Aberdare ranges which form part of the greater East African montane forest ecosystems. Integration of Geographical Information system (GIS) and AHP techniques was used to evaluate the potential of seven independent variables in contribution of wildfire risk, namely; land cover, NDVI, precipitation, elevation, slope, distances from PELIS and roads. The results indicated that the largest spatial area falls within low wildfire risk zone (43.4%) followed by moderate zone (30.1%). The high and very high wildfire zones occupy about 13.1% and 4.4% respectively (Table 5). High number of validation fire points (over 80%) within moderate and higher wildfire risk zones demonstrate the robustness of our model.

The areas within higher wildfire risk zones corresponds to areas in open forest and wooded grassland, which have low NDVI. This indicates the strength of vegetation variables in modelling wildfire risk. Our results concur with studies of Parajuli et al., (2020) in Nepal, which indicated the importance of vegetation types in fire ignition and spread. Although our study indicated high risk in open forest and grasslands, the studies of Matin et al., (2017) indicated high risk in broadleaved forest and shrub land. However, their study area had myriad of other threats contributing to fire risk such as proximity to settlement areas and road networks. The high and very high wildfire risk areas are located in the national park and transition areas with forest reserves, which are very important for biodiversity conservation.

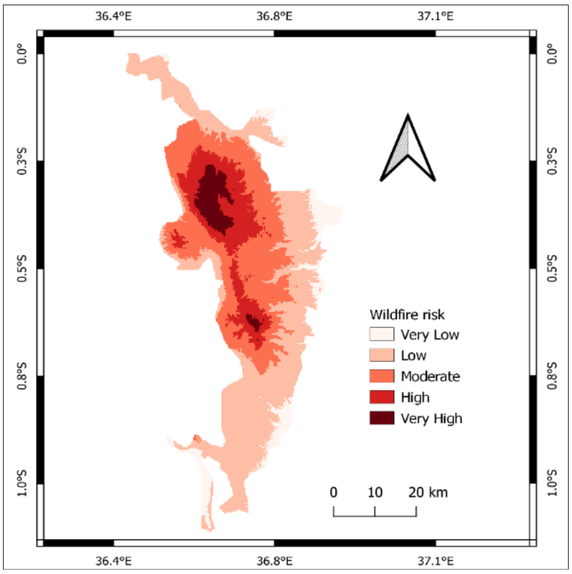

Figure 5. Fire risk map based on seven factors

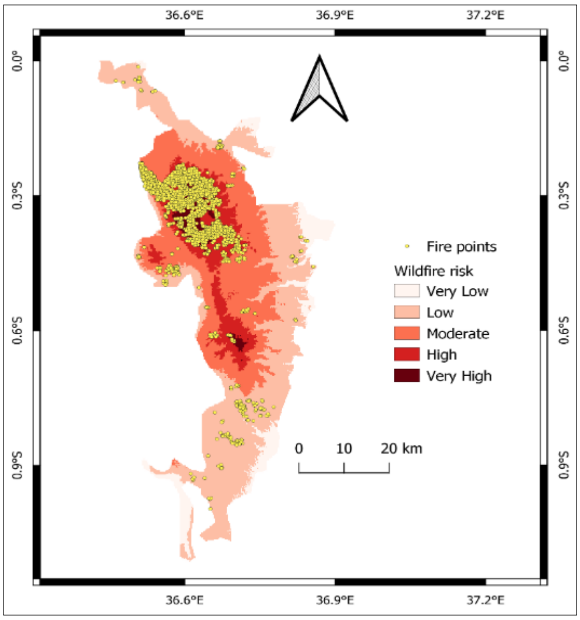

Figure 6. Validation of wildfire risk with VIIRS satellite data

Hence, the risk is a threat to the existence of endemic fauna found nowhere else other than in the Aberdares as listed by a report by Kenya Forest Service (2010). Further, the studies of Kipkoech et al., (2020) documented six plant species endemic to Aberdare namely; *Dendrosenecio brassiciformis, Senecio amplificatus, Senecio margaritae, Lobela gregoriana subsp. Sattimae, Eragrostis Amanda, Ranunculus aberdaricus*. The moorlands which form part of the vegetation in the very high-risk areas has been recognized as having endemic and vulnerable restricted-range bird species such as Aberdare Cisticola, Sharpe's Longclaw and Abbott's Starling (Kenya Forest Service, 2010)

This study has shown that the amount of precipitation is a moderate factor in wildfire risk analysis since in the Eastern side of the Aberdare ranges the risk was low compared to the western side, which had higher risk (Figure 2c). This is in contrast with studies of Abdi et al. (2018) that reported weak relationship of precipitation and wildfires. However, our study is in agreement with the findings of Mohammadi et al., (2014) which reported strong positive relationship of precipitation and wildfire risk. In Mt. Kenya, Poletti et al., (2019); Downing et al., (2017) indicated a fire season pattern that was in tandem with dry period over the years in their study. Figure 3 further exemplifies this scenario of high fire incidences in the month of January to March corresponding to dry period in Kenya. The long dry spell results to moisture deficient making vegetation susceptible to fire ignition and spread.

The findings this study shows anthropogenic factors namely PELIS and roads did not have significant contribution to wildfire risk as attested by low criteria weights during AHP analysis (Table 4). Our findings are contrary to the study of Vilar et al., (2016) which indicated a significant contribution of roads distance to wildfire risk. This can be attributed to poor road network in Aberdares ranges with minimal movements within the national park and forest reserve. Actually, there are no roads in high elevation areas with high wildfire risk. Tourists and government agency officers use the few roads available during sight-seeing and patrol respectively. They are normally guided by strict government guidelines and rules such as periodical fire alerts and preparedness bulletins to avoid wildfire ignitions. Further, there has been government moratorium on logging activities within state and community forests, which include Aberdare ranges (Kagombe et al., 2021). This has rendered most of the roads used during logging operations impassable and consequently reducing the human-forest interaction. On the other hand, lack of better road network could also contribute to spread of fire after ignition since fire suppression requires proper accessible routes for fire fighters and can also act as fire breaks. This study has also demonstrated the minimal contribution of PELIS in wildfire risk (Figure 4). Generally, PELIS is practiced within the forest plantation areas during trees established and early silvicultural operation. However, in areas mapped as PELIS were within the low and very low wildfire risk zones. This study is consistent with a study in Mt. Kenya Forest by Nyongesa and Vacik, (2018) which indicated illegal charcoal burners, honey harvesters and arsonist as key human factors in wildfire occurrences. These illegal activities are normally practiced deep in the natural forest in close vicinity to open forests and grasslands where scout rarely visits due to poor terrain and other threats. According to Nyongesa and Vacik, (2018), PELIS is a highly regarded venture due to provision of livelihoods among the forest adjacent communities. It's guided by strict by-laws among the community Forest Associations (CFAs) formed in close collaboration with KFS hence cases of wildfires risk are minimal as attested by the study of Agevi et al., (2016).

According to studies of Renard et al., (2012) the generated wildfire risk maps can be used to delineate hotspots areas and assist the natural resource practitioners in timely wildfire suppression work. Further, the output of this study will be crucial to strengthen the preparedness and mitigation measures of wildfire management and protect these important biodiversity resources.

Conclusion and Recommendations

A wildfire risk map has been developed using local independent factors generated from the stakeholders, earth observation products and geospatial tools. The vegetation factors and precipitation have been highly prioritized in the prediction of wildfire risk. The developed equation can be used to predict fire risk in Aberdare ranges. However, for the equation to be applied in other regions, there is a need to update the weights of the factors based on prevailing ground conditions. There is also need to validate the model in different forest ecosystems.

Whereas this study has demonstrated the strength of vegetation variables in modelling wildfire risk, the anthropogenic factors cannot be ignored especially if the study area is not a nature reserve as the case of Aberdares. It would be crucial to focus future research in other areas with different tenure system like community forests which, have high human related threats such as grazing and other development issues. Further, Aberdare ranges has a very rugged terrain and different topographical features which could have been hindering prompt suppression of wildfires upon occurrence. Therefore, it would be important that future research direction would be geared toward testing our model in other areas with different terrain, agroclimatic zone and land cover characteristics. This study integrated geospatial tools with AHP in predicting wildfire risk; it would be prudent to test the application of other methods in deriving wildfire risk maps

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