



NAMIBIA JOURNAL FOR RESEARCH  
SCIENCE & TECHNOLOGY

# Namibian Journal for Research, Science and Technology



NCRST  
NATIONAL COMMISSION  
ON RESEARCH SCIENCE & TECHNOLOGY

Volume 5. Issue 1  
May 2024

Original Research Article

## Geomorphological-based Remote Sensing and GIS analyses to identify vulnerable zones of forest fire in Zambezi Region, North-eastern Namibia

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### ARTICLE INFO

Received: Sept 2022  
Accepted: Sept 2023  
Published: May 2024

#### Keywords:

Fire vulnerable zones, forest fire, GIS, Namibia, Remote Sensing, Zambezi Region.

### ABSTRACT

Forest fires are a threat to biodiversity, lives, and livelihoods in many parts of the world. In Namibia, there is growing concern over the increasing frequency and severity of forest fires. The aim of this research was to map out fire-vulnerable zones in Zambezi Region in north-eastern Namibia using remote sensing and geographic information system (GIS) techniques. A forest fire risk zone map was developed from a combination of several forest fire-promoting variables. To assess vegetation condition, Normalised Difference Vegetation Index (NDVI) was calculated from Landsat TM images resulting in six classes. A toposheet map was used to classify land cover and land use into six density categories. Using SRTM imagery elevation data and topographic map, the slope, aspect, drainage density, and other coverages were determined. Geomorphologic and meteorological data were also used in the determination of forest fire risk zones. Forest fire vulnerable zones were defined by assigning subjective weights to each layer's classes based on the perceived sensitivity to fire or ability to cause fire. The final product categorized the Zambezi Region into four fire vulnerable categories: extremely high risk, high risk, moderate risk, and low risk. An area of 137000 ha (9.6%) was at very high risk, 665400 ha (46.5%) was at high risk, and 64600 ha (4.5%) was at low risk. Vegetation structure, geomorphology, land cover, and precipitation were major determinants of fire vulnerability. High elevation and low vegetation moisture status increased fire vulnerability. Lower fire risk (than expected) was recorded at low elevations due to the vegetation type being a limiting factor. Mid-elevated areas were at very high fire risk due to interactive effects of elevation, high temperature, and low humidity. Slope, aspect, and drainage density did not significantly influence fire risk due to low occurrence of pronounced slopes and aspects.

### 1. Introduction

Forests are very important in the lives and livelihoods of people since they provide a lot of ecosystem services (Tomar, Kanga, & Singh, 2021). However, over the last few decades forests have been increasingly under threat from various factors

including overharvesting, unsustainable forest management practices, human settlement encroachment and uncontrolled forest fires. Forest fires have presented a significant danger to various forest ecosystems around the world (Cao, et al.,

2021). They have a significant impact on the forest ecosystem, resulting in negative impacts on forest biodiversity (Cao, et al., 2021). Some species have gone extinct or are threatened due to a number of factors including impacts of forest fires. Forest fires disrupt the forest functioning by altering the landscape and affecting the wildlife and flora (Enoh, Okeke, & Narinua, 2021). Forest fires do not only destroy forest resources, but they also endanger people's lives, property, and agricultural production. Due to their vast pace of propagation, forest fires in a given area have the ability to unpredictably change direction from one shape to another (Rios, Pastor, Valero, & Planas, 2016). Forest combustion may spread slowly or quickly depending on the prevailing meteorological conditions (Enoh, Okeke, & Narinua, 2021). Meteorological conditions such as wind, atmospheric temperature, relative humidity and precipitation play a significant role on the extent, affect and spread of forest fires (Cardil, et al., 2021). Coupled with meteorological conditions, land cover, geomorphological features such as slope, aspect, elevation and altitude also play a significant role in the fire regime of an area. Forest fire behavior is characterized by the size of the flame front and the type of spread (Morvan & Frangieh, 2018). Local vegetation structure and attributes are also key determinants of forest fire regimes, and there are feedbacks where each influences the other. Hence, combinations of climatic, geomorphology and vegetation attributes lead to differences in vulnerabilities to fire among zones. Where human activities are within or close to forests, they form the most significant source of ignition. Forest fires are more likely to occur in places that are adjacent to towns, agricultural areas, and road networks (Enoh, Okeke, & Narinua, 2021).

Forest fires are negatively affecting forest biodiversity in many regions of the world, including Namibia's Zambezi Region. Most places in Namibia, particularly the Zambezi and Kavango Regions, experience fires every year (Humphrey, 2018). The Zambezi and Kavango Regions generally receive higher average annual rainfall than other Regions in the country; consequently, they have more woodlands and dry forests, which lead to high risk of fire. Forest fires in Namibia are still mostly caused by human activities, particularly during the dry season when there is a significant water stress (Chuvieco, et al., 2021) and the vegetation is relatively dry while temperatures and wind speeds rise, all of which are conditions, which promote fire occurrence.

Geomorphology, lithology, stratigraphy, climate fluctuation, and landforms are all important variables, which can be used in modelling fire occurrence (Yair, Almog, & Arbel, 2018). The use of remote sensing technology for geomorphological studies has increased its importance for this purpose. Geospatial

approaches such as GIS and remote sensing are used to explore the association between geomorphological factors, climate conditions and forest fires. Climate variables such as precipitation, solar radiation, mean temperature, and relative humidity have been examined in the majority of forest fire research cases (Kumari & Pandey, 2020).

Early identification of forest fires is critical for minimizing fire damage, and geospatial approaches are critical for recognizing and mapping forest fires as well as monitoring the frequency with which different vegetation type's burn, leading to the identification of fire vulnerable zones. Forest fire vulnerable zones are areas where a fire is more likely to start before spreading to other parts of the forest. Forest fire risk zones have been mapped using a number of methodologies, the majority of which relied on remote sensing and GIS using topography, vegetation, land use, population, and settlement data (Pradeep, et al., 2022). This study, which is based on geospatial technology, sought to identify vulnerable forest fire in the Zambezi Region in Namibia. Such information would help decision-makers and practitioners to develop appropriate early warning systems and fire management plans or strategies in order to conserve biodiversity as well as saving lives.

### **1.1. The Objectives the study**

This study, which is based on geospatial technology, sought to identify vulnerable forest fire in the Zambezi Region in Namibia. Such information would help decision-makers and practitioners to develop appropriate early warning systems and fire management plans or strategies in order to conserve biodiversity as well as saving lives.

## **2. Methodology**

### **2.1 Study area**

The study was conducted in the Zambezi region north-eastern part of Namibia, at latitude of -17° 29' 59.99" S and Longitude of 24° 15' 60.00" E (Akashambatwa, Zuwarimwe, & Teweldemedhin, 2017) (see Supplementary Fig. S1). The Zambezi Region has a population size of 90 422 and a total area of 22,000 km<sup>2</sup> (Akashambatwa, Zuwarimwe, & Teweldemedhin, 2017). It has a tropical climate with hot temperatures and substantial rainfall (600–700 mm) during the summer season, which lasts from December to March, making it Namibia's wettest region. Average summer and winter temperatures are 35oC and 28oC in the afternoon respectively. Permanent rivers (Chobe, Kwando, Linyanti and Zambezi) supporting riverine woodlands and floodplains traverse thick deposits of Kalahari sands dominated by savannah woodlands (Gondwe, et al., 2021). The area is covered in dunes, dune valleys, and sandy substrates and has an average elevation of 930 meters above sea level. Swamps, floodplains,

wetlands, and woodlands make up the majority of the topography.

## 2.2 Data collection and analysis

The study involved data building concerning the geomorphological characteristics or landscape of the Region leading to the identification of forest fire vulnerable places (see Supplementary Fig. S2). The work was done in three phases as described below.

In the first phase, the thematic layer of vegetation was obtained by calculating the Normalised Difference Vegetation Index (NDVI) employing a Landsat TM image (see Supplementary Fig. S6). NDVI is an index that is sensitive to the amount of vegetation above ground that is computed based on the following formula:

$$NDVI = (Near\ Infrared - RED) / (Near-infrared + RED);$$
 where NIR is the reflectance measured in the near-infrared channel and red is the reflectance measured in the red channel; the higher the NDVI value, the denser or healthier the green vegetation (Timmer, Reshitnyk, Hessing-Lewis, Juanes, & Costa, 2022). In general, NDVI values range from -1.0 to 1.0.

Terrain mapping was generated using SRTM image downloaded from [www.earthexplorer.usgs.gov](http://www.earthexplorer.usgs.gov). Based on the terrain map, a drainage network and density were generated. With the help of the drainage network, micro-watershed regions and water divide were also generated. Based on the micro-watershed regions, a geomorphological classification of the region was generated and the hydrology map (see Supplementary Fig. S3). This completed the first phase of data procurement and data capture.

## 2.3 Ranking and weighting factors for different layers

The input information on factors influencing forest fire is in descriptive form and reveals the parameters favouring the fire risk. To achieve effective conclusions through computation and other mathematical operations in the subsequent GIS analysis, the factors that lead to a place being vulnerable to a forest fire in an area were analysed in the following order of importance: Digital Elevation Model, land use/ land cover, NDVI, vegetation structure, drainage density, relief, slope, average annual rainfall and average temperature (see Supplementary Fig. S3 to S15). After determining the influence of each factor on forest fire risk, the different classes of each factor were given suitable ratings. A higher rating indicates that the factor has a high degree of influence on the fire risk in an area. The considered factors were then integrated for calculating the forest fire vulnerability places (see Supplementary Table S1). The factors were rated on a scale of 1 - 10, where the digital elevation model was ranked first meaning that it has a high degree of influence on the fire risk in an area (Sakellariou, Sfoungaris, & Christopoulou, 2022). Based on the digital elevation model geomorphology was

derived and classified into five classes (wet valley land, partly wet mid-valley, mid dry land, mid elevated partly and elevated damp land).

The mid-elevation (941- 960 m) area was given the highest weight because in this area rainwater received gets drained to lower regions (Xavier, Leite, Kyle Dexter, & Mato, 2019), thus less moisture makes these areas more vulnerable to forest fire. These areas normally are not evergreen; vegetation dries up in summer because of high temperature and less water percolation. Land use/ land

cover of the area followed DEM during analysis; vegetation was given the highest weight because even though an environment may be favourable to fire, a forest fire cannot occur unless inflammable material is present. The vegetation cover in the mid dryland regions were given a higher weight because dryness makes them more susceptible to forest fire (Thoha & Triani, 2021). Drainage density was awarded a medium rank meaning that it has a moderate degree of influence on the fire risk in an area. The slope was assigned a lower rank because it does not necessarily influence the probability of ignition but has a strong influence on the behaviour of fire (Ciesielski, et al., 2022). Other factors such as temperature and rainfall were given lower ranks because they have a lower degree of influence on the fire risk in an area as they are mostly used in determining the spread of forest. The approach used in rankings and weightings followed standard practice in similar studies as exemplified by (Enoh, Okeke, & Narinua, 2021; Parajuli, et al., 2020) and (Zhao, Zhang, Lin, & Xu, 2021), among others.

In the second phase, depending upon the physiographical region categorised, overlain analyses were done in the ArcGIS platform. Based on the overlain analyses of the final map, the forest area prone to forest fire was identified (Figure 1). With the help of work and final results obtained, the project report was prepared with maps and a table.

## 3. Discussions and Conclusions

### *Forest Fire Susceptibility analysis based on Geomorphology*

The theme layers generated from satellite images and topographic maps were drainage density, drainage network, aspect, slope, relief, digital elevation model, land use/ land cover, geomorphology, national parks in the Zambezi Region, NDVI and vegetation structure (see Supplementary Fig. S3 to S15). Meteorological data on rainfall and temperature were also among the theme layers generated (see Supplementary Fig. S14 & S15). The Digital Elevation Model was extracted from SRTM data to show the elevation of the study area, ranging from 860 to 1040 m above mean sea level (see Supplementary Fig. S5). The geomorphological classification of the region derived from the Digital Elevation Model resulted in six classes, namely wet valley land, partly wet mid-valley,

mid dry land, mid elevated land, partly dry land and elevated damp land, correlating to the elevation of the region (see Supplementary Fig. S3). The Zambezi Region was classified into different forest regions derived from NDVI, namely sparse vegetation; moderate vegetation and dense green vegetation. The vegetation cover from the topographic map was classified into (very dense bush/forest, dense bush/forest, medium bush/forest, open bush/forest, grassland and marshes with swamps). More of the forests are found in the western part of the Region and less towards the eastern part of the Region because the western part largely falls in protected areas (where there is less human disturbance, no settlements and different geomorphology, while towards the eastern part there are floodplains (see Supplementary Fig. S6 and S8). It is well known that most woody plants cannot tolerate waterlogging (Xavier, Leite, Kyle Dexter, & Mato, 2019), hence the very little woody vegetation in the eastern part of the Region. The level of correlation between forest and the micro-geomorphological region was such that there is more forest in the elevated damp land than in lower wet valley land conforming to a soil catena sequence (García-Gamero, Vanwalleghem, Peña, Román-Sánchez, & Finke, 2022), thus the upper slopes support more woody vegetation where soils are better drained than bottom slopes where the soil is more clayey and gets waterlogged.

*Forest fire vulnerable zones of the Zambezi Region*

The final output map of zones vulnerable to forest fire in the Zambezi Region was in four classes; very high risk, high risk, moderate risk and low risk (Figure 1).

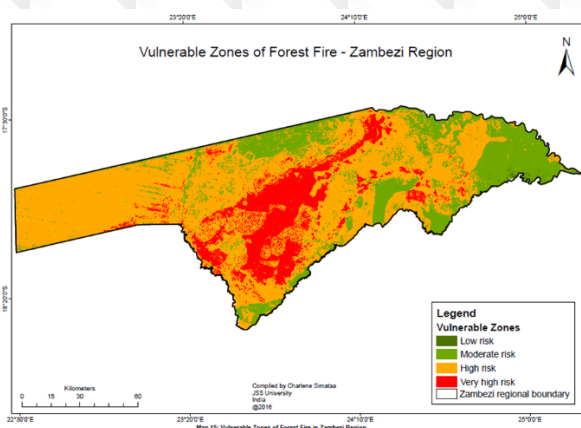


Figure 1: Vulnerable zones of Forest fire in Zambezi region

The Region is dominated by areas of Moderate risk (39.5%) to high risk (46.5%)

Table 1: Area (km<sup>2</sup>) and percentage (%) of forest fire vulnerable zones.

Fire vulnerable zones	Area (km <sup>2</sup> )	Proportion (%)
Low risk	646	4.5
Moderate risk	5654	39.5
High risk	6654	46.4
Very high	1370	9.6
Total	14324	100

Such a situation may be a cause for concern, especially during the high fire season, which normally runs from August to November each year.

The main factors influencing the level of risk as clearly shown from the maps are vegetation structure, geomorphology, land cover and precipitation while other factors seem to play a less pronounced role. However, it must also be noted that there are complex interactions among these determinants such that the maps may offer a simplification of how the determinants function. It was shown that the mid elevated land regions and the mid dry land of elevations above 940m were at very high risk of forest fire than other areas of high and low elevation. Hence, the high position on the landscape and the low moisture status of the vegetation increases vulnerability to fire. Elevation influences vegetation composition, fuel moisture and air humidity. More than 90% of incidents of forest fire occur above 100m altitude. Low elevation is reported to be associated with high temperatures, low levels of fuel moisture and high wind speeds, all of which tend to increase fire risk (Sivrikaya & Kucuk, 2022). However, results from this study do not present such a clear trend for low elevations, indicating that there are other factors such as the vegetation type (less woody fuel) which were limiting determinants.

Slope also influences fire behaviour, particularly its rate of spread. Fire spreads faster upslope, and as slope increases so does the fire spread rate, the ignition of the canopy fuels and hence the fire risk (Sivrikaya & Kucuk, 2022). Ignition point of the vegetation increases because of pre-heating of the vegetation ahead of the fire, and this effect is higher when burning upslope. Closely related to slope is the aspect. Aspect influences the fire behaviour by affecting the amount of solar radiation received on a site. Generally, northern and western aspects receive more direct heat from the sun, leading to more drying of the soil and vegetation than on southern or eastern aspects. The results show that the influence of slope, aspect and drainage density did not seem to influence fire risk in a significant way. This may be due to the fewer pronounced slopes and aspects; hence, the fire

risks were more influenced by other variables (discussed above) than by slope and aspect. This is expected in such landscapes as shown by Burrows, Stephens, Wills, & Densmore (2021) who reported similar less influence of aspect on fire behaviour near Sydney in Australia, and they interpreted it as a 'surprising' result.

Forest fire risk and behaviour are related to meteorological variables such as precipitation, temperature and humidity. Higher temperatures reduce relative humidity and lead to high vulnerability to fire (Sivrikaya & Kucuk, 2022). The results show that mid elevated areas are at very high fire risk because of dry conditions, which makes them more susceptible to forest fire. There is clear interactive influence between elevation, temperature and humidity on fire risk. Dryland areas provide dry fuel to start a fire and for it to easily spread to other areas. In summer, these areas are likely to dry up because of high temperature and most of moisture drains out to the lower areas as explained by catenal effects (García-Gamero, Vanwalleghem, Peña, Román-Sánchez, & Finke, 2022). These areas support more woody vegetation, which provides more fuel, thus increasing the risk of forest fire in the zone. The area also has some Conservancies where there are human settlements from where fire can be started intentionally or unintentionally, thereby spreading out to other areas. A number of studies (e.g. (Sivrikaya & Kucuk, 2022; Jiménez-Ruano, et al., 2022; Hoang, et al., 2020) have shown the importance of humans as key determinants of fire dynamics, particularly as sources of ignition and promoters of its spread. Lower risk areas of forest fire are mostly in the elevated land and towards the eastern part where it is mostly covered by water (floodplain). Elevated regions have more vegetation than lower wet valley land because high-elevated land receives high rainfall which promotes more woody vegetation. There is also good water percolation due to the more sandy soils compared to the more clay soils in valley bottoms. Out of the 14324 km<sup>2</sup> total area sampled of the Zambezi region, 1370 km<sup>2</sup> was of very high risk of a forest fire with 9.6% with 64.6% area being in the lower risk area (Table 1). Most area vulnerable to forest fire is in high-risk zones with an area of 6645 km<sup>2</sup> (46.5 %) (Table 1).

#### 4. Conclusions

The aim of this study was to identify and map out areas of various vulnerability to forest fires in Zambezi Region in north-eastern Namibia using remote sensing and GIS. More than 50% of the Zambezi Region was classified as being at least high fire risk (9.6% at very high risk, 46.5% at high risk). Vegetation structure, geomorphology, land cover, and precipitation were major determinants of fire vulnerability. High elevation and low vegetation moisture status increased fire vulnerability.

Contrary to widely reported trends, a lower fire risk was recorded at low elevations due to the vegetation type which had lower woody fuel loads, making it a limiting factor. Mid-elevated areas were at very high fire risk due to the interactive effects of the higher elevation, high temperatures, and lower humidity which tend to promote fire. Slope, aspect, and drainage density did not significantly influence fire risk due to the low occurrence of pronounced slopes and aspects in the Region. This study has demonstrated the capabilities of using remote sensing and GIS for the delineation of areas of different fire vulnerability status. It is critical to improve our understanding of the main determinants and spatial distribution of different fire vulnerable zones in order to manage the growing problem of forest fires and their associated threats to biodiversity, human lives, and livelihoods.

#### 5. Acknowledgements

The authors would like to extend their appreciation to the following institutions; JSS Academy of Higher Education & Research (India), Mysore University (India), National Remote Sensing Center (Ministry of Agriculture, Water & Land Reform, Namibia) who assisted in the completion of the project and provided data.

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