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The influence of bioclimatic and topographic variables on grassland fire occurrence within an urbanized landscape

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ABSTRACT

Unplanned veldfires (or wildfires) characterize vegetation landscapes and offer a range of ecological benefits that promote, among others, the health of the grasslands and other fire-adapted ecosystems. However, in urbanized areas, uncontroled fires are often a threat to property, life, the environment, and economy. The eThekwini Municipal area, a global biodiversity hot-spot experiences frequent unplanned veld fires that threatens the valuable remnant grasslands. This necessitates an understanding of key drivers to fire occurrence as a first step towards the remnant grasslands sustainability. In this study, the probability of fire occurrence within the study area was determined using the Near Real-Time (NRT) MODIS Collection 6 Active Fire Data, topographic and bioclimatic variables within the Maximum Entropy (Maxent) environment. The predictor variables were assessed using jackknife analysis, percentage contribution, and Area Under Curve (AUC). The results showed that the mean temperature of the coldest quarter (33%), isothermality (12.3%), elevation (8.9%), and precipitation of the warmest month (8.8%) were the most influential predictor variables affecting fire occurrence within the study area. The Area Under Curve (AUC) values for training and test data-sets were 0.728 and 0.716 respectively, indicating good accuracy for the fire occurrence probability modeling. The study concludes that the Maxent modeling algorithm is suitable for determining fire occurrence and identifying key topographic and bioclimatic fire drivers within an urban landscape. These results are valuable in informing the protection and conservation of urban ecological systems, useful for the provision of urban ecosystem goods and services.

Introduction

Veldfires (or wildfires) are a common disturbance to numerous vegetation ecosystems, presenting a challenge to the management of vulnerable landscapes [1,2]. Veldfires occur naturally from among others lightning, falling rocks, accidental ignitions and run-away prescribed burning [3]). In urban areas, vegetation plays a critical socioeconomic and environmental role that includes mitigating climate change, regulating temperature, filtering pollutants, providing recreational spaces and increasing biodiversity. However, uncontroled urban fires on remnant or conserved vegetation are a risk to property, life, the

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environment, and the economy [4–6]). In South Africa for instance, the 2017 Knysna fire resulted in the loss of lives and destruction of over 800 buildings [7]), while in the city of Cape Town, veldfires are common occurrence, with devastating socioeconomic and ecological effects. In California, USA, 22 large wildland/urban interface (WUI) fires in 2017 resulted in 52 casualties, 233 injuries and approximately $12.5 billion in direct property losses [8], while in 2018, China experienced more than 237,000 urban fires that led to 798 injuries, 1 407 casualties, and approximately $557 million direct economic-related losses [9]. Hence, it is crucial to understand the underlying drivers of veldfires to mitigate their adverse socio-ecological and economic impacts on urban landscapes.

Grasslands cover nearly one-third of the Earth's terrestrial surface and offer a range of ecosystem services that include habitat for wildlife, feeds to livestock, climate regulation and stability, maintenance of biodiversity, soil protection, purification of water, and esthetic beauty [10]. Whereas fires are known to be critical to the regeneration of grasslands, uncontroled fires can transform grasslands into woody vegetation, degrade the ecosystem, lead to biodiversity loss, provide niches for alien invasive plant species, and increase species homogenization [11]. Generally, non-urban rangeland wildfire dynamics and effects have been extensively explored in the literature [12–16], however, the occurrence of wildfires on remnant and conserved urban rangelands remain largely unexplored. Hence, with the rapid characteristic transformation from natural to physical landscapes that typifies urban areas, it is necessary to understand the probability of fire occurrence as a first step to conserving the remnant and protected urban grassland patches to maintain urban socio-ecological sustainability and to guarantee ecosystem services accrual.

South Africa's eastern seaboard is characterized by a rich diversity of subtropical grasslands. The eThekwini Municipal Area (EMA), the focus of this study, falls within the Maputaland-Pondoland-Albany Global Biodiversity Hotspots and consists of the endangered subtropical KwaZulu-Natal Sandstone Sourveld (KZNSS), Ngongoni Veld, and the KwaZulu-Natal Coastal Belt ecosystems. Specifically, the KZNSS is a species-rich grassland characterized by dispersed low shrubs, proteas, geoxylic suffrutices, forbes, and a high level of endemism [11,17]. However, this grassland ecosystem is severely modified and its existence threatened by urbanization and uncontroled fires [11,18].

Understanding factors influencing fire occurrence is valuable in mitigating the effects of grassland fires and conserving the remnant urban grasslands. A number of studies (e.g. Trollope et al [19].; Bennett et al [20].; Krawchuck et al [21].) have noted that fire occurrence is influenced by an interaction of fuel load, topography, and weather. Other studies (e.g. Bennet et al [20].; Taylor and Harris [22]; Verma et al [23].; Mpakairi et al [24].; and Kim et al [25].) have identified elevation, temperature, slope, aspect, Topographic Wetness Index (TWI), catchment area, and wind as key variables influencing fire occurrence. For instance, elevation influences the amount of precipitation, exposure to wind, and seasonal fuel drying [20] while temperature and wetness influence fuel load and drying [20]. Hence, literature has noted a range of physical and climatic variables as valuable in predicting fire occurrence and landscape vulnerability [23,25,26,27].

Recently, remote sensing has emerged as a valuable tool for detecting, managing, and monitoring fires [28]. This is attributed to remote sensing ability to facilitate repeated data acquisition, large scale coverage, and cost-effectiveness. In fire related applications, remote sensing can be utilized at pre- during - and post-fire occurrence to predict areas vulnerable to fire occurrence, detect active fires and assess the impact of burnt areas [1]. In remote sensing, fires can be detected as distinct light on grassland at the visible and near-infrared portions of the electromagnetic spectrum and as smoke plumes and higher temperature within the mid-infrared portion of the electromagnetic spectrum [1,28].

In 2001, The National Aeronautics and Space Administration (NASA) initiated the Moderate Resolution Imaging Spectrometer (MODIS) Active Fire and Burnt Area Products. MODIS is onboard sensor Terra (morning) and Acqua (afternoon) satellites with daily coverage and over 30 narrow bands ranging from the visible to thermal infrared portions of the electromagnetic spectrum at variable spatial resolution from 250 m to1000 m. Due to its unique fire detection capabilities and high temporal resolution, MODIS has become a valuable sensor for fire monitoring at local, regional and global scales [1,23]. In concert with topo-climate variables, such data facilitates further research on factors influencing fire occurrence in space and time.

The Maximum Entropy (Maxent) is one of the most popular species distribution models for understanding landscape characteristics. Whereas the approach was initially developed to predict the potential distribution of species based on known occurrence and environmental variables, it has recently become useful in predicting fire related landscape characteristics [25]. Hence, using Maxent species distribution model, this study sought to determine the most important biophysical and climatic variables influencing fire occurrence within an urban landscape. Specifically, this study sought to investigate the drivers of fire occurrence in an urban landscape using historical fire data and climatic and topographic variables in a Maxent environment. In this study, we hypothesized that grassland's fuel load, topography, and climatic variables (e.g. temperature and wind direction) influence fire occurrence.

Material and methods

Study site

This study was conducted in the eThekwini Municipal Area (EMA) in KwaZulu-Natal, South Africa (Fig. 1). The EMA was merged to a Metropolitan in 2016 and covers 2297km^2 with over 3.6 million people [29]. It comprises of South Africa's major port city of Durban and numerous adjacent towns. The area experiences frequent fire outbreaks during the fire season and is characterized by warm and temperate subtropical climate with an average annual temperature of 20.9 °C (a minimum of 13.9 °C and a maximum of 24 °C), dry winters, mild-wet summers and 975 mm per annum. Topography within the area is

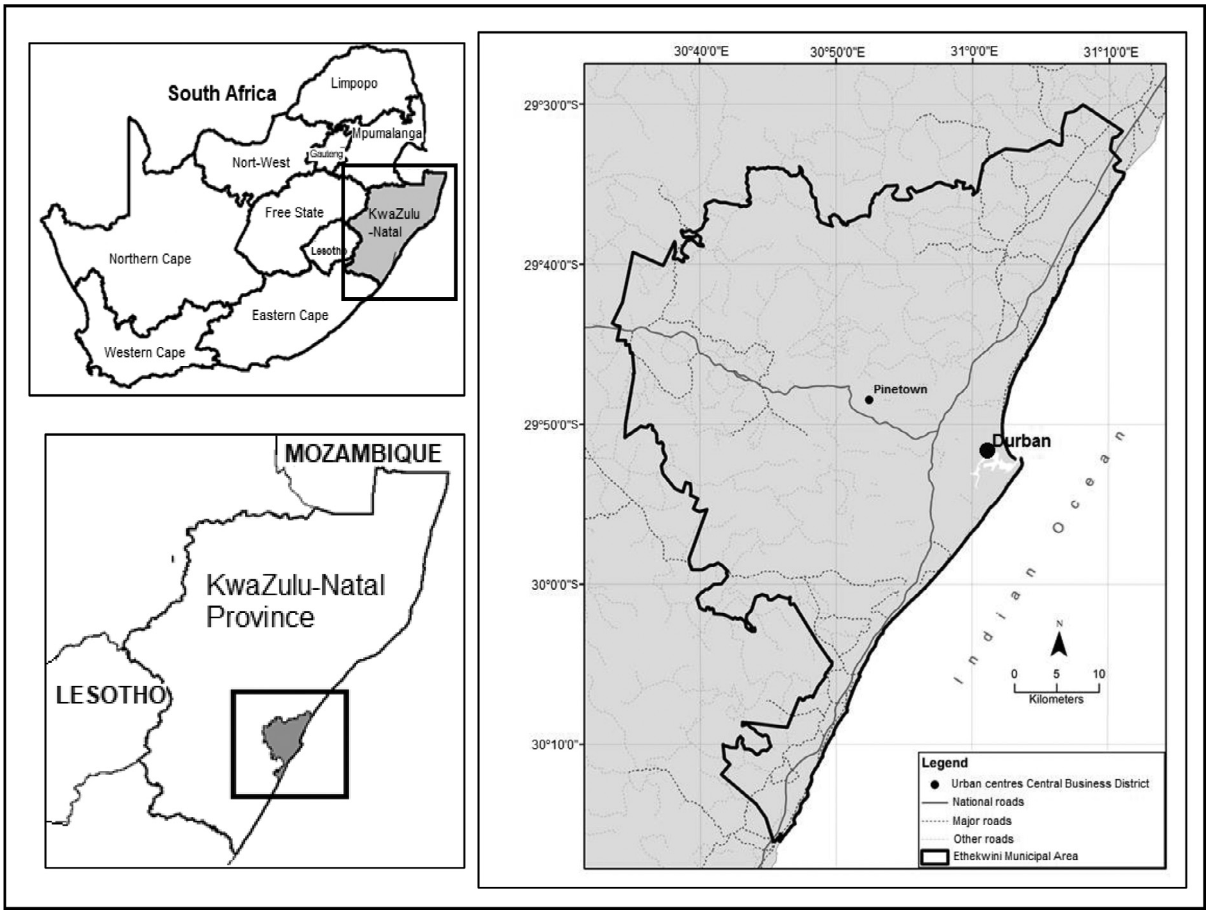

Fig. 1. Study Area map of the ethekwini municipal area.

highly varied with high grounds, flat plains and rugged ravines and gorges. Winds generally blow parallel to the coastline in a south-westerly and north-easterly directions [30]. EMA's varied climate, geology, soils, physiography and biogeographical position result in a wide range of biodiversity-rich aquatic and terrestrial ecosystems [17]. The area consists of natural forest and grassland habitat scattered between built infrastructure and settlements [31]. The EMA is situated in one of the world's 35 Global Biodiversity Hotspots, namely the Maputaland-Pondoland-Albany hotspot and the 940km^2 Durban Metropolitan Open Space System (D'MOSS); a spatial layer of interconnected open spaces under public and private ownership, developed to protect biodiversity based on their recognition of the value of ecosystem services within the municipality [17] (Fig. 1).

Fire data

Archived fire data was downloaded from NASA's Fire Information for Resource Management System (FIRMS) which distributes Near Real-Time (NRT) MODIS Collection 6 Active Fire Data. MODIS has provided global historical fire data from 2000 to date. The MODIS detection algorithm uses unprojected swath 4-, 11-, and 12-μm brightness temperatures derived from the corresponding 1 km MODIS channels. At daytime, reflectance observations are detected at 0.65-, 0.86-, and 2.1-μm and combined to a 1 km spatial resolution [32]. The algorithm identifies fire pixels that contain actively burning fires at satellite overpass. According to Blumenfeld [33], the MODIS C6 offers improved small fire detection, reduced false alarms, improved land surface temperature, and land surface reflectance. The active fire data is recorded in coordinates accompanied by acquisition time and date, brightness, and confidence level. Fire data for this study (1 January 2009 to 31 December 2019) was freely acquired from the EARTHDATA portal.

Bioclimatic data

This study adopted climatic indices, also known as bioclimatic predictor variables developed by the U.S. Geological Survey (USGS) as Geographic Information Systems (GIS) continuous raster surfaces to accentuate climate conditions related to the grasslands [34]. The study used temperature and rainfall averages for the years 1970–2000 obtained in a raster grid format

Table 1
Bioclimatic and topographic variables used for fire occurrence modeling.

Variable			**Description**
Bioclimatic	Temperature (°C)	Bio 1	Annual Mean Temperature
		Bio 2	Annual Mean Diurnal Range
		Bio 3	Isothermality
		Bio 4	Temperature Seasonality
		Bio 5	Max Temperature of Warmest Month
		Bio 6	Min Temperature of Coldest Month
		Bio 7	Annual Temperature Range
		Bio 8	Mean Temperature of Wettest Quarter
		Bio 9	Mean Temperature of Driest Quarter
		Bio 10	Mean Temperature of Warmest Quarter
		Bio 11	Mean Temperature of Coldest Quarter
	Moisture (mm)	Bio 12	Annual Precipitation
		Bio 13	Precipitation of Wettest Month
		Bio 14	Precipitation of Driest Month
		Bio 15	Precipitation seasonality
		Bio 16	Precipitation of Wettest Quarter
		Bio 17	Precipitation of Driest Quarter
		Bio 18	Precipitation of Warmest Quarter
		Bio 19	Precipitation of Coldest Quarter
Topographic	Aspect (°)		The direction the slope faces
	Catchment area (m^3/s)		Run-off velocity and volume
	Elevation (m)		Height above sea level
	Slope (°)		The steepness of the surface
	Topographic wetness index (TWI)		Steady-state wetness index
	Wind effect (m/s)		Effect of wind direction on the surface

with a 30″ ′onds (1 km^2) spatial resolution. These bioclimatic indices are derived from monthly temperature and rainfall values to provide more biologically consequential variables. These variables (Table 1) represent annual trends for temperature, precipitation and seasonal trends such as the temperature of the coldest and warmest month and precipitation of the wettest and driest quarters. These variables are useful in Maxent modeling and have been used to model fire probability across space and time [23].

Topographic variables

Previous studies on fire modeling have identified aspect, elevation, and slope as key topographic variables influencing fire occurrence [23,24]. These topographic variables have been noted as influential as they regulate vegetation distribution and local climate [21,22,35]). In this study, elevation was selected as a determinant to fire occurrence due to its influence on precipitation, exposure to wind, and seasonal fuel drying. Bennett et al [20]. for instance notes that at lower elevation, fuel commonly dries faster due to high temperatures and little rainfall. Aspect and slope were selected because fires often spread faster upslope than downslope. Aspect also influences wind speed and direction of fire spread [35]. The topographic variable used to determine fire occurrence are shown in Table 1. These variables were derived from a 30 m resolution of the Digital Elevation Model in an ArcGIS 10.4 environment. Since Maxent requires compatibility in input format (i.e., extent, projection, and pixel size), the variables were resampled to a 30 m spatial resolution. The fire data was converted from excel to comma-separated values (CSV) format.

Maxent model parameter settings

The freely available, Maxent version 3.4.1 was used to model the probability of fire occurrence within the study area. As aforementioned, Maxent is a maximum entropy approach to the presence-only distribution modeling tool that uses known locations of a phenomenon and environmental variables to predict potential distribution over a larger geographical area. Maxent has been used to predict fire probability in other landscapes with satisfactory results [23–25,27]. The fire data was separated into two samples in the model, 70% for training and 30% for testing. A total of 1002 present records were used for training, and 429 were reserved for testing the model. All the environmental variables used were continuous and other Maxent parameters were kept on default as suggested by Morales et al [36]..

Model evaluation

The predictor variables' importance was assessed using jackknife analysis, percentage contribution, and Area Under Curve (AUC). A comparison of the three jackknife plots is informative in understanding each predictor variable's role in the Maxent model [37]. Maxent runs a jackknife test in the background and generates models. One of Maxent's strengths is that the

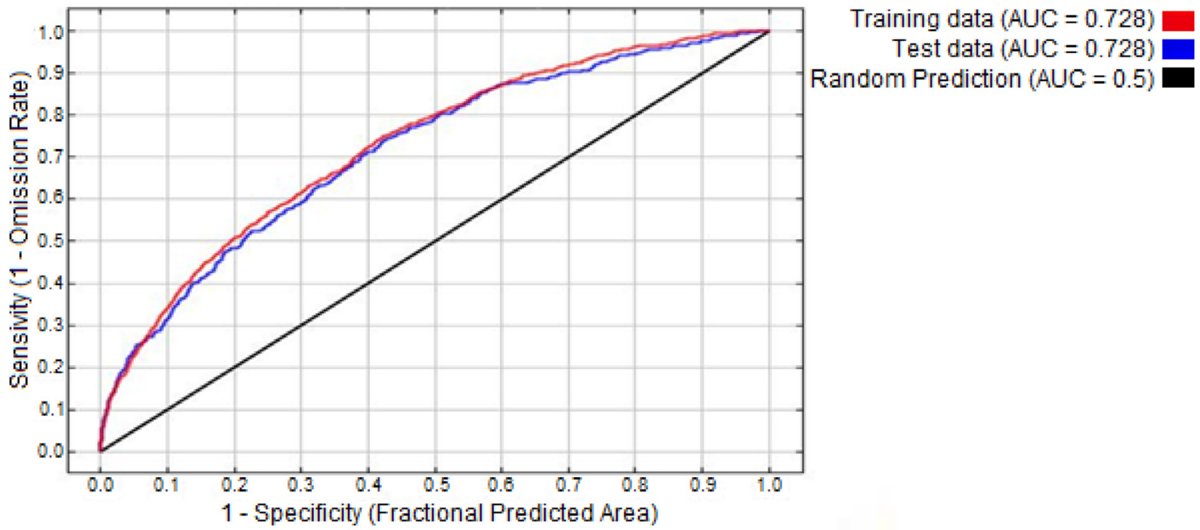

Fig. 2. The receiver operating curve for both training and test data.

model tracks the most influential variables by calculating the percentage contribution for all the input variables from a wide range of input predictor variables. The percentage contribution depends on the path used by the Maxent code to derive an optimal solution [37]. The area under the receiver operating characteristic - ROC curve (AUC) is one of the most used tools to assess the distribution model's accuracy and performance [25]. This tool tests the correlation between the observed and the predicted distribution of a phenomenon through a ROC curve obtained by plotting sensitivity on the Y-axis and 1–specificity on the X-axis for all possible thresholds [38]. Area under the ROC curve values range from 0.0 to 1. A value below or equals to 0.5 indicates a random prediction, whereas an AUC value above 0.5 to 1 indicates a moderate to outstanding model performance [24]. Generally, a good prediction model generates an AUC score above 0.7 [25].

Results

Model performance

Fig. 2 shows the sensitivity against specificity for predicting fire occurrence probability using the area under the receiver operating characteristic curve (AUC) for both training and test data. The Maxent model for fire occurrence derived satisfactory results. As aforementioned, Area Under Curve values range between 0 and 1, where value equals to or below 0.5 indicate a random model while values closer or equal to 1 indicates a good model. The estimate showed that the AUC values of the training and test data-sets were 0.728 and 0.716, respectively, which is an excellent model prediction for fire probability that is better than a random (i.e. 0.5).

Predictor variable contribution

Fig. 3 shows the jackknife test results of the model. A jackknife test determines the most significant variables influencing a phenomenon. The blue bars depict the accuracy and performance of the predictor variable when used in isolation. In contrast, the turquoise bars represent the model's overall accuracy when each variable is excluded from the model. Isothermality (bio3), annual mean temperature (bio1), and mean temperature of coldest quarter (bio11) had the highest gain when used in isolation, hence most influential. The maximum temperature of the warmest month (bio5) decreased the overall model gain when omitted, hence appears to have the most information absent from the other variables. Other topographic predictor variables such as aspect, slope, TWI, and wind effect had little contribution to the overall model, hence were considered insignificant for predicting fire probability occurrence in the study area.

A major advantage of Maxent modeling algorithm is that it allows for assessment of all input predictor variables in order of their significance. In this study, the model was derived from 25 topographic and bioclimatic variables associated with fires. Fig. 4 shows that 6 out of 25 variables had greater influence on fire occurrence. These were mean temperature of the coldest quarter, isothermality, elevation, precipitation of the warmest quarter, temperature seasonality and the annual mean temperature, respectively.

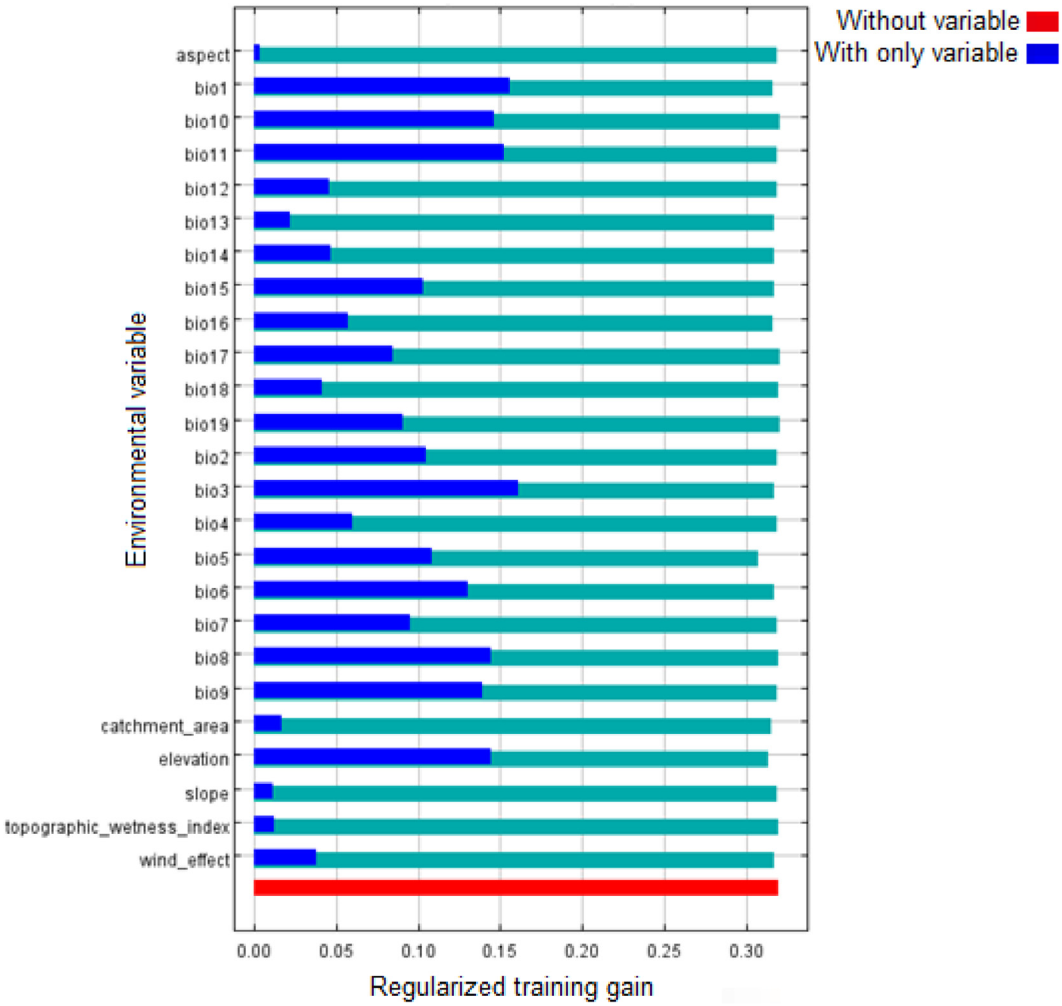

Fig. 3. The jackknife of regularized training gain for modeling of the spatial distribution of fires occurrence within the ethekwini municipality.

Fire occurrence probability

Fig. 5 shows the spatial distribution of the most influential fire occurrence variables within the study area, while Fig. 6 shows a fire occurrence probability map within the EMA using the most influential climatic and topographic variables.

As shown in Fig. 6, the north, outer west, and southern regions of the municipality are associated with moderate to higher probability of fire occurrence than inner west and central areas. The higher fire probability corresponds to a higher elevation, minimum temperatures, higher isothermality, and the low mean temperature coldest quarter, as depicted in Fig. 4.

Discussion

Fires are an important part of ecological landscapes and have been used as a management tool in fire-adapted ecosystems. However, there is a need to manage fires to minimize adverse impacts while maintaining natural processes. socioeconomic and environmental fire-related losses can be averted by adopting appropriate mitigation measures supported by use of GIS and Remote Sensing technologies to detect, predict, and assess fire risk and associated impacts [1]. The Maxent model's percentage contribution and jackknife results showed that 6 of the 25 predictor variables contributed significantly to the model. The Maxent model was also used to produce a fire risk map that showed areas with low to high risk of fire occurrence within the study area (Fig. 6).

Bioclimatic variables associated with temperature (bio1, bio3, bio4 and bio11) had the highest combined contribution to the model. The mean temperature of the coldest quarter (bio 11) contributed 33% to the model, hence it was the most important determinant of fire occurrence in the study area. According to Worldclim data, the mean temperature coldest quarter for the study area ranges from 13 to 17 °C. In this study, areas with lower temperature had a higher probability of fire occurrence than areas of higher temperatures. The significant contribution of the mean temperature of the coldest

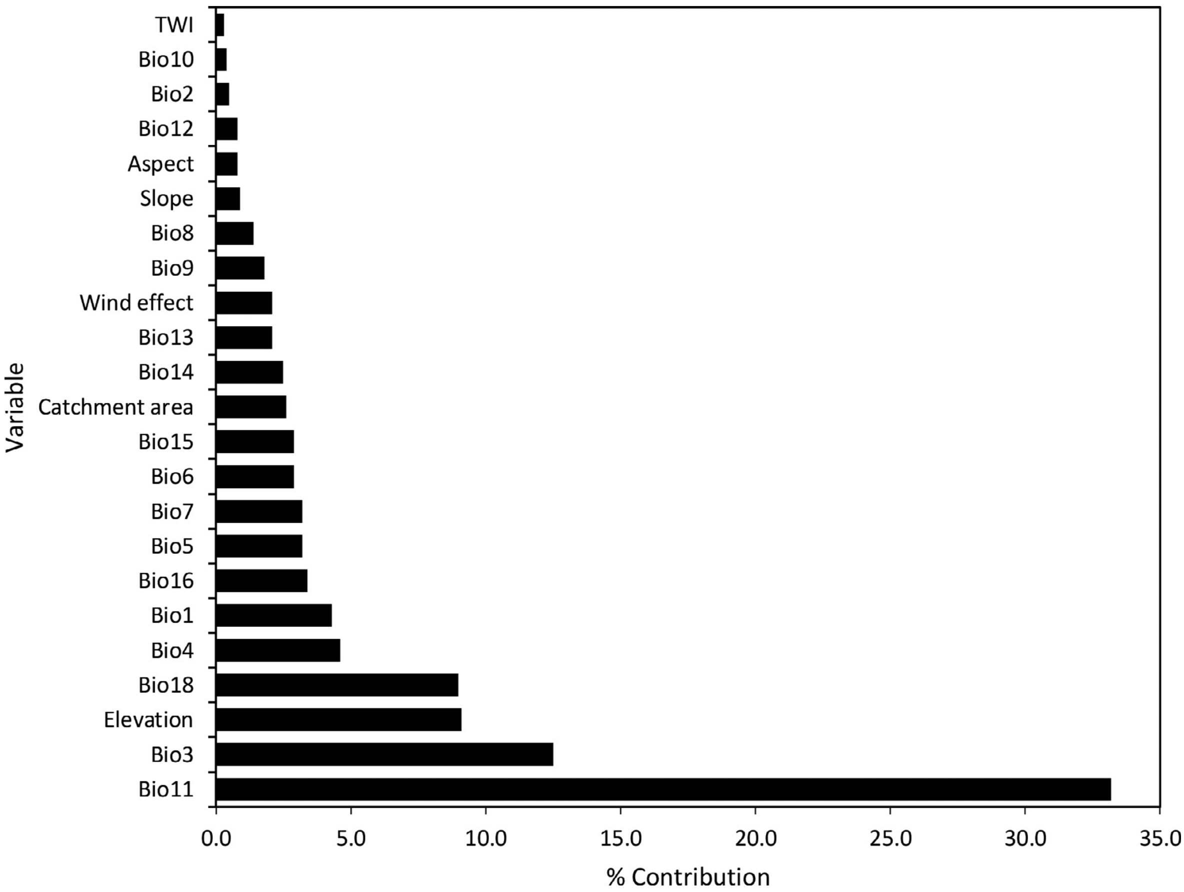

Fig. 4. Percentage contribution of each predictor variable to fire occurrence within the ethekwini municipal area.

quarter results from the correlation between precipitation and temperature as fuel moisture and biomass density depend on rainfall at cooler higher elevations [24]. The eastern part of South Africa is characterized by a June to August winter season. The EMA experience a higher prevalence of fire during winter than any other seasons. Within the study area, winter is associated with a dry climate and favorable conditions for fire outbreaks. In agreement with this study, a cross-regional fire modeling study conducted in Mediterranean Europe using bioclimatic, anthropogenic, and topographic variables found that variables associated with temperature had the highest contribution to the model for most of the regions for both fine and coarse resolution data, achieving AUC >0.7 [38].

Isothermality (12.3%) significantly influenced fire occurrence probability in the study area. Isothermality, calculated from (bio2/bio7) * 100, quantifies how large the day to night temperature fluctuates relative to the summer to winter oscillations [34]. An isothermal value of 100 indicates that the diurnal temperature range is equal to the annual temperature range, while a value less than 100 shows a smaller level of temperature variability within an average month relative to the year [34]. Isothermality for the study area ranged from 50 to 56. Higher isothermality was associated with higher fire probability, a finding consistent with Verma et al [23].) who found that isothermality contributed 12.4% to the Maxent model with at an isothermality value between 38 and 41. Jackknife plots also revealed the highest gain when isothermality was used in isolation. Isothermality, a measure of landscape thermal characteristics influences vulnerability to fire occurrence. Benson et al [39]. notes that higher temperatures heat fuels, hence increasing chances of ignition from lightning or anthropogenic sources, while Johnson and Miyanishi [40] notes that heat influences evaporative and preheating phases of fire ignition and combustion. Generally, air temperature influences fuel moisture in an inverse relationship [41].

The annual mean temperature (bio 1) had a contribution of 4.1% to the model. Areas of lower mean temperatures (17 °C) had a higher fire probability of fire occurrence. These conditions are associated with droughts that cause vegetation to desiccate, leading to a large fuel load susceptible to ignition [38]. There was a decrease in fire probability with the increase in the mean annual temperature. This finding is consistent with Mpakairi et al [24]. who found that mean temperature was among the significant determinant of wildland fire probability in the Kavango-Zambezi Transfrontier Conservation Area in Zimbabwe. According to Littell et al [42]., drought (characterized by prolonged higher average annual mean temperature) interacts with other controls (e.g. wind and topography) to influence fire intensity and severity attributable to dry and flammable fuel loads.

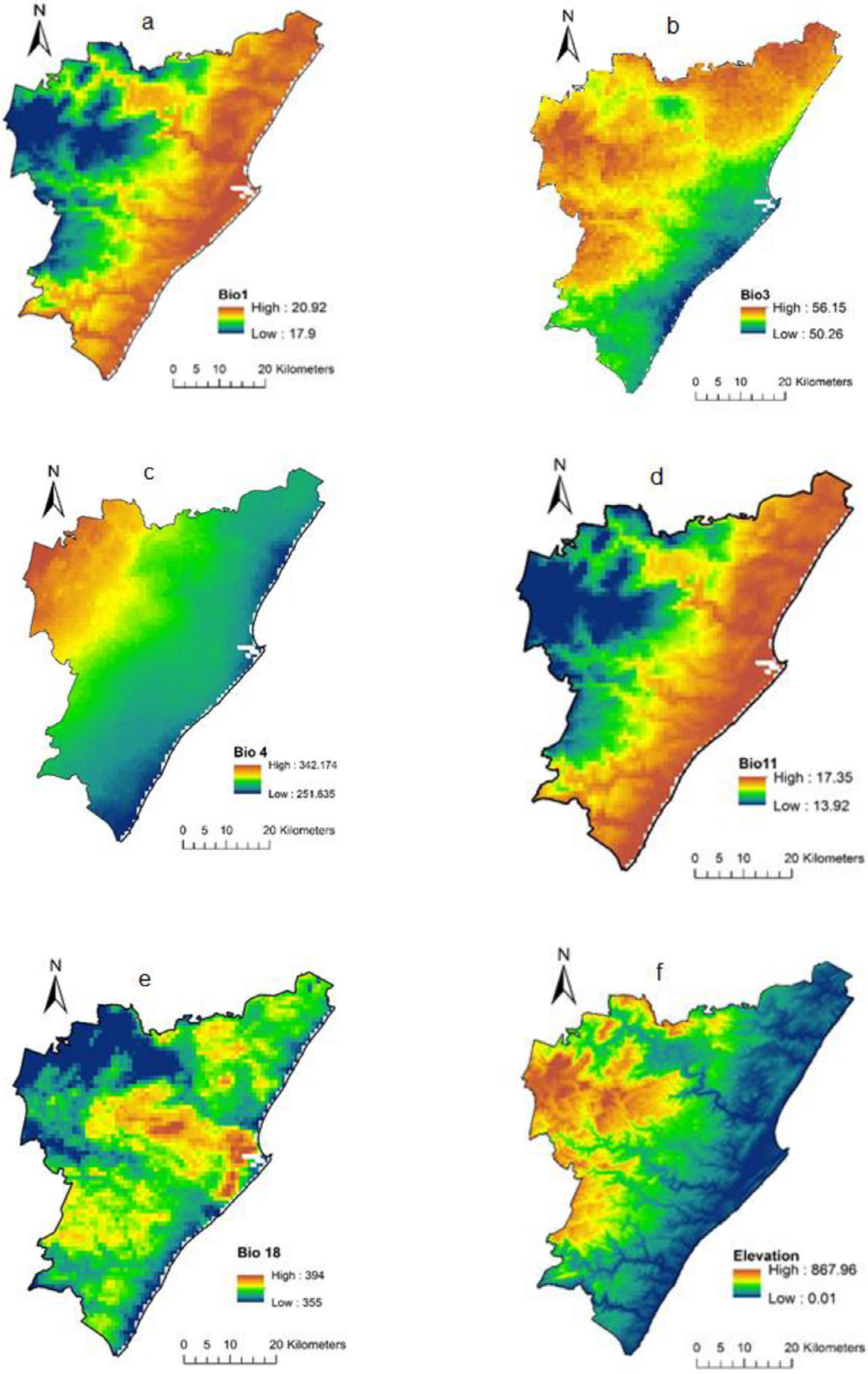

Fig. 5. Spatial distribution of the most influential climatic and topographic variables to fire occurrence within the eThekwini Municipal Area: a) Annual Mean Temperature (Bio1), b) Isothermality (Bio3), c) Temperature seasonality, d) Mean Temperature of Coldest Quarter (Bio11), e) Precipitation of Warmest Quarter (Bio18) and f) Elevation.

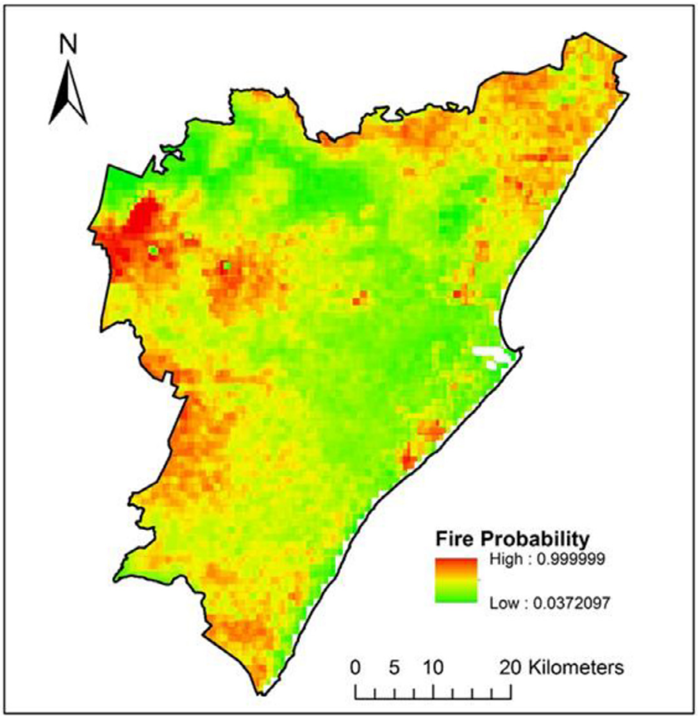

Fig. 6. Maxent derived fire occurrence probability map for the ethekwini municipal area.

Elevation had the highest contribution (8.9%) to the model among topographic variables. Within the study area, the 700 m to 900 m above sea level range had a higher probability of fire occurrence than lower altitudes. This finding is consistent with Strydom and Savage [43] who noted that most fires in the KwaZulu-Natal and Mpumalanga provinces occur in mountainous areas. Also, Mpakairi et al [24]. noted elevation as one of the significant determinants of fire occurrence. Specifically, Mpakairi et al [24]. found a positive co-relation between elevation and fire occurrence, with the 1000–1200 m range particularly vulnerable. In a study by Adepoju and Adelabu [27]) and Kim et al [25]., elevation was identified as the most significant variable in modeling fire probability in a range of landscapes. As shown in Figs. 3 and 4, catchment area, wind effect, aspect, slope, and TWI were less influential to the model, implying that these variables were not useful in determining fire occurrence within the study area.

Conclusion

Veldfires are known to be a common disturbance in numerous vegetation zones and a threat to biodiversity. The interaction of climate and topography, which also regulates fuel load, are the primary drivers of fire behavior. In this study, key variables influencing fire occurrence were mean temperature of the coldest quarter, isothermality, elevation, precipitation of the warmest month, temperature seasonality, and the annual mean temperature, respectively. This study deployed a cost-effective method to predict fire probability within an urban landscape using freely available fire, climatic and topographic data, and a modeling algorithm. The AUC used for the evaluation indicated that the Maxent model is suitable for determining fire occurrence and identifying fire occurrence drivers within an urban landscape; valuable for informing urban authorities on site-specific intervention approaches. Understanding the probability of fire occurrence is useful in identify fire-prone regions and may reduce unplanned fires that may harm the recipient environment, a useful intervention in sustaining urban ecological integrity. Furthermore, this study is useful for understanding key drivers of fire occurrence that could inform fire suppression and prevention, valuable for meeting Sustainable Development Goals that include preservation of natural landscapes and biodiversity. This study provides an approach to model the probability of fire occurrence within the study area, and indeed similar landscapes to mitigate socioeconomic and environmental fire-related losses.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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