THE INFLUENCE OF BIOCLIMATIC AND TOPOGRAPHIC VARIABLES ON FIRE OCCURRENCE AND FREQUENCY WITHIN THE ETHEKWINI MUNICIPAL AREA

By

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ABSTRACT

Fires have been used for decades as a land management tool. Environments such as grasslands and fynbos depend on fire to maintain their ecological integrity. Fires can also become a disturbance in some ecological zones. Veldfires can be planned, but they can also occur naturally driven by a wide range of variables. However, due to changes in both local and global weather patterns, fires are occurring more frequently, posing a threat to the environment and society. The purpose of this study was to assess the influence of bioclimatic and topographic variables on fire occurrence and frequency within a biodiversity-rich urban landscape within the eThekwini Municipal Area. Remote sensing has become a valuable tool for detecting and monitoring fires globally; it is time-efficient and cost-effective. This study used MODIS Active fire product, which has high temporal resolution making it a valuable sensor for monitoring fires and gathering fire data from local to global scales. The interaction between topography, fuel lead and weather has been identified as the primary drivers of fire occurrence in different landscapes. Topographic variables were derived from a 30 m Digital Elevation Model using ArcGIS 10.4. The first part of this study focused on a wide range of topographic and climatic (temperature and precipitation) to determine the most influential drivers of fire occurrence using Maxent modelling algorithm. The results showed that 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 driving fire occurrence in the study area. The model obtained Area Under Curve (AUC) >0.7, indicating that Maxent is suitable for predicting fire probability in an urban landscape. The second part of this study evaluated the relationship between fire frequency and 25 bioclimatic and topographic variables using Pearsons Correlation. The results indicated that variables associated with temperature correlated more with fire frequency. This study can assist land managers in understanding fire probabilities across the municipality, identifying fire-prone regions, and monitoring them to reduce the impact of frequent unplanned fires while protecting ecological systems within the municipality's remnant and conserved urban spaces.

Keywords: Bioclimatic, fire frequency, fire occurrence, Maxent, MODIS, topographic, Pearson correlation, urban landscape, veldfires.

PREFACE

The research contained in this dissertation was completed by the candidate while based in the Discipline of Geography, School of Agricultural, Earth and Environmental Sciences of the College of Agricultural, Engineering and Science, University of KwaZulu-Natal, Pietermaritzburg, South Africa. The research was financially supported by National Research Foundation (NRF).

I declare that the work presented in this dissertation has never been submitted for examination in any form to any other institution. This work represents my original work except where due acknowledgements were made in the text and reference sections of this dissertation.

Candidate

Zanele Makhaya Signe [redacted] Date_15/07/2021_____

As the candidate's supervisors, we certify the above statements and have approved this dissertation for submission.

Supervisor

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Co-supervisor

Prof. Onisimo Mutanga Signed___________________ Date_________________

DECLARATION 1: PLAGIARISM

Form EX1-5

I, Zanele Makhaya, declare that:

1. The research reported in this dissertation, except where otherwise indicated, is my original research.

2. This dissertation has not been submitted for any degree or examination at any other university.

3. This dissertation does not contain other persons' data, pictures, graphs, or additional information unless specifically acknowledged as being sourced from other persons.

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DECLARATION 2: MANUSCRIPT

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TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

CHAPTER ONE: GENERAL INTRODUCTION

1.1Introduction

Since the beginning of human history, fires have been deployed as a tool for deforestation, land management and hunting (Chuvieco et al., 2019). In the past hundreds of years, fires have been used to manage different environments like grasslands, savanna and fynbos to maintain their ecological integrity (Working for Fire, 2021). Generally, fires can be both beneficial and harmful to the recipient environment. Fire benefits include promoting the health, productivity and diversity of several ecosystems, regulating fuel accumulation and plant succession (Smith et al., 2013). Veldfires also aid the removal of alien invasive species, control bush encroachment, firebreaks, and removal of excess herbage (Househam, 2017). Househam (2017) also noted that fires have a significant role in the morphology of the African continent at large and provide numerous ecological activities that include maintaining the health of grasslands, improving production and grass quality.

On the other hand, veldfires are a common disturbance to numerous ecological zones, presenting a challenge for managing ecosystems. Unplanned and uncontrolled fires are a global concern as they are becoming more frequent due to climate change. Wildfires alter hydrological regimes through reduced soil infiltration and increased surface runoff (Szpakowski and Jensen, 2019), accelerating soil degradation (Magomani and Van Tol, 2019). Wildfires are also associated with direct losses such as lives from fire or smoke, infrastructure, agriculture and vegetation, and indirect losses, like psychological and ecosystems impacts (Thomas et al., 2017). Urban areas are generally densely populated; hence fire may impact air quality affecting children, and people with heart disease and respiratory problems (Chuvieco et al., 2019). In South Africa, the 2009 fire season, for instance, had over 40 000 fires reported that resulted in 376 casualties and $277 million in financial losses (Strydom and Savage, 2016), while the California large fires of 2017 resulted in 52 deaths and $12.5 billion losses associated with the property (Badger, 2018). In 2018, China lost 1 407 lives and about $557 million fire-related economic losses (Zhang et al., 2020).

In urban landscapes, urban green spaces consist of remnant patches of indigenous vegetation, gardens and yards, parks and recreational zones in an artificial, semi-natural and natural ecological system (Cilliers et al., 2013 and Aronson et al., 2017). Urban vegetation is a significant ecological infrastructure with economic, ecological, and social benefits that include enhancing urban dwellers' health and well-being (Dingaan and du Preez, 2017), nutrient recycling, flood regulation, ecotourism and soil formation (Millennium Ecosystem Assessment, 2005). Urban vegetation in remnant veldts also regulates carbon dioxide, reduces urban heat island, improve air quality and enhances biodiversity (Lutz, 2020). Thus, the destruction of these remnant vegetation increases carbon dioxide released into the atmosphere, which consequently causes global warming and changes in climate over time (Dennis et al. 2001). Also, greenhouse gases emitted from veldfires have a long-lasting consequence on the atmosphere and the climate. Hence it is vital to monitor fires in an urban landscape to ensure continued supply of socio-economic and ecological goods and services.

Fire activity is driven by numerous factors affecting its occurrence and frequency at different scales. In the pre-industrial period, precipitation was the primary driver of fire activity on a global scale. However, there has been a shift, and climate (temperature) has become the primary driver of fire activity (Pechony and Shindell, 2010). Changes in land use also impact fire activity; hence it is vital to characterise fire activity over time at different scales. Bioclimatic variables derived from monthly precipitation and temperature values provide biologically significant variables associated with fire occurrence and frequency (O'Donnell and Ignizio, 2012; Verma et al., 2018). Precipitation and temperature determine fuel moisture availability and biomass density (Renard et al., 2012; Mpakairi et al., 2019). Warm temperatures are often associated with droughts and heatwaves. High rainfall may result in high vegetation growth that later becomes fuel susceptible to burning, increasing fire occurrence and frequency (Strydom and Savage, 2016). Studies have established that changes in global climate will increase fires; hence, relevant stakeholders need to be aware of the fire drivers to reduce fire risks, deaths and economic losses.

Studies have also noted that fuel, topography and climate are static drivers of fire occurrence and frequency at a mesoscale (Krawchuck et al., 2016; Monmany et al., 2017, Curt, 2018; Fang et al., 2018). Topography refers to the Earth's surface features, and it regulates fuel type, load, and moisture (Bennett et al., 2010). Topographic variables associated with fire occurrence and frequency include aspect, catchment area, slope, elevation, wind effect and Topographic Wetness Index (TWI). Elevation refers to the height above sea level, affecting exposure to wind, seasonal fuel drying, and precipitation received (Bennett et al., 2010). Due to low rainfall and high temperatures in lower elevations, fuel tends to dry earlier, while it is the opposite for fuel in higher elevations. Peterson and Littell (2012) also noted that lightning strikes are common at higher elevations, resulting in fire ignition. Wind effect associated with wind speed and direction is also influential in higher elevation accelerating fires upslope (Bennett et al., 2010). Aspect, the slope's direction determines the amount of solar radiation and the type of vegetation. Shaded slopes delay the rate at which vegetation dries up and may result in low fuel than slopes directly exposed to the sun (Bennett et al., 2010). Hence, it is vital to assess the influence of these variables in fires activity to inform land management practices to conserve biodiversity and ensure continued support of urban life and the economy provided by the natural landscape.

Since the early 20th century, mapping the location and spatial extent of fires has evolved. Traditional methods involved mapping burned areas from field sketches and ground-based surveys (Chuvieco et al., 2019). Other methods involved the use of a Geographic Positioning System (GPS) to map fires. A GPS would be attached to a helicopter to obtain boundary georeference points of the burnt perimeter; in cases where a helicopter is unattainable, fire managers would utilise infrared photography or walk the perimeter of the burned area (Kolden and Weisberg, 2007). The mapped perimeter would be used to calculate the size of the burned area using the Geographic Information System (GIS) tool. However, there were difficulties from these methods, like unclear boundaries and mapping fires in rugged terrain. These approaches are also time-consuming, less accurate, and under detailed (Kolden and Weisberg, 2007). The advancement in satellite remote sensing has enabled the acquisition of fire data efficiently and remotely. Several sensors have been developed to detect fires on different landscapes at varied spatial, radiometric and temporal resolutions.

Numerous studies have used various Earth observing sensors like the Landsat, Radarsat 2, Advanced Very High Resolution Radiometer (AVHRR), Moderate Resolution Imaging Spectrometer (MODIS) and SPOT to map and quantify fires (Oldford et al., 2003, and Boschetti et al., 2015). These studies were conducted post-fire to map and quantify burned areas, and they did not explore the driver of fire occurrence and frequency, which is being assessed by this study. Oldford et al. (2003) used Advanced Very High Resolution Radiometer (NOAA-AVHRR) images to map fire danger, focusing on mean temperature. However, this study did not consider topography and precipitation, which significantly contribute to fire occurrence. Boschetti et al.

(2015) fused Landsat 30 m with MODIS active fire data to map burned areas in the Western United States ecoregions. MODIS data was incorporated to overcome the 16 days Landsat temporal resolution; however, this hybrid methodology presented limitations such as inadequate overlaps of burned area and a lack of consistent pre-processing. Adepoju and Adelabu (2015) used the Maxent model to assess eco-geographical variables' influence on fire occurrence and spread. These variables include day and night land surface temperatures, rainfall, topography and vegetation, built-up snd water index. The model achieved an AUC of 0.926 where rainfall, elevation and differences in day and night land surface temperature were the most contributing variables for fire occurrence in the study area (Adepoju and Adelabu, 2015). However, this study only focused on the Golden Gate Highland National Park, a protected area in the province of Free State. Hence this study will be focusing on a biodiversity-rich urban landscape at a municipal level.

In 2001, the National Aeronautics and Space Administration (NASA) initiated the MODIS fire products programme for fire monitoring. MODIS is an onboard sensor Terra (morning) and Acqua (afternoon) satellites with daily coverage and characterised by 30 narrow bands ranging from the visible, Near Infrared (NIR), Short-Wave Infrared (SWIR), Medium Wavelength Infrared (MWIR) to thermal infrared at a variable spatial resolution that ranges from 250 m to 1000 m (Quintano et al., 2011). The MODIS Collection 6 has improved small fire detection capabilities with reduced false alarms. It also offers improved land surface temperature and land surface reflectance (Blumenfeld, 2015). MODIS has a high temporal resolution which makes this product ideal for mapping a short-lived phenomenon such as fires (MODIS, 2021). MODIS also has global coverage offering consistent fire data globally. This product is helpful for mapping spatial fire patterns and characterising fire regimes and their potential drivers (Chen et al., 2014).

South Africa’s eastern seaboard is characterised by a rich diversity of subtropical grasslands. The eThekwini Municipal Area (EMA), a development hub that includes the city of Durban, is a metropolitan area that falls within the Maputaland-Pondoland-Albany Global Biodiversity Hotspots (Ground et al., 2016). It also consists of the endangered subtropical Ngongoni Veld, KwaZulu-Natal Sandstone Sourveld (KZNSS), and the KwaZulu-Natal Coastal Belt ecosystems (Drury et al., 2016). The KZNSS is characterised by dispersed proteas, low shrubs, forbes, and a high level of endemism (Drury et al., 2016; Boon et al., 2016). However, this grassland ecosystem has been severely modified and threatened by urbanisation and uncontrolled fires (Moritz et al., 2002; Drury et al., 2016; Ground et al., 2016).

Generally, fire mapping has focused on a regional and global scale; however, there is a need to map fires and assess their drivers at a mesoscale. Whereas non-urban rangeland veldfires have been widely explored, fire occurrence, frequency and dynamics in urban areas remain largely unexplored. For example, Buthelezi et al. (2016) assessed disparities of fire regimes on different types of vegetation in KwaZulu-Natal. The study intended to quantify burnt area, fire seasonality and fire frequency at a regional scale. Adepoju and Adelabu (2019) explored climatic and non-climatic drivers of fire risks in protected mountainous grasslands in the Golden Gate Highland National Park. This study highlighted that although topography, vegetation and climate are known to regulate spatial and temporal patterns of fire regimes, their interaction is not well explored. The understanding relative contribution of these variables on fire activity can assist land managers to combat fire-related losses. Several studies have used Maxent to model fire probability using environmental conditions; however, no recent studies have been done for the eThekwini Municipal Area (Smith et al., (2013), Kim et al. (2019). Urbanisation, typified by conversion from natural to physical landscape requires an understanding of the probability of fire occurrence to conserve the remnant and protected urban grassland patches to maintain urban socio-ecological sustainability. This study focuses on a municipal level dominated by urban green spaces to assess drivers of fire activity. This ensures better management of the environment while encouraging species diversity for a continued provision of goods and services supporting urban life (Strydom and Savage, 2016).

1.2 Aim and objectives

The overall aim of this study was to assess the influence of bioclimatic and topographic variables on fire occurrence and frequency within the eThekwini Municipal Area. Accordingly, the following objectives were set:

1. To assess the influence of bioclimatic and topographic variables on grassland fire occurrence within the eThekwini Municipal Area.
2. To assess the correlation between bioclimatic and topographic variables and fire frequency within an urban landscape.

1.3 Structure of the dissertation

This dissertation comprises four chapters. Chapter one covers the general introduction and the motivation of the study. Chapter two and three consists of two research papers formulated from the objectives stated in section 1.2 above. Paper one has been submitted to a journal, and it is currently under review. Whereas both papers were written separately, they both used the same MODIS fire data sets and topographic and bioclimatic variables. However, the objectives and the methodologies adopted differ. Thus, it is crucial to note that there will be inescapable repetition and overlaps within this dissertation.

Chapter two assesses the influence of bioclimatic and topographic variables on grassland fire occurrence within an urbanised landscape. The influence was assessed using Maxent modelling algorithm to predict fire-related landscape characteristics and identify significant contributing variables. Chapter three assesses the correlation between bioclimatic and topographic variables and fire frequency within an urban landscape. This chapter adopts the Pearson correlation methodology and produces a fire frequency map for the study area. Chapter four provides conclusions and a synthesis of the study, as well as recommendations for future studies.

CHAPTER TWO: THE INFLUENCE OF BIOCLIMATIC AND TOPOGRAPHIC VARIABLES ON GRASSLAND FIRE OCCURRENCE WITHIN AN URBANISED LANDSCAPE

Abstract

Unplanned veldfires (or wildfires) characterise vegetation landscapes and offer a range of ecological benefits that promote the health of the grasslands and other fire-adapted ecosystems. However, uncontrolled fires are often a threat to the property, life, the environment, and the economy in urbanised areas. The eThekwini Municipal Area, characterised by varying topo-climatic conditions, falls within the Maputaland-Pondoland-Albany Global Biodiversity Hotspots dominated by the endangered subtropical KwaZulu-Natal Sandstone Sourveld (KZNSS), Ngongoni Veld, and the KwaZulu-Natal Coastal Belt ecosystems that offer a range of valuable socio-ecological goods and services. However, due to frequent unplanned veld fires and rapid urbanisation, they are highly threatened. This necessitates an understanding of key drivers to fire occurrence as the first step towards their 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). Results depicted that mean temperature of the coldest quarter (33%), isothermality (12.3%), elevation (8.9%), and precipitation of the warmest month (8.8%) were more influential predictor variables affecting fire occurrence within eThekwini Municipal 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 modelling. 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 that provide urban ecosystem goods and services.

Keywords: Bioclimatic, topography, fire occurrence, Maxent, MODIS, grasslands, urban landscape.

2.1 Introduction

Veldfires (or wildfires) are a common disturbance to numerous vegetation ecosystems, presenting a challenge to managing vulnerable landscapes (Leblon et al., 2012; Bond and Keane, 2001). Veldfires may occur naturally from lightning, falling rocks, accidental ignitions and run-away prescribed burning (Buthelezi et al. 2016). In urban areas, vegetation plays a critical socio-economic and environmental role that includes mitigating climate change, regulating temperature, filtering pollutants, providing recreational spaces and increasing biodiversity. However, uncontrolled urban fires on remnant or conserved vegetation are a risk to property, life, the environment, and the economy (Pastor et al., 2019; Shikwambana et al., 2019; Working on Fire, 2021). In South Africa, for instance, the 2017 Knysna fire resulted in the loss of lives and destruction of over 800 buildings (Kraaij et al., 2018), while in the city of Cape Town, veldfires are a common occurrence, with devastating socio-economic 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 (Badger, 2018), 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 (Zhang et al., 2020). Hence, understanding the underlying drivers of veldfires is crucial 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 aesthetic beauty (Bengtsson et al., 2019). Whereas fires are known to be critical to the regeneration of grasslands, uncontrolled fires can transform grasslands into woody vegetation, degrade the ecosystem, lead to biodiversity loss, provide niches for alien invasive plant species, and increase species homogenisation (Drury et al., 2016). Generally, non-urban rangeland wildfire dynamics and effects have been extensively explored in the literature (Craig, 1999; Taylor, 2003; Fisher et al., 2003; Pyke et al., 2013); 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 characterised 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), the KwaZulu-Natal Coastal Belt and Ngongoni Veld ecosystems. Specifically, the KZNSS is a species-rich grassland characterised by dispersed low shrubs, proteas, forbes, and a high level of endemism (Drury et al., 2016; Boon et al., 2016). However, this grassland ecosystem is severely modified and threatened by urbanisation and uncontrolled fires (Moritz et al., 2002; Drury et al., 2016).

Understanding factors influencing fire occurrence is valuable in mitigating the effects of grassland fires and conserving the remnant urban grasslands. Several studies (e.g. Trollope et al. 2002; Bennett et al., 2010; Krawchuck et al., 2016) have noted that fire occurrence is influenced by an interaction of fuel load, topography, and weather. Other studies (e.g. Bennet et al., 2010; Taylor and Harris, 2017; Verma et al., 2018; Mpakairi et al., 2019; Kim et al., 2019) have identified elevation, temperature, slope, aspect, Topographic Wetness Index (TWI), catchment area, and wind as key variables influencing fire occurrence. For instance, elevation affects the amount of precipitation, exposure to wind, and seasonal fuel drying (Bennett et al., 2010), while temperature and wetness influence fuel load and drying (Bennett et al., 2010). Hence, literature has noted a range of physical and climatic variables as valuable in predicting fire occurrence and landscape vulnerability (Verma et al., 2018; Kim et al., 2019; Chen et al., 2014; Adepoju and Adelabu, 2019).

Recently, remote sensing has emerged as a valuable tool for detecting, managing, and monitoring fires (Oumar, 2015). This is attributed to remote sensing ability to facilitate repeated data acquisition, extensive scale coverage, and cost-effectiveness. In fire-related applications, remote sensing can be utilised at pre- during - and post-fire occurrence to predict areas vulnerable to fire occurrence, detect active fires and assess the impact of burnt areas (Leblon et al., 2012). 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 (Leblon et al., 2012; Oumar, 2015).

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 sections 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 (Leblon et al., 2012; Verma et al., 2018). Additionally, 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 prominent species distribution models for understanding landscape characteristics. Whereas the approach was initially developed to predict the potential geographical distribution of species based on known occurrence and environmental variables, it has recently become helpful in predicting fire-related landscape characteristics (Shabani et al., 2018; Kim et al., 2019). Chen et al. (2015) noted that Maxent has proven to perform well in predicting habitat distribution compared to other methods. One of Maxent significant features is to fit very complex response functions through incorporating several function types like quadratic, threshold and linear. In contrast, the majority of limber regression methods cannot fit such complex responses. Fires are strongly regulated by the interaction of complex geographical and climatic features of a landscape. Hence, this study sought to determine the most influential biophysical and climatic variables influencing fire occurrence within an urban landscape using the Maxent species distribution model.

2.2 Material and methods

2.2.1 Study area

This study was conducted in the eThekwini Municipal Area (EMA) in KwaZulu-Natal, South Africa (Figure 2.1). The EMA was merged to a Metropolitan in 2016 and covers 2297 km² with over 3.6 million people (Bhugeloo et al., 2019). It comprises South Africa's prominent port city of Durban and numerous adjacent towns. The area experiences frequent fire outbreaks during the fire season and is characterised by a 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 precipitation per annum. The topography within the area is highly varied, with high grounds, flat plains and rugged ravines and gorges. Winds generally blow parallel to the coastline in south-westerly and north-easterly directions (Turpie, 2017). EMA's varied climate, geology, soils, physiography and biogeographical position result in a wide range of biodiversity-rich aquatic and terrestrial ecosystems (Boon et al., 2016). The area consists of natural forest and grassland habitat scattered between built infrastructure and settlements (Zungu et al., 2020). The EMA is situated in one of the world's 35 Global Biodiversity Hotspots, namely the Maputaland-Pondoland-Albany hotspot and the 940 km² Durban Metropolitan Open Space System (D'MOSS); a spatial layer of cognate open spaces under public and private ownership, developed to protect biodiversity based on their recognition of the value of ecosystem services within the municipality (Boon et al., 2016). The study area has five regions: North, Central, Inner West, Outer West, and South (Figure 2.1).

Figure 2.1: The eThekwini Municipal Area

2.2.2 Fire data

Archived fire data was downloaded from NASA's Fire Information for Resource Management System (FIRMS) that circulates 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 obtained from the corresponding 1 km satellite channels. At daytime, reflectance observations are detected at 0.65-, 0.86-, and 2.1- μm and combined to a 1 km spatial resolution (Giglio et al., 2016). The algorithm identifies pixels that contain actively burning fires at satellite overpass. According to Blumenfeld (2015), 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, date, brightness, and confidence level. Fire data for this study (1 January 2009 to 31 December 2019) was freely acquired from the EARTHDATA portal.

Figure 2.2 below shows MODIS annual and seasonal fire occurrences during the study period. The eThekwini Municipal Area fire season begins in late autumn in May and intensifies in winter, and peaks in August when the grasslands and bushvelds start drying out. The fire season is characterized by decreased vegetation water content providing adequate fuel load to ignite fires (Strydom and Savage, 2016).

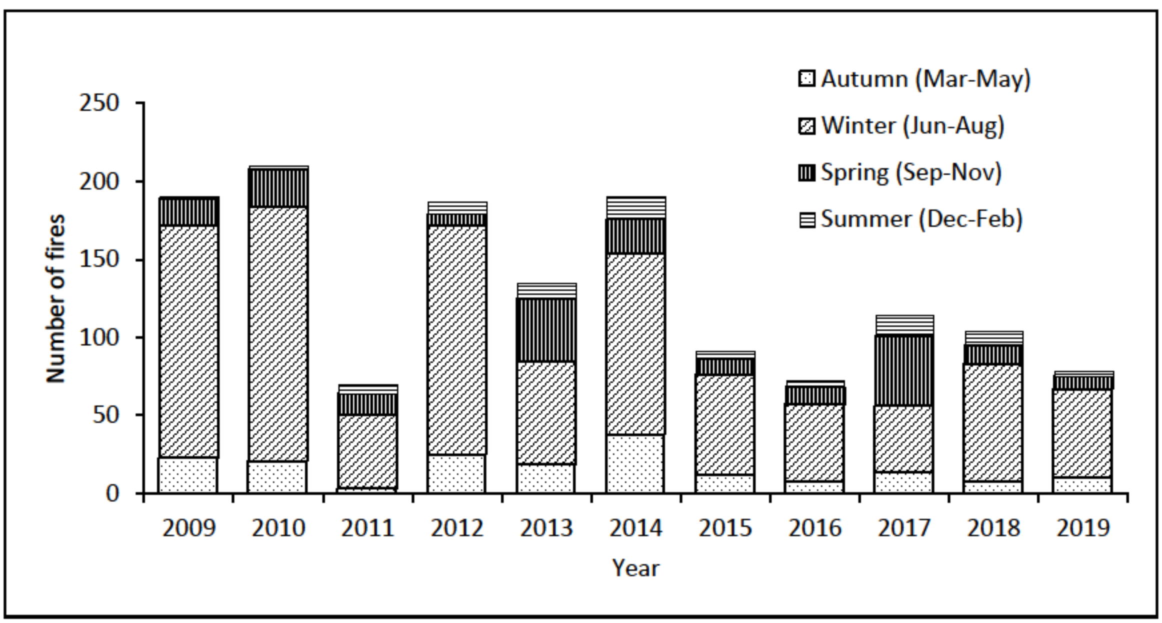

Figure 2.2: MODIS annual and seasonal fires within the eThekwini Municipal Area

2.2.3 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 (O'Donnell and Ignizio, 2012). The study used temperature and rainfall averages for 1970-2000 attained in a raster grid format with a 1 km^2 spatial resolution. These indices are derived from monthly rainfall and temperature values to provide biologically consequential variables. The variables (Table 2.1) portray annual trends for precipitation, temperature, and seasonal trends. These variables are helpful in Maxent modelling and have been used to model fire probability across space and time (Verma et al., 2018).

Table 2.1**:** Bioclimatic and topographic variables used for fire occurrence modelling.

Variable			**Description**	**Unit**
Bioclimatic	Temperature	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	℃
	Precipitation	Bio 12	Annual Precipitation	mm
		Bio 13	Precipitation of Wettest Month	mm
		Bio 14	Precipitation of Driest Month	mm
		Bio 15	Precipitation seasonality	mm
		Bio 16	Precipitation of Wettest Quarter	mm
		Bio 17	Precipitation of Driest Quarter	mm
		Bio 18	Precipitation of Warmest Quarter	mm
		Bio 19	Precipitation of Coldest Quarter	mm
Topographic	Aspect		The direction the slope faces	°
	Catchment area		Runoff velocity and volume	m^3/s
	Elevation		Height above sea level	m
	Slope		The steepness of the surface	°
	Topographic wetness index (TWI)		Steady-state wetness index	-
	Wind effect		Effect of wind direction on the surface	m/s

2.2.4 Topographic variables

Previous studies on fire modelling have identified aspect, elevation, and slope as key topographic variables influencing fire occurrence (Verma et al., 2018; Mpakairi et al., 2019). In addition, these topographic variables have been noted as influential in regulating vegetation distribution and local climate (Krawchuk et al., 2016; Taylor and Harris; 2017; Tien Bui et al., 2016). 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. For instance, Bennett et al. (2010) noted that fuel commonly dries faster due to high temperatures and little rainfall at lower elevations. Aspect and slope were selected because fires often spread faster upslope than downslope. Aspect also influences wind speed and direction of fire spread (Tien Bui et al., 2016). The topographic variable used to determine fire occurrence are shown in Table 2.1. The topographic variables were obtained from a 30 m resolution of the Digital Elevation Model in SAGA GIS and ArcGIS 10.4 software. 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.

2.2.5 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 modelling tool that uses known locations of a phenomenon and environmental variables to predict a potential distribution over a larger geographical area. Maxent has been used to predict fire probability in other landscapes with satisfactory results (Verma et al., 2018; Mpakairi et al., 2019; Kim et al., 2019; Adepoju and Adelabu, 2019). 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. (2017).

2.2.6 Model evaluation

The importance of predictor variables 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 (Phillips, 2010). Maxent runs a jackknife test in the background and generates models. One of Maxent's strengths is that the 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 relies on the path used by the Maxent code to derive the best solution (Phillips, 2010). The area under the receiver operating characteristic - ROC is one of the most commonly used tools to assess the distribution model's accuracy and performance (Kim et al., 2019). This tool tests the correlation between the observed and the predicted distribution of a phenomenon using the ROC curve obtained by plotting sensitivity on the *Y*-axis and specificity on the *X*-axis for all possible model thresholds (Phillips et al., 2006). The area under the ROC curve values ranges from 0.0 to 1. A value below or equal to 0.5 shows a random prediction, while an AUC value above 0.5 to 1 shows a moderate to outstanding model performance (Mpakairi et al., 2019; Phillips, 2006; O'Banion et al., 2014). Generally, a good prediction model generates an AUC score above 0.7 (Kim et al., 2019).

2.3 Results

2.3.1 Model performance

Figure 2.3 below shows the sensitivity against specificity for predicting fire occurrence probability using the ROC curve area for test and training 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 model estimated that the AUC values of the training and test data sets were 0.728 and 0.716; this shows an excellent model prediction for fire probability better than a random (i.e. 0.5).

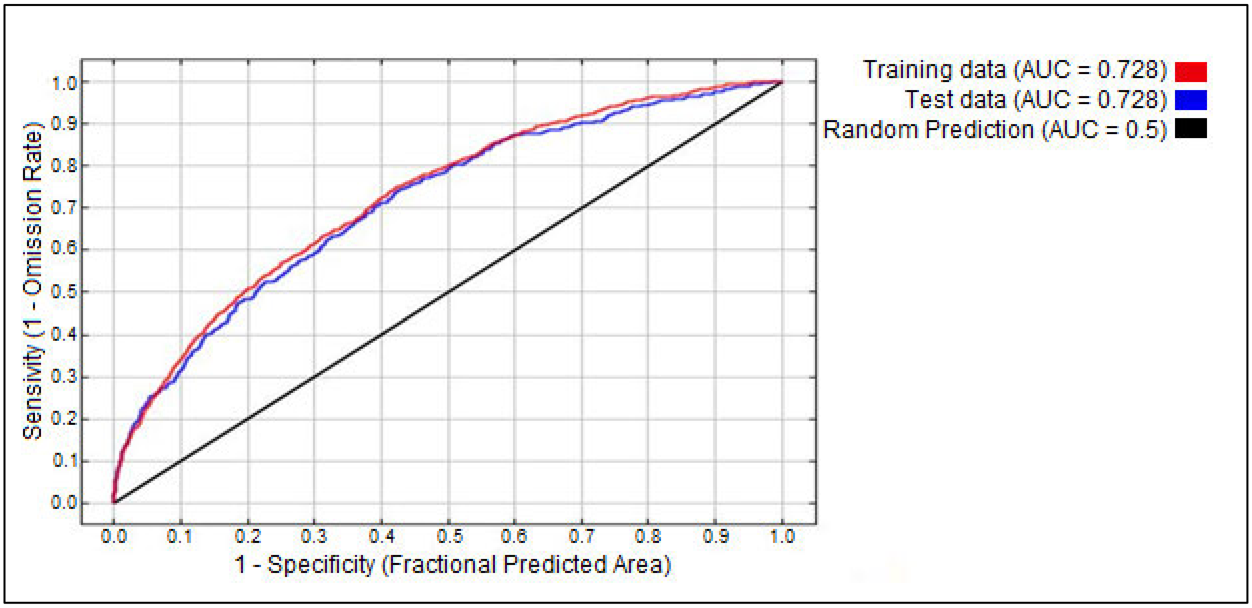

Figure 2.3: The receiver-operating curve for training and test data

2.3.2 Predictor variable contribution

Figure 2.4 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. The annual mean temperature (bio1), isothermality (bio3), and mean temperature of the coldest quarter (bio11) had the highest gain when used in isolation, hence the most influential. The maximum temperature of the warmest month (bio5) decreased the overall model gain when omitted; therefore, it appears to have more information that is absent from other predictor variables. Other topographic predictor variables such as aspect, slope, TWI, and wind effect had little contribution to the overall model; hence they were considered insignificant for predicting fire probability occurrence in the study area.

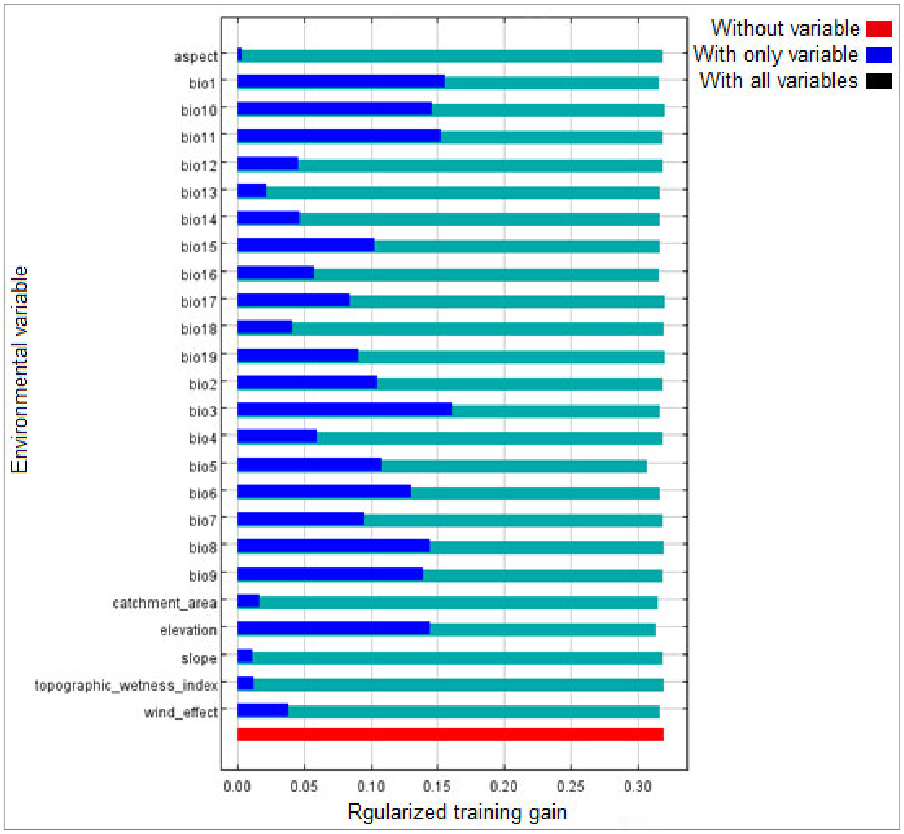

Figure 2.4: The jackknife of regularised training gain for modelling the spatial distribution of fires occurring within the eThekwini Municipality.

A significant advantage of the Maxent modelling algorithm is that it allows for assessing 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. Figure 2.5 shows that 6 out of 25 variables had a more significant influence on fire occurrence. These were mean temperature of the coldest quarter, isothermality, elevation, precipitation of the warmest quarter, temperature seasonality, and annual mean temperature.

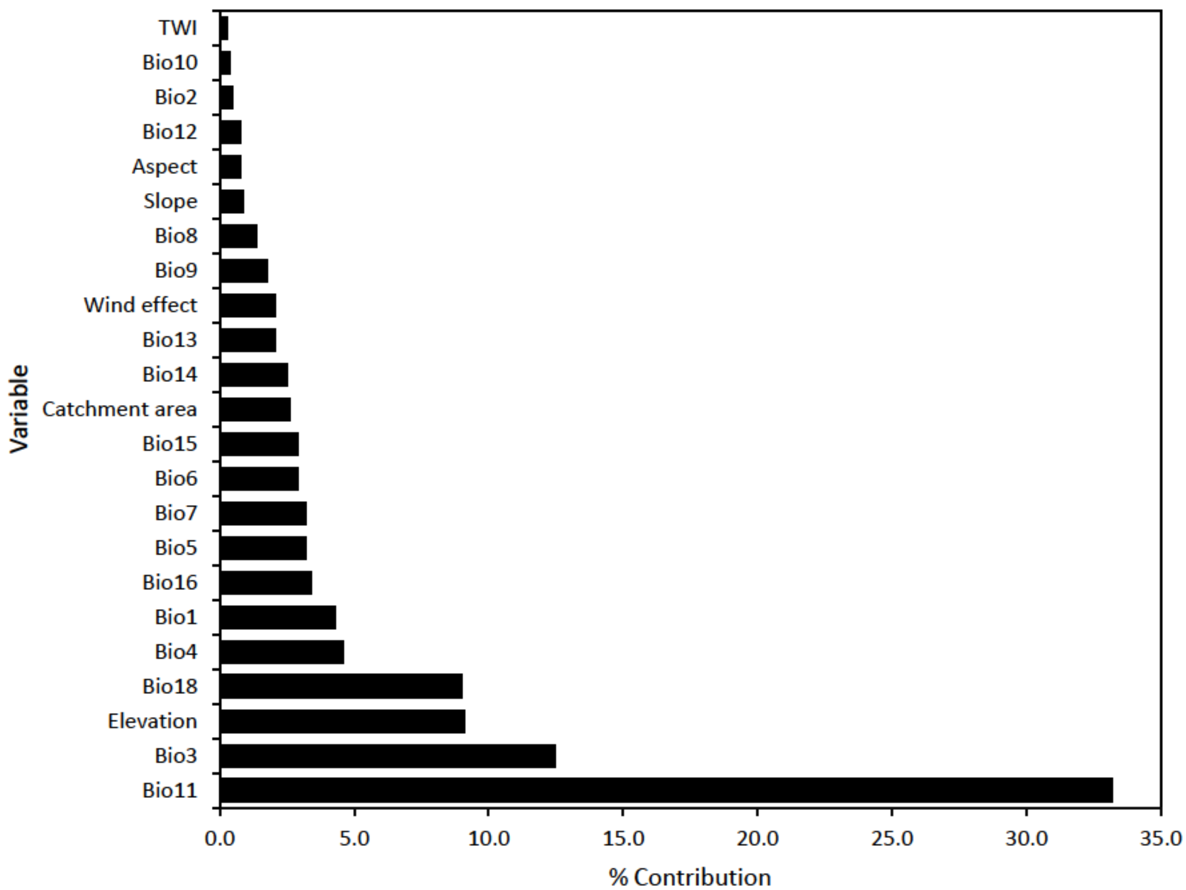

Figure 2.5: Percentage contribution of each predictor variable to fire occurrence within the eThekwini Municipal Area.

2.3.3 Fire occurrence probability

Figure 2.6 shows the spatial distribution of the most influential fire occurrence variables within the study area.

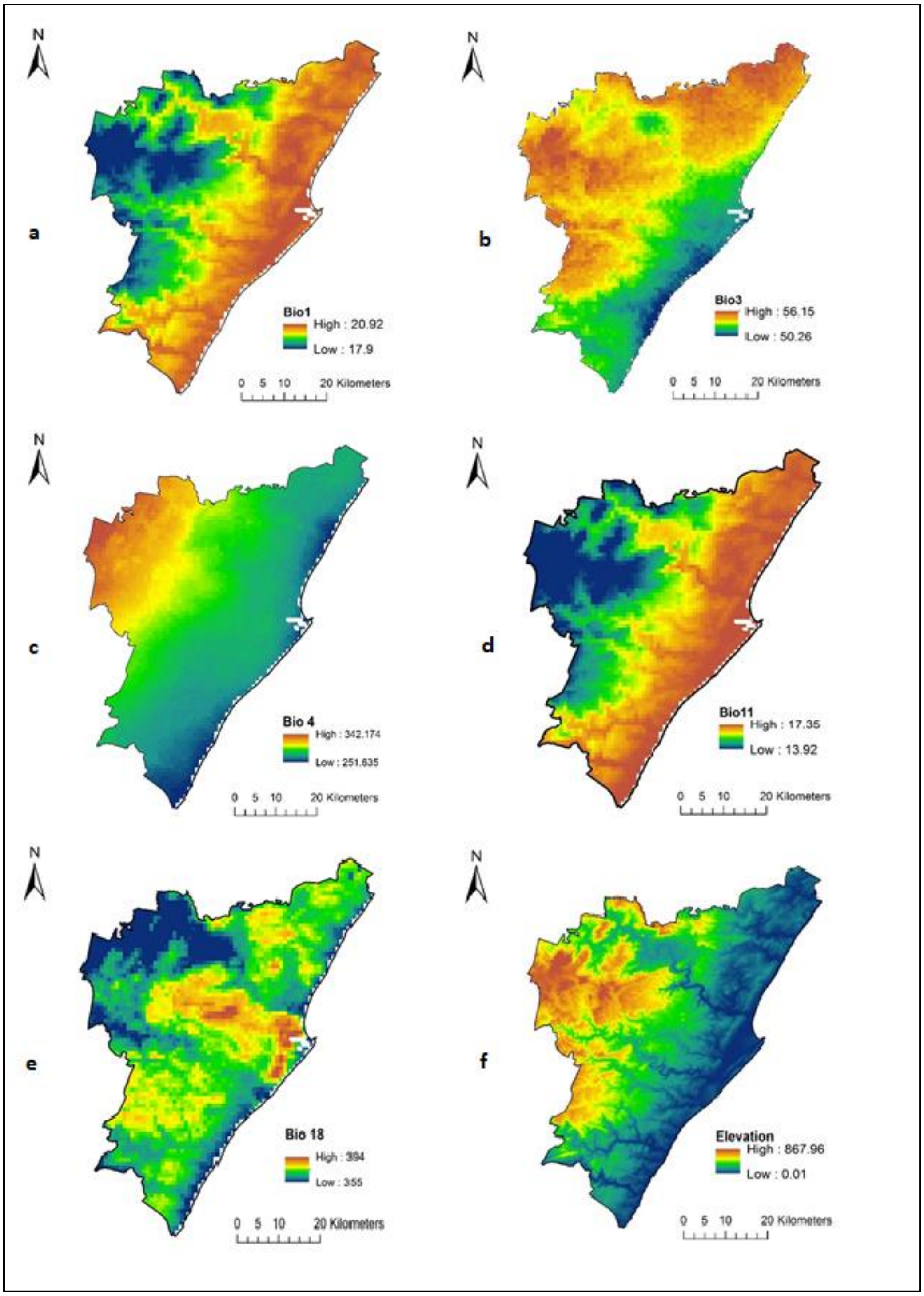

Figure 2.6: Spatial distribution of the most influential climatic and topographic variables to fire occurrence within the eThekwini Municipal Area: a) Annual Mean Temperature (Bio1), b) Isothermality (Bio3), c) Temperature seasonality, d) Mean Temperature of Coldest Quarter (Bio11), e) Precipitation of Warmest Quarter (Bio18) and f) Elevation.

Figure 2.7 shows a fire probability map within the EMA using the most influential climatic and topographic variables. As shown in Figure 2.7, the north, outer west, and southern regions of the municipality are associated with a moderate to a 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 Figure 2.5.

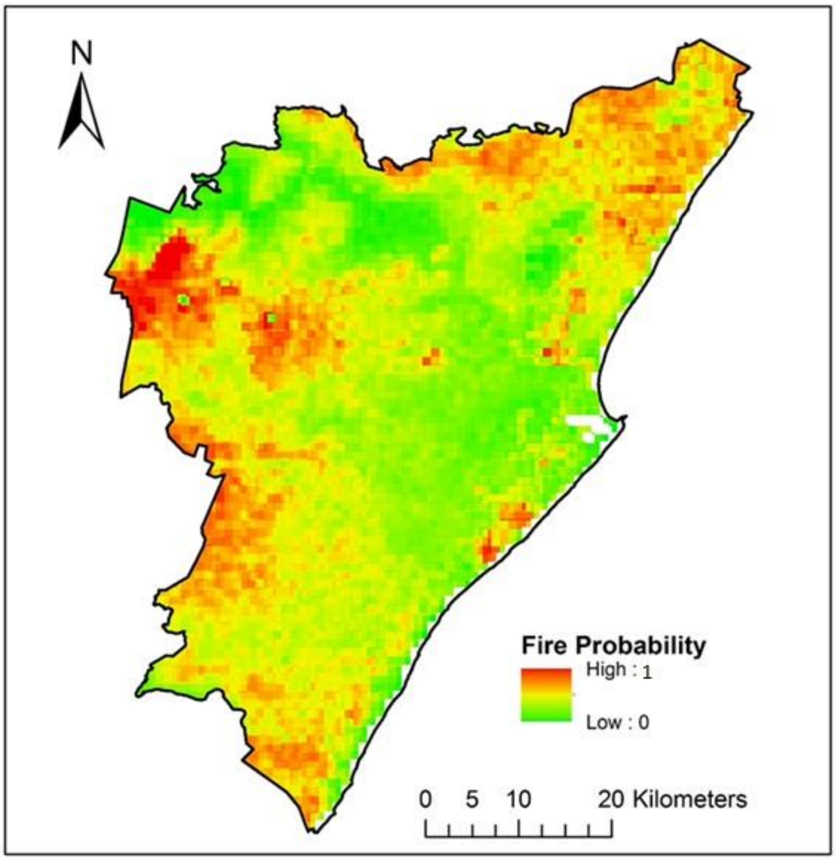

Figure 2.7: Maxent derived fire occurrence probability map

2.4 Discussion

Fires are an essential 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 minimise adverse impacts while maintaining natural processes. Socio-economic and environmental fire-related losses can be averted by adopting appropriate mitigation measures supported by the use of GIS and Remote Sensing technologies to detect, predict, and assess fire risk and associated impacts (Leblon et al., 2012). Hence, 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. The Maxent model's jackknife results and percentage contribution showed that 6 of the 25 predictor variables contributed significantly to the model. The Maxent model also produced a fire risk map that showed areas with low to high risk of fire occurrence within the study area (Figure 2.7).

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 ℃. In this study, regions with lower temperatures had a higher probability of fire occurrence than areas of higher temperatures. The significant contribution of the mean temperature of the coldest quarter results from the correlation between precipitation and temperature as fuel moisture and biomass density depend on rainfall at cooler higher elevations (Mpakairi et al., 2019; Renard et al., 2012).

The eastern part of South Africa is characterised by a June to August winter season. As shown in Figure 2.2, the EMA experience a higher prevalence of fire during winter than any other season. Within the study area, winter is associated with a dry climate and favourable conditions for fire outbreaks. In agreement with this study, a cross-regional fire modelling study conducted in Switzerland, Austria, Spain, and Turkey using bioclimatic, anthropogenic, and topographic variables found that variables associated with temperature had the highest contribution to the model for the majority of the regions for both fine and coarse resolution data, achieving AUC >0.7 Bekar et al., 2020).

Isothermality (12.3%) significantly influenced fire occurrence probability in the study area. Isothermality, calculated from (bio2/bio7) * 100, quantifies the day to night temperature variabilities in relation to the summer to winter oscillations (O'Donnell and Ignizio, 2012). An isothermal value close to 100 stipulates that the daytime temperature range is comparable to the annual temperature range. In contrast, a value less than 100 shows a "smaller level of temperature variability within an average month relative to the year" (O'Donnell and Ignizio, 2012:5). Isothermality for the study area ranged from 50-56. Higher isothermality was associated with higher fire probability, a finding consistent with Verma et al. (2018), who found that isothermality contributed 12.4% to the Maxent model with an isothermality value between 38 and 41. Jackknife plots also revealed the highest gain when isothermality was used in isolation.

The annual mean temperature (bio 1) had a contribution of 4.1% to the model. Areas with lower mean temperatures (17℃) 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 (Turco et al., 2017). There was a decrease in fire probability with the increase in the mean annual temperature. This finding is consistent with Mpakairi et al. (2019) who found that mean temperature was among the significant determinant of wildland fire probability in the Kavango-Zambezi Transfrontier Conservation Area in Zimbabwe.

Elevation had the highest contribution (8.9%) to the model among topographic variables. The 700 m to 900 m above sea level range within the study area had a higher probability of fire occurrence than lower altitudes. This finding is consistent with Strydom and Savage (2016), who noted that most fires in the KwaZulu-Natal and Mpumalanga provinces occur in mountainous areas. Also, Mpakairi et al. (2019) noted elevation as one of the significant determinants of fire occurrence. Specifically, Mpakairi et al. (2019) found a positive correlation between elevation and fire occurrence, with the 1000-1200m range particularly vulnerable. In a study by Adepoju and Adelabu (2019) and Kim et al. (2019), elevation was identified as the most significant variable in modelling fire probability in various landscapes. As shown in Figures 2.4 and 2.5, catchment area, wind effect, aspect, slope, and TWI were less influential to the model, implying that these variables were not valuable in determining fire occurrence within the study area.

This study is helpful as it considers both topographic and climatic variables in modelling the probability of fire occurrence within the EMA. Understanding drivers of fire occurrence are valuable for fire suppression and prevention, hence meeting Sustainable Development Goals 3 (Good health and well-being), 13 (Climate action) and 15 (Life on land) amongst others that involve preserving natural landscapes and biodiversity (Martin, 2018). This study provides an approach to model the probability of fire occurrence within the study area and similar landscapes to mitigate socio-economic and environmental fire-related losses. Methods and results in this study can be used to predict, suppress, and manage wildfires and are valuable for the protection and conservation of the urban natural landscape.

2.5 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 behaviour. This study used a Maxent modelling algorithm to assess the role of various bioclimatic and topographic variables in fire occurrence within the eThekwini Municipal Area. Amongst the 25 variables used, only six were significant in predicting fire probability. These variables were the 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 modelling algorithm. The AUC used for the evaluation indicated that the Maxent model is suitable for determining fire occurrence and identifying drivers within an urban landscape. These results can inform urban authorities on site-specific intervention approaches. Furthermore, understanding the probability of fire occurrence is useful in identifying fire-prone regions and reducing unplanned fires that may harm the recipient environment, a useful intervention in sustaining urban ecological integrity.

CHAPTER THREE: ASSESSING THE CORRELATION BETWEEN BIOCLIMATIC AND TOPOGRAPHIC VARIABLES AND FIRE FREQUENCY WITHIN AN URBAN LANDSCAPE

Abstract

Veldfires have always been part of vegetation ecosystems, offering numerous ecological benefits that include suppressing alien invasive plants, controlling bush encroachment, removing excess herbage, eliminating insects and diseases, and stimulating plant regeneration. Frequent fires can be harmful to people and the environment. Changes in global and local weather patterns have implications on fire frequency and it is anticipated that fires will increase in tropical ecosystems. Fire frequency is regarded as a critical component of the fire regime as it describes the number of fire incidents occurring in a specific area over time. Urban landscapes are highly valuable remnant natural areas with biodiversity that offer socio-economic and ecological benefits that support and regulate urban life. However, unplanned fires remain a threat to the remnant urban ecosystems and present management challenges. Hence, characterising fire frequency within a biodiversity-rich urban landscape is valuable in assessing fire risk and understanding its ecological implications. This study evaluated the correlation between fire frequency derived from the Near Real-Time (NRT) MODIS Collection 6 Active Fire Data and 25 bioclimatic and topographic variables to understand the drivers of fire frequency in the study area. Elevation correlated by $R^2 = 0.74$ with fire frequency, which indicates a strong correlation, while bioclimatic variables associated with temperatures also strongly correlated with fire frequency in the study area. An increase in fire frequency was associated with a decrease in temperatures, increase in precipitation and elevation. Most of the study area has low to medium fire frequency. The outer west part of the study area experienced the highest fire frequency, followed by the north region. Understanding the drivers of fire frequency and identifying areas that burn frequently is essential for land managers to inform their management practices across time and space, valuable in protecting ecological systems within the remnant and conserved urban spaces.

Keywords: Bioclimatic, fire frequency, topographic, Pearson correlation, urban landscape, veldfires.

3.1 Introduction

Fires are an essential natural process that has always been part of vegetation ecosystems and offer numerous ecological benefits. These benefits include suppressing alien invasive plants, bush encroachment control, and excess herbage removal (Househam, 2017 and Wilson et al., 2020). Fires also kill insects and diseases that prey on vegetation and stimulate indigenous plant growth and regeneration (Holsinger et al., 2016; Monmany et al., 2017). Fires are common in grassland, savanna and fynbos biomes as these ecosystems rely on fire to maintain their ecological integrity and complete their cycles (Working on Fire, 2021). On grasslands, fires eliminate unwanted wooded vegetation and promote productivity and diversity (Smith et al., 2013). Generally, fires play an essential role in maintaining the structure, function and composition of numerous African grassland ecosystems (Rebeiro et al., 2019).

However, fires also adversely affect the environment and ecological communities globally. Veldfires can modify hydrological regimes through increased runoff and reduced soil infiltration (Szpakowski and Jensen, 2019). Veldfires also cause air, water, land contamination and pollution from plumes and deposition (Martin et al., 2016) and release harmful airborne particulates and gases like carbon monoxide and carbon dioxide into the atmosphere (Lutz, 2020). These emissions not only affect atmospheric chemistry and ecosystems near the fire site but are transported long distances, affecting the ecology of the area and beyond (Martin et al., 2016; MODIS, 2021). Uncontrolled veldfires can also lead to loss of lives (both human and animals) and property adjacent to the prone ecosystem and where fires are uncommon (Pastor et al., 2019). Large fires can also lead to an ecological disaster resulting in species extinction and soil degradation within a short period (Bradstock, 2009). According to Ardakani et al. (2011), fires influence global changes and transform tropical ecosystems through their connection with atmospheric composition, global carbon cycle, and land-cover dynamics.

Most of the world’s population now reside in urban areas; it is anticipated that by 2050, nearly 70% of the global population will be urban (Cilliers et al., 2013; Boon et al., 2016). Urbanisation affects both local and regional energy balances, carbon cycles, urban ecosystems and the hydrological cycle. Tishi and Islam (2018) noted that urban fire trends are linked to rapid urbanisation, augmented by increasing biomass from the alien invasive plant near urban infrastructure (Potgieter et al., 2020).

Urban green spaces offer valuable social, economic and ecological benefits (Lepczyk et al., 2017). The Millennium Ecosystem Assessment (MEA, 2005) referred to these benefits as ecosystem goods and services and categorised them into four, i.e. provision services that include food, water and traditional medicine, supportive services that include soil formation and nutrient recycling, regulating services like water purification, flood regulation and pollination, and cultural services that involve education, ecotourism and spiritual values. According to Lepczyk et al. (2017), urban green spaces allow citizens to witness ecological processes taking place and connect with nature. Urban green spaces are also areas of high biodiversity of indigenous, endemic and alien plant species (Lepczyk et al., 2017). According to Aronson et al. (2017), cities play a vital role in conserving global biodiversity through urban spaces planning and management. However, species diversity in urban areas depends on the availability of urban green spaces that consist of remnant patches of indigenous vegetation, garden and yards, parks and recreational zones in artificial, semi-natural and natural ecological systems (Cilliers et al., 2013; Aronson et al., 2017). Hence, there is a need to monitor fires to benefit the environment and the urban population.

Fire frequency refers to the number of fires occurring within a defined area over time (Curt, 2018). It is regarded as the main component of the fire regime as it describes the number of fire incidents occurring in a specific area (Eliott et al., 2019). Characterising fire frequency has numerous implications for fire risk assessment and fire ecology. For example, it aids in identifying fire drivers across space and time. As aforementioned, in urban areas, veldfires are continually becoming a threat to the property, human life, health, livelihoods, the environment, and economic development (Pastor et al., 2019). It is anticipated that changes in global climate will increase the fire frequency, causing conservation threats in numerous urban ecosystems (Halofsky et al., 2020).

Fire frequency determines species diversity, evenness, and richness (Smith et al., 2013). Magomani and Van Tol (2019), for instance, notes that frequent burning may adversely affect soil physical properties; hence high fire frequency has been associated with low hydraulic conductivities and water-conducting micro-porosity. Therefore, understanding fire frequency in urban open spaces is critical for conserving and protecting biodiversity that offers numerous benefits for the urban population and the environment.

Fire frequency is driven by a range of factors that influence both ignition and spread. Generally, fire frequency varies at global and local scales due to climate and weather, i.e. regions with hot climate are often associated with high fire frequency. At a regional to sub-continental scale, annual climate variability is recognised as a primary driver of fire activity, i.e. dry and warm year often leads to increased fire activity in subsequent years (Holsinger et al., 2016). At a local scale, fuel, topography, and weather control fire frequency (Krawchuck et al., 2016; Monmany et al., 2017, Curt, 2018; Fang et al., 2018).

This study explores the correlation between fire frequency with topographic and climatic variables. Topography indirectly regulates fuel load, fuel moisture and fuel type (Bennett et al., 2010; Holsinger et al., 2016), while precipitation determines vegetation growth, which later converts to fuel load. Fires from lightning are more common in mountainous areas, and due to the warming climate and rising temperatures, they are expected to increase (Bennett et al., 2010; Peterson and Littell, 2012).

Curt (2018) noted that the computation of fire frequency depends on the quality and duration of fire databases. Hence, technological advances like remote sensing offer improved temporal and spatial variations of fire frequency at local, regional and global scales. Remote sensing methods have been successfully deployed in numerous world regions to detect and monitor veldfires (Ardakani et al., 2011; Leblon et al., 2012). Remote sensing observation provides means to proactively monitor veldfires by offering valuable real-time information for fire management. Airborne instruments and earth satellites are useful in understanding fire frequency and, therefore, vital for fire mitigation and management (Lutz, 2020). Remote sensing system also provides means to measure biophysical quantification of ground conditions before, during and post-fire.

Several products have evolved and improved capabilities to collect fire data across different landscapes. For example, MODIS, an onboard sensor Terra (morning), and Aqua (afternoon) satellites provide daily coverage at over 30 narrow bands ranging from the visible to the thermal infrared (Lizundia-Loiola et al., 2020). In addition, MODIS is easily and freely accessible, has high temporal resolution and offer extensive area analysis (MODIS, 2021). Other products used for studying fire ecology include Landsat MSS, Sentinel 2, ASTER, IKONOS and AVIRIS (Szpakowski and Jensen, 2019). These products have different spatial and temporal resolutions as well as advantages and limitations.

This study adopts the MODIS Fire Information for Resource Management System (FIRMS) to explore the correlation between topographic and bioclimatic variables on fire frequency within an urban landscape. It is essential to study and manage veldfires to protect ecosystems, people, and property, maintain natural resources, and reduce pollution. Also, an understanding of drivers of fire frequency in a remnant biodiversity-rich urban landscape is vital for protecting the environment and allowing the continued provision of ecosystem goods and services supporting and regulating urban life.

3.2 Material and methods

3.2.1 Study area

This study was conducted in the eThekwini Municipal Area (EMA) in KwaZulu-Natal, South Africa (Figure 3.1). In 2016, the EMA was merged to a Metropolitan Municipality and now covers 2297 km² (Bhugeloo et al., 2019). According to the 2016 census, the population of the area was 3.7 million (Municipalities, 2021). Frequent fire outbreaks are often expected during the winter season between June and August (Buthelezi et al., 2016). The EMA has a 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) (https://en.climate-data.org/africa/south-africa/kwazulu-natal-569/). The area is characterised by dry winter and mild wet summer and receives 975 mm of rainfall annually. EMA's varied climate, geology, soils, physiography, and bio-geographical position results in a wide range of biodiversity-rich aquatic and terrestrial ecosystems (Boon et al., 2016). The topography of the study area is rugged, with ravines and gorges. The study area also consists of natural forest and grassland habitats scattered between built infrastructure, settlements and protected areas (Zungu et al., 2020). Settlements include numerous small towns, both urban and rural. The EMA falls within the Maputaland-Pondoland-Albany Global Biodiversity Hotspot, making it an area of high biodiversity and global significance. It also consists of the endangered subtropical KwaZulu-Natal Sandstone Sourveld (KZNSS), Ngongoni Veld, and KwaZulu-Natal Coastal Belt (Drury et al., 2016).

Figure 3.1: eThekwini Municipal Area

3.2.2 Fire data

The Moderate Resolution Imaging Spectrometer (MODIS), owned by the National Aeronautics and Space Administration (NASA), offers both Active Fire and Burned Area Products for free. MODIS detects fires as a result of the recognisable thermal signature. Archived fire data was downloaded from NASA's Fire Information for Resource Management System (FIRMS). MODIS is on board sensor Terra (morning) and Aqua (afternoon) satellites with daily coverage and over 30 narrow bands ranging from the visible to the thermal infrared at a variable spatial resolution from 250 m to1000 m (Lizundia-Loiola et al., 2020). MODIS detects active fires as the satellite overpasses. Due to its high temporal resolution and good fire detection capabilities, MODIS has become a standard sensor for fire monitoring at different scales and landscapes. The MODIS Collection 6 offers improved small fire detection, reduced false alarms, improved land surface temperature, and land surface reflectance (Blumenfeld, 2015). MODIS completes its one orbit worldwide in 98 hours, making it suitable for collecting data on a time-sensitive phenomenon like fires (MODIS, 2021). This study used the Near Real-Time (NRT) MODIS Collection 6 Active Fire data sets covering 11 years (1 January 2009 to 31 December 2019) to classify fire frequency in the study area.

3.2.3 Environmental variables

This study used 25 topographic and bioclimatic variables (Table 3.1) to investigate their relationship with fire frequency. Topographic variables include aspect, catchment area, elevation, slope, Topographic Wetness Index, and wind effect. These variables regulate the local climate, precipitation received, vegetation distribution, seasonal fuel drying, and wind exposure (Bennett et al., 2010). The variables were derived from a 30 m resolution Digital Elevation Model. Bioclimatic data was developed by the U.S. Geological Survey (USGS) as Geographic Information Systems (GIS) continuous raster surfaces to accentuate climate conditions (O'Donnell et al., 2012). These variables are derived from monthly precipitation and temperature values to better present annual trends.

Table 3.1: Topographic and bioclimatic variables used in the study

Variable	Description	Units
Aspect	Aspect	°
Bio1	Annual Mean Temperature	℃
Bio10	Mean Temperature of Warmest Quarter	mm
Bio11	Mean Temperature of Coldest Quarter	mm
Bio12	Annual Precipitation	mm
Bio13	Precipitation of Wettest Month	mm
Bio14	Precipitation of Driest Month	mm
Bio15	Precipitation seasonality	mm
Bio16	Precipitation of Wettest Quarter	mm
Bio17	Precipitation of Driest Quarter	mm
Bio18	Precipitation of Warmest Quarter	mm
Bio2	Annual Mean Diurnal Range	℃
Bio3	Isothermality	℃
Bio4	Temperature Seasonality	℃
Bio5	Max Temperature of Warmest Month	℃
Bio6	Min Temperature of Coldest Month	℃
Bio7	Annual Temperature Range	℃
Bio8	Mean Temperature of Wettest Quarter	℃
Bio9	Mean Temperature of Driest Quarter	℃
Catchment Area	Catchment area	m
Elevation	Elevation	m
Slope	Slope	°
TWI	Topographic Wetness Index	-
Wind Effect	Wind effect	m/s

3.2.4 Fire frequency mapping

MODIS Active fire data from 1 January 2009 to 31 December 2019 was classified to derive a fire frequency map for the EMA depicted in figure 3.2. This study used a Fishnet module in ArcGIS to create 2 by 1.7 km quadrats within the EMA boundary. The fishnet modules create rectangles as quadrats within the boundary of the study area. Every quadrat was assigned the sum of fires per 3.4 km². Areas that experienced 0 to 5 fires were assigned low fire frequency, areas with 6 to 10 fires were assigned medium fire frequency, while areas that experienced 10 or more fires were assigned a high fire frequency, indicating that the quadrats experienced fires every year in the past 11 years.

Ninety sample points were selected from the fire frequency map using the purposive and random sampling technique. Purposive sampling is a non-probability sampling technique where the researcher intentionally decides which points are included in the sample to represent the whole data set (Etikan et al., 2016). Quadrats with fire categories were selected to eliminate quadrats that did not experience fire during the study period. Ninety points were then randomly selected in quadrats that had different fire frequencies. Finally, the random points were chosen in quadrats with vegetation cover, excluding fires detected in inanimate land uses like industrial zones.

The fire frequency was interpolated using an Inverse Distance Weighting (IDW) method for a smoother surface to visualise the fire frequency across the study area. The IDW weighs the nearest point with the assumption that they are more influential than further away points. Kumari and Pandey (2019) notes that IDW has been widely used to depict the spatial distribution of fire hotspots.

3.2.5 Pearson correlation

Pearson correlation assesses the relationship between variables at hand using correlation coefficient (R^2) to indicate the strength of a correlation between variables. Correlation coefficient values range from 0 to 1, where 1 shows a very strong correlation and 0 means no relationship between two variables (Akoglu, 2018). Using Microsoft Excel, the ninety sample points derived from the fire frequency map were then correlated against 25 topographic and bioclimatic variables. Excel is a helpful program for data analysis (Grech, 2018). This was followed by deriving a graph for each variable to visually depict the relationship between fire frequency and topo-climatic variables. The correlation coefficient (R^2) for each variable were also tabulated.

3.3 Results

3.3.1 Fire frequency

Figure 3.2 (a) below shows fire frequency in a vector format for the eThekwini Municipal Area per 3.4 km² over 11 years. Figure 3.2 (b) also shows the fire frequency interpolated into a continuous format for better visualisation. The Outer West region experienced the highest fire frequency, followed by the northern region of the study area.

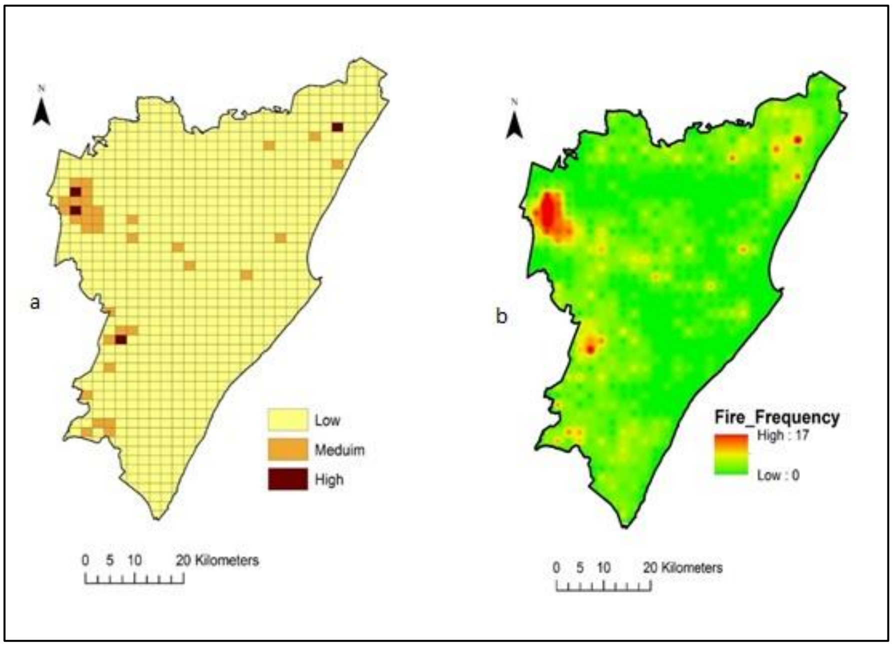

Figure 3.2: eThekwini Municipal Area fire frequency **(a)** categorised and **(b)** interpolated.

3.3.2 Correlation

Numerous factors influence fire frequency. Generally, the outer West of the municipality had the highest fire frequency while the Central region had the lowest. Table 3.2 shows the correlation (R^2) values between topographic and bioclimatic variables and fire frequency in descending order.

Figure 3.3 below also depict variables that had the highest correlation with fire frequency. One topographic and bioclimatic variables associated with temperature (Bio1 to 11) correlated more with fire frequency than precipitation variables (Bio12 to 19). Amongst the topographic variables, elevation had the highest correlation of R^2 = 0.74, where fire frequency increased with elevation. In the study area, fires occurred more frequently at higher altitudes. A decrease in temperature was associated with an increase in fire frequency.

Table 3.2: Correlation coefficient (R^2) between fire frequency and topo-climatic variables

Variable	**Description**	**Correlation (R^2)**
Elevation	Elevation	0.74
Bio1	Annual Mean Temperature	0.70
Bio10	Mean Temperature of Warmest Quarter	0.70
Bio8	Mean Temperature of Wettest Quarter	0.70
Bio11	Mean Temperature of Coldest Quarter	0.69
Bio6	Min Temperature of Coldest Month	0.67
Bio15	Precipitation seasonality	0.66
Bio9	Mean Temperature of Driest Quarter	0.66
Bio17	Precipitation of Driest Quarter	0.62
Bio19	Precipitation of Coldest	0.62
Bio2	Annual Mean Diurnal Range	0.59
Bio7	Annual Temperature Range	0.57
Bio5	Max Temperature of Warmest Month	0.55
Bio4	Temperature Seasonality	0.51
Bio14	Precipitation of Driest Month	0.49
Bio12	Annual Precipitation	0.46
Bio3	Isothermality	0.46
Bio16	Precipitation of Wettest Quarter	0.23
Bio13	Precipitation of Wettest Month	0.22
Wind Effect	Wind effect	0.16
TWI	Topographic Wetness Index	0.04
Slope	Slope	0.01
Aspect	Aspect	0.00
Catchment Area	Catchment area	0.00
Bio18	Precipitation of Warmest Quarter	0.00

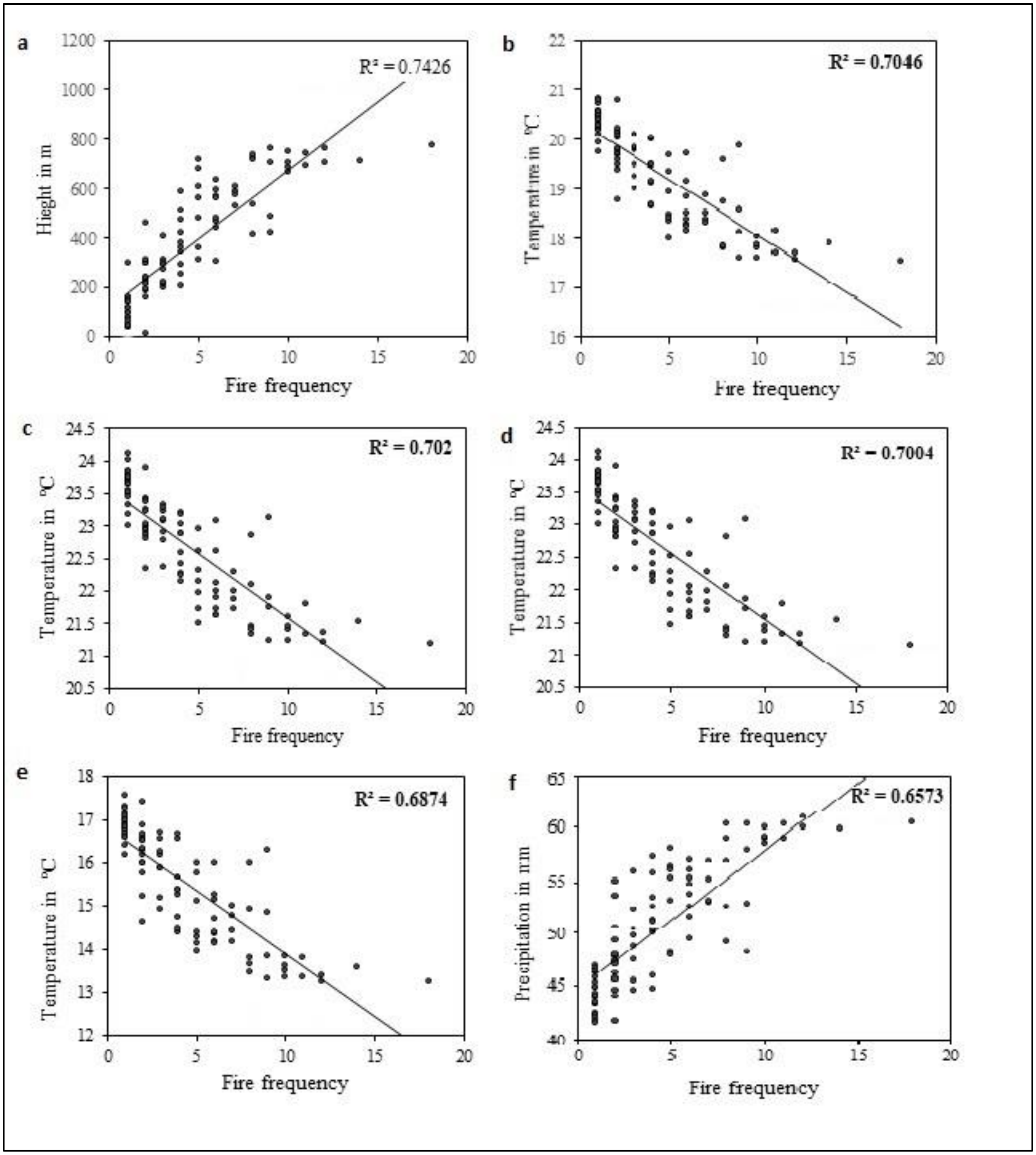

Figure 3.3: Correlation between fire frequency with bioclimatic and topographic variables in the eThekwini Municipal Area: a) Elevation, b) Mean Annual Temperature (Bio1), c) Mean Temperature of the Warmest Quarter (Bio10), d) Mean Temperature of the Wettest Quarter (Bio8) and e) Precipitation Seasonality.

3.4. Discussion

This study assessed the relationship between bioclimatic (temperature and precipitation) and topographic variables with fire frequency to understand the drivers of fire frequency in the study area. As depicted in Table 3.2 and Figure 3.3, the majority of the study area has low to medium fire frequency. The Outer West region experienced the highest fire frequency, followed by the North region. An increase in fire frequency was associated with a decrease in temperature, increase in precipitation and elevation. Low temperatures and dry climate are favourable conditions for fire outbreaks.

Amongst the topographic variables, elevation had a strong positive correlation with fire frequency. Although most of the veldfires in the study area occurred in lower altitudes, fire frequency increased with elevation. Elevation had R^2 = 0.74, indicating a strong correlation with fire frequency. Other topographic variables like aspect, catchment area, slope, and TWI had R^2 = <0.0, indicating they have no influence on fire frequency in the study area. Wind effect had R^2 = 0.16, which indicate a very weak correlation with fire frequency.

In consistency with Kim et al. (2019), veldfires in this study occurred more frequently in higher elevations ranging from 600 m to 800 m above sea level. Strydom and Savage (2016) also noted that the study region experiences frequent veldfires in mountainous areas. Elevation influences precipitation received, seasonal fuel drying, and wind exposure, hence fire occurrence (Bennett et al., 2010; Sullivan et al., 2012). Holsinger et al. (2016) note that topography indirectly regulates fuel load, moisture and type while precipitation determines vegetation growth at a different elevation, which later converts to fuel load. Furthermore, lightning strikes are more common at higher elevations, and they are expected to increase due to the climate getting warmer with rising temperatures (Bennett et al., 2010; Peterson and Littell, 2012).

Most of the variables associated with temperature negatively correlated with fire frequency, which means a decrease in temperatures was associated with an increased fire frequency in the study area. These variables include the annual mean temperature (Bio1), Mean Temperature of the Warmest Quarter (Bio10), Mean Temperature of the Wettest Quarter (Bio8) and Mean Temperature of Coldest Quarter (Bio11) (Figure 3.3). These variables had an average of R^2 = 0.70, indicating a strong correlation with fire frequency.

Climate change has led to a global increase in temperatures and droughts, resulting in changes in different ecosystems. For example, Peterson and Littell (2012) noted that a warmer climate accelerates the drying of fuels, while McWethy et al. (2017) found that warm and dry conditions promoted frequent fires. These findings are consistent with a study by Kumari and Pandey (2020) and Koutsias et al. (2012), who established that mean temperature was a critical climatic variable associated with high fire frequency in Jharkhand, India.

Precipitation of Wettest Quarter (Bio16) had a strong positive correlation with fire frequency. Areas that received 370 to 390 mm of rainfall during summer had the highest fire frequency. These findings are consistent with Ardakani et al. (2011), who established a linear correlation between the mean annual rainfall and fire frequency. This correlation is acceptable because areas that receive more rainfall result in increased plant growth and become fuel material susceptible to burning (Bennett et al., 2010; Wilson et al., 2020). A 44-year experiment in the Kruger National Park explored the long-term impacts of fire frequency on herbaceous vegetation in the savannah found that areas of higher mean annual rainfall were associated with more frequent fires than areas with lower rainfall (Smith et al., 2013). Higher rainfall results in increased plant growth and fuel load that is susceptible to frequent and intense fires in a landscape. Adequate fuel load availability supports frequent fire occurrence.

3.5 Conclusion

Veldfires can be beneficial in fire-adapted ecosystems and can also lead to an ecological disaster at a lower or higher frequency. This study identified factors that influence fire frequency within urban open spaces, including twenty-five temperature, precipitation, and topographic variables. The results showed that higher elevation and temperature variables strongly correlated with high fire frequency in the study area, while precipitation moderately correlated with frequency in the eThekwini Municipal Area. Understanding drivers of fire frequency and identifying regions that burn frequently is essential for land managers to inform their management practices across time and space. Geospatial tools in remote sensing offer timely fire data, which assist in identifying fire trends and hotspots at a mesoscale. The biophysical features of an urban landscape vary in relation to surrounding rural areas due to urbanisation, land uses, and emissions. Hence it is vital to understand their contribution to fire frequency for management purposes within a biodiversity-rich urban landscape. It is vital to study and manage veldfires to protect ecosystems, people and property, natural resources, and reduce pollution.

CHAPTER FOUR: SYNTHESIS

THE INFLUENCE OF BIOCLIMATIC AND TOPOGRAPHIC VARIABLES ON FIRE OCCURRENCE AND FREQUENCY WITHIN THE ETHEKWINI MUNICIPAL AREA

4.1 Introduction

Fires are a common phenomenon that has been deployed for centuries as a tool for hunting, deforestation and land management. Fires also play a significant role in maintaining the ecological integrity of different environments. These include improving grass production and quality, removing alien invasive species and excess herbage, and controlling bush encroachment. However, frequent fire outbreaks are continually becoming a threat to the economy, livelihoods and the environment. They also present a challenge in numerous ecological zones. The advancement in satellite remote sensing has enabled the acquisition of fire data that is time-efficient and cost-effective with global coverage. Numerous studies have attempted to map and quantify fire occurrence with sensors with varied spatial and temporal resolutions. They have also used varying species distribution models to explore the drivers of fire occurrence in different regions. This chapter reviews the aim and objectives that were stated in the introductory chapter. This chapter also provides the conclusions drawn from the study and recommendations for further research.

This study aimed to assess the impact of bioclimatic and topographic variables on the occurrence and frequency of veldfires in a biodiversity-rich urban landscape. The objectives were set as follow:

i) To assess the influence of bioclimatic and topographic variables on grassland fire occurrence within an urbanised landscape,

ii) To assess the correlation between bioclimatic and topographic variables and fire frequency within an urban landscape.

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

Grassland covers about one-third of the Earth's terrestrial surface and offers several ecosystem services that include climate regulation, biodiversity maintenance, soil protection and water purification. Grasslands are fire-adapted ecosystems; however, it is vital to understand the underlying drivers of veldfires to mitigate fire-related socio-economic and ecological impacts within an urban landscape. This objective used Maxent to assess the drivers of fire occurrence in the eThekwini Municipal Area. From a wide range of topographic and bioclimatic (precipitation and temperature) variables, results showed that 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 Maxent modelling obtained Area Under Curve >0.7 indicates a good accuracy for predicting fire probability and identifying drivers within a biodiversity-rich urban landscape at a mesoscale. Strydom and Savage (2016), Adepoju and Adelabu (2019), Kim et al. (2019) also found that elevation played a significant role in modelling fire probability. Areas of higher elevations are more likely to experience fire activities than low lying areas. Studies conducted in Switzerland, Austria, Spain, and Turkey also found that variables associated with temperature had a high contribution in modelling fire probability (Mpakairi et al., 2019; Bekar et al., 2020). This can be attributed to the correlation between temperature and precipitation, where biomass density and fuel moisture rely on precipitation at cooler and higher elevations. These findings are vital for informing conservation and protecting urban ecological systems, ensuring the continued provision of goods and services derived from urban green space, and supporting and regulating urban life.

4.3 Assessing the correlation between bioclimatic and topographic variables and fire frequency within an urban landscape

Fire frequency is regarded as the main component of the fire regime. Characterising fire frequency also aids in identifying the driving factors. Thus this objective sought to assess the relationship between bioclimatic and topographic with fire frequency for eThekwini Municipal Area. Pearson correlation coefficient (R^2) was used to assess the relationship between fire frequency and topo-climatic variables. Most of the study area experienced medium to low fire frequency; however, the outer west region had the highest fire frequency. This region is characterised by higher elevation and lower seasonal temperatures. Elevation correlated by $R^2 = 0.74$ with fire frequency, which indicates a strong correlation. An increase in rainfall and elevation characterised the increase in fire frequency. Bioclimatic variables associated with temperatures also strongly correlated with fire frequency, where the decrease in temperatures was associated with an increase in fire frequency in the study area. Strydom and Savage (2016); Kim et al. (2019) also found that veldfires frequently occurred in mountainous regions. Elevation affects precipitation, exposure to wind and fuel drying. Bennett et al. (2010); Peterson and Littell (2012) also noted that fires caused by lightning are more common in areas of higher elevation, and they are expected to increase attributed to climate change. Ardakani et al. (2011) also established a strong correlation between fire frequency and mean annual rainfall, where regions that experience more precipitation led to the accumulation of fuel susceptible to burning. Thus, this study concludes that areas with higher elevation, dry climate and low temperatures are conducive for frequent fire outbreaks.

4.4 Conclusions and Recommendations

The primary aim of this study was to assess the underlying drivers of fire occurrence and frequency in a biodiversity-rich urban landscape within the eThekwini Municipal Area. Findings showed that bioclimatic variables associated with temperature and elevation were the most important fire occurrence and frequency drivers in the study area. The following conclusions were drawn from chapter two and three.

1. Maxent percentage contribution results showed that 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 eThekwini Municipal Area. Furthermore, 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 modelling. Hence, this study concludes that the Maxent modelling algorithm is suitable for determining fire occurrence and identifying key fire drivers within an urban landscape.
2. The results showed that elevation and temperature variables strongly correlated with higher fire frequency in the eThekwini Municipal Area. Elevation correlation of $R^2 = 0.74$ was the highest amongst other variables; areas in higher elevation had more frequent fires in the study area. Bioclimatic variables associated with temperature strongly correlated with fire

frequency in the study area. These findings can assist in identifying fire-prone regions to establish necessary measures to prevent and monitor unplanned fires in the remnant urban ecosystems. This study also demonstrated that topographic and bioclimatic variables could be used to understand fire activity within an urban landscape.

This study focused on exploring variables that drive fire occurrence and frequency within the remnant urban landscape. Thus, this study recommends using remote sensing fire products and topo-climatic variables to understand fire drivers at a mesoscale to ensure that land managers put appropriate measures to combat the adverse impact of fires on urban life. This study mapped the fire probability for the municipal area and identified topographic and climatic factors that contribute to fire occurrence and frequency. The findings will inform areas more susceptible to fires for prioritization to protect and conserve biodiversity and sustain urban ecological integrity. More research needs to incorporate human factors in understanding the drivers of fire activity as they may vary from region to region.

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