DEVELOPING A REMOTELY-SENSED FRAMEWORK FOR FIRE MONITORING IN THE WESTERN CAPE, SOUTH AFRICA

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ABSTRACT

For a long time, fire dynamics has been misunderstood and viewed as either a destructive force or an ecological necessity. The Western Cape Province in South Africa experiences the frequent occurrence of fires, due to the prevailing Mediterranean climatic conditions. This climate is known for its hot and dry summers and its cold and wet winters, which, along with the highly flammable indigenous flora of the Western Cape, provide suitable conditions for the occurrence of fires. However, the local environmental and ecological variables that influence the occurrence of fires and that could assist with fire management practices remain poorly understood. The development of an integrated operational monitoring framework is therefore imperative for detecting and mapping the occurrence of fires in the Western Cape, South Africa. In this study, the environmental variables, namely, land surface temperature, elevation; net primary productivity, precipitation, wind speed and aboveground biomass were used to model the occurrence of fires, by using the species distribution model, Maxent. The occurrence of fires was modelled over a period of 10 years (2009-2019), based on seven Maxent-based models, depending on the different parameter combinations. The fire-monitoring model that was developed for the study area demonstrates that environmental factors influence fire occurrence. It was also observed that suitable conditions were concentrated mostly in the Cape Winelands and Garden Route municipal districts, due to their prevailing climatic conditions and fuel load. For the seven evaluated models, the general threshold for three of the environmental variables seemed to remain relatively consistent. The probability of fire decreases with an increase in precipitation, with the greatest probability of fire occurring where precipitation is (0 mm) and with an increase in the land surface temperature (14600 – 14800 kelvins or 18.85 -22.85˚C). Fire occurrence also peaked in areas with a high net primary productivity (~ 900 gC/m^2) or (≥ 1800 gC/m^2). The results showed an average AUC of >0.80, with the exception of 07 April 2009, which achieved an AUC of 0.787, which suggests that this model performed considerably better than a random prediction model. The response of fire to elevation seemed to be largely based on where the suitable fire conditions were concentrated, rather than on the physical effect of the elevation. Overall, the study concluded that moisture-deficient climatic conditions and fuel-load availability provide suitable conditions for the occurrence of fires in the Western Cape, South Africa. The proposed fire-monitoring framework provides an insight into the areas that are prone to fires and the possible drivers in the Mediterranean climate of the Western Cape. There is, however, a need to test this approach in other climatic zones for operational purposes.

Keywords: Fire suitable conditions; fire monitoring framework; Maxent; Mediterranean; moisture limited; fuel load.

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CHAPTER 1: INTRODUCTION

1.1 Introduction

Fires are deemed to be an environmental hazard and can cause severe damage to the biodiversity and infrastructure. Consequently, different methodologies have been developed to detect and monitor the occurrence of fires and to provide early warning systems (San-Miguel-Ayanz, Ravail, Kelha, *et al.*, 2005). However, the most commonly used man-made techniques do not seem to fully consider the ecological dynamics of fires, which results in poor fire detection and which can have a negative impact on the fire return intervals and their intensity when they recur. Several studies show that in cases where the prescribed burning is applied too early or too late, or when the fire climate conditions are not understood, there is the likelihood that larger wild fires will occur and that the natural fire regime will have less of an impact (Allan *et al*., 2003; Backer *et al*., 2004; Piñol *et al.*, 2005; van Wilgen *et al.*, 2010). However, when properly managed and maintained, fires are, in essence, an environmental control that facilitate the diversity of the plant species within the natural fire regime (Cowling, Rundel, Lamont, *et al.*, 1996; Rundel, Arroyo, Cowling, *et al.*, 2018). Controlled fires can be useful and indicative of a healthy environment that is not destructive. More specifically, a Mediterranean climate, such as in the Western Cape, facilitate fires and is a very necessary ecological phenomenon for the natural life-cycle of the Fynbos biome (Schwik *et al.*, 1997).

The Western Cape is an area in South Africa that is well-known for the frequent occurrence of fires, due to its Mediterranean climate, which is characterized by hot dry summers and cold wet winters (Meadows, 2003). Mediterranean climates are typically the most flammable climates in the world due to the associated extreme climate conditions, as well as the prevailing vegetation types and characteristics (Kraaij & van Wilgen, 2014). These climates provide environmental conditions that are conducive for the study of the occurrence of fires and for identifying the environmental variables that induce such conditions. In retrospect, when one considers the past techniques used to control fires, they tend to have been counteractive as they relied heavily on reactive or preventive measures. To mitigate the occurrence of fire and to be eco-friendly and prevent their destructive nature, there is a need to adopt a proactive approach that attempts to predict the occurrence of fires. This can be done by using modelling techniques that will help to understand the dynamics of fire in relation to the suitable environmental conditions that necessitate their occurrence. This information will therefore help to facilitate better decision-making for fire prevention and management.

It is therefore evident that fire-prone environments require a great understanding, in order to reduce the ecological impact and financial burden where preventive measures target areas that are inappropriate for such interventions. This study seeks to develop a spatially-explicit remotely-sensed fire monitoring method that will help us to understand where, when and why fires occur in the Western Cape region of South Africa. Specifically, this study intends to determine the potential for fire probability based on the variability of selected environmental variables in this area by using multi-source spatial data. This will, in turn, aid in the development of relevant and effective knowledge-based fire management strategies that are cognizant of the natural fire cycles, including the optimal period for human intervention, in order to ensure the integrity and diversity of the natural fauna and flora. It is believed that this methodology will help to minimize unforeseen biodiversity and infrastructural damage and to curb potential financial loss.

1.2 Aim

The aim of this study is to develop an operational framework for monitoring and mapping fire occurrence in the Mediterranean climate of the Western Cape region in South Africa.

1.3 Objectives

The objectives of this study are:

- to model the occurrence and distribution of fires in the Western Cape by using remote sensing spatial modelling techniques; and
- to determine the environmental and climatic factors that influence fire occurrence in the Mediterranean region of the Western Cape Province, South Africa.

1.4 Significance of the Study

Fire monitoring and management requires the coherent selection of environmental covariates, that are based on climate due to the different vegetation characteristics and atmospheric conditions that contribute to the occurrence of fires (Moritz et al., 2012). Currently, most models that predict the incidence of fires in fire-prone areas use different environmental covariates and often neglect to look at the full spectrum of climatic conditions that contribute to fires (Chingono & Mbohwa, 2015; Gonzalez, Palahi, Trasobares, *et al.*, 2006; Mpakairi, Tagwireyi, Ndaimani, *et al.*, 2018). Therefore, there is a need to develop an operational framework for fire monitoring in the Western Cape, South Africa. The Western Cape experiences a Mediterranean climate, which makes it unique, as conditions under which fires can occur differ at the smallest scale, from the point of ignition to the influence of vegetation, which determines their intensity and spread (van Wilgen *et al*., 2010). Even though regions with a Mediterranean climate have been described as the most fire-prone regions in the world (van Wilgen *et al.,* 1994), there are currently no models in operation that attempt to determine the localized conditions needed for fire occurrence.. Furthermore, satellite systems are by far the most efficient and cost-effective means of predicting and monitoring fires in fire-prone areas, when compared to ground- and airborne-based sensors. Ground-based sensors detect fires in three main formats, namely, the detection of hotspots through an increase in temperature, the detection of hotspots with reference to the background temperature, and lastly, detection through the smoke plumes that are produced by a fire (Alkhatib, 2014). Their major limitation is that their algorithms are based on the assumption that average temperatures are lower than that produced by a fire, which results in the false detection of fires, especially in fire-prone climates (San-Miguel-Ayanz *et al*., 2005). Airborne sensors are also used to detect fires through smoke-plume detection or by identifying high-energy fires. Their main limitation is that smoke plumes can only be detected after a fire has begun. In addition, airborne sensors are incapable of detecting smaller fires and cannot cover a fire that spreads over larger areas, mainly because of the limitations in sensor technology and the running costs (Allison, Johnston, Craig, *et al.*, 2016). Thus, from a fire management perspective, it is not proactive enough to prevent damage.

Remote sensing allows for the application of a GIS-based modelling process for fire occurrence. This allows for the integration of different environmental covariates that influence fire occurrence by using indices that provide information on burn scars and fire probability. The current satellite sensors have more advantages and are more applicable, when compared to ground-based and airborne sensors. These advantages include having a higher sensitivity to low-temperature fires, having the ability to conduct a multispectral analysis, low sampling costs, greater spatial coverage and an increased accessibility to data (Fuller, 2000; San-Miguel-Ayanz *et al.*, 2005). There is therefore a need for a spatially-explicit framework for fire monitoring, which will allow for the precise representation of the environmental variables that contribute to the occurrence of fires and which will provide repeated monitoring, based on the needs of fire management agencies. This study stands to provide a concise means for the monitoring of fire occurrence and can provide further inference of the dynamics of fire. Advancements in the monitoring of fire occurrence can improve our ability to assess where intervention through the means of fire management strategies are needed, which alternatively can reduce the costs of fire management strategies and thus increase the economic viability of such undertakings. Furthermore, the low sampling costs involved with using satellite data can also directly reduce the costs of research whilst not reducing the integrity of said research due to the previously mentioned advantages involved with satellite data.

1.5 Conclusion

In conclusion, fires are thus a natural part of the ecosystem and thus while they can be unquestionably destructive cannot be avoided entirely. As such there is a need to understand the dynamics of fire occurrence based on the natural fire regime of any given area. This study thus aims to develop an operational framework for monitoring and mapping fire occurrence in the Mediterranean climate of the Western Cape region in South Africa in order to gain such an understanding. As such, the following study will gauge relevant scientific literature and develop and adopt methods based on remote sensing in order to develop the aforementioned framework.

CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

For a long time, fire dynamics have often been misunderstood and viewed as either a destructive force or an ecological necessity. It has, however, since been recognized that fires act as 'herbivores', from an ecological perspective, which is contrary to the belief that only climate and soils dictate the structure of an ecosystem (Bond & Keeley, 2005). The idea between the parallels of fire and herbivory is that, in the absence of fire controls, large populations of plant species will be lost and the ecosystem will be transformed into one that consists of fire-tolerant plant species. This suggests that fires are not necessarily a destructive force, but a necessity for ecological diversification and the suppression of bush encroachment. Therefore, if fires are not regularly monitored and managed in a manner that allows them to follow the natural regime of fire occurrence in a given area, this can lead to the destruction of large pieces of land and it can also incur major economic losses or, in the worst case scenario, the loss of human lives (Dube, 2013; Strydom & Savage, 2018). Hence, there is a need to develop models that can help to predict the occurrence of wildfires, based on environmental factors that influence the dynamics of fires.

It has been globally recognized that the severity and frequency of fires are the result of three factors, namely, the atmospheric conditions, the fuel load and the ignition (Moritz, Parisien, Batllori, *et al.*, 2012). Various models have disagreed on the environmental covariates that ought to be used when predicting the probability of fires because of different environmental conditions across various regions. For example, from a global perspective, Moritz *et al*. (2012) used net primary productivity, annual precipitation, the precipitation in the driest month, temperature seasonality, the mean temperature of the wettest month and the mean temperature of the warmest month. Liu *et al*. (2010) used the Keetch-Byram drought index, which is based on the soil moisture deficit and which relies on daily temperature and daily and annual precipitation data to determine the distribution of fires globally. The different parameters used by Liu *et al*. (2010) and Moritz *et al.* (2012) to measure the global fire distribution have resulted in contrary results that agree only on the fact that global fire distribution will increase in some places and decrease in others, due to climate.

From a regional perspective, Gonzalez *et al.* (2006) used the elevation, tree size, stand structure and species composition in a statistical model to predict fire distribution in forest stands in Catalonia, North-east Spain. Mpakairi *et al.* (2018), in turn, used elevation, Normalized Difference Vegetation Index (NDVI), human population density and mean air temperature in the MaxEnt model, to predict the distribution of fires and possible hotspots in Zimbabwe. The conflict between these two abovementioned studies is that the parameters used to determine wildfire probability differ with regard to the physical template of the environment and the model type. This suggests that models need to be calibrated specifically for the conditions that they model and that such models cannot be extrapolated to climates outside of the areas in which they fall.

In South Africa, fires have also been recognized for the role that they play in the ecological structure and function (Bond & Keeley, 2005; van Wilgen & Richardson, 1985). Bond and Keeley (2005) suggested that, in the absence of fire, indigenous grassland and Fynbos biomes would be dominated by tree species, which would ultimately result in the loss of diversity. In contrast, fires that occur outside of the natural regime would promote the encroachment of invasive species (van Wilgen *et al*., 2010). Fire management in South Africa occurs by using prescribed burning, which has proven to be inefficient and does not reduce the fuel load (van Wilgen *et al*., 2010). According to van Wilgen et al. (2010), most fires in the Western Cape occur as wild fires, with only a small percentage actually taking place as prescribed burning. The Western Cape experiences a Mediterranean climate and its most abundant plant species is Fynbos, which creates an interesting environment where a highly-flammable plant species occurs within highly-flammable climatic conditions (van Wilgen *et al*., 1994). From a South African perspective, it is therefore important to understand the environmental conditions that favour the occurrence of fires, in order to effectively determine where fire management efforts should be directed. A study by Chingono and Mbohwa (2015) used Dry Mass Production (DMP) and NDVI to model the incidence of fires in southern Africa. The model showed an increase in the incidence of fire where the DMP and NDVI increased and performed well, but it excluded climate variables, like temperature and precipitation. Whilst the application of remote sensing has been widely discussed from a fire-mapping perspective (San-Miguel-Ayanz *et al.*, 2005), a knowledge gap exists, both globally and regionally, as most models disagree on the environmental covariates that must be used when mapping the incidence of fires. Furthermore, models often do not include a bi-temporal analysis to determine the predictive capability of the said model, even though this has since been proven to be valuable (Escuin, Navarro & Fernández, 2008). Therefore, this study will attempt to develop a model that is suited specifically for the physical template of the Western Cape, in order to predict the potential distribution of fires more successfully. This will help to develop a more proactive approach to fire management that will not only minimize the damage caused by fires but also increase the ecological benefits thereof.

2.2 The Physical and Climatic Conditions that Influence the Occurrence of Wildfires

On a global scale, Moritz *et al.* (2012) described fires to be influenced by the following three main physical factors, namely: (a) atmospheric conditions pertaining to any weather, in terms of their length and severity, that allow for flammability, (b) the resources that are needed to start a fire, such as vegetation structure and growth rate, and lastly, (c) ignitions, which refers to any activity that starts a fire. While these factors undoubtedly influence fires, they do not consider smaller-scale disturbances that are climate-specific, such as precipitation pulses, where an increase in precipitation in an already moist climate will diminish fires, but a similar increase in precipitation in a drier climate will increase flammability.

Regionally, most studies concur that fires are influenced by elevation, soil moisture, precipitation, vegetation characteristics, anthropogenic activities and temperature; however, very few actively apply all of these in their models (Chingono & Mbohwa, 2015; Mpakairi *et al.*, 2018). Vegetation characteristics, such as structure, oil and moisture content, all determine the flammability of a plant and its contribution to the fuel load (van Wilgen *et al.*, 1990). For example, the Fynbos species consist of dry shrubland plants that are naturally fire-prone, due to their dry, woody-like structure and high oil content, which makes them more flammable than most other plant species found in South Africa. Likewise, plants that hold more moisture or produce less leaf litter, such as succulent plants, will naturally be less flammable. With that being said, studies in southern African countries, in particular, show that the wildfire probability increases with an increase in the NDVI, with the highest fire probability being where it ranges between (0.5-0.9) (Chingono & Mbohwa, 2015; Mpakairi *et al.*, 2018).

Warmer temperatures facilitate drier conditions through evaporation. This is indicative of fire-prone areas that have less available moisture, such as savannahs and Mediterranean climates.

Various studies concur that temperatures of between 20˚C and 27˚C have the highest probability for wildfires (Mpakairi *et al.*, 2018).

Similarly, precipitation determines the amount of available moisture. This, in turn, influences the dryness of any given area, where a balance between a variable precipitation and the dry season increases the plant growth rate, which facilitates the available dry biomass during the dry season (Archibald, Roy, Wilgen, *et al.*, 2008). Archibald *et al*. (2008) showed that the burned areas decrease where the tree cover is greater than 40%, and tree cover that exceeds 40% only occurs in areas that receive rainfall of more than 800 mm. This suggests that the perfect precipitation threshold that is necessary for fire to occur ranges between 500 mm and 700 mm. Elevation influences the spread of fires in a linear fashion, where a higher frequency of fire is related to a higher elevation, which often influences the moisture conditions and the resultant varying vegetation (Kitzberger, Veblen & Mermoz, 2005; Maingi & Henry, 2007). It is important to note that the aforementioned environmental factors are all independent variables that act in a flammable environment, whilst there are also other factors that influence fires, most of which are dependent and act to intensify a fire, rather than to initiate it.

2.3 Current Fire Control Mechanisms and their Effectiveness

To date, many studies have discussed the importance of fire for biodiversity (Bond & Keeley, 2005; van Wilgen *et al*., 2010; van Wilgen *et al*., 1994; van Wilgen & Richardson, 1985), and most of them concur that fire is necessary to promote species richness and to eradicate alien invasive species. Unmanaged fires can, however, have an adverse effect on the environment, economy and human lives, as shown by Dube (2013). Thus, to prevent fires and to ensure that they promote species richness, various management techniques are used to control the fire regime.

These methods mainly include prescribed burns, firebreaks and slash-and-burn techniques. Prescribed burns are fires that are initiated in a controlled environment, usually by trained personnel, with the intention of maintaining the natural fire regime of an area and protecting the richness of the indigenous species. Firebreaks usually consist of a physical break that acts as a boundary between the vegetation stands, with the intention of suppressing the spread of fire from one sector to the next. The slash-and-burn technique involves the logging of trees, leaving the material to dry and then burning the said material as a means of increasing the fertility of the soil and eliminating invasive species. While these techniques are carried out with good intentions, they can have an adverse effect on the environment when the targeted areas are inappropriate for proper management. These effects include but are not limited to, soil erosion, soil contamination, air pollution, sedimentation and turbidity (Crutzen & Andreae, 1990; Rosenfeld, 1999; Swanson, 1981).

Contrary to popular belief, a study by van Wilgen *et al*. (2010) showed that the probability of fires in Fynbos biomes remain largely unaffected by the post-fire age (time since last fire). Furthermore, the study showed that only a small area was burned under prescribed burns and that most fires occurred as wildfires, which suggests that prescribed burning in these environments will not reduce the risk of wildfires. Van Wilgen *et al*. (1994) suggested that, instead of having prescribed burning, a better option would be to allow wildfires to burn freely in delineated areas, based on an assessment of the following four characteristics: (a) where fires should not occur; (b) where fires are allowed to burn; (c) where vegetation has reached complete maturity and/or are adding detritus; and lastly, (d) where prescribed burns are essential for wildfire control. Thus, there is a continuous need for remotely-sensed data and specifically for models that allow for the prediction and characterization of fire-prone areas, based on the environmental conditions that facilitate them. Currently, a vast majority of models exist that cater for the spatial distribution of fires on a global scale, and there are also some that cater for hotspot analyses on a regional scale (Chingono & Mbohwa, 2015; Gonzalez *et al*., 2006; Liu *et al*., 2010; Moritz *et al*., 2012; Mpakairi *et al*., 2018).

2.4 Traditional and Conventional Remotely Sensed Fire Monitoring Systems

Throughout history, many fire-monitoring systems have been developed to detect fires, with variable success. These methods can be divided into two main categories, namely, long-range and short-range remote-sensing devices. The most successful of these developed systems can be subdivided further into three main categories, namely, satellite-borne systems, airborne systems and fixed-ground platforms (San-Miguel-Ayanz *et al.*, 2005). These three remote-sensing systems detect fires in the following way: (a) by using the difference in temperature with respect to the normal temperature conditions; (b) by using the difference in temperature with respect to the background temperature conditions; and (c) by detecting the smoke plume. These methods commonly use the mid-infrared and thermal bands to allow for the detection of fires. According to Kennedy *et al.* (1994), the mid-infrared and thermal bands are optimal for the detection of fires as they occur far from the peak of the earth's solar radiation, which is measured at 0.5 μm – 9.7 μm and 8 μm – 12 μm, respectively, for the aforementioned bands.

Fixed-ground platforms are operated either under human surveillance, or autonomously, and they are advantageous in that they allow for the continuous surveillance of large areas with mid-infrared and thermal cameras. The validity of fixed-ground platforms can be influenced by different factors, for example, the solar effects, heated objects, artificial lights and combustion points from human activities, and these may cause the false detection of fires.

Airborne systems, which are similar to fixed-ground systems, are also operated mainly under human surveillance. The operation of these systems is based on smoke plume detection by the humans and they may inherently be influenced because of this, as detection can only occur once a fire has occurred. Although airborne systems are reactive, as opposed to proactive, in their response, they are still advantageous as they can assist with the ongoing fire-fighting once a fire has been detected. Airborne systems also make use of the mid-infrared, thermal and visual portions of the electromagnetic spectrum to detect fires, by using algorithms; however, similar to fixed-ground platforms, there are different background factors that can produce a false alarm.

Satellite systems are by far the most advantageous systems, due to their low operational costs and their high spatio-temporal resolution, and they are widely used for fire monitoring (Table 2.1). They also provide greater information about the fires, as opposed to other systems, by including fire severity through indices such as Normalized Burned Ratio (NBR) (Escuin *et al.*, 2008). While they can still suffer from detection errors for various reasons, such as the fire size and/or fire temperature, these can be corrected more effectively not only through algorithms, but also through the exploitation of other bands, to remove cloud masking. Thus, image processing is also cost-effective and can be time-efficient when done through geospatial data analytical platforms.

Table 2.1 Satellite sensors and their specifications

Sensor name [launch date]	Bands (spectral reflectance)	Spatial Resolution	Temporal Resolution	Examples
Moderate Resolution Imaging Spectroradiometer MODIS (MOD14A1) [November 2000]	• 16 Visible near-infrared bands • 3 Shortwave-infrared bands • 17 Thermal bands	250 m 500 m 1000 m	1 day	• (Giglio *et al*., 2008) • (Justice, Giglio, Korontzi, *et al*., 2002) • (Chand, Badarinath, Murthy, *et al*., 2007) • (MODIS, Moderate Resolution Imaging Spectroradiometer,2019)
Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) [2000 - April 2008]	• 4 Visible near-infrared bands • 6 Shortwave-infrared bands • 5 Thermal bands	30 m	Does not collect continuous data due to hardware and data issues	• (Yamaguchi, Kahle, Tsu, *et al*., 1998) • (Giglio *et al*., 2008)
LANDSAT-8 OLI [11 February 2013]	• 5 Visible bands • 1 Near-infrared bands • 1 Band for Cirrus cloud detection • 2 Shortwave infrared bands • 2 Thermal bands	30 m	16 days	• (Schroeder, Oliva, Giglio, *et al*., 2016)

Visible Infrared Imaging Radiometer Suite (VIIRS) [October 28, 2011]	• 6 Visible bands • 3 Near-infrared bands • 5 Shortwave-infrared bands • 3 Mid-infrared bands • 4 Longwave-infrared bands • 1 day-night band	375 m	12 hour	• (Schroeder, Oliva, Giglio, *et al.*, 2014)
Defense Meteorological Program Operational Line-Scan System (DMSP-OLI) [1992-2013]	• Visible near-infrared (0.58-0.91) • Thermal (10.5-12.5)	0.56 km Fine resolution 2.7 km-smooth resolution	12 hour	• (Chand *et al.*, 2007) • (Huang, Yang, Gao, *et al.*, 2014)
Advanced Very High Resolution Radiometer AVHRR/3 (NOAA-15 THROUGH 18) [since 1998]	• Red (0.58-0.68) • Near-infrared (0.73-0.98) • Mid-infrared (1.58-1.64) • High temp thermal (3.55-.3.93) • Thermal (10.3 -11.3) • Thermal (11.5-12.5)	1.1 km	1 day	• (Giglio *et al.*, 1999)

Satellite systems that are used for fire monitoring, extract information from the visual, mid-infrared, shortwave-infrared and thermal portions of the electromagnetic spectrum. Most active fire detection algorithms use brightness temperatures as a means of detecting active fires via temperature thresholds. These thresholds are divided into fire temperature and/or background temperature, and examples of these can be seen in the Moderate Resolution Imaging Spectroradiometer (MODIS) and Visible Infrared Imaging Radiometer Suite (VIIRS) systems. MODIS, for instance, determines absolute fires if the temperatures are above a given threshold, and it determines weaker fires (that are not above the absolute threshold) based on the thermal emissions of the surrounding pixels i.e. background temperatures (Justice *et al.*, 2002). Furthermore, the red and near-infrared channels are used to remove 'false detection' if the fire pixels have a reflectance above 30% in these channels. Landsat 8 OLI uses an active fire detection algorithm that is split into day and night modules and that are driven by the shortwave infrared channel. Thus, during the day, the NIR channel is used alongside the SWIR channel to remove the reflective solar component that may cause 'false alarms', as it is unresponsive to fire-affected pixels, but it correlates well with the SWIR channels over fire-free surfaces (Schroeder *et al.*, 2016). Fire detection algorithms function like algorithms that make use of thermal infrared channels, in that they use SWIR radiance to detect the fire-affected pixels, based on their background values. This section does not focus on the algorithms of the other sensors mentioned above, namely The Defense Meterological Program Operational Line-Scan System (DMSP-OLS) and The Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER), due to the limitations that are associated with them. DMSP-OLS, for example, can only provide valuable night-time data due to its available spectral channels in the visual and thermal portion (Chand *et al.*, 2007). ASTER, on the other hand, is no longer fully operational and cannot provide the continuous data that is required for active fire detection (Yamaguchi *et al.*, 1998). Therefore, DMSP-OLS and ASTER are frequently used alongside other sensors, or as validation tools.

Thus, when reflecting upon which sensors are the most efficient, it is important to consider the factors listed in Table 2.1. Temporal resolution refers to the frequency at which any satellite passes and collects data from a geographical location on earth during its orbit. Therefore, for successful active fire monitoring, one will require a high temporal resolution that will preferably allow for the diurnal cycles of data acquisition, which allows for a more rapid response to fire detection. Spatial resolution refers to the number of pixels in a given sample and directly affects the amount of detail perceived and thus the quality of the data that can be retrieved. For example, the lower the spatial resolution, the greater the size and temperature of the fire that is needed, for detection to occur, thus excluding the occurrence of smaller fires. Spatial resolution also influences the environmental factors that can be included in a model, based on the physical size of the phenomenon, e.g. the vegetation type. Spectral reflectance influences the intensity of the fire that can be captured by the sensor, or more specifically, the saturation of the band, thus error propagation is dependent on the number of channels available and the range of spectral reflectance for the said channels. For example, a false alarm may occur if the temperature of a given area is high enough to saturate the bands. However, if the temperature of the fire is too low for the active fire algorithm to detect, smaller fires may be excluded, based on the spectral threshold. In the MODIS active fire algorithm, for example, fires have to meet the following conditions for absolute fire detection: T4>360K (330K at night) and T4>330K (315 K at night) and T4-T11 >25K (10K at night). Therefore, most studies on fire detection and fire severity exploit these bands in order to extract information from them about the said fires (Chingono & Mbohwa, 2015; Escuin *et al.*, 2008; Gonzalez *et al.*, 2006; Liu *et al*., 2010; Moritz *et al.*, 2012; Mpakairi *et al*., 2018).

Table 2.2 Current studies that try to predict fire occurrence, based on various modelling techniques

Application	Scale of application	Data	Variables incorporated into model	Techniques	Results	Reference
Distribution of wildland fires and possible hotspots	North-Western Zimbabwe/ Kavango-Zambezi transfrontier conservation areas (~71479 km^2)	• MODIS wildland fire point data • SPOT 10-day, 1 km NDVI data • human population data was obtained from www.worldpop.org.uk • ASTER • Mean air temperature data was obtained from: http://biogeo.uc.davis.edu/data	• NDVI • Elevation • Human population density • Mean air temperature	• Maximum entropy was used to model wildland fire probability • Getis–ord was used for hotspot analysis • AUC was used to determine accuracy of model	• MaxEnt was successful in predicting potential distribution of wildland fire AUC = 0.78 • Percentage contribution of Mean annual temperature (MAT) = 61.4% ,Elevation= 26.3%,Human population density = 9.8% NDVI = 2.5% • The MaxEnt model showed that fire probability increased with an increase in MAT and NDVI but population density had no	(Mpakairi *et al.*, 2018)

					effect	
Fire probability for forest stands	North-East Spain/ Catalonia (~0.2 km^2)	Fire reports were compared with images from (LANDSAT,SPOT, CASI and orthophotos)	• Elevation (*Ele*) • Basal-area-weighted mean diameter (D_g) • 12-year probability of fire occurring in a given stand (P_{fire}) • Total basal area (*G*) • Portion of hardwood species of the number of trees (P_{hard}) • standard deviation of the breast height diameters of trees (*SD*) • Relative	• Logistical distribution model • Logistic model was fitted to modelling data by using a binary logistic procedure in SPSS	• Variables used in equation were found to be the best fit as they gave a NagelKerke R squared of 0.181 • Furthermore, the variables included in the model were proven significant based on the Wald test (p<0.5) • The results showed that there was a higher probability of fires at lower *Ele*, where *G* and *SD* are	(Gonzalez *et al.*, 2006)

			variability of tree diameter (SD/D_g+0.01)		higher • Stands with higher values of P_{hard} and D_g have a lower probability of fire	
The effect of climate change on the geographical distribution of fires	The entire terrestrial surface of the world with the exception of Antarctica and small islands	• MODIS collection 5 CMG • European space agency's advanced and along track scanning radiometer	• Mean annual precipitation • Precipitation of driest month • Temperature seasonality • Mean temperature of the wettest month • Mean annual precipitation of the warmest month	• Winnowing was performed to remove variables that were highly correlated • The 'climate+baseline NPP' model was used to model the global distribution of biomass • The 'climate-only' model was used model future distributions of fire • MaxEnt was used to model fires • The fire models were evaluated respectively by 16 GCMs which was validated	• Both models predicted low fire potential where biomass is sparse • In the "climate+ Baseline NPP" model , NPP contributed 36% is as such the most important variable • Whereas in the 'Climate only' model, mean temperature of warmest month and annual precipitation had the	(Moritz *et al.*, 2012)

					using the AUC technique	biggest contribution. • The AUC values were 0.93 and 0.92 for 'Climate+ Baseline NPP' and "Climate only" respectively when adjusted for prevalence • 37.8% of the world show model agreement for the 2010-2039 period, whilst 54.1% show low agreement. • 61.9% of the world show model agreement for increases in the 2077-2099 period, with 20.1% showing agreement for decreases and 17.9% showing no agreement	

					with the model	
Global trends of fires based on changing climate	The terrestrial surface of the Earth from (90 N- 90 S) and (180 E – 120 W)	• Climate Research Unit (CRU) Global climate dataset • Four general circulation models (HadCM3,CGCM2,CSIRO and NIES)	• Moisture deficiency of current and previous day • KBDI increment • Daily maximum temperature at 2m above the ground • Daily precipitation • Mean annual rainfall • A time increment set equal to one day	• The Keetch-Byram Drought Index (KBDI) was used to model and classify fire trends • A sensitivity analyses was used to examine the dependence of fire potential on changes in meteorological variables, emission scenarios, choice of GCMs and to determine the importance of precipitation and temperature • GCMs simulation output was used for four emission scenarios (A1,A2,B1,B2) • Present and future KBDI values were determined using	• Regions with the most significant future increase in potential are synonymous with those with the greatest fire potential at present with the exception of Southern Europe and Northern Africa. • KBDI is function of increased temp and decreased precipitation • Large KBDI increases are found in areas where temperature increases by at least 4ºC and where precipitation decreases by	(Liu *et al.*, 2010)

				the observed and simulated GCM meteorological data, respectively	0.25mm/day • A1 and A2 scenarios produce the largest KBDI values globally with B1 and B2 being less pronounced • NIES and HadCM3 produce the largest KBDI values out of the 4 GCMs used in the study	

Examination of the drivers of burnt area in Southern Africa	100 km × 100 km sampling window for 899 sample points	• MODIS burned area product • Southern Africa Fire Network • MODIS active fire product • FAO livestock distribution dataset • Land tenure maps for South Africa, Namibia, Botswana, and Zimbabwe were combined with the World Protected Areas map • The Global Land Cover 2000 Africa product • The monthly Tropical Rainfall Measuring Mission (TRMM) best-estimate precipitation rate product • Shuttle Radar Topography Mission (SRTM) elevation data • Global Hydrology Resource Centre	• Mean annual rainfall (previous 2 years) • Soil fertility • Tree cover • Grazing • Length of dry season • Topographical roughness • Road density • Fraction of transformed land • Mean lightning strikes over the burn season • Population density • Percentage communal land	• Statistics of each dataset was defined by a fixed 100 km × 100 km sampling window • Mean values were used to determine all the independent variables with an exception to grazing and human population density. • Grazing and human population were determined using median • A random forest regression tree was used to investigate the drivers and their relationship with burnt area and was created using the splitting procedure. • The influence of a variable was tested by the	• Both the predictive capability of the random forest regression tree as well as the number of nodes decreased with an increase in window size with the latter being more pronounced • r^2 for the predicted values from the random forest and observed burned area was 0.62	(Archibald *et al.*, 2008)

				difference in mean square error between a tested sample and randomly permuted test sample.		

Most studies incorporate different variables into their respective models, based on the spatial scale of their study area, the type of model used or the physical template of their study area. For example, the difference between the variables described in Liu *et al.* (2010) and Moritz *et al*. (2012) (Table 2.2) is rooted in the different models that they used to determine the fire trends; for example, Liu *et al*. (2010) used KBDI and Moritz *et al.* (2012) used MaxEnt modelling. Furthermore, a close look at the differences between the variables selected for the global models and the regional scale models mentioned above highlights the fact that the spatial scale influences the variables selected for each of the models. More specifically, the variables selected for the global model have a coarser spatial scale, compared to the regional model, which prefers more locally-factored variables at a much finer spatial scale (Archibald *et al.*, 2008; Gonzalez *et al.*, 2006; Mpakairi *et al.*, 2018). The role of the physical template in the decision of which variables to select can also be seen in the study by Gonzalez *et al*. (2006), which catered specifically for forest stands, as opposed to a more climate-specific model (Table 2.2).

There is, however, clear concurrence between the majority of the reviewed studies in Table 2.2, which determined that the elevation, NDVI, temperature and precipitation were among the most important, although not the only, contributors to the fire potential, whether it was on a regional or global scale. In Mpakairi *et al*. (2018) and Archibald *et al.* (2008), population density had very little effect on the occurrence of wildfires. Archibald *et al*. (2008) showed that the population density had a negative effect on burnt area occurrence, and more specifically, where the population density decreased, so the size of the wildfires would also increase. Mpakairi *et al*. (2018) found no change in the occurrence of wildfires, based on the effect of population density.

The results in Moritz *et al*. (2012) and Liu *et al.* (2010) differed significantly, even though both studies aimed to understand the present and future distribution of fires, based on the effects of climate change. While some of the aforementioned factors could potentially drive the differences between these models, this was not actively determined and thus it remains speculation. It does, however, become clear that models that cater for 'climate-specific' functions or variables, with the exception of elevation, tend to show a significant influence on the occurrence and distribution of wildfires. Thus, the influence of climatic differences is impossible to ignore when one considers, for example, that the drying-rates differ across climates, which is ultimately a function of precipitation (Liu *et al.*, 2010). Hence, the error propagation would be greater if a model designed for a different climate is used, as the conditions are not climate-specific.

Ultimately, there is a need for climate-specific models when trying to develop a remote-sensing framework for fire monitoring that relies on specific climatic variable thresholds, in order to achieve greater model success.

2.5 Frequently used mathematical models for fire description

Table 2.3 Examples of frequently-used models for fire management

Model Type	Advantages	Limitations	References
Species distribution models	• Certain SDM requires presence-only data along with associated features to model reality • It can utilize both continuous and categorical data and model interactions between different variables • Algorithms exist that allow for the optimal determination of maximum entropy • MaxEnt modelling is generative, rather than discriminative, which can prove advantageous when the amount of training data is limited	• Not much is known about its general use and there are limited methods for error propagation • It uses exponential modelling for probabilities which means that it can return values for environmental conditions that are larger than what actually occurs in the study area. • MaxEnt is not available in standard statistical packages and thus special software is required for its use. • Some SDM require presence and absence data to operate • Does not predict well with smaller sample sizes	(Phillips, Anderson & Schapire, 2006)
Decision Tree Models	• Allows for the use of qualitative and quantitative data • Extensive methods by which to do model evaluation • Able to explain variation within original dataset • Semi-qualitative data can be used when full qualitative dataset is unavailable • They include non-additive behaviour and	• The implication of qualitative data requires a great understanding • Greater error propagation when trying to extrapolate model • Mainly used to determine burnt areas, as opposed to being used for predictive modelling • Mainly used in forest areas and not suitable for other areas (i.e shorter vegetation types)	(McKenzie *et al.*, 2000)

	complex interaction between variables • Can model large datasets with quick feedback		
Dynamic Global Vegetation Model (DGVM) and Global Climate Model (GCM)	• Allows for the projection of potential future distributions of natural phenomena, such as fire, based on scenarios (i.e. climate changes, emissions) • Allows for the projection of continuous or very large-scale datasets	• Coarse scale resolution can limit available data sets • Model valuation tends to be difficult at a global scale due to lack of data at certain times, long time scales required and the effects of human activities • Dependence of vegetation on bioclimatic constraints	(Bond & Keeley, 2005) (Moritz *et al.*, 2012) (Liu *et al.*, 2010)

Table 2.3 represents examples of the models that are frequently used to predict fire distribution and potential. GCM's and DGVMs are reviewed together in this section, as they are analogous and share similar advantages and disadvantages, but not similar functions. DGVM's are models that 'grow' plants, based on a set of physical and biological constraints that are often represented mathematically (Bond & Keeley, 2005). The main function of the model is to predict the projected change in the vegetation/potential biomass, based on global climate change, and it can therefore simulate these changes across large temporal and spatial scales. DGVMs are primarily ecological models that focus specifically on vegetation dynamics, such as photosynthesis, respiration, surface energy fluxes and carbon and nutrient allocation (Quillet, Peng & Garneau, 2010). However, they have since been used for fire monitoring due to the dynamics shared between fire and vegetation. DGVMs are also used to facilitate the vegetation component of GCMs and they are often coupled in studies (Bonan, Levis, Sitch, *et al.*, 2003; Kucharik, Foley, Délire, *et al.*, 2000; Sitch, Smith, Prentice, *et al.*, 2003). GCMs, likewise, aim to calculate climate behaviour, based on various physical laws, through mathematical equations that focus specifically on fluid dynamics and thermodynamics. Thus, inherently, GCMs are used to understand climate change, or else they are used for weather forecasting. They have also recently been widely used to determine the future and present distribution of fires, based on the changing climate. These aforementioned GCMs focus specifically on precipitation, temperature and potential biomass dynamics, in order to determine the climates that are more fire-prone. Multiple versions of GCMs and DGVM exist that all serve similar functions. A few examples of the DGVMs are LPJ, IBIS, MC1, HYBRID, SDGVM, SEIB-DGVM, TRIFFID, VECODE, and CLM-DVGM, and a few examples of the GCMs are CSIRO, HadCM3, CGCM2, NIES, SPEEDO and MIROC-ESM.

Decision tree-based models were developed as an alternative to the more linear regression models that could not handle complex relationships. Tree-based models are non-parametric statistical models that fit data into increasingly homogenous sub-sets (Pham, Jaafari, Avand, *et al.*, 2020). They are primarily used as exploratory techniques to reveal the differences and correlations in data, in order to clarify the factors that influence the phenomena being modelled. Regression models, in particular, consist of stochastically trained data sub-sets that allow for estimates that are more independent by using binary recursive portioning (Felicísimo, Cuartero, Remondo, *et al.*, 2013; Pashynska, Snytyuk, Putrenko, *et al.*, 2016). While it is possible to use decision trees for predictive modelling, this only works when the predictors in the new database fall within the range of the modelling database; thus, they do not allow for an efficient predictive fire monitoring system. Examples of tree-based models can be seen in support vector machines, multiple regression trees, random forest trees, classification and regression trees and partial least squares regression.

Species Distribution Models (SDMs) are used to model the geographical distribution of species by using numerical methods that combine the observed number of species with the environmental estimates (Phillips *et al.*, 2006). Examples of SDMs are GBM, MAR-INT, MaxEnt, Bioclim, OM-GARP, LIVES, GLM, DOMAIN, and DK-GARP. They work specifically by means of a type of binary classification with two types of common model outputs (Liu *et al.*, 2009), namely: (a) classification results are typically seen as sites that are classified as part of the distribution of the species or outside their distribution; and (b) the results are continuous and given as a probability of being part of a species distribution. With this in mind, most SDMs require two training samples to function properly, namely, presence and absence data. Thus, not all SDMs are widely used for fire modelling, with the exception of MaxEnt. The intention of MaxEnt is to allow for predictive modelling of environment requirements and geographical distributions under conditions where presence-only data are available. MaxEnt functions by determining an estimate for the probability distribution of a given target by determining the probability distribution of maximum entropy, based on the set of constraints being the incomplete information of absence data (Phillips *et al.*, 2006; Phillips & Dudík, 2008). In this case, the information given by MaxEnt modelling is represented as 'features', where each 'feature' should represent a value that matches its empirical values. Essentially, each feature should closely relate to the average of all the sample points taken for the said feature. Features refer to various factors, such as climatic variables, elevation, soil moisture, the species type and other environmental variables and functions. Thus, when MaxEnt is used to model presence-only data, the pixels of the study area determine the area where the MaxEnt probability distribution is possible and the pixels with occurrence data represent the sample points.

2.6 Conclusion

In conclusion, fire is needed for ecological diversification and occurs under a natural fire regime because of climatic conditions and available fuel load. Thus, if this is not understood properly, fire management strategies will be rendered useless and wild fires will remain the most frequent form of fire occurrence. Current fire management strategies rely mainly on measures, such as prescribed burns, firebreaks and slash-and-burn techniques, that require an understanding of the target area to ensure that the right approach is used, based on the localized conditions. The most common form of fire monitoring that is used to assist in fire management strategies is remote sensing, as it can provide for early detection and/or it has predictive capabilities. However, the limitations of ground-based and airborne remote-sensing techniques are that they are either too expensive or inefficient, as they lack the required spatial and temporal resolution necessary for fire monitoring. Current studies for fire monitoring therefore focus mostly on satellite-based techniques, which increase the spatial and temporal resolution for fire monitoring and reduce the data acquisition costs. The use of models alongside satellite-based monitoring facilitates a better understanding of the conditions that are required for fires to occur and can be used to predict which areas are in need of fire management. Thus, a remotely-sensed framework for fire monitoring will assist with the fire management strategies and it will improve the efficiency of such strategies.

CHAPTER 3: MATERIALS AND METHODS

3.1 Study Area

This study was conducted in the Western Cape Province of South Africa. The province provides an interesting template for developing a fire-monitoring framework by using multi-source spatially-explicit datasets. The area experiences a Mediterranean climate that is characterized by warm, dry summers and cool, moist winters, with indigenous vegetation that is naturally fire-prone and adapted to fire (Midgley, Hannah, Millar, *et al.*, 2003). The Western Cape is located at 33.2278˚ S latitude and 21.8569˚ E longitude and it covers a total area of 129,462 km^2 (Figure 1). The average summer temperature ranges between 15˚C and 27˚C, whereas the average winter temperatures range from 5˚C to 22˚C (Botai, Botai, Wit, *et al.*, 2017). The average annual rainfall for the Western Cape Province varies greatly with the altitude. Mountainous regions can receive up to 3000 mm/yr, whilst lower-altitude regions receive progressively less, and it can be as low as ≤ 200 mm (Govender & Grab, 2019). Geologically, the Western Cape falls under the Cape Fold Belt, which belongs to the Cape Super group. The Cape Fold Belt is comprised mainly of sandstone (from the Peninsula formation) and shale (from the Bokkeveld group). The Western Cape is characterized mainly by Fynbos woody shrubland vegetation, and it has the largest diversity of this vegetation in the whole of South Africa (Muncina & Rutherford, 2006). The Fynbos biome is highly susceptible to invasion by alien plants and is thus under great threat. The diversity of the Fynbos species in the Western Cape is maintained by means of prescribed burning. However, prescribed burning does not necessarily reduce the fuel load, which results in the occurrence of wildfires (van Wilgen *et al*, 2010). The invasion of Fynbos by alien vegetation complicates the prescribed burning and fire management.

Figure 3.1: Map of the Western Cape and district municipalities situated in South Africa

3.2 Satellite Data Acquisition

These data were sourced from the Food and Agriculture Organization of the United Nations (FAO), the Consortium for Spatial Information (CGIAR CSI), the National Aeronautics and Space Administration Fire Information for the Resource Management System (NASA FIRMS), the Wind Atlas for South Africa (WASA), and the Level-1 and Atmosphere Archive & Distribution System Distributed Active Archive Center at the Goddard Space Flight Center (LAADS DAAC). Seven climatic variables were selected to represent the conditions needed to deem an area as having a high potential of fire occurrence (Table 3.1). Remotely sensed fire occurrence points from across the province were used as presence points within Maxent. The selected climatic variables include net primary productivity, precipitation, land surface temperature, aboveground biomass, elevation and wind speed. The data were collected over a 10-year period, more specifically from 2009-2019. The temporal resolution of the spatial data was in the dekadel form, with the exception of three variables, namely, the wind speed, the land surface temperature and aboveground biomass (Table 3.2). The wind speed and aboveground biomass was only found as annual data, whilst the land surface temperature was only found over an 8-day period. The spatial resolution of the climatic variables were as follows: net primary productivity (250 m), aboveground biomass (250 m), precipitation (5 km), land surface temperature (1 km), elevation (90 m) and fire occurrence points (1 km) (Table 3.2). While these conditions are by no means the only conditions that contribute to an area being considered a 'hotspot', they have been widely shown to be the fundamental climatic and fuel characteristics that influence fire occurrence.

3.3 Description of the Environmental Variables included for Fire Occurrence Modelling

Precipitation influences the fuel load moisture and the moisture that is available to the vegetation. Wet conditions will decrease the likelihood of fire but available precipitation during the growth stage of plants can significantly increase the fire probability during the summer season (Koutsias *et al.*, 2013, Xystrakis *et al.*, 2014). Like precipitation, the land surface temperature was used as it also influences the available moisture and thus the overall aridity of an area. Increased land surface temperatures can influence the evaporation rate and lead to moisture-limited vegetation and fuel loads, thus increasing the flammability

(Flannigan *et al.*, 2016). Aboveground biomass (AGBP) was used as a measure of the available fuel load and it therefore influences fuel continuity, as areas where enough fuel has accumulated are fire-ready and thus more likely to burn. It has been proved that elevation has an effect on the amount of evapotranspiration that takes places and therefore also on the variability of the plant ecotypes (Kitzberger *et al*., 2005, Maingi & Henry, 2007). Thus, elevation was used in the model due to its influence on the moisture conditions, owing to the fact that the Western Cape experiences a great variability in elevation. Net primary productivity was used as a proxy for NDVI to draw an inference to the moisture that is available to plants. Studies have shown that the Net Primary Productivity can be used as an indicator of drought occurrence (Zhao & Running, 2010) and to determine whether plants are under drought stress and whether their flammability has been increased. However, the wind speed data were too sparse to allow for the determination of its exact effect on fire occurrence. It was used more as a proxy to determine whether it could have an effect, based on the model results, for future reference. Wind speed has been described as having an influence on the spread of fires, as opposed to actually starting a fire (Cheney, Gould & Catchpole, 1993; Cheney & Sullivan, 2008; Sharples, McRae, Weber, *et al.*, 2009). Thus, the inclusion of wind speed in the model is exploratory and it is used purely to determine whether it can be used in future frameworks to determine where fire may occur.

Table 3.1 Online data sources used to collect environmental variables

Platform	Descriptions of spatial data	Source
FAO	• Net primary productivity • Precipitation • Aboveground biomass	[© FAO] [Food and Agriculture Organisation of the United Nations] [https://wapor.apps.fao.org/catalog/1] [Net primary productivity, precipitation, Total Biomass Production]
NASA FIRMS	• Fire occurrences	MODIS Collection 6 NRT Hotspot / Active Fire Detections MCD14DL. Available online [https://earthdata.nasa.gov/firms]. doi: 10.5067/FIRMS/MODIS/MCD14DL.NRT.006
LAADS DAAC	• Land surface temperature	Zhengming Wan - University of California Santa Barbara, Simon Hook, Glynn Hulley - JPL and MODAPS SIPS - NASA. (2015). MOD11A2 MODIS/Terra Land Surface Temperature and the Emissivity 8-Day L3 Global 1km SIN Grid. NASA LP DAAC.

		http://doi.org/10.5067/MODIS/MOD11A2.006
CGIAR CSI	• Digital elevation model	Jarvis, A., H.I. Reuter, A. Nelson, E. Guevara, 2008, Hole-filled SRTM for the globe Version 4, available from the CGIAR-CSI SRTM 90m Database (http://srtm.csi.cgiar.org).
WASA	• Maximum and minimum wind speed data	Wind Atlas for South Africa (WASA) SANEDI.2010. Available online [http://www.wasaproject.info/index.html]

Table 3.2 The unprocessed cell sizes and processing extents of the data

Climatic variable	Temporal resolution	Cell size (degrees)
Aboveground biomass	Annual	X:0.002 Y:0.002
Precipitation	Dekadal	X: 0.05 Y: 0.05
Net primary productivity	Dekadal	X:0.002 Y:0.002
Land surface temperature	8-day period	X: 926.625 Y: 926.625
Elevation (after mosaic stitch)	N/A	X:0.001 Y:0.001
Wind speed	Annual	N/A

3.4 Image Processing

The image processing consisted of transforming the climatic variables into a homogenous state, so that all the raster files have the same cell size and processing extent. The relevant software used to perform the pre-processing were ArcGIS version 10.8 and Quantum GIS version 3.4.9. The land surface temperature data processed within QGIS used Python to convert the HDF file type into TIF, as well as to convert the spatial coordinate reference system to GCS-WGS-1984. The digital elevation model images required a process known as 'mosaic to new raster' which can be found under the data-management tools within ArcGIS and which is used to combine separate raster images into one whole image. This was required in order to create and extract one continuous elevation raster image of the Western Cape.

The wind speed data was interpolated by using the circular kriging method. More specifically, circular kriging estimates the circular spatial data, based on a model of circular-spatial correlation. Circular correlation is defined as the mean cosine of the angle between random components of directions versus the distance between observation locations (Morphet, 2009). This means that the direction will become increasingly similar as the distance between the observations points decreases. Based on the physical characteristics of wind, circular kriging therefore allows for a more realistic interpolation of wind speed dynamics.

The spatial analyst tool and the conversion tool in a GIS environment were used in further data processing and analytics. The spatial analyst tool was used to perform the 'extract by mask', which was used to extract the area of the Western Cape region from the respective environmental rasters which included all of Africa. A GIS layer of the Western Cape was used to change the processing extent of the precipitation raster files. This layer was used to fit the processing extent and the cell size of all other climatic GIS layers to ensure uniformity across all data, and this was all done via the feature 'extract by mask', which was used to maintain the values associated with the unprocessed pixel. This process was used only to achieve uniformity in the cell sizes and in the processing extent of the generated GIS files associated with the environmental variables. The precipitation files were used as the 'mask feature'. These had the greatest cell sizes and thus all the cell sizes of remaining environmental variables (net primary productivity, land surface temperature, elevation and above ground biomass) were changed to match its 5 km spatial extent. The reason for this is that environmental data in GIS can only be as accurate as the least accurate layer (the greatest cell size). Thus, transforming the data to match the smallest cell size available would limit computational processing, but it would also not increase the amount of detail obtained from the said data. The cell size of the processed data was 0.05 decimal degrees, whilst the processing extent of the data was as follows: Xmin, Ymin (17.75,-34.85), Xmax, and Ymax (24.25,-30.40). The processed raster files were transformed into an ascii file format, which is a readable file format in R studio. This was done by using the 'raster to ascii' function under the conversion GIS tools.

3.5 The Implementation of K-fold Cross-validation Techniques and the Removal of Sampling Bias for Maxent Calibration

The R-studio software was used to create a bias file and to run the ENMeval package. The creation of a bias file has proved to be useful in species distribution models and it is used predominantly to remove sampling bias that may occur in areas that are 'easier' to sample (Kramer-Schadt, Niedballa, Pilgrim, *et al.*, 2013). ENMeval is an R package that allows for the creation of data-sets for K-fold cross-validation, the construction of candidate models using MaxEnt and user-defined settings and the use of a multitude of evaluation methods to aid in model setting selection (Muscarella *et al.*, 2014). In this study, the ENMeval package was used to do the following: (a) to run a K-fold cross validation process; and (b) to assist with the selection of model settings. ENMeval uses five metrics for evaluation that help to describe the best settings for the model, namely: AUC_{TEST}, AUC_{DIFF}, OR_{MTP} ('Minimun Training Presence' omission rate), OR_{1O} (10% training omission rate) and AICc (an Akaike Information Criterion corrected for small sample sizes). In this chapter, AIC_c will be described, as it ultimately influences which MaxEnt settings were chosen in this study, and it has also been shown to perform better than the metrics AUC_{TEST} and AUC_{DIFF} (Warren & Seifert, 2011). However, a description, of each of the other metrics mentioned can be found in Muscarella *et al.* (2014). To summarize, the K=10 cross-validation method, the regularization multiplier, as well as the Delta AICc, were run and determined under ENMeval's primary function 'ENMevaluate'. Cross-validation is a process that is used to estimate prediction errors in fitted models. In particular, K=5 and K=10 fold cross-validation models are preferred over other K-fold and the leave-one-out cross-validation methods, as the former allow for a more efficient computational process when the datasets are large (Fushiki, 2011; Rodríguez, Pérez & Lozano, 2010). It is worth noting, however, that the leave-one-out method was proven to have the least bias, even though it was the most computationally demanding (Rodríguez *et al.*, 2010).

The regularization multiplier is a parameter that helps to smooth the model by limiting the potential of over-complexity and over-fitting; this is done by controlling the strength of the chosen feature classes that build the model. An in-depth description of how the regularization multiplier affects the model can be found in Merow *et al.*(2013), where it is shown that it is basically an increase in sample size that results in a decrease in the regularization effect. Therefore, a greater regularization multiplier results in a greater penalty and thus an overall ‘smoother’ model.

As for Δ_i, this was developed under the premise that the individual values of AIC are uninterpretable due to the fact AIC is influenced by its sample size, as it contains arbitrary constants, and hence there was a need to re-scale (Burnham & Anderson, 2007). Thus, Δ_i forces the best model to carry a value of 0 and other models to carry positive values, which allows for a more meaningful interpretation, where; $\Delta_i \leq 2$ is supported through evidence, $\Delta_i \leq 7$ has considerably less support and $\Delta_i > 10$ has very little to no support.

While Maxent as a software comes installed with default settings, it has since been proven to be advantageous to alter the settings, based on parameters suggested by the EMNevaluate file (Muscarella *et al.*, 2014). This process ensures minimal model overfitting and over-complexity. This section will therefore describe the steps taken within MaxEnt to ensure the best settings for each model. The MaxEnt version that was used to run the model in this study was Version 3.4.1 (Phillips *et al.*, 2021). In MaxEnt, there are four main sub-sections, under the settings, of which have to be modified to obtain the most interpretable and best model results. These sub-sections are divided into the main user interface, the basic settings, the advanced settings and the experimental settings. The model settings used in the main user interface were enabled and included the ‘create response curves’ and ‘do jack-knife to measure variable response’. In the basic settings, the ‘random seed’ setting was enabled, the regularisation multiplier was set, based on the advised enmevaluate results, and the number of replicates was changed, based on the number of occurrence points (Table 3.3). In the advanced settings tab, the ‘write plot data’ setting was enabled, and lastly, the ‘write background predictions’ function was enabled in the experimental settings tab.

The number of replicates was set based on the number of occurrence points for the fire data; for example, if the number occurrence points was >50, then the number of replicates was set to 10 (K=10 cross fold validation), and if the number of occurrence points was <50 then the number of replicates was equal to the number of occurrence points (the leave-one-out method). The reason behind this is the same as previously explained in Section 3.4, namely, to facilitate a more efficient computational process. The number of background points was set to 1000, as predetermined within RStudio. Fire presence data was not manually split into validation and calibration sets as the available background points and subsequent occurrence points were too low to justify this. “cross-validation” was used instead which splits the fire presence data into test and training data used for model prediction evaluation (Merow *et al.,* 2013). The following table represents the models that were run with their associated settings within Maxent (Table 3.3).

Table 3.3 Parameters used for each individual model

Model	Features	Regularization Multiplier	Environmental Variables	#Replicates (Method of cross validation)
09.01.2009	Hinge	2.5	Land surface temperature Net primary productivity Precipitation Aboveground biomass Elevation	11 (leave-one-out method)
18.02.2009	Linear Quadratic	2.5	Land surface temperature Net primary productivity Precipitation Aboveground biomass Elevation	15 (leave-one-out method)
07.04.2009	Linear	1	Land surface temperature Net primary productivity Precipitation Aboveground biomass Elevation	10 (leave-one-out method)
15.04.2009	Hinge	2.5	Land surface temperature Net primary productivity Precipitation Aboveground biomass Elevation	10 (leave-one-out method)
17.01.2010	Hinge	2.5	Land surface temperature Net primary productivity Precipitation Aboveground biomass Elevation	31 (leave-one-out method)
09.01.2012	Linear Quadratic Hinge Product	1.5	Land surface temperature Net primary productivity Precipitation Aboveground biomass Elevation	31 (leave-one-out method)
17.01.2012	Linear	2	Land surface temperature Net primary productivity Precipitation	17 (leave-one-out method)

			Aboveground biomass Elevation	
19.12.2014	Linear Quadratic Hinge Product	1.5	Land surface temperature Net primary productivity Precipitation Aboveground biomass Elevation	10 (leave-one-out method)
10.02.2015	Linear Quadratic	0.5	Land surface temperature Net primary productivity Precipitation Aboveground biomass Elevation	37 (leave-one-out method)
17.01.2016	Linear Quadratic	0.5	Land surface temperature Net primary productivity Precipitation Aboveground biomass Elevation	18 (leave-one-out-method)
09.01.2017	Linear Quadratic Hinge Product	1	Land surface temperature Net primary productivity Precipitation Aboveground biomass Elevation	24 (leave-one-out method)
10.02.2017	Linear Quadratic Hinge	2	Land surface temperature Net primary productivity Precipitation Aboveground biomass Elevation	21 (leave-one-out method)
26.02.2017	Linear Quadratic Hinge Product	1.5	Land surface temperature Net primary productivity Precipitation Aboveground biomass Elevation	73 (K=10 cross fold validation)
22.03.2017	Linear Quadratic Hinge Product	1.5	Land surface temperature Net primary productivity Precipitation Aboveground biomass Elevation	16 (leave-one-out method)

09.01.2018	Linear Quadratic	1	Land surface temperature Net primary productivity Precipitation Aboveground biomass Elevation Wind	23 (leave-one-out method)
17.01.2018	Linear Quadratic Hinge	3	Land surface temperature Net primary productivity Precipitation Aboveground biomass Elevation Wind	18 (leave-one-out method)
25.01.2019	Hinge	3.5	Land surface temperature Net primary productivity Precipitation Aboveground biomass Elevation	28 (leave-one-out method)

3.6 Area Under the Curve (AUC) as a Representation of Model Performance and Validation

In this study, the AUC was used to measure the model performance, and it is expressed as a range of values between 0 and 1 (Fielding & Bell, 1997). More specifically, where the AUC value is 0 this means that the positive classes were classified as negative classes. Where the AUC value expressed for a model is 0.5, this simply means that the model did not perform better than a random prediction model (Swets, 1988), whereas if the expressed AUC value is 1, this simply means that there is no overlap between the positive and random classes and the model shows perfect discrimination (Swets, 1988). Whilst the Receiver Operating Curves (ROC) only consider the presence (positive instances) and absence data (negative instances) points to draw a curve, Maxent, in the form of AUC, works slightly differently. This means that instead of absence points, AUC attempts to discriminate between the presence and random instances. This is done by including negative (random) and positive instances for each pixel x in a study area, as well as for each pixel that is included in the species' true geographical distribution (Phillips *et al.*, 2006). Simply, this allows the species distribution model to distinguish between positive and negative instances, without the bias created by labels, such as presence and random.

3.7 Conclusion

In conclusion, the Western Cape provides and interesting template on which to explore the conditions required to deem an area fire suitable as it experiences the most fire frequent climate. This study adopts various remote sensing and GIS techniques in order to explore and understand the environmental variables that influence fire occurrence. These conditions include fire occurrence and land surface temperature data sourced from MODIS and environmental variables sourced from the FAO and WASA based on a study of literature that informed the inclusion of said data. The species distribution model, Maxent, was used to explore the contribution of each environmental variable used with the key justification being that this model requires presence-only data. The model configuration was evaluated and changed based on various parameters determined within R-studio, using the ENMeval package. These configurations include, background points, regularization multiplier, occurrence points and model run-type. Lastly, model performance was evaluated using AUC which provides insight on how well the model was able to discriminate between random and positive instances. This chapter therefore details the methods used to adopt an operational framework for monitoring and mapping fire occurrence in the Western Cape region in South Africa and thus the following chapters will outline the results as well as describe the overall performance of the framework based on the aforementioned methods.

CHAPTER 4: RESULTS

4.1 The Three Model Run Types and the Performance of each Model

Based on the AUC results for each model run type (Figure 4.1), the bootstrap replicate run type was the one that performed the best across all models, irrespective of the number of replicates available. The K=10 cross-validation method also performed fairly well across all models, with some digressions where the AUC fell well below 0.70. The sub-sample replicate run type generally performed the worst of all three run types and thus has the least predictive capability. The bootstrap replicate run type method also consistently achieved an AUC value greater than 0.80, which suggests that this run type has a strong predictive capability. With this in mind, the K=10-fold cross-validation results will be discussed in greater detail in this section, as it uses all the data for validation and thus uses smaller data-sets more efficiently, therefore decreasing the bias.

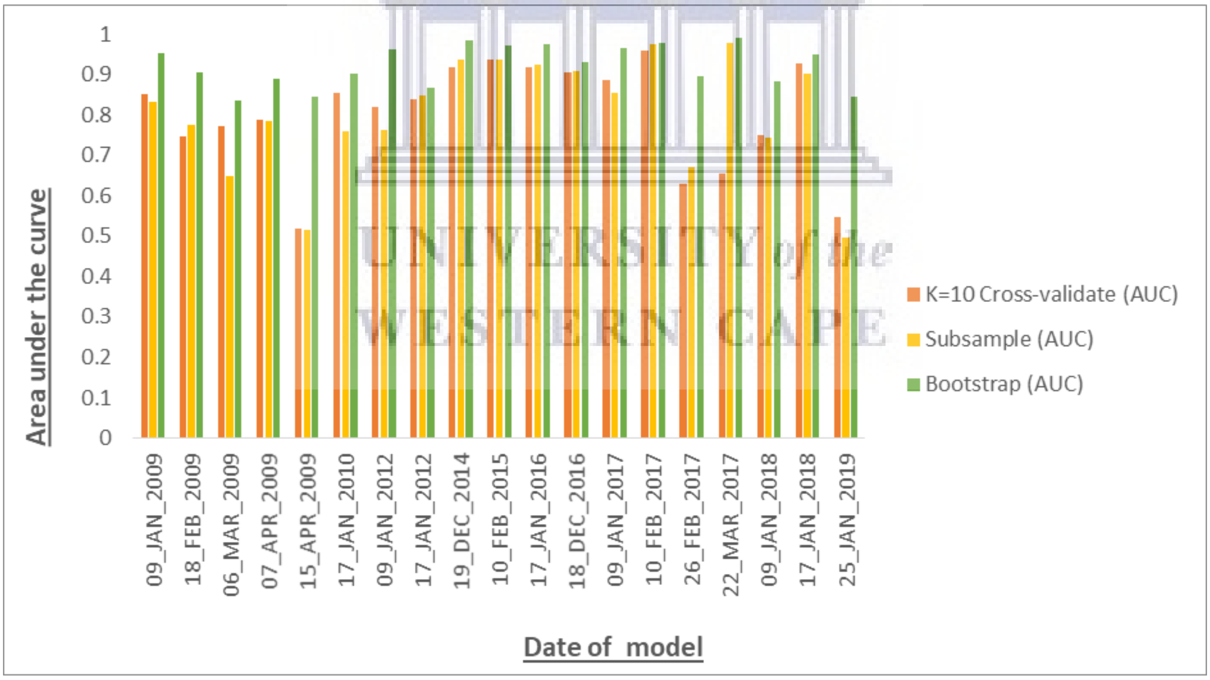

Figure 4.1 Model performance of each replicate run type within Maxent

4.2 The Performance of the Model reviewed on a Monthly Basis

The majority fire models that were run for January achieved a desirable AUC value of over 0.80, with the exception of 09 January 2018 and 25 January 2019 (Figure 4.2). With the exception of the models that underperformed, it can be assumed that the variables that influence the training data did well at predicting the fire occurrence for the month of January. In the latter sections of Chapter 4, the models that will be focused on will be 17 January 2010 and 09 January 2012, to determine a generalized trend for January.

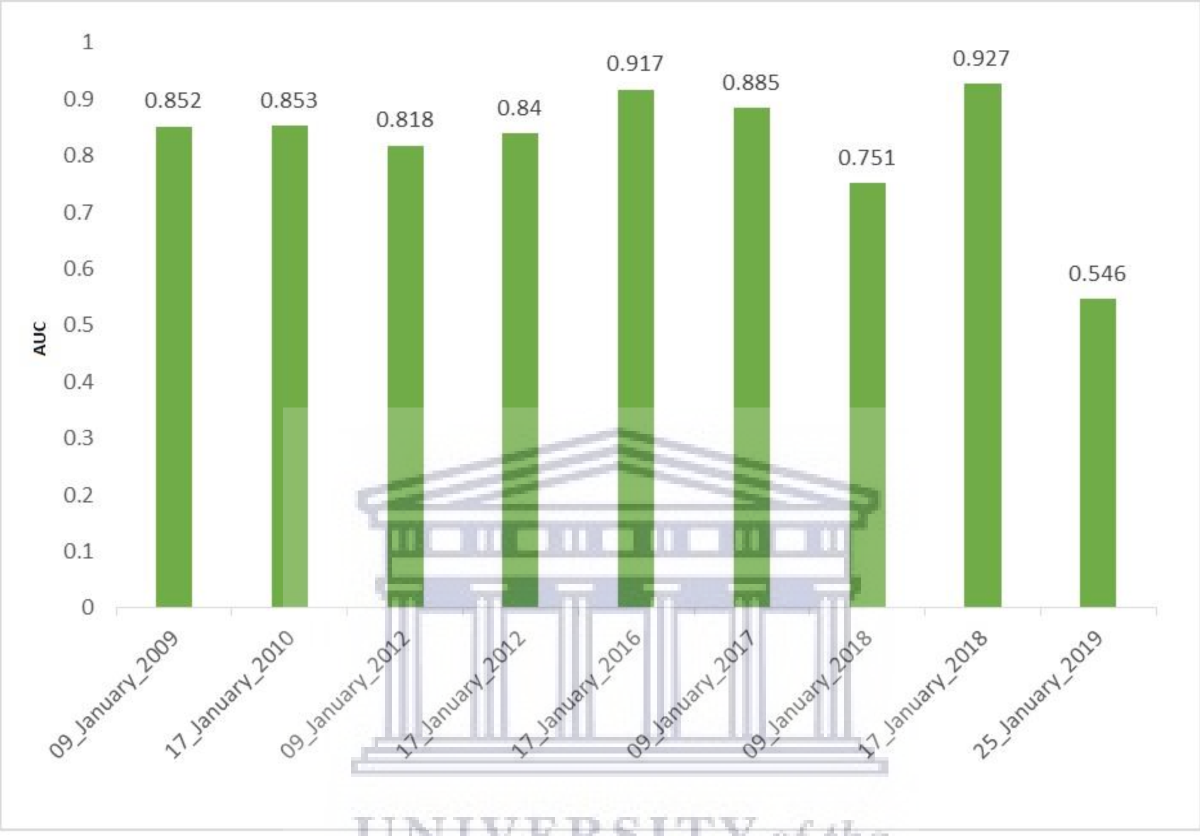

Figure 4.2 The AUC values for each model processed for January

Half of the models shared between February, March, April and December achieved an AUC value of above 0.80, with only two of the models achieving an AUC of below 0.70 (Figure 4.3). The models that achieved an AUC of below 70, namely, 26 February 2017 and 15 April 2009 will not be discussed in terms of the variables that could possibly describe the fire probability for their respective months, due to their inability to predict accurately Therefore, the models being reviewed in Chapter 4 are 10 February 2015, 10 February 2017, 22 March 2017, 07 April 2009 and 19 December 2014.

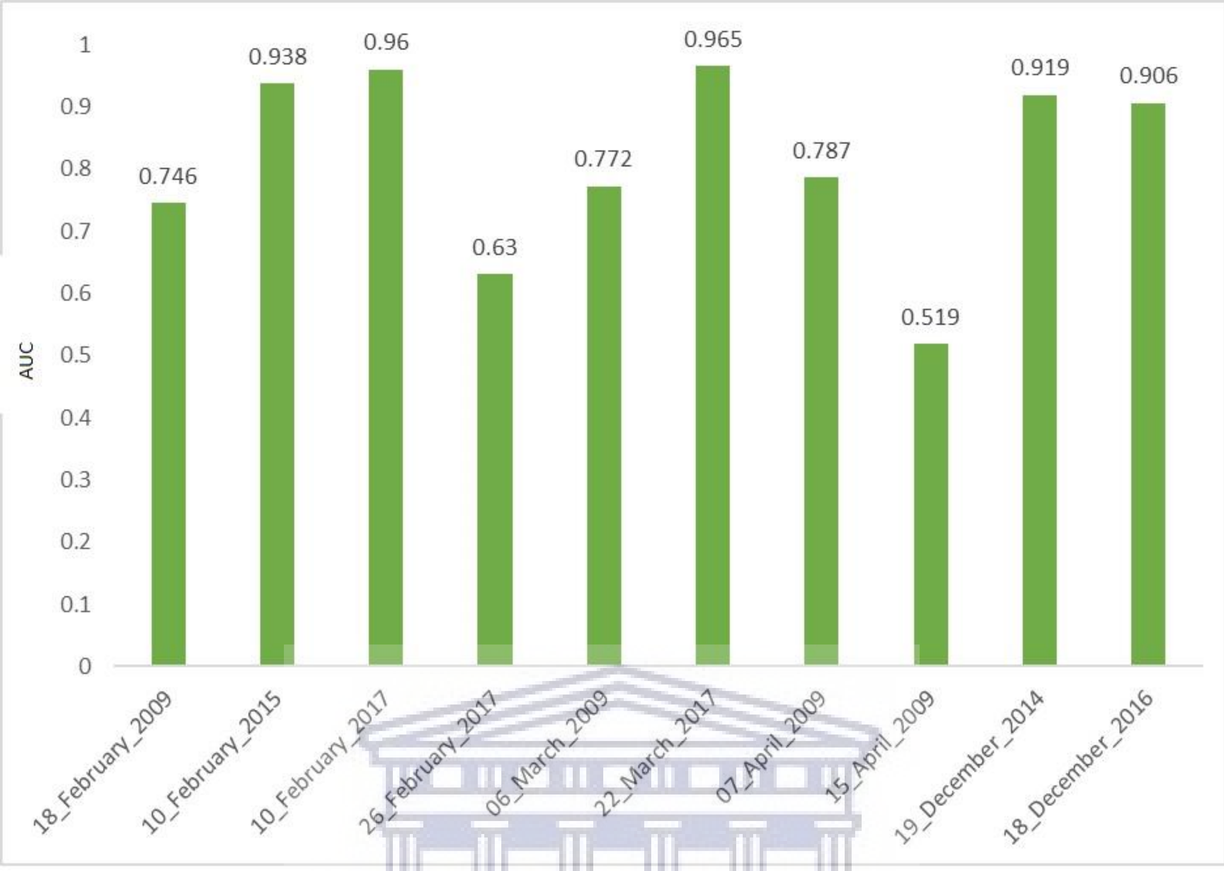

Figure 4.3 The AUC values for the months February, March, April and December

4.3 Model Performance for the Month of January

For 17 January 2010, the land surface temperature and the net primary productivity were identified as the most influential environmental variables that explain the occurrence of fire, based on their percentage contribution (Figure 4.4a). The general response of fire to the land surface temperature is shown as a decrease in fire occurrence with an increase in land surface temperature. This means that fire response seems to peak when the land surface temperature is between 14600 -14800 kelvins (18.85 - 22.85 ˚C) (Figure 4.4b).The general response of fire to the net primary productivity is seen as an increase in fire response with an increase in net primary productivity, even though fire response remains constant beyond ~900 gC/m^2. More specifically, the fire response with the net primary productivity is greatest where the net primary productivity is ~900 gC/m^2 and only increases beyond 0 gC/m^2 (Figure 4.4c). For 17 January 2010, the fire-suitable conditions were concentrated around the municipal areas of the Garden Route and the Cape Winelands (Figure 4.4d). Furthermore, along the coastlines of the Overberg, the Garden Route, the City of Cape Town and the West Coast, fire-suitable conditions also seem to be present for 17 January 2010. The majority of the Western Cape averages ~ ≤ 0.54 in terms of standard deviation. Most of the West Coast and Central Karoo municipal districts for 17 January 2010 seemed to be relatively fire-free, based on their overall standard deviations.

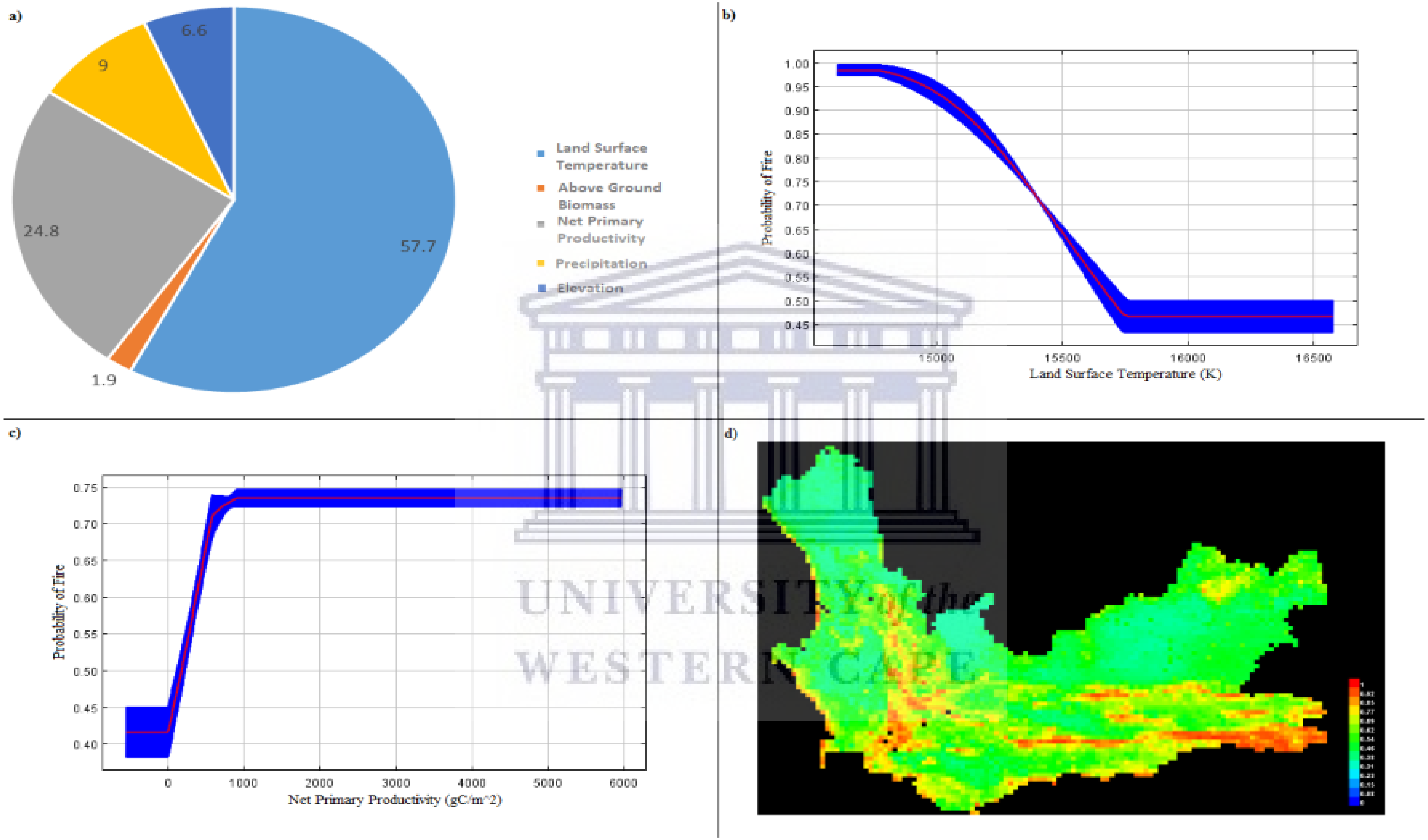

Figure 4.4 a) Percentage contribution of environmental variables, b) response of fire to variability in the land surface temperature, c) response of fire to variability in net primary productivity, and d) point-wise mean of fire presence points for 17 January 2010

The variables that influenced fire occurrence on 09 January 2012 were net primary productivity, precipitation and elevation (Figure 4.5a). The fire response to the net primary productivity increases where 0 < NPP< ~900 gC/m^2 (Figure 4.5b). More specifically, the fire response peaks where the net primary productivity is ~900 gC/m^2 and it decreases thereafter. For precipitation, the fire response is greatest where precipitation is 0 mm and decreases with a further increase in precipitation, until the fire probability is 0 where precipitation is 5 mm (Figure 4.5c). However, the peak for the fire response with the peak threshold for precipitation is relatively low and is 0.6, irrespective of the fact that precipitation is an important contributing factor in training the model. Furthermore, the response of fire to elevation seems to be that it decreases with an increase in elevation and that peak fire response occurs in lower lying regions (Figure 5 in the Appendix). Fire suitable conditions were concentrated, albeit not significantly, in terms of the standard deviation values in the City of Cape Town, the Overberg, the West Coast and parts of the Garden Route and Cape Winelands municipal districts (Figure 4.5d). The Central Karoo district showed no fire-suitable conditions for 09 January 2012 and most of the Cape Winelands municipal district was relatively fire-free, based on the standard deviation values for fire presence points. The Overberg and part of the Garden Route municipal district seem to have had the greatest concentration of fire occurrence, based on the area covered by relatively high standard deviation values.

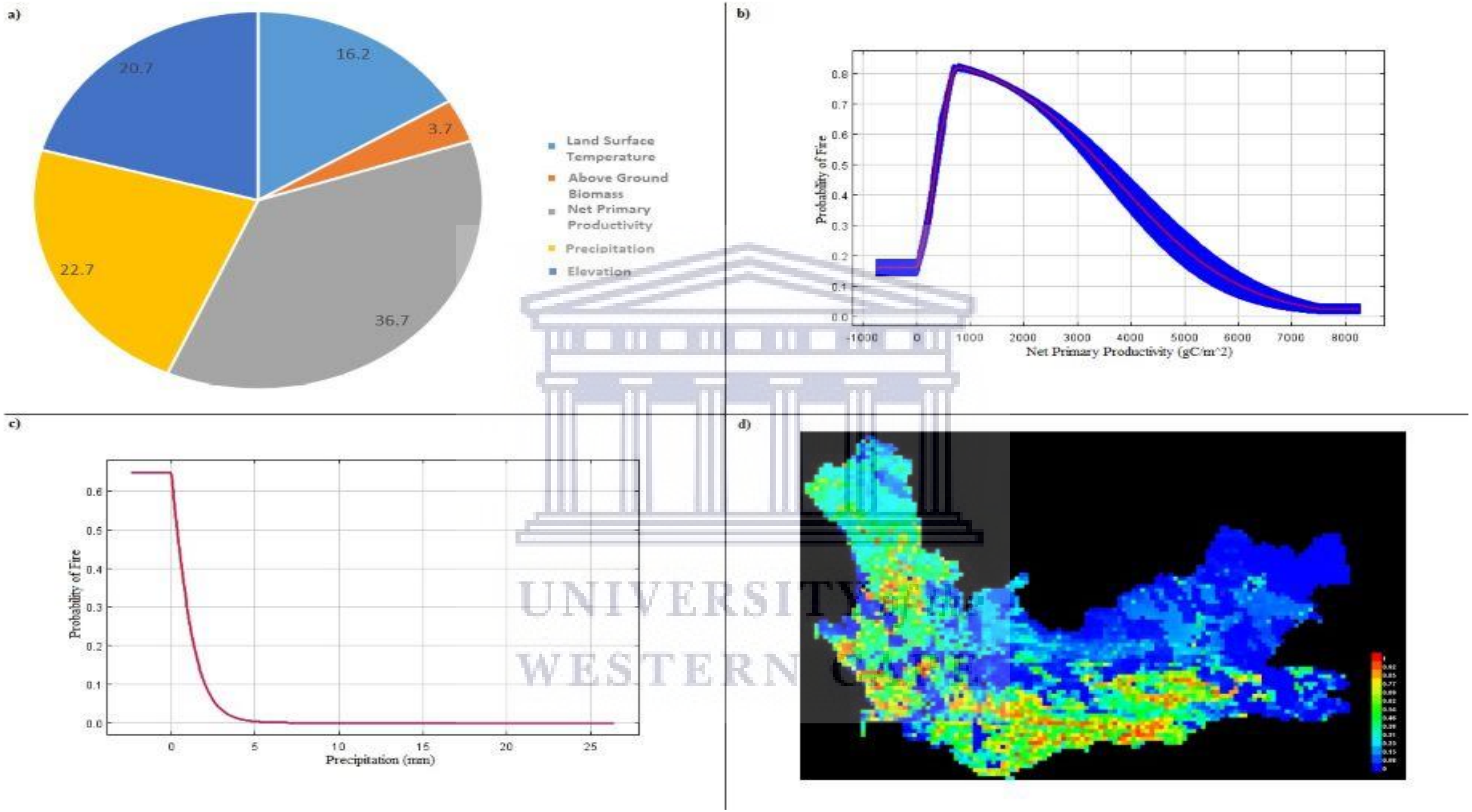

Figure 4.5 a) Percentage contribution of environmental variables, b) fire response to variability in net primary productivity, c) fire response to variability in precipitation, and d) point-wise mean of fire presence points for 09 January 2012

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4.4 Model Performance for the Month of February

For 10 February 2015, net primary productivity, precipitation and aboveground biomass were the most influential variables, based on their percentage contribution (Figure 4.6 a). The response of fire increased with an increase in the net primary productivity, until the peak fire response, which occurred when the net primary productivity was ~2400 gC/m^2 (Figure 4.6b). The fire response beyond this point decreases with a further increase in the net primary productivity. For precipitation, the fire response increased with an increase in precipitation, with a peak in fire response occurring where it was 21 mm (Figure 4.6c). The fire response in relation to the aboveground biomass seems to increase with an increase in the aboveground biomass, till there is a peak, which occurs when it is ~7000 kg/ha/yr (Figure 4.6d). Thereafter, the fire response decreases with a further increase in the aboveground biomass. Even though the aboveground biomass is an annual representation of the variable for 2015, whilst other variables are in a dekadal temporal resolution, it still provides a relative idea about the effects of the availability of fuel materials on the potential of fire occurrence. The greatest concentration of fire-suitable conditions for 10 February 2015 were distributed around the Cape Winelands and the Garden Route municipal districts (Figure 4.6e). Other municipal districts, namely the Central Karoo, the West Coast and the City of Cape Town, were relatively unaffected by fire-suitable conditions for 10 February 2015, as they have relatively low point-wise mean values.

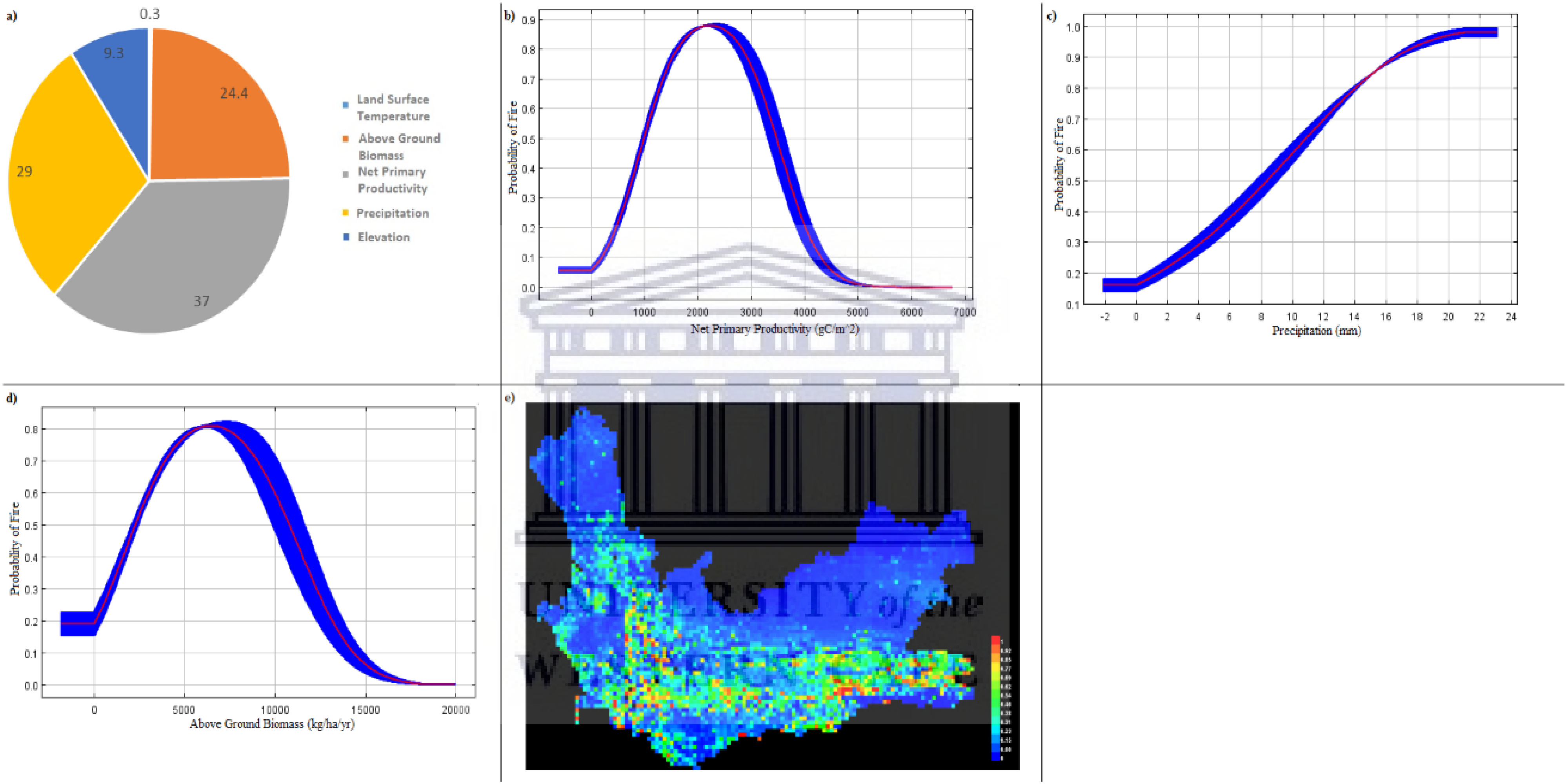

Figure 4.6 a) Percentage contribution of environmental variables, b) fire response to variability in net primary productivity, c) fire response to variability in precipitation, d) fire response to variability in aboveground biomass, and e) point-wise mean of fire presence points for 10 February 2015

The most influential environmental variables for 10 February 2017, based on their percentage contributions, are precipitation, elevation and net primary productivity (Figure 4.7a). The response of fire to precipitation shows that fire decreases with an increase in precipitation, while it is greatest where the precipitation is 0 mm (Figure 4.7b). The response of fire increases with an increase in the net primary productivity, till it reaches a peak when it is ~800 gC/m^2 (Figure 4.7c). Beyond this, the fire probability decreases with a further increase in the net primary productivity. The response of fire to elevation for 10 February 2017 shows an increase in fire with an increase in elevation (Figure 6 in the Appendix). Fire-suitable conditions were concentrated in the northern parts of the Central Karoo, Garden Route and West Coast (bordering on the Cape Winelands) municipal districts for 10 February 2017 (Figure 4.7d). Furthermore, most of the City of Cape Town, the Overberg and Cape Winelands municipal districts were virtually unaffected by fire-suitable conditions for 10 February 2017.

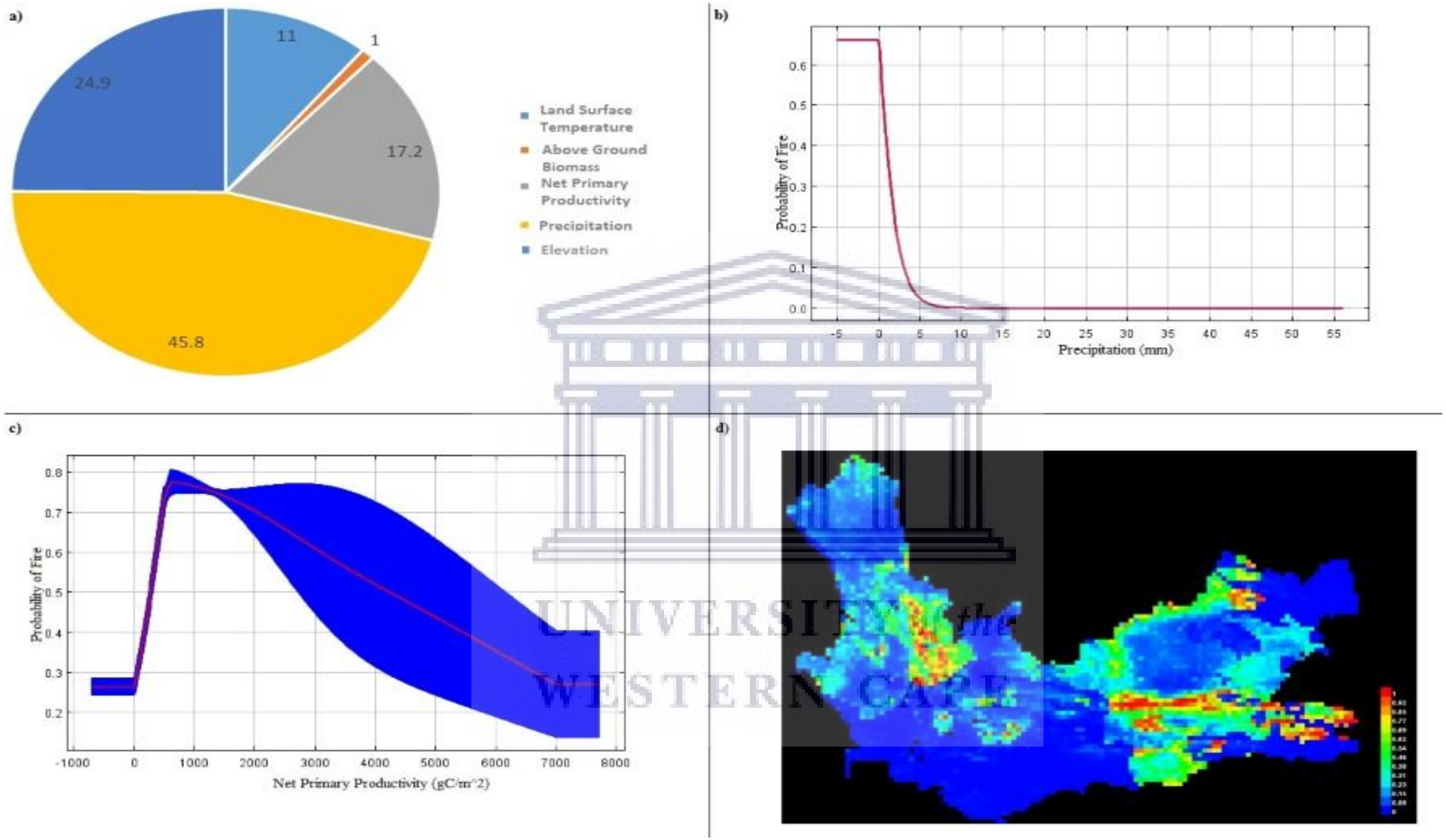

Figure 4.7 a) Percentage contribution of environmental variables, b) fire response to variability in precipitation, c) fire response to variability in net primary productivity, and d) point-wise mean of fire presence points for 10 February 2017

4.5 Model Performance for the month of March

For 22 March 2017, the most influential variables that trained the model about fire occurrence were net primary productivity, elevation and aboveground biomass (Figure 4.8a). The response of fire increases with an increase in aboveground biomass, till it reaches a peak, which occurs when it is ~4000 kg/ha/yr (Figure 4.8b). Thereafter, the response of fire decreases with a further increase in aboveground biomass. The response of fire to the net primary productivity shows that fire increases with an increase in the net primary productivity till it reaches a peak, when it is ~1800 gC/m^2 (Figure 4.8c). Thereafter fire decreases with a further increase in the net primary productivity. As for the response of fire to elevation for 22 March 2017, fire increases with an increase in elevation (Figure 7 in the Appendix). Fire suitable conditions were greatly concentrated in the Cape Winelands (bordering the West Coast) and they were less significant in the Garden Route municipal districts (Figure 4.8d). When focusing on the values associated with the point-wise mean, the majority of the Western Cape is free of fire-suitable conditions. Furthermore, the areas that were deemed as fire-suitable still maintained mainly lower point-wise means <0.62, which suggests that the conditions that were present for 22 March 2017 were only able to influence specific areas in the Cedarberg Nature Reserve, in Kannaland and in George.

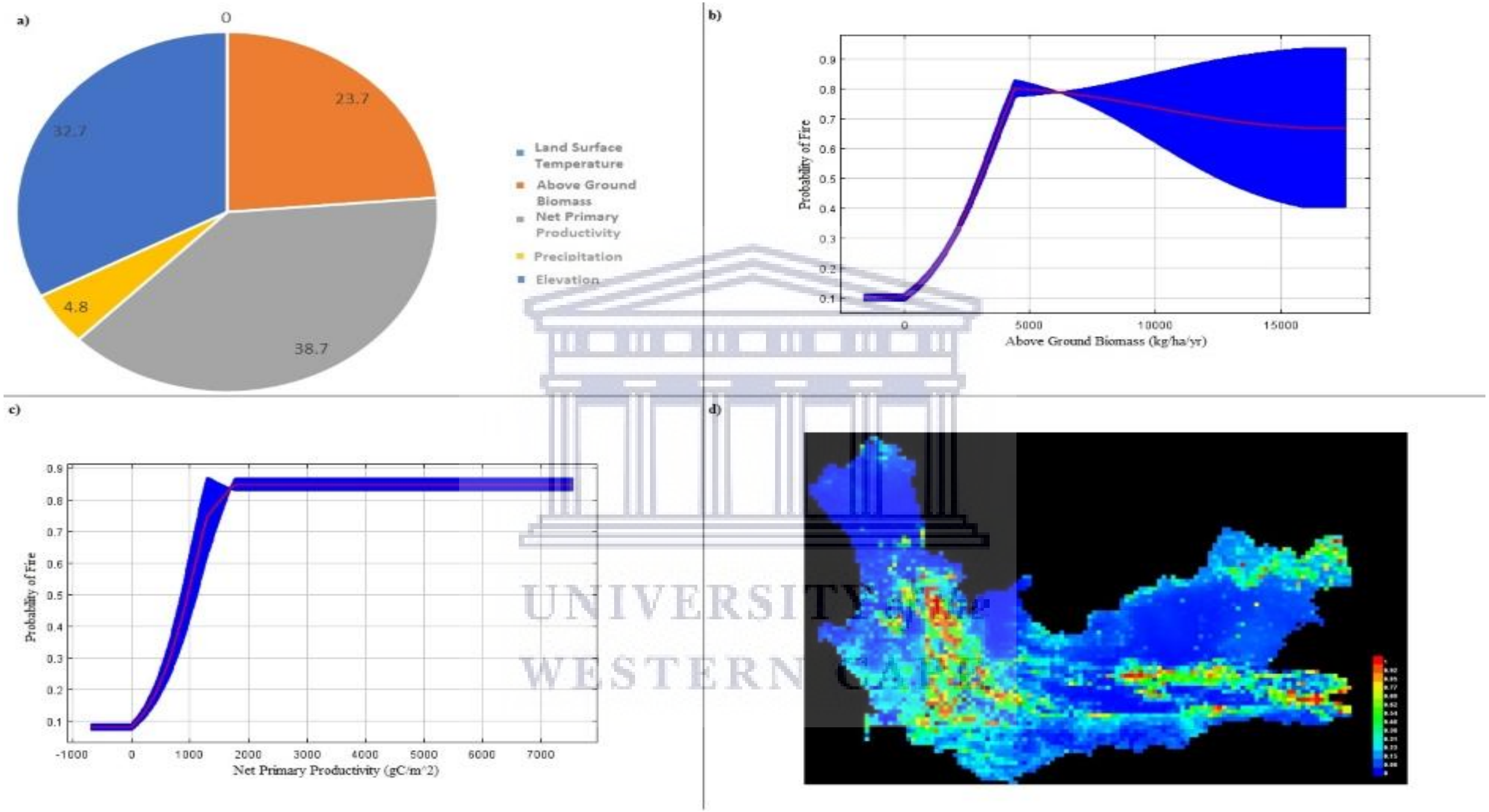

Figure 4.8 a) Percentage contribution of environmental variables, b) fire response to variability in aboveground biomass, c) fire response to variability in net primary productivity, and d) point-wise mean of fire presence points for 22 March 2017

4.6 Model Performance for the Month of April

For 07 April 2009, the aboveground biomass and elevation were the most influential variables in terms of describing fire occurrence (Figure 4.9a). The response of fire to aboveground biomass is that as it increases, so too does the fire response, with it reaching a peak when the aboveground biomass is ~17500 kg/ha/yr (Figure 4.9b). For elevation, the fire response decreases with an increase in elevation, with the probability of fires occurring at lower elevations (Figure 8 in the Appendix). Fire-suitable conditions were concentrated around the Overberg, the City of Cape Town and the southern parts of the West Coast and the Garden Route municipal districts (Figure 4.9c). A smaller area that forms part of the Cape Winelands municipal district, just north of the Overberg, also showed a reasonable concentration of fire-suitable conditions, which were concentrated more specifically along the coast of the Western Cape. As for the Central Karoo and most of the West Coast and Cape Winelands areas, they were seen as unsuitable for fire occurrence for 07 April 2009.

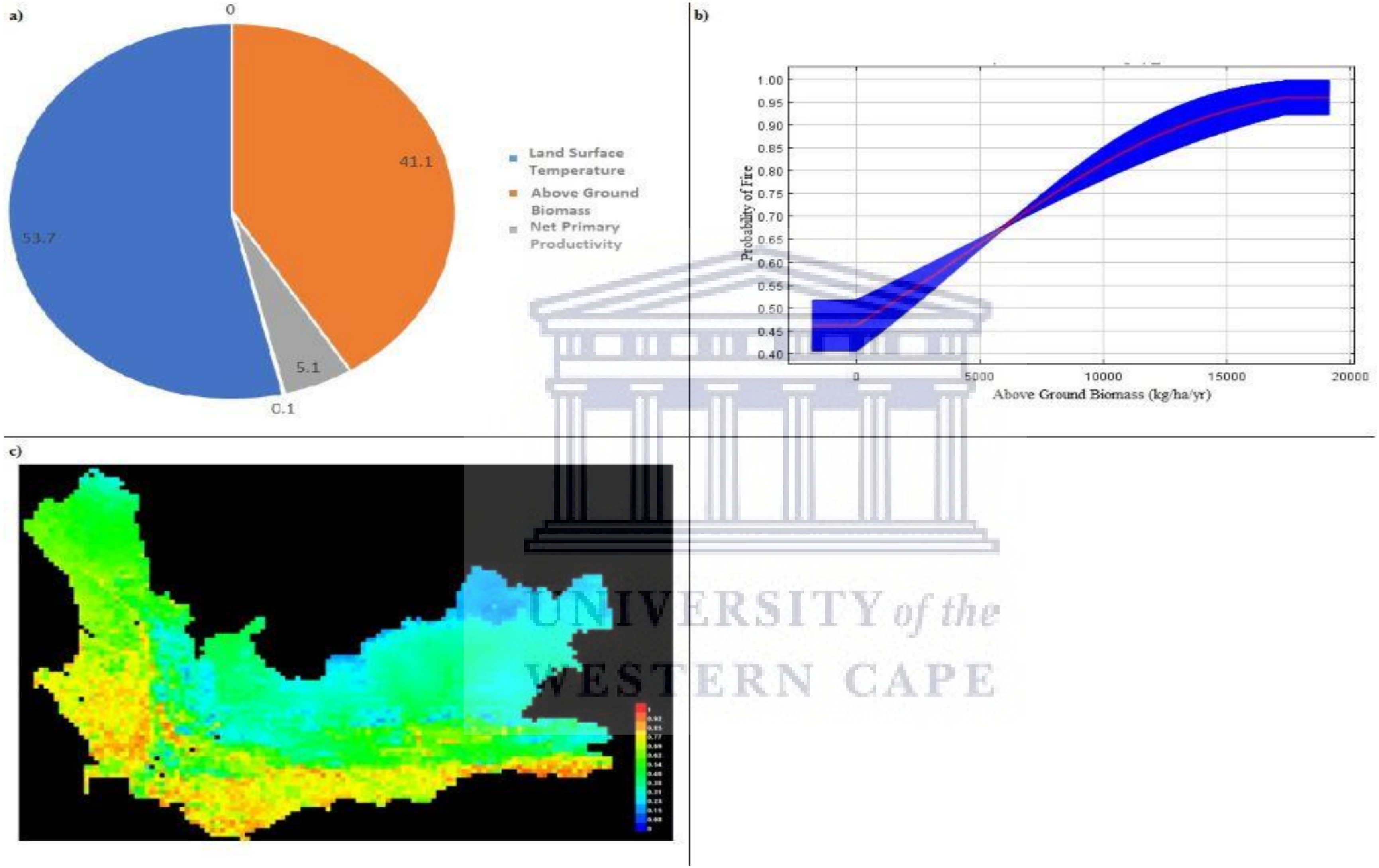

Figure 4.9 a) Percentage contribution of environmental variables, b) fire response to variability in above-ground biomass, and c) point-wise mean of fire presence points for 07 April 2009

4.7 Model Performance for the Month of December

Precipitation, land surface temperature and net primary productivity were shown to be the most influential variables in terms of training the model about fire occurrence for 19 December 2014 (Figure 4.10a). The response of fire to precipitation indicates that as the precipitation increases, the fire response decreases, with a peak response in fire occurring where precipitation is 0 mm (Figure 4.10b). For the land surface temperature, the response of fire indicates that as it increases, the fire response decreases, with a peak in fire response occurring where the land surface temperature is 14600-14800 kelvins (18.85-22.85˚C) (Figure 4.10c). The response shows that fire increases with an increase in the net primary productivity till it reaches a peak when it is ~2600 gC/m^2 (Figure 4.10d). Thereafter, the fire response remains constant, despite a further increase in the net primary productivity. Fire-suitable conditions were concentrated along the Garden Route and parts of the Overberg and Cape Winelands (bordering the West Coast) municipal districts (Figure 4.10e). Large parts of the West Coast, the Cape Winelands, the Overberg and City Cape Town were not subject to fire-suitable conditions, with most of the Western Cape being subject to a point-wise mean of <0.62. The Central Karoo was virtually free of fire-suitable conditions for 19 December 2014.

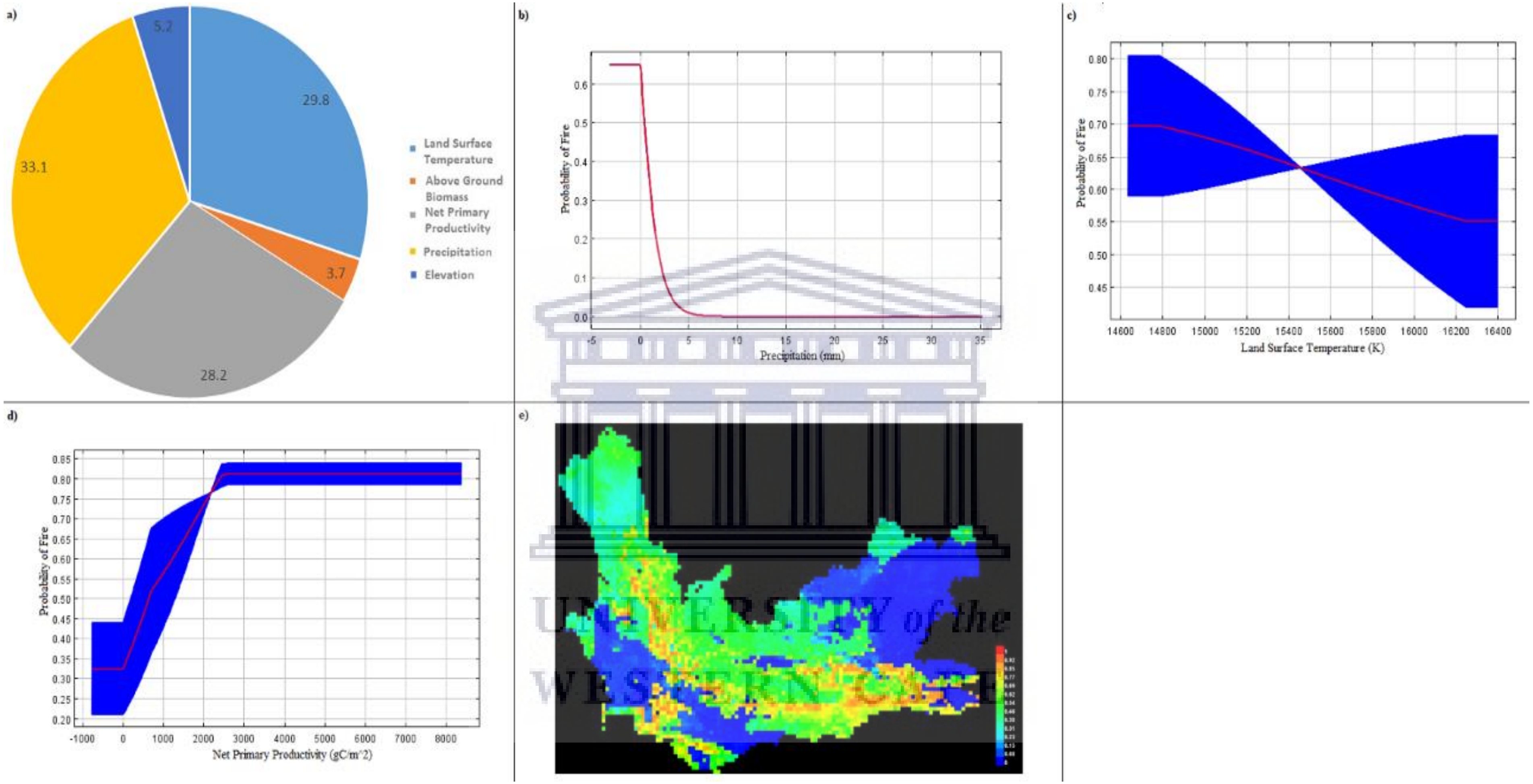

Figure 4.10 a) Percentage contribution of environmental variables, b) fire response to variability in precipitation, c) fire response to variability in land surface temperature, d) fire response to variability in net primary productivity, and e) point-wise mean of fire presence points of 19 December 2014

CHAPTER 5: DISCUSSION

5.1 The Influence of Environmental Descriptors on Fire Occurrence

In the models that were run for the study period of 2009 – 2019, it would seem that elevation was essentially the only environmental descriptor that was directly correlated to fire occurrence. This means that if the majority of fires occurred in areas of low or high elevation, then elevation would be described as an environmental variable that greatly trained the model about fire occurrence. Therefore, the information provided in this study on elevation does not provide any unique details about its effects on fire occurrence and it will thus not be considered when discussing the general environmental trends linked with fire occurrence over the various years. However, elevation has since been shown to have an influence on fire frequency and probability. For example, a study done on a Sierra Nevada landscape found that the burning probability increased with an increase in ignition density, but only where the influence of elevation was controlled, so as to limit its strong correlation (Parks, Parisien & Miller, 2011). The study found that on a finer spatial scale, elevation and fuel were the most important variables, while on a broader spatial scale, fuel and aspect influenced fire occurrence the most. Furthermore, even though the study found that the burning probability decreased with an increase in fire, elevation masked the effects of ignition density on the burning probability. A fire probability model applied to the forest stands in Catalonia found that the fire probability decreased with an increase in elevation and that the decline occurred sharply at elevations of above 700 m (Gonzalez *et al.*, 2006). The explanation given for the importance of elevation as a variable was explained by the high correlation between elevation and evapotranspiration. A study performed in the Canadian Rocky Mountains also found that the fire probability decreases with an increase in elevation and that the warmer aspects are more likely to burn than the cooler aspects (Rogeau & Armstrong, 2017). Thus, the consensus seems to be that fire probability decreases with an increase in elevation, but it still seems to be a significant variable for a fire probability analysis, because of its correlation with other variables that contribute to fire occurrence. These potential correlations could explain the response of elevation to fire occurrence in this study, which could also be explained by the correlation between aboveground biomass and elevation, as an example.

Wind speed could only be applied as an environmental variable for two of the models (09 January 2018 and 17 January 2018) due to constraints in the availability of existing wind speed data for the rest of the study period. Furthermore, kriging was used as a function to extrapolate wind speed as a variable across a map of the Western Cape, as it was only available in the form of vector data. Therefore, the effects of wind speed could not be monitored as there was no definitive information about its effects on the occurrence of fire, as the information provided by the variable was not extensive enough to ensure a reasonably accurate interpretation on how wind influences fire occurrence. Irrespective of this discrepancy, the influence of wind speed on fire has since been widely examined and incorporated into many fire models (Goodrick, 2002; Noble *et al.*, 1980; Sharples *et al.*, 2009). In terms of wind speed as an environmental variable for fire occurrence, it is widely agreed that it affects the spread of fires, as opposed to the actual occurrence thereof, as has since been discussed in many studies (Cheney *et al*., 1993; Cheney *et al*., 1998; Cheney & Sullivan, 2008). In summary, the influence of wind speed on the fire spread rate is undeniable and should be considered when examining fuel continuity. The discrepancies in wind speed data for this study, however, are too great to draw any reasonable conclusions and they are not aligned with the aims of the study, namely, to analyse the influence of climatic variables on the actual occurrence of fires. Therefore, the influence of wind speed on fire occurrence should not be considered as conclusive in this study, but rather should be regarded as an important variable for future studies.

Aboveground biomass is defined as the aboveground standing dry mass of live or dead matter from tree or shrub (woody plant) life forms, expressed as a mass or mass per unit area. The main distribution of natural flora in the Western Cape consists of dry herbaceous Fynbos plant species. This means that the majority of the available fuel load for these ecosystems will be observed as aboveground biomass. A study done in Swartboskloof in the Western Cape found that Fynbos fuels have a very low natural fuel moisture content and that they are therefore not subject to seasonal curing. Furthermore, the decomposition rate of litter fall in this Fynbos biome is relatively low (van Wilgen & Hensbergen, 1992). This suggests that the available fuel loads can persist longer than in most other plant biomes. Another study on Fynbos in the Swartboskloof area found that enough fuel load accumulation for fire can occur within 4- to 6-year intervals, which is almost the same as for some other Fynbos biomes, such as ericoid shrub lands (van Wilgen, 1982). This suggests that fuel accumulation in Fynbos biomes can be relatively rapid and that fire regimes are not necessarily limited to the fuel-load. For the models that were run in this study, aboveground biomass was found to be linked to the climatic conditions, where the fire potential peaked under limited precipitation and/or with an increase in the land surface temperature. This general trend is supported by evidence from other studies, where fire frequency was highest at lower fuel moisture levels and the connectivity of burnable fuel loads was the greatest at an intermediate fire frequency (Miller & Urban, 2000; Xystrakis, Kallimanis, Dimopoulos, *et al.*, 2014). In summary, when the fuel moisture is low, essentially most of any given landscape is flammable, and thus connectivity of the fuel load will not increase with a further decrease in fuel moisture. A study by Pausas & Paula (2012) on Mediterranean ecosystems suggested that the fuel structure shapes the fire-climate relationship, as opposed to the climate shifting to become more flammable Therefore, aboveground biomass becomes increasingly important as a variable where drier conditions correlate with a higher fire potential.

Precipitation plays a very significant role as a descriptor of fire, particularly when it concerns its interaction with the fuel load and the impact of the environments being oversaturated or dry. The seasonality of precipitation is therefore the most important factor when determining the likelihood of fire occurrence. The timing of precipitation can be correlated with the availability of ignition-probable fuel loads, as has been shown by Koutsias *et al*. (2013), Littell *et al*. (2009) and Xystrakis *et al*. (2014). More specifically, high precipitation in the summer season often results in a low fire potential, due to saturation, resulting in the lower probability of ignition. High precipitation in the spring often results in a high fire probability, most likely because of the accumulation of fuel load during the growth stage of the plants.

It has been shown that the land surface temperature shares a relationship with precipitation and air temperature, and that an increase in the air temperature, together with a prolonged spell of limited precipitation, leads to an increase in the land surface temperature. Similar to precipitation, it has an effect on the fuel load moisture, where an increase in the land surface temperature results in a decreased fuel moisture content (Flannigan, Wotton, Marshall, *et al.*, 2016). In relation to the model, this simply means that as the land surface temperature increases, the probability for fire increases, as the drier fuel loads are more readily ignitable (Chuvieco, Riaño, Aguado, *et al.*, 2002).

Net primary productivity is a measure of the ability of plants to produce organic compounds as a result of carbon dioxide intake from the atmosphere or aquatic zones, mainly as a result of photosynthesis. Studies have shown that drought intensity, drought duration, drought-affected areas and the cumulative and lag effects of vegetation responses to precipitation have an influence on its variability (Cramer, Kicklighter, Bondeau, *et al.*, 1999; Xiao, Zhuang, Liang, *et al.*, 2009; Zhao & Running, 2010).A study conducted by Xiao *et al*. (2009) in China, shows that extended periods of severe drought seem to cause the largest reduction in the annual net primary productivity and while this change was not observed in some areas, the likely reason given for this was the increased temperature and/or CO_2 enrichment. While a study performed in Europe also showed a reduction in the net primary productivity as a result of a severe heat wave in 2003. A predicted 30% reduction in the annual net primary productivity was owed to a deficit in precipitation and extreme temperatures, which is contrary to the belief that an increase in temperature would enhance plant growth (Ciais, Reichstein, Viovy, *et al.*, 2005). Although much of the prolonged effects of such conditions on net primary productivitiy are yet to be fully understood, a simple conclusion can be drawn from the results of such studies, namely, that drought conditions do influence the net primary productivity and that they are therefore correlated, to some extent. It has since been suggested that the most obvious correlation between the drought and net primary productivity anomalies can be observed during the drought, and after the drought intensity reaches its peak value (Pei, Li, Liu, *et al.*, 2012). Furthermore, evidence has shown that an increase in global temperature could result in a global reduction in the net primary productivity; for instance, it is decreasing in the southern hemisphere, which is counteracting its increase in the northern hemisphere (Zhao & Running, 2010). The main issue with the use of net primary productivity as a modelling variant is that it is controlled mainly, but not solely, by solar radiation, temperature and precipitation (Cramer *et al.*, 1999). This means that when using a model such as Maxent, which requires the use independent variables, it could result in inaccuracies, due to the variables being correlated. This is the case of the current study, where land surface temperature and precipitation are variables that form part of the model description. In summary, while the net primary productivity is correlated to some variables that influence the occurrence of fire, and therefore might cause inaccuracies, it can still provide a valuable inference on conditions, such as droughts or heat waves, which can allow us to better understand fire hotspots. Thus, they should still be considered in future studies.

5.2 Variable Importance for the Month of January and its Influence on Fire-suitable Conditions

For 17 January 2010, the variables that trained the model the most about fire occurrence were the land surface temperature and net primary productivity. The model, based on the AUC, performed well and it distinguished between the positive and random instances. The fire potential increased with an increase in the net primary productivity, but peaked where it was

900 gC/m^2 and stagnated beyond that point. For the land surface temperature, the fire potential decreased with an increase in temperature, but it was greatest where 14600<LST<14800 Kelvins (18.85-22.85˚C). The fire-suitable conditions for 17 January 2010 were greatly concentrated in the municipal areas of the Garden Route and the Cape Winelands, as well as in the Overberg near Swellendam. The combination of land surface temperature and net primary productivity as important variables for fire occurrence on 17 January 2010 could be similar to the conditions that were present for 09 January 2012 and as such could indicate moisture-limited fuel loads. As previously explained, the net primary productivity has been used in studies to indicate drought conditions. In combination with the land surface temperatures this could indicate an environment primed for evapotranspiration and thus results in drier conditions. As such the likely reason for fire occurrence on 17 January 2010 could have resulted primarily from the water-stressed plants being more highly flammability.

For 09 January 2012, the variables that were most influential, in terms of training the model about fire occurrence, were net primary productivity, precipitation and elevation. The model's performance, based on the AUC, suggests that it performed well and distinguished between positive and random instances. On 09 January 2012, fire-suitable conditions were the greatest in the City of Cape Town, the Overberg and the Garden Route. The fire potential was greatest where the net primary productivity was approximately 900 gC/m^2. For precipitation, the fire potential decreased with an increase in precipitation and fire probability was greatest where precipitation was 0 mm. The fire potential decreased with an increase in elevation suggesting that fire probability was greatest in the lower lying regions of the Western Cape. This indicates that fire occurrence occurred primarily because of the drier conditions, together with moisture-limited fuel loads because of limited precipitation. When focusing on the discussion on net primary productivity, many studies have shown that it is correlated to drought conditions. Therefore, for 09 January 2012, it is possible that the net primary productivity did not only act as a measure of the available fuel load, but that it was also, together with limited precipitation, an indicator of the drier climatic conditions during this period. Whilst the aboveground biomass was not a major contributing factor, living plants that are water-stressed and/or of a dry herbaceous biomass-limited species, would still be viable candidates for high flammability. Based on the evidence for the two models that were run for January, the fire-suitable conditions for the month of January seem to suggest that fire occurrence is a result of moisture-limited fuel loads (i.e. the vegetation being water-stressed).

5.3 Variable Importance for the Month of February and its Influence on Fire-suitable Conditions

For 10 February 2015, the net primary productivity, precipitation and aboveground biomass were described as the most influential variables in terms of training the model about fire occurrence. The model, based on the AUC, performed well and it distinguished between the positive and random instances. Fire-suitable conditions occurred in the Cape Winelands and the Garden Route municipal districts; however, in relation to the surface area covered by these conditions above a point-wise mean of 0.50, the relative area covered was significantly small. In relation to the net primary productivity, fire potential peaked where it was approximately 2400 gC/m^2 and decreased beyond that threshold. As for the above ground biomass the fire potential was greatest where it was approximately 6000 kg/ha/yr and it decreased with a further increase in the above ground biomass. For 10 February 2015, the fire potential seemed to increase with an increase in precipitation, with a peak occurring where the precipitation was 21 mm. Whilst the precipitation was relatively high for 10 February 2015, it makes sense that fire-suitable conditions were incredibly limited for this period. Based on the influence of the net primary productivity and aboveground biomass on fire-suitable conditions, it would seem that the fire occurrence for 10 February 2015 was primarily due to fuel availability, rather than to fire-prone climatic conditions influencing the moisture in the vegetative structures.

For 10 February 2017, the precipitation, elevation and net primary productivity were the most important descriptors for fire. The model, based on the AUC, performed well and distinguished between the positive and random instances. Fire-suitable conditions were concentrated in the Garden Route, the West Coast (bordering on the Cape Winelands) and part of the Central Karoo (Beaufort West). For precipitation, the fire potential decreased with an increase in precipitation and fire probability was greatest where precipitation was 0 mm. For elevation, the fires increased with an increase in elevation. For net primary productivity, the fire response peaked where it was approximately 800 gC/m^2. Based on the conditions that were present for 10 February 2017, the likely result of fire-suitable conditions can be accounted for by the moisture-limited vegetation and fuel load, which is contrary to the evidence presented for 10 February 2015, and which can be explained by the drought that plagued the Western Cape during 2017. Therefore, whilst no conclusive results can be drawn about the necessary conditions for fire occurrence for the month of February, it seems that, under relatively normal seasonal conditions, fire occurrence in February can be attributed to fuel availability, whilst under drought conditions, the limited moisture conditions in the vegetation and the available fuel load is likely to be the primary instigator for the occurrence of fires.

5.4 Variable Importance for the Month of March and its Influence on Fire-suitable Conditions

In March, only one model was useable as an example of fire occurrence. For 22 March 2017, the three variables that were the main descriptors for fire occurrence were the net primary productivity, elevation and aboveground biomass. The model, based on the AUC, performed well and it distinguished between positive and random instances. Fire-suitable conditions were concentrated in the Cape Winelands and the Garden Route municipal districts. For the net primary productivity, the fire potential showed an increase, but it peaked where the net primary productivity was ~1800 gC/m^2 and remained constant thereafter. For elevation, fire potential increased with an increase in elevation, but it peaked where it was at ~ 1000 m. For aboveground biomass, fire potential increased with an increase in aboveground biomass, but peaked at ~ 4500 kg/ha/yr. All of the above variables that influenced fire occurrence seem to point to the fact that the fire occurrence for 22 March 2017 was influenced greatly by the availability of ignitable fuel.

For 22 March 2017, similar conditions were seen to those in 10 February 2015, with the exception of there being relatively high precipitation values. Fires were therefore also mainly concentrated in the Cape Winelands and the Garden Route municipal districts. When looking at 22 March 2017 as a continuation of 10 February 2017, it could explain why the conditions suitable for fire occurrence were primarily explained by fuel availability. The likely reason for this is that the moisture-limited conditions of the previous month, as a result of the drought, caused an increased loss in the fuel moisture for the already-available fuels, thereby creating a lag effect. This lag affect could potentially be attributed to the availability of ignitable fuel loads and, therefore, the fire suitable conditions for March were expressed primarily as a result of fuel availability.

5.5 Variable Importance for the Month of April and its Influence on Fire-suitable Conditions

Only one model was applicable as an example of fire occurrence for the month of April. For 07 April 2009, the variables that were the most significant descriptors of fire occurrence were the aboveground biomass and elevation. The model, based on the AUC, performed well and it distinguished between the positive and random instances. Fire-suitable conditions were concentrated in the Overberg, the City of Cape Town and southern parts of the West Coast and the Garden Route, mainly along the coast. The fire-suitable conditions became increasingly less pronounced further inland. The fire potential decreased with an increase in elevation suggesting that fire probability was greatest in the lower lying regions of the Western Cape. The relationship between fire and elevation for this particular model could be explained by the occurrence of fires that were concentrated closer to the coastal parts of the Western Cape and that were therefore at a lower elevation. For aboveground biomass, the fire potential increased with an increase in the aboveground biomass, suggesting that, for this model, fire was largely due to an increase in the available fuel load. The two contributing variables, however, were too vastly different to the other environmental variables considered for 07 April 2009. This, of course, brings the overall accuracy of the model into question, as it could be that the model was largely over-fitted due to the correlation between the variables. A plausible reason for this could be found in the elevation; this consensus is based on the evidence found in other studies, as previously discussed, where elevation was often found to be heavily correlated with other variables that influence fire occurrence.

5.6 Variable Importance for the Month of December and its Influence on Fire-suitable Conditions

In December, one model was applicable for the description of fire occurrence. For 19 December 2014, the variables that seem to train the model significantly were precipitation, land surface temperature and net primary productivity. The model, based on the AUC, performed well and it distinguished between positive and random instances. Fire-suitable conditions were concentrated in the Garden Route and parts of the Overberg and Cape Winelands. For precipitation, It was observed that the fire potential for 19 December 2014 decreased with an increase in precipitation and fire probability was greatest where precipitation was 0 mm. As for the land surface temperature, the fire potential decreases with an increase in temperature and the greatest observed fire potential occurs where the land surface temperature is between 14600 -14800 kelvins (18.85 - 22.85˚C). For the net primary productivity, the fire response peak was approximately 2600 gC/m^2.

For December, the occurrence of fire seems to be linked primarily to the moisture-limited vegetation and fuel loads, based on the fact that fire peaks, where precipitation shows a deficit, and land surface temperature seem to show the same general threshold as was the case for the previously-discussed models, that implicated land surface temperature. The net primary productivity, whilst being relatively high for this particular model, has been shown to be influenced by drought-like conditions, as previously discussed. Therefore, its presence in the model for 19 December 2014 could further support the idea of the fire-suitable conditions being a result of moisture-limited conditions, or it could simply be an estimation of the viable fuel loads. Therefore, based on the environmental conditions on 19 December 2014, it would seem that fire occurrence was primarily caused by moisture-limited conditions that probably caused the vegetation and the available fuel load to become more ignitable.

5.7 The Implication of Elevation and Wind Speed and their Effects on the Overall Model Performance

Elevation as a significant environmental variable that influenced the training of the model with regard to fire occurrence, and it appears in four of the seven models that were run in this study, namely, on 09 January 2012, 10 February 2017, 22 March 2017 and 07 April 2009. Based on the studies reviewed in this chapter, fire response was found to generally decrease with an increase in elevation, particularly beyond an elevation of 700 m. Interestingly, however, in two of the models (22 March 2017 and 10 February 2017) that were run in this study, the fire potential was found to increase with an increase in elevation, while the remaining two models that included elevation (07 April 2009 and 09 January 2012) showed that the fire potential decreased with an increase in elevation suggesting that fire probability was greatest in the lower lying regions of the Western Cape. For 10 February 2017 and 22 March 2017, fire-suitable conditions occurred in the same general areas for both models. More specifically, fire-suitable conditions for both these models were concentrated mainly in the Cedarberg Wilderness, Laingsburg and Ladismith areas, which have points of elevation that range between 500 – 900 m. This could explain why the model suggests that fires increased with an increase in elevation, because the fire-suitable conditions occurred mainly on the surrounding mountainous regions or areas of high elevation. Another reason for the increase in fires with elevation could be that heavily correlated environmental variables, such as evapotranspiration and/or fuel continuity, are linked to elevation. On 07 April 2009, the fire-suitable conditions occurred mainly along the coastal areas in the Western Cape, with them becoming less pronounced further inland. This could explain the reason why the fire response to elevation showed that fire decreases with an increase in elevation, as most fire suitable conditions occurred in areas where the elevation was low. Similarly, for 09 January 2012, fire-suitable conditions were concentrated mainly along the low-lying areas in the areas of Langebaan, Albertinia, Bonnievale and Robertson, where the elevation ranges from 13-183 m, 68-416 m, 166-486 m and 145-935 m, respectively. With the exception of Robertson, the majority of these areas occur at a very low elevation, and furthermore, if fires occurred mainly in the lowest-lying parts of these areas, it could explain the trend that was seen for 09 January 2012. In summary, elevation, as seen in the model, seems to be influenced mainly by whether the majority of fire occurrences appear in low- or high-lying areas. Therefore, the information provided by elevation as a variable does not have a great influence on the conditions needed for fire occurrence. It is therefore likely that other variables that are highly-correlated with elevation, but which are excluded from the model framework, such as evapotranspiration, could provide a clearer picture as to why fire-suitable conditions were mainly concentrated in these areas.

Because of data constraints for wind speed, only two models were applicable. Furthermore, as previously explained, the wind speed data had to be interpolated for the Western Cape via a function of circular kriging, as it was only available as vector data for four occurrence points. Therefore, the interpreted results for wind speed cannot be viewed as significant; instead, they can be used as a proxy. However, studies have shown that wind speed, as a variable, does not impact the occurrence of fires, as such, but rather that it affects the spread of a fire and is therefore a function of intensity. The two models in which wind speed was implicated as an environmental variable were for 09 January 2018 and 17 January 2018. For each of these models there seems to be over-fitting, based on the fact that only one of the seven variables showed a significant percentage contribution. For 09 January 2018, the land surface temperature showed a 65% contribution, with the next closest variable being the net primary productivity, which accounted for only 21% (Figure 9 see in Appendix). For 17 January 2018, the maximum wind speed showed a 75% contribution, with the next closest variable being land surface temperature, which only accounted for 20% (Figure 10). Therefore, wind speed was not included in the discussion of the results in this study, as no significant scientific conclusions could be drawn from the results pertaining to the influence of wind speed on fire-suitable conditions.

CHAPTER 6: CONCLUSIONS AND RECOMMENDATIONS

6.1 Summary of findings

Based on the results of this study, certain conclusions can be drawn about the observed trends, based on the environmental variables that were considered. For the majority of the models, the Cape Winelands and the Overberg municipal districts were the areas in which fire-suitable conditions appeared most frequently. The Garden Route municipal district was shown to be the only municipal district in which fire-suitable conditions were present in all of the models that were run. For two of the three models (10 February 2015 and 22 March 2017), the fire response to the net primary productivity was greatest where NPP ≥ 1800 gC/m^2 and the fires were concentrated only in the Garden Route and Cape Winelands areas. These two models were also the only models in which fuel availability, in the form of aboveground biomass, influenced fire occurrence, with the exception of 07 April 2009, which had questionable results that cannot be considered to represent the norm. In the other remaining models, climate seems to be the main influence on fire occurrence, Specifically moisture-limited environments in which fire response to precipitation peaks at ≤ 0 mm or land surface temperatures at 18.85 – 22.85˚C. For three of the four models in which moisture-limited conditions were the reason for fire occurrence, fire response to the net primary productivity peaked where it was ~900 gC/m^2 and showed no further increase beyond this threshold. As previously discussed, the implication of this threshold could be an identifier of moisture-limited conditions, as it can be linked to drought. With the exception of 19 December 2014, this seems to be the case when the models in which fire response peaks with a greater net primary productivity value all seem to implicate fuel availability as the primary reason for fire occurrence. In summary, fire-suitable conditions seem to be most prevalent where fire probability decreases with an increase in precipitation, specifically where fire probability is greatest with a precipitation is 0 mm, where the land surface temperature is between (18.85 – 22.85˚C) and where the net primary productivity is either ~900 gC/m^2 or ≥ 1800 gC/m^2. Furthermore, based on the overall model performance, the selected variables can be used as a working framework for fire monitoring with the help of additional environmental variables. However, the framework proposed in this study is only applicable to Mediterranean climates, and whilst most of the environmental variables that were used can be extrapolated to other climatic zones, the same thresholds will not apply. This is because many of the fire-suitable conditions that apply to Mediterranean climates are due to the vegetation characteristics and the moisture-limited conditions. For example, climates that are wetter, will potentially only be fire suitable under much more severe climatic conditions; therefore, the localized effects need to be understood first, before applying this framework.

6.3 Limitations and Challenges

Due to time-constraints there has been a limitation of statistical tests that could have been performed in further support of model evaluation. Furthermore the limitation of wind speed data influenced the validity of the contribution of wind speed as an environmental variable and thus was only exploratory.

6.2 Recommendations for future research

Based on the results achieved in this study, certain recommendations can be made to inform future frameworks on the potential environmental variables that might better inform models about the conditions that are required for the occurrence of fires. As previously discussed, wind speed, rather than the actual occurrence of fire, influences the spread of fire and it should therefore be primarily used in frameworks that attempt to predict where fires might spread. Wind direction, however, should also be considered when attempting to predict the fire spread rate. More specifically, fires that are found backing into winds do not show an increase in their spread rate with an increase in the wind speed, but rather, they could potentially be extinguished if the wind speeds are high enough. With regard to elevation, as previously discussed, most studies seem to agree that fires show a general decrease, with an increase in elevation. In this study, no conclusive information was provided about fire occurrence and its relationship to elevation, but this is probably because other fire-relevant variables are masked out by their high correlation with elevation. It is therefore recommended that other variables be considered in the place of elevation in future fire frameworks, for example, fuel continuity based on plant ecotypes, evapotranspiration and the aspect. With regard to fuel continuity, the occurrence of Fynbos plants that are spread in the mountainous regions across the Western Cape, influences the availability of a potential fuel load at higher elevations. Evapotranspiration influences the water content of the vegetation and it has been shown to be correlated to elevation; the significance for fire occurrence is that plants that are moisture-limited are inherently more flammable. The idea is that evapotranspiration could influence the flammability of vegetation at higher elevations and could thus have a greater influence on the required conditions for the occurrence of fires at greater elevations. Lastly, the slope aspect is a variable that could allow for greater scrutiny, particularly in terms of solar radiation, as well as elevation. This aspect could allow for more information on fire-suitable conditions in mountainous regions and thus the identification of hotspots alongside the other elevation-related variables mentioned in this section. This is because studies have shown that aspect is an influential variable that influences fire occurrence and warmer aspects have been shown to be more likely to burn than cooler aspects.

6.3 Conclusion

In conclusion, the advancement of future frameworks for fire monitoring can provide strategic advantages to fire monitoring with the ultimate goal of achieving a natural fire regime. Furthermore, understanding the dynamics of local climate can better advise future fire monitoring efforts with a clear description of the environmental variables needed to determine fire probability. The framework provided within this study, however, was considerably successful but the performance of said framework can be enhanced with the inclusion of multi-collinearity tests to better understand the influence of variables on each other.

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APPENDICES

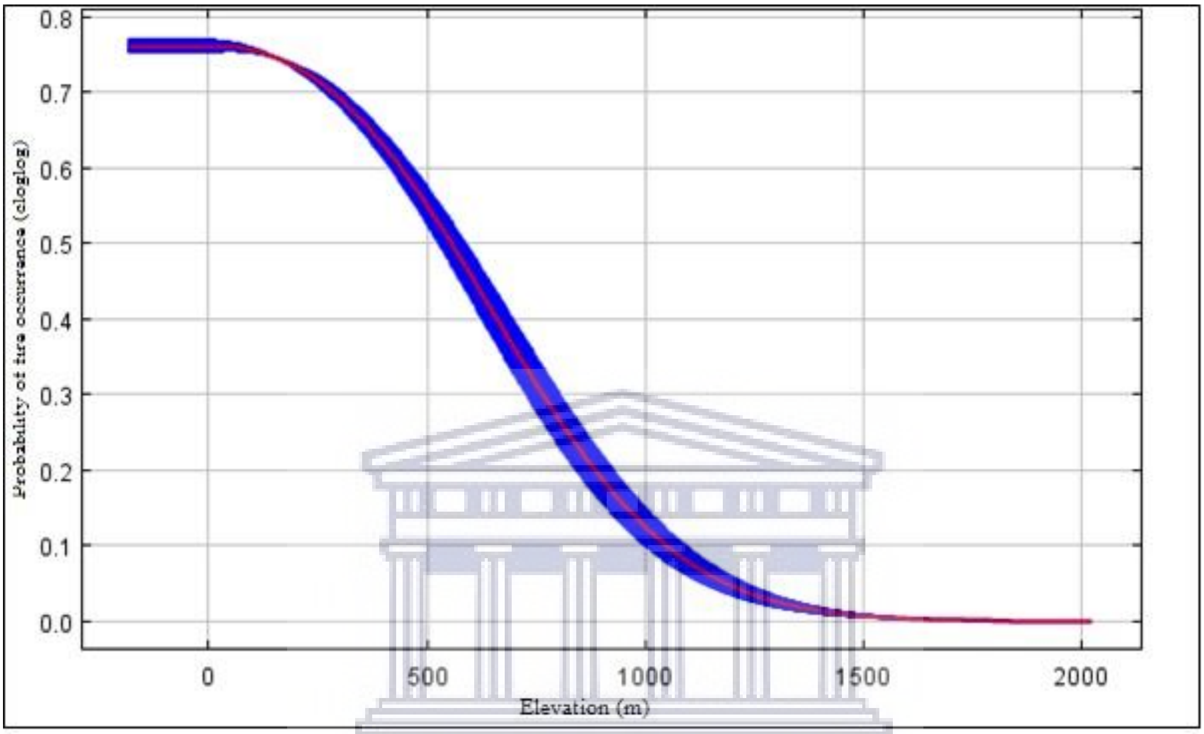

Figure 5 Fire response to variability in elevation for 09 January 2012

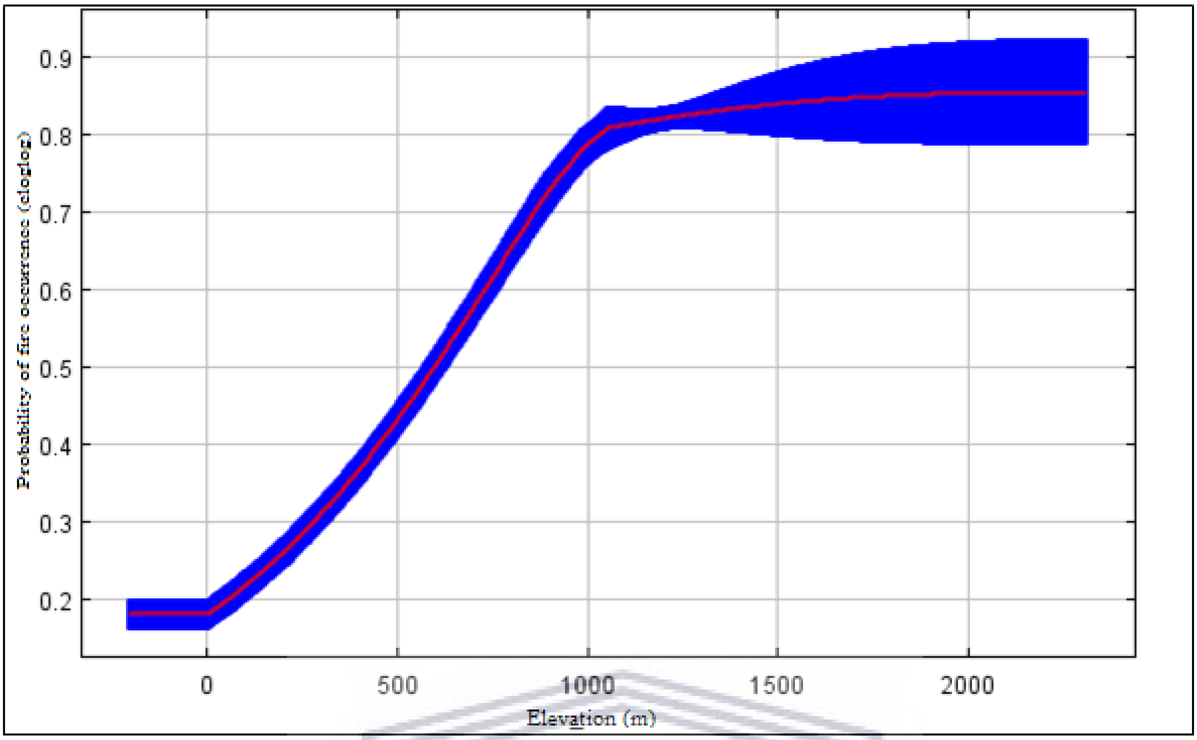

Figure 6 Fire response to elevation for 10 February 2017

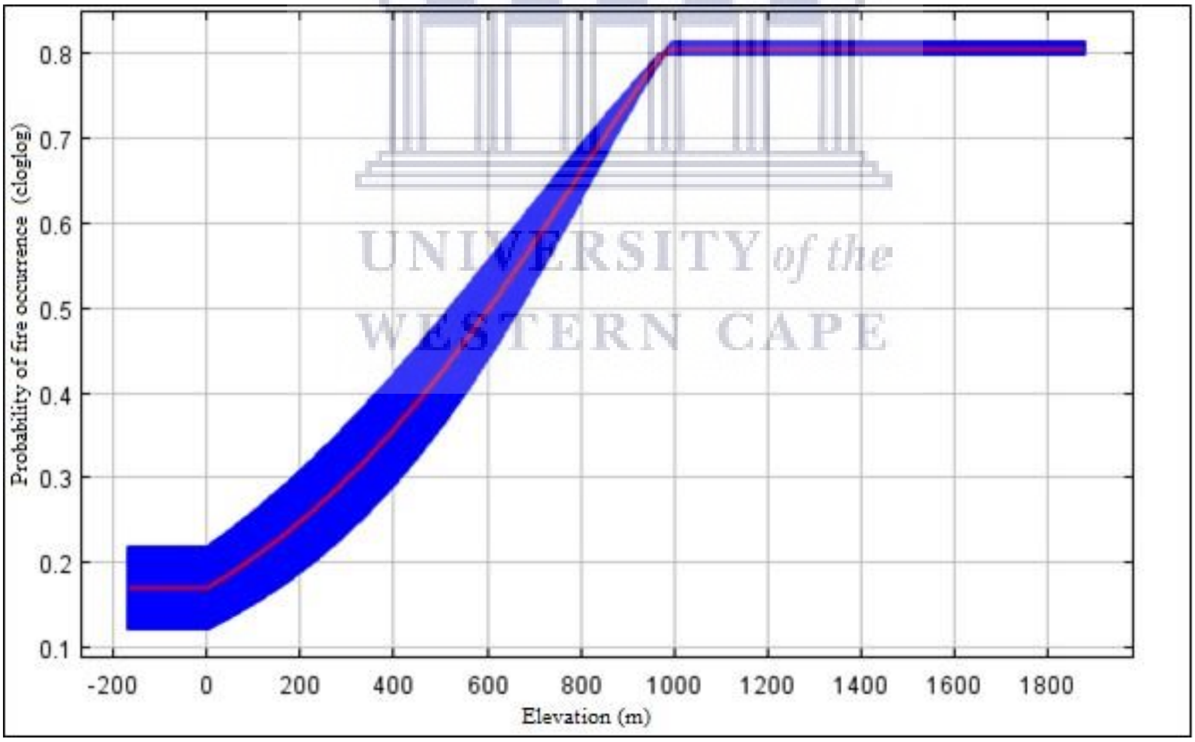

Figure 7 Fire response to elevation for 22 March 2017

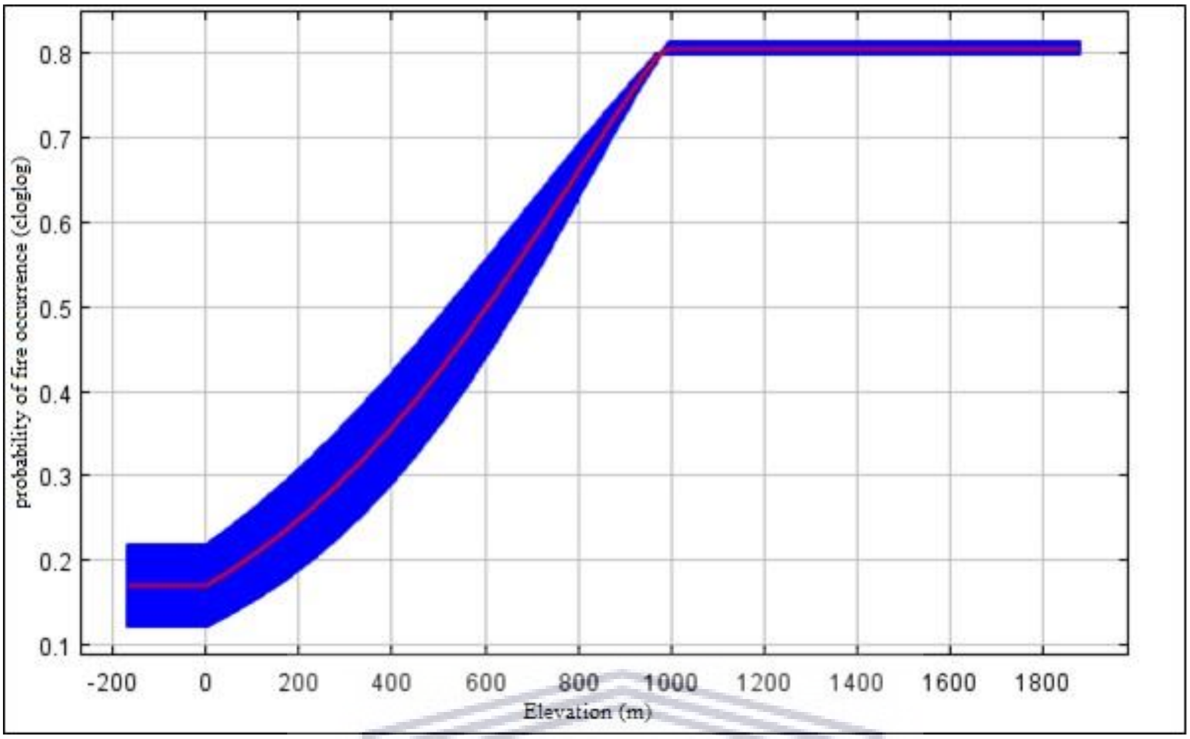

Figure 8 Fire response to elevation for 07 April 2009

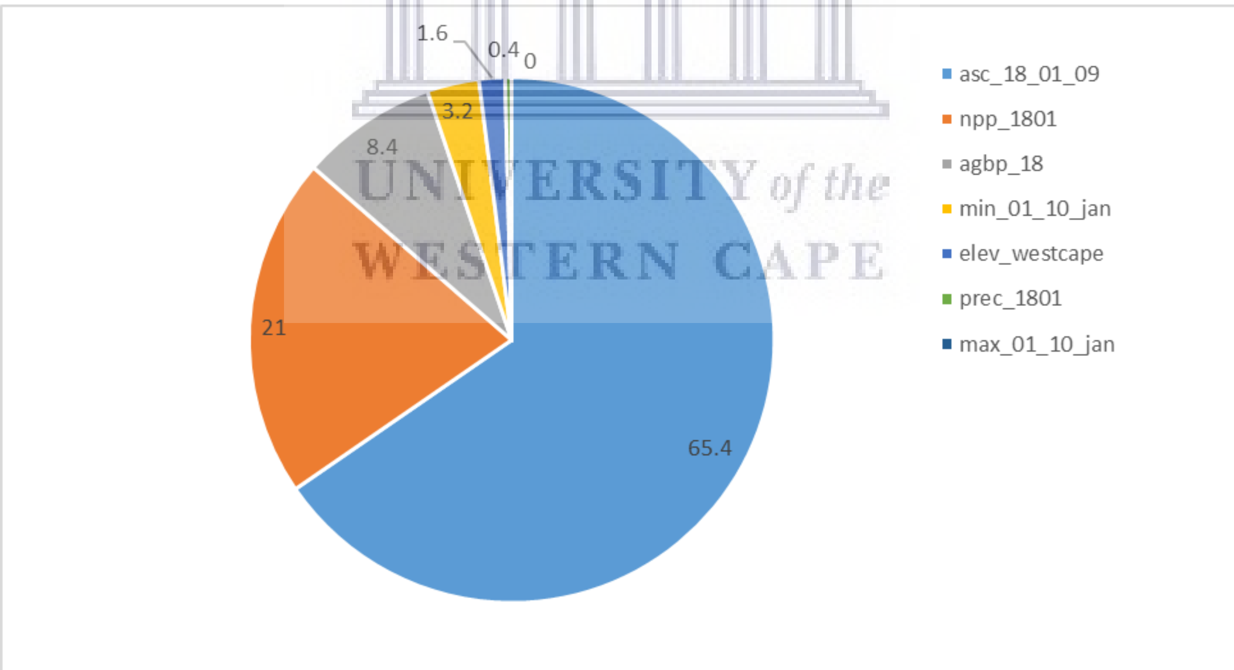

Figure 9 Percentage contribution of environmental variables for 09 January 2018

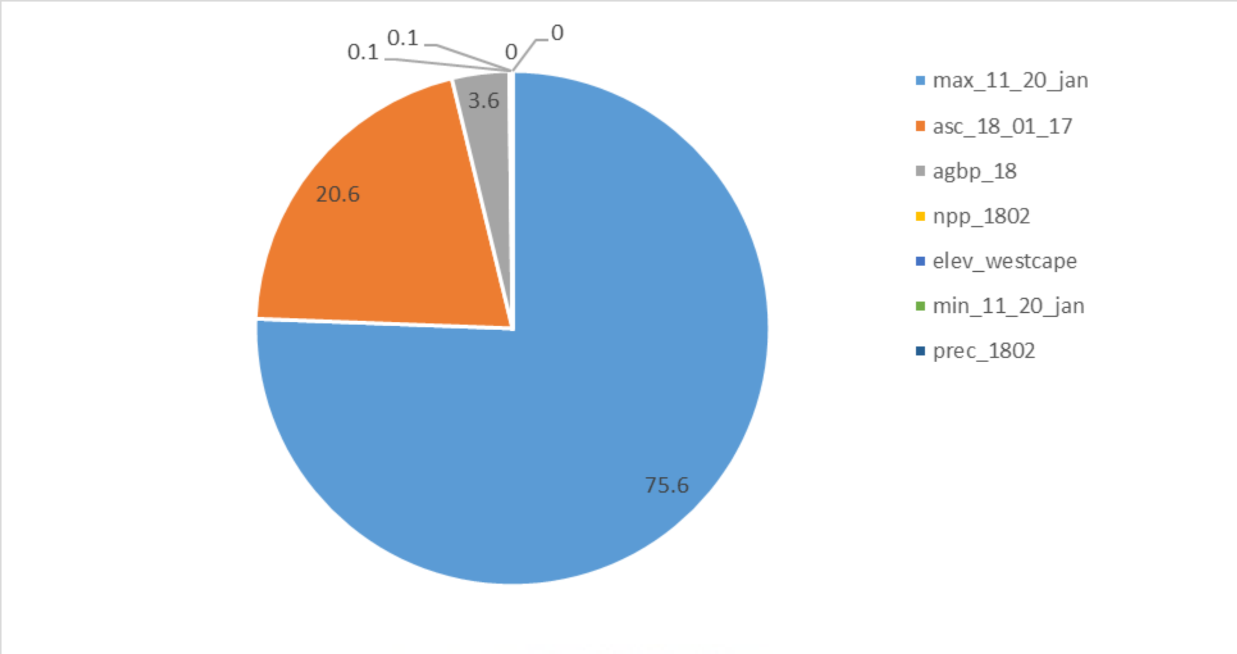

Figure 10 Percentage contribution of environmental variables for 17 January 2018