Estimating critical grassland vegetation moisture parameters using topo-climatic variables and remotely sensed data in relation to fire occurrence

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This thesis is submitted in fulfilment of a Master of Science degree in the School of Agriculture, Engineering and Science

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January 2021

Abstract

Quantifying grassland Fuel Moisture Content (FMC) and Equivalent Water Thickness (EWT) is critical for establishing early fire-warning systems as well as encouraging proactive fire management strategies. This also facilitates the preservation of grassland functions such as carbon sequestration under the influence of climate change. Fire danger has been monitored using local weather information from multiple stations, which is tedious and lacks spatial representation. Meanwhile, using remote sensing and statistical algorithms to estimate grass moisture elements such as FMC and EWT could facilitate a better understanding of fire regimes even in inaccessible areas. In this regard, this work sought to i) assess the utility of topo-climatic and Sentinel 2 Multispectral Instrument (MSI) satellite data in estimating grass FMC and ii) to estimate EWT using Sentinel 2 MSI derived variables in the rangelands of Southern Africa using the Random Forest (RF) algorithm. Results of this study showed that FMC could be estimated to an R^2 and RMSE of 0.68 and 0.039 % m^2, respectively. The optimal variables in this model were channel networks and elevation. In estimating EWT using Sentinel 2 MSI variables only, the RF results yielded an R^2 and RMSE of 0.75 and 0.019 g/m^2, respectively. The important variables identified using RF were Modified Normalised Difference Vegetation Index (NDVI) (Short Wave Infra-red (SWIR)1/Band 2), Band 2, Soil Adjusted Vegetation Index, and the Modified Simple Ratio (SWIR1/Band 2). This study demonstrates the prospects of utilizing Sentinel 2 MSI satellite remotely sensed and top-climatic data in estimating EWT and FMC as fire risk indicators in South African grasslands.

Preface

This study was conducted in the School of Agricultural, Earth and Environmental Sciences, University of KwaZulu-Natal, Pietermaritzburg, South Africa, under the supervision of Professor Onisimo Mutanga and Dr Mbulisi Sibanda in fulfilment of the requirements of Master of science.

I declare that the current thesis represents my ideas and has not been submitted to any other academic institutions. Acknowledgements have been made for statements originating from other authors.

Wenzile Shinga Signed [redacted] Date 24 January 2020

1. Prof Onisimo Mutanga (Supervisor) [redacted] Signed Date 24 January 2020

2. Dr Mbulisi Sibanda (Co-Supervisor) Signed Date: 26 January 2020

Declaration

I Wenzile Shinga declare that:

1. The work reported in this document is my original work unless indicated otherwise.
2. This thesis has not been submitted for the attainment of a degree or examination purposes at another university.
3. This thesis does not contain any data, graphics, and other information from other persons and the internet unless duly acknowledged.
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    a. Their words have been paraphrased and general information attributed to them has been referenced.
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Dedication

This thesis is dedicated to my parents and my younger sisters.

Acknowledgements

I would like to thank God for giving me the strength to see this opportunity through.

I would also like to thank Professor Mutanga and Dr Sibanda for their supervision throughout this MSc.

This study was funded by the Durban Research Action Partnership and the National Research Foundation of South Africa (NRF) Research Chair initiative in Land Use Planning and Management (Grant Numbers: 84157), NRF Grant (119791).

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Chapter one: Background and introduction

1.1 Introduction

Grassland landscapes cover approximately 40% of the global surface area and are seen as model ecosystems due to their vast socio-economic services at national, local, and catchment levels (Le Maitre *et al.* 2014; Hönigová *et al.* 2012; Kirkman *et al.* 2014). In South Africa, grasslands cover 336,544 km^2 and 73% of all cultivated timber resources occur in this biome (De Wit and Blignaut 2006; Gombakomba 2008). In addition, South African grassland ecosystems contribute a total of R9, 761 million to the country's economy and they are the most productive biomes providing food crops such as maize and rice (Bommert *et al.* 2005; Neke and Du Plessis 2004; van Zyl Engelbrecht 2018). They also play a vital role in processes such as atmospheric carbon sequestration, biodiversity conservation, air quality purification, regulating the hydrological cycle (Hönigová *et al.* 2012; Shoko *et al.* 2018) as well as providing habitats for animals, including terrestrial isotopes seeking shelter from strong currents (Hassall and Tuck 2007). However, the occurrence of disturbances such as wildfires in grassland biomes has become a global pandemic Chuvieco *et al.* 2004. This is because grasses are incapable of holding moisture and they wilt and dry relatively faster than other biomes making them more vulnerable to fire ignition leading to increased fire frequencies. Meanwhile, there are very limited spatial explicit techniques for monitoring wildfire ignition and the impact of these wildfires on the grassland ecosystem. There is, therefore, a need for accurate, continuous, and effective wildfire monitoring frameworks to understand and manage wildfires to sustain the availability of these diverse ecosystem functions and services. Specifically, quantifying and understanding factors such as grass Fuel Moisture Content (FMC) and Equivalent Water Thickness (EWT) that influence fire occurrence and intensity is a critical step towards building robust wildfire monitoring frameworks.

Conventional methods that involve the cutting of grass samples in the field have been used in assessing grass moisture elements, such as the EWT and FMC. However, these traditional methods are point-based, can be subjective, time-consuming, costly and are difficult to conduct especially in remote areas (Lu 2006; Chen *et al.* 2016). Alternatively, remote sensing has overcome some of these limitations (Kerr and Ostrovsky 2003) by providing relatively cheaper data acquisition techniques and datasets that cover larger spatial extents at high revisit frequencies (Arroyo *et al.* 2008; Chen *et al.* 2016). Remotely sensed datasets thus offer an accurate and robust platform for FMC and EWT quantification and determining the occurrence of fire probability data that may overcome the limitations of traditional fire monitoring (Dasgupta *et al.* 2007; Adab *et al.* 2016).

Satellite sensors that have been applied in fire management studies include Advanced Very High-Resolution Radiometer (AVHRR) and Moderate Resolution Imaging Spectroradiometer (MODIS) sensors, which provided moderate spatial, temporal and spectral resolution data. However, limitations of older sensors such as the AVHRR include the unsuitability of the middle-infra red channel for fire observation as well as coarse spatial resolutions (Chen *et al.* 2005a; Hantson *et al.* 2012; Chen *et al.* 2005b). Landsat sensors were then largely applied in the estimation of FMC and EWT studies as an alternative to its coarse resolution predecessors (Chuvieco *et al.* 2002a; Riaño *et al.* 2002; Xiao-rui *et al.* 2005). Although characterized by a higher spatial resolution than the previous sensors, the utilization of Landsat TM/ETM in vegetation water content mapping is limited by its low temporal resolution of 16 days as well as its spectral band set which does not cover the red edge region of the electromagnetic spectrum (EMS) that is fundamental in characterizing vegetation traits.

New freely available multispectral sensors such as Sentinel 2 Multispectral Imager characterized by high spectral, spatial and temporal resolutions offer datasets that could be suitable for mapping grass EWT and FMC (Delegido *et al.* 2011). Specifically, Sentinel 2 MSI has a temporal resolution of 5-days, which could be useful for assessing environmental phenomena such as fire occurrence. With a spatial resolution at 10m to 60m, it allows for direct measurements of vegetation properties (Sibanda *et al.* 2015; Li and Roy 2017). This makes it suitable for large-scale applications (Vafaei *et al.* 2018). Moreover, it's unique spectral resolution of 13 bands from the visible (560 nm), near infrared (853 nm) and the shortwave infrared regions (1610 nm) important water absorption bands, further increases its accuracy in vegetation moisture retrieval and deriving vegetation indices (VIs) (Drusch *et al.* 2012).

A large and growing body of literature illustrates that the use of vegetation indices derived from the new generation of multispectral sensors increases the accuracy of estimating vegetation traits, such as FMC and EWT (Drusch *et al*. 2012; Tian *et al*. 2016; Yebra *et al*. 2013). This is because VIs show better sensitivity of vegetation to water content than individual spectral bands (Yebra *et al.* 2008; Yebra *et al.* 2013; van Zyl Engelbrecht 2018). This is because VIs allow for the combination of spectral bands for a clearer understanding of vegetation quantity and quality while removing variability caused by canopy geometry, soil background, sun-view angles and atmospheric condition when measuring biophysical properties (Wang *et al.* 2008). The use of VIs in estimating FMC and EWT is based on the hypothesis that chlorophyll content of leaves and the degree of drying are proportional (Chuvieco *et al.* 2004). Meanwhile, fire occurrence and minimal moisture content are generally associated with semi-dry and dry leaves with less chlorophyll content. VIs applied in monitoring vegetation include the Enhanced Vegetation Index (EVI), Normalized Vegetation Index (NDVI), and the Normalized Difference Water Index (NDWI), to mention a few. In both FMC and EWT quantification studies, literature shows that the NDVI which is the ratio of the visible and near-infrared wavelengths, is the most popular but is limited in explaining water quantity in grasses because it is independent of errors in atmospheric corrections, topography distortions and saturation when vegetation cover is dense (Chuvieco *et al.* 2004; Chuvieco *et al.* 2002a; Dilley *et al.* 2004; Tian *et al.* 2016). Other studies applied the Normalized Difference Wetness Index and the Global Vegetation Moisture Index because they are less sensitive to atmospheric effects than the NDVI (Pu *et al.* 2008). However, validation from other studies is still needed to identify and assess the robustness of VIs used in FMC and EWT quantification (Sow *et al.* 2013).

Meanwhile, it has been noted that the incorporation of environmental variables improves the accuracies of models in estimating vegetation attributes (Hawbaker *et al.* 2008; Yebra *et al.* 2013). Moreover, FMC and EWT of vegetation are generally affected by topographic and climatic variables amongst others (Holden and Jolly 2011; van Zyl Engelbrecht 2018). Topographic variables are important in explaining FMC and EWT variations because they are critical drivers of soil moisture content which in-turn regulates plant moisture content. Meanwhile, climatic variables such as temperature and precipitation are the most common in establishing and explaining plant moisture content as they also regulate evapotranspiration as well as plant and soil moisture content (Nyman *et al.* 2015; Holden and Jolly 2011). Considering that vegetation health and productivity are affected by seasonality, there is a need to evaluate how these climate-related variables will affect the variations in EWT and FMC (Shinoda *et al.* 2010). It is, therefore, paramount to identify and utilize techniques that can be efficient in combining remotely sensed, topographic and climatic data variables for accurate characterisation of FMC and EWT required in drawing up better wildfire monitoring initiatives.

The combination of optimal satellite sensors, vegetation indices, and topographic data can be further optimized by using robust statistical algorithms for fire-monitoring frameworks. Machine learning algorithms like multiple linear regression, support vector machines and random forest (RF) have been widely used to improve vegetation moisture modeling and fire management studies (Gottuk *et al.* 2002). Rated among the top data science algorithms, the RF algorithm has been applied to vegetation monitoring and mapping (Chen *et al.* 2020). Random forest is a simple, robust and accurate regression algorithm that can perform both regression and classification tasks (Cootes *et al.* 2012). The RF has been widely used because of its ability to handle missing and large data sets without compromising model accuracies (Guo *et al.* 2016). Literature on the utility and application of regression algorithms shows that the RF algorithm produced higher predictive ability and processing speed than logistic regression and multiple linear regressions in understanding spatial patterns Oliveira *et al.* 2012; Guo *et al.* 2016; Collins *et al.* 2018). The RF is a machine-learning algorithm that uses bootstrap aggression to determine and combine random trees (Guo *et al.* 2016; Zhou *et al.* 2016).It is in this regard that random forest was perceived to be the most suitable algorithm for estimating grass moisture elements in this study. Therefore, this study aimed to model the spatial distribution of FMC and EWT in parts of the eThekwini municipality grasslands during the dry season using the random forest algorithm.

1.2 Aim and objectives

The overarching objective of this study was to model the spatial distribution of FMC and EWT in parts of the KwaZulu-Natal Sandstone Sourveld (KZNSS) rangelands during the dry season. This was achieved based on two specific objectives which were are as follows:

1. To assess the utility of Sentinel 2 MSI derived variables in estimating grass EWT.

2. To estimate grassland FMC using topo-climatic and Sentinel 2 MSI derived variables.

1.3 Summary of the Thesis

Chapter One: *General Introduction*

The general introduction of the thesis provides a background to the economic and ecosystem importance of grasslands on a global and national level. The chapter also explored the need to quantify critical grassland moisture parameters (FMC and EWT) that can be used as indicators of fire incidence. The chapter discusses the use of remote sensing techniques to estimate these parameters compared to using traditional techniques. Lastly, the chapter provides the aim and objectives of the study.

Chapter Two: *Testing the Utility of Sentinel 2 MSI In Estimating Equivalent Water Thickness (EWT) Of the Endangered Grasslands in Southern Africa As A Proxy for Fire Incidence*

This chapter investigates the utility of remote sensing to estimate EWT in endangered South African rangelands. Specifically, the chapter tests the utility of Sentinel 2 MSI derived spectral bands and vegetation indices (standard, moisture-based and SWIR-based) using the robust RF machine learning algorithm. The chapter also investigates the relationship between estimated rangeland EWT and fire occurrence.

Chapter Three: *Estimating Grass Fuel Moisture Content (FMC) In Communal Grasslands of South Africa Using Remotely Sensed Data Combined with Topo-Climatic Variables*

This chapter demonstrated the use of DEM and WorldClim data in concert with Sentinel 2 MSI derived variables in estimating the EWT of communal grasslands. The chapter discusses the optimal results derived using the RF algorithm. The relationship that exists between estimated grassland EWT and fire incidence is also established using the logistic regression.

Chapter Four: *Synthesis*

The synthesis chapter provides a summary of the major results, implications of the study and final conclusions.

Chapter two

Testing the utility of Sentinel 2 MSI in estimating Equivalent Water Thickness (EWT) of the endangered grasslands in South Africa as a proxy for fire incidence

Rangelands visited in Thoyana (Photo captured by Wenzile Shinga 2019)

Abstract
For years, fire danger has been monitored using methods such as local weather information from multiple stations to provide a good basis for monitoring fire over complex, inaccessible terrains. The shift to the utility of remote sensing to better understand periods where vegetation experiences more water stress across different biomes has been successful in demonstrating the timeliness and accuracy of such methods. Equivalent Water Thickness (EWT) is a crucial vegetation moisture parameter in managing fire-prone communities such as the endangered South African KwaZulu-Natal Sandstone Sourveld (KZNSS), especially during the dry season. It is in this regard, that the utility of Sentinel 2 Multispectral Instrument (MSI) satellite data was tested in estimating grass EWT in the rangelands of South Africa using the random forest (RF) algorithm as a proxy for fire incidence. Specifically, the performance of standard spectral bands, general vegetation health, modified and moisture-related vegetation indices (VIs) were compared in estimating EWT. The results of the study showed that the SWIR region (1376.9 nm - 2185.7 nm), in particular SWIR Band 12, was the most important Sentinel 2 MSI derived band in estimating EWT. The moisture indices yielded an R^2 of 0.66, outperforming the standard and modified VIs. Modified NDVI and simple ratio vegetation indices estimated EWT to an R^2 = 0.65 and RMSE of 0.031 g/m^{-2} and standard VIs estimated EWT with an R^2 = 0.62 and RMSE of 0.019 g/m^{-2}, respectively. EWT was estimated with an R^2 of 0.75 and RMSE of 0.018 g/m^{-2} when the optimal variables were used (Modified NDVI (SWIR1/Band2), Band 2, SAVI, and the Modified SR (SWIR1/Band 2)). Therefore, this study demonstrates the prospects of utilizing Sentinel 2 MSI satellite remotely sensed data in estimating EWT as a proxy and a pathway towards understanding fire occurrences and frequency in endangered grasslands of southern Africa such as the KZNSS.

Keywords: Equivalent Water Thickness, KZNSS, Moisture indices, Modified vegetation indices, Fire management

2.1 Introduction

Understanding water content in grasslands is a fundamental step towards assessing rangeland fire hazards (Yebra *et al.* 2013). As a backbone to the agricultural system, grasslands cover 40% of the earth (6 billion hectares) (Lemaire *et al.* 2005; Féret *et al.* 2019; Ward *et al.* 2016). The global grassland community, in its entirety, helps to mitigate climate change by storing more carbon than the forest biome (Dass *et al.* 2018). In the Southern African context, rangelands play a critical role in animal and plant biodiversity and carbon and nutrient cycles, among other ecosystem services (Lemaire *et al.* 2005; Ward *et al.* 2016). Rangelands also contribute to rural livelihoods and national economies. For instance, South African grassland services contribute approximately R2.88 billion towards its economy (Drury *et al.* 2016). Grasslands such as the KwaZulu-Natal Sandstone Sourveld (KZNSS) are home to an array of endemic bird species like the Blue Crane that is listed under the critically endangered species (Arnott 2006; Maphisa 2015). However, the functioning of this biome is threatened by climate change, heavy transformation to feed the growing human populations, overgrazing, urban sprawl and wildfires (Liu *et al.* 2018; Lopes *et al.* 2017; Neke and Du Plessis 2004). However, frequent fires are the principal threat to livelihoods and biodiversity in these rangelands and require urgent attention (Liu *et al.* 2018; Lopes *et al.* 2017). Therefore, the need for optimal assessment of Southern African rangelands is critical and paramount to preserving their biodiversity and function.

KZNSS is a prominent Southern African type of grassland which covers 179 671 hectares. It is prominent because it is a portion of the Maputuland-Pololand-Albany biodiversity hotspot in South Africa. In this regard, it requires frequent monitoring and assessment according to the Biodiversity Act 10 of 2004 which states that to maintain biodiversity there should be appropriate management and conservation of South Africa's biodiversity (Drury *et al.* 2016). The KZNSS is predominantly characterized by endemic vegetation of forbs, bushclamps and geoxylic suffrutices and approximately 90% is under-protected (Boon *et al.* 2016). Due to changing fire regimes, further grassland patches are degraded and encroached by woody vegetation. Although an essential tool in maintaining the grassland landscape structure, frequent fire occurrences presents a growing threat to such ecological landscape, biodiversity, ecological function and stability (Russell-Smith *et al.* 2002; McGranahan *et al.* 2016; Sow *et al.* 2013). There is, therefore, an imperative need to quantify fire events swiftly and accurately to manage such endangered ecosystems and preserve their function. The management of such rangelands has been facilitated by investigating, extrapolating and quantifying critical vegetation fire parameters such as canopy water content (Ceccato *et al.* 2001; Sow *et al.* 2013).

Plant water content constitutes 40-80% of the plant's leaf volume and as such, it is a critical biochemical parameter in understanding fire propagation, intensity and pattern (Chuvieco *et al.* 2002b; Ceccato *et al.* 2001; Mobasheri and Fatemi 2013; Wang *et al.* 2010). High percentages of water content reduce fire propagation and result in low fire intensities since there will be limited dry matter to initiate combustion. Plant water content in relation to fire is calculated as Fuel Moisture Content (FMC) or Equivalent Water Thickness (EWT), the latter is defined as the volume of water per unit area (Datt 1999; Féret *et al.* 2019). EWT is quantified throughout the fire season using empirical traditional laboratory methods which are tedious, time-consuming and spatially limited. These generally include the cutting and weighing of wet and dry grass biomass to quantify their moisture content. EWT is an indicator of grass curing and fire intensity; hence there is a need for more robust and efficient spatially explicit approaches for characterizing it (Jackson *et al.* 2004; Shen *et al.* 2005; Yilmaz *et al.* 2008).

Meanwhile, remote sensing facilities provide a quicker, cheaper and non-destructive approach to estimate EWT for fire management at local to regional scales (Danson and Bowyer 2004; Datt 1999; Yilmaz *et al.* 2008). Literature on the potential of remote sensing in retrieving EWT illustrates that the sensitivity of reflectance is wavelength-dependent, with water absorption peaks observed at 970nm, 1200nm, 1450nm and 1950nm being highly sensitive to grass foliar and grass canopy moisture content (Cao and Wang 2017; Shen *et al.* 2005; Sjöström *et al.* 2009). Specifically, the reflectance in the SWIR section of the EMS tends to increase with the decrease of leaf water content. Moreover, the sensitivity of the SWIR to plant water content variations provides a good basis for estimating EWT compared to other vegetation biophysical properties like Fuel Moisture Content (Danson and Bowyer 2004; Wang and Shi 2007). Therefore, there is a need to assess the potential of the SWIR section with other sections of the EMS in estimating EWT as a step towards drawing up robust and effective fire monitoring and management strategies in the Southern African context.

Numerous space-borne earth observation satellites have been widely used to estimate EWT as a proxy for fire incidences. These space-borne EO facilities include Landsat, Hyperion, Moderate Resolution Imaging Spectroradiometer (MODIS) and World-View (Hunt Jr *et al.* 2016; Maffei and Menenti 2014). Despite the high temporal resolution and moderate spectral resolutions associated with MODIS and Landsat, their spatial and spectral resolutions are still somewhat coarse in characterizing elements of vegetation canopy water content such as EWT (Chen *et al.* 2005a; Hantson *et al.* 2013). It is anticipated that the new generation, freely-available sensors such as the Sentinel 2 Multispectral Sensor (MSI) with greater prospects in remote sensing of vegetation elements could accurately estimate ETW, specifically when considering its high spatial resolution of up to 10 m in comparison to its predecessors (i.e. Landsat with a spatial resolution of 30 m to 120 m and MODIS with a spatial resolution of 250 m to 1000 m). This makes it suitable for local to regional scale remote sensing of rangeland fire-related elements such as EWT as a proxy for fire occurrence and intensity (Sibanda *et al.* 2015; Sonobe *et al.* 2017; Toming *et al.* 2016). Its high spectral resolution of 13 bands covers the red–edge section (720 nm) of the EMS which is very critical in characterizing vegetation subtle variations of plant elements such as chlorophyll, leaf area index and water content. Therefore, the presence and provision of freely available Sentinel 2 MSI could make it possible to assess vegetation health and extrapolate key vegetation fire parameters like EWT.

However, it is insufficient to base fire hazard and vegetation moisture content assessments on standard spectral bands only as they are highly susceptible to noise. Vegetation indices (VIs) tend to circumvent and normalize the effects of internal leaf structure and other noise effects by combining individual spectral bands (Chuvieco *et al.* 2002b; Shen *et al.* 2005). For example, Yilmaz *et al.* (2008) achieved excellent results in estimating EWT using VIs like the Normalized Difference Infrared Index (NDII). Popular VIs used in estimating EWT include the Normalized Difference Vegetation Index (NDVI), moisture-based indices such as the Normalized Difference Water Index (NDWI) and the Global Vegetation Moisture index (GVMI) (Ferreira *et al.* 2011; Sow *et al.* 2013). However, to the best of our knowledge, there is no specified VI suitable for mapping a specific vegetation parameter. Meanwhile, with respect to the proven relationship between SWIR and foliar water, there is, therefore, a need to assess the influence of Sentinel 2 MSI's SWIR derived VIs in relation to moisture. Moisture-related VIs such as the NDWI as well as conventional VIs can therefore be used as a proxy to characterise EWT for fire-related incidence and intensities in South African rangelands such as the KZNSS.

The integration of new generation sensors such as Sentinel 2 MSI with machine learning algorithms like stochastic gradient boosting, support vector machine and random forest regression (RF) has been proven to be effective in characterizing vegetation traits using remotely sensed data (Chuvieco *et al.* 2002b; De Wit and Blignaut 2006; Yuan *et al.* 2019). For instance, the RF algorithm is flexible, relatively robust and has been proven to have high prospects of accurately and effectively estimating grassland elements such as EWT (Blanco *et al.* 2018; Oliveira *et al.* 2012). The RF algorithm can handle large data inputs and can maintain accuracy when dealing with missing data (Yuan *et al.* 2019). For example, in monitoring the variation of vegetation water content, Yuan *et al.* (2019) concluded that the RF algorithm performed better than the generalized regression neural network and back-propagation neural network, producing RMSEs lower than 0.03 g/m^{-2}.

In this regard, it is perceived that combining the robust RF algorithm with Sentinel 2 MSI's superior spectral data will be instrumental in building a framework for mapping and monitoring fire hazards in the rangelands of Southern Africa based on EWT estimation. Therefore, this study aimed to estimate EWT (g/m^2) of the endangered KZNSS using Sentinel 2 MSI standard spectral bands (VIS, NIR-SWIR bands) and VIs based on the RF ensemble. To achieve this, the overall objective compared the performance of the bands and standard, moisture and modified VIs is estimating grassland EWT as a proxy for characterizing the fire hazards.

2.2 Methods

2.2.1Study site description

This study was conducted at Thoyana (30.77083 S, 30.76002 E) (Figure 2.1which is a rural community situated south of the eThekwini Municipality in KwaZulu-Natal, South Africa. This area is incorporated under the Durban Metropolitan Open Space System (D'MOSS) which is a program that aims to connect open spaces in public, private and traditional owned communities to protect and conserve biodiversity. The biodiversity in Thoyana includes various native forbs, invasive alien like *Cromolaena odorata* plants and snake species. Thoyana is mainly characterised by small scale farming, sugar cane plantations, *Eucalyptus* plantations and extensive grasslands that include *Themeda triandra*, *Aristida junciformis* and *Hyparrhenia hirta*.

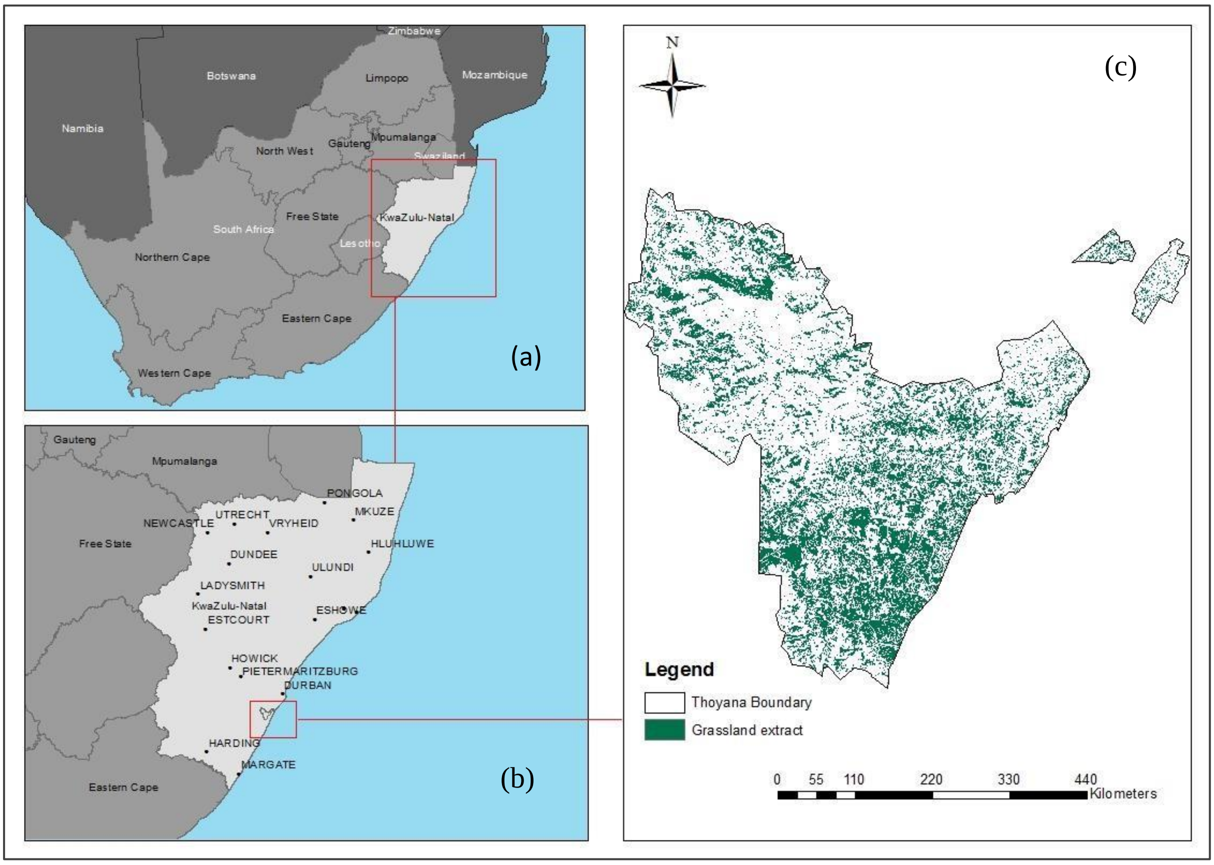


Figure 2.1: Map of (a) South African province (b) the study are within KwaZulu-Natal and (c) map showing Thoyana boundary and grasslands.

2.2.2 Fieldwork

Field data was collected during the dry season of 2019 (06 September- 09 September). Pri or to field data collection, the Generate random sample points tool in ArcMap 10.4 was used to generate 120 sample points in the grassland stratum. The randomly generated points were loaded in the hand-held Trimble GPS with an accuracy of 10 cm to 20 cm and was then used to navigate to each sampling point in the field. Upon arrival at each sampling point, a 10 m × 10 m quadrat corresponding with the 10 m spatial resolution of Sentinel 2 MSI was established. Within each quadrat, three sub-sampling plots measuring 0.5 m × 0.5 m were randomly selected for characterizing grass EWT. Specifically, grass samples were clipped from each subplot and the wet biomass (g) was measured along with the Leaf Area Index (LAI). The LI-COR 2200 was used to measure the leaf area index above the canopy level at each sub-sampling point. Wet grass biomass weight was then measured soon after clipping using a digital scale. The weight was recorded along with the center coordinate of the 10 m x 10 m quadrat. These samples were then packed, clearly labelled in paper bags and transported to the laboratory to be oven-dried. Samples were dried in the oven at a temperature of 100℃ for 48 hours to derive their dry biomass (g) and moisture content. The measured and recorded wet biomass, dry biomass as well as LAI were then used to derive EWT (g/m^2) using the formula:

$$EWT\ (g\ m^{-2}) = (FW) - (DW) / (LAI)$$

where EWT is Equivalent Water Thickness in $g\ m^{-2}$, FW is the wet biomass, DW is the dry biomass and LAI is Leaf area index estimate measured using the Li-COR 2200. Subsequently, these measurements were then averaged for each 10 m plot.

2.2.3 Image acquisition and pre-processing

A freely available, cloud-free Sentinel 2 MSI image acquired on the 1st of September 2019 was selected and downloaded from the Earth explorer website (https://earthexplorer.usgs.gov/). Sentinel 2 MSI has spectral information of 13 spectral bands at a spatial resolution of 10 m - 60 m, covering the visible (560 nm), red-edge (740 nm), near-infrared (853 nm), and SWIR (1610 nm) sections of the EMs. The image was then pre-processed for geometric and radiometric distortions. The Q-GIS semi-automatic plugin with a DOS1 atmospheric correction function was used to pre-process and convert the images from DN values to surface reflectance. The bilinear resampling tool in ArcMap 10.4 was then used to resample all 20 m and 30 m spatial resolution Sentinel 2 MSI bands to match the 10 m by 10 m grass sample plots.

2.2.4 Deriving spectral variables

Ahead of calculating VIs, pre-processed Sentinel 2 MSI spectral bands were clipped to the boundary of Thoyana using the Mask layer tool on the Q-Gis software 3.14. Individual reflectance values for each sample point (n = 121) were extracted using the Extract multiple values to points tool in ArcGis 10.1. The ArcGis 10.1 software was used to calculate a total of 51 VIs comprising of moisture-based, SWIR based SR and NDVI and conventional vegetation health VIs using the Raster calculation function in ArcGIS 10.4. A large portion of the VIs used for this study were chosen based on their performance in other studies that estimated EWT (Danson and Bowyer 2004; Wang *et al.* 2009; Sow *et al.* 2013). The SWIR based SR and NDVI VIs were computed based on the following equations;

$$\mathrm{NDVI} = \frac{R\gamma_i - R\gamma_j}{R\gamma_i + R\gamma_j}$$

$$\mathrm{SR} = \frac{R\gamma_i}{R\gamma_j}$$

where $R\gamma^i$ and $R\gamma^j$ are different possible SWIR based Sentinel 2 MSI spectral band combinations.

2.2.5 Statistical analysis and accuracy assessment

RF is a robust statistical algorithm that uses a bootstrap aggregation where several trees (*ntree*) are constructed from a random number of samples derived from the training data (spectral variables). The RF algorithm is made up of trees generated by bootstrap aggregation where a third of the original sample size is left out for model validation. At each node, a random subset of predictors is used to split each tree. The resulting average from all tress combined is used to predict an outcome (Oliveira *et al.* 2012). The RF algorithm used a total of 121 sample points which were randomly split into 70% training and 30% testing data for each analysis (Yilmaz *et al.* 2008; Arevalo-Ramirez *et al.* 2020). To determine which predictor variables are more important to the dependent variable, RF selects and ranks predictor variables in order of importance and in this study variable importance scores (VI) were assigned to the important input spectral variables (Rodriguez-Galiano *et al.* 2014). The R^2, RMSE and RRMSE parameters were used to evaluate the accuracy of each RF model. To evaluate the accuracy of the estimated EWT map, the relationship between fire presence and EWT was established using the logistic regression algorithm. To achieve this, MODIS freely available fire point data (n = 50) at a spatial resolution of 1 km (https://firms2.modaps.eosdis.nasa,gov/map/) was downloaded to run a logistic regression. A further 50 sample points where fire did not occur in the study area were generated using the Create random points function on ArcGis 10.1 to run the logistic regression.

2.2.6 Analysis stages and Random Forest models

A total of four analysis stages were followed in this study to estimate EWT (Table 2.1). The first stages compared all Sentinel 2 MSI bands excluding the SWIR and all Sentinel 2 MSI spectral bands in estimating EWT. The second stage tested the performance of Modified VIs based on the SWIR and moisture VIs in relation to general VIs in estimating EWT using the RF ensemble. In the final stage, the optimal spectral variables from the combined datasets were used to estimate EWT. The final optimal model was used to create the final FMC distribution using the most important variables of the model.

Table 2.1: Sentinel 2 MSI derived parameters and stages followed in estimating grassland EWT

Analysis stage	**Variable**	**Description**	**Spectral reflectance**
1	Individual spectral bands	Sentinel 2 MSI Single reflectance	Visible bands (blue, green, red),Red edge (Re1,Re2,Ee3),Near-infrared (NIR, NIRn), Shortwave infrared (SWIR1, SWIR2)
2	Standard VIs	General health vegetation indices	NDVI, NDVI2, EVI, EVI2, SAVI, GNDVI, NDSI, DVI
	Moisture VIs	Indices that are indirectly related to water content in plants	NDWI, MSI, SIWSI, MNDI, GVMI, MI
	Modified VIs	SWIR-based modified NDVI And Simple Ratio indices	SWIR/Blue, SWIR1/Green, NDVI_SWIR1/Green, NDVI_SWIR2/Blue, SWIR2/NIRn, SWIR2/Green
3	Combined VIs	All vegetation indices combined	
4	Combined variables (VIs and Bands)	All data sets (VIs and Spectral Bands) combined	

2.3 Results

2.3.1 Descriptive statistics of measured EWT.

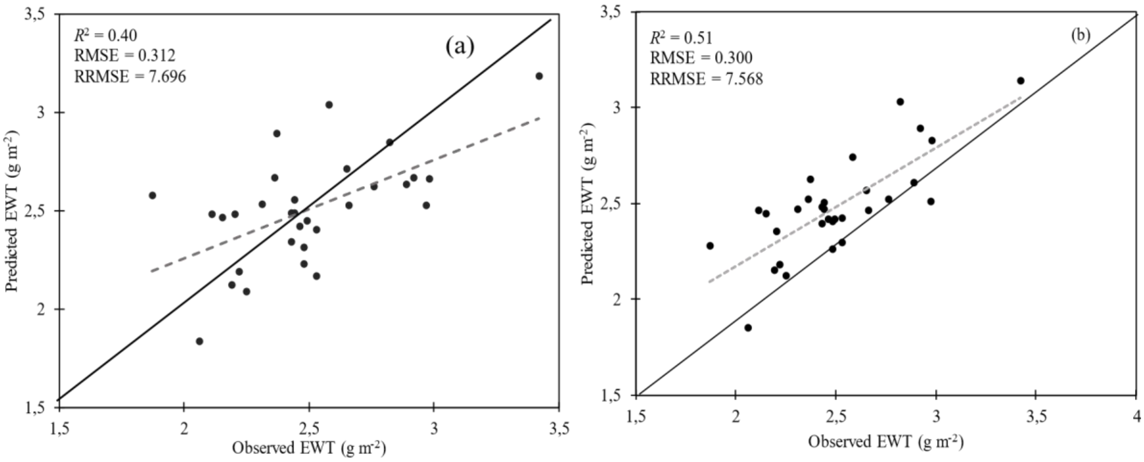
Table 2.2 illustrates the descriptive statistics of the measured EWT. The normality test shows a mean of 2.55 g/m^{-2} and a deviation of 2.50 to the mean.

Table 2.2 Descriptive statistics of measured EWT

Parameter	**Value (g m^{-2})**
Minimum Maximum	1.12 4.30
Mean	2.55
Median	2.45
Standard Deviation	2.50
Skewness	0.90

2.3.2 Estimating KZNSS grasslands EWT using Sentinel 2 MSI bands

Figure 2.2 shows that estimating EWT using all wavebands (including the SWIR region) produces significantly a higher estimation accuracy when SWIR bands are excluded. The results show that including the SWIR region resulted in an R^2 of 0.51 and an RRMSE of 7.568 (RMSE = 0.300 g/m^2) whereas its exclusion resulted in an R^2 of 0.40 and an RRMSE of 7.696 (RMSE = 0.312 g/m^2) (Figure 2.2 (a)). The SWIR2 Band proved to be the most influential spectral variable in estimating EWT (Figure 2.2 (d)) whereas in exclusion (Figure 2.2 (c)) the visible Band 2 had the highest variable importance score.



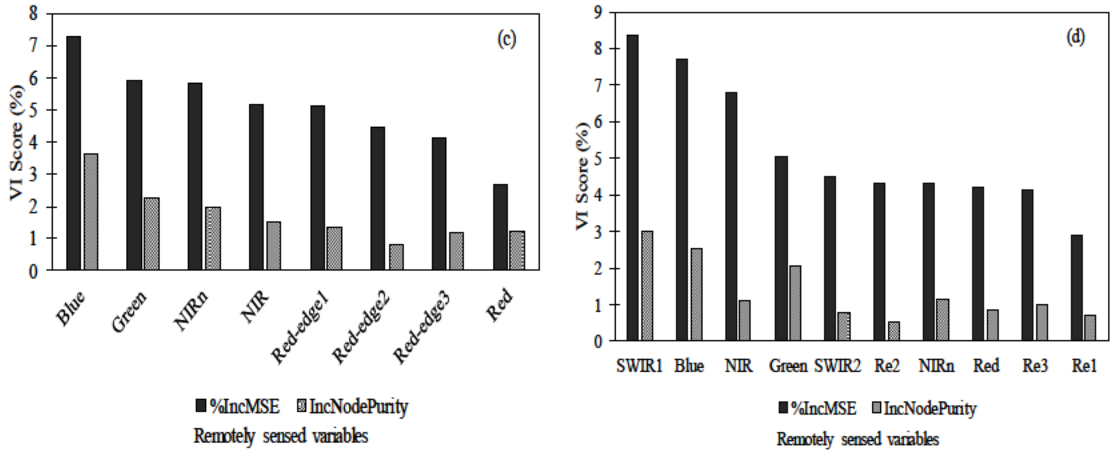


Figure 2.2 One to one relationship between the observed and predicted EWT models derived based on (a) Sentinel 2 MSI spectral bands (excluding the SWIR) (b) Sentinel 2 MSI spectral bands (including the SWIR bands) and (c) as well as (d) being the variables importance for the two models, respectively

2.3.3 Estimating KZNSS grasslands EWT using vegetation indices

Meanwhile, in comparing the performance of conventional VI, moisture-based VIs and the modified SR and NDVI indices in estimating EWT, conventional VIs exhibited the least accuracies, with an R^2 value of 0.62 and RMSE of 0.019 g/m^2 (Figure 2.3 (a)). The most influential VIs in this model were Global Normalised Difference Vegetation Index (GNDVI), Normalised Difference Salinity Index (NDSI) and Modified Normalised Difference Vegetation Index (MNDVI), in order of importance (Figure 2.3 (b)). Moisture-based indices yielded a higher R^2 of 0.66 and an RMSE of 0.041 g/m^2. In this model, the most optimal spectral variables were the NDWI, SIWI and NDMI in order of importance (Figure 3.4 (b)). The Modified NDVI and SR VIs derived based on the possible combination of SWIR with other Sentinel 2 MSI bands exhibited relatively higher accuracies (R^2 = 0.65 and RMSE = 0.031 g/m^2) in estimating EWT in relation to the other two categories of VIs (Figure 2.3 (c)). The SR_SWIR2/Blue, SR_SWIR2/Green and NDVI_SWIR1 / Green were the most influential variables for this model (Figure 2.4 (c)). When all vegetation indices were combined, the accuracies in estimating EWT improved to an RMSE of 0.009 g/m^{-2} and an R^2 of 0.68 and the most influential VIs again were SR_SWIR2/Blue, SR_SWIR2/Green and NDVI_SWIR/ Green, in order of importance (Figure 2.4 (d)).

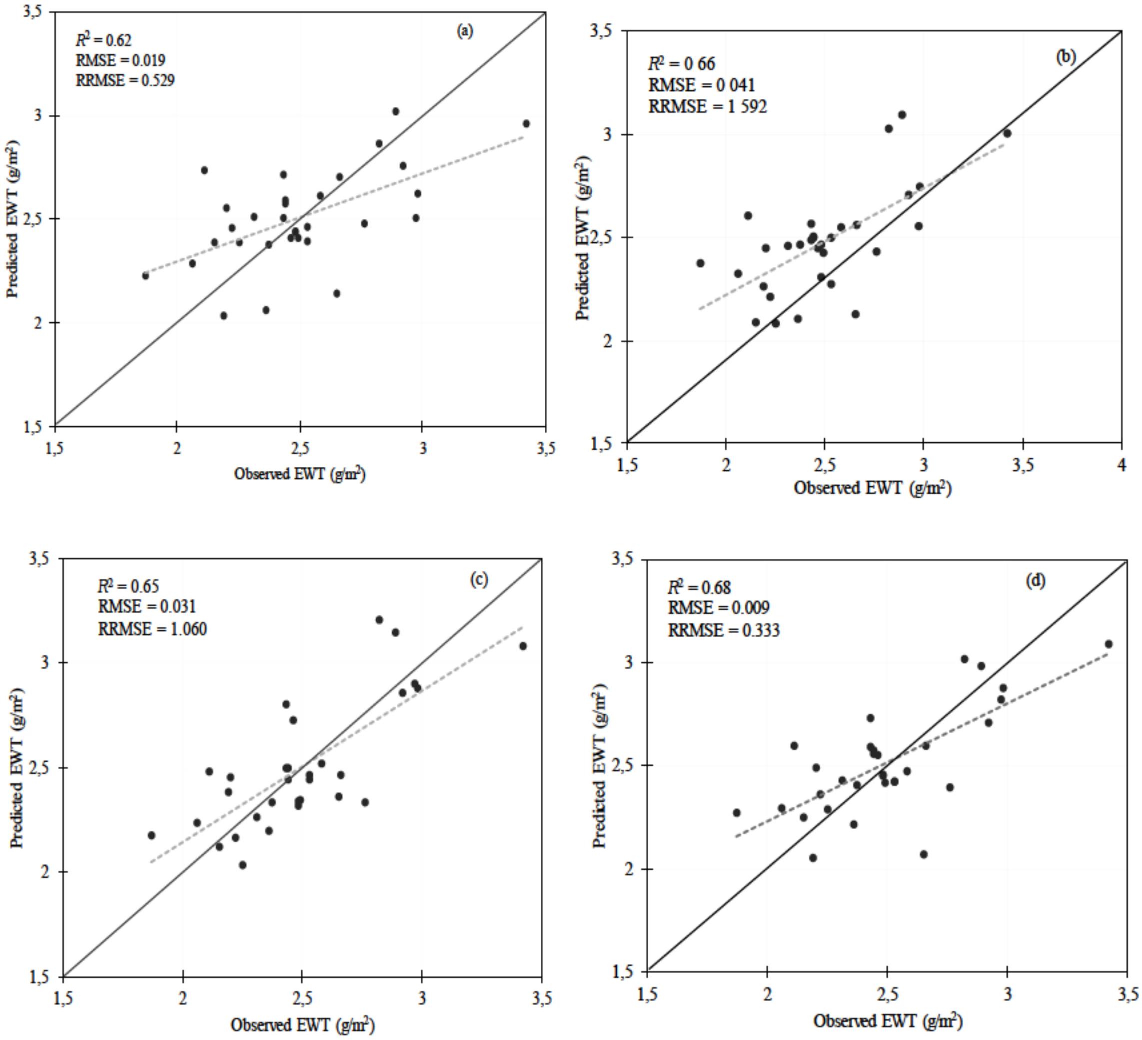


Figure 2.3: One to one relationship between predicted and observed EWT based on (a) general health VIs, (b) moisture-based VIs; (c) Modified Simple Ratio and NDVI and (d) EWT estimated using optimal VIs based on VI score.

Aligned with Figure 2.3, the results shown in Figure 3.4 show the variable importance for each analysis done in Figure 2.3.

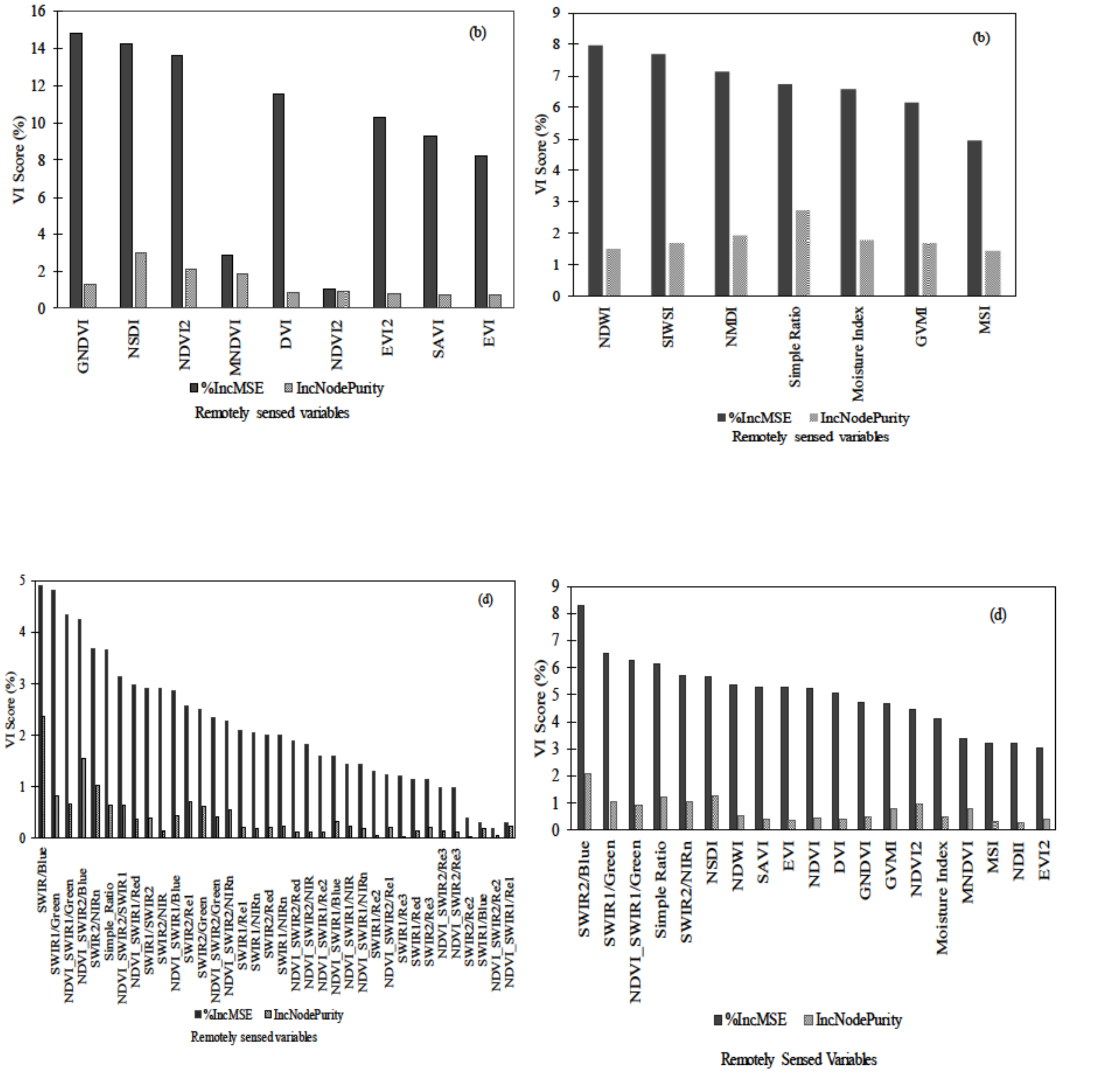


Figure 2.4: VI scores of (a) standard VIs, (b) moisture VIs, (c) Modified VIs and (d) all optimal VIS.

2.3.4 Estimating KZNSS using optimal spectral variables

The final model for estimating EWT (g/m^2) using all spectral bands and VIs yielded an R^2 of 0.75 with an RMSE of 0.018 g/m^2 and an RRMSE of 0.743. The most influential variables for the final model, in order of importance, were the Modified NDVI_SWIR2/Blue2, DVI, Blue band, SAVI and the Modified SR_SWIR1/Blue (Figure 2.5 (a) and (b)).

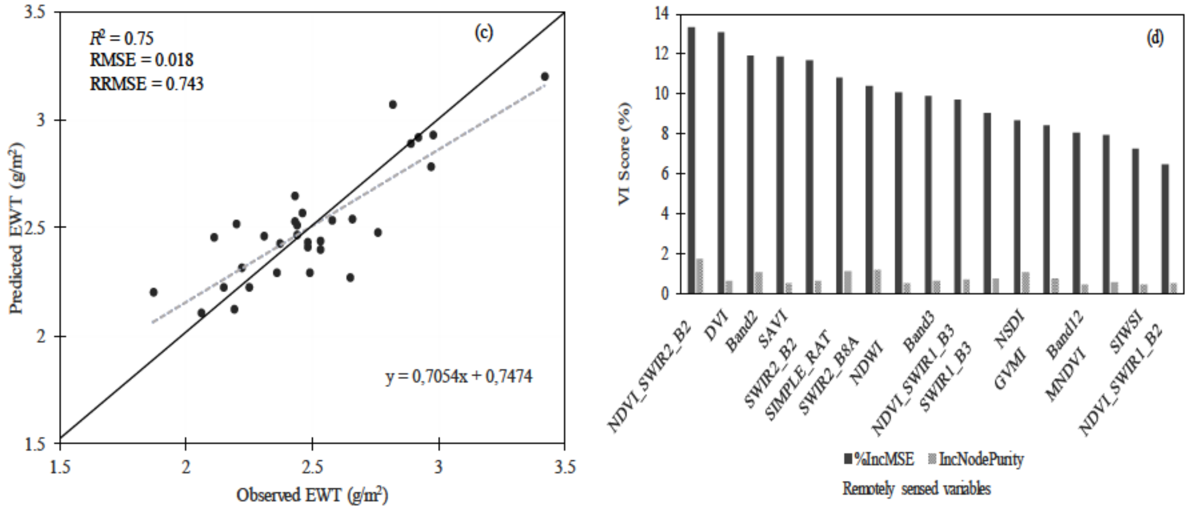


Figure 2.5: (a) One to one relationship between predicted and observed EWT using optimal spectral variables and (b) variable importance (VI) scores of selected best variables.

2.3.5 Spatial distribution of EWT and Fire incidences in the study area

Figure 2.6 (a) shows that observed fires from the MODIS archives occur in the mid-EWT ranges with most fires occurring in the central and south-central areas in the study area and no fires observed in the north-western region. Figure 2.6 (b) show that the logistic regression of fire presence in relation to the estimated EWT is such that the probability of fire occurrence in the study area decreases with an increase in the estimated EWT (g/m^{-2}).

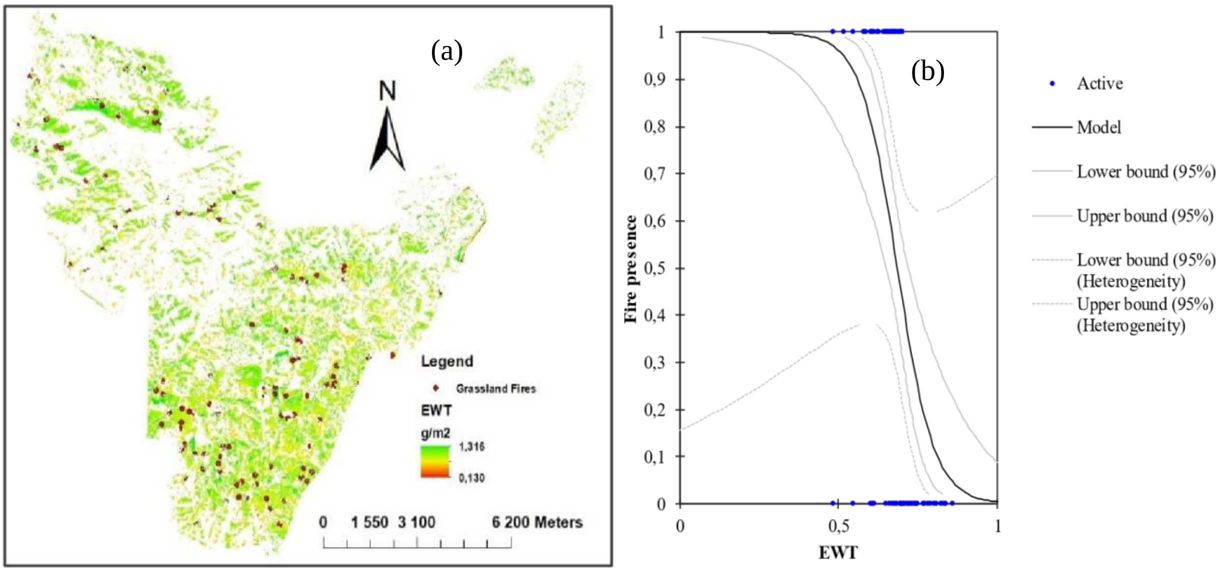


Figure 2.6: Map showing the estimated spatial distribution of grassland EWT (a) and (b) the logistic regression relationship that exists between predicted fires and estimated EWT.

2.4 Discussion

This study sought to investigate the use of Sentinel 2 MSI derived spectral bands and standard and modified vegetation indices in estimating grassland EWT in the KZNSS, South Africa.

2.4.1 Estimation KZNSS grassland EWT using Sentinel 2 MSI data

Findings of this study showed that EWT could be optimally estimated using a combination of Sentinel 2 MSI spectral derived data, to an R^2 = 0.75 and an RMSE of 0.018 g/m^2 using modified NDVI (SWIR2 / Blue), DVI, Blue , the SAVI and modified Simple Ratio (SWIR1 / Blue), in order of importance. The importance and influence of the SWIR region in this study is due to the sensitivity of this region to vegetation water content (Sow *et al.* 2013). Specifically, the region 1565 nm to 1655 nm and 2100 nm to 2280 nm covered by Sentinel 2 MSI's Band 11 and 12 are proximal to the known water absorption regions (1450 nm, 1950 nm and 2500 nm) (Curran 1989; Sims and Gamon 2003). This then explains the strong influence of SWIR derived VIs. These results also are similar to those of Wang and Shi (2007) who noted that the SWIR based Simple ratio indices had a stronger relationship with EWT. Meanwhile, the importance of visible Blue band in this study could be attributed to the lack of pigmentation in grasslands as some were not photosynthetically active. Generally, plants absorb the visible blue light during the process of photosynthesis, and they reflect highly in this region. During the senescence period of plants and a lack of pigmentation in the drier seasons (Mashaba *et al.* 2016; Roy 1989).

2.4.2 The performance of vegetation indices and spectral bands in estimating grassland EWT

Overall, the study confirms the findings of an increasing body of literature showing that VIs outperform spectral bands in estimating vegetation traits such as EWT (Mobasheri and Fatemi 2013; Yi *et al.* 2014; Zhang *et al.* 2018). Vegetation indices outperformed spectral bands in estimating KZNSS grassland EWT by an R^2 magnitude of 0.11 and an RMSE magnitude of 0.0.012 g/m^2. This conclusion is attributed to the ability of VIs to limit the effect of variations in leaf scattering which is common when using individual spectral bands.

The performance of VIs is attributed to their ability to interpret spectral information while simultaneously removing variability caused by canopy geometry and atmospheric conditions (Pu *et al.* 2008). Earlier studies such as Danson and Bowyer (2004) support that normalized ratios suppress the effects of variations in internal leaf scattering that are otherwise prominent in the utility of individual spectral data. The study also concluded that VIs such as those derived based on NIR wavelengths where water absorption is weak and SWIR bands where water absorption is strong, producing RMSEs as low as 0.0029 g/m^2.

In comparing the performance and importance of moisture-related indices with general vegetation health indices, the results of Figure 2.3(b) show that overall, moisture-related vegetation indices, particularly the NDWI were more critical in estimating EWT. This is because moisture-based indices are designed to be more sensitive to water absorption. The results in Figure 2.4(b) specifically are similar to those of Mashaba *et al.* (2016), where the NDWI and Shortwave Infrared Water Stress Index (SIWSI) were highly sensitive to vegetation moisture compared to general vegetation health assessment VIs like the NDVI and EVI. An earlier study by Dennison *et al.* (2006) found that the water-based NDWI had a stronger statistical relationship to vegetation water content compared to chlorophyll absorption-based indices despite being less sensitive to sparse vegetation like grasslands. Estimating EWT with the utility of modified VIs proved to produce an increase of 0.04 in R^2 compared to that of standard VIs. The results of the final analysis in Figure 2.3(d) show that the combination of all optimal VIs produced the highest R^2 of 0.68 and a low RMSE of 0.009 g/m^2 in estimating EWT.

In estimating EWT using spectral bands with the inclusion of the SWIR produced a higher accuracy (R^2 = 0.51 (Figure 2.2a)) when compared to its exclusion ((R^2 = 0.40) Figure 2.2c)). The influence of the SWIR region in estimating EWT as a proxy for foliar moisture content could be explained by the fact that the SWIR is highly sensitive to the variations in foliar moisture content hence its significant influence in estimating EWT in this study (Cao and Wang 2017). Particularly, the SWIR observed peaks at 97 0nm, 1200 nm, 1450 nm and 1950 nm are the most sensitive to and therefore more suitable to retrieving EWT (Shen *et al.* 2005; Cao and Wang 2017; Sjöström *et al.* 2009). Our findings, with the exception of visible Blue band (490 nm) are similar to findings by Mobasheri and Fatemi (2013) who found that reflectance in the visible and NIR produced the lowest correlation with EWT in relation to the SWIR. Similarly, Danson and Bowyer (2004) explained that the NIR region is primarily controlled by internal leaf structure and therefore has a lower correlation with EWT. Meanwhile, the foliar water content is significantly associated with the SWIR region. However, the study noted that the SWIR region, Band 11, was not as important as the SWIR Band 12 in estimating EWT. This is because it falls within the region of atmospheric water absorption and this may limit its use with satellite-borne data (Cao *et al.* 2017).

The results of this study have demonstrated the success of the Sentinel 2 MSI derived variables in estimating EWT using the RF model. The study specifically showed that moisture VIs and Modified SWIR VIs have the greatest potential in estimating grassland EWT. The resulting spatial distribution of estimated EWT shows that fires are more likely to occur in areas of lower EWT.

2.5 Relevance of the observed findings

The findings of this study demonstrate the opportunities presented by Sentinel 2 MSI data for deriving insightful baseline information on near real-time rangeland conditions that could help in fostering sustainable utilisation of these cost-effective resources. Specifically, Sentinel 2 MSI developed models could be very useful in deriving routine rangeland information that can support decision-making on the type of fire management practices to adopt. Furthermore, these results illustrate the unique potential of EO facilities in informing policy and decision making as well as operational implementation in mainly under-resourced regions such as Southern Africa where agriculture and grassland ecosystems still play a critical role in rural economies and livelihoods.

2.6 Conclusion

This study tested the utility of Sentinel 2 MSI remotely sensed data in estimating grassland EWT as a proxy for characterising fire hazards in the endangered KZNSS grasslands. The study tested, in particular, the utility of the Sentinel 2 MSI SWIR derived spectral variable in relation to the visible and NIR spectral variables in estimating the EWT of the KZNSS grassland using the random forest Regression algorithm. The results demonstrated that:

- Sentinel 2 MSI has great potential in estimating Southern Africa local scale grassland EWT with RMSEs ranging from 0.008-0.312 g/m^2.
- The inclusion of the SWIR proved to yield a significant increase in the accuracies from R^2 of 0.40 to 0.51 in estimating EWT.
- SWIR derived VIs proved to be influential in estimating EWT of South African grasslands during the dry season

The results of this study show that there is a strong relationship between remote sensing and grassland EWT. Therefore, it proves that cost-effective remote sensing methods will confidently estimate EWT in South African grasslands. This study may aid in future research on the seasonal variation of EWT as a proxy of fire occurrence across endangered South African grasslands. However, more research is still needed in identifying the seasonal relationships that exist between EWT and remote sensing across more South African rangelands and different vegetation covers like forests, to foster and support fire management studies at the national to regional level. Together with EWT, FMC has also been used to identify areas that are at higher risk of intense fire ignition and spread using remotely sensed variables. However, there is a shortage of studies investigating the relationship between EWT, remotely sensed variables and topo-climatic variables in South Africa. Therefore, after successfully assessing the performance of Sentinel 2 MSI remotely sensed data in estimating grassland water elements, this work then sought to assess whether the incorporation of topographic and climatic variables could improve the estimation of grass moisture element (FMC) related to fire occurrence.

Chapter three
Estimating grass Fuel Moisture Content (FMC) in communal grasslands of South Africa using remotely sensed data combined with topo-climatic variables

Rangelands visited in Thoyana (Photo captured by Wenzile Shinga 2019)

Abstract
Quantifying grassland Fuel Moisture Content (FMC) is critical for establishing early fire-warning systems to encourage proactive fire-management strategies and preserve grassland functions such as carbon sequestration. Although seemingly accurate, traditional methods are limited in terms of efficiency and temporal coverage or sampling frequency. Therefore, remotely sensed data combined with statistical algorithms could be efficiently used to derive FMC for a better understanding of fire regimes. In this regard, the objective of this paper was to assess the performance of topo-climatic variables in concert with Sentinel 2 Multispectral Instrument (MSI) data in estimating grassland FMC using the random forest (RF) algorithm in communal rangelands. Three models were performed in estimating grassland FMC based on (i) topo-climatic variables, (ii) remotely sensed data as well as (iii) a combination of topo-climatic and remotely sensed data. Results of the study showed that when topo-climatic variables were combined with remotely sensed data an RMSE of 0.190 %/m^2 and an R^2 of 0.73 were attained. The variables used in the optimal model for estimating FMC were channel networks, elevation, wind speed and water vapour, Normalized difference Infrared Index (NDII), Normalized difference water index (NDWI) as well as the SWIR Band 11 (1910 nm). Remotely sensed data (RMSE = 0.20 %/m^2 and R^2 = 0.70) outperformed the topo-climatic variables (RMSE = 0.039 %/m^2 and R^2 = 0.68) in estimating FMC. Overall, these results show that there is great potential for using topo-climatic and remotely sensed data in estimating FMC in communal rangelands. This is a critical step for developing proactive fire monitoring frameworks in the context of southern African grasslands.

3.1 Introduction

Grassland landscapes cover approximately 40% of the global surface area and are critical ecosystems due to the vast ecosystem services that they offer at national, catchment, and local scales (Hönigová *et al.* 2012; Kirkman *et al.* 2014; Lemaire *et al.* 2005; Sibanda *et al.* 2015). In South African grasslands cover 336,544 km^2 of the total 1, 268, 991 km^2 of land (Gombakomba 2008). However, it is where approximately 73% of all cultivated timber resources occur (Egoh *et al.* 2011; Gombakomba 2008; Kotzé *et al.* 2013). Additionally, South Africa, grasslands contribute substantially to the economy. For instance, they inject a total of R9, 761 million annually through agriculture and mining and it is the most suitable and productive biome in terms of livestock farming (Bommert *et al.* 2005; Kotzé *et al.* 2013; Neke and Du Plessis 2004). Grasslands also play a vital role in processes such as atmospheric carbon sequestration, biodiversity conservation, air quality purification, and regulating the hydrological cycle (Hönigová *et al.* 2012; Shoko *et al.* 2018). However, the sustainability and perpetuity of such ecosystem services is threatened by catastrophic events such as fire occurrences which lead to loss of life and the destruction of natural habitats, despite the efforts of fire-fighters (Vallejo and Alloza 2015). Furthermore, grassland ecosystem disturbances such as wildfires are not well understood. Therefore, there is a need for robust spatially explicit mechanisms and frameworks for effectively forecasting wildfire occurrences to preserve these ecosystem services. To effectively forecast and understand the occurrence of fires, there is a need to quantify factors such as Fuel Moisture Content (FMC) that influence their occurrence and intensity.

Literature investigating the occurrence of wildfires in grasslands has mainly focused on quantifying above-ground biomass (AGB) as a proxy of fuel load, and fire scar mapping (Johansen *et al.* 2001; Lentile *et al.* 2006; Slik *et al.* 2008). However, other than biomass accumulation, a host of other factors such as FMC affect the propagation, intensity, and spread of fires (Cardoso *et al.* 2018). FMC plays a critical role in fire ignition, intensity, and spread. Low levels (%) of grass moisture content mean higher probabilities of fire occurrence (Bond *et al.* 2003). Grass FMC tends to be affected by a range of variables which include topographic and climatic variables (Holden and Jolly 2011; van Zyl Engelbrecht 2018). Literature states that low lying areas coupled with south-facing slopes in the southern hemisphere tend to exhibit low levels of FMC. Complex relationships between topo-climatic factors like solar radiation and elevation which in turn creates biophysical gradients that affect FMC (Holden and Jolly 2011). Quantifying and understanding how these factors influence grassland FMC, particularly during the dry season is imperative to managing fire patterns (Hurteau *et al.* 2014). Therefore, there is a need to examine the relationship between FMC as a function of topographic and climatic variations, especially in communal rangeland areas to facilitate the establishment of effective fire forecasting and monitoring measures.

Conventionally, FMC and fuel load are quantified using point-based destructive empirical field sampling approaches which are labour intensive due to the cutting and weighing of grass samples. Such traditional methods are time-consuming and subject to error, especially when conducted at landscape scales (Lentile *et al.* 2006). Meanwhile, EO facilities through remote sensing have made it possible to accurately quantify fire-related grass attributes such as FMC at a landscape scale in grassland ecosystems (Chen *et al.* 2005a; Dilley *et al.* 2004). Particularly, in the study by Chen *et al.* (2005a), vegetation water content for corn and soybeans in Iowa, USA was estimated to a maximum R^2 of 0.84 using Moderate Resolution Imaging Spectroradiometer (MODIS) NIR (1240 nm) and SWIR (1640 nm – 2130 nm) bands showing the potential of remotely sensed data in retrieving vegetation moisture content. Also, satellite-borne digital elevation models (DEM), have provided a better platform to retrieve topographic factors to facilitate the quantification of grassland FMC. Therefore, remote sensing platforms can provide more cost-effective and efficient FMC retrieval techniques.

For instance, the Moderate Resolution Imaging Spectroradiometer (MODIS), National Oceanographic and Atmospheric Administration- advanced very high-resolution radiometer (NOAA-AVHRR) and Systeme pour L'Observation de la Terre have been widely used studies relating to fire ecology(Chen *et al.* 2005a; Hantson *et al.* 2012). However, MODIS and NOAR-AVHRR have a low spatial resolution of 250 meters (m) and 1 kilometer (km) respectively which results in poor satellite imagery. Alternatively, new generation sensors such as the Landsat 8 Operational Land Imager (OLI) and Sentinel 2 (MSI) have made characterization of vegetation traits such as moisture content more effective. For example, Sentinel 2 MSI is characterized by 13 spectral bands, a spatial resolution of up to 10 m and has as an improved swath width of 290 km, which makes it suitable for mapping grassland FMC (Badi 2019). When testing the utility of Sentinel 2 MSI in retrieving shrubland FMC, fairly good result of an R^2 of 0.66 and an RMSE of 44.16 % (Kwang *et al.* 2018). Therefore, the spatial and spectral capabilities of Sentinel 2 MSI need to be investigated in characterizing grass canopy FMC. When compared to its predecessors, the recently launched Sentinel 2 MSI with a robust and higher spectral resolution, could help facilitate more accurate retrieval of FMC. Hence there is a need to assess its utility in estimating grass FMC.

Studies that used remotely sensed data in estimating FMC focused on the utility of the SWIR region (Chuvieco *et al.* 2002a; Sow *et al.* 2013). The SWIR region observes water absorption peaks at 1400nm-2500nm when determining vegetation water content (Sow *et al.* 2013). Additionally, several studies have proven the potential of using vegetation indices (VIs) such as the NDVI in estimating grassland FMC. However, these studies note that, although NDVI is the most popular index, it is limited in explaining water quantity in grasses because it is susceptible to atmospheric influences, topographic distortions and it saturates when vegetation cover is dense (Chen *et al.* 2005a; Chuvieco *et al.* 2002a; Chuvieco *et al.* 2004; Dilley *et al.* 2004). Therefore, this facilitates and motivates the need to assess the utility of additional measures such as topographic and climatic factors in concert with remotely sensed data to estimate FMC (Sow *et al.* 2013).

To improve FMC studies, the combination of remotely sensed data and powerful statistical algorithms has been proven to further increase the accuracy and reliability of spatial models. Support vector machines and random forest (RF) are amongst the popular robust statistical algorithms (Lu and He 2019; Pan *et al.* 2018). Meanwhile, the RF algorithm has been shown to improve estimation accuracies of fire extent and fire spread models and FMC distribution models (Gottuk *et al.* 2002). As a non-parametric ensemble, the RF algorithm is computationally light, offers ease of access and use when applied in vegetation modeling studies, especially in concert with remotely sensed data. Moreover, RF offers flexibility and performs well even with limited training data sets (Karlson *et al.* 2015; Pal 2005). In a study by Yuan *et al.* (2019), the RF algorithm outperformed the generalized regression, neural network, and the back-propagation neural network with reported RMSE values as low as 0.03 g/m^{-2} when investigating variations in water content of forest vegetation. It is in this regard that this study sought to determine the effectiveness of combining topo-climatic variables and remotely sensed data in estimating the spatial distribution of FMC in a communal grassland area, using the RF regression algorithm.

3.2 Methods

3.2.1 Study area

The study was conducted in Thoyana communal area, KwaZulu-Natal province in South Africa (refer to figure 2.1). Thoyana is a traditional community recently adopted under the EThekwini Municipality and Durban Metropolitan Open Space Systems that covers an area of 119.300468 km^2. This area is characterised by built-up areas and a variety of vegetation. Vegetation is characterised by a wide variety of invasive alien plants such as *chromolaena odorata*, an extensive area of communal *Eucalyptus* plantations, and a range of grassland species. Thoyana sits at an elevation ranging from a minimum of 0.98838 m to a maximum of 592 m with an annual rainfall average of 1010 mm.

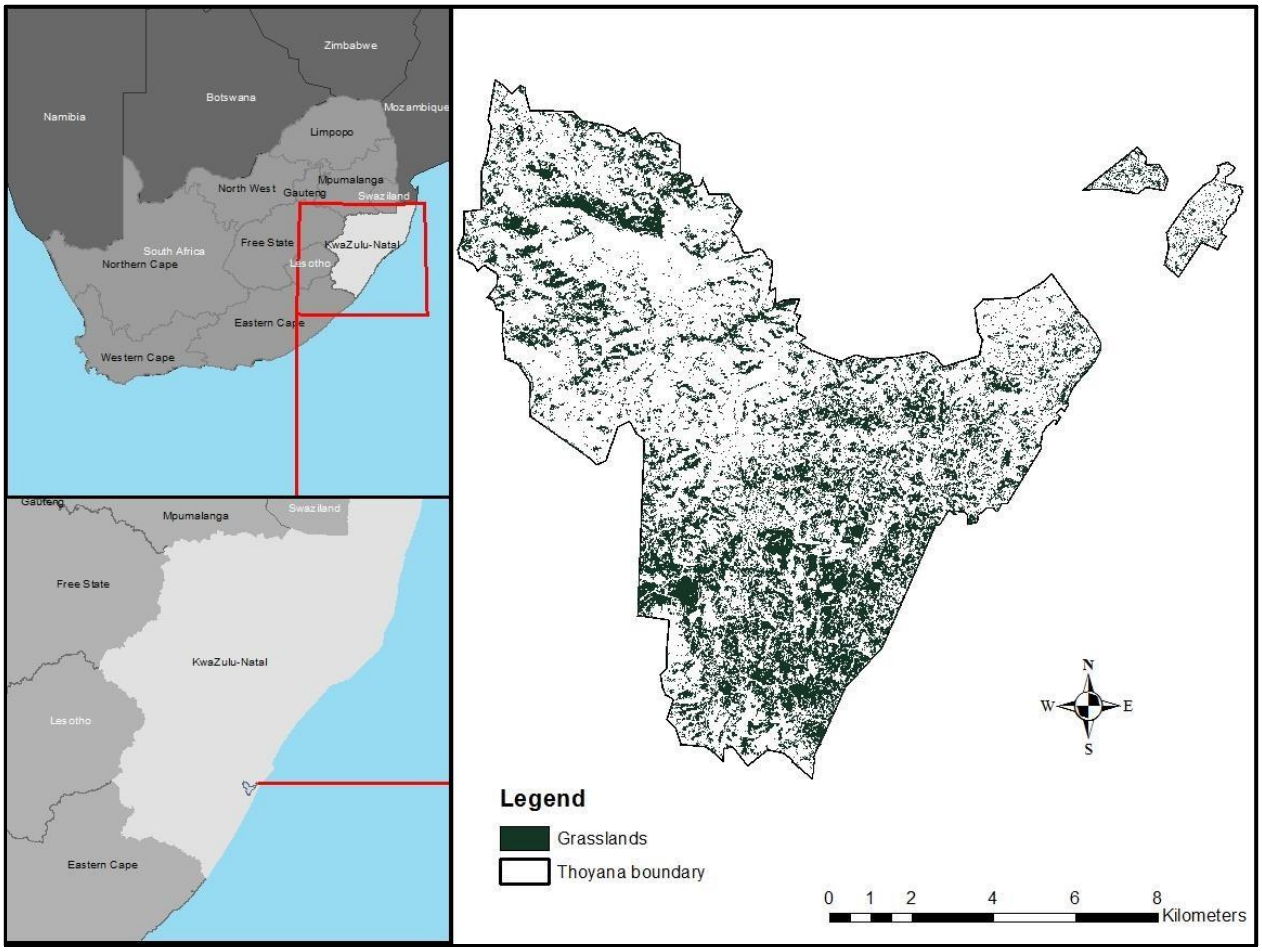


Figure 3.1: Map showing the extent of Thoyana, KwaZulu-Natal grasslands

3.2.2 Image acquisition and pre-processing

To determine the extent of Thoyana's grassland community, two Sentinel 2 MSI images acquired on the 1st and 10th of September 2019 were selected and downloaded from Earth Explorer (https://earthexplorer.usgs.gov/). The images were then pre-processed and corrected for geometric and radiometric errors in QGIS software and the individual bands stacked to produce a stacked image in order to classify the first image. To perform a supervised classification on the first image, training classes were produced in ArcMap 10.4 with the classes being grasslands, bare area, built-up areas, water bodies, and other land cover types. The grassland stratum was then extracted from the pre-processed and classified image to observe the spatial extent of Thoyana grasslands. The second pre-processed Sentinel 2 MSI image was then atmospherically corrected using the DOS1 function on Q-Gis to convert DN to canopy reflectance. The pre-processed image was then used to calculate VIs (n = 15) (refer to Table 3.1) using the Raster Calculator tool on the ArcMap 10.4 platform.

3.2.3 Field data collection and analysis

In this study, fieldwork was conducted from the 6th to 9th of September 2019 during the dry season to characterise biomass. Prior to the fieldwork, 120 sample points were randomly generated from the grassland stratum on Arcmap 10.4 and imported to a 30 cm hand-held Tremble global positioning System (GPS) with a 10 cm to 20 cm field accuracy for navigation in the field. Upon arrival at each sampling point, quadrats covering an area of 10 m × 10 m were established. A plot size of 10 m × 10 m was chosen such that it corresponds with the 10 m spatial resolution of Sentinel 2 MSI. Within each quadrat, three 0.5 m × 0.5 m, sub-quadrats were randomly selected. In each quadrant, grass samples were clipped and their wet biomass derived using a digital scale and the sub-quadrants of each 10 m × 10 m quadrat were averaged to provide a good representation of the wet weight for each quadrant. The samples were then packed in clearly labelled paper containers and transported to the laboratory. In the laboratory, grass samples were dried in an oven set at a temperature of

100℃ at the University of KwaZulu-Natal grassland science facilities. After 48 hours, the grass samples were weighed again to determine their dry weight and the dry weight of each sub-quadrat was also averaged to represent the entire quadrant. Recorded measurements were then used to derive FMC using the following formula:

$$FMC = [(W_f - W_d) / W_d] \times 100$$

Where W_f is the fresh weight and W_d the dry weight.

3.2.4 Topo-climatic variables

The study used twenty-one topo-climatic variables consisting of local, non-local, and combined topographic variables as well as climatic variables (i.e. temperature and precipitation) (Table 3.2). The topographic variables were derived from a 30 m resolution NASA Shuttle Radar Topography Mission (SRTM) digital elevation model (DEM) downloaded from Earth Explorer. Topographic indices were derived using SAGA in QGIS (2.3.2). Bioclimatic raster data with a 1 km spatial resolution prior to re-sampling was downloaded from World-Clim data website (https://www.worldclim.org/). The derived grid datasets were resampled to match the 10m spatial resolution of Sentinel 2 MSI and sample plot size.

Thereafter, a Pearson's correlation test between the topographic indices was conducted to assess their correlation to each other. Another correlation analysis was conducted between all the variables and the measured FMC.

Spectral and topo-climatic variables used in the study:

Table 3.1: Sentinel 2A spectral variables used to estimate FMC

Variable	***Description***	***Name***
Individual spectral bands	Sentinel 2 MSI Single reflectance	Blue, Green, Red, Red-edge 1 (Re1), Red-edge 2 (Re2), Red-edge 3 (Re3), Near-infrared (NIR), Near-infrared narrow (NIRn), Shortwave infrared Band 11 (SWIR1), Shortwave Infrared Band 12 (SWIR2)
Standard VIs	Individual band combinations	NDWI, NDSI, EVI, EVI2, DVI, NDVI, NDVI2, GNDVI, MNDVI, GVMI, SIWSI, SAVI, MI, MSI, NDII

Table 3.2: Table showing topo-climatic variables used in the RF model

Number	*Variable*	*Unit*	*Reference*
1	Slope	m	Nyman, Baillie et al., 2015
2	Aspect	radian	Nyman, Baillie et al., 2015
3	Elevation (DEM)	m	Nyman, Baillie et al., 2015
4	Topographic wetness index	-	-
5	LS Factor	-	-
6	Ruggedness index	-	-
7	Vertical Direction	-	-
8	Analytical Distance	-	-
9	Channel Networks	-	Nyman, Baillie et al., 2015
10	Convergence index	-	-
11	Cross-sectional flow	-	Nyman, Baillie et al., 2015
12	Flow accumulation	-	Nyman, Baillie et al., 2015
13	Longitudinal curvature	degree m-1	-
14	Relative slope		-
15	Valley depth	m	Skentos 2017
16	Precipitation	mm	Nyman 2015
17	Solar radiation	kJ m^{-2} day^{-1}	Cheney et al 1993

18	Maximum temperature	°C	Nyman Baillie et al., 2015
19	Minimum temperature	°C	Nyman, Baillie et al., 2015
20	Wind speed	m s^{-1}	Fernandez, Paul., 2001
21	Water vapour	kPa	Catchpole et al., 2001

3.3 Statistical analysis

3.3.1 Random forest regression algorithm

Regression algorithms allow scientists to perform complex environmental analysis such as modelling of urgent phenomena that would otherwise take time to observe (Radosavljevic *et al*. 2010). The study used the RF algorithm to estimate the FMC using Sentinel 2 MSI data, topographic and climatic data. The RF machine-learning algorithm uses bootstrap aggression, where several trees are constructed based on a random dataset derived from the training dataset (Zheng *et al*. 2018, Lu and He 2019). The RF algorithm assigns a variable (Sentinel 2 MSI bands, vegetation indices and topo-climatic variables) to a response variable (FMC) using averaged estimates and the value is assigned from all the trees (Zheng *et al*. 2018). RF algorithm uses approximately one-third of the dataset that is excluded in the training sample through the out-of-bag method to evaluate the generated RF model.

RF regression algorithms use the mean decrease in accuracy and the mean node in impurity to measure the importance of each variable (Sentinel 2 MSI bands, vegetation indices and topo-climatic variables) in each model. The mean decrease in accuracy accounts for how much accuracy decreases (%) if a variable is excluded in a model. The mean node in impurity shows the overall importance of each variable relative to the others. The most important variable will, therefore, have a higher mean decrease in accuracy and mean node in impurity score (Blanco *et al.* 2018; Oliveiria *et al.* 2012) .

3.3.2 Accuracy assessment

To evaluate the accuracy of each generated model, the R^2 which represents the variance of the predicted values in relation to the variance of the original data values (Gelman *et al.* 2019; Miles 2014) , root mean square error (RMSE) and relative root mean square error (RRMSE) were calculated. R^2 is a statistical measure of how close the data (FMC) is to the fitted regression line with an output value ranging from one to zero. The RMSE measures the average deviation of the estimates from the observed values. The RF result of estimating FMC using the most important variables were then used to develop the spatial distribution map grass FMC. To further evaluate the results of the estimated distribution of FMC, the relationship between fire occurrence and estimated FMC needed to be established. To do this, MODIS detected fire occurrences (n =50) at a spatial resolution of 1 km were downloaded from the NASA fire data archive (https:/firms2.modaps.eosdis.nasa.gov/map/). These were then used as presence data to run a logistic regression to determine the relationship between FMC and the probability of fire occurrence. An additional 50 points were randomly generated in ArcMap 10.1 to run the logistic regression denoting the absence of fires.

3.3.3 Stages followed in estimating FMC

Before regression analysis was conducted, we conducted exploratory data analysis which included the computation of descriptive statistics and correlation analyses amongst the topographic variables as well as between all explanatory variables and measured FMC. Three models were computed using three datasets. The first regression model was conducted using the remotely sensed data as input datasets i.e. raw bands and vegetation indices. Thereafter, the Topo-climatic variables were used to derive the second RF regression. In the third stage, a regression combining both remotely sensed data and Topo-climatic variables was computed. The final stages included mapping the spatial distribution of FMC and establishing if it was related to fire occurrence in the study area based on the logistic regression.

The RF results of estimating FMC using the most important variables were then used to develop the spatial distribution map MODIS fire data (https:/firms2.modaps.eosdis.nasa.gov/map/) was then used to run a logistic regression in order to determine the relationship between estimated FMC and fire occurrence.

3.4. Results

3.4.1 Descriptive statistics

Even though a non-parametric algorithm was used in this study, the FMC data did not significantly deviate from the normal distribution curve. The observed data had a mean of 3.87 %/m^2 and a standard deviation of 1.92 were calculated. Further descriptive statistics of measured grassland FMC showed FMC (%) to be ranging from 0.157 %/m^2 to 7.5101 %/m^2.

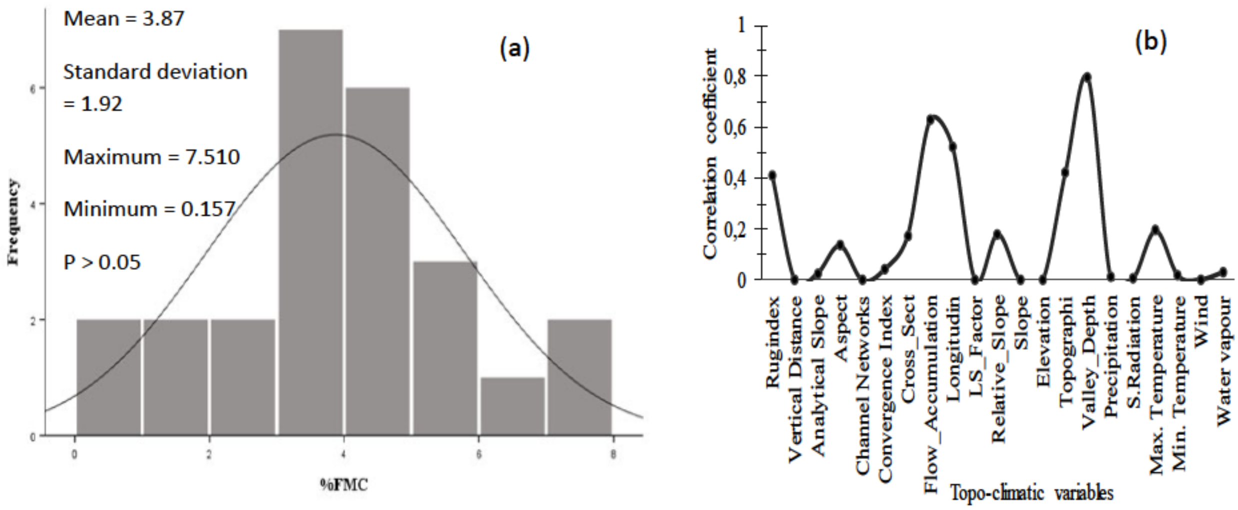


Figure 3.2: (a) Normal distribution curve for measured FMC and (b) Pearson's correlation test between observed FMC and topo-climatic variables

Two correlation tests were performed on the derived topo-climatic data. In the first test, a pearson's correlation analysis was done to establish the magnitude of the relationship between various topo-climatic variables and FMC. In Figure 3.2b, variables like channel networks, wind and slope reported a p-value less than 0.05, therefore, showing to have a good correlation with measured FMC. The Pearson test was then used to perform a correlation test between the various topo-climatic variables used in the study to also determine which variables may be best suited for future research (Table 3.2). The reported p-values highlighted in black show a difference from the value 0 and have a significance level alpha = 0.05. Values between 0 and 1 showed a positive correlation between corresponding topo-climatic variables. The results showed that precipitation and water were positively correlated ($p = <0.0001$) and a positive correlation of <0.0001 between topographic variables elevation and channel networks were noted and therefore can be used in future studies estimating FMC within Southern African rangelands.

Table 3.3: Pearson correlation test p-values between topo-climatic variables

Variables	Vertical_D	Analytical	Aspect	Channel_Ne	CI	Cross_Sect	Flow_Accum	Longitudinal	LS_Factor	Relative_S	Slope	Elevation	TWI	Valley_Dep	Precipitation	SRadiation	Max.Temperature	Min Temperature	Wind	W. v apour
Vertical_D	**0**	0.4850	0.9626	**0.0169**	0.0645	**0.0001**	**0.0002**	**0.0000**	**0.0001**	**0.0000**	**0.0000**	**0.0000**	**0.0000**	**0.0000**	0.8171	0.4549	0.8940	0.7142	0.9285	0.7026
Analytical	0.4850	**0**	**< 0.0001**	0.3185	0.7336	0.8099	0.0979	0.2029	**< 0.0001**	0.6532	**< 0.0001**	0.1625	0.4248	0.6832	0.6955	0.9036	0.4224	0.9294	0.9761	0.8059
Aspect	0.9626	**< 0.0001**	**0**	**0.0239**	0.4526	0.1828	**0.0029**	0.1158	0.2358	0.4611	0.4231	0.0921	0.1556	0.6703	0.7578	0.9458	0.4503	0.9576	0.9190	0.8521
Channel_Ne	**0.0169**	0.3185	**0.0239**	**0**	0.2222	**0.0313**	0.4596	**0.0026**	**0.0269**	**0.0170**	**0.0237**	**< 0.0001**	0.2802	**0.0027**	**0.0022**	**0.0094**	**0.0134**	**0.0059**	**0.0230**	**0.0094**
CiI	0.0645	0.7336	0.4526	0.2222	**0**	**< 0.0001**	**< 0.0001**	**< 0.0001**	0.2092	**< 0.0001**	0.7714	**0.0367**	**< 0.0001**	**< 0.0001**	**0.0262**	**0.0413**	0.3890	0.2374	**0.0294**	0.2773
Cross_Sect	**0.0001**	0.8099	0.1828	**0.0313**	**< 0.0001**	**0**	**< 0.0001**	**< 0.0001**	0.5110	**< 0.0001**	0.0633	**0.0027**	**< 0.0001**	**< 0.0001**	**0.0338**	0.1024	0.1528	0.1580	0.1075	0.1687
Flow_Accum	**0.0002**	0.0979	**0.0029**	0.4596	**< 0.0001**	**< 0.0001**	**0**	**< 0.0001**	0.2623	**< 0.0001**	0.5475	0.3568	**< 0.0001**	**< 0.0001**	0.0782	0.2863	0.8987	0.7098	**0.0170**	0.7291
Longitudinal	**< 0.0001**	0.2029	0.1158	**0.0026**	**< 0.0001**	**< 0.0001**	**< 0.0001**	**0**	0.2429	**< 0.0001**	**0.0256**	**0.0002**	**< 0.0001**	**< 0.0001**	**0.0304**	0.3225	0.3481	0.3506	0.1049	0.3542
LS_Factor	**0.0001**	**< 0.0001**	0.2358	**0.0269**	0.2092	0.5110	0.2623	0.2429	**0**	0.0869	**< 0.0001**	**0.0116**	**< 0.0001**	0.5951	0.7087	0.7341	0.4055	0.5868	0.4158	0.6635
Relative_S	**< 0.0001**	0.6532	0.4611	**0.0170**	**< 0.0001**	**< 0.0001**	**< 0.0001**	**< 0.0001**	0.0869	**0**	**0.0081**	**< 0.0001**	**< 0.0001**	**< 0.0001**	0.9669	0.5886	0.9929	0.7676	0.9904	0.8104
Slope	**< 0.0001**	**< 0.0001**	0.4231	**0.0237**	0.7714	0.0633	0.5475	**0.0256**	**< 0.0001**	**0.0081**	**0**	**0.0058**	**< 0.0001**	0.7601	0.8939	0.9294	0.3331	0.4303	0.7946	0.5035
Elevation	**< 0.0001**	0.1625	0.0921	**< 0.0001**	**0.0367**	**0.0027**	0.3568	**0.0002**	**0.0116**	**< 0.0001**	**0.0058**	**0**	**0.0118**	**< 0.0001**	**0.0466**	0.0814	**0.0133**	**0.0265**	0.2143	**0.0260**
TWI	**< 0.0001**	0.4248	0.1556	0.2802	**< 0.0001**	**< 0.0001**	**< 0.0001**	**< 0.0001**	**< 0.0001**	**< 0.0001**	**< 0.0001**	**0.0118**	**0**	**0.0001**	0.1982	0.4913	0.4611	0.5044	0.2003	0.5401
Valley_Dep	**< 0.0001**	0.6832	0.6703	**0.0027**	**< 0.0001**	**< 0.0001**	**< 0.0001**	**< 0.0001**	0.5951	**< 0.0001**	0.7601	**< 0.0001**	**0.0001**	**0**	0.3994	0.7295	0.5089	0.5155	0.9475	0.4501
Precipitation	0.8171	0.6955	0.7578	**0.0022**	**0.0262**	**0.0338**	0.0782	**0.0304**	0.7087	0.9669	0.8939	**0.0466**	0.1982	0.3994	**0**	**< 0.0001**	**< 0.0001**	**< 0.0001**	< **0.0001**	**< 0.0001**
S.Radiation	0.4549	0.9036	0.9458	**0.0094**	**0.0413**	0.1024	0.2863	0.3225	0.7341	0.5886	0.9294	0.0814	0.4913	0.7295	**< 0.0001**	**0**	**< 0.0001**	**< 0.0001**	< **0.0001**	**< 0.0001**
Max.Temp	0.8940	0.4224	0.4503	**0.0134**	0.3890	0.1528	0.8987	0.3481	0.4055	0.9929	0.3331	**0.0133**	0.4611	0.5089	**< 0.0001**	**< 0.0001**	**0**	**< 0.0001**	**0.0457**	**< 0.0001**
Min.Temp	0.7142	0.9294	0.9576	**0.0059**	0.2374	0.1580	0.7098	0.3506	0.5868	0.7676	0.4303	**0.0265**	0.5044	0.5155	**< 0.0001**	**< 0.0001**	**< 0.0001**	**0**	0.7887	**< 0.0001**
Wind	0.9285	0.9761	0.9190	**0.0230**	**0.0294**	0.1075	**0.0170**	0.1049	0.4158	0.9904	0.7946	0.2143	0.2003	0.9475	**< 0.0001**	**< 0.0001**	**0.0457**	0.7887	**0**	0.9135
W.Vapour	0.7026	0.8059	0.8521	**0.0094**	0.2773	0.1687	0.7291	0.3542	0.6635	0.8104	0.5035	**0.0260**	0.5401	0.4501	**< 0.0001**	**< 0.0001**	**< 0.0001**	**< 0.0001**	0.9135	**0**

Vertical_D = Vertical Distance, Analytical_S = Analytical Slope, Channel_Net = Channel Networks, CI = Convergence Index, Cross sectional = Cross sectional curvature, Flow_Acc = Flow Accumulation, Longitudinal_Curve = Longitudinal curvature, Valley_Dep = Valley Depth, TWI = Topographic wetness index, Valley_Dep = Valley Depth, Relative S = Relative Slope, LS Factor = Slope Length and Steepness Factor, S.Radiation = Solar Radiation , Max Temp = maximum temperature Min Temp = minimum temperature, W.Vapour = Water Vapour

3.4.2 Estimating Fuel Moisture Content using topo-climatic variables

The estimation of FMC based on topographic indices yielded an R^2 of 0.68, an RMSE of 0.039 %/m^2 and an RRMSE of 1.111% (Figure 3.3). Channel networks, elevation, and wind were identified as the most influential topo-climatic variables in estimating FMC during the dry season using topo-climatic variables.

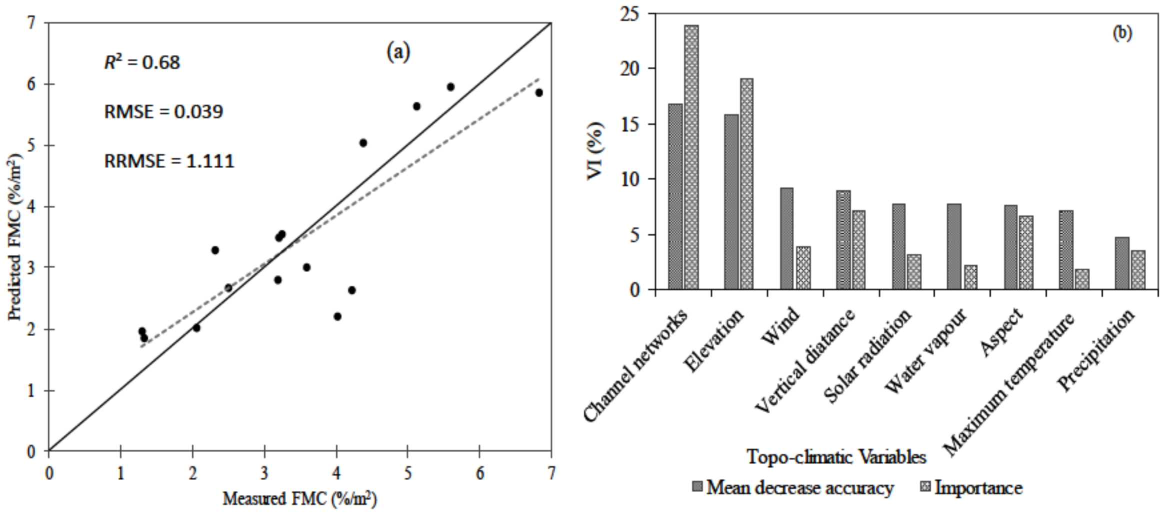
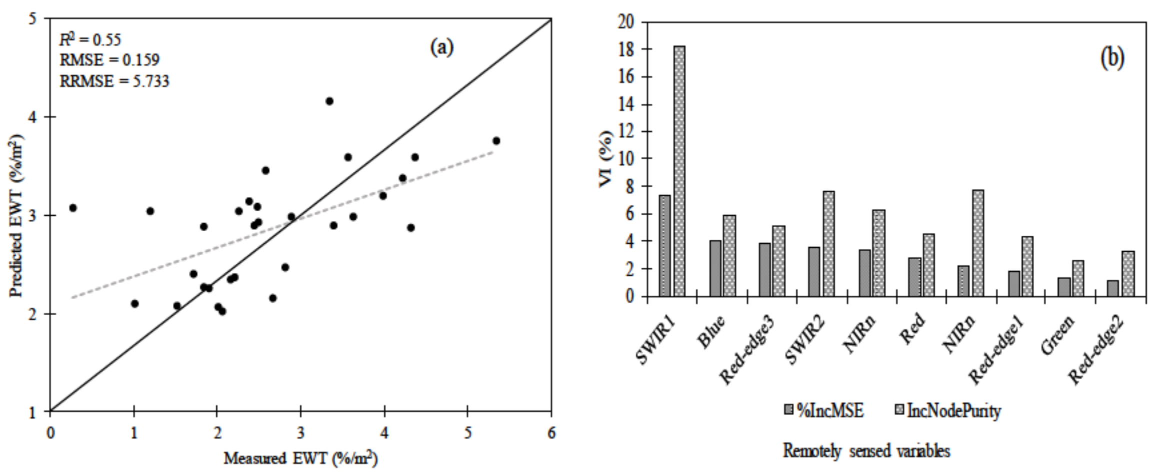


Figure 3.3: Graph showing the one to one relationship between measured and FMC predicted using (a) topo-climatic variables and (b) the importance of each topo-climatic variable in estimating FMC

3.4.3 Estimating Fuel Moisture Content using remotely sensed data

In estimating FMC using bands only, the RF model produced an R^2 f 0.55 and an RMSE of 0.159 %/m^2 with the most important variables being the SWIR Band 11, Blue band and Red-edge 3. Accuracy showed a slight improvement (R^2 of 0.57, RMSE = 0.101 %/m^2) when FMC was estimated using Sentinel 2 MSI derived VIs with the most important variables being the MI, NDSI and EVI2. Figure 3.4 (e) and (f) show that when remotely sensed variables were combined (bands and vegetation indices) to estimate FMC, there was a significant improvement in the model producing an R^2 of 0.70, an RMSE of 0.20 %/m^2. The most influential variables in estimating FMC were Band 11, EVI and NDII in order of importance. Sentinel 2 MIS derived spectral variables exhibited a magnitude of 0.0073 %/m^2 improvement in model accuracy from an RMSE of 0.039 %/m^2 derived using topo-climatic variables.



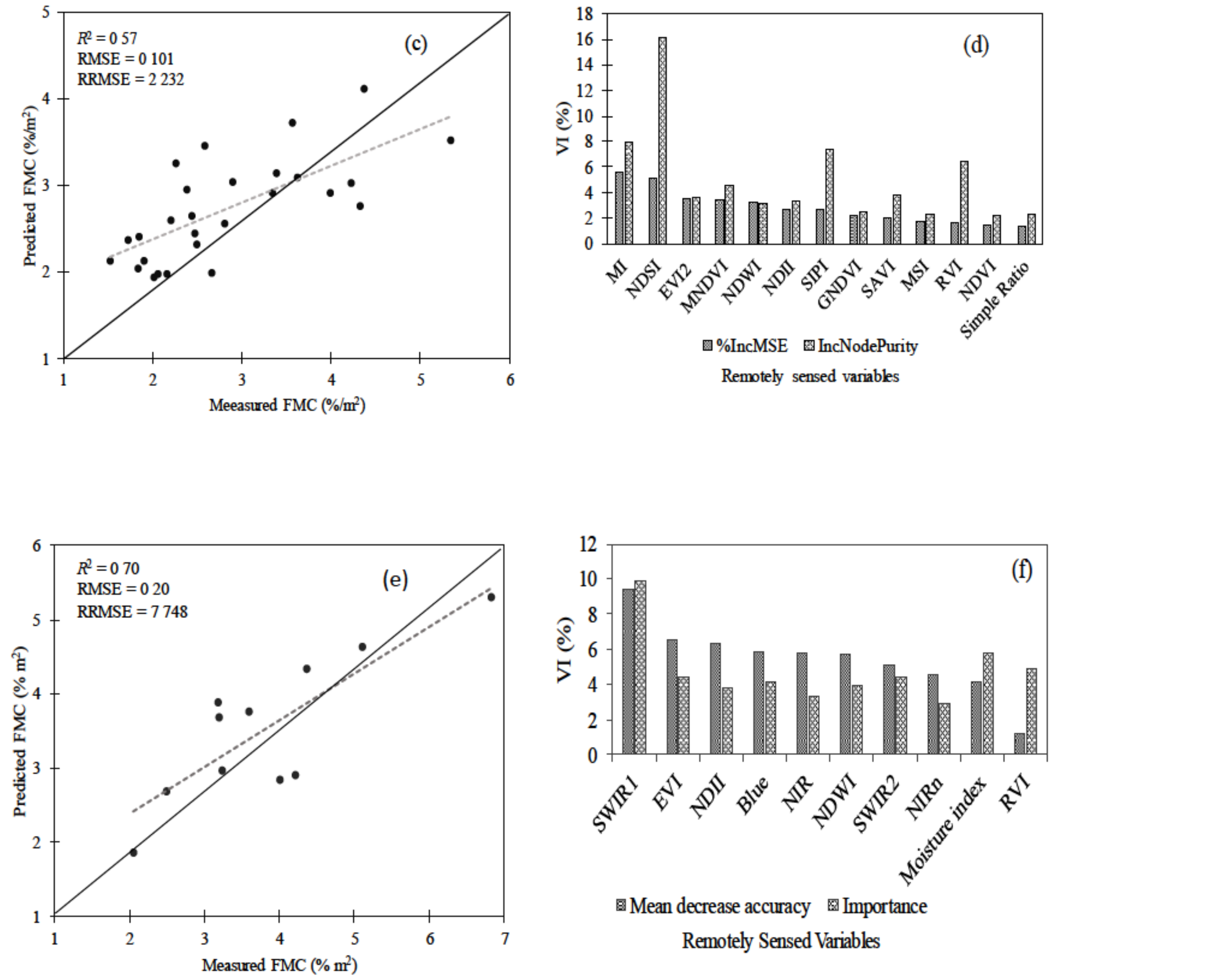


Figure 3.4: Graphs showing one to one relationship between measured and predicted FMC based on (a) Sentinel 2 MSI derived raw bands, (c) Sentinel 2 MSI derived VIs (e) Sentinel 2 MSI raw bands and VIs and (b,d,f) the importance of the spectral variables in each analysis.

3.4.4 Estimating Fuel Moisture Content using topo-climatic and remotely sensed variables

When Sentinel 2 MSI and topo-climatic variables were combined, an R^2 of 0.73, an RMSE of 0.190 %/m^2 and an RRMSE of 7.601 % were obtained in estimating grass FMC. The most influential variables selected using the RF algorithm in this model were channel networks, elevation, vertical distance wind, water vapour and Band 11 in order of importance. The combined data model showed a magnitude of 0.105 %/m^2 RMSE improvement when Sentinel 2 MSI derived VIs and conventional spectral bands were used.

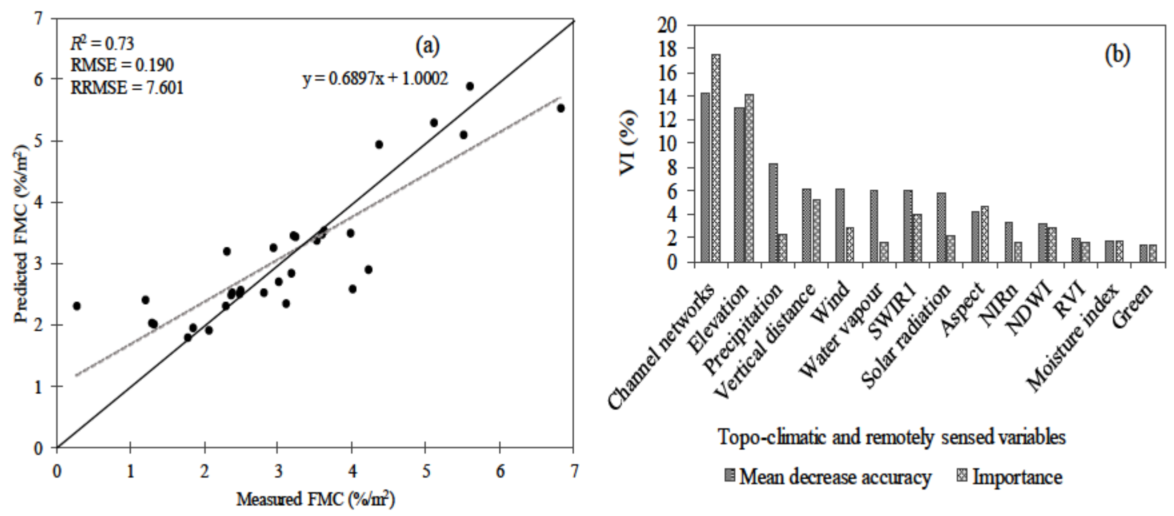


Figure 3.5: Graphs showing the one to one relationship between measured and FMC predicted using (a) spectral and topo-climatic variables and (b) the importance of each variable used in estimating FMC.

3.4.5 Spatial distribution of FMC in the study area.

Figure 3.6 shows the spatial distribution of estimated FMC (Figure 3.6a) and the resulting relationship between the probability of occurrence of fires and estimated FMC (Figure 3.6b). FMC is higher in the north-east and the southern central areas (Figure 3.6a). To determine this relationship a logistic regression was performed. The analysis showed that there was a negative relationship between the modelled FMC and fire occurrences. High probability of fire occurrence was associated with low FMC whereas high FMC was associated with a low probability of fire occurrence.

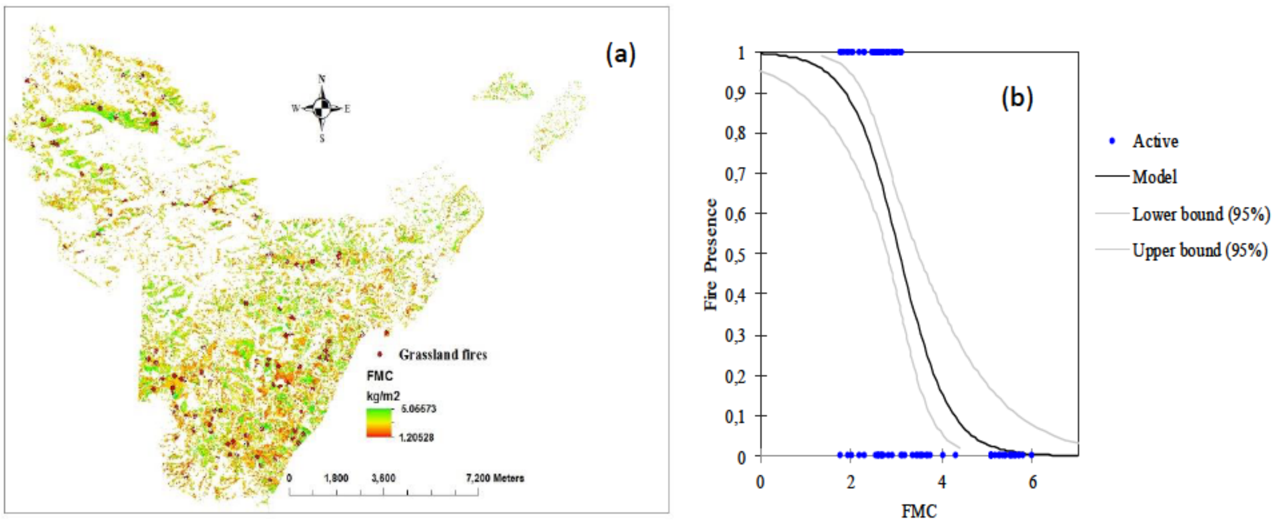


Figure 3.6: Map showing (a) the estimated spatial distribution of grassland FMC and (b) the logistic regression relationship that exists between predicted fires and estimated FMC.

3.5 Discussion

The use of time-efficient, cost-effective and reliable fire-management techniques derived through remotely sensed data, statistical algorithms and spatial models could be instrumental in assessing, measuring and understanding fire propagators and regulators such as FMC (Chuvieco and Kasischke 2007; Yebra *et al.* 2013). In this study, the RF algorithm was used to model grassland FMC using topo-climatic and Sentinel 2 MSI derived spectral in communal rangelands as a proxy for fire occurrence.

3.5.1 Estimating FMC based on Sentinel 2 MSI and Topo-climatic variables

Results of this study showed that FMC can be optimally estimated when topo-climatic variables are combined with Sentinel 2 MSI derived spectral variables to an R^2 value of 0.73 and RMSE of 0.190 $\%/m^{-2}$. Specifically, channel networks, elevation, wind, water vapour and Band 11 were the most influential variables in estimating grass FMC. Although not greatly explored in literature, the optimal influence exhibited by channel networks could be attributed to the influence of soil moisture properties on vegetation moisture content (Chen *et al.* 2017). Associated with the effect of channel networks in FMC variations, vertical distance is linked to the topographic lateral flows of underground water available for plant uptake (Vafaei *et al.* 2018). With regards to the significant influence of elevation, literature notes that areas in higher elevations are subject to lower FMC due to the accumulation of most water in the lower-lying areas i.e. valleys. In addition, elevation determines the temperature plants experience. When in higher elevations, the presence of higher temperatures leads to the faster curing of grass (Drusch *et al.* 2012; Rehm and Feeley 2015). Holden and Jolly (2011); Drusch *et al.* 2012, also found elevation to have a significant relationship with FMC. They noted that in lower lying areas, grass dries faster because of higher temperatures and lower precipitation, in turn this directly affects the occurrence and severity of fires (Dillon *et al.* 2011).

Meanwhile, according to Andrews (2012), the significance of wind speed on FMC post fire is such that higher wind speeds facilitate dryer fuels and encourage the higher spread and intensity of fires post fire ignition. The significance of precipitation is recognised for its effect on the availability of soil and plant moisture available for plants as higher precipitation values encourage moisture vegetation and therefore less intense fires. In their study, Vejmelka *et al.* (2016) found that FMC can be estimated with a relatively low RMSE of 0.006 %. The significance of water vapour in this study could be because as seen as a secondary source of moisture for plants(Machmuller 2014). However, in the dry season it is expected that there are fewer water vapour molecules in the atmosphere. Therefore, in the dry season there is less moisture for plants to assimilate, leading to drier fuels (Machmuller 2014).

A study by Nyman *et al.* (2015) , concluded that in smaller scales, FMC is primarily affected by factors such as aspect, slope, elevation and relative humidity. In a similar study by Martínez *et al.* (2009) investigating the importance of weather conditions on determining surface fuels, it was found that precipitation (mm) and temperature were significant and highly significant to FMC levels. Temperature exhibited an $R^2 = 0.85$ in estimating FMC. However, this study did not find a high significance between temperature and FMC.

The significance of the SWIR variable Band 11 to the optimal estimation of FMC has been widely discussed in literature because the variable lies in the moisture absorption region of the EMS where water absorption peaks are observed (Sow *et al.* 2013). In their study estimating herbaceous Senegal, West Africa FMC of grasslands , Sow *et al.* (2013) found that FMC was estimated to an R^2 of 0.82 when using MODIS NIR (841 nm – 876 nm) and SWIR (1230 nm – 1652 nm) based on VIs like the Global Vegetation Moisture Index. This study also showed a significant relationship between the NIR-SWIR derived VIs, especially those using the SWIR region ((1376.9 nm – 2185.7 nm).

3.5.2 Comparing the performance of Sentinel 2 MSI and Topo-climatic variables in estimating grassland FMC

In comparing the results of the performance of Sentinel 2 MSI and topo-climatic variables, results show that estimating FMC using exclusively topo-climatic variables outperform the performance of raw bands and VIs. The use of topo-climatic variables also proved to yield a lower RMSE (0.039 %/m^2) than that of raw bands (RMSE = 0.159 %/m^2) and VIs (RMSE = 0.101 %/m^2). The good performance of using strictly topo-climatic variables is as a result of grass being herbaceous vegetation. Grassland FMC therefore is influenced mainly by topographic and climatic factors because of a level of co-dependence between topo-climatic variables and FMC variations (Moeslund *et al.* 2013). An example of this was discussed by Nyman *et al.* (2015) who noted that in higher elevations there are aspect-related effects on incoming solar radiation showing that there is a significant relationship between elevation, aspect and solar radiation in relation to the availability of water in plants.

With regards to estimating FMC using Sentinel 2 MSI variables, the use of raw bands only yielded the lowest R^2 ($R^2 = 0.55$) and yielded a slightly higher RMSE (RMSE = 0.159 %/m^2) than when VIs (RMSE = 0.101 %/m^2) were used. When comparing the results of the Sentinel 2 MSI variables ((i)VIs and (ii) raw bands and VIs) there is a successive increase in R^2. This shows that the combination of all Sentinel 2 MSI facilitates higher accuracy and lower error of estimation (R^2= 0.70; RMSE = 0.20 %/m^2) compared to using strictly VIs or raw bands due to the model's ability to further limit errors due to effects like structural leaf effects (Chen *et al.* 2016). The RF model using VIs yielded a higher accuracy ($R^2 = 0.57$), with the most important variables being the MI, NDSI, MNDVI and the NDWI.

In a similar study by Bisquert *et al.* (2014), the EVI estimated vegetation water content with an accuracy of $R^2 = 0.84$. Studies estimating FMC using remotely sensed data have shown that moisture-related VIs such as the NIR and SWIR based NDII and the NDWI correlation with FMC (Cao *et al.* 2017; Dennison *et al.* 2006). This is because the NIR and SWIR regions are more sensitive to changes in liquid water content of vegetation canopies than they are to atmospheric effects (Wang *et al.* 2008; Wang and Shi 2007).

In a study monitoring variations of vegetation water content, Yuan *et al.* (2015) found that the NDVI produced higher correlation results compared to NDWI and NDII, while the study by ZORMPAS *et al.*

(2017) contradicted this showing that the NDVI produced a weak relationship ($R^2 = 0.01$) with FMC. This is because the NDVI does not directly measure the variations of vegetation moisture content, although it measures the effect of moisture content on chlorophyll (Cao *et al.* 2017; Sow *et al.* 2013). This is influenced by the type of vegetation that is being investigated because, in denser vegetation, the NDVI will perform better than when it is used to retrieve moisture from sparse vegetation cover. In this study the NDVI was not influential in estimating FMC.

Topo-climatic variables showed to have a significant relationship with FMC in the optimal model. However, a major limitation to the study was the lack of literature on the use and effectiveness of topo-climatic variables in estimating the spatial distribution of FMC within South African grasslands.

3.6 Relevance of the findings of this study

Results of the study illustrate that there is a strong relationship between grassland FMC of communal grasslands and topo-climatic factors, such as elevation. Therefore, the modelling of critical FMC using these factors can be used to show its spatial variation and to feed into early fire warning systems in grasslands across South Africa to facilitate cheaper, timely and cost-effective methods of fire management practices. However, more studies on the seasonal relationship between FMC and topo-climatic factors are needed in order to determine the seasonal relationships that exist between these factors.

3.7 Conclusion

This paper investigated (i) the effectiveness and influence of combining topo-climatic and Sentinel 2 MSI derived variables in modelling South African grasslands FMC in and around communal areas, (ii) the use of the RF variable importance selection to determine important topo-climatic and Sentinel 2 MSI derived variables in modelling FMC levels.

The results demonstrated that:

- Topo-climatic variables have a high association with estimated grassland FMC compared to Sentinel 2 MSI derived variables in the optimal model.
- The Sentinel 2 MSI has great potential in modelling biophysical factors like FMC that influence fire propagation, spread and intensity in South Africa.
- In the dry season, topo-climatic variables like channel networks and elevation showed to be critical in estimating FMC and overall surpassed the performance of remotely sensed variables in the combined RF model.
- The probability of fire occurrence is associated with lower FMC variations within rangelands.

Overall, the study shows that there is a significant relationship between FMC of South African grasslands topo-climatic factors and remote sensing. Therefore, the integration of these variables in early fire-warning will enable higher and more reliable results. Additionally, the study shows that the use of the Sentinel 2 MSI has the potential of accurately characterising and modelling FMC during the dry season.

2.8 Acknowledgements

We wish to thank the Durban Research Action Partnership (D'RAP) and the National Research Foundation of South Africa (NRF) Research Chair initiative in Land Use Planning and Management (Grant Numbers: 84157), NRF Grant (119791) for funding this research. We would also like to thank Siphiwokuhle Buthelezi and Helen Snethemba Ndlovu for their field and laboratory assistance.

Chapter Four: Synthesis

Rangelands visited in Thoyana (Photo captured by Wenzile Shinga 2019)

4.1 Introduction

Grasslands are among the most diverse ecosystems that sustain human livelihoods, animals and atmospheric processes (Dass *et al*. 2018). However, these grasslands are extensively transformed by frequent wildfires. Hence, the management of wildfires is critical in preserving these functions. Fire management techniques stem from understanding critical fire ignition parameters such as Fuel Moisture Content (FMC) and Equivalent Water Thickness (EWT) to global monitoring and observation systems of live fires (Chuvieco *et al*. 2002b, Pu *et al*. 2008). The moisture conditions of different vegetation types tend to determine the occurrence and intensity of fires (Mistry and Berardi 2005, *Pan et al*. 2018). Rangelands, in particular, are more vulnerable to fire ignition because they hold less moisture and wilt faster than other vegetation types. In this regard, there is a need to establish practical techniques to quantify these grassland moisture parameters. FMC and EWT are also a function of environmental factors including elevation and precipitation, as such, these need to be incorporated in quantifying them. However, more traditional techniques of quantifying these parameters are time-consuming and costly. Therefore, there is a need to adopt efficient and more affordable techniques to accurately quantify FMC and EWT in relation to fire occurrence. Remote sensing techniques offer more accurate techniques by satellite imagery with high spatial and temporal resolutions, suitable for assessing and quantifying vegetation FMC and EWT. In this regard, this study sought to test the utility of estimating EWT and FMC using topo-climatic and Sentinel 2 MSI derived variables (raw bands and VIs). To achieve this objective, the following specific objectives were investigated;

- To estimate the spatial distribution of EWT in the KZNSS using remotely sensed data
- To estimate the spatial distribution of FMC in communal grasslands at Thoyana, South Africa using topo-climatic variables and remotely sensed data

4.1.2 Testing the utility of Sentinel 2 MSI in estimating Equivalent Water Thickness (EWT) of the endangered grasslands in Southern Africa as a proxy for fire incidence

The SWIR region (1376.9 nm – 2185.7 nm) has proven to be sensitive to canopy water content and therefore it was hypothesised that it could be applicable in retrieving grassland EWT for understanding fire occurrences (Cao *et al.* 2017, Danson and Bowyer 2004a, Hantson *et al*. 2012). In that regard, this study tested the utility of Sentinel 2 MSI derived variables in estimating rangeland EWT using random forest. Specifically, the performance of Sentinel 2 MSI derived bands, standard VIs, moisture-based VIs and SWIR-based VIs was evaluated in estimating EWT using the RF ensemble.

The model derived using bands only, with the exclusion of the SWIR region (1376.9 nm – 2185.7 nm), exhibited an R^2 of 0.40 and an RMSE of 0.312 g/m^2 with the most important variables being Blue (Band 2), Green (Band 3) and Near-infrared narrow (Band 8A). The inclusion of the SWIR region (1376.9 nm – 2185.7 nm) in the bands only RF model improved the accuracies to an R^2 of 0.51 and an RMSE of 0.300 g/m^2, with the most influential variables being SWIR (Band 11), Blue (Band 2) and broad NIR (Band 8). Meanwhile, the model derived using standard VIs yielded an R^2 of 0.62 and an RMSE of 0.019 g/m^2 where the GNDVI, NDSI and NDVI2 were the optimal predictor variables. The importance of SWIR-based VIs further cemented the findings of other studies that evaluated the effectiveness of the SWIR region in estimating EWT. In comparing the results of moisture-based VIs and standard VIs the former produced higher accuracy (R^2 = 0.66; RMSE = 0.041 g/m^2) than that of standard VIs (R^2 = 0.62; RMSE = g/m^2). Variable importance scores for the model derived using moisture VIs showed that the NDWI, SIWSI and the NDMI were the most important predictor variables. The model derived using SWIR based VIs yielded an R^2 of 0.65 and an RMSE of 0.031g/m^2 and RF identified the SR SWIR 2 (Band 12) / Blue (Band 2), SR SWIR 1(Band 11) / Green (Band 3) and NDVI SWIR1 (Band 11) / Blue (Band 2) as the most influential variables. The optimal model derived when all Sentinel 2 MSI variables (bands, standard VIs, moisture-based VIs and SWIR-based VIs) were combined, exhibited the best performance (R^2 = 0.75, RMSE = 0.018 g/m^2) in estimating EWT when compared to the other models. The SWIR-based VIs were the most important variables selected by RF. This optimal (combined data) model was then used to map the spatial variation of rangeland EWT across the study area. Logistic regression was used to illustrate that there was a significant relationship between modelled EWT and fire incidences. An increase in the probability of fire incidences was associated with a decrease in EWT.

4.1.3 Estimating grass Fuel Moisture Content (FMC) in communal grasslands of South Africa using remotely sensed data combined with topo-climatic variables

In fire management studies, it is critical to establish efficient, cost-effective and relatively accurate techniques for quantifying FMC as well as understanding its relationship with fire incidences. Topo-climatic variables such as elevation, precipitation, and wind speed are integral in the spatial variation of FMC across different landscapes (Pan et al. 2018, Vallejo and Alloza 2015). In addition, remote sensing has demonstrated its ability in retrieving grassland moisture properties, with the SWIR region being highly sensitive to vegetation moisture at canopy level (Sow et al. 2013). Therefore, understanding the effect of estimating FMC with topo-climatic and remotely sensed data is important for estimating its spatial variation across communal grasslands. This study sought to test the combination of the STRM DEM derived topographic variables, climatic variables and Sentinel 2 MSI derived variables in estimating FMC using the RF algorithm.

The RF model derived using topo-climatic variables produced an R^2 of 0.68 and RMSE of 0.039 %/m^2 with the most influential variables being channel networks, elevation, precipitation and Band 11. The performance of Bands only yielded an R^2 of 0.55 and RMSE of 0.159 %/m^2. The most influential variables identified using the RF ensemble were SWIR (Band 11), Blue (Band 2) and the Red edge (Band 7). The RF model derived using VIs produced slightly higher accuracies of R^2 = 0.57 and an RMSE of 0.101 %/m^2. The most important variables in the RF model based on VIs were identified as the Moisture Index, EVI and NDWI. Meanwhile, the RF model combining bands and VIs exhibited an R^2 of 0.70 and an RMSE of 0.20 %/m^2 with the SWIR (Band 11), EVI and NDII being the most influential variables. The optimal RF model derived when topo-climatic and remotely sensed variables were combined exhibited an R^2 of 0.73 and an RMSE of 0.190 %/m^2. Specifically, the most influential topo-climatic variables included the channel networks, elevation, precipitation and wind while the most influential Sentinel 2 MSI derived variables were SWIR (Band 11), NDWI and the vegetation Red-edge Band 8A. Overall, variable importance showed that optimal Sentinel 2 MSI derived variables for estimating grassland FMC were the SWIR Band 11 among the raw bands and the NDWI and Moisture Index among the VIs. The RF optimal model was then used to generate a map of FMC distribution within the communal grasslands of Thoyana. The probability of fire incidences increased with a decrease in FMC, based on logistic regression.

4.2 Implications of the study

This work serves a baseline study to future academic research investigating the utility of topo-climatic and remotely sensed data with regards to fire incidence in South African grasslands. The utility of freely available sensors like the Sentinel 2 MSI can be successfully adopted in vegetation analysis by various industries, especially the public sector to implement and facilitate more inexpensive vegetation monitoring practices in relation to fire management. Moreover, this study is a step towards developing robust timely and effective frameworks for monitoring wildfire occurrences, especially in grassland ecosystems.

4.3 Conclusion and Recommendations and Limitations

The main aim of this study was to test the utility of DEM derived topographic variables, climatic variables and Sentinel 2 MSI derived variables in estimating grassland moisture parameters in Southern Africa. The findings of this study illustrated that combining topo-climatic and Sentinel 2 MSI variables is effective in estimating FMC. Meanwhile, rangeland EWT can be successfully estimated using Sentinel 2 MSI derived using the SWIR based VIs. Moreover, FMC and EWT proved to be good indicators of fire incidence in grasslands. There were some limitations to the study. The first limitation is concerning the lack of previous studies to reference with regards to methods of estimating FMC and EWT in South Africa. This may have affected have the quality of the theory and the understanding of methods used to estimate grassland FMC and EWT. The second limitation concerns the sample size used in the study. Generally, if a large sample size is used there is expected to be better results, therefore as a recommendation the sample size of future studies can be increased to observe better estimation results. Future research on fire incidence still needs to test the utility of topo-climatic and remotely sensed data in different seasonal conditions to understand the magnitude of how seasonal moisture variations affect fire incidences in the Southern African rangeland.

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