Remote sensing drought variability across different selected biomes of South Africa

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Abstract

Drought has been recognized as the leading extreme weather event in Southern Africa which causes major impacts on terrestrial environments, water resources and general functioning of the society across the region. Southern African biomes are increasingly getting vulnerable to drought conditions due to climate change, affecting vegetation health and biome distribution. Establishing the major effects of drought conditions on vegetation health at a regional scale is intricate, considering landscape variability with changes in climatic conditions, elevation, and soil dynamics. Previous research studies on drought assessment and monitoring have applied meteorological drought indices derived using point data from ground weather stations. However, the allocation of ground weather stations is commonly limited, hence, these meteorological drought indices are point limited and lack precise spatial coverage and accuracy in evaluating and monitoring the spatial distribution of drought periods at regional scale. Hence, vegetation indices derived from remotely sensed data have proven to be an effective method to track changes in vegetation over time and at a comparatively large scale. In this regard, this study sought to i) evaluate the relative performance of conditional and combinative drought indices in quantifying the magnitude of drought across different major biomes of Kwa-Zulu Natal. ii) assess the impact of various moisture and temperature contribution coefficients in estimating drought severity across different vegetation types. The findings of this study illustrated that the drought magnitude across the country could be optimally estimated using combinative drought indices to an R^2 and RMSE of 0.98 and 0.074 for the Savanna biome, 0.93 and 0.013 for the Grassland Biome and 0.99 and 0.016 for the Forest biome. The optimal index in this model was the Vegetation Moisture Stress Index (VMSI). In assessing the impact of various moisture and temperature contribution coefficients in estimating drought severity, high temperature predictor variables yielded the highest accuracies with VMSI_2 model (90%TCI:10%VMCI) being the most accurate model. The results produced an R^2 and RMSE of 0.78 and 0.0589 for the Savanna biome, 0.66 and 0.0511 for the Grassland biome and 0.76 and 0.0034 for the Forest biome. These findings demonstrates the potential of new combinative drought indices that combines multiple drought factors in effectively quantifying and monitoring drought conditions across different vegetation types of Southern Africa.

Keywords: Drought, Biomes, Conditional Indices, Combinative Indices, Kwa-Zulu Natal.

Preface

The research project reported on this document was conducted at the University of Kwa-Zulu Natal, Pietermaritzburg, under the School of Agriculture, Engineering and Science from February 2020 to February 2022. The research was conducted to fulfil the academic requirement for the degree of Master of Science in Applied Environmental Science. Research project was supervised by Professor Onisimo Mutanga and Dr Mbulisi Sibanda.

My declaration is that the work presented in this thesis is my original ideas which have not been presented and examined in any other academic institution. Proper acknowledgement has been made where other authors have been cited.

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……………………… Date: 09/02/2022………….

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Signature (Supervisor)

Prof Mutanga

Declaration

I, Duduzile Diza proclaim that:

1. The research presented in this document is my original work, unless where suggested differently.
2. Herein research project have never been examined at any other academic institution.
3. Herein research project do not comprise of any primary or secondary data, graphs, tables or additional information from any other person, unless where specifically acknowledged.
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   (i) Overall ideas were properly paraphrased and referenced.
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CHAPTER ONE:

General Introduction

1.1 Background

Drought is regarded as one of the most extreme natural disasters affecting more than half of global terrestrial ecosystems, natural habitats, and water resources leading to major impacts on the society as a whole (Jiao *et al.* 2016; Zambrano *et al.* 2016; Du *et al.* 2018; Bento *et al.* 2020). Droughts have illustrated an increasing trend in frequency and severity over time, owing to changes in climatic conditions worldwide (Unganai and Kogan 1998; Bahta *et al.* 2016; Zambrano *et al.* 2016; Bento *et al.* 2020). This is a common occurrence in semi-arid regions such as Southern Africa which is characterised by spatial and temporal rainfall variability and recognised as naturally susceptible to drought incidents (Usman and Reason 2004; Baudoin *et al.* 2017; Ndlovu and Demlie 2020). South Africa in particular was declared by national authorities as a disaster zone in 2015/16, owing to one of the worst drought episode ever experienced in the past decades (Baudoin *et al.* 2017). This extreme incident was associated with the most robust regional processes, the El Nino southern oscillation (ENSO) coupled with the conditions of sea surface temperature (SST) ever recorded on climatic conditions (Bahta *et al.* 2016; Xulu *et al.* 2019; Ndlovu and Demlie 2020). The El Nino signal impacts rainfall variability with negative periods indicating severe drought conditions while changes in sea surface temperature influence atmospheric dynamics, mainly moisture supply quantities over Southern Africa (Xulu *et al.* 2019; Ndlovu and Demlie 2020). According to Baudoin *et al.* (2017), the 2015/16 El Nino related drought event resulted in high temperatures coupled with a decrease in rainfall levels over South Africa. Hence, drought events associated with these processes are recognised as main effects of regional dry conditions which affects terrestrial ecosystems productivity and vegetation distribution at various spatial and temporal scales (Archer *et al.* 2017; Baudoin *et al.* 2017; Lang 2017; Xulu *et al.* 2019).

Approximately 30% of primary endemic vegetation in South Africa has been lost due to adverse impacts from climate change that subsequently cause recurring drought episodes (Harris *et al.* 2014). The constant increase of frequent drought events have extremely changed the distribution of Southern African biomes (Moncrieff *et al.* 2015). According to Bhuiyan *et* *al.* (2017) and Li *et al.* (2019), there is a strong association between drought conditions and hot temperature extremes, indicating warm future climatic conditions. Recent studies have also revealed major changes in grass cover and forest tree abundance, owing to recent changes in temperature conditions and water supply (Skowno *et al.* 2017). The shift in biome distribution threatens a range of ecosystem services provided by different biomes, such as availability and regulation of soil and surface water that subsequently affect vegetation and water resources across the country (Moncrieff *et al.* 2015). Others include carbon sequestration and storage, soil moisture properties, plant water loss and ecotourism, which has more implications on biodiversity conservation and on socio-economic aspects of the country (Crk *et al.* 2009; Moncrieff *et al.* 2015). Given that drought impact on terrestrial ecosystems leads to changes on spatial and temporal pattern of vegetation (Tfwala *et al.* 2018), developing the ability to predict and respond to these changes is of major significance in order to provide accurate mitigation and adaptation measures of the redistribution of the Southern African vegetation cover (Moncrieff *et al.* 2015).

Early drought detection is significant to assist in disaster monitoring and disaster mitigation measures (Nhamo *et al.* 2019). However, this process has been challenging given that drought incidents occurs around incompatible spatial environments with varying temporal patterns (Lang 2017). Reliant on contribution factors driving drought conditions, drought can be classified into three distinct kinds, namely, meteorological drought (rainfall deficiencies), agricultural drought (moisture deficiencies), and hydrological drought (low groundwater level and stream flow) (Halwatura *et al.* 2017). According to Carrão *et al.* (2016), these kinds of drought correspond to varying stages of continuous occurrences of meteorological process. Although different types of droughts occur at various timescales, there is a strong association between each kind of drought conditions (Carrão *et al.* 2016). The meteorological drought is considered as the main constitute, which stirs the succeeding types of droughts over time (Halwatura *et al.* 2017; Carrão *et al.* 2016). Since meteorological drought is considered as the core of other types of drought, crucial monitoring of this type of drought has been significant with the aid in early drought warning signs (Zhang and Jia 2013). The observed amplification of evaporation and evapotranspiration demand driven by the conditions of climatic changes on precipitation and temperature factors, have contributed to a prevalent increase in drought severity (Bento *et al.* 2018), and an increase in spatial coverage of areas impacted by drought incidents (Abuzar *et al.* 2019).

Numerous drought indices have been established to assess and quantify drought severity from local to national scales and across various types of vegetation (Du *et al.* 2018; Marumbwa *et al.* 2021). The Standardised precipitation index (SPI) and the Standardised evapotranspiration index (SPEI) are among the most commonly used meteorological drought indices, solely based on precipitation and/or temperature anomalies derived from ground weather stations (Du *et al.* 2018; Bento *et al.* 2020). Marumbwa *et al.* (2021) outlined that these are robust meteorological drought indices which can be applied across different climatic regions and are also standardised drought indices that allows for the comparison of drought impact across various ecosystems and vegetation types. The main advantage of these indices is centered on their comparative capability to estimate and monitor drought impact on a range of timescales (1 to 48 months), indicating that the different types of droughts can be captured and monitored (Park *et al.* 2018; Du *et al.* 2018; Zhang *et al.* 2020; Tirivarombo *et al.* 2018). However, given that ground weather stations allocation is limited and uneven across space, specific to a particular site and are limited in representing the true nature of events across larger scales (Hao *et al.* 2015), meteorological drought indices must be complemented by a vegetation based drought index which can explicitly determine drought impact on vegetation and can provide continuous spatial coverage at a regional scale (Jiao *et al.* 2016; Marumbwa *et al.* 2021).

The development of high spatial coverage and multi-temporal data of remote sensing techniques is ideal in assessing and monitoring long-term droughts at local and regional scales through spatial and temporal assessments (Harris *et al.* 2014). Remote sensing-based drought indices are thus applied in quantifying and mapping drought related changes on terrestrial ecosystems, particularly using vegetation vigour as an indicator of ecosystem response to climatic changes (Zhu *et al.* 2016; Zambrano *et al.* 2016). Hence, attributes of drought incidents could be effectively acquired directly from the optical, near infrared (NIR), shortwave infrared (SWIR) and thermal bands (TIRS) of remote sensing satellite sensors (Nhamo *et al.* 2019). The Vegetation Condition Index (VCI), the Temperature Condition Index (TCI) and the Vegetation Moisture Condition Index (VMCI) are among the commonly applied remote sensing-based drought indices for assessing and monitoring drought conditions (Jiao *et al.* 2016; Zambrano *et al.* 2016; Du *et al.* 2018; Park *et al.* 2018). These are drought indices derived from spatial features of solar radiation (Normalised difference vegetation index, NDVI), land surface temperature (LST) and moisture availability (Normalised difference water index, NDWI), respectively (Bhuiyan *et al.* 2017; Park *et al.* 2018; Du *et al.* 2018).

However, multiple preceding research studies have indicated that a single vegetation index derived from a single drought factor cannot fully capture the complexity of drought incidents across space and time (Park *et al.* 2018; Bento *et al.* 2020). Hence, various combinative drought indices have been developed, including the soil wetness deficit index (SWDI), the vegetation health index (VHI), and the vegetation moisture stress index (VMSI) based on variables that constitute drought incidents (Bhuiyan *et al.* 2017; Park *et al.* 2018; Du *et al.* 2018; Zhang *et al.* 2020). These are based on weighted sum of two sub-indices, each derived from different portions of the electromagnetic spectrum and designed to capture the contribution of each index in assessing and monitoring drought events (Bento *et al.* 2020; Zhang *et al.* 2020). However, the accuracy of the aforementioned drought indices in drought prediction, assessment and monitoring are dependent on the type of region, vegetation cover, temporal scale, and relative contribution of drought factors such as precipitation and temperature. Hence, this study sought to improve drought assessment and monitoring across different terrestrial biomes of Southern Africa through the application of multiple conditional and combinative remotely sensed drought indices.

1.2 Aim and objectives

The overall aim of this study was to characterise drought variability across different major biomes of Kwa-Zulu Natal, using remote sensing based conditional and combinative drought indices.

The main objectives of the study were:

1. To evaluate the relative performance of conditional and combinative drought indices in quantifying the magnitude of drought.
2. To derive optimal drought index which can be applied across different vegetation types
3. To evaluate the impact of various moisture and temperature drought contribution coefficients in estimating drought severity.
4. To assess the main drought factor contribution coefficient which stirs drought conditions across different biomes of Southern Africa.

1.3 Study site

The biomes considered in this study are located in Kwa-Zulu Natal (28°33’36.78’’ S, 30°54’12” E) illustrated in Figure 1. The altitude in the region ranges from sea level to approximately 3000m above sea level (Dube and Jury 2003). Kwa-Zulu Natal is dominated by three major biomes, namely, Savanna, Grasslands and Forests. Savanna biome is the largest biome with forest being the smallest land cover type. To minimise the impact of anthropogenic activities such as land degradation by footpaths, three protected national parks were considered in this study which fall under each biome. The Isimangaliso wetland park – Savanna biome (27°38’10.07’’ S, 32°34’57.11” E), uKhahlamba Drakensberg park – Grassland biome (29°22’36.27’’ S, 29°32’54.28” E) and Ngoye Forest Reserve – Forest biome (28°50’33.54’’ S, 31°42’07.84” E).

Isimangaliso Wetland Park is a large protected area that extends 230 km along the east coast of Kwa-Zulu Natal and it is a RAMSAR site (Buah-Kwofie *et al.* 2018). Isimangaliso Wetland Park is approximately 328 000 hectares and is pronounced as the world heritage site that forms part of the Maputaland-Pondoland Albany biodiversity hotspot (Buah-Kwofie *et al.* 2018). The area comprises of various relative protected environments such as Mkhuze Game Reserve and Kosi Bay (Hart *et al.* 2014; Buah-Kwofie *et al.* 2018). It also includes widespread freshwater wetlands, savannah, coral reef communities and coastal forests (Buah-Kwofie *et al.* 2018). The Park also incorporates major coastal lakes and estuaries such as Lake St Lucia, Lake Sibaya and Lake Kosi Bay (Buah-Kwofie *et al.* 2018). The area is situated at an elevation of ≤ 40m above sea level (Hart *et al.* 2014). There is a drastic variation in mean annual rainfall with areas along the coast experiencing 1000 to 1100 mm, while areas inland experience 600 mm of precipitation (Hart *et al.* 2014). This biome is characterised by hot and wet summers with relatively cool winters. Vegetation found in this biome is a mixture of trees and grasses with regular fires that prevent trees from dominating the area.

uKhahlamba Drakensberg park is a globally recognised World Heritage Site, declared by UNESCO for its biological and cultural diversity in year 2000 (Lodder *et al.* 2018). The conservation area lies in the inland mountains of south-eastern Africa (Krüger and Crowson 2004). uKhahlamba Drakensberg park is approximately 242 813 ha with varying topography, resulting in strong seasonality and varying precipitation, temperature, wind and humidity (Ndlovu *et al.* 2018; Lodder *et al.* 2018). The area lies within an elevation ranging from 1280 m to 3500 m above sea level (Krüger and Crowson 2004). The area experiences varying precipitation, ranging from 1000 mm to 1800 mm, owing to increase in altitude (Krüger and Crowson 2004). Summer rainfall is predominant with approximately 75% of rainfall with snowfalls occurring in winter, mainly at high altitude (Ndlovu *et al.* 2018; Krüger and Crowson 2004). The mean annual temperatures in the area is approximately 16℃ but varies with different seasons and varying altitude (Ndlovu *et al.* 2018). uKhahlamba Drakensberg park has more than 80% of the area covered by grasslands (Morris *et al.* 2021).

Meanwhile, Ngoye Forest reserve occupies 3903 ha and is situated in northern Kwa-Zulu Natal, 50 km inward from Mtunzini (Phadima 2005). The reserve is characterised by a large contiguous forest patch which is approximately 2800 hectares with multiple peripheral patches of forests and climax grasslands (Kruger and Lawes 1997). The forest reserve is regarded as one of the exceptional subtropical evergreen forest with structural and floristic qualities equivalent to those of tropical rainforest (Kruger and Lawes 1997). The forest is at an altitude that ranges from 305m to 490m above sea level and it is known for its high diversity of rare and endemic plant species such as *Millettia grandis* (umzimbeet) (Boudreau *et al.* 2005). The forest reserve is found within frost free zones and receives an average annual rainfall of approximately 800 – 1100 mm (Phadima 2005). Temperatures in this reserve range from a minimum of ~8 ^{0}C which occurs in winter months to a maximum temperature of ~37℃ which occurs in summer months (Phadima 2005).

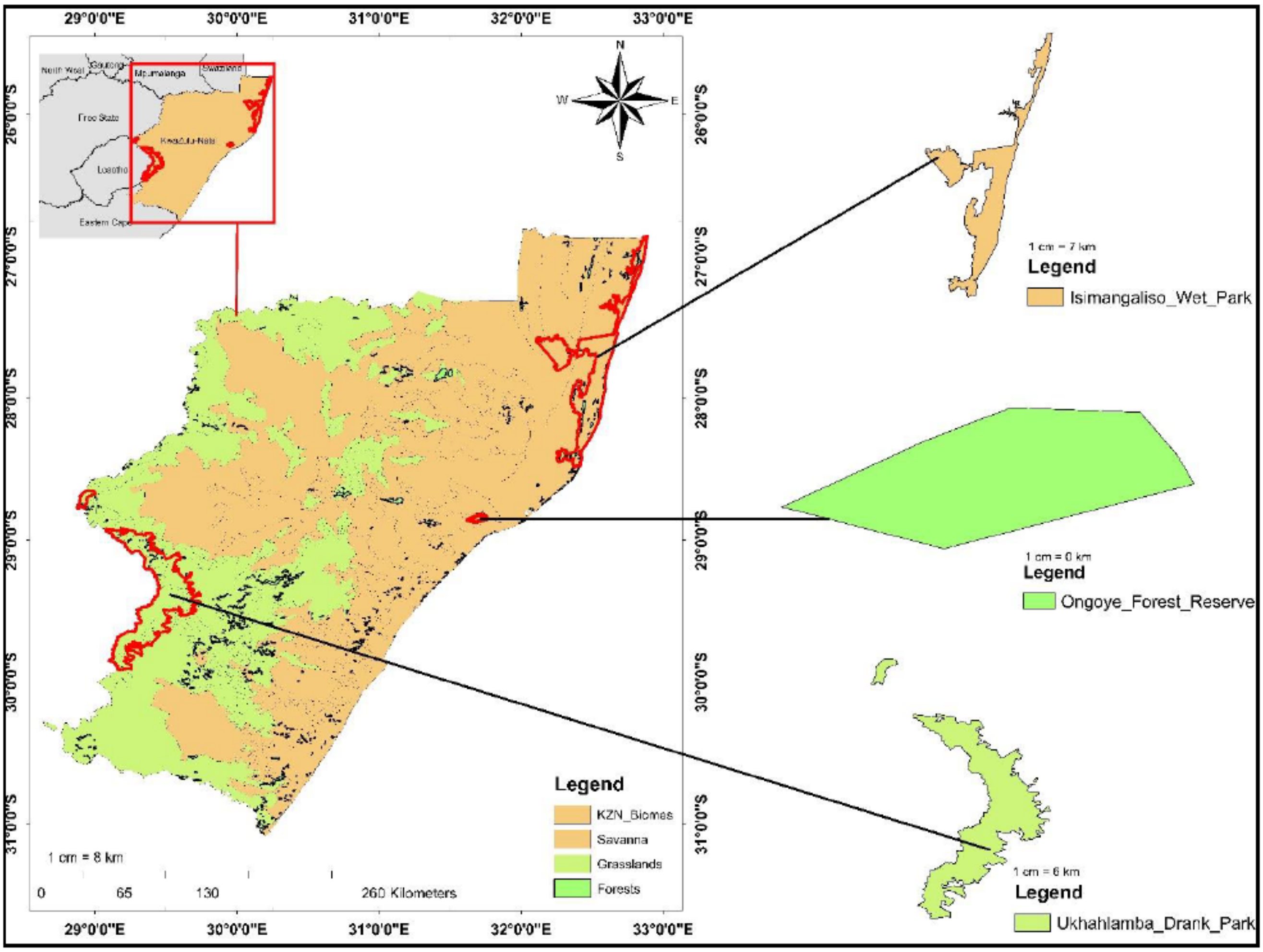


Figure 1.1: Study sites map of three major biomes of Kwa-Zulu Natal, South Africa

1.4 Summary of the thesis

Chapter One: *General introduction*

This chapter provides the general introduction of this study, outlining the aim and objectives set out for this research. It further includes the study area description and map outline.

Chapter Two: *Remote sensing standardised precipitation index (SPI) as a proxy for estimating drought variability across different selected biomes of South Africa using various Landsat 8 vegetation indices*

This chapter is based on evaluating the use of remote sensing based conditional and combination drought indices in estimating drought magnitude using a meteorological multiscalar index as a drought indicator. It reports the main findings obtained across three major biomes of Kwa-Zulu Natal.

Chapter Three: *Assessing the impact of moisture and temperature contribution coefficients in estimating drought severity of selected Southern African biomes using Landsat 8 data and a multiscalar meteorological drought index as a drought indicator*

This chapter assesses the impact of various moisture and temperature contributions in stirring drought severity across different vegetation types of Kwa-Zulu Natal. Main findings and implications are reported in this chapter.

Chapter Four: *Synthesis*

This chapter explores the main findings of this study in relation to each objective outlined for this research. Additionally, it includes the limitations encountered in this study and provides overall conclusion and future recommendations.

CHAPTER TWO:

Remote sensing Standardised precipitation index (SPI) as a proxy for estimating drought variability across different selected biomes of South Africa using various Landsat 8 vegetation indices.

Abstract

Drought is considered as one of the efficacious disasters of the 21st century in Southern Africa, causing adverse impacts on ecosystem diversity, societal issues, and economic aspects. Establishing drought impacts on vegetation health across multiple scales is multifaceted, due to landscape variability which is characterised by varying climatic conditions, elevation, and soil dynamics. Most studies have applied drought indices based on point data from ground weather stations. However, due to the limited and uneven allocation of weather stations across space, the meteorological drought indices are point based and lack spatial coverage and precision to assess and monitor drought spatial pattern at larger scales. Hence, the use of vegetation indices derived from remote sensing satellite sensors have demonstrated to be the most effective technique in tracking vegetation health changes based on various temporal periods and at a comparatively large scale. Therefore, this study evaluated the performance of conditional and combinative drought indices in quantifying the magnitude of drought across three major biomes of Kwa-Zulu Natal, using the standardised precipitation index (SPI) as a drought indicator. The study considered the Savanna, Grassland and Forest biomes across a 6-year temporal period. The findings of this study revealed that both combinative and conditional predictor variables were successful in estimating drought magnitude across the biomes based on 1-month SPI drought indicator. The optimal Vegetation Health Index-Vegetation Moisture Stress Index (VHI-VMSI) variables were the best performing predictor variables of drought magnitude with an R^2 of 0.89 (RMSE = 0.074) for the Savanna biome, R^2 of 0.93 (RMSE = 0.013) for the Grassland biome and R^2 of 0.99 (RMSE = 0.016) for the Forest biome. The most influential combinative drought index was the Vegetation Moisture Stress Index (VMSI) for all the biomes. Meanwhile, slightly lower accuracies were observed when using the Vegetation Condition Index- Temperature Condition Index- Vegetation Moisture Condition Index (VCI, TCI, VMCI) predictor variables which yielded an R^2 of 0.93 (RMSE = 0.168) for the Savanna biome, R^2 of 0.89 (RMSE = 0.021) for the Grassland biome and R^2 of 0.97 (RMSE = 0.033) for the Forest biomes. The most optimal conditional drought index was the Vegetation Moisture Condition Index (VMCI) across all the biomes. These findings are critical for the

Southern African biomes in developing a robust and spatially explicit drought index that can be applied across space in quantifying and monitoring drought conditions at a regional scale.

Keywords: Drought, biomes, conditional indices, combinative indices, Kwa-Zulu Natal.

2.1 Introduction

Drought events in Southern Africa have been the main leading natural disasters driven by severe climatic conditions, causing major impacts on terrestrial environments and major water resources around the country (Baudoin *et al.* 2017). Southern African biomes are increasingly getting vulnerable to drought conditions owing to multiple factors such as climate change, decrease in precipitation level and inadequate quantification and monitoring measures by environmental stakeholders (Orimoloye *et al.* 2019; Marumbwa *et al.* 2021). Biomes have a major role of providing significant ecosystem services and and stirring the function of different ecosystems (Marumbwa *et al.* 2021). However, Lawal *et al.* (2019) reported that in the Southern African region, drought impacts on vegetation have resulted in the shift of vegetation within the region from their original biome distribution. The growth of drought conditions in frequency and intensity amplified by changing climatic conditions had also been projected to affect substantial loss of biodiversity in species-rich biomes of Southern Africa (Lawal *et al.* 2019; Bento *et al.* 2018). Marumbwa *et al.* (2021) argued that this is also due to the rapid increase of population growth in Southern African countries that further places more pressure on vegetation resources. Furthermore, Southern African biomes play a major role in supporting various worldwide proclaimed wildlife National Parks and Game Reserves (Marumbwa *et al.* 2021). For instance, South African heritage sites such as ISimangaliso Wetland Park and UKhahlamba Drakensberg Park in Kwa-Zulu Natal are recognised internationally for their high species diversity and endemism. Hence, quantifying and monitoring the spatial distribution and variability of drought impact on vegetation will aid in providing imperative information for early drought warning systems and monitoring measures to the national park authorities (Marumbwa *et al.* 2021; Lawal *et al.* 2019).

Establishing the major effects of drought conditions on vegetation health at a global or sub-continental scale is complicated, considering landscape variability with changes in climatic conditions, elevation and soil dynamics (Marumbwa *et al.* 2021). This is also influenced by the slow unnoticeable onset, progression and yet accumulative and detrimental drought impacts

(Du *et al.* 2018; An *et al.* 2020). So, it is essential to account for the differences of climatic factors in order to accurately assess and monitor the impact of drought on vegetation (Marumbwa *et al.* 2021). Multiple studies have been able to effectively assess and monitor drought conditions using traditional drought indices such as Rainfall Anomaly Index (RAI), Palmer Drought Severity Index (PDSI) and Standardised Precipitation Index (SPI) (Jiao *et al.* 2016; Karnieli *et al.* 2010). These drought indices are classified as meteorological drought indices derived using ground weather station measurements of precipitation and temperature, that can evaluate drought conditions around the vicinity of the meteorological ground station (Jiao *et al.* 2016).

The Standardised Precipitation Index (SPI) is the commonly used meteorological drought index because of its simplicity and flexibility (Quiring 2009; Tfwala *et al.* 2018; Tirivarombo *et al.* 2018). SPI was developed as a multi-scalar index that includes cumulative precipitation deficiencies at several spatial and temporal scales (Tirivarombo *et al.* 2018). This index provides a flexible way to characterize and monitor drought episodes at different timescales (i.e. at 1-, 3-, 6-, 12- and 24- months) (Tfwala *et al.* 2018; Tirivarombo *et al.* 2018). This is the fundamental strength of SPI which separates it from other meteorological drought indices (Quiring 2009). Hence, SPI is applicable in assessing and quantifying meteorological, hydrological and agricultural drought events (Tfwala *et al.* 2018). This meteorological drought index is effective and robust in quantifying and monitoring drought events, hence, it is generally utilized as an empirical drought indicator computed for each weather station across different timescales (Jiao *et al.* 2016). However, the allocation of weather stations is commonly uneven and limited, thus, the aforementioned drought indices lack spatial coverage and precision across space in assessing and monitoring the spatial patterns of drought conditions from local to global scale (Jiao *et al.* 2016; Zambrano *et al.* 2016; Baniya *et al.* 2019; Du *et al.* 2018). There is therefore a need to identify other spatially explicit methods and techniques to characterise SPI as a proxy for drought conditions across various vegetation types.

In this context, the availability of satellite-based remotely sensed data have proven to be an effective technique that offers substantial advantages for monitoring drought conditions from local to regional scale by allowing for both spatial and temporal drought impact assessments (Du *et al.* 2018; Bento *et al.* 2018; Zambrano *et al.* 2016). Moreover, remote sensing based vegetation indices have been widely utilized to track changes in vegetation over time, mainly as an indicator of ecosystem response to weather conditions, therefore, monitoring drought events (Zambrano *et al.* 2016; Du *et al.* 2018). Vegetation response to drought conditions have been extensively explored using vegetation indices that utilizes the ratios of the near-infrared (NIR), red, short-wave infrared (SWIR) and thermal infrared (TIRS) bands of the electromagnetic spectrum and their relative multiple combinations (Xulu *et al.* 2019). Xulu *et al.* (2019) outlined that out of these bands, vegetation indices derived from NIR and SWIR bands have illustrated the greatest sensitivity to drought conditions. The normalised difference vegetation index (NDVI) based Vegetation Condition Index (VCI), land surface temperature (LST) based Temperature Condition Index (TCI) and the normalised difference water index (NDWI) based Vegetation Moisture Condition Index (VMCI) are the most widely used conditional drought indices for monitoring drought magnitude, severity and frequency from local to regional scales (Du *et al.* 2013; Bhuiyan *et al.* 2017). They have been successfully applied in several studies under various environmental conditions to monitor vegetation changes, estimating crop yield and for analysing drought conditions (Bhuiyan *et al.* 2017; Zambrano *et al.* 2016).

For example, Du *et al.* (2013) established that VCI is a suitable vegetation index that can monitor large scale drought impact, given that it has a strong correlation with vegetation vigour. However, Quiring *et al.* (2010) concluded that VCI showed low correlations with meteorological drought indices in Texas and thus cannot be applied in some regions. Therefore, VMCI was considered as a water related index which is a direct indicator of leaf water content hence more sensitive to drought conditions than greenness related vegetation indices (VCI) (Du *et al.* 2018). Additionally, studies by Singh *et al.* (2003) and Bhuiyan *et al.* (2017) in drought monitoring also concluded that VCI alone is not a suitable predictor for drought conditions, given its low correlation values with meteorological and hydrological drought indices. Hence, Kogan (1995b) developed the Temperature Condition Index (TCI) to account for vegetation thermal stress based on the assumption that increase in temperature , results in inferior vegetation conditions. Multiple studies have utilized these conditional drought indices successfully as reported by Du *et al.* (2013). Although applied successfully as separate drought indices, studies such as that by Kogan (1997), Du *et al.* (2013) and Bhuiyan *et al.* (2017) established that combining these indices yielded higher accuracy, due to the combination of greenness index (NDVI) and brightness temperatures (TCI). Hence, the Vegetation Health Index (VHI) and Vegetation Moisture Stress Index (VMSI) were developed as combinative drought indices that accounts for multiple drought indicators (precipitation, temperature, evapotranspiration, and moisture deficiency) of a specified region. Multiple studies have applied and reported the effectiveness of these drought indices in drought monitoring at a global scale (Zambrano *et al.* 2016; Bhuiyan *et al.* 2017). However, Bento *et al.* (2020) outlined that the accuracy of these indices may differ given that moisture and temperature conditions vary with different vegetation types.

The utility of the aforementioned vegetation indices have been commonly applied across different parts of the globe for drought impact assessment on vegetation (Du *et al.* 2018; Marumbwa *et al.* 2021). However, within the Southern African context, several studies have focused on monitoring drought conditions at local scale and mainly focusing on agricultural drought (crops) (Marumbwa *et al.* 2021). Furthermore, local studies have solely used raw vegetation indices on drought analysis such as the normalised difference vegetation index (NDVI) due to their simplicity and ease of computation (Marumbwa *et al.* 2021). Therefore, the impact of drought on natural vegetation across different biomes still remains a challenge (Marumbwa *et al.* 2021). In this regard, this study sought to assess the utility of remotely sensed conditional and combinative drought vegetation indices in quantifying the magnitude and spatial extent of drought across different biomes of Kwa-Zulu Natal. The objectives of the study were: (i) to evaluate the relative performance of conditional and combinative drought indices in quantifying the magnitude of drought across the Savanna, Grassland and Forest biomes, using SPI as a drought indicator, computed across various timescales. (ii) to identify the most optimal drought indices that can effectively quantify drought episodes across the different biomes within a 6-year temporal period. Lastly, to map drought spatial variability across the biomes using the most optimal drought index.

2.2 Methodology

The following chapter consists of remote sensing imagery acquisition used in this study. The processing of the images and computation of drought indices include the predictor drought variables which include three combinative drought indices and two conditional drought indices. A multiscalar meteorological index was included as a benchmark index of drought. Furthermore, a statistical analysis and accuracy assessment was conducted on the outputs of the study.

2.2.1 Image acquisition and pre-processing

Long-term data of at least 20 years is required to compute long-term minimum and maximum values of vegetation drought indices. Two Landsat sensors, namely, Landsat 7 and 8, were acquired in this study by both the Operational Land Imager (OLI) and the Thermal Infrared Sensor (TIRS) sensors. Landsat 7 was only considered in the study with the aid to compute long-term minimum and maximum values of drought indices, given that Landsat 8 was launched in 2013. Hence, its scenes were acquired from 2014 – 2019 which were the main scenes considered for analysis in the study. Available annual imagery was selected and downloaded from Google Earth Engine (https://code.earthengine.google.com/). The images were acquired using a script indicating standard USGS format, with terrain corrected Top-of-Atmosphere (TOA) reflectance in a GeoTiFF format ("LANDSAT/LC08/C01/T1_TOA"). Buthelezi (2020) argued that Landsat scenes are susceptible to atmospheric and sensor distortions, therefore, to eliminate these effects, only high-level pre-processed imagery with geometric and radiometric corrections were considered using a script. A total of 20 annual images were acquired, ranging from 2000 to 2019.

Landsat 8 OLI is a push broom multispectral imager that has 9 spectral bands ranging from the visible to the near-infrared wavelengths of the spectrum (Vanhellemont and Sensing 2020). These bands have a spatial resolution of 30m, excluding the panchromatic band which has 15m resolution. Landsat 8 TIRS is a push broom imager with 2 spectral bands, B10 and B11 with thermal characteristics, recording data at 100m, however, it is resampled to 30m (Vanhellemont and Sensing 2020). This study used B10 TIRS, following Guha *et al.* (2018) who suggested the use of band 10 as a single spectral band owing to the larger calibration uncertainty associated with band 11.

2.2.2 Computation of remote sensing drought indices

Normalised Difference Vegetation Index (NDVI), Normalised Difference Water Index (NDWI) and Land Surface Temperature (LST) were calculated initially using Landsat 8 (OLI &TIRS) data as primary raw vegetation indices with the aim of using these indices to acquire the conditional and combinative drought indices used in the study. This study utilised three conditional drought indices, namely, Vegetation Condition Index (VCI), Vegetation Moisture Condition Index (VMCI) and Temperature Condition Index (TCI) and two combinative drought indices, namely, Vegetation Health Index (VHI) and Vegetation Moisture Stress Index (VMSI) illustrated in table 2.1.

Table 2.1:Vegetation indices used in the study including raw vegetation indices, conditional and combinative drought indices and meteorological drought index.

Index	**Source**	**Formula**	**Reference**
NDVI	*Landsat 8 OLI*	$NDVI = \dfrac{NIR - RED}{NIR + RED}$	(Saleh 1973)
NDWI	*Landsat 8 OLI*	$NDWI = \dfrac{NIR - SWIR}{NIR + SWIR}$	(Gao 1996)
LST	*Landsat 8 TIRS*	$LST = (BT / (1 + (0.00115 * BT / 1.4388) * Ln(\varepsilon)))$	(Ulivieri *et al.* 1994)
VCI	*Landsat 8 OLI*	$VCI = \dfrac{NDVIi - NDVImin}{NDVImax - NDVImin}$	(Kogan 1995a)
TCI	*Landsat 8 TIRS*	$TCI = \dfrac{LSTmax - LSTi}{LSTmax - LSTmin}$	(Kogan 1995a)
VMCI	*Landsat 8 OLI*	$VMCI = \dfrac{NDWIi - NDWImin}{NDWImax - NDWImin}$	
VHI	*Landsat 8 OLI & TIRS*	$\alpha VCI + (1 - \alpha)TCI$	(Kogan 1995a)
VMSI	*Landsat 8 OLI & TIRS*	$\alpha VMCI + (1 - \alpha)TCI$	
SPI	*In situ data*	$SPI = \dfrac{Xi - Xm}{\sigma}$	(McKee *et al.* 1993)

For NDVI, NDWI and LST, further minimum and maximum values for each index were calculated in ArcMap version 10.4 using cell statistics for a 20-year period (2000 – 2019), normalizing each vegetation index (Zhuo *et al.* 2016) to acquire the desired conditional and combinative indices.

2.2.3 Conditional drought Indices

I. Vegetation Condition Index (VCI)

This algorithm was developed by Kogan (1995a) to discriminate overall differences in ecosystem productivity (Jiao *et al.* 2016), by separating short-term weather component from long-term ecological component (Dutta *et al.* 2015). VCI was developed as a normalisation of NDVI, by scaling NDVI values from 0 – 1 using their relative minimum and maximum values for that composite period and location (Zhuo *et al.* 2016).

$$VCI = \frac{NDVIi - NDVImin}{NDVImax - NDVImin} \qquad (1)$$

Where $NDVI_i$ is the actual annual NDVI for that composite period, $NDVI_{min}$ and $NDVI_{max}$ are the relative multi-year minimum and maximum values for that composite period (2000 – 2019), respectively. VCI values range from 0 – 1, with low values representing stressed vegetation conditions, middle values representing fair vegetation conditions and high values representing optimal vegetation conditions (Karnieli *et al.* 2006).

II. Temperature Condition Index (TCI)

This is an LST derived algorithm developed by Kogan (1995a) to determine temperature related vegetation stress and excessive wetness related stress (Singh *et al.* 2003; Du *et al.* 2018). This algorithm is similar to VCI, it is a normalisation of LST, scaled from 0 – 1 with conditions estimated relative to their minimum and maximum temperature values for that time period (Singh *et al.* 2003; Du *et al.* 2018).

$$TCI = \frac{LSTmax - LSTi}{LSTmax - LSTmin} \qquad (2)$$

Where LST_{max} and LST_{min} are the absolute multi-year maximum and minimum LST values for that time series (2000 – 2019), respectively, while LST_i is the actual annual LST for that composite time-period. It is significant to note that this index was developed as an inverse ratio to VCI, following the hypothesis that high temperatures exhibit extreme unfavourable conditions on vegetation (Karnieli *et al.* 2006). Therefore, TCI values ranging from 0 – 1 indicate changes from unfavourable conditions (high temperature) to most optimal conditions closer to one (low temperatures) (Karnieli *et al.* 2006; Du *et al.* 2018).

III. Vegetation Moisture Condition Index (VMCI)

This is a relatively new index, computed similar to the VCI algorithm, however, this index is computed from NDWI which is an indicator of vegetation water content (Chinnasamy *et al.* 2021). VMCI is also scaled from 0 – 1 utilising their relative minimum and maximum values for that specific-period.

$$VMCI = \frac{NDWIi - NDWImin}{NDWImax - NDWImin} \qquad (3)$$

Where $NDWI_i$ is the actual annual NDWI for that specific time, $NDVI_{min}$ and $NDVI_{max}$ are the relative minimum and maximum values for the time series (2000 – 2019), respectively. Low VMCI are associated with harsh unfavourable conditions (low water content) while high values closer to 1 are associated with favourable conditions (high water content).

2.2.4 Combinative drought Indices

IV. Vegetation Health Index (VHI)

This is an additive combination index, developed by Kogan (1995a) based on the hypothesis that higher temperatures (TCI) has a negative impact on vegetation vigour (VCI), subsequently causing stress (Karnieli *et al.* 2006).

$$\alpha VCI + (1 - \alpha)TCI \qquad (4)$$

where α is the relative contribution (weight) of each index which depends on various conditions between moisture conditions and temperature conditions (Du *et al.* 2018). In most instances the value of α is been unknown, therefore, 0.5 has been assigned for most studies, assuming equal weights for each index due to lack of accurate data knowledge for each contributing index (Karnieli *et al.* 2006).

V. Vegetation Moisture Stress Index (VMSI)

This is a combinative index similar to VHI. However, this index considers VMCI for vegetation stress related to vegetation vigour. This index also works under the assumption that higher temperatures will results in unfavourable vegetation conditions (low water content).

$$\alpha VMCI + (1 - \alpha)TCI \qquad (5)$$

The validity of this index also relies on the relative contribution of each input index in VMSI computation (α). Alpha (α) was considered as 0.5, indicating equal weight for both indices across KZN biomes.

2.2.5 Meteorological drought Index

VI. Standardised Precipitation Index (SPI)

This is a meteorological drought index developed by McKee *et al.* (1993), to assess and monitor drought conditions solely based on long-term precipitation data (Tirivarombo *et al.* 2018; Zambrano *et al.* 2016; Caccamo *et al.* 2011). SPI was utilised as a drought indicator index with the aid to validate the findings of the conditional and combinative drought indices used in the study. SPI has significant advantages over other meteorological drought indices since it has temporal flexibility and only require precipitation data which is readily available in ground weather stations (Caccamo *et al.* 2011; Guenang *et al.* 2014). SPI is computed by fitting long-term monthly precipitation data of a specific location and timescale (e.g. 1-month, 3-months) to a density probability distribution function (Caccamo *et al.* 2011; Guenang *et al.* 2014). The gamma distribution is then transformed into a standardized normal distribution based on cumulative distribution of points. This guarantees that the mean value of SPI is zero and the variance is one, for any given locality and period (Quiring 2009). This normalization technique is repeated for all the desired timescales. This study considered 1-, 3-, 6-, 9-, 12- and 24-months SPI timescales. With positive SPI values representing precipitation above median, while negative SPI values represented precipitation less than median (Table 2.3) (Tirivarombo *et al.* 2018; Quiring 2009). In this study this procedure was done using R studio, using a script computed from a package called precintcon. This procedure can be simplified using the equation below:

$$SPI = \frac{Xi - Xm}{\sigma} \quad (6)$$

Where X_i is the actual precipitation for that specific period, X_m is the long-term mean precipitation and σ is the standard deviation. Monthly rainfall data from 19 weather station of Kwa-Zulu (Buah-Kwofie *et al.* 2018) were considered. Final SPI measurements were interpolated in ArcGIS 10.4 using Kriging interpolation technique with the aid to produce continuous spatial raster images. Table 2.2 below shows drought classification technique based on SPI which differentiates drought and non-drought episodes.

Table 2.2: SPI drought magnitude classification with relative probability occurrences, as characterised by McKee et al. (1993).

SPI Value	**Drought Classification**	**Probability Percentages (%)**
≥ 2	Extremely wet	2.3
1.50 -1.99	Severely wet	4.4
1.0 -1.49	Moderately wet	9.2
0.99-0	Mildly wet	34.1
0-(−0.99)	Mild drought	34.1
−1.0-(−1.49)	Moderate drought	9.2
−1.5-(−1.99)	Severe drought	4.4
≤ 2	Extreme drought	2.3

Source: (Caccamo *et al.* 2011)

2.2.6 Statistical analysis

i. Random Forest Regression Algorithm

Random forest (RF) algorithm was considered in the study to estimate the magnitude of drought episodes using Landsat 8 (OLI&TIRS) derived conditional and combinative drought indices, due to its simplicity and its nature of being vigorous (Sibanda *et al.* 2021b). The RF algorithm is an ensemble machine learning algorithm that amalgamates a large set of regression trees (Zhou *et al.* 2016). It is dependent on the assumption that various independent predictors estimate incorrectly in various areas, hence, the accuracy of the overall prediction can be improved by combining the prediction results of the independent predictors (Liang *et al.* 2018). The regression trees structures of RF show significant differences when there is a slight variation in the training data (Zhou *et al.* 2016; Liang *et al.* 2018). Using this characteristic and amalgamating it with bootstrap aggregating and random feature selection, independent predictors can be generated with the aid of constructing random decision trees (Liang *et al.* 2018). During RF regression modelling, training data is generated by providing samples and replacing all those samples for each predictor in the ensemble. The RF can also determine the most influential predictors in the overall prediction model. In predicting drought magnitude, independent predictor variables/ models were built, using conditional drought indices (VCI, TCI and VMCI) and combinative drought indices (VHI and VMSI). The sample points used in the RF algorithm were determined by the relative area of the study sites. A total of 150 sample points were used for the Savanna and Grassland biomes while a total of 100 points were used for the Forest Biome since it is a relatively small study site. Each data was split into two sets, 70% of training data and 30% of testing data. The training data was used to evaluate the model for the prediction of drought magnitude which gives an optimistic estimate of the performance of the model. While the testing data was used in the accuracy assessment of the prediction models.

ii. Accuracy Assessment

To evaluate the accuracy of each RF derived regression model in predicting drought magnitude, the coefficient of determination (R^2) and the root mean square error (RMSE) were assessed and compared across the models. The coefficient of determination (R^2) was used to determine the proportion of variance between the measured and predicted drought magnitude (goodness of fit). The root mean square error (RMSE) was used to assess the accuracy i.e., the magnitude of error between the measured and predicted value plots. The performance of the of RF models was evaluated by comparing the differences in R^2 and RMSE values of the indicator and predictor drought variables across the biomes. The optimal performing model was determined by higher R^2 and lower RMSE values which corresponds to high precision and accuracy of drought predictor variables. Based on the optimal predictor variables, the most influential drought index amongst other predictor variables were determined and used to produce drought spatial variability maps across the biomes. The RMSE was calculated using the following equation:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N} (Predicted_i - Actual_i)^2}{N}} \quad (7)$$

Where N is the total count of the sample points.

2.3 Results

2.3.1 Relationship between ground rainfall data and spatially interpolated rainfall data

Table 2.3 illustrates rainfall data accuracies obtained between ground rainfall data and spatially interpolated rainfall data across the biomes. The reported accuracies were obtained using Excel statistics based on monthly rainfall data from 2014 to 2019 across the biomes. Generally, there was a strong relationship between the observed ground rainfall data and the interpolated rainfall data for all the biomes. The Grassland biome rainfall exhibited the highest accuracy with an R^2 of 0.76 and an RMSE of 0.452, while the Savanna biome rainfall exhibited the lowest accuracy with an R^2 of 0.56 and an RMSE of 2,963. The Forest biome rainfall exhibited an R^2 of 0.65 and an RMSE of 0.352. Thereafter, the spatially interpolated rainfall data was utilised to compute the Standardised precipitation index (SPI) as a drought indicator, computed at various timescales.

Table 2.3:Rainfall data accuracies of Savanna, Grassland and Forest biomes computed between ground rainfall data and spatially interpolated rainfall data.

Biome (s)	**Coefficient of determination (R^2)**	**RMSE**
Savanna	0.56	2,963
Grassland	0,76	0,452
Forest	0,65	0,352

2.3.2 Characterising drought magnitude and variability across the three major biomes of Kwa-Zulu Natal using the Standardised Precipitation Index (SPI)

A Single-Factor Analysis of Variance was conducted to determine and compare the significant difference of drought magnitude amongst the six various SPI timescales. The analysis of variance showed that there was a significant difference in drought magnitude derived from the various SPI timescales (1, 3, 6, 9, 12 and 24-months SPI) across the biomes. For the Savanna biome there was a significant difference with $F(5) = 91.063$; $p<0.001$, for the Grassland biome $F(5) = 448.649$; $p<0.001$ and for the Forest biome $F(5) = 5358(5)$; $p<0.001$. Further analysis was conducted to compare the means of the data using standard error. Figure 2.2 shows the great variation of drought magnitude computed from various SPI timescales with no overlap of error bars in the Savanna and Forest biomes. While Grassland biome showed slight overlaps of error bars between 6, 9 and 12 months-SPI.

SPI ranges from -2 to +2, with negative values indicating extreme to severe drought conditions while positive values indicate moderate to no drought conditions. Drought magnitude is clearly demonstrated in figure 2.2 with a significant variation across the biomes. For instance, for the Savanna biome, the results show that drought magnitude decreases from 1-month SPI to 24-months SPI with a range from mild to no drought magnitude, indicated by relatively high positive values. For the Grassland biome, 1-month SPI shows extreme to severe drought magnitude, indicated by negative values, while a decreasing pattern of drought magnitude from moderate to no drought magnitude was observed from 3-months SPI to 24-months SPI, indicated by positive values. For the Forest biome, 1-month SPI shows extreme to severe drought magnitude, indicated by negative values, while 3-months SPI to 12-months SPI shows moderate and mild droughts and 24-months SPI showing no drought magnitude with a +2 value.

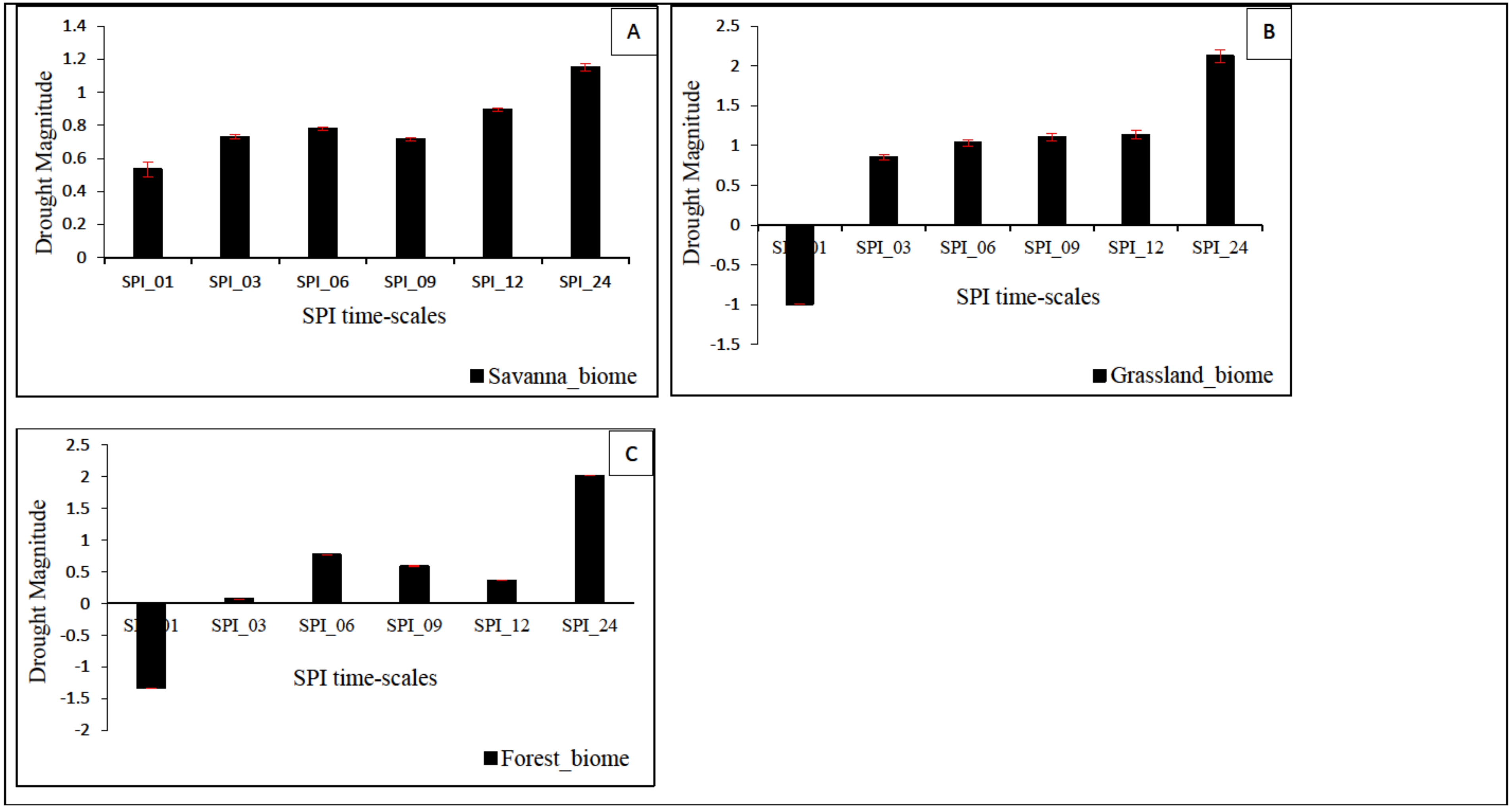


Figure 2.1: Drought magnitude variation computed from 1-month SPI, 3-months SPI, 6-months SPI, 9-months SPI, 12-months SPI and 24-months SPI for the (a) Savanna biome, (b) Grassland biome and (c) Forest biome, based on a 6-year temporal period (2014-2019)

2.3.3 Evaluating the performance of combinative and conditional drought predictor drought indices and drought indicator index across three major biomes of Kwa-Zulu Natal.

Table 2.3 illustrates the accuracies of the predictor variables obtained when predicting 1-month SPI, 3-months SPI, 6-months SPI, 9-months SPI, 12-months SPI, and 24-months SPI based on Random Forest Regression (RFR) model. There was a great variation in the performance of different predictor variables across various SPI timescales and biomes. However, similar patterns were observed across all the biomes, firstly, the combinative drought predictor variables (VHI-VMSI) performed better than the conditional drought predictor variables (VCI-TCI-VMCI) across the 6-year temporal period. Secondly, both the combinative predictor variables (VHI-VMSI) and the conditional predictor variables (VCI-TCI-VMCI) yielded high accuracies with 1-month SPI across the 6-year temporal period, while showing low accuracies with 24-months SPI.

Specifically, when predicting drought in the Savanna biome, the optimal predictor variables, VHI-VMSI yielded the highest accuracy with 1-month SPI in 2014 with an R^2 of 0.98 and RMSE of 0.074, while showing the lowest accuracy with 24-months SPI with an R^2 of 0.71 and RMSE of 0.144. Similarly, the VCI-TCI-VMCI predictor variables, yielded the highest accuracy with 1-month SPI in 2014 with an R^2 of 0.93 and RMSE of 0.168, while also showing the lowest accuracy with 24-months SPI with an R^2 of 0.69 and RMSE of 0.149.

When predicting drought in the Grassland biome, a similar pattern was observed. The VHI-VMSI predictor variables yielded the highest accuracy with 1-month SPI in 2016 with an R^2 of 0.93 and RMSE of 0.013, while showing lowest accuracy with 24-months SPI with an R^2 of 0.70 and RMSE of 0.398. The accuracy obtained from the VCI-TCI-VMCI predictor variables was lower than the VHI-VMSI predictor variables but similar in pattern with the highest accuracy obtained with 1-month SPI characterised by an R^2 of 0.89 and RMSE of 0.021 and the poorest accuracy obtained with 24-months SPI with R^2 of 0.77 and RMSE of 0.462.

Similarly, for the Forest biome, the optimal accuracy was obtained using VHI-VMSI predictor variables with 1-month SPI in 2017 characterised by an R^2 of 0.99 and RMSE of 0.016, while also showing the lowest accuracy with SPI-24 with an R^2 of 0.75 and RMSE of 0.062. The VCI-TCI-VMCI predictor variables yielded a slight difference in accuracy with an R^2 of 0.97 and RMSE of 0.033. These predictor variables also yielded lowest accuracy with 24-months SPI with an R^2 of 0.67 and RMSE of 0.067.

Table 2.4: Drought prediction model accuracies of VHI-VMSI and VCI-TCI-VMCI predictor variables derived using SPI as a drought indicator across various timescales.

(a) Savanna biome

Predictor variables	Year	SPI-1		SPI-3		SPI-6		SPI-9		SPI-12		SPI-24	
VHI-VMSI Predictor variable		R^2	RMSE	R^2	RMSE	R^2	RMSE	R^2	RMSE	R^2	RMSE	R^2	RMSE
	2014	0.98	0.074	0.90	0.076	0.77	0,067	0.84	0.057	0.77	0.051	0.71	0.144
	2015	0.93	0.102	0.77	0.067	0.68	0.054	0.60	0.058	0.88	0.031	0.66	0.136
	2016	0.95	0.094	0.87	0.074	0.88	0.059	0.87	0.053	0.77	0.050	0.75	0.133
	2017	0.95	0.102	0.83	0.063	0.78	0.051	0.74	0.053	0.83	0.039	0.77	0.128
	2018	0.95	0.089	0.82	0.066	0.81	0.046	0.76	0.048	0.88	0.032	0.79	0.120
	2019	0.93	0.111	0.75	0.067	0.71	0.049	0.69	0.050	0.79	0.042	0.62	0.150
VCI-TCI-VMCI Predictor variable	2014	0.93	0.168	0.77	0.105	0.76	0.077	0.72	0.077	0.70	0.062	0.69	0.149
	2015	0.86	0.167	0.71	0.074	0.66	0.058	0.59	0.061	0.77	0.046	0.64	0.147
	2016	0.84	0.192	0.70	0.079	0.73	0.094	0.72	0.093	0.81	0.054	0.64	0.185

	2017	0.86	0.178	0.72	0.079	0.68	0.061	0.62	0.063	0.83	0.042	0.66	0.153
	2018	0.85	0.183	0.79	0.076	0.73	0.059	0.71	0.058	0.85	0.041	0.76	0.141
	2019	0.84	0.210	0.76	0.076	0.70	0.061	0.65	0.063	0.85	0.040	0.72	0.149

(b) Grassland biome

Predictor variables	Year	SPI-1		SPI-3		SPI-6		SPI-9		SPI-12		SPI-24	
		R^2	RMSE	R^2	RMSE	R^2	RMSE	R^2	RMSE	R^2	RMSE	R^2	RMSE
VHI-VMSI Predictor variable	2014	0.79	0.029	0.91	0.114	0.93	2.089	0.92	2.236	0.91	2.373	0.95	4.266
	2015	0.89	0.015	0.76	0.149	0.77	0.178	0.77	0.191	0.82	0.171	0.74	0.376
	2016	0.93	0.013	0.75	0.154	0.75	0.189	0.71	0.219	0.74	0.236	0.70	0.398
	2017	0.84	0.018	0.74	0.167	0.76	0.198	0.75	0.218	0.72	0.272	0.77	0.364
	2018	0.92	0.011	0.81	0.134	0.80	0.163	0.81	0.176	0.72	0.215	0.85	0.286
	2019	0.90	0.015	0.80	0.141	0.81	0.165	0.82	0.175	0.75	0.207	0.89	0.231
	2014	0.67	0.037	0.72	0.232	0.71	0.279	0.70	0.306	0.75	0.463	0.73	0.552
	2015	0.87	1.993	0.71	1.752	0.78	2.122	0.76	2.283	0.81	2.407	0.72	0.471

VCI-TCI-VMCI Predictor variable	2016	0.89	0.021	0.74	0.206	0.74	0.246	0.71	0.275	0.83	0.202	0.77	0.462
	2017	0.77	0.021	0.76	0.164	0.74	0.204	0.74	0.215	0.73	0.205	0.78	0.381
	2018	0.81	0.023	0.76	0.146	0.75	0.178	0.75	0.192	0.69	0.201	0.81	0.316
	2019	0.72	0.027	0.67	0.180	0.66	0.218	0.65	0.236	0.63	0.238	0.70	0.408

(c) Forest biome

Predictor variable	Year	SPI-1		SPI-3		SPI-6		SPI-9		SPI-12		SPI-24	
		R^2	RMSE	R^2	RMSE	R^2	RMSE	R^2	RMSE	R^2	RMSE	R^2	RMSE
VHI-VMSI Predictor variable	2014	0.98	0.020	0.79	0.008	0.94	0.019	0.94	0.016	0.95	0.016	0.75	0.061
	2015	0.98	0.017	0.83	0.007	0.97	0.015	0.96	0.011	0.97	0.013	0.83	0.051
	2016	0.98	0.016	0.81	0.007	0.95	0.017	0.95	0.014	0.95	0.014	0.75	0.059
	2017	0.99	0.016	0.85	0.006	0.94	0.018	0.96	0.013	0.96	0.012	0.75	0.062
	2018	0.97	0.021	0.86	0.007	0.95	0.020	0.96	0.015	0.97	0.015	0.86	0.065
	2019	0.97	0.025	0.87	0.006	0.95	0.017	0.97	0.012	0.97	0.014	0.90	0.044
	2014	0.93	0.039	0.74	0.009	0.89	0.028	0.91	0.020	0.92	0.023	0.72	0.068

VCI-TCI-VMCI Predictor variable	2015	0.94	0.036	0.59	0.011	0.90	0.026	0.88	0.022	0.89	0.022	0.73	0.066
	2016	0.94	0.037	0.68	0.010	0.89	0.028	0.89	0.023	0.88	0.025	0.64	0.082
	2017	0.97	0.033	0.70	0.009	0.93	0.025	0.92	0.021	0.93	0.021	0.67	0.067
	2018	0.92	0.047	0.76	0.010	0.88	0.035	0.89	0.030	0.89	0.031	0.67	0.093
	2019	0.92	0.044	0.71	0.012	0.82	0.033	0.82	0.028	0.83	0.028	0.61	0.088

2.3.4 Optimal predictor variables for estimating drought magnitude across the biomes, derived using the best drought indicator

Figure 2.3 illustrates the results obtained from the best drought indicator, 1-month SPI, estimated from the optimal predictor variables across the biomes, using Random Forest Regression (RFR) model. The results revealed that both the combinative and conditional predictor variables optimally predicted drought magnitude across the biomes based on 1-month SPI drought indicator. The optimal VHI-VMSI variables were the best performing predictor variables of drought magnitude with an R^2 of 0.98 (RMSE = 0.074), R^2 of 0.93 (RMSE = 0.013) and R^2 of 0.99 (RMSE = 0.016) for the Savanna, Grassland and Forest biomes, respectively (Figure 2.3, A, C, E). The most influential combinative drought index in these predictor variables was the Vegetation Moisture Stress Index (VMSI) for all the biomes (Figure 2.4, A, C, E).

While slightly lower accuracies were observed in the VCI-TCI-VMCI predictor variables with an R^2 of 0.93 (RMSE = 0.168), R^2 of 0.89 (RMSE = 0.021) and R^2 of 0.97 (RMSE = 0.033) for the Savanna, Grassland and Forest biomes, respectively (Figure 2.3, B, D, F). The most optimal conditional drought index in these predictor variables was the Vegetation Moisture Condition Index (VMCI) across all the biomes (Figure 2.4, B, D, F).

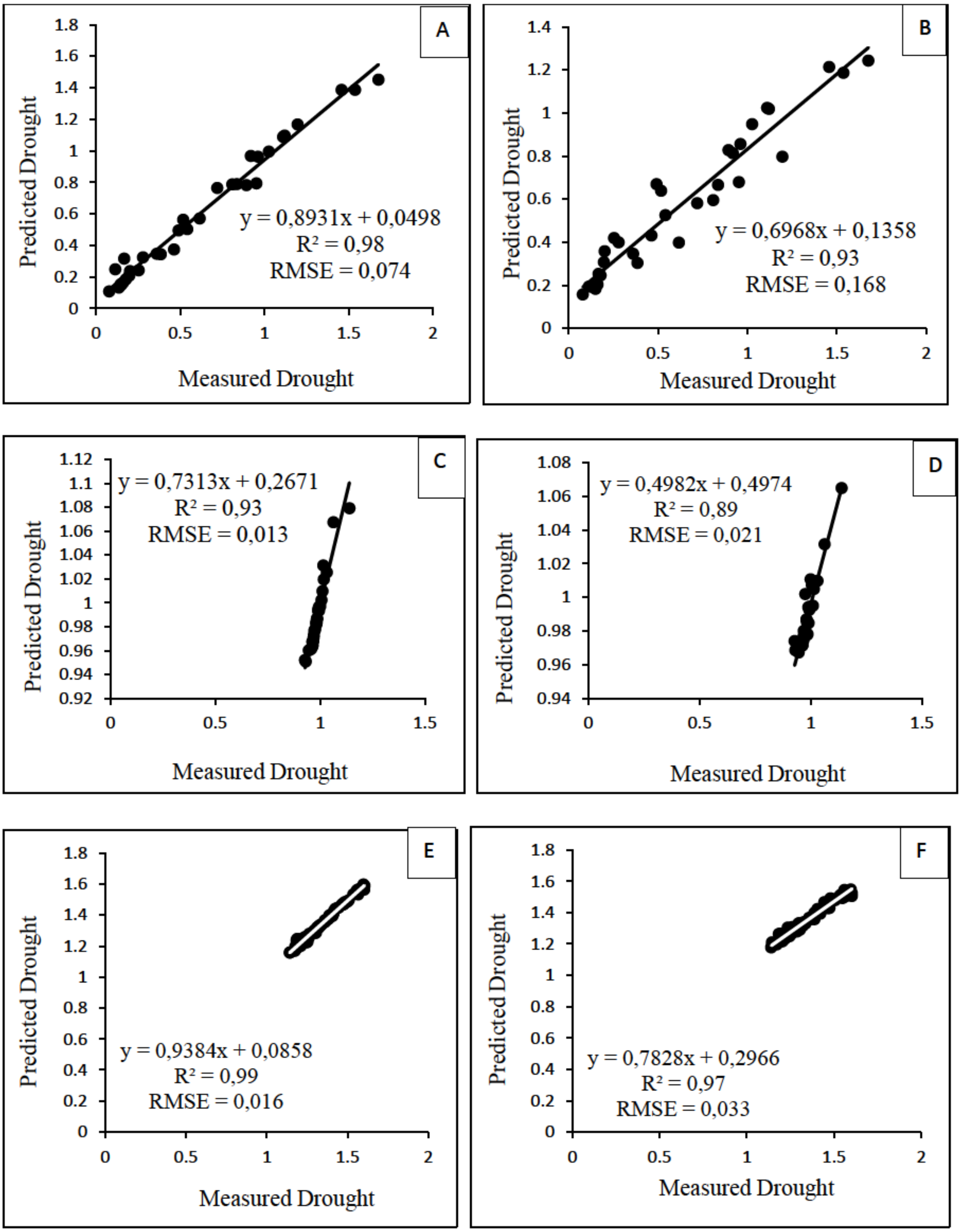


Figure 2.2: Relationship between the observed and predicted drought magnitude across the biomes computed from optimal prediction variables, VHI-VMSI (A-C-E) and VCI-TCI-VMCI (B-D-F), derived using the best drought indicator, 1-month SPI. Where A and B is the Savanna biome, C and D is the Grassland biome and E and F is the forest biome.

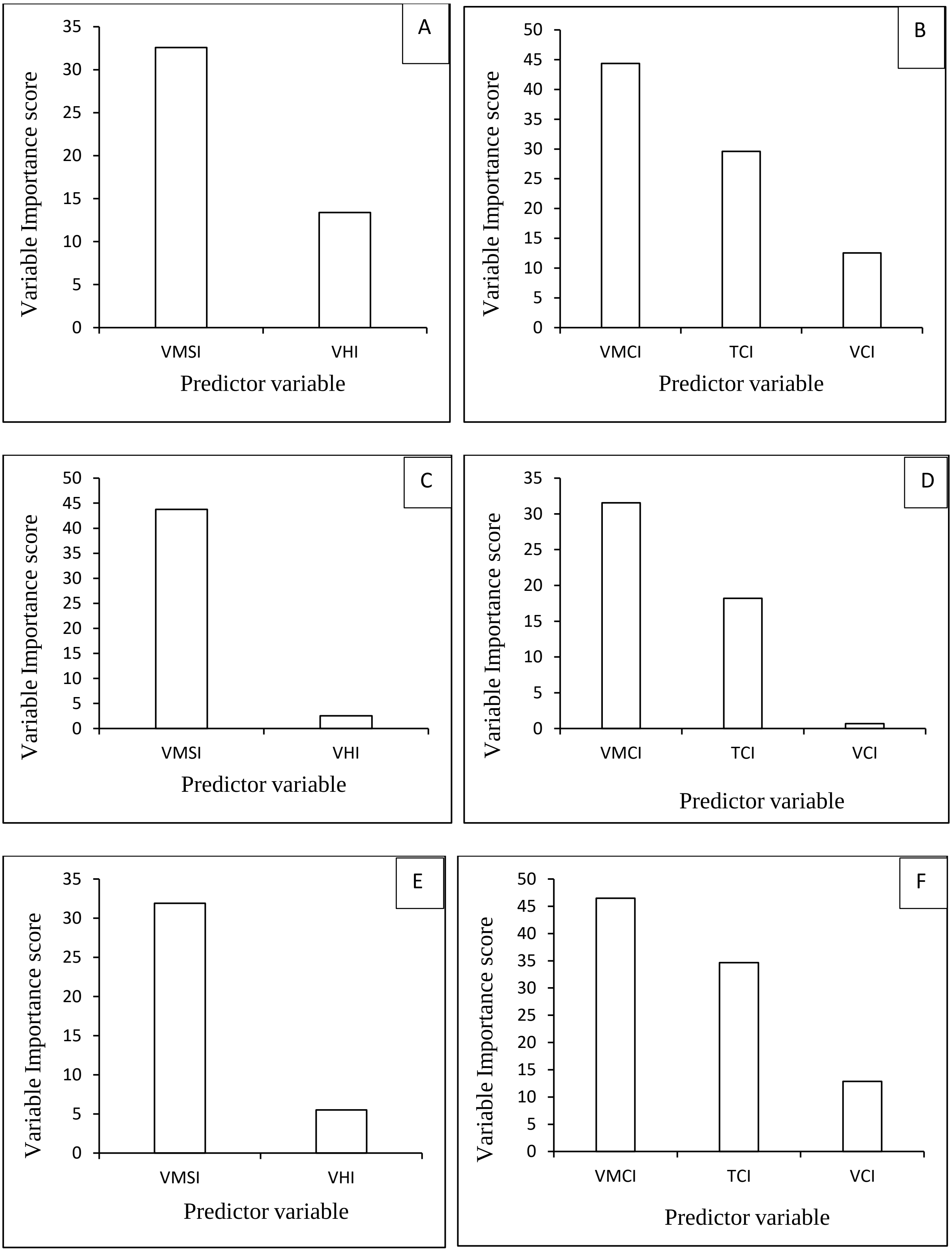
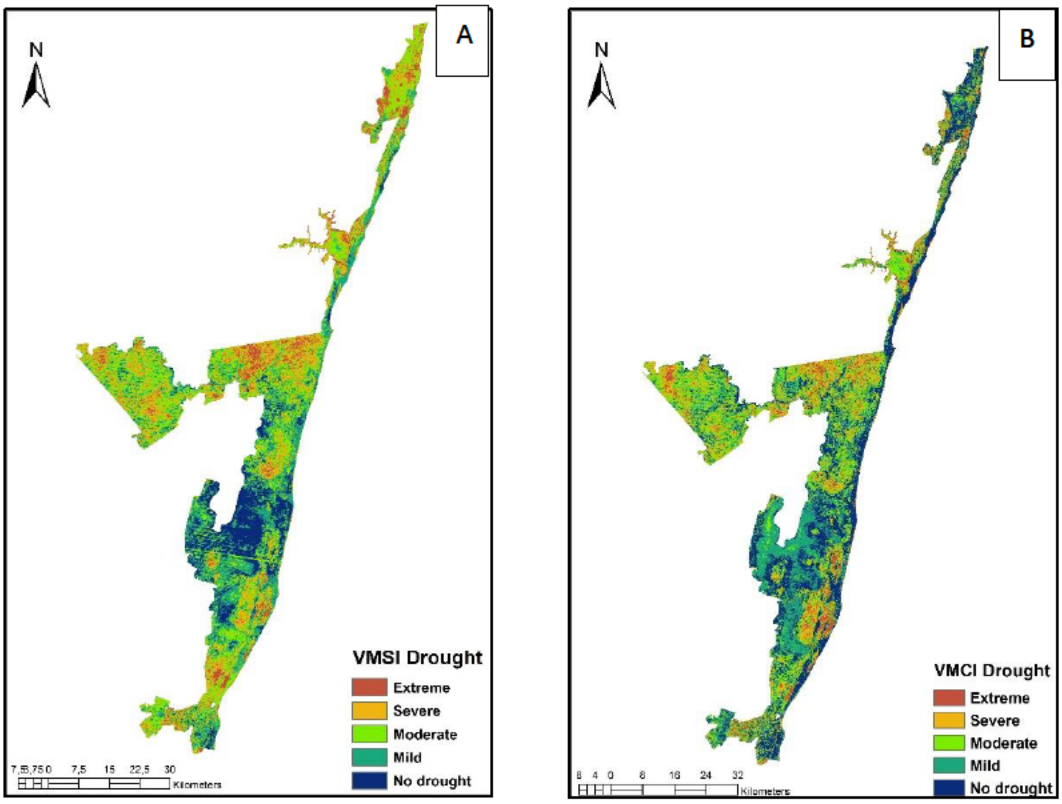


Figure 2.3: Variable importance score of optimal selected variables of RF models that showed the highest scores in predicting drought magnitude across the biomes, using 1-month SPI as the best drought indicator. A and B is the Savanna biome, C and D is the Grassland biome and E and F is the Forest biome.

2.3.5 Mapping drought spatial variability across three major Biomes of Kwa-Zulu Natal using the most optimal drought predictor variables.

Figure 2.5 shows drought variability maps of major biomes of Kwa-Zulu Natal, computed from optimal drought predictor Indices. There are significant differences noted between drought magnitude estimated from VMSI combinative drought Index and VMCI conditional drought Index across the biomes. The maps revealed that the Vegetation Moisture Stress Index (VMSI) was able to successfully capture the smallest magnitude of drought episode for all the biomes, while the Vegetation Moisture Conditional Index (VMCI) shows an under estimation of drought magnitude. For example, for the Savanna biome (a and b), VMSI shows an overall drought range from Extreme to Moderate, while VMCI shows overall drought range from Moderate to No drought magnitude. These results are further explained by the ability of VMSI to detect no drought magnitude in the Savanna biome where there is presence of Lake St Lucia, whereas VMCI generalized Moderate to Mild drought quantities. Similar patterns are observed for the Grassland (c and d) and Forest (e and f) biomes, where VMSI was able to capture small drought variations across the study sites.



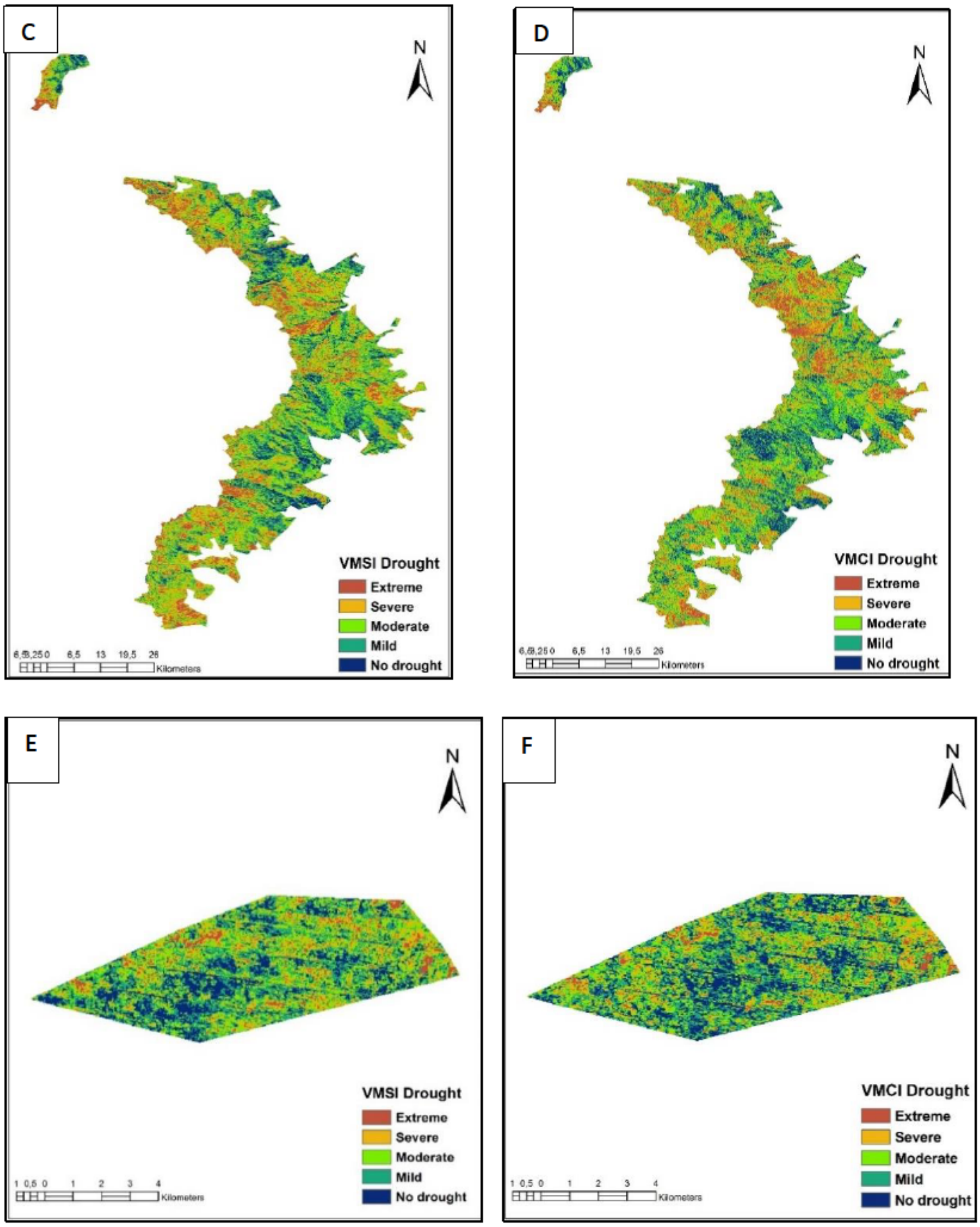


Figure 2.4: Drought variability maps derived from optimal drought indices, Vegetation Moisture Stress Index (VMSI) and Vegetation Moisture Condition Index (VMCI) in (a and b) Savanna biome, (c and d) Grassland biome, as well as (e and f) Forest biome, using 1-month SPI as the best drought indicator.

2.4 Discussion

This study evaluated the performance of Landsat 8 (OLI and TIRS) derived conditional and combinative drought indices in quantifying the magnitude of drought, using SPI as a drought indicator, computed across various timescales across three major biomes of Kwa-Zulu Natal.

The findings of this study have shown that both combinative and conditional drought indices are suitable predictor variables for quantifying and monitoring drought episodes across different biomes. Optimal estimation accuracies were obtained using 1-month SPI drought indicator for all the biomes, with lower accuracies shown with an increase in time lag, particularly when using 24-months SPI. These findings align with those obtained by Ahmadi *et al.* (2019) who noted that NDVI and SPI had a positive correlation, however, vegetation response to SPI decreased with increasing time lag. This outlines that overall vegetation health depends on moisture availability (Sibanda *et al.* 2021b). When there is considerable amount of precipitation, vegetation acquires a high vigour which reflects highly in the NIR section of electromagnetic spectrum while absorbing extremely in the red band section (Ahmadi *et al.* 2019; Sibanda *et al.* 2021b). In this context, the results of this study showed that instant deviations in precipitation level (1-month SPI) causes immediate response of vegetation vigour, outlining short-term drought conditions. Hence, both combinative and conditional drought indices optimally captured the onset of drought conditions across the biomes, following a study by Jiao *et al.* (2016) who presented that 1-month SPI and 2-months SPI were most appropriate in evaluating meteorological remote sensing drought indices, while, 24-months SPI was more suitable in evaluating long-term agricultural remote sensing drought indices.

The findings of this study showed that drought magnitude could be optimally estimated from combinative drought indices (VHI-VMSI) with an accuracy of $R^2 = 0.98$ (RMSE = 0.074) for the Savanna biome, $R^2 = 0.93$ (RMSE = 0.013) for the Grassland biome, and $R^2 = 0.99$ (RMSE = 0.016) for the Forest biome, based on VMSI, computed from NIR, SWIR and TIR bands. These findings concur with those of Bhuiyan *et al.* (2017) who noted that combinative drought indices yielded higher accuracies than conditional drought indices due to their capability of quantifying direct drought impacts based on vegetation's photosynthetic activity, direct moisture availability and thermal related vegetation stress. Furthermore, Holzman *et al.* (2021) observed similar findings that the assimilation of multiple spectral signatures of vegetation water content from NIR, SWIR and LST are the key variables in estimating the effects of drought on vegetation, given that these indices accounts for both vegetation water content as well as soil water availability from the effect of evapotranspiration.

The importance and most influence of VMSI in this study agrees with findings of growing body of literature which outlines that moisture related indices outperform the vegetation greenness indices, given their ability to capture direct water content from the vegetation leaves (Du *et al.* 2018). This is also due to their sensitivity to the water absorption region of the electromagnetic spectrum (SWIR) (Sow *et al.* 2013). Literature further outlines that there is a strong agreement between vegetation moisture and temperature conditions, hence, vegetation moisture stress and vegetation temperature stress commonly occur together (Holzman *et al.* 2021; Bhuiyan *et al.* 2017). Therefore, when there are extremely high temperatures from changing climatic factors (precipitation deficiencies), moisture related indices are able to capture the immediate response of vegetation (Holzman *et al.* 2021). Hence, the major influence of VMSI in the study in comparison to VHI which is computed from vegetation greenness indices. Holzman *et al.* (2021) further outlined that greenness vegetation indices, computed from NIR and red bands are less effective in estimating vegetation water stress, due to their lower sensitivity to leaf water content changes, compared to SWIR derived vegetation indices.

Meanwhile the study observed slightly lower accuracies in conditional drought indices (VCI, TCI, VMCI) with an accuracy of R^2 = 0.93 (RMSE = 0.168) for the Savanna biome, R^2 = 0.89 (RMSE = 0.021) for the Grassland biome and R^2 = 0.97 (RMSE = 0.033) for the Forest biome. These findings were most influenced by VMCI across all the biomes which is computed from only NIR and SWIR bands of the spectrum. Multiple studies have revealed a high accuracy in estimating vegetation drought stress from SWIR and NIR derived indices (NDWI) due to their high sensitivity to water absorption section of the EM spectrum (Shinga 2021; Holzman *et al.* 2021; Buthelezi 2020). However, studies by Quiring *et al.* (2010); Du *et al.* (2018) and Bento *et al.* (2020) outlined that the use of conditional drought indices alone in estimating vegetation drought stress is limited, given that there are multiple drought variables that contributes to drought. Literature further outlined that the performance of conditional drought indices in mainly influenced by different land cover and different climates changes within regions (Quiring *et al.* 2010). Hence, in order to account for multiple climatic factors of a regions, multiple drought variables must be considered which improves the ability of monitoring drought conditions (Du *et al.* 2013).

In terms of drought impact across the major biomes of Kwa-Zulu Natal, the Grassland biome had the greatest impact of extreme to severe drought conditions throughout the 6-year time period. These results are comparable to findings obtained by Marumbwa *et al.* (2021) who noted that the recent extreme drought conditions experienced by Sothern African biomes had the most impact on grassland biome with approximately 58% of the area affected by drought conditions. Wilcox *et al.* (2020) further outlined that Grasslands are particularly susceptible to extreme drought conditions given their high sensitivity to water availability which consequently affects their ecosystem productivity. In contrast the forest biome showed the least impact of moderate to no drought conditions, with small patches of severe drought experienced in the peripheral patches of the forest. A plausible explanation of these results could be attributed to the extensively deep tree root systems that allows the vegetation to tap underground water enabling it to withstand severe to extreme drought episodes (Marumbwa *et al.* 2021). Furthermore, these conditions are driven by soil type of the biome which is high in clay quantities (39%) resulting in high water retention that subsequently maintains vegetation during prolonged drought periods (Du *et al.* 2018; Xulu *et al.* 2019; Marumbwa *et al.* 2021). Major impacts of drought conditions in the Savanna biome was experienced within the drought years followed by rapid recovery of vegetation growth. A plausible explanation of these results has been discussed by multiple studies including Abbas *et al.* (2019), Cho *et al.* (2019) and Marumbwa *et al.* (2021), who outlined that there has been a growing proportion of tree cover over time proportional to grass cover leading to woody encroachment.

2.5 Conclusion

This study sought to characterize interannual drought variability across different biomes of Kwa-Zulu Natal, using remote sensing derived vegetation indices. In this regard, the study evaluated the performance of Landsat 8 derived conditional and combinative drought indices in quantifying the magnitude of drought across three major biomes of Kwa-Zulu, using SPI as a drought indicator, computed across different timescales. The study identified the most optimal drought indices that can effectively quantify drought episodes across the different biomes within a 6-year temporal period with the aid of mapping the spatial variability of drought magnitude across the major biomes of Kwa-Zulu Natal. The results of this study have demonstrated that:

- Drought variability in Southern African biomes can be effectively characterized using both combinative and conditional drought indices.

- Drought magnitude across different biomes could be optimally estimated from combinative drought indices.
- Vegetation moisture stress index (VMSI) yields highest accuracy in estimating drought conditions.

This study demonstrates the potential of new combinative drought indices that combines multiple drought factors in effectively quantifying and monitoring drought conditions across different vegetation types. These findings provide a basis in deriving an optimal drought index that will eliminate the limitation of raw vegetation indices and can be applied across all biomes from local to regional scales. However, the performance of these remotely sensed drought indices needs to be further tested using a multi scaler drought index that accounts for both precipitation and temperature. Therefore, future studies may evaluate the impact of temperature in these drought indices while also evaluating the contribution of each input index in VMSI, given that equal contributions are assumed.

CHAPTER THREE:

Assessing the impact of moisture and temperature contribution coefficients in estimating drought severity of selected South African biomes using Landsat 8 data and a multiscalar meteorological drought index as a drought indicator

Abstract

Droughts are a frequent and recurring phenomenon in semi-arid regions such as Southern Africa which is characterised by spatial and temporal rainfall variability. This threatens water resources and multiple terrestrial and aquatic ecosystems. Quantifying the impact of drought across spatial scale has been complex, given the nature of drought which varies in the degree of occurrence across different regions and over various timescales. Previous research have focused on the use of meteorological drought indices such as the standardised evapotranspiration index (SPEI) to quantify and characterise the impacts of drought severity across different biomes and vegetation types. However, given that meteorological drought indices are derived from point data, they lack explicit spatial coverage at various scales in evaluating and monitoring drought conditions. Thus, remotely sensed vegetation indices that integrates different spectral bands have been widely used to quantify and monitor changes in drought conditions. Hence, this study sought to evaluate the impact of various moisture and temperature drought contribution coefficients of the Vegetation Moisture Stress Index (VMSI) in estimating drought severity across the Savanna, Grassland and Forest biomes of Kwa-Zulu Natal, using 24-months SPEI as a drought indicator. Results indicated that during peak drought conditions in Southern Africa, high temperature predictor variables yielded the highest accuracies, where the weights (α) associated with the Temperature Condition Index (TCI) were larger than the adopted value of 0.5, in comparison to moisture predictor variables for all the biomes. Optimal estimation accuracies were obtained from VMSI_2 model (90%TCI:10%VMCI) which yielded an RMSE of 0.0589 and an R^2 of 0.78 for the Savanna biome, an RMSE of 0.0511 and an R^2 of 0.66 for the Grassland biome and an RMSE of 0.0034 and an R^2 of 0.76 for the Forest biome. These findings are crucial in the development of improved coefficients, in the face of changing climatic conditions in arid and semi-arid regions, thereby facilitating early drought detection and monitoring mechanisms.

Keywords: Drought, biomes, Temperature Condition Index (TCI), Vegetation Moisture Condition Index (VMCI), Vegetation Moisture Stress Index (VMSI), Standardised Evapotranspiration Index (SPEI), Kwa-Zulu Natal.

3.1 Introduction

Drought disasters are a catastrophic natural phenomenon characterised by an imbalance of water availability, exacerbated by long-term precipitation deficiencies and above normal average temperatures, threatening water resources as well as multiple terrestrial and aquatic ecosystems (Botai *et al.* 2016; Xulu *et al.* 2019; Zhang *et al.* 2020; Cui *et al.* 2021). Droughts are frequent and recurring phenomenon in semi-arid regions such as Southern Africa, which is characterised by spatial and temporal rainfall variability that subsequently distinguish it as a water stress region (Xulu *et al.* 2019; Ndlovu and Demlie 2020). Baudoin *et al.* (2017) and Ndlovu and Demlie (2020) outlined that South Africa in particular is naturally susceptible to drought episodes, owing to atmospheric processes such as the El Nino Southern Oscillation (ENSO) and sea-surface temperature conditions. The El Nino Southern Oscillation is established to mainly impact precipitation variability while variations in sea surface temperatures influences moisture supply and atmospheric dynamics across Southern Africa (Baudoin *et al.* 2017; Ndlovu and Demlie 2020). Hence, the occurrence of meteorological drought varies in severity, duration and spatial extent from region to region and from time to time across space (Bhuiyan *et al.* 2017). Marumbwa *et al.* (2021) reported an increasing trend in the occurrence of meteorological drought over Southern Africa, affecting the spatial and temporal patterns of terrestrial biomes.

Different terrestrial biomes across the region have demonstrated different responses to drought conditions attributable to differences in climate, ecological and environmental factors (Tfwala *et al.* 2018; Xulu *et al.* 2019; Zhang *et al.* 2020). However, preceding studies by Baudoin *et al.* (2017) and Xulu *et al.* (2019) have outlined that moisture and temperature anomalies related to drought conditions are the main driving factors of extreme dry conditions within the region that eventually affect biome distribution and functioning. Furthermore, studies such as Bhuiyan *et al.* (2017) and Tirivarombo *et al.* (2018) have argued that in arid and semi-arid regions, extreme temperatures alone are a major climatic factor that directly affects vegetation health leading to temperature stress and increase in drought development, frequency and intensity. Driven by climate change, an increasing trend of global mean temperatures has been projected, indicating major impacts on vegetation in arid and semi-arid regions which are characterised by higher evapotranspiration with lower annual precipitation levels (Zambrano *et al.* 2016; Tirivarombo *et al.* 2018; Zhang *et al.* 2020). Therefore, it is crucial to account for both moisture and temperature components in quantifying and predicting the drought response of different terrestrial biomes (Tirivarombo *et al.* 2018; Zhang *et al.* 2020).

As a result of the sophisticated nature of drought with varying degree of occurrences across different regions, limited knowledge of the impacts of drought on different terrestrial biomes has been acquired over various timescales (Tfwala *et al.* 2018; Tirivarombo *et al.* 2018; Zhang *et al.* 2020). One major challenge in assessing the impact of drought on vegetation is the selection of good drought indicators, given that the accuracy of a single indicative variable is erratic across different regions (Zhang *et al.* 2020). Considering that drought is associated with climatic events, climatic factors such as precipitation and temperature have been characterised as good indicators of drought severity, frequency and spatial extent across different regions (Tirivarombo *et al.* 2018; Páscoa *et al.* 2020). Additionally, these meteorological drought variables can be utilised to derive multiscalar drought indices which can thus be utilised as drought indicators to quantify and characterise the impacts of drought across different biomes and vegetation types (Páscoa *et al.* 2020). Such indices include the Evaporative Stress Index, the Standardised Precipitation Index (SPI) and the Standardised Precipitation Evapotranspiration Index (SPEI) (Tirivarombo *et al.* 2018; Barbosa *et al.* 2019; Páscoa *et al.* 2020; Bento *et al.* 2020). The main advantage of utilising multiscalar drought indices is associated with their relative ability to discriminate vegetation response timescales to water shortages, hence facilitating an understanding of the relationship between ecosystem variables and drought severity (Páscoa *et al.* 2020).

The Standardised Precipitation Evapotranspiration Index (SPEI) is a recently established multiscalar meteorological drought index which considers both the effect of precipitation deficits and temperature surplus presented in the form of evapotranspiration (Zambrano *et al.* 2016; Tirivarombo *et al.* 2018; Bento *et al.* 2020; Zhang *et al.* 2020). SPEI has been classified as a suitable drought indicator index, given its combined ability to capture the impact of both precipitation and temperature variables while also able to identify drought occurrences at multiple temporal periods (e.g. 1, 3, 6, 9, 12 and 24 months SPEI) (Tirivarombo *et al.* 2018; Bento *et al.* 2020; Zhang *et al.* 2020). Henceforth, SPEI has been successfully utilised across diverse regions to characterise and monitor drought severity under changing climatic conditions, particularly in arid and semi-arid regions (Bento *et al.* 2020; Marumbwa *et al.* 2021). However, given that SPEI is a meteorological drought index derived from ground weather stations, its main disadvantage is that it lacks direct information of the impact of drought on vegetation health and spatial representation across regional scale (Marumbwa *et al.* 2021). Therefore, direct drought impact on vegetation needs to be captured using vegetation-based drought indices which will complement the meteorological indicator drought indices and provide spatial representation from local to global scales (Zhang *et al.* 2020; Marumbwa *et al.* 2021; Chicco *et al.* 2021).

The availability of satellite based remote sensing data has brought about development of numerous vegetation indices that has the capacity to provide direct vegetation health conditions, allowing for the assessment of vegetation drought response signals over large terrestrial areas (Barbosa *et al.* 2019; Peng *et al.* 2019; Marumbwa *et al.* 2021). Additionally, remotely sensed vegetation indices that integrates numerous spectral bands have been extensively utilised to quantify and monitor changes of vegetation response to different climatic conditions, using the visible, Infrared and thermal bands of the electromagnetic spectrum (Du *et al.* 2018; Peng *et al.* 2019). The Vegetation Moisture Condition Index (VMCI) and the Temperature Condition Index (TCI) are amongst the main remotely sensed conditional drought indices that have been successfully used in quantifying and monitoring drought severity, frequency and spatial extent under different ecosystems and environmental conditions at a global scale (Zambrano *et al.* 2016; Peng *et al.* 2019). VMCI is a water-related vegetation index based on the near Infrared (NIR) and shortwave Infrared (SWIR) sections of the spectrum and is derived from the Normalised Difference Water Index (NDWI) (Bento *et al.* 2018; Du *et al.* 2018), while TCI is a temperature-related vegetation index based on the thermal Infrared window and is derived from Land Surface Temperature (LST) (Du *et al.* 2013; Du *et al.* 2018; Bento *et al.* 2020). The aforementioned drought indices are derived from a single drought indicator, region specific, time dependent and mostly effective during vegetation growing season (Zambrano *et al.* 2016; Bhuiyan *et al.* 2017; Bento *et al.* 2020).

Therefore, to enhance drought assessment across different regions, Kogan (1995a) introduced the application of combinative drought indices such as the Vegetation Health Index (VHI) and the Vegetation Moisture Stress Index (VMSI) which accounts for multiple drought indicators such as precipitation and temperature combined. VMSI comprises of a linear combination of VMCI and TCI components of comparable magnitude and assume an inverse relationship at a given pixel over time, determined by local moisture conditions (Karnieli *et al.* 2010; Achmad and Muftiadi 2019; Bento *et al.* 2020). Since a concurrent contribution of both moisture and temperature on vegetation health and cycle depends on vegetation type which vary from region to region, an equal contribution of 0.5 is assumed for both VMCI and TCI (Achmad and

Muftiadi 2019; Bento *et al.* 2020). However, studies by Bhuiyan *et al.* (2017) and Bento *et al.* (2020) have indicated that the relative contribution of each drought indicator may deviate from the adopted value of 0.5, owing to variations in regional climatic conditions and ecosystems heterogeneity. Bento *et al.* (2018) further emphasized that the contribution of each variable to vegetation conditions depends on seasonality, vegetation growth stage and vegetation type. Where, for example in arid and semiarid regions, water availability during vegetation growing stages may be the main limiting factor that consequently stir severe drought conditions (Bento *et al.* 2018). Therefore, it is significant to complement VMSI with a multiscalar meteorological drought index such as SPEI which can account for the impact of various precipitation and temperature fluctuations across different terrestrial ecosystems.

Moreover, assigning comparable contribution coefficients across different ecosystems will aid in deriving optimal single weight to utilise as a representative of moisture and temperature conditions over semi-arid regions of Southern Africa and independently of the user's analysis approach (Bento *et al.* 2020; Marumbwa *et al.* 2021). As proposed by Bento *et al.* (2018), the use of combinative drought indices (VMSI) in relation to a SPEI provides an absolute spatial evaluation and monitoring of severe drought events. In this context, this study sought to assess the relative contribution of remotely sensed moisture-related vegetation index (VMCI) and temperature-related vegetation index (TCI) in characterising drought severity across different biomes of Kwa-Zulu Natal. The main objectives of the study were to: (i) evaluate the impact of various moisture and temperature drought contribution coefficients of VMSI in estimating drought severity across the Savanna, Grassland and Forest biomes, using 24-months SPEI as a drought indicator; (ii) derive the optimal moisture and temperature contribution coefficient that can be applied across different ecosystems and biomes of semi-arid region of Southern Africa; (iii) to map the spatial distribution of drought severity across the biomes, using optimal moisture and temperature contribution coefficients. The anticipated outcome will aid in future development sets of similar contribution coefficients, especially with changing climatic conditions in arid and semi-arid regions, allowing for early drought detection and monitoring.

3.2 Methodology

3.2.1 Image acquisition and pre-processing

Remote sensing images acquired by the Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS) aboard Landsat-8 satellite was considered in this study. A total of 24 available monthly images from January 2015 to December 2016 were acquired for each study site using a script on Google Earth Engine (GEE) platform. Monthly images of this time period were considered with the aid to cover the phenological cycle of vegetation during peak drought season, hence monitoring the impact of major drought conditions on vegetation health. The GEE derived data is administered from the United States Geological Survey (USGS), hence, a standard USGS format was followed acquiring the images. All the GEE images are pre-processed and geo-referenced, enabling its direct usage (Mateo-García *et al.* 2018). In this regard, all required Landsat 8 images were acquired from the *LANDSAT/LC08/C01/T1_TOA* image collection available in GEE platform. The terrain of these images consists of top of atmosphere (TOA)" reflectance in a GeoTIFF format.

Landsat 8 sensor offers two science instruments (OLI and TIRS) which acquire multispectral images with eleven spectral bands covering the Visible, NIR, SWIR and Thermal Infrared sections of the spectrum. These are captured at a spatial resolution of 30m for the Visible, NIR and SWIR; and at a 100m for the TIR which is then resampled into the 30m spatial resolution (Ogunode and Akombelwa 2017). This study considered the NIR, SWIR and Thermal Infrared in estimating drought severity across different vegetation types based on water and temperature sensitive bands found within these sections.

3.2.2 Computation of Drought Indices

Primary vegetation indices, the Normalised difference water index (NDWI) and the Land surface temperature (LST) were computed from NIR, SWIR and Thermal Infrared bands of the electromagnetic spectrum with the aid to compute the moisture and temperature components of the combinative drought index, and the Vegetation moisture stress Index (VMSI). Using long-term NDWI and LST minimum and maximum values, the Vegetation Moisture Condition Index (VMCI) and the Temperature Condition Index (TCI) were computed, respectively, as shown in table 3.1 below:

The drought index used to assess the moisture component of vegetation is the Vegetation Moisture Condition Index (VMCI). This is a comparatively new index that is a direct indicator of water content of vegetation. VMCI ranges from 0 – 1,

$$VMCI = \frac{NDWIi - NDWImin}{NDWImax - NDWImin} \tag{1}$$

where high values resemble high water vegetation content and low values resemble low water vegetation content. Therefore, VMCI values were expected to decrease during drought period due to water stress, in this context the 2015/16 drought period.

The TCI component derived from minimum and maximum LST values was utilised to assess the temperature-related vegetation stress based on the inverse ratio to VMCI. This follows the hypothesis derived by Kogan (1995a) which states that the condition of vegetation health worsens with an increase in temperatures.

$$TCI = \frac{LSTmax - LSTi}{LSTmax - LSTmin} \tag{2}$$

TCI ranges from 0 – 1, where low TCI values correspond to unfavourable vegetation health attributable to high temperatures whereas high values correspond to favourable vegetation health.

Table 3.1: Vegetation Indices used in the study, including raw vegetation indices, conditional drought indices, a combinative drought index and a meteorological drought index.

Index	**Source**	**Formula**	**Reference**
NDWI	*Landsat 8 OLI*	$NDWI = \frac{NIR - SWIR}{NIR + SWIR}$	(Gao 1996)
LST	*Landsat 8 TIRS*	$LST = (BT / (1 + (0.00115 * BT / 1.4388) * Ln(\varepsilon)))$	(Ulivieri *et al.* 1994)
VMCI	*Landsat 8 OLI*	$VMCI = \frac{NDWIi - NDWImin}{NDWImax - NDWImin}$	
TCI	*Landsat 8 TIRS*	$TCI = \frac{LSTmax - LSTi}{LSTmax - LSTmin}$	(Kogan 1995a)

VMSI	*Landsat 8 OLI & TIRS*	$\alpha VMCI + (1 - \alpha)TCI$	
SPEI	*In situ data*	$SPEI = W - \frac{\mathrm{Co + C1W + C2W2}}{\mathrm{1 + d1W + d2W2 + d3W3}}$	(Abramowitz and Stegun 1964)

3.2.3 Estimating VMCI and TCI contributions to VMSI

Literature illustrates that the impact of moisture and temperature on vegetation vary depending on the type of region, vegetation, and time (e.g., seasonality), however, accurate information has not been acquired on the relative contribution of each variable on stirring drought episodes (Karnieli *et al.* 2006; Masitoh and Rusydi 2019; Bento *et al.* 2020). Hence, a constant value of 0.5 (50%) has been assigned to the α, assuming an equal contribution from both variables in the combined drought index (Karnieli *et al.* 2006; Bento *et al.* 2020). Therefore, in estimating the contributions of VMCI and TCI to the overall VMSI combined index, α = 0.5 was used as a benchmark equal contribution for both variables with the aid to determine how each variable deviates during peak drought conditions for all the biomes. Thereafter, contribution coefficients ranging from α=0.1 to α=0.9 were generated, interchanging the dominance of one variable to another and vice versa, as illustrated in table 3.2 below. VMSI_2 to VMSI_5 illustrated high contributions of temperature, thereby assessing the impact of temperature on vegetation conditions, while VMSI_6 to VMSI_9 illustrated high moisture contribution, hence, assessing the impact of moisture on vegetation during peak drought conditions across different regions and vegetation types. The VMSI combined index was computed using the following equation:

$$VMSI = (\alpha * VMCI) + (\alpha * TCI) \qquad (3)$$

Where α was used for model development across 9 moisture and temperature contributions (table 3.2).

Table 3.2: Various moisture and temperature contribution coefficients.

Coefficient (α)	VMCI (NDWI)	TCI (LST)
VMSI_1	**0.5**	**0.5**
VMSI_2	0.1	0.9
VMSI_3	0.2	0.8
VMSI_4	0.3	0.7
VMSI_5	0.4	0.6
VMSI_6	0.9	0.1
VMSI_7	0.8	0.2
VMSI_8	0.7	0.3
VMSI_9	0.6	0.4

3.2.4 Meteorological drought Index: SPEI

The multiscalar meteorological drought indicator index SPEI was utilised to estimate the relative contributions of VMCI and TCI to VMSI during the 2015/16 drought episode (Tirivarombo *et al.* 2018; Bento *et al.* 2020; Marumbwa *et al.* 2021). SPEI drought indicator was chosen because of its robust nature that accounts for both the impact of precipitation and evapotranspiration in determining drought conditions (Marumbwa *et al.* 2021). These primary variables are considered as proxies of both VMCI and TCI, respectively (Bento *et al.* 2020). The SPEI data was acquired from the (https://catalogue.ceda.ac.uk/uuid/89e1e34ec3554dc98594a5732622bce9) Climatic Research Unit (CRU), provided at a spatial resolution of 0.5°x0.5° from 1901 to 2019. As a multi-scalar index, SPEI is available on different timescales, ranging from 1-month to 48-months. In this particular dataset, only 24-months SPEI was considered, covering the period from January 2015 to December 2016. This timescale was chosen since it covers all the phenological stages of vegetation during the 2015/16 peak drought conditions. Hence, determining the response of vegetation to drought events. The SPEI values are interpreted based on the McKee *et al.* (1993) classification scheme illustrated in Table 3.3 below.

Table 3.3: SPEI classification scheme, characterised by (McKee et al. 1993).

SPEI value	**Drought category**
>2	Extremely wet
1.5 to1.99	Severely wet
1.0 to1.49	Moderately wet
−0.99 to 0.99	Near normal
−1.0 to −1.49	Moderate drought
−1.5 to −1.99	Severe drought
<-2	Extreme drought

Source: (Caccamo *et al.* 2011)

3.2.5 Statistical analysis

To evaluate the impact of various moisture and temperature drought coefficients in estimating drought severity across different biomes of Kwa-Zulu Natal, a regression analysis was conducted using 24-months SPEI as a drought indicator. Using the R studio 4.1.0 package, the Random Forest (RF) algorithm was used to evaluate the 9 contribution coefficients against the meteorological drought indicator index (SPEI). The RF is a robust statistical algorithm which estimates a response parameter (measured drought) based on a set of explanatory predictor variables by constructing a number of numerous regression trees (Odebiri *et al.* 2020). Each regression tree is grown from a subset of random predictor variables (moisture and temperature coefficients) (Sibanda *et al.* 2021a). At each splitting tree (node), a subset of random predictors is derived for a limited number of parameters, where thereafter, the overall average value is obtained from all the individual trees (Odebiri *et al.* 2020; Sibanda *et al.* 2021a). The overall average value is then used to estimate the prediction outcome for all the models (Liang *et al.* 2018). The RF utilised a total of 100 sample points for the Forest biome and 150 sample points for both the Savanna and Grassland biomes. Sample points derived were based on the relative size (km) of each study site. The data was split into 70/30 to generate training and testing data sets, respectively for each RF derived model.

3.2.6 Accuracy assessment

An accuracy assessment was conducted to evaluate the impact of various moisture and temperature coefficients in estimating drought severity magnitude across different vegetation types (biomes), during peak drought conditions. The root mean square error (RMSE) and the coefficient of determination (R^2) were utilised to distinct and compare accuracies between the various coefficients. Particularly, the root mean square error (RMSE) which assesses the magnitude of error between the drought coefficients and the drought indicator value plots. The coefficient of determination (R^2) was also utilised to measure the distinction between the measured and estimated drought severity magnitude (the proportion of variance) (Liang *et al.* 2018). Thereafter, the performance of the RF derived models was evaluated by comparing the difference in RMSE and R^2 between the moisture and temperature estimating drought coefficients and the drought indicator. The optimal moisture and temperature drought coefficient model was derived based on low RMSE and high R^2 values across all the biomes.

3.3 Results

3.3.1 Estimating drought severity using multiscalar meteorological drought indicator index (SPEI), across three major biomes of Kwa-Zulu Natal

Figure 3.2 illustrates the averaged 2015/16 peak meteorological drought severity variations across the major biomes of Kwa-Zulu Natal based on the Standardised evapotranspiration index (SPEI) drought indicator. Generally, all the biomes were subjected to drought conditions, indicated by negative values for all the biomes. The Grassland biome experienced the most extreme-to-severe drought conditions with the highest SPEI value of <-2, illustrating extreme drought severity. The Forest biomes showed severe-to-moderate drought conditions with the highest SPEI value of -1.6. The Savanna biome experienced the least drought severity of moderate-to-normal conditions with the highest SPEI value of -0.2.

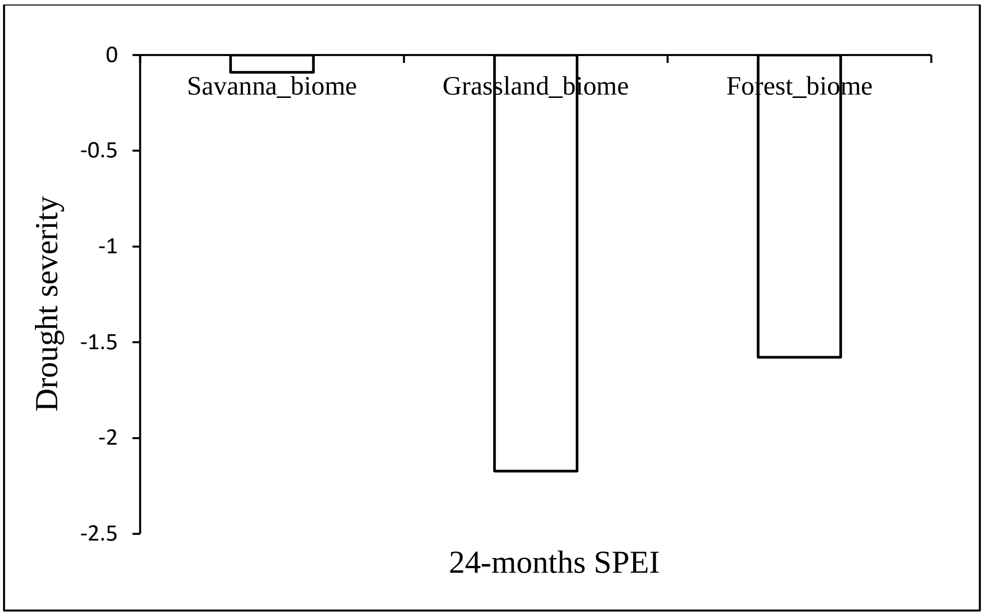


Figure 3.1: The 2015/16 drought severity variation across the major biomes of Kwa-Zulu Natal, estimated from meteorological drought index (24-months SPEI).

3.3.2 Evaluation of various moisture and thermal drought coefficients in estimating drought severity across three major biomes of Kwa-Zulu Natal

Table 2 illustrates the accuracies obtained in estimating 24-months SPEI based on different moisture and temperature contribution coefficients. The accuracies of drought prediction models varied significantly for the 2-year peak drought period across all the biomes. However, a similar pattern was observed for all the biomes. Generally, high temperature contributions yielded the highest model accuracies across different contribution coefficients for all the biomes, while showing lowest accuracies with high moisture contribution coefficients across the biomes.

For example, VMSI_2 (90%TCI:10%VMCI) yielded the highest model accuracy in estimating drought severity with an RMSE of 0.0589 and an R^2 of 0.78 for the Savanna biome, an RMSE of 0.0511 and an R^2 of 0.66 for the Grassland biome and an RMSE of 0.0034 and an R^2 of 0.76 for the Forest biome. The estimation of drought severity decreased with a decrease in temperature contribution for VMSI_3(80%TCI:20%VMCI), VMSI_4(70%TCI:30%VMCI) and VMSI_5(60%TCI:40%VMCI).

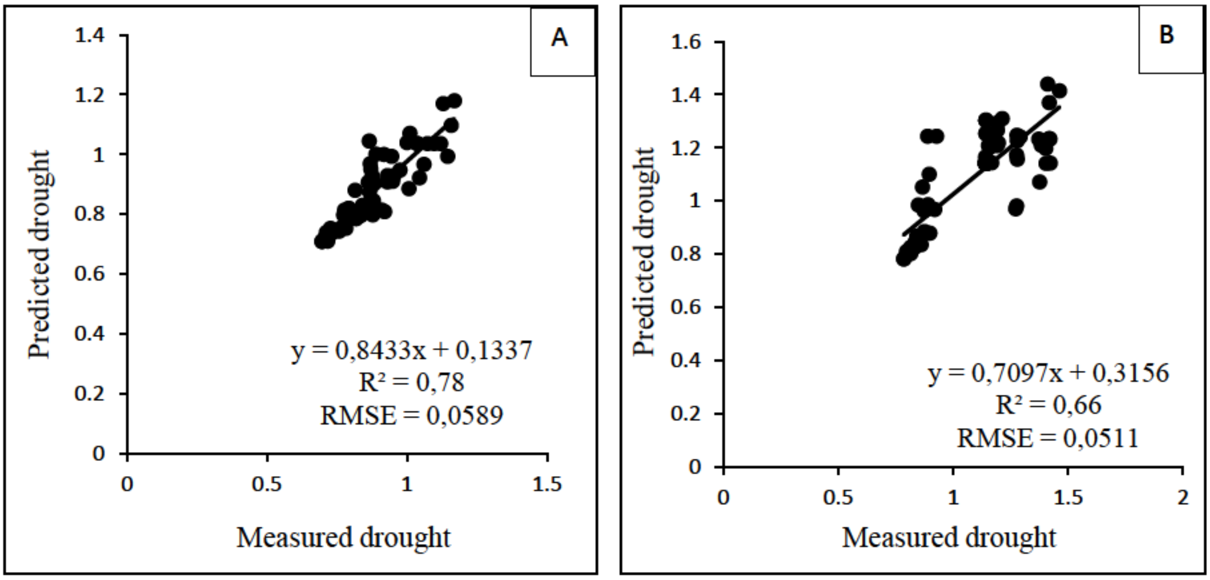
When predicting drought severity using high moisture contributions coefficients as predictor variables, lowest accuracies were observed across the biomes for the 2-year drought period. However, the lowest accuracies varied in moisture contribution levels for each biome. Where the highest maximum values was observed for VMSI_6 (90%VMCI:10%TCI) with an RMSE of 0.1488 and an R^2 of 0.18 for the Savanna biome, an RMSE of 0.2016 and an R^2 of 0.23 for the Grassland biome and an RMSE of 0.0064 and an R^2 of 0.29 for the Forest biome.

Table 3.4: Estimation model accuracies of estimating drought severity derived from different moisture and temperature contribution coefficients, using 24-months SPEI as a drought indicator.

Predictor Variables	Savanna Biome		Grassland Biome		Forest Biome	
	24-months SPEI		24-months SPEI		24-months SPEI	
Coefficient contribution	R^2	RMSE	R^2	RMSE	R^2	RMSE
VMSI_1	0.66	0.0560	0.68	0.0413	0.77	0.0017
VMSI_2	0.78	0.0589	0.66	0.0511	0.76	0.0034
VMSI_3	0.47	0.0961	0.57	0.0471	0.59	0.0044
VMSI_4	0.38	0.0118	0.41	0.1999	0.42	0.0053
VMSI_5	0.27	0.1440	0.38	0.2146	0.36	0.0061
VMSI_6	0.18	0.1488	0.23	0.2016	0.29	0.0064
VMSI_7	0.13	0.1347	0.15	0.2207	0.12	0.0075
VMSI_8	0.09	0.0056	0.08	0.2649	0.02	0.0079
VMSI_9	0.16	0.0032	0.13	0.1709	0.04	0.0070

3.3.3 Optimal moisture and temperature contribution coefficients in estimating drought severity across major biomes of Kwa-Zulu Natal, using SPEI as drought indicator

Figure 3.3 illustrates the results obtained from optimal moisture and temperature contribution coefficients in estimating drought severity across three major biomes of Kwa-Zulu Natal, using Random Forest Regression (RFR) model. The results showed that high temperature contributions (TCI) optimally estimated drought severity across the biomes, using 24-months SPEI as a drought indicator. The optimal predictor model, VMSI_2 was based on 90% contribution of temperature-derived vegetation index (TCI) and 10% contribution of moisture-derived vegetation index (VMCI). VMSI_2 yielded an RMSE of 0.0589 and an R^2 of 0.78 for the Savanna biome (Fig.3.3a), an RMSE of 0.0511 and an R^2 of 0.66 for the Grassland biome (Fig.3.3b) and an RMSE of 0.0034 and an R^2 of 0.76 for the Forest biome (Fig.3.3c).



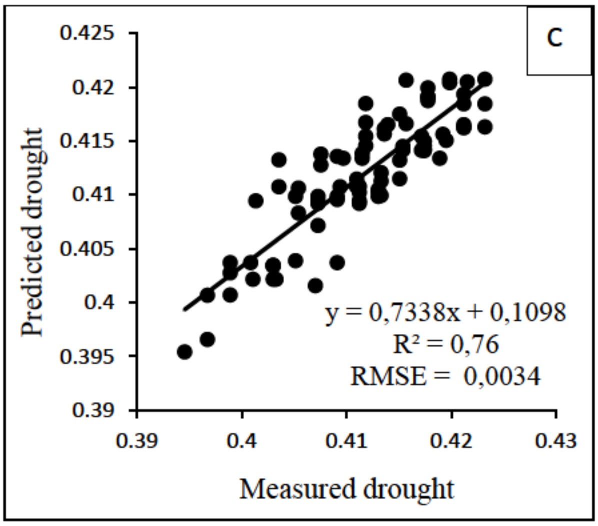


Figure 3.2: Relationship between the observed and predicted drought severity across the biomes estimated from optimal moisture and temperature contribution coefficients, derived using 24-months SPEI as a drought indicator. Where A is the Savanna biome, B is the Grassland biome and C is the forest biome

3.3.4 Mapping the spatial distribution of drought severity across major biomes of Kwa-Zulu Natal using the most optimal moisture and temperature contribution coefficients

Figure 3.4 illustrates the spatial distribution of drought severity maps of the Savanna, Grassland and Forest biomes of Kwa-Zulu Natal, during the 2015/16 peak drought conditions. It can be observed that all the biomes, the Savanna, grassland, and Forest biomes were mainly impacted by extreme to severe drought conditions with patches of Moderate to No drought conditions in some areas. The Savanna biome only experienced no drought conditions where there is presence of Lake St Lucia, while the Forest biome only experienced no drought conditions within the deepest cluster of forest vegetation. The Grassland biome was mainly impacted by Severe to Moderate drought conditions showing patches of Extreme drought conditions central to the study site and patches of No drought conditions in the northern parts of the study site.

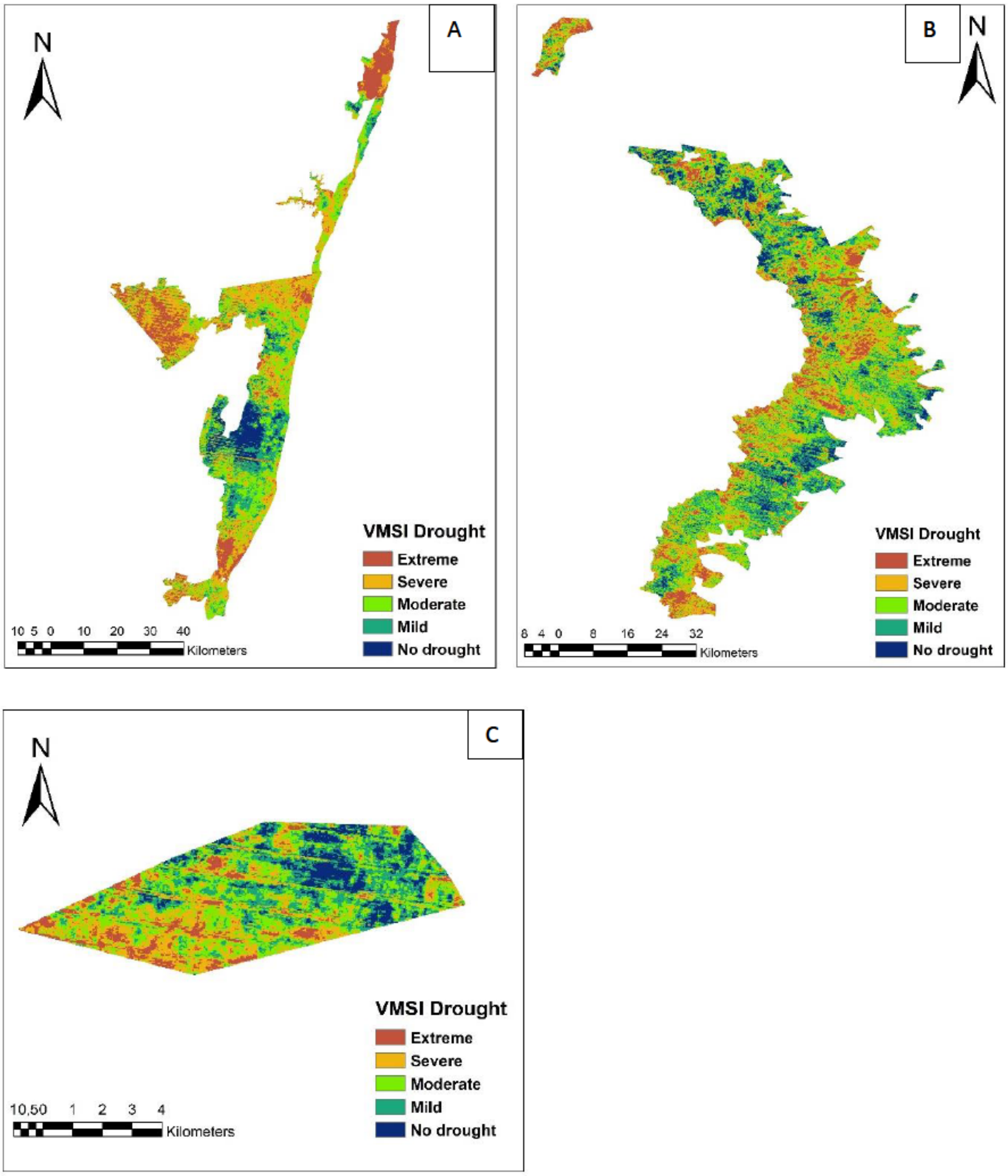


Figure 3.3: Drought variability maps derived from optimal drought indices, Vegetation Moisture Stress Index (VMSI) and Vegetation Moisture Condition Index (VMCI) in (a and b) Savanna biome, (c and d) Grassland biome, as well as (e and f) Forest biome, u using 1-month SPI as the best drought indicator.

3.4 Discussion

This study sought to evaluate the impact of various moisture and temperature drought contribution coefficients of VMSI in estimating drought severity across the Savanna, Grassland and Forest biomes of Kwa-Zulu Natal, using 24-months SPEI as a drought indicator.

Main findings of this study indicated that when estimating drought severity in a semi-arid region, the relative contribution of moisture (VMCI) and temperature (TCI) to VMSI can be effectively evaluated using a multiscalar meteorological drought index (SPEI) which is also derived from both moisture and temperature drought variables. These findings concur with those obtained by Marumbwa *et al.* (2021) who outlined that during the 2015/16 drought period, there were high correlations observed between an El Nino-derived index and SPEI. Thereafter, any slight precipitation deficiencies observed resulted in extreme impacts on vegetation conditions (Marumbwa *et al.* 2021). However, Jiao *et al.* (2016) outlined that 24-month SPEI was more suitable for determining long-term meteorological drought based on the ability to capture vegetation stress response from precipitation deficiencies coupled by excessive temperatures. Xulu *et al.* (2019) and Ndlovu and Demlie (2020) also noted that these conditions were further exacerbated by extreme temperatures driven by abnormal sea surface temperatures characterised by warm conditions which further impacted moisture availability on vegetation.

Results attained in this study illustrated that during peak drought conditions in Southern Africa, high temperature contributions yielded the highest accuracies, where the weights (α) associated with TCI was larger than the adopted value of 0.5, in comparison to moisture contributions for all the biomes. Optimal estimation accuracies were obtained from VMSI_2 model (90%TCI:10%VMCI) which yielded an RMSE of 0.0589 and an R^2 of 0.78 for the Savanna biome, an RMSE of 0.0511 and an R^2 of 0.66 for the Grassland biome and an RMSE of 0.0034 and an R^2 of 0.76 for the Forest biome. Literature confirms that moisture and temperature contribution coefficients typically deviates from the commonly adopted value of 0.5, given that sensitivity of different regions are based on three constraints to vegetation health: radiation, temperature and moisture availability (Bhuiyan *et al.* 2017; Bento *et al.* 2020). Mostly, drier regions characterised by more sensitivity to water stress than thermal stress are dominated by large VMCI component since lack of water is the main limiting factor that impacts vegetation health (Du *et al.* 2018; Bento *et al.* 2020). Regions characterised by high moisture levels are more sensitive to thermal stress due to temperature and radiation being the main limiting factors to vegetation health, hence large contributions of TCI (Bhuiyan *et al.* 2017; Bento *et al.*

2020). Therefore, these regions are mainly prone to the increasing trend of climate change which subsequently affect terrestrial ecosystems (Bento *et al.* 2020).

Previous studies such as Jiao *et al.* (2016) and Du *et al.* (2018) have established that TCI have been mainly successful in detecting drought severity during dry season which usually ranges from April to August based on high LST values. However, from 2011 till 2016 TCI have been more sensitive to vegetation stress during longer periods of the year, capturing increase in drought conditions of varying intensity and severity, mostly affecting fire prone grasslands which are susceptible to high temperatures (Du *et al.* 2018). Hence, TCI has been recognised as a better drought indicator which can distinguish between drought and non-drought periods and can also indicate drought impacts of thermal stress on vegetation health (Jiao *et al.* 2016; Bento *et al.* 2020). Using TCI Jiao *et al.* (2016) identified drought years of severe vegetation stress ranging from 2011 to 2016 while Du *et al.* (2018) identified drought years in forest vegetation using TCI from 2012 to 2015 based on 12-months SPEI. While some studies argue that water scarcity is the main factor that constitutes to drought conditions, leading to severe drought impacts, Bhuiyan *et al.* (2017) outlined that temperatures also has a significant impact in maintaining moisture content in vegetation, hence, high temperature anomalies affects vegetation health leading to thermal stress. Therefore, temperature-derived drought indices are most suitable in capturing and monitoring drought events on vegetation, especially with changing climatic conditions (Bhuiyan *et al.* 2017).

Meanwhile, the study observed low model accuracies where high moisture contributions were observed in comparison to temperature contributions for all the biomes. Optimal estimation accuracies based on moisture were obtained from VMSI_6 model (90%VMCI:10%TCI) which yielded an RMSE of 0.1488 and an R^2 of 0.18 for the Savanna biome, an RMSE of 0.2016 and an R^2 of 0.23 for the Grassland biome and an RMSE of 0.0064 and an R^2 of 0.29 for the Forest biome. These findings can be accounted by following the 'the Law of Minimum', as stated by Bento *et al.* (2018) which outlines that vegetation growth is determined by the scarcest resource accessible in the ecosystem, meaning that vegetation health thus depends on vegetation stress based on either moisture scarcity (VMCI) or temperature stress (TCI). Hence, using SPEI as a drought indicator, VMSI showed that the grassland biome experienced the most extreme drought conditions since it is characterised as a water dependent region, sensitive to water availability that subsequently affects biome productivity (Wilcox *et al.* 2020; Marumbwa *et al.* 2021). The forest biome was also subjected to severe drought conditions, owing to temperature as the main limiting factor mostly impacted by the 2015/16 El Nino and SST changes (Bento *et al.* 2020). The savanna biome was also subjected to severe drought conditions which is explained by the classification of this region as a wetland site. Hence, both moisture availability and optimum temperature conditions play a crucial role in maintaining vegetation health (Bhuiyan *et al.* 2017). However, increase in temperatures, mainly influenced by El Nino event and sea surface temperatures generated vegetation thermal stress, lowering moisture availability and thereby severely affecting vegetation health (Bhuiyan *et al.* 2017; Marumbwa *et al.* 2021).

3.5 Conclusion

This study sought to: (i) evaluate the impact of various moisture and temperature drought contribution coefficients of VMSI in estimating drought severity across the Savanna, Grassland and Forest biomes, using 24-months SPEI as a drought indicator; (ii) derive the optimal moisture and temperature contribution coefficient that can be applied across different ecosystems and biomes of semi-arid region of Southern Africa; (iii) to map the spatial distribution of drought severity across the biomes, using optimal moisture and temperature contribution coefficients.

The main findings of this study illustrated that:

- The relative contribution of moisture (VMCI) and temperature (TCI) drought input variables can effectively estimate drought severity of Southern African biomes, using a multiscalar meteorological drought index (SPEI) which accounts for both precipitation and temperature variables.
- Drought severity across different biomes can be optimally estimated using high temperature contributions in comparison to moisture contributions for all the biomes, especially during peak drought season.
- The VMSI_2 estimation model of 90% TCI dominance and 10% of VMCI dominance yielded the highest accuracy in estimating drought severity during peak drought conditions across all vegetation types and biomes.

The finding of this study laid the basis for future work, where the application of relevant contribution coefficients within different ecosystems and regions may be considered as a significant asset in determining drought severity. The dependence of the type of vegetation to these contribution coefficients could aid in deriving the drought variable/factor that exacerbate drought conditions, leading an early identification of drought warning signs and monitoring mechanisms, particularly in semi-arid regions of Southern Africa. Given changing climatic conditions, the application of temperature-derived vegetation indices could aid in increasing the accuracy of estimating drought severity and extent across semi-arid regions, mainly Southern Africa.

CHAPTER FOUR: SYNTHESIS

4.1 Introduction

Drought is recognised among the leading natural hazards around the globe, characterised by below average precipitation deficiencies over time which affects natural habitats and terrestrial ecosystems (Du *et al.* 2018; Tfwala *et al.* 2018). Ecosystem health and distribution is increasing vulnerable to the impact of drought intensity and frequencies due to increase in climatic conditions. Hence, assessing and monitoring drought conditions is critical in deriving early drought detection and copying mechanisms. The use of traditional meteorological drought indices has various limitations across different regions which include the lack of spatial coverage and ability to account for spatial heterogeneity. Hence, drought prediction and monitoring within multiple ecosystems requires accurate strategies and methods that account for the variations. In this regard, remote sensing derived vegetation indices provides a practical technique which offers substantial advantages for monitoring drought conditions from local to regional scale by allowing for both spatial and temporal drought impact assessments (Zambrano *et al.* 2016; Bento *et al.* 2018). Furthermore, vegetation drought indices based on remote sensing allows to track changes in vegetation over time, mainly as an indicator of ecosystem response to weather conditions, therefore, monitoring drought. In this regard, this study sought to improve drought assessment and monitoring across different terrestrial biomes of Southern Africa, using multiple conditional and combinative remotely sensed drought indices.

4.2 Objectives Review:

4.2.1 To evaluate the relative performance of conditional and combinative drought indices in quantifying the magnitude of drought across the Savanna, Grassland and Forest biomes, using SPI as a drought indicator computed across various timescales

The key findings of this study have shown that when estimating drought magnitude from remote sensing-based vegetation indices, both combinative and conditional drought indices are suitable predictor variables for quantifying and monitoring drought episodes across different biomes. However, optimal results were obtained from combinative drought indices which performed better than conditional drought indices. The results highlighted the main limitations of using conditional drought indices which are derived from a single drought factor thus lacking the ability to capture the most extreme drought conditions. These results were acquired using a meteorological multi-scalar drought index (Standardised evapotranspiration index, SPEI), as a drought indicator computed across several timescales (1-, 3-, 6-, 9-, 12- and 24 months). The optimal results were obtained from 1-month SPEI, indicating the ability to detect and capture the onset of drought conditions (short-term drought). Specifically, optimal estimation accuracies obtained using combinative drought indices produced an R^2 of 0.98 and RMSE of 0.074 for the Savanna biome, an R^2 of 0.93 and RMSE of 0.013 for the Grassland biome and an R^2 of 0.99 and RMSE of 0.016 for the Forest biome. While the conditional drought indices lower maximum accuracies with an R^2 of 0.93 and RMSE of 0.168 for the Savanna biome, an R^2 of 0.89 and RMSE of 0.021 for the Grassland biome and an R^2 of 0.97 and RMSE of 0.033 for the Forest biome. The optimal combinative drought predictor variables was then utilised to map the spatial distribution of drought magnitude across the three major biomes of Kwa-Zulu Natal.

4.2.2 To evaluate the impact of various moisture and temperature drought contribution coefficients of VMSI in estimating drought severity across the Savanna, Grassland and Forest biomes, using 24-months SPEI as a drought indicator

Drought is a climatic natural event primarily influenced by climatic factors such as precipitation and temperature. Driven by climate change, an increasing trend of global mean temperatures resulting in water shortages across the region has indicated major impacts on ecosystems. Therefore, in drought assessments studies it is crucial to account for both moisture and temperature components in quantifying and predicting the drought response of different terrestrial regions. Hence, this study evaluated the impact of various moisture and temperature drought contribution coefficients, using a remotely sensed combinative drought index (the Vegetation moisture stress index, VMSI) in estimating drought severity across the Savanna, Grassland and Forest biomes. The 24-months Standardised Evapotranspiration Index (SPEI) was utilised as a drought indicator.

The main findings of the study illustrated that high temperature contributions yielded the highest accuracies, where weights (α) associated with TCI were larger than the adopted value of 0.5, in comparison to moisture contributions for all the biomes. Optimal estimation accuracies were obtained from VMSI_2 model (90%TCI:10%VMCI) which yielded an RMSE of 0.0589 and an R^2 of 0.78 for the Savanna biome, an RMSE of 0.0511 and an R^2 of 0.66 for the Grassland biome and an RMSE of 0.0034 and an R^2 of 0.76 for the Forest biome. The optimal moisture and temperature contribution coefficients were thus used to map spatial distribution of drought severity across the biomes of Kwa-Zulu Natal.

4.3 Conclusion, limitations, and future recommendations

The main aim of this study was to characterise drought variability across different major biomes of Kwa-Zulu Natal, using remote sensing based conditional and combinative drought indices. The results of this research illustrated that the use of remote sensing based combinative drought indices is effective in estimating drought magnitude across major biomes of Kwa-Zulu Natal. Furthermore, using high temperature contributions in relation to moisture contribution coefficients when using the Vegetation moisture stress index (VMSI) can successfully estimate drought severity across different vegetation types, during peak drought season. Additionally, the use of meteorological multiscalar drought indices such as the standardised precipitation index (SPI) and the standardised evapotranspiration index (SPEI) as drought indicators have proved to be effective across different biomes of Kwa-Zulu Natal.

Some limitations were encountered in the study. The main limitation is the lack of preceding reference studies which applied the aforementioned combinative drought index, especially in the Southern African context. This limitation have had a major impact on the quality of theory and methodology applied in estimating drought magnitude and severity. This is also true for chapter two, where different moisture and temperature contributions were used to estimate drought severity across different vegetation types, due to the lack of supporting studies for Southern African context. The second limitation was obtaining monthly Landsat 8 data for chapter two due to the 16-days temporal resolution of the sensor. Future research on drought assessments and monitoring using conditional and combinative drought indices still needs to evaluate the relative contributions of moisture and temperature across different regions with the aid to acquire a single weight which could be applied from local to global scale and across different vegetation types. More studies should adopt this methodology in the Southern Africa context in order to derive the most influential drought factor to monitor before and during drought incidents.

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