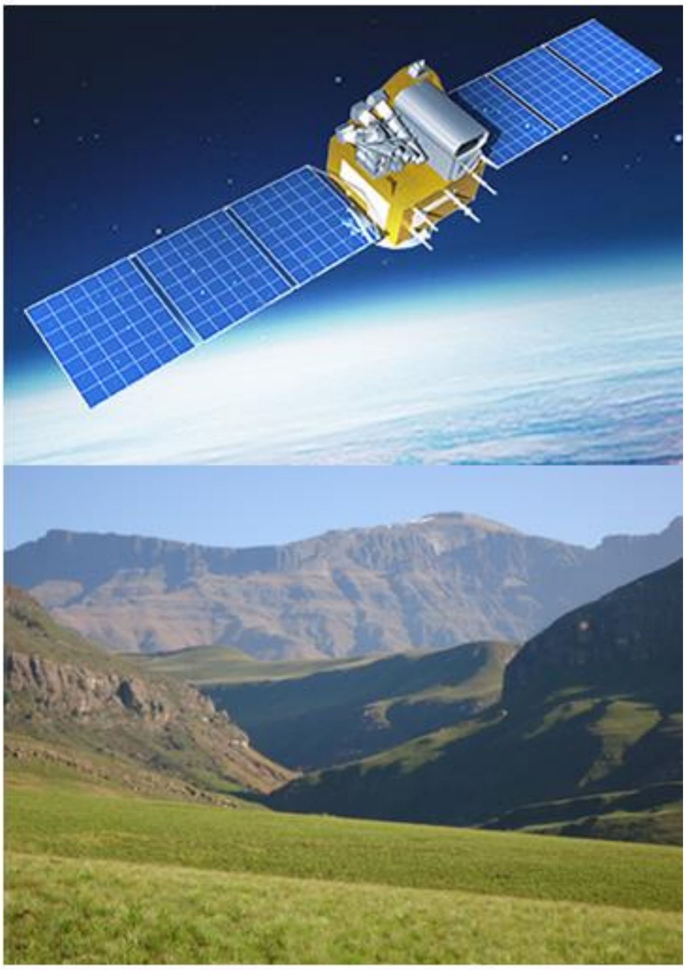
Discrimination and biomass estimation of co-existing C3 and C4 grass functional types over time:

A view from space



Cletah Shoko

A thesis submitted to the College of Agriculture, Engineering and Science at the University of KwaZulu-Natal, in fulfilment of the academic requirements for the degree of Doctor of Philosophy in Environmental Science

(Specialization: GIScience and Earth Observation)

February 2018

Pietermaritzburg

South Africa

ABSTRACT

The co-existence of C3 and C4 grass species significantly influence their spatio-temporal variations of biochemical cycling, productivity (*i.e.* biomass) and role in provision of ecosystem goods and services. Consequently, the discrimination of the two species is critical in understanding their spatial distribution and productivity. Such discrimination is particularly valuable for accounting for their socio-economic and environmental contributions, as well as decisions related to climate change mitigation. Due to the growing popularity of remotely sensed approaches, this study sought to discriminate the two grass species and determine their AGB using new generation sensors. Specifically, the potential of Landsat 8, Sentinel 2 and Worldview 2, with improved sensing characteristics were tested in achieving the above objectives.

Generally, the results demonstrate the suitability of the adopted sensors in the discrimination and determination of C3 and C4 AGB using Discriminant Analysis and Sparse Partial Least Squares Regression models. Using multi-date Sentinel 2 data, the study established that winter period (May) was the most suitable for discriminating the two grass species. On the other hand, the winter fall (August) was found to be the least optimal period for the two grass species discrimination. The study also established that the amount of AGB for C3 and C4 were higher in winter and summer, respectively; a variability attributed to elevation and rainfall. The study concludes that Sentinel 2 dataset, although had weaker performance than Worldview 2; it offers a valuable opportunity in understanding the C3 and C4 spatial distribution within a landscape; hence useful in understanding both temporal and multi-temporal distribution of the two grass species. Successful seasonal characterization of C3 and C4 AGB allows for inferences on their contribution to forage availability and fire regimes; therefore, this contributes to the development of well-informed conservation strategies, which can lead to sustainable utilization of rangelands, especially in relation to the changing climate.

PREFACE

The research work described in this thesis was carried out in the School of Agricultural, Earth and Environmental Sciences (SAEES), University of KwaZulu-Natal, Pietermaritzburg, from July 2015 to March 2018, under the supervision of Prof. Onisimo Mutanga (SAEES, University of KwaZulu-Natal; South Africa).

I would like to declare that the research work reported in this thesis has never been submitted in any form to any other university. It therefore represents my original work except where due acknowledgments are made.

Cletah Shoko Signed: _ Shoko _ Date: 30/07/2018

As the candidate's supervisor, I certify the above statement and have approved this thesis for submission.

Prof. Onisimo Mutanga Signed: ___________________Date:_________________

DECLARATION 1-PLAGIARISM

I, **Cletah Shoko**, declare that:

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

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

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

4. This thesis does not contain other persons' writing, unless specifically acknowledged as being sourced from other researchers. Where other written sources have been quoted, then:

    a. Their words have been re-written, but the general information attributed to them has been referenced.
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5. This thesis does not contain text, graphics, or tables copied and pasted from the Internet, unless specifically acknowledged and the source being detailed in the thesis and in the References section

Signed Shoko

DECLARATION 2- PUBLICATION AND MANUSCRIPTS

1. **Shoko C**, Mutanga O and Dube T (2016): Progress in the remote sensing of C3 and C4 grass species aboveground biomass over time and space: *ISPRS Photogrammetry and Remote Sensing*, (120):13-24.

2. **Shoko C** and Mutanga O (2017b): Seasonal discrimination of C3 and C4 grasses functional types: An evaluation of the prospects of the varying spectral configurations of the new generation sensors. *International Journal of Applied Earth Observations and Geoinformation*, (62): 47–55.

3. **Shoko C** and Mutanga O (2017a): Examining the strength of the newly-launched Sentinel 2 MSI sensor in detecting and discriminating subtle differences between C3 and C4 grass species. *ISPRS Photogrammetry and Remote Sensing*, (129): 32–40.

4. **Shoko C**, Mutanga O, Dube T and Slotow R. Determining the optimal season for discriminating the eco-physiological distinction between C3 and C4 grass functional types using multi-date Sentinel 2 data. (*Under Review*) *International Journal of Applied Earth Observations and Geoinformation* (Manuscript ID: JAG-D-17-00702).

5. **Shoko C**, Mutanga O and Dube T. Determining optimal new generation satellite for accurate C3 and C4 grass species aboveground biomass estimation in South Africa. *Remote Sensing*, 10(4), 564.

6. **Shoko C**, Mutanga O, Dube T and Slotow R (2018): Characterizing the spatio-temporal variations of C3 and C4 dominated grasslands aboveground biomass in the Drakensberg, South Africa. *International Journal of Applied Earth Observations and Geoinformation*, (68): 51–60.

7. **Shoko. C**, Mutanga. O and Dube. T. Remotely-sensed C3 and C4 grass species AGB variability response to seasonal climate and topography. *Journal of Applied Geography* (Manuscript ID: 2018_117).

Signed Shoko

DEDICATION

To my parents and to my son Kabelo Reginald Dube

ACKNOWLEDGEMENTS

I am very grateful to my supervisor, Professor Mutanga, for believing in me and giving me the opportunity to further my studies under your supervision. It was a wonderful period of learning in the scientific arena and at personal level. That will go a long way! I could not have imagined a better supervisor. Thank you for your tireless effort you devoted to my research, you provided the required guidance, insightful comments and you were always available to assist throughout the study period.

I would like also to extend my gratitude to the School of Agricultural, Earth and Environmental Sciences, University of KwaZulu-Natal within which the research was conducted. My appreciation further extends to the Geography Departmental staff, particularly Mrs Shanitha Ramroop, Mr Brice Gijsbertsen and Mr Donavan De Vos, for their valuable logistical and administrative support. My sincere gratitude also goes to all my colleagues and friends in the Department, for their wonderful support during the period of my study. In particular, I thank Charles Otunga, Mbulisi Sibanda, Terence Mushore, Trylee Matongera and Samuel Khumbula; you were always willing to assist, whenever necessary.

It is my pleasure to recognize the support offered by the Applied Centre for Climate and Earth Systems Science and the National Research Foundation, by providing funds, which brought this research to completion. I also thank the South African Weather Services and South African Earth Observation Network for providing meteorological data for Cathedral Peak within which the study was conducted. The Ezemvelo KwaZulu-Natal Wildlife is also appreciated for granting the required permit to access the area and conduct the required fieldwork. The United States Geological Survey and the European Space Agency are thanked for the provision of Landsat 8 and Sentinel 2 remote sensing data.

To my forever-enthusiastic family, thank you very much. You were always keen to know what I was doing, how I was proceeding and when I was finishing. To my sister Karen, I will always cherish your encouragement and prayers that gave me the strength to keep going. To my dear husband, you did your best. You were always there for me, providing the necessary insights, support and criticism; I needed that. Above all, to the source of life, the Almighty God, who gave me the strength and brought this research to completion, thank you!

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

CHAPTERS ONE AND TWO: GENERAL OVERVIEW AND CONTEXTUALISATION

1.1. Importance of grassland ecosystems

Grasslands are an important component of the global terrestrial ecosystems. This biome occupies more than 30% of the global land area, contributing approximately 20% of total terrestrial primary productivity (Barbehenn et al., 2004; Jin et al., 2014). These ecosystems play a significant role in biodiversity conservation and in regulating biospheric and atmospheric carbon (Hill, 2013; O'Mara, 2012). Grasslands are also an important source of forage for livestock, which supports the livelihoods of the majority of communities and wildlife populations (Schmidt and Skidmore, 2001; Xu and Guo, 2015). For instance, in the rangelands of South Africa, which occupy more than 70% of the land area, grasslands are a critical foraging source for wildlife and livestock (Mansour et al., 2013), contributing approximately ZAR 2.88 billion to the country’s Gross Domestic Product per year (Mbatha and Ward, 2010).

It has also been established that the photosynthetic pathway (*i.e.* C3 and C4) followed by these grass species is a crucial component of grassland ecosystems, which influence their functioning within an ecosystem (Barbehenn et al., 2004). For example, C4 species have a high carbon storage capability per unit of nitrogen, compared to the C3 species (Foody and Dash, 2007; Pau and Still, 2014). Although it has been generally accepted that C3 and C4 grass species prefer certain conditions, there is also a co-existence of these species, due to the influence of local topographic and climatic factors (Yan and de Beurs, 2016). The co-existence of C3 and C4 has been identified, for example, in the montane grasslands of South Africa (Adjorlolo et al., 2014), the Prairies of the United States (Foody and Dash, 2007) and temperate northern China (Guan et al., 2012). Their co-existence plays a considerable role in governing the spatial and temporal variations of biochemical cycling and productivity (*i.e.* biomass accumulation). The morphological, physiological and phenological variations between C3 and C4 grass species also influence their biophysical properties, their response to environmental changes and their ability to provide ecosystem goods and services (Barbehenn et al., 2004; Foody and Dash, 2010), which varies over space and time.

Scientific evidence also shows that climate change impose significant threat to C3 and C4 grass species, with implications on their geographical distribution, abundance and productivity (Xia et al., 2014). For example, there are concerns that an increase in atmospheric carbon dioxide (CO_2) concentrations will be favourable to C3 species, and they are more likely to increase in distribution at the expense of C4 (Barbehenn et al., 2004).

These changes compromise the ability of C3 and C4 grass species to provide ecosystem goods and services. Therefore, monitoring these grass species becomes fundamental for proper management of these ecosystems, so as to ensure their sustainability. In addition, it enlightens the contribution of these grass species to forage, fuel load and as potential carbon pools, especially in the light of climate and land cover changes.

So far, information on C3 and C4 grass species has traditionally been obtained by means of conventional field surveys (Adjorlolo et al., 2012b; Barbehenn et al., 2004). However, these approaches have been found to be costly, labour intensive, time consuming and restricted to smaller areas (Schmidt and Skidmore, 2001). This is insufficient to understand the spatial and temporal variability of co-existing C3 and C4 dominated grasslands, for continuous monitoring, as well as for development of management strategies. Alternatively, remote sensing data offers robust, instantaneous and efficient spatial and temporal data useful, at different spatial scales and geographical coverage, in a spatially explicit manner (Knox et al., 2013; Peterson et al., 2002; Wang et al., 2013; Wang et al., 2010). The data therefore becomes more appropriate for characterizing and monitoring co-existing C3 and C4 grass species.

1.2. Remote sensing of co-existing C3 and C4 grass species

Since the emergence of remote sensing, monitoring of C3 and C4 grass species has been recognized (Adjorlolo et al., 2015; Liu and Cheng, 2011; Lu et al., 2009; Tieszen et al., 1997). However, the remote sensing of C3 and C4 grass species has been associated with some challenges, which hinders continuous monitoring efforts. The major problem has been on finding appropriate datasets for optimum monitoring. For instance, the widely-used broadband multispectral sensors, such as the Advanced Very High Resolution Radiometer (AVHRR) and the Moderate Resolution Imaging Spectroradiometer (MODIS) have been reported to yield poor results. This has been attributed mainly to their coarse spatial resolution (*i.e.* 1 km^2), which limits their potential to capture the spatial characterization of C3 and C4 biophysical properties (Peterson et al., 2002; Price et al., 2002). Moreover, their broad spectral settings have limited their ability to spectrally discern between C3 and C4 species characteristics. On the other hand, the use of hyperspectral data, although it produces accurate results, literature shows that the acquisition cost, high data dimensionality and the inherent multi-collinearity makes their application a challenge in resource-constrained areas (Adjorlolo et al., 2012b; Mansour et al., 2012a). Hyperspectral data is also limited to small geographical coverage, due to high acquisition cost. This limits any prospects for continuous monitoring of C3 and C4 grass species using hyperspectral datasets at large geographical coverage.

Emerging remote sensing datasets, with advanced sensing capabilities are therefore perceived to provide new prospects for monitoring C3 and C4 grass species. Particularly, the development of new generation sensors, such as Landsat 8 Operational Land Imager (OLI), RapidEye, Worldview-2 and Sentinel-2 Multispectral Instrument (MSI) although not yet fully tested, offer more hope for monitoring C3 and C4 grass species from local to regional scales. The improved spatial and spectral properties (*e.g.* 10 m with 13 spectral bands for Sentinel 2) are likely to provide a better spatial and spectral characterization of C3 and C4 grass species. This is also critical considering their phenological, morphological and physiological variations. Most importantly, the high temporal resolution (*e.g.* 5 days for Sentinel 2) and large geographical coverage (*e.g.* 185 km for Landsat 8 and 195 km for Sentinel 2 sensors) are invaluable for temporal analyses, over large geographical areas.

Studies which applied new generation sensors demonstrated that they have the potential to characterize various species characteristics (Atzberger et al., 2015; Dube and Mutanga, 2015a; Dudley et al., 2015; Ramoelo et al., 2014; Richter et al., 2012). For instance, the study by Dube and Mutanga (2015a) has highlighted the utility of the Landsat 8 sensor design, which improves its sensitivity to characterizing species biomass. The study by Mutanga et al. (2015) also reported the ability of the Worldview 2 multispectral data in predicting foliar grass nitrogen with high accuracy. Ramoelo et al. (2014), using Sentinel 2 observed that the sensor's unique spectral configuration has high potential to monitor rangeland conditions in Southern Africa. These sensors are therefore more likely to be sensitive to various subtle properties of C3 and C4 grass species and their associated environmental conditions, thereby improving their accurate characterization and monitoring. It is upon this background that this work sought to seasonally discriminate and characterize AGB of C3 and C4 grass species in a spatially explicit manner, using new generation remote sensing sensors. This is perceived to offer a new horizon in the remote sensing of C3 and C4 grass species; a previously difficult task, due to lack of appropriate datasets, for large spatial monitoring, over time.

1.3. Study Aim and Objectives

The primary aim of this research was to discriminate and estimate spatial and temporal variations of C3 and C4 grass species aboveground biomass in KwaZulu-Natal, South Africa using new generation multispectral remote sensing datasets. Specifically, the study aimed to:

1. Evaluate the prospects of the varying spectral configurations of the new generation sensors for the seasonal discrimination of C3 and C4 grasses functional types,
2. Examine the strength of the newly-launched Sentinel 2 MSI sensor in detecting and discriminating subtle differences between C3 and C4 grass,
3. Determine the optimal season for discriminating the eco-physiological distinction between C3 and C4 grass functional types using multi-date Sentinel 2 data,
4. Determine optimal new generation satellite for accurate C3 and C4 grass species aboveground biomass estimation in South Arica,
5. Characterize the spatio-temporal variations of C3 and C4 dominated grasslands aboveground biomass in the Drakensberg, South Africa, and
6. To determine remotely-sensed C3 and C4 grass species AGB variability in response to seasonal climate and topography.

1.4. Study area

The study site, covering an area of approximately 200 km^2 is located in KwaZulu-Natal (Figure 1.1), which is one of the largest natural grassland areas in South Africa (Everson and Everson, 2016). The area is predominantly grassland, with patches of Afro-montane forests and rocky out crops. The climate varies remarkably, with wet humid summers, which extend from November to March and cold dry winters, from May to August (Nel, 2009). Temperatures are quite variable, from as low as 5°C in winter, to above 16°C in summer (Everson and Everson, 2016). The elevation of the area, according to the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) digital elevation model (DEM) varies between 1200 and 3050 m above sea level. The area experiences regular snowfall and frost during the winter period, especially in higher altitude zones (Mansour et al., 2012b). Misty conditions, fire and herbivory are also typical across the study area, which influence the distribution and productivity of C3 and C4 grass species (Adjorlolo et al., 2014). The Drakensberg is regarded as a zone of biological transition, occurring within the intermediate temperate–tropical climatic conditions, characterized by patches of C3 grasses and C4 grasses, which are highly responsive to environmental changes, thereby compromising their distribution, productivity and functioning (Adjorlolo et al., 2012b).

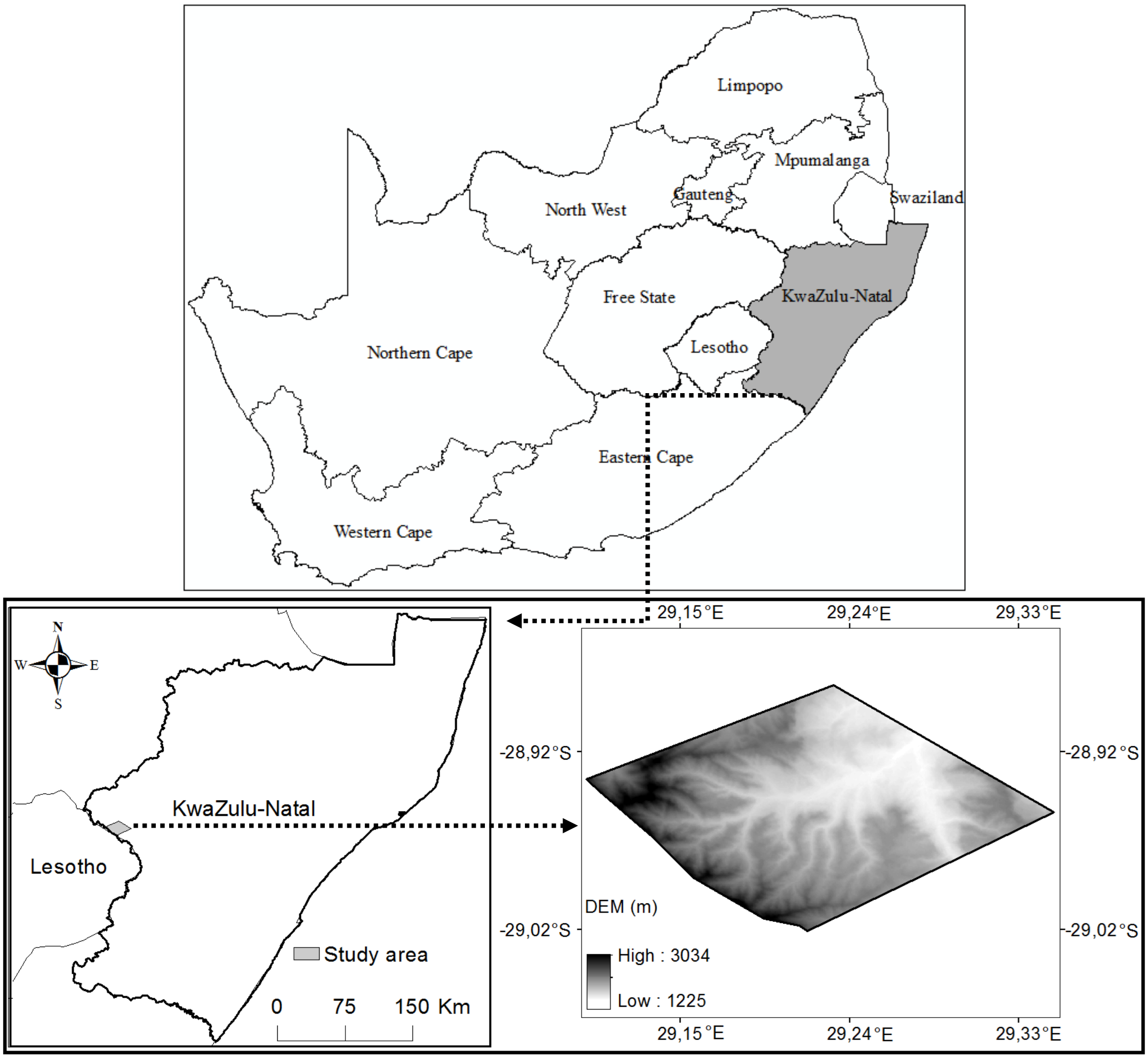


Figure 1.1: Study site location and DEM (DEM source: ASTER global DEM)

1.5. Thesis outline

Overall, this thesis focused on two key research areas of the remote sensing of C3 and C4 grass species: single and multi-date discrimination and AGB estimation. The structure of the thesis is in eight chapters. The thesis/dissertation is structured as eight chapters, mostly stand alone papers. Consequently, repetitions in some sections may occur, since these chapters constitute stand-alone papers, which were or are intended to be submitted for publication to different journals.

1.5.1. Chapters 1 and 2: General Overview and Contextualisation

The first Chapter is the general introduction to the study, as well as highlighting the main aim and specific objectives intended to be achieved. Chapter Two provides a review of literature on the progress of the remote sensing of C3 and C4 grass species AGB. The review highlights previous studies, sensors used, algorithms, as well as their performance, applicability and limitations. The review also noted prospects for C3 and C4 grass species AGB estimation, for improved management of these ecosystems.

1.5.2. Chapters 3 – 5: C3 and C4 Grass Species Discrimination

Chapter Three is based on a research paper focusing on the discrimination of C3 and C4 grass species. The study used *in situ* hyperspectral data to test spectral settings of new generation sensors, particularly, Landsat 8, Sentinel 2 and Worldview 2. These sensors have emerged with better spectral capabilities, than the previously-used broadband multispectral sensors. In this regard, they present a better opportunity for the discrimination of C3 and C4 grass species. Chapter Four further investigated how Landsat 8, Sentinel 2 and Worldview 2 sensors used in Chapter three discriminate and map the spatial distribution of C3 and C4 grass species. These sensors have different resolutions, which all influence their ability to detect and map C3 and C4 grasses. The study specifically examined the potential of the freely-available Sentinel 2, which has been recently launched in orbit, in discriminating and mapping C3 and C4 grasses.

In Chapter Five, Sentinel 2 was used to determine the optimum period for the better discrimination and mapping of C3 and C4 grass species, using multi-temporal images. The sensor has demonstrated its potential in relation to the freely-available Landsat 8 and the Worldview 2 commercial sensor. This study was therefore intended to improve not only the discrimination and mapping of C3 and C4, but also for future prediction of their potential shifts, under the anticipated climate change.

1.5.3. Chapters 6 and 7: C3 and C4 Grass Species Biomass Estimation

After identifying the optimum period, the AGB estimation of these grasses was explored. Identifying sensors for AGB estimation was one of the challenges identified in exploring the progressing of C3 and C4 grass species AGB estimation. In Chapter Six, the three sensors were first tested to determine their ability in estimating and representing the spatial variations of C3 and C4 grass species AGB. This demonstrated the opportunity offered by Sentinel 2 in estimating C3 and C4 grasses AGB, when compared to Landsat 8 and Worldview 2. The study was relevant in preparation for the estimation of spatial variations of species AGB over time. Chapter Seven therefore characterized AGB spatial variations over time, using Sentinel 2 multi-temporal images.

1.5.4. Chapters 8 and 9: Modelling and Synthesis

In Chapter Eight, possible climatic and topographic factors influencing the observed AGB patterns within the study area were explored. This Chapter specifically examined the response of remotely-sensed C3 and C4 grasses AGB to seasonal climate and topography. Chapter Nine finally provides the synthesis of the study, by summarizing the major findings and conclusions. The relevant recommendations in the discrimination and AGB estimation of C3 and C4 grasses, using emerging remote sensing data are also presented for future studies.

CHAPTER TWO

2. Progress in the remote sensing of C3 and C4 grass species aboveground biomass over time and space: A review

This chapter is based on:
Shoko C, Mutanga O and Dube T (2016): Progress in the remote sensing of C3 and C4 grass species aboveground biomass over time and space: *ISPRS Photogrammetry and Remote Sensing*, (120):13-24.

Abstract

The remote sensing of grass aboveground biomass (AGB) has gained considerable attention, with substantial research being conducted in the past decades. Of significant importance is their photosynthetic pathways (C3 and C4), which epitomizes a fundamental eco-physiological distinction of grasses functional types. With advances in technology and the availability of remotely sensed data at different spatial, spectral, radiometric and temporal resolutions, coupled with the need for detailed information on vegetation condition, the monitoring of C3 and C4 grasses AGB has received renewed attention, especially in the light of global climate change, biodiversity and, most importantly, food security. This paper provides a detailed survey on the progress of remote sensing application in determining C3 and C4 grass species AGB. Importantly, the importance of species functional type is highlighted in conjunction with the availability and applicability of different remote sensing datasets, with refined resolutions, which provide an opportunity to monitor C3 and C4 grasses AGB. While some progress has been made, this review has revealed the need for further remote sensing studies to model the seasonal (cyclical) variability, as well as long-term AGB changes in C3 and C4 grasses, in the face of climate change and food security. Moreover, the findings of this study have shown the significance of shifting towards the application of advanced statistical models, to further improve C3 and C4 grasses AGB estimation accuracy.

Keywords: climate change; food security; phenology; forage; spectral and spatial infidelity; sensor resolution

2.1. Introduction

Grasslands are an important component of global terrestrial ecosystems, occupying over 30% of the land, with an estimated contribution of 20% to the total terrestrial primary productivity (Barbehenn et al., 2004; Jin et al., 2014). Furthermore, grasslands play a significant role in biodiversity conservation, in regulating biospheric and atmospheric carbon concentration and, most importantly, forms the backbone of the food web (Hill, 2013; O'Mara, 2012). In the tropics of southern Africa, grasslands are predominantly an important source of forage for livestock, which supports the livelihoods of the majority of communities, as well as for the vast wildlife populations (Schmidt and Skidmore, 2001; Xu and Guo, 2015). For instance, in the rangelands of South Africa, which occupy more than 70% of the land area, grasslands are a critical foraging source for wildlife and livestock (Mansour et al., 2013), contributing approximately ZAR 2.88 billion to the country's Gross Domestic Product per year (Mbatha and Ward, 2010). Similarly, the Sahelian region in West Africa is characterized by an extensive use of rangeland pastures for livestock production (Diouf et al., 2015).

However, literature shows that grassland ecosystems are vulnerable to climate change effects (*e.g.* the prevalence of drought and erratic rainfall) (Bond and Keeley, 2005; Kalwij et al., 2014; Kemp and Michalk, 2007). These conditions compromise the Aboveground Biomass (AGB) of grassland ecosystems, with adverse effects on rangeland health, thereby posing significant challenges, not only to biodiversity conservation, but also to farmers and the livelihoods of communities at large. Therefore, the monitoring of grassland ecosystems becomes vital, to ensure their sustainability in maintaining ecosystem services.

Within the grassland ecosystems, the photosynthetic pathways (C3 and C4) of grass species represent a unique functional type of species sharing physiological (physical and chemical processes *e.g.* carbon cycle or photosynthesis), phenological (life cycle *e.g.* annual or seasonal) and morphological (structure) properties (Díaz and Cabido, 1997; Duckworth et al., 2000; Paruelo and Lauenroth, 1996). Typically, C3 are grasses characterized by incorporating carbon dioxide (CO_2) into an initial three-carbon compound, whereas C4 are those grasses which incorporate CO_2 into an initial four-carbon compound, during photosynthesis and are therefore, regarded as C3 and C4 grasses, respectively (Adjorlolo et al., 2012a; Foody and Dash, 2007).

In terms of their geographical distribution, C4 grasses are dominant in the warmer savannah areas of the tropics and the southern hemisphere (Fig.2.1 (a)) (Woodward and Lomas, 2004; Woodward et al., 2004). C4 grasses thus, prefer low latitude and altitude. On the other hand, C3 grasses predominantly occur in cool regions (Fig.2.1 (b)), particularly the high latitude and altitude Arctic and temperate zones of the northern hemisphere (Woodward and Lomas, 2004; Woodward et al., 2004; Yao et al., 2011). Previous studies (Adjorlolo et al., 2014; Bremond et al., 2012; Yan and de Beurs, 2016) have also reported the co-existence of C3 and C4 grass species. The study by Yan and de Beurs (2016) have further highlighted that the distribution of C3 and C4 grass species at regional scale is influenced by rainfall and temperature variations, whereas at a local scale, topographic and edaphic variables exert more influence. It is well documented that C3 grass species prefer cool conditions, with higher moisture content and lower solar radiation, are hence, regarded as cool season grasses (Adjorlolo et al., 2012b; Foody and Dash, 2007). Moreover, C3 grasses are less sensitive to frost, have been reported to be active throughout the year and are sometimes referred to as annual grasses (Tieszen et al., 1997). In contrast, C4 grasses prefer lower moisture content, warm temperatures, and are sometimes referred to as warm season grasses (Pau and Still, 2014; Ricotta et al., 2003; Tieszen et al., 1997). C4 grasses are highly sensitive to frost conditions, when compared to C3.

The phenological profiles of C3 and C4 grasses also vary, which influence the availability and quantity of their AGB within the ecosystem (Bremond et al., 2012; Guan et al., 2012). It has been reported that the growth of C3 grasses begins in the early spring, reaching their peak in late spring and in summer they become senescent, whereas C4 grasses begin in the late spring and reach their peak in summer (Pau and Still, 2014; Wang et al., 2013). The different phenological profiles of C3 and C4 grasses have been attributed to their climatic requirements and any alterations to these profiles have major implications on the timing and accumulation of AGB (Rigge et al., 2013). Monitoring the AGB of C3 and C4 grasses therefore, becomes a major concern, especially considering the projected effects of climate change on their distribution and abundance.

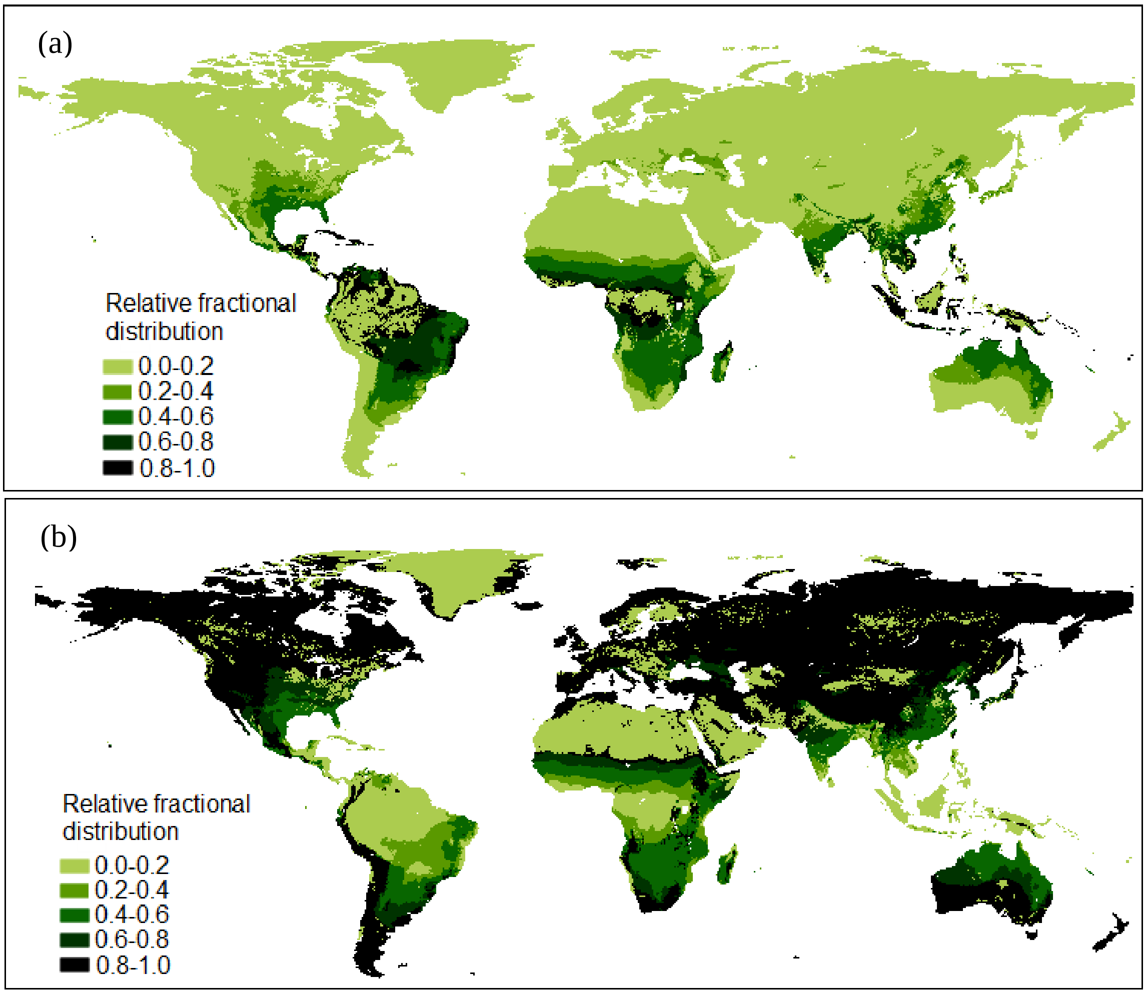


Figure 2.1: The global distribution of relative fraction of (a) C4 and (b) C3 grass species functional types (*Source: North American Carbon Program*)

The current concerns and the projected effects of global climate change on ecosystem functioning require the monitoring of C3 and C4 grasses AGB (Jin et al., 2014), considering their role in the carbon cycle. For example, C4 grass species tend to store more carbon, when compared to C3 (Davidson and Csillag, 2001). The study by Bremond et al. (2012) has also highlighted that C4 grasses respond positively, with an increase in warming, when compared to C3 grasses, whereas under elevated CO_2 concentration, C3 species are anticipated to respond positively, when compared to C4 (Lee, 2011). Similarly, the projected changes in climatic conditions (*e.g.* the seasonality of rainfall), coupled with warming, are likely to influence the phenological profiles of C3 and C4 grasses (Thornton et al., 2014). This has major implications on the timing and accumulation of species AGB, thereby affecting their ability to provide services and maintain the integrity of the ecosystem.

So far, there have been different approaches for monitoring the AGB of C3 and C4 grass species, based on ground measurements and remote sensing (empirical and physical-based approaches). Ground-based measurements have been regarded as the most direct and accurate method of estimating AGB (Auerswald et al., 2012; Niu et al., 2008). However, ground-based approaches are costly, time-consuming, labour-intensive and are difficult to implement effectively in assessing the spatial variations of AGB, especially across large areas (Adjorlolo et al., 2012b; Psomas et al., 2011). There is therefore, a widespread consensus that remote sensing approaches hold a pivotal and irreplaceable role in monitoring the AGB of C3 and C4 grass species (Davidson and Csillag, 2003; Ustin and Gamon, 2010).

Remote platforms gather remarkable information on the condition, distribution, spatial configuration, invasion and spread of vegetation (Tieszen et al., 1997), which is relevant to the monitoring of C3 and C4 grasses AGB at both local and regional scales. Furthermore, the ability of remote sensing to frequently offer data in a spatially distributed manner, with varying resolutions, provides a valuable complimentary data source and opportunity to monitor these grasses, when compared to the use of *in situ* measurements (Adjorlolo et al., 2012a; Foody and Dash, 2007; Liu and Cheng, 2011). Since the emergency of remote sensing, the possibility of monitoring C3 and C4 grasses at different resolutions has been enlightened (Rigge et al., 2013; Tieszen et al., 1997). The advances in remote sensing technology, which have progressively expanded over the years, further enhance the ability to detect and distinguish the various morphological, physiological and phenological properties of C3 and C4 grass species, expanding their monitoring horizon.

This paper demonstrates the progress of remote sensing applications in determining the AGB of C3 and C4 grass species. Firstly, the review highlights the significance of functional types in the remote sensing of C3 and C4 grasses, as well as its implications on AGB quantification. Parallel to this, the effect of species properties (*e.g.* leaf area index and the concentration of photosynthetic pigments) in the remote sensing of C3 and C4 grasses is also provided. The applicability of the available remote sensing sensors in determining seasonal and long-term variations in C3 and C4 grass species AGB is also discussed in detail. The potential of different algorithms for the remote sensing of grasses functional types is explored and future prospects in the monitoring of C3 and C4 grasses AGB is also provided.

2.2. The importance of the remote sensing of vegetation according to functional types and its implications on AGB estimation

The use of species functional types, although it dates back to the 19^{th} century, has recently received renewed attention as a possible approach for monitoring vegetation conditions (Cousins and Lindborg, 2004; Gondard et al., 2003). Monitoring vegetation species according to functional type is an approach that quantifies the AGB of a group of species (*e.g.* grasses) that shares physiological, phenological and morphological properties. Compelling evidence has shown that functional types indicate close similarities of vegetation species in their use of resources and their responses (*e.g.* in their distribution and abundance) to environmental controls, such as climate variability (*e.g.* temperature and rainfall) or elevated CO_2 (Díaz and Cabido, 1997; Louault et al., 2005). It also shows that the differences between species of the same functional type (*e.g.* C3 grasses) is quite negligible, when compared to those between functional types, such as C3 and C4 grasses (Duckworth et al., 2000; Skarpe, 1996).

In addition, functional types influence variations in species AGB within an ecosystem (Homolová et al., 2013; Louault et al., 2005; Skarpe, 1996). Alterations in the key properties of species functional types (*e.g.* phenology) have a substantial effect on AGB and this can cascade across the ecosystem, with unpredictable consequences. Monitoring species AGB, based on functional types, is therefore indispensable, as it encompasses different species sharing morphological, physiological and phenological characteristics (Duckworth et al., 2000; Gondard et al., 2003; Ivits et al., 2013), thereby providing a powerful approach, when compared to the use of broad vegetation biomes (*e.g.* grasslands) or the taxonomic approach, which is typically performed at species level.

The use of species functional types in monitoring vegetation AGB, using field-based methods, remains restricted to small geographic coverage, for a specific period of time and, it focuses mainly on individual species (Homolová et al., 2013). Similarly, it is also impractical to develop models for monitoring C3 and C4 grass species at individual levels, considering the high demand for the large-scale monitoring of vegetation, especially in the light of the global effects of climate change and the provision of ecosystem services. Remote sensing therefore provides an invaluable means of monitoring vegetation AGB, according to their functional types.

Remote sensing offers spatially explicit data, repeated observations, covers large geographic areas, which cannot be achieved, when using ground-based observations (Díaz and Cabido, 1997; Ustin and Gamon, 2010). For instance, the study by Woodward et al. (2004) reported the potential of the MODIS sensor in mapping the global distribution of different vegetation functional types. The availability of time-series satellite data and repeated observations also allow consistent monitoring of species cyclic patterns (*i.e.* phenology), which is one of the key concepts of species functional types. This improves the monitoring of species AGB, based on their asynchronous seasonality. Remote sensors have the ability to spectrally and spatially differentiate the species functional types (*e.g.* C3 and C4) from broad vegetation biomes, such as grasslands (Homolová et al., 2013; Ustin and Gamon, 2010). For instance, a body of literature has reported the ability of remote sensing to distinguish between the C3 and C4 grass species functional types (Foody and Dash, 2007; Peterson et al., 2002; Price et al., 2002), which enhances the monitoring of their AGB. The ability of remote systems to detect the physiological and morphological characteristics of a species, which relate to AGB, also proves its potential in monitoring the species functional types.

Advances in technology with improved image acquisition characteristics have progressively expanded the ability to distinguish the structure, phenology and physiology of vegetation, providing new insights into the concept of species functional types (Adjorlolo et al., 2014; 2015; Ustin and Gamon, 2010). These systems have the capability to detect fine distinctions between species functional types, using hundreds of narrow spectral bands, ranging from the visible, near-infrared, to the shortwave-infrared portions of the spectrum. Thus, the aforementioned capabilities of remote sensing in discriminating and mapping C3 and C4 grass functional types become relevant in determining their AGB and contribution to the functioning of grassland ecosystems. Remote sensing also facilitates change detection in AGB between C3 and C4 grass species for carbon or climate change modelling. Detailed information on the use of remote sensing technology to monitor the AGB of C3 and C4 grass species functional types is described in the following sections.

2.3. Seasonal and long-term monitoring of C3 and C4 grass species AGB

C3 and C4 grass species AGB varies spatially and temporarily, due to the influence of topography (*e.g.* soil type) and climatic conditions (*e.g.* temperature and rainfall). Of particular importance is the phenology of the C3 and C4 grass species, which determines the temporal variability in their AGB (Pau and Still, 2014; Ricotta et al., 2003; Wang et al., 2013). At different phenological phases, these grasses exhibit variations in their exchange of energy, water and carbon fluxes, as well as in nutrient uptake, storage and release, throughout the growing season, influencing the availability and amount of AGB (Adair and Burke, 2010; Jin et al., 2013). The timing, availability and amount of AGB is therefore sensitive to any alterations to the phenological profiles (*e.g.* the onset of green-up) of these grasses (Rigge et al., 2013). These unique and asynchronous phenological profiles of C3 and C4 grass species therefore facilitate the seasonal monitoring of their AGB using remote sensing.

The seasonal monitoring of C3 and C4 grass species allows stakeholders to identify and predict potential variations in AGB, which is critical for effective management of forage, as well as for developing proper conservation strategies (Diouf et al., 2015). Moreover, Karlsen et al. (2008) stipulates that a shift in the phenological cycle (*e.g.* late green-up) of grasses is regarded as the foremost, immediate and observable indication of seasonal transition, due to environmental changes. This has immediate impacts on the timing of AGB, which affects the availability of forage for grazers. In this regard, the seasonal monitoring of these grasses AGB becomes more relevant, in the light of food security. In addition, a shift in the phenological cycle of C3 and C4 grasses can serve as a possible indicator of the effect of climate change on terrestrial ecosystems (Richardson et al., 2013).

Considering the current trends and the anticipated impacts of global climate change on vegetation, long-term and systematic observations of C3 and C4 AGB are required, given the possibility that these changes are difficult to detect with short-term observations. Long-term observations provide a better understanding of the ecological transition of C3 and C4 dominated grassland (Rigge et al., 2013). This is also supported by the studies of Diouf et al. (2015) and Eastman et al. (2013), which emphasized that any changes in vegetation AGB require repeated observations to be discernible. Long-term temporal coverage also increases the efficiency of rangeland management, by detecting areas of low AGB and the likely occurrence of degradation (Rigge et al., 2013), as well as assessing proper management practices to boost AGB (Atzberger et al., 2013).

Thus far, remote sensing of C3 and C4 grass species AGB has focused on the long-term temporal coverage, such as annual variations, using large spatial resolution datasets (Pau and Still, 2014; Rigge et al., 2013; Tieszen et al., 1997). For instance, the study by Pau and Still (2014) determined the annual AGB of C3 and C4 grass species, using MODIS, from the year

2000 to 2010, covering a period of ten years, whereas Tieszen et al. (1997) and Rigge et al. (2013) covered a period of five (1989-1993) and seven years (2000-2008), respectively. Nevertheless, a few studies have attempted to determine short-term or cyclic variations in C3 and C4 species AGB (Davidson and Csillag, 2001;). These studies were confined to specific phenological phases, such as the start or end of the season. For instance, the study by Davidson and Csillag (2001) was limited to a two-day coverage, at the start and end of the season, whereas Foody and Dash (2010) focused on the period when grass growth was most active. In this regard, the phenological or cyclical variations of AGB in C3 and C4 grass species have been underestimated. This has resulted in uncertainties about the actual variations in the AGB of these grass species, especially considering their asynchronous seasonality. In addition, the use of large spatial resolution also results in the poor representation of AGB of these species functional types.

2.4. C3 and C4 grass species properties and their influence on remote sensing measurements

Although remote sensing provides a valuable tool for monitoring the AGB of grass species, the properties (*i.e.* leaf/canopy properties) of C3 and C4 grasses affect the reliable and accurate retrieval of spectral reflectance measurements, thereby playing a fundamental role in the discrimination and AGB estimation accuracy of these grasses. C3 and C4 grasses exhibit different properties over time and space, which influence their interaction with the incoming radiation (Dengler et al., 1994; Ustin and Gamon, 2010). For instance, Asner (1998) highlighted that the spectral signature of grass leaves within the visible and near infrared (NIR) portions of the electromagnetic spectrum is primarily affected by its properties (*e.g.* leaf area index and water content), as well as the concentration of photosynthetic pigments (*e.g.* chlorophyll), within these grasses (Clevers and Gitelson, 2013).

In addition, it has also been discovered that leaf thickness, aggregation and orientation, strongly influence remote sensing measurements (Adam et al., 2010; Homolová et al., 2013). For instance, the study by Slaton et al. (2001) mentions that C4 grass leaves are significantly thinner, when compared to those of the C3 grass species. Leaves with thinner cell walls are generally associated with long palisade cells, which reflect more of incident radiation in the NIR region, than those with thick walls, which are normally associated with short, cylindrical mesophyll cells (Ollinger, 2011). The leaf internal properties of C3 and C4 grasses also influence the retrieval of reflectance and AGB estimation. C4 grass leaves are characterized by more compact, spongy mesophyll cells, when compared to their C3 counterparts (Ueno et al., 2006). The study by Slaton et al. (2001) postulates that this enables them to spread light deep into the interior of the leaves. In agreement, Ustin and Gamon (2010) noted that the more compact mesophyll cells also strategically increase the internal scattering of light, thereby reducing its transmission through the leaf. C4 leaves also constitute a denser vascular system, with small interveinal distances, when compared to C3 leaves (Dengler et al., 1994). This influences leaf water content, with both direct and indirect effects on reflectance from water and other leaf absorption properties, which are associated with water stress and hydration (Ollinger, 2011). C4 grass leaves have few intercellular air spaces, which reduce light scattering from the air-water interface, when compared to C3 leaves, which comprise less compact and thinner cell structures (Ueno et al., 2006).

Therefore, the spatial and temporal changes in the properties of C3 and C4 grass species (*e.g.* Leaf Area Index (LAI) and concentration of photosynthetic pigments) influence the ability of the remote sensing sensors to accurately estimate their AGB. Previous studies (Friedl et al., 1994; Madugundu et al., 2008) have, for instance, reported the relationship between LAI and spectral vegetation indices (*e.g.* NDVI), as well as with AGB. The study by Friedl et al. (1994) reported a significant relationship between LAI and AGB and they exhibit the same spatial variations with elevation and the same responses to burning. In this regard, variations in the LAI of C3 and C4 grasses influences the variations in their AGB, as well as the ability of the remote sensing systems to accurately discern these variations. Recent studies have reported that the application of multispectral sensors under a high canopy cover (high LAI) results in saturation problems (Dube et al., 2015; Mutanga et al., 2012). Thus, the accurate estimation of C3 and C4 AGB under a high canopy cover will be achieved, using more advanced sensors, with strategically-positioned bands. This underscores the need to identify suitable remote sensing datasets, as well as variables (*e.g.* vegetation indices), which have the ability to characterize and discern C3 and C4 species characteristics for optimal AGB estimation.

2.5. Remote sensing systems and their role in estimating the AGB of C3 and C4 grass species

Remote sensing systems hold great potential for monitoring grass AGB on a local and a global scale, due to the availability of various satellite datasets (Price et al., 2002). Above all, remote sensing presents an appropriate solution to the labour-intensive, spatial coverage and time challenges, which have been identified in the use of ground-based methods in estimating grass AGB (Psomas et al., 2011; Zhao et al., 2014). Ecological studies currently benefit from a variety of active and passive sensors, providing data at different resolutions, with the ability to extract various structural and physiological properties for determining grass AGB (Pau et al., 2013; Price et al., 2002; Ustin and Gamon, 2010). Moreover, remote sensors have the ability to detect important phenological indicators of grass species, such as the peak and senescence, which influence the timing and amount of AGB (Rigge et al., 2013).

A range of remote sensing platforms, with different image acquisition characteristics (Ahamed et al., 2011; Shen et al., 2014) are currently in orbit (Table 2.1), providing an opportunity for the seasonal and long-term monitoring of AGB for C3 and C4 grass species. The emergence of broadband multispectral sensors (in this study referred to as traditional multispectral sensors), such as the Landsat TM/MSS/ETM+, the Advanced Very High Resolution Radiometer (AVHRR), the Moderate Resolution Imaging Spectroradiometer (MODIS), the MEdium Resolution Imaging Spectrometer (MERIS) and the Satellite Pour l'Observation de la Terre (SPOT), *etc.* (Cocks et al., 1998; Dube et al., 2014) marked a new beginning of the continuous and systematic monitoring of C3 and C4 grass species AGB. The availability of these affordable and freely-accessible sensors at large geographic coverage, with a high frequency for some sensors (*e.g.* daily for MODIS and AVHRR) and a long history of earth imaging (*e.g.* AVHRR since 1978 and since 1972, for Landsat series data), have facilitated the long-term monitoring on a regional and global scale (Tieszen et al., 1997). For instance, the study by Tieszen et al. (1997) reported the potential (R^2 = 0.52) of AVHRR-derived NDVI in predicting C3 and C4 grass species AGB across the Great Plains of North America, over a five-year period. Multispectral sensors have also been useful in determining C3 and C4 grass species AGB at a particular seasonal stage or phenological phase. The study by Foody and Dash (2010) reported the ability (R^2 ranged from 0.46 - 0.52) of the MERIS sensor in estimating the variations of C3 grasses AGB, during the peak phenological phase.

Broadband multispectral sensors also form the backbone in the development of algorithms, which are currently available for the estimation of C3 and C4 grasses AGB, using remote sensing, and further facilitate advances in the development of algorithms. Specifically, much of the development in spectral vegetation indices, which are currently available to determine the spatial and temporal variations of grass AGB, was facilitated by the availability of multispectral sensors (Xie et al., 2008). For example, the widely-used Normalized Difference Vegetation Index (NDVI) was originally developed, using broadband channels from the Landsat data series. However, the use of freely-available medium-resolution sensors, such as Landsat (TM and MSS), has currently become a challenge, due to the fact that these satellites are no longer operating, whereas the ENVISAT MERIS mission became mulfunctional in early 2012. In the case of the Landsat ETM+, all images acquired after the 31st of May 2003 have since developed an anomaly caused by the failure of the Scan Line Corrector (SLC), which compensated for the forward motion of the spacecraft, so that all the scans were aligned parallel with each other. The malfunctioning of the sensor's SLC has since resulted in approximately 22% data loss of the normal scene area (Chander et al., 2009; Dube and Mutanga, 2015a; Storey et al., 2005). The failure of the aforementioned medium resolution sensors (*i.e.* Landsat TM, MSS, and MERIS) to deliver real time images and the loss of data for the operational ETM sensor has resulted in considerable challenges in estimating C3 and C4 grass species AGB, especially considering their better performance, when compared to MODIS or AVHRR sensors.

The development of hyperspectral sensors presents an advanced opportunity for the extraction of the important biophysical and chemical properties of vegetation (Asner et al., 2000; Clevers et al., 2007) and it thus holds greater potential for estimating grass AGB. These sensors constitute hundreds of narrow and unique spectral bands, which are strategically-positioned, increasing their ability to discriminate species spectral signatures for estimating species AGB (Lu et al., 2009; Mutanga et al., 2009). For example, the Airborne Visible and Infrared Imaging Spectrometer (AVIRIS) and Hyperion sensors deliver high resolution images in 224 and 220 spectral bands, respectively, at different wavelengths, ranging from 400 to 2500 nm. The narrow spectral bands of these sensors are capable of separating grass species functional types, as well as across complex mixed grasslands for the accurate estimation of AGB, which is very difficult, when using broadband multispectral images (Xie et al., 2008). The development of *in situ* hyperspectral spectrometers also plays a significant role in extracting accurate vegetation reflectance at different wavelengths, which is necessary for the estimation of grass AGB, at plot level, or for "project-based application" (Chen et al., 2009; Lu et al., 2009). However, the required pre-processing, high cost and limited spatial and temporal resolutions of hyperspectral data remain a challenge for their large-scale implementation or "wall-to-wall" monitoring, especially in resource-constrained regions (Adjorlolo et al., 2012b; Chen et al., 2009).

The advent of new generation sensors (*e.g.* Landsat 8, Worldview 2, Sentinel-2 MultiSpectral Instrument (MSI), Hyperspectral Infrared Imager (HyspIRI) and RapidEye (Dube et al., 2014; Mutanga et al., 2015; Pahlevan and Schott, 2013; Sibanda et al., 2015a), with advanced image acquisition characteristics, offers a new outstanding dimension for the accurate and timely estimation of C3 and C4 grasses AGB, especially at both local and regional scales. These sensors have improved resolutions, which enhance their performance in acquiring images, when compared to the traditional broadband multispectral sensors (*i.e.* MODIS, MERIS, *etc.*) (Dudley et al., 2015; Roth et al., 2015a). Most importantly, some of these sensors acquire data at high frequency, with a large geographic footprint (*e.g.* 5 days, at 290 km for Sentinel 2 MSI), in a cost-effective manner, hence the capacity to provide for the cyclical variations in C3 and C4 grass species AGB at large geographic coverage. Particularly, the strategically-positioned bands of some sensors (*e.g.* Worldview 2 and Sentinel 2 MSI) have the ability to extract the important subtle spectral variations in the structural, phenological and morphological characteristics of species functional types, at a more refined resolution (Roy et al., 2014), currently a challenge, when using broadband multispectral sensors.

Table 2.1: Availability of sensors for C3 and C4 grasses AGB estimation

Sensor	**Pixel size (m)**	**Swath width (km)**	**Bands**	**Revisit time**	**Acquisition Cost**	**Scale of application**	**Predictive Performance**
AVHRR	1100	2900	5	1	Readily available	Regional to global	Low
Hyperspectral	< 1	-	>100	-	Very Expensive	Plot	High
HyspIRI	60	600, 150	8, 213	5, 19	-	Local to regional	Not yet tested
IKONOS	4	11	5	1-2	Expensive	Local	Not yet tested
Landsat	30	185	7; 11	16	Readily available	Local to regional	Moderate
MERIS	300	1150km	15	3	Readily available	Regional	Low
MODIS	500, 1000	2330	7	1	Readily available	Regional to global	Low
Quickbird	2.4	16	5	1-3.5	Expensive	Local	High
RapidEye	5	77	5	5.5	Expensive	Local	High
Sentinel 2 MSI	10, 20, 60	290	13	5	Readily available	Local to regional	Not yet tested
SPOT	10, 20	120	4	26	Readily available	Local to regional	Moderate
SPOT VGT	1150	2250	-	1	Readily available	Regional to global	Low
Worldview 2	< 1	16.4	8	1-3.7	Very Expensive	Local	High

* Shaded rows represent sensors which have been used in estimating C3 and C4 grass species AGB, whereas unshaded rows are those sensors which have been used in AGB estimation for grasslands ecosystems, without considering species functional types

However, with a variety of remote sensing datasets available, the affordable and freely-accessible broadband multispectral sensors (Table 2.2), notably MODIS and AVHRR, have thus far been the primary data sources for the estimation of C3 and C4 grass species AGB (An et al., 2013; Davidson and Csillag, 2003; Foody and Dash, 2010; Pau and Still, 2014; Rigge et al., 2013). For instance, Pau and Still (2014) have shown the applicability of MODIS in determining the annual variations of C3 and C4 grasses AGB, over a ten-year period (2000 - 2010), whereas the study by Rigge et al. (2013) used the integrated weekly MODIS NDVI dataset to determine the annual variations in C3 and C4 grasses AGB. However, these studies also noted a high probability of overlap in grass species reflectance, which results in uncertainties, such as the over- or under-estimation of species AGB, due to the coarse spatial and spectral resolutions of the sensors. In addition, the AVHRR sensor acquires images, using only the red and the near infrared spectral bands, at a coarse spatial resolution, which is not sufficient to distinguish the varying spectral signatures; hence the AGB of species functional types is poorly represented.

The medium spatial resolution Landsat, SPOT and MERIS data series have also contributed to the remote sensing of C3 and C4 grass species AGB (Grant et al., 2013; Peterson et al., 2002). The use of these sensors yielded better predictive accuracy (Table 2.2), when compared to the use of MODIS and AVHRR. These studies reported that these sensors provide suitable datasets for assessing the temporal and spatial variations of grass AGB at a coarse temporal resolution, such as bi-weekly, monthly or at a specific phenological phase (*e.g.* the green-up phase). With the exception of a few studies (*e.g.* Lu et al. (2009)), the use of hyperspectral data in estimating the AGB of C3 and C4 grass species has thus far been proved to be difficult to achieve. This is supported by the fact that only a few studies have used these sensors, despite their high predictive accuracy in estimating AGB of species functional types, when compared to broadband multispectral sensors.

Table 2.2: The remote sensing of C3 and C4 grass species AGB

Method	Major findings reported	References
NOAA/AVHRR-based NDVI	The grass AGB derived using ground-based measurements and statistical modelling were significantly ($P = 0.037$) related to NDVI derived from NOAA/AVHRR. C3 and C4 grasses AGB measurements were moderately correlated ($R = 0.58$) with those derived from remotely sensed data.	Tieszen et al. (1997)
NOAA/AVHRR-based NDVI	The NDVI weekly composite data produced a reasonable agreement ($R^2 = 0.\ 54$) with field based measurements.	An et al. (2013)
Cropscan Multispectral Radiometer-based NDVI	A high measure of association (Kendall's $\tau = 0.778$) and strength of fit (Cohen's k =0.631) between NDVI and ground-based AGB was produced.	Goodin and Henebry (1997)
MERIS Terrestrial Chlorophyll Index (MTCI)	The MTCI has a potential to explain approximately 60% of the variation in the prediction of C3 grasses AGB, with a better relationship (R^2 of 0.62) from a weekly compositing period, compared to the use of longer time periods (*e.g.* two weeks, which produced an R^2 of 0.46).	Foody and Dash (2010)
MODIS-based NDVI	A moderate relationship ($R^2 = 0.58$) was reported between field measured C3 AGB and NDVI-based estimates. However, field data produced AGB ranging between 55.4 and 69%, while remotely sensed data estimates ranged from 78.9 to 84.4%. The study further reported that a significant overlap occurred, which led to an overestimation of C3 AGB from remotely sensed data.	Rigge et al. (2013)
MODIS-based NDVI	Remotely-sensed estimates resulted in the underestimation of C4 grasses AGB. The study reported that C4 accounted for only 39% of AGB.	Guan et al. (2012)
Exotech Model 100BX radiometer measurements, based on Landsat TM bands and VIs (NDVI, SAVI, MSAVI2, MSR, DVI, RDVI, RVI and IPVI).	C4 grasses AGB variations were best explained using NDVI, SAVI, MSAVI2, and MSR, producing an R^2 of 0.64, whereas the DVI explained the least variations with an R^2 of 0.51.	Davidson and Csillag (2001)
SPOT-based VIs (SR, NDVI, TVI, DVI, RDVI, MSR, NDGI and RI).	The RDVI and TVI yielded the best overall prediction ($R^2 = 0.68$), whereas the NDGI and the RI had the least overall predictions ($R^2 = 0.25$) of AGB, but only marginally better than the NDVI, MSR and other indices tested. Transformation of VIs using the power function improves statistical predictive capabilities to an R^2 range between 0.42 and 0.68, compared to untransformed indices (R^2 ranging from 0.25 - 0.62).	Grant et al. (2013)

Landsat TM 5-based NDVI	There were no significant differences (MANOVA, $p = 0.063$) between C4 and C3 grass species AGB, based on NDVI. The study also reported that there were inconsistencies between NDVI-based estimates and field-based measurements.	Peterson et al. (2002)
MODIS NDVI	The AGB of C3 and C4 grass species was not significantly different ($p = 0.07$), based on remote sensing NDVI. The study reported that there was a significant overlap, which led to an overestimation of C3 AGB from remotely sensed data, compared to field measurements.	Pau and Still (2014)
AISA Eagle Hyperspectral sensor	The band ratio method was the best approach for predicting AGB, with R^2 values of 0.96 and 0.69, compared to the use of the PCA, which produces the lowest R^2 values of 0.83 and 0.63, for the two C3 grass species, respectively.	Lu et al. (2009)

*SR = Simple ratio, NDVI = Normalised Difference Vegetation Index, TVI = Transformed Vegetation Index, DVI = Difference Vegetation Index, AISA = Airborne Imaging Spectroradiometer for Application, VI = Vegetation Indices, PCA = Principal Component Analysis, MANOVA = Multivariate Analysis of Variance

2.6. Available approaches for quantifying grass AGB using remote sensing

Different algorithms are available for quantifying C3 and C4 grass species AGB, using satellite remote sensing data (Table 2.3). The remote sensing of AGB can be achieved using either physical-based or empirical models (Fang et al., 2003; Hall et al., 1997). The physical-based approaches use radiative transfer models to estimate AGB (Darvishzadeh et al., 2008; Fang et al., 2003; Kimes et al., 2000). The study by Kimes et al. (2000) further reported that physical-based approaches use physical laws and the inversion of remote sensing data to derive vegetation biophysical properties. Although physical-based methods have been used, their application, especially for AGB estimation, has been limited. This might be attributed to the ill-posed nature of model inversion and the requirement of specific additional input variables (*e.g.* soil background reflectance), which complicates the successful inversion and estimation accuracy (Atzberger, 2004). Additional challenges include a large number of input parameters that must be specified, the computational load of inverting the radiative transfer models, and the fact that a stable and optimum inversion is not guaranteed (Houborg et al., 2007; Kötz et al., 2004; Walthall et al., 2004). The study by Kimes et al. (2000) also reported that physical-based methods do not appear to be a realistic alternative for the continuous operational application of remote sensing data. This poses challenges for the accurate estimation of AGB for C3 and C4 grasses functional types.

The empirical approach remains the widely-used approach for estimating AGB. Empirical methods involve the use of remote sensing variables (*e.g.* spectral bands, spectral vegetation indices and texture metrics) and statistical algorithms (Darvishzadeh et al., 2011; Hall et al., 1997) to estimate AGB. The approach relates remote sensing variables to *in situ* grass AGB, which enables the identification of the most suitable variable that optimally predicts grass AGB (Chen et al., 2009; Clevers et al., 2007; Jin et al., 2014). Algorithms developed for the remote sensing of AGB have been generally identified as parametric and non-parametric (Verrelst et al., 2015). Parametric algorithms assume a linear relationship between AGB and remote sensing variables, and the most commonly used are the simple and multiple linear regression models (Davidson and Csillag, 2001; Foody and Dash, 2010; Grant et al., 2013; Rigge et al., 2013; Tieszen et al., 1997). These have produced moderate predictive accuracies (R^2 ranging from 0.25 to 0.62), depending on the remote sensing dataset used to estimate C3 and C4 grasses AGB.

However, although they produce satisfying predictions in estimating grass AGB, the use of parametric algorithms is associated with multiple challenges. Researchers have pointed out that parametric algorithms are insufficient to capture the complex relationships between remote sensing variables and AGB (Lu et al., 2014; Verrelst et al., 2015). For instance, the stepwise linear regression fails to correspond with known absorption bands, and parametric methods suffer from multi-collinearity, over-fitting and produce unstable estimates, when using small sample sizes and missing values (Chen et al., 2009). Conversely, the more advanced and flexible non-parametric machine learning algorithms present a powerful tool for estimating grass AGB.

The more advanced machine learning algorithms enhance the predictive accuracy of grass AGB. These algorithms include the Partial Least Squares Regression (PLSR) (Wold et al., 1984), Sparse PLSR (SPLSR), Random Forest (RF) (Breiman, 2001), Discriminant Analysis (DA), Support Vector Machines (SVM), Artificial Neural Network (ANN) and Boosted Regression Trees (BRT), *etc*. These algorithms have been reported to be robust and more efficient alternatives, operating in a data-driven manner and reducing dimensionality problems with high accuracy, when compared to parametric algorithms (Rodriguez-Galiano et al., 2012; Verrelst et al., 2015). Machine learning algorithms thus overcome the challenges associated with the use of parametric algorithms, such as multi-collinearity (Chun and Keleş, 2010; Sibanda et al., 2015a), over-fitting, handling small sample sizes and missing values, among others (Barrett et al., 2014; Rogan et al., 2008). Moreover, unlike parametric algorithms, non-parametric machine learning approaches are independent of data distribution (*i.e.* normality) and are flexible, with large volumes of data from different sources (Barrett et al., 2014; Rogan et al., 2008). For example, the studies by Rogan et al. (2008) and Ramoelo et al. (2015b) reported that the RF explained over 84% variation of grass AGB. The study by Rogan et al. (2008) also regarded the RF as the most superior algorithm, which is robust to noise and outliers, and has the ability to handle thousands of input variables, as well as to estimate variable importance.

However, despite their outstanding predictive performance in estimating grass species AGB, using remote sensing, some of these machine learning algorithms are associated with some limitations. For example, ANN and SVM have been reported to be too complicated, too difficult to automate and they require an adjustment of large number of parameters (Mas and Flores, 2008). In addition, ANN is regarded as a black-box model, which does not easily reveal the internal mechanism of the relationship between the dependent and the selected independent variables (Lu et al., 2014; Mas and Flores, 2008; Verrelst et al., 2015), and if the parameters used are not properly optimized, AGB estimation accuracy may be poor (Mas and Flores, 2008). In addition, some machine learning algorithms tend to be site-specific, hence the models developed are not applicable to other environments (Lu et al., 2014), and in the case of RF, it has been reported that the algorithm tends to underestimate the high values and overestimate the low values of AGB.

Table 2.3: Available algorithms for C3 and C4 grasses AGB estimation, using remotely sensed data

Algorithm	**Remote sensing dataset**	**Performance (R^2)**	**Reference**
Simple linear regression	AVHRR	0.58	Tieszen et al. (1997)
	MERIS	Ranged from 0.46 – 0.62	Foody and Dash (2010)
	MODIS	0.58	Rigge et al. (2013)
	Envisat MERIS	Ranged from 0.51 – 0.64	Davidson and Csillag (2001)
	MODIS	Ranged from 0.25 – 0.68	Grant et al. (2013)
Stepwise multiple linear regression	Eagle Airborne Imaging Spectroradiometer for Application (AISA)	Ranged from 0.63 – 0.96	Lu et al. (2009)
*RF	WorldView-2	Ranged from 0.84 - 0.91	Ramoelo et al. (2015b)
*PLSR	Hyperspectral	Ranged from 0.52-0.54	Chen et al. (2009)
*SPLSR	Hyperspectral Sentinel 2 MSI Landsat 8 OLI	0.92 0.76 0.65	Sibanda et al. (2015a)
*SVM	Hyperspectral	0.683 – 0.751	Marabel and Alvarez-Taboada (2013)
*ANN	Landsat ETM+ 7	0.817	Xie et al. (2009)

Algorithms with steric (*) are the more advanced which have been used in grassland AGB estimation, but have not yet been fully explored (based on available literature) in remote sensing of C3 and C4 grasses functional types

The quantification of grass AGB can also be achieved using advanced aircraft, such as the Small Unmanned Aircraft System (SUAS) (Wang et al., 2014; Watts et al., 2010; Zhang and Kovacs, 2012). These systems have the capability to acquire high spatial and temporal resolution images at lower altitudes, under different weather conditions (*e.g.* without the influence of cloud cover), have the potential to acquire data from a smaller geographic area and upscale it to aerial photos or satellite images that cover larger geographic areas, and they have therefore been successfully used in grassland ecosystems, especially of the developing world (Rango et al., 2009; Zhang and Kovacs, 2012). Consequently, although they hold the potential to monitor grasses functional types (*i.e.* C3 and C4), their application is limited by their cost.

2.7. Challenges of remote sensing of C3 and C4 grass species AGB

Despite the availability of different remote sensors with considerable potential to estimate C3 and C4 grasses AGB, finding the correct dataset, with the optimal spectral and spatial resolution, remains a major challenge to the remote sensing community. Currently, C3 and C4 AGB estimates are required over a large geographic coverage. Similarly, these sensors should also be able to provide sufficient information for well-informed management and conservation purposes at a reasonable cost and accuracy.

Thus far, the available data on C3 and C4 grass species AGB have been derived, using coarse spatial resolution datasets, such as MODIS and AVHRR. Despite having a global footprint, a high frequency, being readily available and having a longer history of operation, which are all necessary for seasonal and long-term monitoring, data from these sensors have a low prediction accuracy (see Table 2), especially in mixed grasslands, which makes it difficult to apply and monitor these grasses. The spatial and spectral infidelity of MODIS in estimating C3 and C4 grasses AGB has been recently reported (Grant et al., 2013; Rigge et al., 2013). For instance, the study by Rigge et al. (2013) reported that remotely sensed AGB estimates, using MODIS, resulted in a significant overlap between the C3 and C4 grass species, which led to an overestimation of C3 AGB. The spatial resolution of MODIS is less appropriate to adequately characterise the inherent heterogeneity in mixed grassland ecosystems. These sensors fail to discriminate spatial and spectral variations in mixed grasslands, hence posing significant challenges in the estimation of C3 and C4 grassland AGB. Low spatial resolution sensors also result in inconsistency, with regard to the scale of observation, between the ground-based sampled plots and the satellite imagery (Shen et al., 2014). This results in uncertainties in the estimation of AGB, although the estimates are provided over a large geographic coverage.

Moreover, broadband sensors sample at wavelengths that are too wide to distinguish subtle, but important, features that are related to the physiological and biochemistry properties of species functional types (Ustin and Gamon, 2010). The study by Forkel et al. (2013) has emphasized that one of the key elements for the application of remote sensing datasets in determining vegetation species AGB, lies in their ability to extract species structural, physiological and morphological characteristics over space and time. In this regard, the applicability of MODIS, AVHRR and other related multispectral sensors, with a coarser spatial and spectral resolution, is discredited. Currently, the failure of the SLC of the operational Landsat ETM+ (which result in 20% data loss) and the lack of services of other freely-available broadband multispectral satellites (*e.g.* Landsat TM, MSS and MERIS), with a better estimation accuracy, also affect the accurate monitoring of AGB of C3 and C4 grass species functional types, especially considering the current demand of vegetation information and their role in the carbon cycle, in the light of current and projected climate change effects.

In this regard, the remote sensing community is caught in the inherent trade-offs between image acquisition costs, spectral and spatial resolution, geographic coverage, as well as optimal prediction accuracies in determining AGB variations of C3 and C4 grass species, using the available sensors. Studies which have been conducted using broadband multispectral data have shown low accuracies, when compared to high resolution datasets, for instance, the study by Lu et al. (2009) demonstrates this aspect.

The use of vegetation indices is also one of the major concerns in estimating the temporal variations of C3 and C4 grasses AGB using remote sensing. Initially, the remote sensing of C3 and C4 grasses AGB was estimated using spectral band information and vegetation indices, such as the standard NDVI, derived from the NIR and red bands (Paruelo et al., 1999; Tieszen et al., 1997). However, some studies that have been conducted in grassland ecosystems, have reported the limitations of NDVI in estimating grass AGB (Chen et al., 2009; Kawamura et al., 2005), which include its poor performance in sparsely vegetated areas and its saturation problem in densely vegetated areas or during the peak phase (Mutanga et al., 2012; Mutanga and Skidmore, 2004a). This has prompted researchers to develop and implement other indices, which outperform the NDVI, such as the NDVI-based indices (*e.g.* NDVI derived using red edge bands) (Mutanga et al., 2012), the Enhanced Vegetation Index (EVI), the Soil Adjusted Vegetation Index (SAVI) and the Modified Soil Adjusted Vegetation Index (MSAVI) (Davidson and Csillag, 2001; Foody and Dash, 2010; Grant et al., 2013). For instance, the study by Grant et al. (2013) has reported the better performance of SAVI, EVI and MSAVI indices in estimating C3 and C4 grasses AGB, using SPOT imagery under sparsely vegetated areas, when compared to NDVI. The study further reported an increase in predictive accuracy, when using transformed vegetation indices in estimating the AGB of C3 and C4 grasses. The implementation of an appropriate algorithm in estimating the spatial and temporal variations of C3 and C4 grasses AGB is also of particular importance. Different algorithms exist for estimating AGB, using remote sensing data (Table 3), and their performances may vary, depending on the remote sensing dataset used. The study by Lu (2006) has also emphasized the importance of an appropriate algorithm for identifying the optimal remote sensing variables to improve the AGB estimation accuracy.

2.8. Progress on C3 and C4 grasses AGB estimation over the years and the future

The influence of inter-seasonal variability in C3 and C4 grass species AGB, due to changes in climatic conditions, has been undermined by previous studies, using broadband multispectral remote sensing datasets. This underscores the need for a substantial attention to the remote sensing of cyclical AGB in C3 and C4 grasses, which is a fundamental step towards the management of these grasslands. With the current demand for vegetation information at a regional scale, the future of C3 and C4 grasses AGB estimation lies on the implementation of remote sensing datasets, with appropriate resolutions, variables, as well as algorithms, which improve the prediction accuracy. The advances in remote sensing datasets at more refined resolutions have renewed the monitoring of C3 and C4 grasses AGB. As a major forage supply of wildlife and livestock, with multi-functions, the remote sensing of C3 and C4 grassland will be continuously advanced in the next millennium, as societal and ecological demands increase.

The availability of more advanced and affordable new generation sensors, with improved spatial (*e.g.* RapidEye and Worldview-2), temporal (*e.g.* newly launched Sentinel-2 MSI and the Hyperspectral InfraRed Imager (HyspIRI)), spectral (*e.g.* Sentinel-2 MSI) and radiometric (*e.g.* the Landsat 8 OLI) resolutions, offers a unique opportunity for the remote sensing of grass species AGB, based on functional types. For instance, the upcoming HyspIRI sensor will deliver 14-bit imagery, using the visible and shortwave infrared imaging spectrometer, with 213 spectral bands between 380 and 2 500 nm, and the multispectral thermal infrared instrument, with eight spectral bands (Devred et al., 2013), making it more sensitive to detect and distinguish subtle differences in grass species reflectance, that are undetectable, using broadband multispectral sensors. The Landsat 8 OLI has improved radiometric resolution (12-bit), signal to noise ratio and a refined NIR band (Dube and Mutanga, 2015b; El-Askary et al., 2014; Shoko et al., 2015), which enhance its sensitivity to grass species characteristics, compared to its predecessors. These sensors therefore provide potential prospects for future studies, to improve the monitoring of C3 and C4 grass species AGB.

Studies that have used new generation sensors have demonstrated that they have the potential to characterize various species parameters. For instance, the study by Ramoelo et al. (2014) reported that the Sentinel-2 MSI sensor has a unique spectral configuration, which has a high potential to monitor the AGB of rangelands. Similarly, Dudley et al. (2015) demonstrated the possibility of using the HyspIRI imagery, as representing new access to high spectral resolution imagery for vegetation mapping and ecosystem monitoring. They reported that the sensor presents an opportunity to integrate the phenological effects in mapping species that have so far been unavailable. This was also confirmed by Roth et al. (2015a), who reported the applicability of the HyspIRI imagery in mapping species distribution, disturbance and ecosystem function on a scale much larger than ever before. The recent study by Sibanda et al. (2015a) has also reported the better performance (R^2 = 0.76) of Landsat 8 OLI in estimating grass AGB under different management practices. In this regard, the future research on the monitoring of C3 and C4 grass species AGB is enlightened, and the improved properties associated with new generation datasets are more likely to offer the better temporal characterization of these grass species, for the better management of rangelands, in order to maintain food security, biodiversity and carbon cycling.

With refined spatial and temporal resolutions, some of the new generation sensors provide appropriate datasets to monitor the inter-seasonal or cyclical variability in C3 and C4 species AGB, which is a major challenge of the multispectral datasets. For instance, the Sentinel 2 MSI has two bands within the red edge, which can be used to derive vegetation indices for the estimation of C3 and C4 grasses AGB (Clevers and Gitelson, 2013). Studies which have used vegetation indices derived from the red edge band (Mutanga et al., 2012; Ramoelo et al., 2015b) reported improved performance in estimating grasses AGB, when compared to the standard NDVI, derived from the NIR and red bands. Similarly, the high temporal resolution of Sentinel 2 MSI (5 days) and spatial coverage (290 km swath width) provide appropriate data for the large-scale monitoring of C3 and C4 cyclical AGB, especially in the light of environmental changes.

In addition, the variations in the proportion of C3 and C4 grass species AGB at different phenological phases is also a possibility, for understanding the contribution of these grasses to food security over time. With varying temporal conditions, it is most likely that species AGB to support grazer populations will be different. This is supported by a study by

Bremond et al. (2012) in Colorado, USA, who reported that, although C3 grasses covered more than 50% of the area, they account for only 10% of AGB. Therefore, not only does the distribution, or the spatial extent of C3 and C4 grasses influence the functioning of the ecosystem, but also the proportion of their AGB over space and time.

The use of more advanced non-parametric algorithms in estimating C3 and C4 grasses AGB has also been undermined, despite their higher predictive accuracy, when compared to parametric algorithms, even when using the broadband multispectral sensors. Advanced machine learning algorithms improve the use of remote sensing data to quantify grasses AGB. Studies which have been conducted in grassland ecosystems in general, have reported the potential of advanced algorithms in predicting AGB (Cho et al., 2007; Mutanga et al., 2012; Ramoelo et al., 2015b). For instance, the study by Cho et al. (2007) reported the potential of the partial least squares, using hyperspectral indices, whereas Mutanga et al. (2012) and Ramoelo et al. (2015b) reported the strength of the random forest in the prediction of grasses AGB. Although these algorithms have not been specifically tested for the estimation of C3 and C4 grass species AGB, their reported high predictive performance in grassland ecosystems in general, offer great potential for C3 and C4 grasses. In the absence of remote sensing datasets, it is also possible to resample field spectra to upcoming or existing sensors' band settings, in order to explore their potential in estimating grasses AGB (Sibanda et al., 2015a). Resampling of hyperspectral measurements is becoming a reliable alternative in testing the potential of available or upcoming sensors, especially considering the challenges associated with hyperspectral datasets.

2.9. Conclusion

The remote sensing of C3 and C4 grasses AGB has gained considerable attention, since the emergence of broadband multispectral datasets, which have enabled substantial research to be conducted over the past decades. Although multispectral sensors were the primary data sources for the estimation of C3 and C4 grass species AGB, their large pixel resolution imposes significant challenges in discerning subtle, but important and relevant, grass species parameters. Similarly, hyperspectral datasets are associated with their own challenges, including their small geographic coverage, their acquisition cost and pre-processing. This underscores a shift towards the use of affordable new generation sensors, with strategically-positioned spectral bands, high temporal resolution and large geographic coverage, in the estimation of C3 and C4 grass species AGB. The development of these sensors, such as

Sentinel 2 MSI, provides an invaluable opportunity for the phenological monitoring of C3 and C4 grasses AGB, which is a challenge, when using broadband multispectral sensors. The advances in algorithms have the potential to improve the identification of the optimal remote sensing variable for the accurate estimation of C3 and C4 grasses AGB. This prompt the need for future studies to test the applicability of new generation sensors, with advanced image acquisition characteristics, coupled with the use of non-parametric and robust machine learning algorithms, such as Discriminant Analysis, random forest, partial least squares, support vector machines and neural networks, for the well-informed management of rangelands.

The review has provided detailed progress in the remote sensing of C3 and C4 grasses AGB. It was noted that information on the variability of C3 and C4 grass species AGB over space and time is still rudimentary and uncertain. A lack of appropriate sensors is one of the major challenges to characterize these species. Emerging new generation sensors have also been identified to offer better characterization of C3 and C4 grass species AGB. To have a better characterization of these species AGB or accounting for their productivity over space and time, their discrimination becomes a fundamental foundation. The next chapter therefore constitute an experimental survey that tested the potential of emerging sensors' spectral settings in the seasonal discrimination of C3 and C4 grass species, using in situ hyperspectral measurements.

CHAPTERS THREE TO FIVE

C3 AND C4 GRASS SPECIES DISCRIMINATION

View of *Festuca* (C3) dominated landscape, with a patch of *Themeda* (C4) in the study site (Photograph courtesy: Trylee Matongera; in May 2016).

CHAPTER THREE

3. Seasonal discrimination of C3 and C4 grasses functional types: An evaluation of the prospects of the varying spectral configurations of the new generation sensors

This chapter is based on:

Shoko C and Mutanga O (2017a): Seasonal discrimination of C3 and C4 grasses functional types: An evaluation of the prospects of the varying spectral configurations of the new generation sensors. *International Journal of Applied Earth Observations and Geoinformation*, (62):47–55.

Abstract

The present study assessed the potential of varying spectral configurations of Landsat 8 Operational Land Imager (OLI), Sentinel 2 Multi-Spectral Instrument (MSI) and Worldview 2 sensors in the seasonal discrimination of *Festuca costata* (C3) and *Themeda Triandra* (C4) grass species in the Drakensberg, South Africa. This was achieved by resampling hyperspectral measurements to the spectral windows corresponding to the three sensors at two distinct seasonal periods (summer peak and end of winter), using the Discriminant Analysis (DA) classification ensemble. In summer, standard bands of the Worldview 2 produced the highest overall classification accuracy (98.61%), followed by Sentinel 2 (97.52%), whereas the Landsat 8 spectral configuration was the least performer, using vegetation indices (95.83%). In winter, Sentinel 2 spectral bands produced the highest accuracy (96.18%) for the two species, followed by Worldview 2 (94.44%) and Landsat 8 yielded the least (91.67%) accuracy. Results also showed that maximum separability between C3 and C4 grasses was in summer, while at the end of winter considerable overlaps were noted, especially when using the spectral settings of the Landsat 8 OLI and Sentinel 2 shortwave infrared bands. Test of significance in species reflectance further confirmed that in summer, there were significant differences ($P < 0.05$), whereas in winter, most of the spectral windows of all sensors yielded insignificant differences ($P > 0.05$) between the two species. In this regard, the peak summer period presents a promising opportunity for the spectral discrimination of C3 and C4 grass species functional types, than the end of winter, when using multispectral sensors. Results from this study highlight the influence of seasonality on discrimination and therefore provide the basis for the successful discrimination and mapping of C3 and C4 grass species.

Keywords: spectral-separability-windows, Festuca costata, Themeda triandra, climate change, carbon cycle, ecosystems goods and services

3.1. Introduction

C3 and C4 grasses represent a unique species functional type, which influences the function and provision of ecosystem goods and services. For instance, C3 and C4 grass species play an important role in regulating the carbon cycle, whereby C4 species store more carbon, when compared to their C3 counterparts (Foody and Dash, 2007; Pau and Still, 2014). C3 and C4 grasses also play a fundamental role in maintaining biodiversity and are an important source of forage for livestock and wildlife populations (Mansour et al., 2012a; Niu et al., 2008; Pau and Still, 2014). The ability of these grass species to provide services also varies with season (Pau and Still, 2014; Rigge et al., 2013; Wang et al., 2013). For instance, the study by Rigge et al. (2013) has highlighted that the timing or availability of rainfall and temperature variations influence the phenology and chemical processes of C3 and C4 grasses. However, the current and projected environmental changes, notably temperature and rainfall variations, are more likely to compromise C3 and C4 grass species' distribution, seasonal forage availability and timing (Díaz and Cabido, 1997; Xia et al., 2014). There is also a growing concern that increase in atmospheric CO_2 concentrations will be favourable to C3 species, and they are more likely to increase in distribution and abundance at the expense of C4 (Barbehenn et al., 2004; Bremond et al., 2012). On the other hand, other studies (Adair and Burke, 2010; Niu et al., 2008) have reported that increase in temperature favour C4, when compared to C3. Therefore, accurate and routine information is required to monitor these grass species functional types, especially considering the anticipated environmental change effects, their contribution to biodiversity conservation, biochemical cycles (*e.g.* carbon cycle) and most importantly food security.

Remote sensing has proven to be a suitable means to monitor the subtle seasonal variations of vegetation species, according to their functional types (Roth et al., 2015b; Woodward et al., 2004). The ability of remote sensors to spectrally distinguish species functional types, as well as detecting species physiological and morphological characteristics further enhances the seasonal discrimination for mapping and monitoring (Homolová et al., 2013; Ustin and Gamon, 2010). Spectral discrimination of C3 and C4 grass species, using remotely sensed data could provide a basis for mapping their spatial variations, with high accuracy, as well as a platform upon which to determine their possible shifts, especially in the face of climate change. Advances in sensor technology with improved image acquisition characteristics have progressively expanded the ability to distinguish the structure, phenology and physiology of vegetation, providing new insights into the seasonal monitoring of C3 and C4 species functional types (Adjorlolo et al., 2014; Adjorlolo et al., 2015; Shoko et al., 2016b; Ustin and Gamon, 2010). Moreover, with different emerging remote sensing systems, knowledge of the seasonal spectral dynamics of C3 and C4 grasses provides a foundation on the relevance of these systems in discriminating grass species according to their functional types.

Currently, *in situ* hyperspectral data is regarded as one of the most advanced remote sensing technology for vegetation discrimination at species level and its measurements have been successfully acquired to extract and understand species spectral profiles (Adam et al., 2010). The technique acquires detailed spectral data using hundreds of narrow bands, ranging from the visible, near-infrared, to the shortwave-infrared portions of the spectrum (Adam et al., 2012; Adelabu et al., 2014; Liu and Cheng, 2011), which enables accurate and reliable seasonal spectral separability of C3 and C4 grasses. However, previous studies (Adam et al., 2012; Adjorlolo et al., 2013; Peerbhay et al., 2015) have noted that the high expenses required for the acquisition of hyperspectral data, as well as the high dimensionality, inherent multi-collinearity associated with the data and technical difficulties concerned with the extraction of information and data analysis impose challenges in species discrimination. The study by Price et al. (2002) also reported a decrease in the discrimination accuracy when using hundreds of bands. This has prompted researchers to resample hyperspectral measurements to the spectral configuration of existing multispectral sensors to determine accurate species spectral signature (Adam et al., 2012; Adelabu and Dube, 2015; Sibanda et al., 2015b). The resampling of hyperspectral measurements has also been frequently performed to examine the potential and suitability of sensors' spectral configuration or settings in discriminating vegetation species. The future of C3 and C4 grass species monitoring therefore lies on the potential of the operational and upcoming multispectral sensors.

The new generation of multispectral sensors that have emerged, which are characterised by strategically-positioned spectral bands, notably the Landsat 8 Operational Land Imager (OLI), Sentinel 2 Multi-Spectral Instrument and Worldview 2 present a valuable opportunity to monitor the seasonal variations of C3 and C4 species functional types (Shoko et al., 2016b). These sensors have improved image acquisition characteristics for detecting subtle spectral seasonal variations between C3 and C4 grasses, critical in their discrimination and monitoring. For example, the additional red edge bands (*e.g.* four bands for Sentinel-2 MSI and 1 for Worldview-2) are perceived to have the capability of expanding the detection windows for the spectral separability of C3 and C4 grass species. In addition, red edge windows have been reported to be highly sensitive to vegetation species characteristics (Marshall et al., 2012; Mutanga et al., 2012; Rapinel et al., 2014), which improve their ability to discriminate between species. The high frequency and large swath width (*e.g*. 285 km of Sentinel 2) further enhance the cyclical monitoring of C3 and C4 species at large geographic scales (Stratoulias et al., 2015). The studies by Richter et al. (2012) and Immitzer et al. (2016) highlighted the strength of the spectral configuration of Sentinel 2 in estimating crop leaf area index and tree species classification, respectively. Landsat 8 OLI has also been reported for vegetation monitoring, particularly species biomass quantification and mapping (Dube and Mutanga, 2015a; El-Askary et al., 2014; Hauglin and Ørka, 2016). These studies have revealed the potential of the sensor spectral configuration (*e.g.* refined near infrared band) in expanding the monitoring of vegetation at large geographical coverage, in a cost effective manner. However, the performance of these sensors in discriminating and mapping C3 and C4 grass species remains unknown.

Therefore, in an attempt to renew and expand the continuous monitoring of vegetation species according to functional types, this study assessed the potential of the Landsat 8 OLI, Sentinel 2 MSI and the Worldview 2 spectral configurations in discriminating between C3 and C4 grass species at two distinct seasons, using *in situ* hyperspectral measurements. Despite the importance of spatial resolution or any other image acquisition characteristics, which play significant roles in species discrimination, this study held these characteristics constant. This was aimed to evaluate the robustness of new generation spectral configurations in the seasonal discrimination of C3 and C4 applications. Although the mentioned sensors are available for monitoring C3 and C4 spectral discrimination; the high acquisition cost of Worldview 2 present a major challenge to understand the seasonal spectral differences of the target grasses. In addition, hyperspectral data provide the most accurate and reliable measures of species spectra and the high dimensionality and large volumes of the data further emphasize the need for spectral resampling to reduce such problems. The objectives of this research were therefore to: (i) determine the most suitable seasonal period to spectrally distinguish and classify *Festuca* (C3) and *Themeda* (C4) grass species, with better accuracy, (ii) identify the most relevant sensor's spectral windows in seasonal discrimination of the two grasses and (iii) identify the most relevant variables (among standard bands, vegetation indices and combined indices and standard bands) in the seasonal discrimination of the two species when using multispectral sensors.

3.2. Materials and Methods

3.2.1. Field data collection

The collection of hyperspectral data was conducted at two distinctive seasons; specifically during the peak of summer (February) and end of winter (August) in 2016. The target grasses were *Festuca costata* (C3) and *Themeda triandra* (C4) grass species, which predominantly occur in the area. In addition, a close association has been noticed between these two species with different photosynthetic pathways. Hyperspectral measurements were collected during the two periods, using an Analytical Spectral Device (ASD) FieldSpec spectrometer (FieldSpec®3, ASD, Inc., Boulder, CO, USA). The ASD device records canopy reflectance between the range of 350 and 2500 nm. The collection of spectral measurements was performed using a random sampling strategy after Adjorlolo et al. (2012a). The reflectance data for the target grasses was recorded between 1000 hr and 1400 hr, under clear conditions, which is regarded as the ideal period for determining vegetation spectral characteristics. Spectral measurements were also normalized using a standard white panel to take into account any changes in the atmospheric condition and irradiance of the sun (Sibanda et al., 2015b). In each plot, 30 spectral measurements were consistently taken at nadir, for each grass species. A total of 120 plots were sampled for each grass resulting in 3600 spectral samples, for each season.

3.2.2. Spectral resampling

Prior to analysis using hyperspectral measurements, previous studies (Adjorlolo et al., 2013; Thenkabail et al., 2004) have emphasized the removal of some noise wavelengths in the spectral range of 350–390, 1350–1440, 1790–1990 and 2360–2500 nm. The data were then resampled to Landsat 8 OLI, Sentinel 2 MSI and Worldview 2 sensors spectral configuration using the spectral analysis routine in ENVI 4.7 software (ITT Visual Information Solutions, 2009).The technique fits a Gaussian model with the Full Width at Half Maximum (FWHM) equal to a specified band width. The procedure involved resampling in situ data to the specific bandwidth interval across the 400 – 2500 nm spectrum, matching those of the Landsat 8, Sentinel 2 and the Worldview 2. This was done to simulate the spectral response function of the sensors presented in Table 3.1. Detailed information on this hyperspectral resampling approach used in this study is provided in Adjorlolo et al (2013). In addition, not all bands of the three sensors were considered for resampling and analysis in this study. For example, using the Landsat 8, the thermal infrared and the panchromatic bands were excluded. Similarly, for the Sentinel 2, bands 1 (coastal aerosol), 9 (water vapour) and eleven (SWIR cirrus) were also excluded. These bands were previously reported to be inapplicable for vegetation monitoring (Féret et al., 2015; Immitzer et al., 2016). For the Worldview 2, all bands were considered for resampling and further analysis.

Table 3.1: New generation sensors spectral configurations

	Sentinel 2 MSI			**Landsat 8 OLI**		**Worldview 2**	
Band	Name	Centre	Width	Name	Range	Name	Range
1	*Coastal aerosol*	443	20	Coastal blue	435-451	Coastal blue	400–450
2	Blue	490	65	Blue	452-512	Blue	450–510
3	Green	560	35	Green	533-590	Green	510–581
4	Red	665	30	Red	636-673	Yellow	585–625
5	Red edge	705	15	NIR	851-879	Red	630–690
6	Red edge	740	15	SWIR1	1566-1651	Red edge	705–745
7	Red edge	783	20	SWIR2	2107-2294	NIR1	770– 895
8	NIR	842	115	*Panchromatic*	*503-676*	NIR 2	860–1040
8a	Red edge	865	20				
9	*Water vapour*	945	20	*Cirrus*	1363-1384		
10	*SWIR-Cirrus*	1375	30	*TIR1*	1060-1119		
11	SWIR	1375	30	*TIR2*	1150-1251		
12	SWIR	2190	180				

Italized bands were not used in this analysis

3.3. Data Analysis

To determine the potential of the three sensors' spectral configuration in discriminating the two species functional types at two distinct seasonal periods, the Discriminant Analysis (DA) function embedded in Microsoft Excel 2013 was used. The data used with the DA was randomly split into 30% testing and 70% training sets, which is a requirement for all machine learning algorithms (Adelabu et al., 2014; Adjorlolo et al., 2013; Sibanda et al., 2015a). The training sample trains the model in discriminating between the two species, whereas the test sample validates the performance of the model. The DA function was used to: (i) determine the most suitable seasonal period to spectrally distinguish and classify *Festuca* and *Themeda* grass species with better accuracy, (ii) to identify the relevant sensor's spectral configuration in seasonal discrimination and classification of the two grasses and (iii) identify the most relevant variables in the seasonal discrimination of the two species. The vegetation indices which were used with the resampled hyperspectral measurements are shown in Table 3. 2. These indices were chosen based on their performance in discriminating C3 and C4 grass species, which has been reported by previous studies (Adjorlolo et al., 2012a; Davidson and Csillag, 2001; Peterson et al., 2002; Price et al., 2002).

Table 3.2: Vegetation indices calculated using the resampled hyperspectral measurements

Vegetation Index	Formula	Reference
Simple ratio	NIR/R	Jordan (1969)
Standard NDVI	(NIR–R)/(NIR+R)	Tucker (1979)
NDVI 4	(NIR2− Y)/(NIR2+ Y)	Adjorlolo et al. (2012)
NDVI 5	(RE− CB)/(RE + CB)	Adjorlolo et al. (2012)
SAVI	((NIR2-R)*(1+L))/(NIR2+R+L)	Huete (1988)
G Chl index	(NIR2/G)-1	Gitelson et al. (2003)
EVI	2,5((NIR2-R)/(1+NIR2+6R-7,5*B))	Huete et al. (1997)

3.3.1. Accuracy assessment

The classification accuracy for the two species at different seasonal periods was assessed using the classification matrices generated from the DA model. The classification accuracies of the individual species using the different variables derived from the resampled data were also reported using the user's and producer's accuracies. The method by Pontius Jr and Millones (2011) was also used to assess the seasonal classification accuracies produced by the different sensors' spectral configuration for the two species. The method provides accuracy assessment at individual classes (*i.e.* species level) using the errors of omission and commission, which in this case measure the seasonal ability of the resampled variables to correctly classify the target species. Commission error stems from the incorrect inclusion of the species in the other class or category, whereas omission error occurs when a sample of a particular class is excluded from the class under consideration (Zhou et al., 2014). Statistical significance test was also performed to determine significance difference in seasonal reflectance between the two species using the different sensors spectral settings. The overall classification accuracies derived from the three sensors spectral configurations were also tested for significance difference. These tests were performed using the T-test of significance embedded in Microsoft Excel 2013.

3.4. Results

3.4.1. Grass species spectral response patterns during the two distinct seasonal periods

Figure 3.1 shows the derived seasonal spectral response patterns of *Themeda* and *Festuca* grasses, using hyperspectral measurements resampled to Landsat 8, Sentinel 2 and Worldview 2 spectral configurations. The graph illustrates that *Themeda* grass species exhibit higher reflectance across the spectrum, when compared to the *Festuca*. The two grass species were spectrally distinct during the summer period across the spectrum of all the sensors spectral configuration. During winter, although there were considerable spectral separability for some portions of the spectrum (*e.g.* Sentinel 2 bands 5 to 8), it was noted that using the

Landsat 8 spectral configuration, notably the SWIR bands 6 and 7, the two species were spectrally identical. The same was observed from SWIR band 10 of Sentinel 2 and red band 5 of Worldview 2. The visual comparison was also confirmed by the T-test of significance difference in reflectance between the two species at different spectral windows. In summer, the spectral difference between *Festuca* and *Themeda* was significant ($P < 0.05$), for all bands of the sensors spectral configuration, whereas in winter, a limited number of bands exhibited significant differences ($P < 0.05$), notably all sensors' blue band.

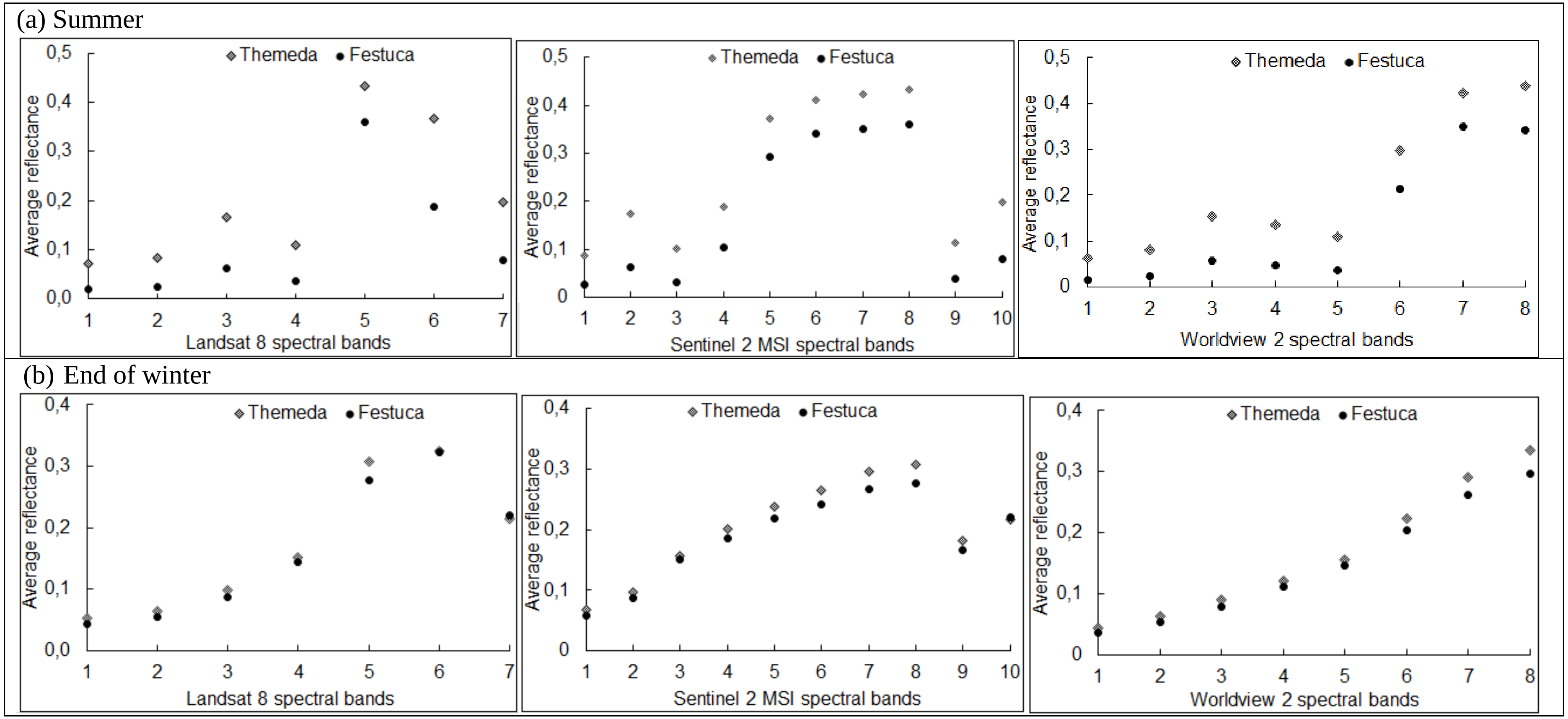


Figure 3.1: Seasonal spectral signatures of the two species derived from averaged resampled hyperspectral measurements

3.4.2. Influence of sensor variables on seasonal species discrimination

Overall, all sensors' spectral configurations revealed high potential in seasonal discrimination of the two grass species functional types, especially in summer. The Sentinel 2 MSI and Worldview 2 spectral configurations provided more bands which influence species discrimination, whereas for the Landsat 8, it was only the green and the SWIR1 bands. Furthermore, the Landsat 8 SWIR 1, the red edge bands of the Sentinel 2 and the Worldview 2 yellow band were the most influential wavebands in summer, whereas in winter, the blue band of all the three sensors was the most influential band in discriminating the two grasses. It was also found that the Landsat 8 NIR, the Sentinel 2 NIR and the Worldview 2 blue bands were the least influential in summer, whereas in winter, the green band of all sensors was the least influential in discriminating between the two species. The derived vegetation indices have agreed that during the two distinct seasonal periods, the G Chl index, EVI and the standard NDVI were the most influential indices in discriminating between the two species, with the standard NDVI identified as the most influential variable, whereas the SAVI was the least.

3.4.3. Seasonal classification of C3 and C4 grass species

Figure 3.2 shows the overall classification accuracies produced using the three variables (standard bands, vegetation indices (VIs) and combined standard bands and indices), derived from the resampled data, during the peak of summer and end of winter. All sensors' spectral settings produced high classification accuracies, for both grass species, although the summer period showed slightly higher accuracies than winter. In summer, Worldview 2 produced the highest overall accuracy of 98.61%, followed by the Sentinel 2 (97.52%), using standard bands spectral configurations. In winter, the Sentinel 2 standard bands spectral configuration outperformed the other sensors, with 96.18% classification accuracy, followed by Worldview 2 (94.44%). The performance of the Sentinel 2 and Worldview 2 standard bands was also as good as the use of indices for the two periods. The spectral configuration of Landsat 8 comparatively yielded the least overall classification accuracies, ranging between 90.14% and 95.83%, with standard bands producing the lowest accuracies. In winter, lower classification accuracies were produced compared to summer. For example, in summer Landsat 8 produced overall accuracies ranging from 90.24 to 95.83% and Worldview 2 varied from 97.18 to 98.61%, whereas in winter, Landsat 8 yielded a range between 90.18 and 91.67%, whereas Worldview 2 dropped to a range between 90.28 and 94.44%.

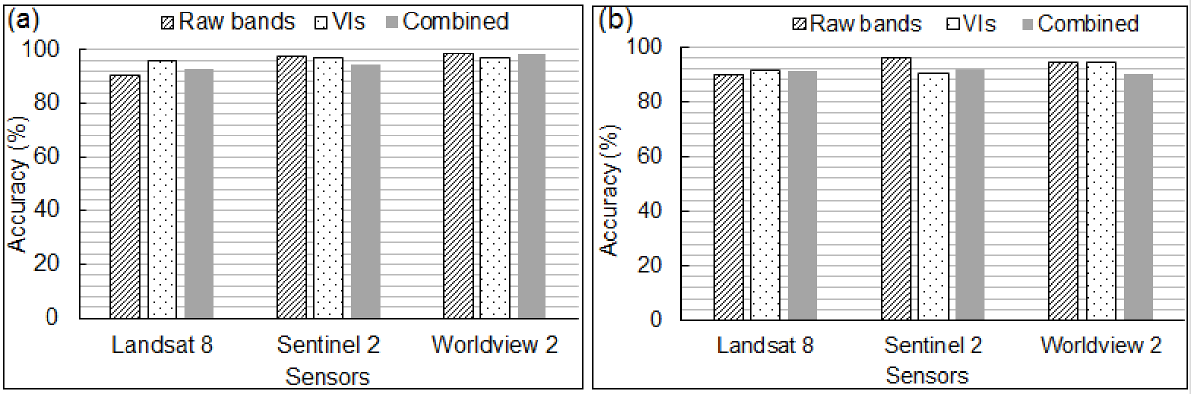


Figure 3.2: Overall accurracies in (a) summer and (b) winter derived using different variables

Considering the performance of the different variables, the use of indices using the Worldview 2 and Sentinel 2 did not improve the overall classification in summer, it actually decreased it. However, for the Landsat 8, indices slightly improved the overall classification accuracy by 5.59% in summer and by 1.49% in winter, from standard bands. The use of combined variables using all sensors also resulted in considerable decrease in overall classification accuracies, during the two seasonal periods. For example, the Sentinel 2 overall classification dropped by 3.15% in summer and by 8.33% in winter, whereas for the Worldview 2, it slightly dropped (by 0.02%) in summer and by 4.16% in winter.

3.4.4. Classification assessment results

Figures 3.3(a) and (b) show the commission and omission errors encountered using standard bands and indices, respectively, in the seasonal classification of *Festuca* and *Themeda* grass species. In summer, (Figure 3.3b (i)), indices had the lowest commission and omission errors (ranging between 2.7% and 5.7%), than standard bands (Figure 3.3a (i), ranging between 0 and 13.8%), whereas in winter, standard bands (Figure 3.3a (ii)) produced lower errors (ranging between 0 and 11.1%), compared to indices (Figure 3.3b (ii), ranging between 5.4 and 11.4%). In summer, standard bands spectral windows of the Worldview 2 image produced the lowest commission and omission errors (between 2.77 and 2.85%), followed by Sentinel 2 (between 0 and 10.8%), whereas the Landsat 8 produced the largest errors between 5.71 and 13.89% in classifying the two species. In winter, standard bands of the Landsat 8 also had the highest errors (between 8.3 and 10.8%), followed by Worldview 2 (between 2.70 and 8.57%), whereas the Sentinel 2 had the lowest (between 0 and 6.25%) errors in classifying the target species.

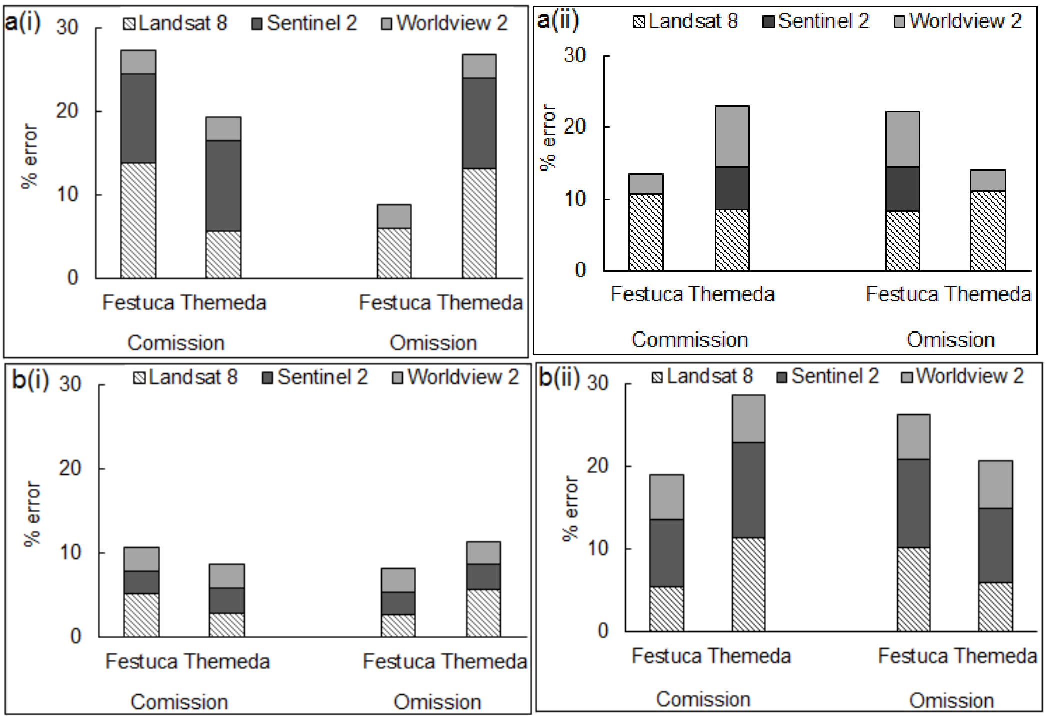


Figure 3.3: The classification errors using (a) standard bands and (b) indices in summer (i) and winter (ii) for the two grass species

It was also found that Landsat 8 derived variables produced the lowest user's and producer's accuracies in summer, ranging between 86.11% (for *Festuca*) and 97.30% (*Themeda*), whereas the Worldview 2 produced the highest between 97.14 and 100% in classifying the target species. The classification of *Themeda* species also produced higher user's accuracies (ranging between 94.29 and 97.22%) in summer, compared to *Festuca* (ranging between 86.11 and 97.37%), using all sensors. There were also mixed results in the producer's and user's accuracies obtained when classifying the two species using the three sensors' variables. Some accuracy for the individual species slightly improved, while others worsened, especially in winter. For example, the Landsat 8 standard bands produced 89.19% and 91.43%, indices produced 94.59% and 88.57%, whereas the use of combined variables produced 91.89% and 88.43%, user accuracies, for *Festuca* and *Themeda*, respectively.

3.5. Discussion

The seasonal accurate and reliable spectral information of C3 and C4 grass species is becoming critical for species mapping with higher accuracy, for understanding their response to environmental changes and for well-informed management. This study aimed to assess the potential of the spectral configurations of Landsat 8 OLI, Sentinel 2 MSI and Worldview 2 sensors in the seasonal discrimination of C3 and C4 grass species functional types in the Drakensberg of South Africa, using *in situ* hyperspectral measurements.

3.5.1. Species seasonal spectral response curves

Overall, the spectral signature of *Themeda* grass was higher than that of *Festuca*, especially in summer, based on all sensors spectral configuration. This confirmed the previous findings by Adjorlolo et al. (2013), which was conducted during the peak of the summer period. This may be attributed to the interior leaf properties (*e.g.* the concentration of nitrogen) which influence the species interaction with incoming radiation and subsequently reflectance. For example, previous studies (Adjorlolo et al., 2014; Adjorlolo et al., 2015) have revealed that *Themeda* consists of significantly higher nitrogen and crude protein content, compared to *Festuca*, during the peak of the summer period. The concentration of these variables has been reported to influence species spectral signatures. For instance, the study by Walburg et al. (1982) has demonstrated the influence of nitrogen on the seasonal reflectance of corn and reported a positive response of reflectance with nitrogen application.

It was also found that the two grass species were spectrally distinct in February across the spectrum of all sensors spectral configurations. Consequently, for a successful discrimination of these species, the period when both species are active becomes most suitable, especially when using multispectral sensors. This was also noted in a separate study by López-Granados et al. (2006), which used hyperspectral measurements to discriminate grass weeds from wheat. They reported that the discrimination of grass weeds is feasible before vegetation becomes inactive or reach their senescence stage, which makes them become spectrally identical. In agreement, Féret et al. (2015) and Schmidt et al. (2014) have identified the period of photosynthetically active as optimal for vegetation spectral discrimination, compared to senescence or dormancy. In contrary, at the end of winter, some portions of the spectrum (*e.g.* Landsat 8 SWIR bands), were spectrally identical. Thus at the end of the winter period, a limited number of spectral windows have the potential to discriminate between the two species, compared to the summer period. This might result in over or under-estimation of the target species, thereby compromising the overall classification accuracy of the two species. The spectral signatures at the end of the winter period for both species also showed lower reflectance, compared to the summer period; thus both species were photosynthetically active in February, whereas in August they were less active. This is supported by the study of Everson and Everson (2016) which highlighted the high frequency of frosts during the winter period within the study area, resulting in both grasses becoming dormant. Although the two species have been reported to have different phenological profiles, this study has revealed that at the end of the winter period in August, the two grasses are difficult to distinguish. In agreement with the findings of this study, Price et al. (2002) noted that during the winter period, especially where snow is frequent, both C3 and C4 grass species become dry thereby appearing spectrally similar. This period therefore becomes a challenge to distinguish these species.

3.5.2. The influence of sensors spectral configuration on seasonal discrimination

Different sensors' spectral configuration showed different abilities in the seasonal discrimination of grass species functional types. The influence of the Landsat 8 SWIR 1, Sentinel 2 red edge four and the Worldview 2 yellow spectral bands in summer is consistent with the findings of previous studies which resampled hyperspectral measurements to different sensors (Féret et al., 2015; Marshall et al., 2012). The study by Féret et al. (2015) revealed that the yellow region of the Worldview 2 is an intermediate domain which is more sensitive to chlorophyll content, when compared to the green domain, thereby enhancing its ability to discriminate vegetation species. The studies of Collin and Planes (2011) and Robinson et al. (2016) further confirmed the potential of the yellow spectral window in the classification of vegetation species. They revealed that the detection windows of the yellow band provide critical information about the carotenoid and chlorophyll pigments of the species, respectively, which enhance the classification accuracy.

The potential of the red edge and SWIR spectral windows, notably of the Sentinel 2, which are currently not present within the spectral configuration of multispectral broadband sensors, becomes promising in the seasonal discrimination of C3 and C4 grass species. Considerable studies have admitted the strength of the red edge spectral window in species discrimination and mapping (Rapinel et al., 2014; Robinson et al., 2016; Schmidt et al., 2014; Schuster et al., 2012). However these studies have used commercial sensors, notably Worldview 2 and RapidEye; in this regard the presence of this region within the Sentinel 2 spectrum provides a valuable window for species discrimination in a cost-effective manner. Similarly, findings from this study concur with those of Ramoelo et al. (2015a) and Laurin et al. (2016) who reported the substantial importance of the two SWIR and the red edge 1 spectral configurations of the Sentinel 2 in determining grass nitrogen, as well as in discriminating species functional types, respectively. They further emphasized that the availability of the red edge which is available in commercial satellites, such as RapidEye and Worldview 2, as well as the refined SWIR provide easy accessibility of refined spectral data for grasslands monitoring. The potential of the SWIR region, notably above 2000 nm was also reported by Adjorlolo (2013), as critical for classifying C3 and C4 grass species functional types. Similarly, Ferreira et al. (2015) has also confirmed the potential of the Worldview 3 SWIR spectral window in discriminating forest species, using hyperspectral measurements.

This study also found that the green spectral window of all the three sensors was the least influential in discriminating between the two species in winter. This confirms the fact that during the end of winter, the species lose their vigour, with less chlorophyll content, hence less reflectance in the green and NIR portions (Gitelson et al., 1996; Gitelson and Merzlyak, 1996; Marshall et al., 2012). This possibly explains why the green band was less influential in discriminating the two species. On the other hand, during the summer period, the green band was not influential; this may be attributed to the fact that although it was a period of high chlorophyll concentration, the band was not as sensitive as the red edge of Sentinel 2, yellow of the Worldview 2 and SWIR of the Landsat 8. In addition, Landsat 8 NIR, the Sentinel 2 NIR and the Worldview 2 blue spectral bands were the least influential in summer. Similar findings, notably of Worldview 2 were reported by Marshall et al. (2012); the study found that the traditional NIR band contributed the least in discriminating *buffel*, an invasive C4 grass species in Australia, during the summer season.

3.5.3. Sensors performance in the seasonal classification of C3 and C4 grass species

The Worldview 2 and Sentinel 2 produced better and comparable results during the two seasonal periods, whereas the Landsat 8 was the least performer. This was also reported by a previous study (Féret et al., 2015), the best performances were produced from either Worldview 2 or Sentinel 2 sensors spectral configurations. This possibly results from the presence of red edge windows of these sensors which enhance their discrimination ability, compared to Landsat 8. In this regard, this provides an insight to the potential of the Sentinel 2 spectral windows in the discrimination and possible means for the spatial representation of these grass species. The sensor spectral separability windows thus provides a suitable alternative for the spectral discrimination of C3 and C4 grass species in a cost-effective manner, since Worldview 2 images are provided on a commercial basis. However, the performance of the Landsat 8 is much better than the findings of Féret et al. (2015). Their findings showed that the Landsat 8 produced overall classification accuracies between 81.1

and 88.6% for different vegetation types (grasslands, ferns and fields), which are lower than those produced in the present study in classifying grass species of different photosynthetic pathways. They also noticed misclassification of the vegetation species using the Landsat 8 spectral bands; hence they recommended the use of indices or combined variables for better species discrimination. Furthermore, the study of Price et al. (2002), which used Landsat TM in discriminating C4 and C3 grass species under different management practices, during the winter period of the Great plains of Kansas in United States reported the poor classification performance, which they attributed to the dryness of the grasses during that period, making it difficult to distinguish them. The lower performance of the Landsat 8 OLI spectral setting was also reported by Sibanda et al. (2016); the sensor produced the lowest classification accuracies across all the grassland management practices, compared to other sensors. The lower performance of the Landsat 8 sensor may be primarily attributed to its much wider spectral settings and limited bands (Féret et al., 2015; Sibanda et al., 2016), compared to Sentinel 2 or Worldview 2; which all limit its potential in discriminating between the species.

The use of indices did not significantly improve the overall classification accuracies for all the sensors, except for the Landsat 8. This might be attributed to the fact that the spectral separability windows of the Landsat 8 are much wider such that the species spectral differences are difficult to detect. The lower performance of the Landsat 8 standard bands was also confirmed by the assessment results at species level, where the sensor reported the largest commission and omission errors in classifying the two grass species. This indicated a spectral confusion between the two species, when using the spectral configuration of Landsat 8, which may result in considerable over or under-classification of the target species, although it showed high overall classification results. Indices therefore present a better solution to discern such variations, when using the Landsat 8 sensor. The absence of the red edge spectral window within the Landsat 8 (which is present within the other sensors spectral range) possibly limits its potential in species discrimination.

3.6. Conclusion

The present study assessed the potential of new generation sensors, with strategically-positioned spectral bands in discriminating between *Festuca* (C3) and *Themeda* (C4), its counterpart. Based on the findings of this study, it can be concluded that:

(a) the ability of Landsat 8 OLI, Sentinel 2 MSI and the Worldview 2 spectral configurations to successfully detect species spectral differences and classification varies with season,
(b) the performance of standard bands spectral configuration, notably of the Sentinel 2 and Worldview 2 was as good as that of vegetation indices in classifying the target grass species,
(c) the peak of the summer season (when both species are photosynthetically active) has been identified as the suitable period for the successful discrimination of C3 and C4 grass species functional types, and
(d) the use of hyperspectral measurements still remains critical to understand the seasonal spectral behaviour of vegetation species with high accuracy.

Overall, results from this chapter have highlighted the potential of the spectral windows of new generation sensors in the seasonal discrimination of C3 and C4 grass species. Most importantly, the experiment have highlighted that when species are active, they become more distinct and separable using remote sensing. However hyperspectral measurements are limited to plot level; there is therefore a need for further research to explore these new generation sensors' fidelity in detecting and mapping the spatial distribution of the target species, considering their varying acquisition characteristics. The succeeding chapter therefore used the real images of Landsat 8, Sentinel 2 and Worldview 2 to test how the sensors, particularly the newly-launched Sentinel 2 can achieve the task, within a specific period.

CHAPTER FOUR

4. Examining the strength of the newly-launched Sentinel 2 MSI sensor in detecting and discriminating subtle differences between C3 and C4 grass species

This chapter is based on:

Shoko C and Mutanga O (2017a): Examining the strength of the newly-launched Sentinel 2 MSI sensor in detecting and discriminating subtle differences between C3 and C4 grass species. *ISPRS Photogrammetry and Remote Sensing*, 129: 32–40.

Abstract

C3 and C4 grass species discrimination has increasingly become relevant in understanding their response to environmental changes and to monitor their integrity in providing goods and services. While remotely-sensed data provide robust, cost-effective and repeatable monitoring tools for C3 and C4 grasses, this has been largely limited by the scarcity of sensors with better earth imaging characteristics. The recent launch of the advanced Sentinel 2 MultiSpectral Instrument (MSI) presents a new prospect for discriminating C3 and C4 grasses. The present study tested the potential of Sentinel 2, characterized by refined spatial resolution and more unique spectral bands in discriminating between *Festuca* (C3) and *Themeda* (C4) grasses. To evaluate the performance of Sentinel 2 MSI; spectral bands, vegetation indices and spectral bands plus indices were used. Findings from Sentinel 2 were compared with those derived from the widely-used Worldview 2 commercial sensor and the Landsat 8 Operational Land Imager (OLI). Overall classification accuracies have shown that Sentinel 2 bands have potential (90.36%), than indices (85.54%) and combined variables (88.61%). The results were comparable to Worldview 2 sensor, which produced slightly higher accuracies using spectral bands (95.69%), indices (86.02%) and combined variables (87.09%), and better than Landsat 8 OLI spectral bands (75.26%), indices (82.79%) and combined variables (86.02%). Sentinel 2 bands produced lower errors of commission and omission (between 4.76 and 14.63%), comparable to Worldview 2 (between 1.96 and 7.14%), than Landsat 8 (between 18.18 and 30.61%), when classifying the two species. The classification accuracy from Sentinel 2 also did not differ significantly (z = 1.34) from Worldview 2, using standard bands; it was significantly ($z > 1.96$) different using indices and combined variables, whereas when compared to Landsat 8, Sentinel 2 accuracies were significantly different ($z > 1.96$) using all variables. These results demonstrated that key vegetation species discrimination could be improved by the use of the freely and improved Sentinel 2 MSI data.

Keywords: grassland ecosystems, climate change, remote sensing, spatial representation, red edge

4.1. Introduction

C3 and C4 grasses are an important species functional type of terrestrial ecosystems responsible for carbon sequestration, maintaining biodiversity and as forage for wildlife and livestock (Bremond et al., 2012; Foody and Dash, 2007; 2010). The distribution of these grass species is primarily linked to climatic and topographic conditions (Bremond et al., 2012; Woodward et al., 2004; Yan and de Beurs, 2016) and so does their ability to provide services. Thus, any changes in climatic conditions are most likely to alter their distribution and function. For example, C3 species are anticipated to move to cooler and moister south-facing slopes or to higher altitudes areas in response to rises in temperature, whereas C4 grasses will have an advantage of expanding (Adjorlolo et al., 2012b; Bremond et al., 2012; Shoko et al., 2016b). In contrast, accumulating evidence have confirmed that increase in carbon dioxide will favour the expansion and abundance of C3 grasses than C4 (Chamaillé-Jammes and Bond, 2010). Consequently, environmental changes are more likely to compromise C3 and C4 grasses distribution and these changes are anticipated to vary from place to place (Lei et al., 2016). It has also been noticed that grassland areas are facing considerable threats from bush encroachment and invasion by alien species (Everson and Everson, 2016). The discrimination and mapping of C3 and C4 grass species is therefore inevitable, so as to monitor their possible shifts, as a result of environmental changes. It is also desirable to evaluate the contribution of these grasses to the provision of services (*e.g.* forage) over time and ensure their sustainability in providing the required services.

The discrimination of C3 and C4 grass species, using remote sensing has so far been primarily achieved, using broadband and coarse spatial resolution multispectral sensors, notably Advanced Very High Resolution Radiometer (AVHRR), MEdium Resolution Imaging Spectrometer (MERIS), Moderate Resolution Imaging Spectroradiometer (MODIS), (Foody and Dash, 2007; Guan et al., 2012; Liu et al., 2015; Wang et al., 2013; Wang et al., 2010), and to a lesser extent, using Landsat TM (Guo et al., 2003; Liu et al., 2015; Price et al., 2002). However, studies which have used MODIS and AVHRR have noted that these sensors mis-represent the spatial variations of C3 and C4 grasses. Currently, the inability of the medium resolution MERIS and Landsat TM sensors to provide real time images further hampers the monitoring of C3 and C4 grass species. As the need for more detailed characterization of vegetation species arises and new ecological questions emerge, hyperspectral and commercial multispectral sensors (*i.e.* Worldview 1-3 and RapidEye) have been reported to be the most accurate sensors in monitoring C3 and C4 grass species

(Adjorlolo et al., 2012a; Liu and Cheng, 2011; Lu et al., 2009). Although the use of hyperspectral data has gained considerable attention in discriminating C3 and C4 grasses, their limitation in spatial coverage, high acquisition cost, challenges in data pre-processing, due to high volumes of data, as well as multi-collinearity problems, present major challenges for large scale and continuous monitoring of C3 and C4 grasses (Price et al., 2002; Shoko et al., 2016b). Similarly, the high acquisition cost of commercial satellites, hampers continuous monitoring of C3 and C4 grasses at large geographic coverage. In this regard, the monitoring of C3 and C4 grasses lies in the ability of emerging sensors to accurately discriminate and map their spatial variations.

Recent advances in technology have produced innovative remote sensing sensors, creating new opportunities for vegetation monitoring according to functional types. The emergence of multispectral sensors with improved image acquisition characteristics, notably Landsat 8 OLI and Sentinel 2 has renewed the monitoring of C3 and C4 grasses. The provision of data by these sensors at large geographical coverage is becoming necessary as vegetation information is now required at broader scales for ecological monitoring and to enhance management practices. For instance, the Sentinel 2 was recently launched to enhance the monitoring of terrestrial and coastal ecosystems (Delegido et al., 2011; Richter et al., 2012; Stratoulias et al., 2015). The sensor is a polar-orbiting one that acquires super-spectral high-resolution images at a nadir position, covering 290 km field of view, at a high temporal resolution of five days (Immitzer et al., 2016; Laurin et al., 2016). The sensor thus presents an invaluable opportunity for monitoring C3 and C4 grass species functional types, when compared to the available broadband multispectral sensors. For instance, the refined spatial resolution (10 and 20m) allows for better and more accurate spatial representation of species, which is one of the major challenges, that have been encountered from the use of broadband multispectral sensors (*i.e.* MODIS and AVHRR). Furthermore, the presence of four bands within the red edge region, centred at 705 (band 5), 740 (band 6), 783 (band 7) and 865 nm (band 8A), which are not present in freely-available multispectral sensors, widens the spectral windows for species identification and discrimination at broader scales. Red edge bands have so far been typically restricted to commercial satellites; hence Sentinel 2 now provides the easy accessibility of this key information. Previous studies (Clevers and Gitelson, 2013; Marshall et al., 2012; Robinson et al., 2016; Schuster et al., 2012) have also reported the red edge region as critical for enhancing species spectral responses and understanding vegetation status. For example, the study by Schuster et al. (2012) indicated that the incorporation of red edge spectral bands increases the classification accuracy of vegetation species, whereas Marshall et al. (2012) demonstrated the potential of red edge band of the Worldview 2 sensor in discriminating *buffel* C4 grass, from other vegetation types.

The aforementioned image acquisition characteristics currently make the Sentinel 2 sensor a prime data source for vegetation monitoring, especially in resource-constrained areas of Africa. In this regard, this study examined the potential of the newly-launched Sentinel 2 MSI sensor in discriminating *Festuca*, C3 and *Themeda*, C4 grasses. The performance of the sensor was also examined against that of the Landsat 8 OLI and well-known Worldview 2 sensor. The choice of the two sensors has been motivated by their previous application and performance in vegetation species mapping (Mustafa et al., 2015; Rapinel et al., 2014; Robinson et al., 2016), biomass estimation (Dube and Mutanga, 2015a; b; Mutanga et al., 2012) and land cover studies (El-Askary et al., 2014; Jia et al., 2014; Momeni et al., 2016). The slightly weak performance of previous Landsat data series (TM4, TM5 and ETM+7) in classifying C3 and C4 grasses (Guo et al., 2003; Lauver and Whistler, 1993; Liu et al., 2015; Price et al., 2002) therefore underscores the need to examine the recently-launched Landsat 8 sensor, which has better acquisition characteristics than its predecessors.

4.2. Materials and methods

4.2.1. Field data collection

Ground-based location points of the target grass species were collected using a sub-metre Trimble Global Positioning System (GPS) during summer period of February 2016. The collection of ground points was performed using randomly generated sampling points across the area. The points were randomly-generated using ARGIC 10.2. A total of 120 points were collected for each grass, resulting in 240 points. These points were then used to classify the two grass species functional types, for the study area, using the three satellite images. The sampled points were also used to extract grass species spectral data from the remote sensing images for further analysis.

4.2.2. Satellite image acquisition and processing

The Landsat 8 OLI, Sentinel 2 MSI and Worldview 2 remote sensing images were acquired to test their ability in discriminating between the target species. The characteristics of the images used for analysis are presented in Table 4.1. The area under study is covered by a single Landsat 8 scene with path/row of 169/80. A cloud-free image was downloaded from the United States Geological Survey (USGS) website and calibrated as outlined at the website (http://landsat.usgs.gov/). Atmospheric correction was also performed for the Landsat 8 OLI image using the Fast Line-of-sight Atmospheric Analysis of Spectral Hypercube (FLAASH) model and ground points for geometrical correction in ENVI environment. Sentinel 2 MSI images are delivered orthorectified top of atmosphere reflectance in Universal Transverse Mercator (UTM) projection, with the World Geodetic System (WGS84), and are freely-available for download at the Sentinels Scientific Data Hub website (https://scihub.copernicus.eu/). The data is acquired in 13 spectral bands, spanning from the visible through the near infra-red (NIR) and red edge, to the short wave infra-red (SWIR) at 10, 20 and 60 spatial resolutions (Table 4.1). Bands acquired at 60 m (coastal aerosol band 1, water vapour band 9 and cirrus band 10) spatial resolution are dedicated primarily for detecting atmospheric features and were therefore excluded from the analysis (Drusch et al., 2012). The atmospheric correction of the Sentinel 2 image was also performed using the Sen2cor atmospheric correction toolbox, an inbuilt algorithm within the Sentinel Application Platform (SNAP) tool version 4.0. The tool was developed primarily to work with Sentinel images. The Worldview 2 image was on the other hand purchased and delivered with orthorectified and radiometric corrections already applied by the supplier (Digital Globe, Longmont, Colorado, USA). These images were then used for classification of the two grass species using the ground truth points.

Table 4.1: Sensors spectral and spatial characteristics

	Sentinel 2 MSI		Landsat 8 OLI		Worldview 2	
Band	**Centre (nm)**	**GSD (m)**	**Range (nm)**	**GSD (m)**	**Range (nm)**	**GSD (m)**
1	443	60	435-451	30	400-450	0.5
2	490	10	452-512	30	450-510	0.5
3	560	10	533-590	30	510-581	0.5
4	665	10	636-673	30	585-625	0.5
5	705	20	851-879	30	630-690	0.5
6	740	20	1566-1651	30	705-745	0.5
7	783	20	2107-2294	30	770-895	0.5
8	842	10	503-676	15	860-1040	0.5
8a	865	20	-		-	
9	945	60	1363-1384	30	-	
10	1375	60	1060-1119	100	-	
11	1375	20	1150-1251	100	-	
12	2190	20	-		-	

*GSD: Ground sampling distance

4.3. Data analysis

The Discriminant analysis (DA) algorithm was used to examine the potential of the Sentinel 2 against that of Worldview 2 and Landsat 8 OLI in discriminating between the two grass species. The DA has been used successfully in discriminating between C3 and C4 grass species (Foody and Dash, 2007; Marshall et al., 2012; Price et al., 2002; Roth et al., 2015b). The model discriminates between species using a linear transformation of the remote sensing variables by aggregating the variables into latent factors, in which their influence to species discrimination is determined by variable scores. The performance of the DA also produces confusion matrices derived in species discrimination using the remote sensing variables.

The DA was performed using three sets of remote sensing variables; (i) standard bands, (ii) vegetation indices and (iii) combined variables, in XLSTAT, Microsoft Excel 2013. The data used with the DA were randomly split into 30% testing and 70% training sets, which is a requirement for all machine learning algorithms (Adelabu et al., 2014; Adjorlolo et al., 2013; Sibanda et al., 2015a). The vegetation indices which were used are presented in Table 4. 2. These indices were chosen considering their previous performances in C3 and C4 grass species discrimination as highlighted in literature (Adjorlolo et al., 2012a; Davidson and Csillag, 2001; Peterson et al., 2002; Price et al., 2002). The red edge-based Normalized Difference Vegetation Indices (NDVIs) were derived by replacing the standard red band with the red edge bands according to previous studies (Gitelson and Merzlyak, 1994; Kross et al., 2015; Sharma et al., 2015). Red edge-based NDVIs 1-4 were derived using Sentinel 2 red edge bands, whereas 5 and 6 were derived from Worldview 2.

Table 4.2: The derived vegetation indices used in the analysis

Indices		Formula	References
Standard NDVI		(NIR-R)/(NIR+R)	Tucker (1979)
NDVI 4		(NIR2−Y)/(NIR2+Y)	Adjorlolo et al. (2012a)
NDVI 5		(RE−CB)/(RE+CB)	Adjorlolo et al. (2012a)
Simple ratio		(NIR/R)	Jordan (1969)
SAVI		((NIR2-R)*(1+L))/(NIR2+R+L)	Huete (1988)
G Chl index		(NIR/G)-1	Gitelson et al. (2003)
EVI		2.5*((NIR-R)/(1+NIR+6R-7.5B))	Huete et al. (1997)
Red edge-based NDVIs:	1	(NIR-RE1)/(NIR+RE1)	
	2	(NIR-RE2)/(NIR+RE2)	(Gitelson and Merzlyak (1994); Kross et al., 2015)
	3	(NIR-RE3)/(NIR+RE3)	
	4	(NIR-RE4)/(NIR+RE4)	
	5	(NIR1-RE)/(NIR1+RE)	Pu and Landry (2012)
	6	(NIR2-RE)/(NIR2+RE)	Pu and Landry (2012)

*B, G, R, NIR, RE, represent blue, green, red, near infrared and red edge spectral bands, respectively, whereas EVI, SAVI and G Chl represent enhanced vegetation index, soil adjusted vegetation index and green chlorophyll, respectively

4.3.1. Accuracy assessment

Accuracy assessment of the classification results produced by the DA model was performed using the Pontius Jr and Millones (2011) approach. This has been regarded as more accurate and reliable in assessing classification accuracies using remote sensing data. The approach was therefore used to assess the ability of the sensors, the model and the derived variables in classifying the target grass species to their respective classes. Errors of commission and omission were therefore used to report the performance of the sensors and the derived variables in classifying *Festuca* and *Themeda* grass species. A McNemar test was also performed to compare classification accuracies derived using Landsat 8 OLI, Sentinel 2 MSI and Worldview 2 sensors in classifying the two grasses. McNemar is a robust test that has been successfully used to compare classification accuracies (Adelabu et al., 2013; Manandhar et al., 2009; Sibanda et al., 2016). More details on the execution of the test are well documented (de Leeuw et al., 2006; Petropoulos et al., 2012). A McNemar test result (indicated by z score) above 1.96 indicates that the classification accuracies derived from the different sensors and associated variables are significantly different, at a confidence of 95%.

4.4. Results

4.4.1. Species spectral response profiles using different sensors

Figure 4.2 illustrates the species spectral response curves derived from the three respective remote sensing images. These are averaged reflectance values extracted from the three images using ground points of the target grasses. Overall, *Themeda* shows higher reflectance, when compared to *Festuca*, using all the three sensors, at all wavelengths. Sentinel 2 also show separable species response curves, comparable to Worldview 2, whereas Landsat 8 show a close spectral response between the two grasses.

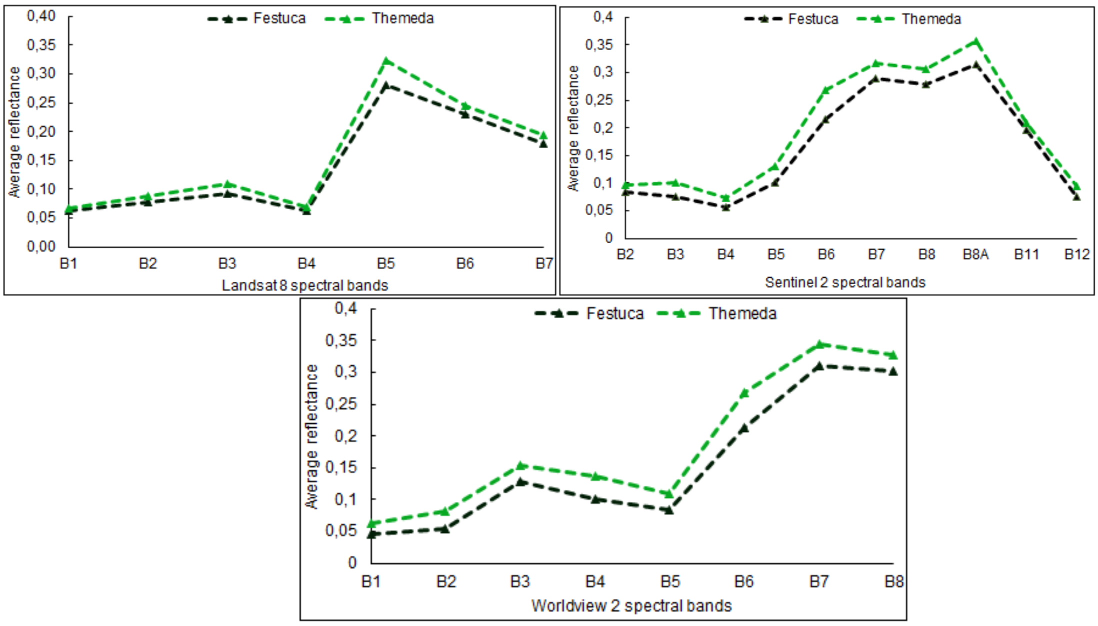


Figure 4.1: Species spectral response using the different sensors

4.4.2. Sensors classification performance

Figure 4.2 illustrates the derived overall classification accuracies when classifying the two species using the three sensors' variables. Overall, Sentinel 2 sensor outperformed the Landsat 8 in classifying the two grasses, and it was slightly lower, when compared to Worldview 2. Sentinel 2 standard bands produced high overall classification accuracy (90.36%), comparable to that of Worldview 2 (95.69%) and better, when compared to those produced using the Landsat 8 (75.26%). The use of indices and combined variables did not improve the classification results, when using Sentinel 2 and Worldview 2 sensors, the variables actually decreased the overall accuracies. For example, the use of derived indices decreased the overall classification of Sentinel 2 by 4.89%, whereas for Worldview 2, it dropped by 9.68%, from standard bands. The use of indices increased the overall classification accuracy of the Landsat 8 sensor by 7.527%, from standard bands.

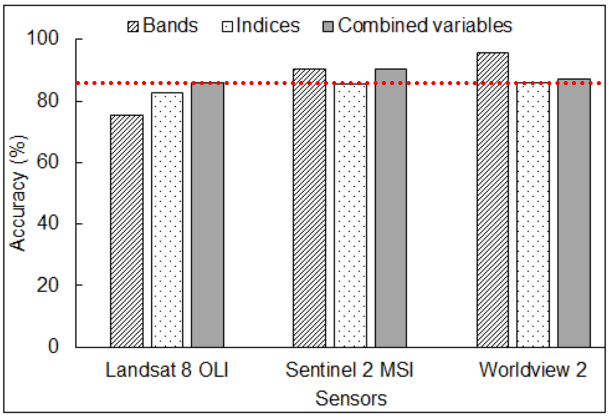


Figure 4.2: Overall classification accuracies derived using the three sensors' variables. The red line marks the lowest accuracy using Sentinel 2 in relation to the other sensors

4.4.3. The influence of sensors spectral bands on species discrimination

Figure 4.3 shows the influence of the spectral bands of the three sensors on discriminating between *Festuca* and *Themeda* grass species, using variables scores, derived from the DA model. Sentinel 2 sensor provides more bands which have great potential (indicated by the high variable scores) in discriminating between the two species. The red edge bands, notably centred at 705 and 740 nm, the blue (490 nm) and the SWIR (centred at 2190 nm) spectral bands of the Sentinel 2 were the most influential in classifying *Festuca* and *Themeda* grasses. Comparatively, for Worldview 2 sensor, the blue (between 450 and 510 nm) and red edge bands between 705 and 745 nm were also the most influential bands, whereas for the Landsat 8, it was the red (636-673 nm) and the NIR (851-879 nm). On the contrary, the SWIR (centred at 1375 nm) and green (centred at 560 nm) bands of Sentinel 2 were the least influential in the classification of the two grasses, whereas for the Worldview 2 and Landsat 8, the green (between 510 and 595 nm) and blue (between 452 and 512 nm) were the least influential, respectively. When using indices, the standard NDVI was the most influential index in discriminating between the two species using all the three sensors, whereas the least influential index varied with sensor. Using Sentinel 2, the EVI was the least influential, the SAVI for Worldview 2 and for Landsat 8 sensor it was the G Chlorophyll index. When indices and standard bands were combined, Sentinel 2 red edge band (centred at 783 nm) and the Landsat 8- derived standard NDVI were the most influential in discriminating between the two grasses, whereas using the Worldview 2 variables, it was the red edge-based NDVI, which is derived using the additional NIR (between 860 and 1040 nm) band.

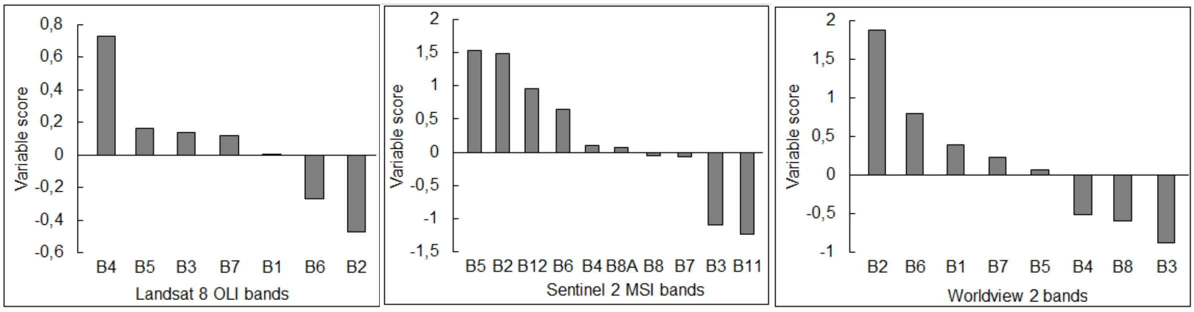


Figure 4.3: Influence of sensors' spectral bands on the discrimination of the two grasses

4.4.4. Classification accuracy assessment results

Figure 4.4 shows the commission and omission errors encountered when classifying *Themeda* and *Festuca* grasses using standard bands, indices and combined variables of the three remote sensing images. Sentinel 2 standard bands produced errors between 4.76 and 14.63%, between 2.38 and 21.15% using indices, whereas combined variables produced between 7.69 and 12%. This was better than those encountered using Landsat 8, which produced errors between 18.18 and 30.61% using standard bands, between 9 and 26.82% using indices, as well as between 12 and 16.27% using combined variables. The errors encountered using Sentinel 2 were better close to those of the Worldview 2 sensor, which resulted in the minimum errors encountered, ranging between 1.96 and 7.14% using standard bands, 10.24-17.98%, using indices and between 8.33 and 17.78%, using combined variables.

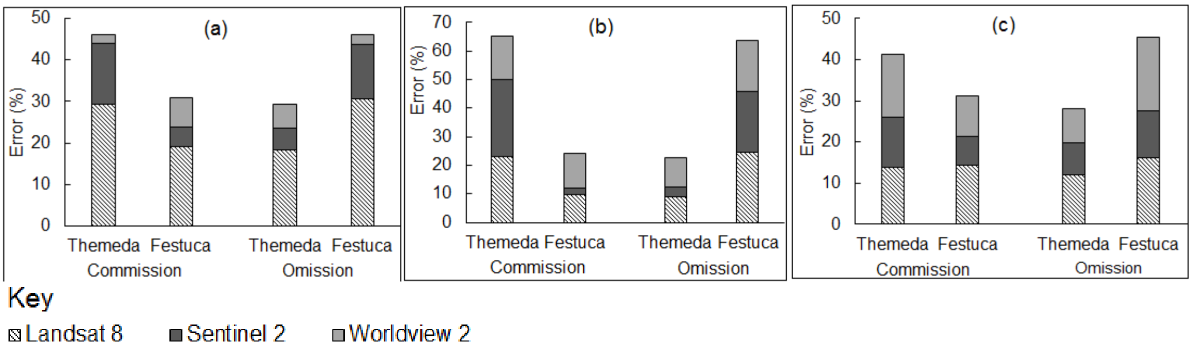


Figure 4.4: Commission and omission errors encountered when classifying the two species using: (a) standard bands, (b) indices and (c) combined variables of the three sensors

McNemar test results have also shown that there were statistically significant differences ($z > 1.96$) in classification accuracies using the different sensors. For example, Sentinel 2 accuracies were significantly higher than Landsat 8, when using standard bands ($z = 3.87$), indices ($z = 2$) and combined variables ($z = 2.23$). Sentinel 2 and Worldview 2-derived classification accuracies using standard bands were not significantly different ($z = 1.34$), whereas significant differences were found when using indices ($z = 3.01$) and combined variables (z = 2.11). The DA model was also found to perform well in classifying the two species using the different remote sensing datasets. High amount of agreement was shown between the training and the validation samples. For example, using the Landsat 8, the training sample produced an overall accuracy of 75.26%, whereas the validation sample was 70.33%. Similar findings were observed for Sentinel 2 and Worldview 2 datasets, with differences between training and testing samples within 5%.

4.4.5. Potential of the three sensors in mapping the spatial variations of the target species

Figure 4.5 shows the potential of the three sensors in mapping the spatial variations of *Festuca* and *Themeda* grass species. Overall, the western and southern most parts of the study area are largely composed of *Festuca*, whereas the eastern parts are dominated by *Themeda*, according to the three sensors. The visual inspection of Figure 4.5 also illustrates an observable improvement of the quality of the classification of the two species with Sentinel 2 data. Sentinel 2 shows a fine representation of the target grasses, which is as good as that of the Worldview 2 sensor, whereas the Landsat 8 sensor provides a coarse spatial representation. Like the Worldview 2, Sentinel 2 managed to detect the small patches of *Themeda*, which were not detectable using the Landsat 8 sensor.

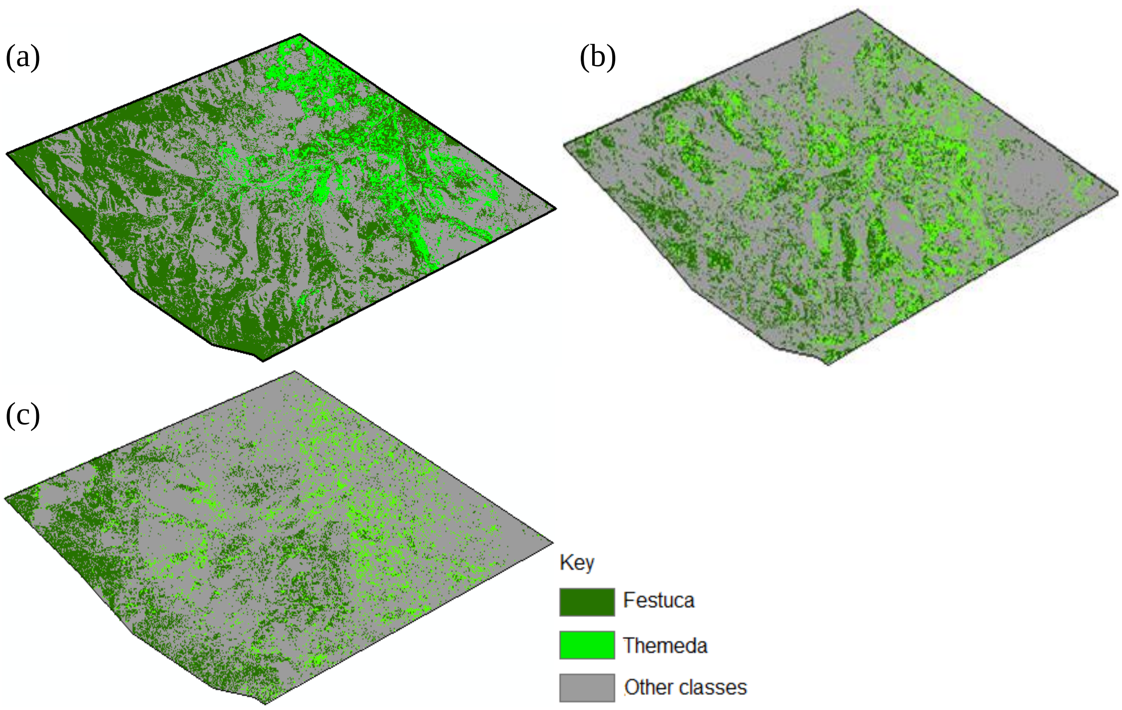


Figure 4.5: Potential of (a) Landsat 8, (b) Sentinel 2 and (c) Worldview 2 sensors in mapping the spatial distribution of *Festuca* and *Themeda* grass species

4.5. Discussion

The prime focus of this study was to explore the feasibility of the newly-launched Sentinel 2 MultiSpectral sensor in discriminating and mapping the spatial variations of *Festuca* (C3) and *Themeda* (C4) grasses in the Drakensberg of KwaZulu-Natal, South Africa. This study therefore investigated the potential of the unique data acquisition properties of Sentinel 2, notably more spectral bands, availability of red edge and refined spatial resolution, in discriminating between the two species. The results were compared to those derived using the freely-available Landsat 8 and the Worldview 2 commercial sensor. For the first time, this study attempted to examine the potential of the newly-launched Sentinel 2 in mapping the subtle spatial variations of C3 and C4 grass species.

The study proved the ability of the newly-launched Sentinel 2 MSI in classifying C3 and C4 grasses. Overall classification results obtained from the sensor were comparable to those obtained using the Worldview 2 and better than when using the Landsat 8 sensor. The performance of the Sentinel 2 in the overall classification is primarily attributed to the presence of more spectral bands, which provide more windows for the spectral separability of the two species. For example, ten (excluding aerosol, cirrus and water vapour bands) spectral bands were used in this analysis, with four of them within the red edge, compared to the Landsat 8. In addition, the relevance of Sentinel 2 spectral band width and position in vegetation monitoring has been documented (Aria et al., 2012; Dian et al., 2016; Pesaresi et al., 2016). They noted that Sentinel 2 bands are more refined, than those of the Landsat 8 or the available broadband sensors.

Sentinel 2 also provides better spatial variations of the target species, compared to those of Landsat 8. For example, according to the Landsat 8 sensor, the western parts of the area under study are composed of the *Festuca*, without *Themeda*. In contrary, Sentinel 2 managed to capture and represent the small patches of *Themeda* grasses, within the western part, comparable to the performance of the high resolution Worldview 2 sensor. The combined contribution of more spectral bands and better spatial resolution of Sentinel 2 improves the capability of the sensor in detecting the spatial and spectral differences between the two species. The spatial resolution of the Sentinel 2 thus offers a better spatial characterization of C3 and C4, which has been one of the major challenges associated with the widely-used broadband multispectral (*e.g.* MODIS and AVHRR) sensors in classifying C3 and C4 grasses

(Shoko et al., 2016b). Consequently, Sentinel 2 provides a beneficial alternative, than the available broadband and low spatial resolution sensors.

The 30 m Landsat 8 was not as good as Sentinel 2 in characterizing the spatial distribution of *Festuca* and *Themeda* grasses. The use of the Landsat 8 results in considerable over or under classification of the target species, as it becomes too coarse to represent the fragmentation in their distribution. This confirms the coarse spatial representation map produced using the 30m Landsat 8 sensor, when compared to that derived from Sentinel 2 and Worldview 2. This possibly emanates from the spatial configuration *(e.g.* patch area) of the target species, which influence the ability of the sensor to capture those patches (Hauglin and Ørka, 2016; Roth et al., 2015b). For example, the study by Hauglin and Ørka (2016) has highlighted that small patches, particularly less than the spatial resolution of the sensor are more likely to be dissolved within the major surrounding class. On the other hand, large stands or patches of species have been reported to be reliably detected, than smaller patches, especially when using coarse or medium resolution multispectral sensors (Bradley, 2014; Fuller, 2005).

Nevertheless, the 30m spatial resolution of the Landsat 8 sensor most likely provides better performance, than the reported previous Landsat series, MODIS or AVHRR sensors. For example, using the Landsat 7 ETM+ in classifying C3 and C4 grasses, the study by Liu et al. (2015) has reported overall classification accuracies ranging between 62.65 and 72.35%. This study has produced better accuracies (between 75.26 and 86.02%); also, given the 22% data loss of the Landsat 7 ETM, Landsat 8 provides a better alternative for large scale mapping of C3 and C4 grasses. The better performance of the Landsat 8 also confirms previous findings by Yan and de Beurs (2016) in classifying C3 and C4 grass species for the mixed grassland Prairies of United States. The study found overall classification accuracies between 73.21 and 79.23%, which are comparable to the present study.

Sentinel 2 spectral bands also prove their valuable potential in discriminating C3 and C4 grasses. For instance, highest classification accuracy was obtained using standard bands, than when using indices or a combination of variables. The species spectral response using Sentinel 2 shows separable curves between the grasses, when compared to that of Landsat 8. In addition, the unique red edge bands (centred at 705 and 740nm) and SWIR (centred at 2190 nm) were the most influential in classifying the two grasses. The classification accuracy produced using the Sentinel 2 standard bands also did not differ significantly ($z < 1.96$) from

Worldview 2, when using standard bands, but it was significantly different ($z > 1.96$) from Landsat 8. These results confirm the reported potential of the strategically-positioned, as well as additional bands in enhancing the ability of the sensor in discriminating species (Immitzer et al., 2016; Laurin et al., 2016). Previous studies (Clevers and Gitelson, 2013; Delegido et al., 2011; Ramoelo et al., 2015a; Richter et al., 2012; Sibanda et al., 2016) have reported the potential of the unique spectral settings of the Sentinel 2 in vegetation monitoring, over those of the available multispectral sensors. For example, the study by Ramoelo et al. (2015a) reported the importance of the red-edge and SWIR bands in estimating grass nitrogen concentration, whereas Sibanda et al. (2016) reported its potential in discriminating grasses under different management practices. In agreement, the study by Adjorlolo (2013) have admitted the influence of the SWIR (above 2000 nm) in discriminating C3 and C4 grasses, whereas Laurin et al. (2016) identified the SWIR as carrying water, nitrogen and carbon (lignin, cellulose) content information, which all enhance its ability to separate species. Sims and Gamon (2002) have also noted the sensitivity of reflectance near the 705 nm portion to changes in the concentration of chlorophyll. This possibly enlightens why the red edge of the Sentinel 2 centred at 705 nm was the most influential in discriminating the two grasses.

This was contrary to the performance of the Landsat 8 variables; indices produced better classification accuracies than standard bands, and the most influential index was the standard NDVI. This confirmed previous findings using Landsat TM 5 data (Price et al., 2002), where indices were better in discriminating among different C3 and C4 grasses than standard bands. Thus, when using Landsat 8 sensors, the use of vegetation indices provides a better classification of C3 and C4 grasses, than standard bands. Landsat 8 also agrees with the other sensors that the standard NDVI, derived using the standard red and NIR bands was the most influential in discriminating between the two species, when using vegetation indices. This indicated the strength of the long-established and widely-used NDVI, not only in C3 and C4 grasses discrimination, but in different vegetation species at large. On the contrary, the performance of the standard NDVI was not as sensitive as the standard or original bands of Sentinel 2 and Worldview 2 spectral range. The original spectral bands of the Sentinel 2 and Worldview 2 have shown unprecedented level of performance over the use of indices in discriminating between *Festuca* and *Themeda* grasses.

However, the discrimination of the target species in this study was limited to a specific period; in summer. C3 and C4 grass species functional types has different phenological phases, which influence their spectral response and subsequently, species classification. In this regard, there is need to identify the optimal period to map these grass species to provide more detailed understanding of their spatial or temporal variations for successful management and monitoring of these ecosystems. Although the Worldview 2 provides better spatial variations of the target species than the other sensors, its high acquisition cost hinders the continuous or seasonal monitoring of these grass species, especially considering the need for detailed vegetation information in the face of climate change and its effect on their distribution and productivity. Sentinel 2 and Landsat 8 therefore present primary data sources suitable for large scale mapping and monitoring of C3 and C4 grasses.

4.6. Conclusion

The present study examined the potential of the newly-launched Sentinel 2 multispectral instrument, with that of the Landsat 8 and the Worldview 2 in discriminating and mapping *Festuca* and *Themeda* grasses. Based on our findings we conclude that:

1. The newly-launched Sentinel 2 offers an invaluable primary data-source required for C3 and C4 species discrimination,
2. The spatial representation of the Sentinel 2 sensor is not as good as that of the Worldview 2, but it is better than that of the Landsat 8 OLI,
3. The Sentinel 2 sensor provides more bands which have the potential in discriminating C3 and C4 grasses, compared to Worldview 2 and the Landsat 8.

This chapter have demonstrated the potential of the Sentinel 2 as an invaluable primary data source currently promising for monitoring of vegetation species according to functional types, which was previously a challenge using broadband multispectral sensors. Although Sentinel 2 showed ability in discriminating and mapping C3 and C4 grass species, the discrimination of these species is linked to their biophysical, morphological and phenological characteristics, which influence their interaction with radiation. It is therefore a need to consider classification accuracies derived using images acquired at different periods. This provides the optimal period to discriminate and map the target grass species, with high accuracy. The succeeding chapter therefore used multi-temporal Sentinel 2 images to determine the most optimal period for discriminating and mapping C3 and C4 grass species.

CHAPTER FIVE

5. Determining the optimal season for discriminating the eco-physiological distinction between C3 and C4 grass functional types using multi-date Sentinel 2 data

This chapter is based on:

Shoko. C, Mutanga. O, Dube. T and Slotow. R. (2018): 5. Determining the optimal season for discriminating the eco-physiological distinction between C3 and C4 grass functional types, using multi-date Sentinel 2 data.

Abstract
The ability of remote sensing systems to optimally discriminate and map C3 and C4 grass species varies over time. This is due to environmental changes, which influence their phenological, physiological and morphological characteristics. These variations determine their classification accuracy from remotely-sensed data. In this regard, the discrimination of C3 and C4 grasses is insufficient when using a single image acquired at a specific period. In this study, multi-date Sentinel 2A MultiSpectral Instrument (MSI) data was explored to determine the optimal period for discriminating and mapping the eco-physiological distinction between C3 and C4 grass functional types in the montane grasslands of South Africa. The results showed that seasonality influence species discrimination accuracy, spatial representation and the performance of remote sensing variables. The winter period presents a better temporal window for discriminating C3 and C4 target grass species, with higher overall classification accuracies (between 91.8 and 95.3%), than summer (between 81.4 and 90.3%). Lower classification errors (between 2.5 and 14.2%) were also observed when discriminating using winter images, as compared to those acquired in summer (between 4.7 and 22.2%). The two grass species were found to occupy more than 40% of the studied area. However, *Festuca* (C3) occupied the majority of the area, compared to *Themeda* (C4), except using an image acquired in November. The largest species areal coverage was also derived in March, whereas August produced the least coverage.

Keywords: Environmental change; grass type; separability windows; phenological characteristics; seasonal variability

5.1. Introduction

C3 and C4 grass species discrimination present a fundamental foundation towards monitoring their integrity, as an important component of grassland ecosystems. These grasses contribute immensely to forage availability (Auerswald et al., 2009; Barbehenn et al., 2004), store a significant amount of carbon (Davidson and Csillag, 2001; Still et al., 2003) and contribute to the occurrence of fire, which is an important mechanism in maintaining grasslands (Everson and Everson, 2016). At a global scale, C4 grasses predominantly occupy low altitudes and latitudes areas, whereas C3 typically occupy higher altitude and latitude areas (Woodward et al., 2004; Yao et al., 2011). Moreover, C4 photosynthetic pathway constitute most grass species of southern Africa, than C3 (Milton, 2004). There is also a co-existence of C3 and C4 grass species, due to the influence of local topographic and climatic factors (Yan and de Beurs, 2016), for example, in the montane grasslands of South Africa (Adjorlolo et al., 2014), the Prairies of the United States (Foody and Dash, 2007) and temperate northern China (Guan et al., 2012). Their co-existence plays a considerable role in governing the spatial and temporal variations of biochemical cycling, ecological productivity (*i.e.* biomass accumulation) and plant–animal interactions.

The distribution of C3 and C4 grass species is facing substantial threat from global environmental changes, at both local and regional scales (Liu and Cheng, 2011; Liu et al., 2015) and these changes are anticipated to vary spatially and according to species functional types (Adjorlolo et al., 2012b). It is projected that elevated carbon dioxide (CO_2) will be favourable to C3 grass species and they will increase in abundance, whereas increase in warming will favour C4 grass species, such that they will expand to currently cooler areas (Bremond et al., 2012; Moncrieff et al., 2015). Considerable uncertainties about the future distribution of C3 and C4 grass species also exist under a CO_2-enriched and warmer environment, as well as under the influence of local environmental conditions (Chamaillé-Jammes and Bond, 2010). These shifts in the distribution of C3 and C4 grass species will result in variations in the provision of a range of ecosystem services, such as forage and carbon storage.

Although substantial strides have been made to discriminate C3 and C4 grass species (Adjorlolo et al., 2013; Dronova et al., 2012; Liu et al., 2015; Shoko and Mutanga, 2017a), these studies have been restricted to specific seasonal periods. For example, the studies by Dronova et al. (2012) and Shoko and Mutanga (2017a) were conducted during the summer season in China and South Africa, respectively. The influence of seasonality and the potential of using images acquired at different periods to discriminate C3 and C4 grass species have not been fully explored. Results based on a specific period undermine the phenological and eco-physiological variations of these species, which influence their classification accuracy. In addition, the success of discriminating C3 and C4 grass species is quite variable during the growing season and this change dramatically from one wavelength to another, even within the same portion of the spectral range. Species photosynthetic pigments (*e.g.* chlorophyll) are also seasonally unique, with distinct interactional features with radiation, which cannot be captured, using single-date image of a specific period.

The discrimination of C3 and C4 grass species using images acquired at different seasonal periods has been largely limited by the availability of free sensors with appropriate temporal, spatial and spectral capabilities. For example, the daily availability of the MODIS sensor has so far made it the primary data source for discriminating C3 and C4 grass species (Guan et al., 2012; Pau et al., 2013). Nevertheless, the coarse spatial resolution and broad spectral range have been reported to mask the spectral and temporal separability of C3 and C4 grasses, hence are insufficient to characterize their variations (Guan et al., 2012). As the significance of C3 and C4 species became increasingly recognized, the remote sensing community prompted to use more advanced hyperspectral and commercial satellites to discriminate them (for example, Adjorlolo et al., 2012a). Although the use of these data sources provides more accurate spectral variations of C3 and C4 grasses, it is challenging to acquire multi-temporal data, due to their acquisition cost. The development and free availability of the Sentinel 2A MultiSpectral Instrument (MSI) provide much needed high quality and unique information for terrestrial monitoring over time (Immitzer et al., 2016; Shoko and Mutanga, 2017a). The sensor has emerged, overcoming the spectral, temporal and spatial limitations of the available multispectral systems, for better accurate and reliable characterization of C3 and C4 grass species. The five to nineteen-day revisit time and 13 spectral bands, with unique red edge capture their phenological asynchronicity, whereas refined spatial resolution is bound to be an added advantage for mapping. The objective of this study was therefore to determine the most suitable period and influential bands to discriminate (C3) and (C4) grasses using multi-temporal Sentinel 2A images.

5.2. Methodological approach

5.2.1. Field data collection

Festuca costata (C3) and *Themeda Triandra* (C4) grasses were the target of the present study. These will be referred to as C3 and C4 grasses thereafter. The location of these grasses was captured in February 2016, by means of a Trimble GEO XH 6000 hand held Global Positioning System (GPS) at sub-metre accuracy. The GPS captures locational information more accurately, especially for the extraction of reflectance values from high spatial resolution data. The sampled points were collected based on randomly generated points in a GIS environment. A total of 120 points were collected for each grass species and then used to extract the corresponding grass spectral reflectance from the Sentinel 2 data, using the extraction tool in ARCGIS 10.2 environment, for further analysis. For each image, species reflectance was obtained by extracting the pixel (at 10 m spatial resolution) value that covered the point.

5.2.2. Remote sensing data acquisition and pre-processing

High resolution multispectral Sentinel 2A images are freely-available for download from the ESA website (https://scihub.copernicus.eu/) through the Sentinels Scientific Data Hub. Table 5.1 provides detailed characteristics of Sentinel 2A Level 1C images that are available for download. For this study, a total of eight cloud-free images (Table 5.2), covering the entire study area were selected and downloaded. These images were delivered orthorectified and geometrically corrected in the Universal Transverse Mercator projection and World Geodetic System 84 ellipsoid. The images were acquired in top of atmosphere reflectance and then corrected for atmospheric effects. Atmospheric correction was performed, using the Sen2Cor prototype processing tool in Sentinels Application Platform (SNAP), based on the ATCOR algorithm (Clevers *et al.,* 2017). Bands 1, 9 and 10, at 60 m spatial resolution were not included in this analysis. The spectral bands have been considered to be inapplicable in vegetation monitoring (Immitzer et al., 2016). All the 20 m spatial resolution spectral bands were also resampled to 10 m, using the nearest neighbour resampling tool in SNAP.

Table 5.1: Sentinel 2 image data characterization

Band name (-)	Band #	Central λ (nm)	GSD (m)
Blue	2	490	10
Green	3	560	
Red	4	665	
NIR	8	842	
RE	5	705	20
RE	6	740	
RE	7	783	
RE	8a	865	
SWIR	11	1610	
SWIR	12	2190	
Coastal aerosol	1	443	60
Water vapour	9	945	
Cirrus	10	1380	

*RE, NIR, and SWIR represent red edge, near infrared and short wave infrared spectral bands. GSD is Ground sampling distance. The row highlighted in grey indicates bands excluded in this study.

Table 5.2: Sentinel 2 image acquisition and their characteristics

Season	Acquisition date	Sun zenith angle (°)	Sun azimuth angle (°)
Summer	07/02/2016	41.57	44.02
	05/03/2016	46.94	36.32
	03/11/2016	24.59	60.95
	03/12/2016	22.41	77.97
Winter	27/05/2016	55.99	28.94
	26/06/2016	58.34	29.29
	16/07/2016	47.16	37.10
	25/08/2016	36.49	43.65

5.3. Statistical analysis

To determine the optimal period to discriminate the two grasses, Discriminant Analysis (DA) model was used. The DA model discriminates between species using a linear transformation of remote sensing data. Its performance has been widely acknowledged in discriminating C3 and C4 grass species (Foody and Dash, 2007; Price et al., 2002; Shoko and Mutanga, 2017a). Prior to analysis, the samples were randomly grouped into training (70%) and validation (30%). This is critical when classifying species, using machine learning models (Adelabu et al., 2013; Guerschman et al., 2003). The model produces confusion matrices and overall classification accuracies for each satellite imagery applied. Overall accuracies indicate the performance of each image or image acquisition period in classifying the two species. The derived overall accuracies were also transformed. The transformation was performed by centering the data, using ExcelStats transformation tool. Transformation was performed for comparison purposes and it provides a better understanding of how the derived overall accuracies varied over time. The most and least influential spectral bands for each satellite image were also identified, using variable scores derived from the DA model. Variables with score value above the threshold (score > 1) contribute significantly ($\alpha = 0.05$) to species discrimination, whereas those below the threshold, were considered less influential.

5.3.1. Statistical test and classification accuracy assessment

Overall classification accuracies derived using images acquired in both summer and winter were tested for significant differences ($\alpha = 0.05$). Data was first tested for normality, using the Shapiro Wilk normality test (Shapiro and Wilk, 1965). Test results showed a deviation ($\alpha = 0.543$) from the normal distribution, hence the Mann-Whitney non-parametric test (Mann and Whitney, 1947) was then applied. The test was also further done for the two species spectral reflectance data derived from the 10 Sentinel 2 bands applied in this study. The results are shown in Table 5.3. Accuracy assessment was determined at species level, for the two species, using errors of commission and omission. The two errors indicate the potential of each satellite image in correctly assigning the species to their respective classes, without misclassifications (Bork and Su, 2007; Zhou et al., 2014). Errors of commission and omission thus provide more details to the classification results at species level.

5.4. Results

5.4.1. Species spectral response over time

Averaged spectral response for C3 and C4 grasses during summer *(a-d)* and winter (*e-h*) periods are illustrated in Figure 5.1 (*a – h*). Figures *a-d* correspond to February, March, November and December, whereas *e-h* correspond to May, June, July and August 2016. Overall, species spectral response varies over time. For example, in summer Sentinel 2 satellite images showed a close similarity (overlap) between the two species, especially in the visible (*e.g.* blue, green and red) and the SWIR portions, when compared to winter results. Significant differences ($\alpha = 0.05$) were only exhibited in the red edge and the NIR portions, where separable species spectral response were observed.

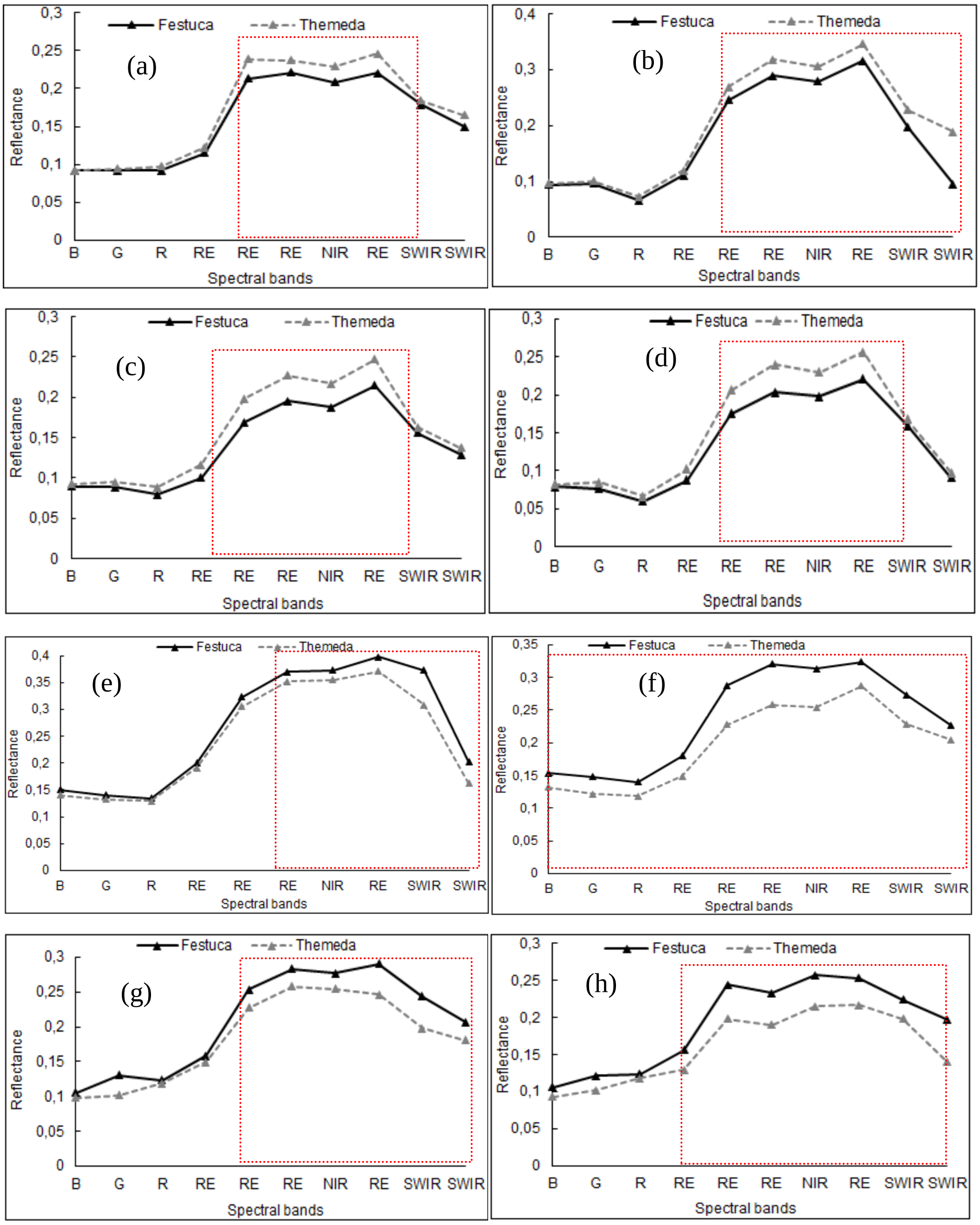


Figure 5.1: Species spectral response curves for summer: (*a-d*) and winter *e-h*. Red boxes show the bands with separable spectral response

Table 5.3: Test of significant difference results in spectral response between the two species

Acquisition Date	B	G	R	RE	RE	RE	NIR	RE	SWIR 1	SWIR 2
07/02/2016	0.97*	0.40*	0.16*	0.31*	0.01	0.01	0.05	0.01	0.29*	0.01
05/03/2016	0.79*	0.32*	0.55*	0.04	0.01	0.01	0.02	0.09	0.11*	0.01
03/11/2016	0.34*	0.01	0.01	0.01	0.01	0.01	0.01	0.11*	0.44*	0.01
03/12/2016	0.04	0.21*	0.04	0.01	0.01	0.48*	0.01	0.14*	0.04	0.08*
27/05/2016	0.06*	0.39*	0.18*	0.02	0.02	0.01	0.74*	0.23*	0.01	0.01
26/06/2016	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
16/07/2016	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.03
25/08/2016	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01

P-values with an asteric "*" indicate no significant differences (α = 0.05) in spectral response between the two species using that particular band.

5.4.2. Multi-temporal classification accuracies

Figures 5.2 (a) and (b) illustrate the untransformed and transformed overall classification accuracies derived from the classification of C3 and C4 grass species, using Sentinel 2 data, over time. Overall, higher classification accuracies were derived. However, the variability in classification over time was observable when results were transformed. These results indicate that the two grass species were better discriminated during the winter period, with end of June as the most suitable. On the other hand, summer period showed lower classification accuracies, with the lowest overall accuracy produced in November. Statistical test also confirmed that images acquired during summer months produced significantly different (α = 0.05) overall accuracies, for the two species than winter data.

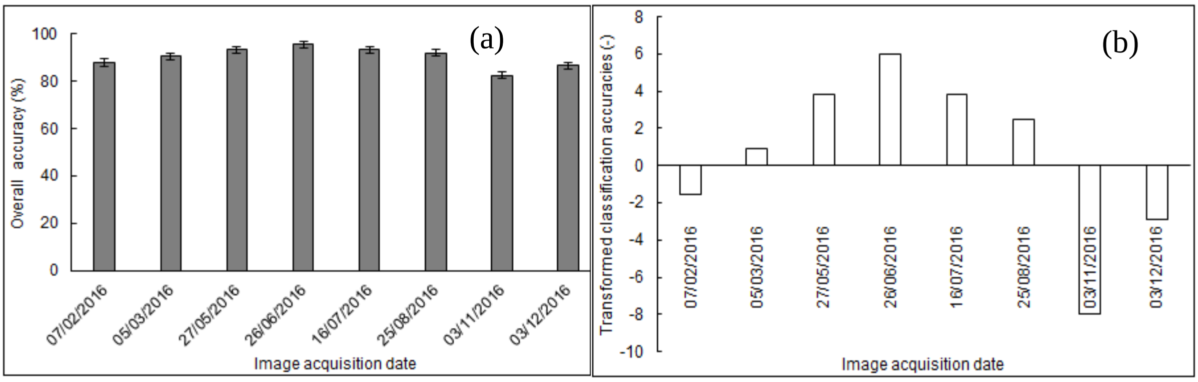


Figure 5.2: Untransformed (a) and transformed (b) overall accuracies over time

5.4.3. Influence of spectral bands on discriminating C3 and C4 grass species over time

Figure 5.3 shows the influence of the Sentinel 2 spectral bands on discriminating C3 from C4, expressed as their frequency over time. Red edge 1 (705 nm) was found to be the most influential band in discriminating between C3 and C4 grasses, with the highest frequency of 7, followed by NIR, with 5 and SWIR 2 with 4, whereas RE 4 (865nm) did not significantly ($\alpha = 0.05$) contribute to species discrimination, over time.

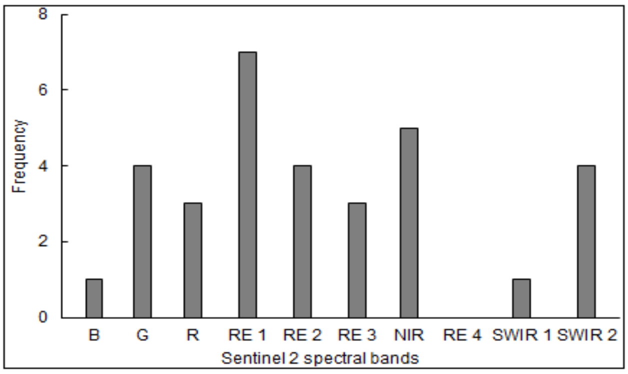


Figure 5. 3: Spectral bands frequency in discriminating C3 and C4 over time

5.4.4. Classification accuracy assessment results

Figure 5.4 shows the errors encountered when classifying C3 and C4 using images acquired at different periods. Overall, when classifying C3 and C4, omission errors ranged from 2.9 to 19.5% and commission errors from 2.5 to 22.2%. It was also found that images acquired in winter (*i.e.* May, June, July and August) classified the two grasses with lower omission errors (2.9 - 11.6%) and commission errors (2.5 - 14.3%). On the other hand, summer Sentinel 2 data produced higher omission errors (5.4 - 19.5%) and commission errors (4.7 - 22.2%). November had the highest omission (19.5%) and commission (22.2%) errors, when classifying C3 and C4 grasses and the lowest omission (2.9%) and commission (2.5%) errors were observed using June data.

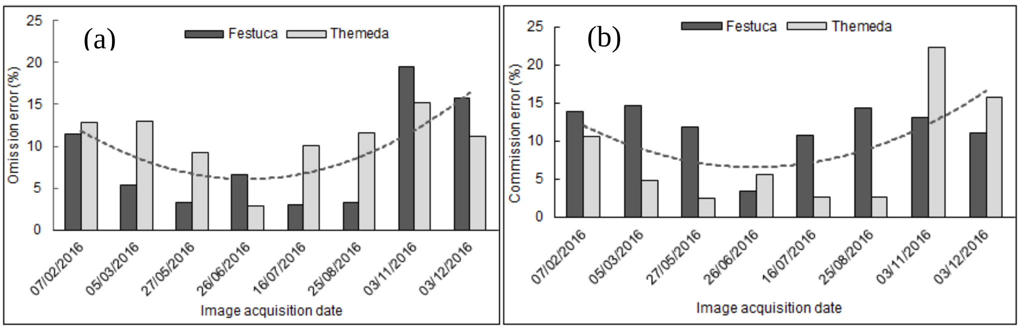


Figure 5.4: Errors encountered in classifying the target grasses, using multi-temporal Sentinel 2 data. Dotted lines show the trend of species classification errors, overtime

5.4.5. Spatial distribution of C3 and C4 grass species using different images

A sample of the distribution of the two species derived using images acquired at different seasonal periods is presented in Figure 5.5. These maps were produced by classifying the Sentinel 2 data, using the maximum likelihood classifier algorithm in ENVI 4.3 and the most influential bands based on DA model. The GPS points were used as training samples to classify the images. Images with the highest and lowest classification accuracies for the two distinct seasonal periods were shown. It was found that image acquisition date influenced the spatial representation of the two grass species. However, noticeable agreement, especially within the central and eastern parts was derived from the four images.

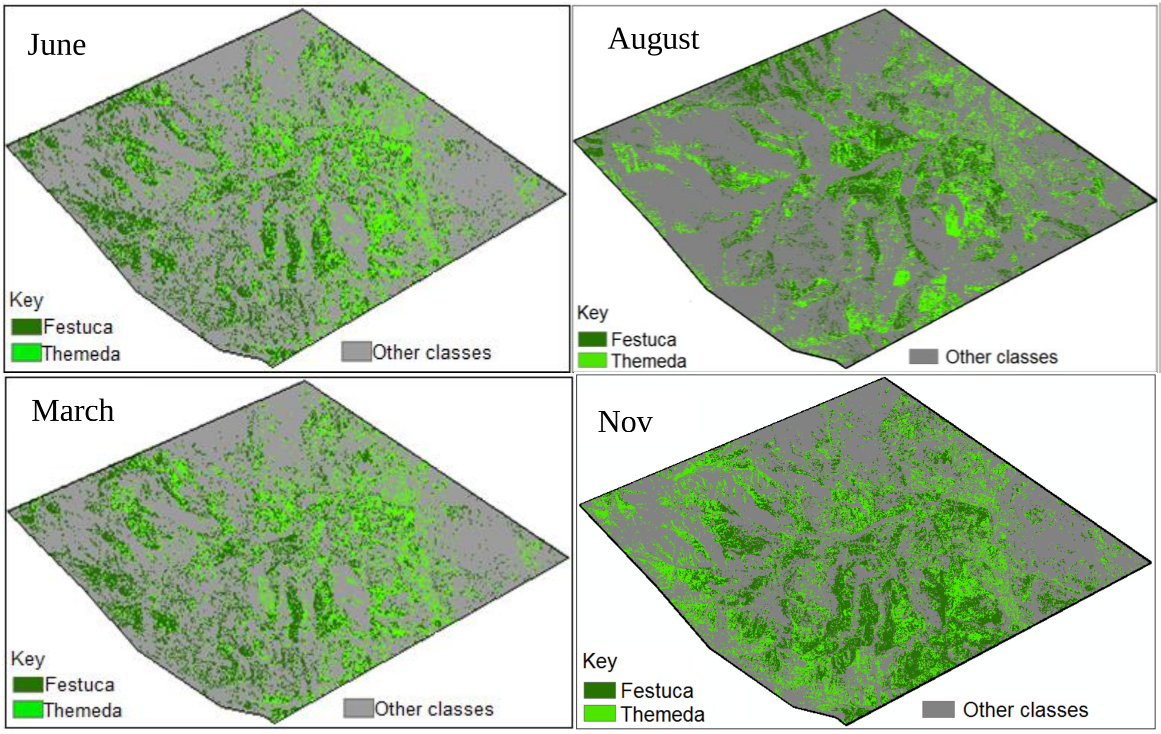


Figure 5.5: The spatial distribution of C3 and C4 grass species across the study area using images acquired at different seasonal periods in 2016

Figure 5.6 further explores the derived areal coverage occupied by the two grass species in the study, using images acquired at different seasonal periods over time. Overall *Festuca* (C3) was also found to occupy the majority of the area studied, compared to *Themeda* (C4), except using an image acquired in November. The largest species areal coverage was also derived in March, whereas in August, a noticeable decrease for both species was observed.

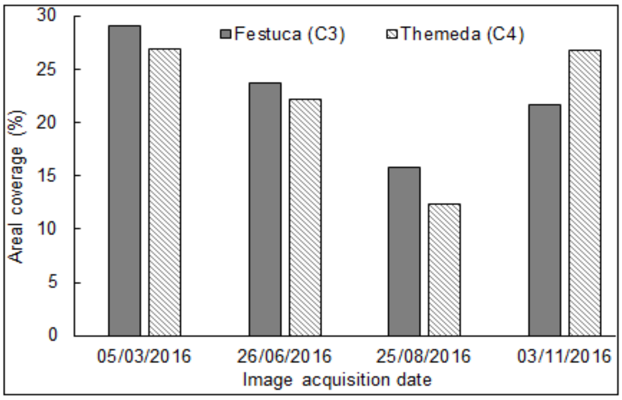


Figure 5.6: Species areal coverage derived using different image acquisition dates

5.5. Discussion

The findings of this study have demonstrated the winter period as the most favourable and optimal time for the classification C3 and C4 grass species. Sentinel 2 images acquired during the winter period had more potential to detect and correctly assign the grass species to their respective classes. This is an indication that during the winter period, the two grass species had distinct phenological, physiological and morphological contrasts, which enhanced their accurate discrimination by the sensor. In confirmation, it is well documented that C4 grass is a warm season grass, which is most active during the summer season, whereas in winter it becomes dormant (Dell'Acqua et al., 2013; Snyman et al., 2013). In contrast, C3 is typically active during the winter period, as well as thriving throughout the year (McGranahan et al., 2015).

Although images acquired in summer produced higher overall accuracies, considerable misclassifications errors were encountered, for example, when using an image acquired in November, the beginning of summer. This was supported by high commission errors above 20%, associated with summer images. Thus although higher overall classification were achieved, about 20% of the species samples were wrongly assigned to the respective classes. Possibly higher classification accuracy might be due to misclassifying species. Both species, as well as other surrounding grass species within the area become active in summer, despite the fact that C3 will be less active, due to unfavourable environmental conditions. This led to spectral confusion between the two grass species and other species (*e.g.* ephemeral weeds and forbs), which emerge during the onset of summer rains. This facilitates species spectral similarity, during this period, thereby compromising the classification accuracy. Nevertheless, considerable differences exist between C3 and C4 grasses, which enhance their spectral differences detectable during the summer period. For instance, the study by

(Adjorlolo et al., 2014; 2015), which determine quality variations of C3 and C4 grass species during the summer period have reported that the two species have significant different concentrations of nutrients. C4 grass was found to have higher content of nitrogen and crude proteins than C3. These variations in pigment concentrations have been reported to enhance C3 and C4 species discrimination (Peterson et al., 2002). Although the quality of these grasses was not performed in winter, when both species have reached their maturity and C4 begins to become inactive. It is most likely that their pigments concentration will be more different, which might possibly contribute to the spectral variations.

It was also revealed that the seasonal variations have an influence on the spectral response of C3 and C4 grass species. This was confirmed by the spectral response curves between the two species over time. Higher reflectance response from C4 in summer is mainly attributed to its growth. In summer C4 is very active with higher levels of pigments concentrations, which all contribute to higher reflectance. As the year progresses, C4 loses its vigour and within the Drakensberg Mountains, this is most observable during the winter fall, in August, and it continues to dry until the beginning of summer in November. As the grass loses its vigour, its reflectance lowers. On the other hand, C3 is an evergreen grass, and most active during the winter peak, which typically offers its most favourable conditions. However, although it remains green, the conditions are not favourable during the winter fall, hence it becomes less active. This confirms previous findings which have noted the changes in vegetation species spectral response to seasonal variations (Guerschman et al., 2003; Murakami et al., 2001; Schriever and Congalton, 1995). These researchers have emphasized the significance of seasonal variations, particularly in rainfall and temperature in determining vegetation status and spectral characteristics. They also highlighted that vegetation spectral response is quite variable over time and classification accuracies therefore vary. Using the red edge portions, which is one of the unique bands of the Sentinel 2, the curves showed separable species spectral responses over time.

When considering the spatial representation of the two grasses across the study area, images acquired in summer identified more areas as being occupied by the target grasses, whereas those acquired in winter showed a decrease. In summer, vegetation across the study area are active, due to favourable climatic conditions (*i.e.* high rainfall and temperatures), which promote vegetation growth and productivity. In addition, at the beginning of summer (*i.e.* in November), as surrounding warm season grasses emerge; their spectral response will be difficult to separate from that of the target grasses. This might result in misclassification, thereby over estimating their spatial distribution. In addition, as the target species reach their maturity, before they become dry or inactive, they become more distinct and separable using remotely-sensed data. This provides a better spatial representation of the grasses, for example in June. Although June is peak of winter, these effects on C4 within the study area are more observable at the end of winter, as temperatures begin to rise.

At the end of winter (in August), the classification, especially of C4 is possibly confused with bare areas, as it becomes dry, as a result of dry conditions. This makes it difficult to distinguish it from other surrounding vegetation, especially other wilting grasses and bare surfaces. A similar finding was noted by Kaszta et al. (2016), using high spatial resolution Worldview 2 to separate different components of the African Savannah vegetation during the wet and dry seasons. The study found that wilting grasses were confused with bare soil. However, C3, which remains active in dry season exhibit distinct spectral response from dry grasses, improving its discrimination and mapping abilities. To improve the discrimination and spatial representation of C3 and C4 grass species, especially during the winter fall and early summer, future work might consider using Sentinel 2A derived vegetation indices or textural metrics.

The use of Sentinel 2 multi-temporal images proves its potential in detecting the temporal eco-physiological variations between C3 and C4 grass species functional types, over time. This is in agreement with the study of Laurin et al. (2016), which tested the potential of Sentinel 2 in classifying species according to their functional types. The study noted that the sensor opens a new opportunity for vegetation monitoring, based on functional types. Similarly, the performance of the red edge bands in influencing species discrimination further confirms previous studies which have predicted that these bands are more valuable than the visible or NIR portions in distinguishing vegetation status over time (Immitzer et al., 2016; Kaszta et al., 2016; Shoko and Mutanga, 2017a). Red edge bands extract unique vegetation information beyond the reach of the visible or NIR bands, which have been primarily used in discriminating C3 and C4 grass species. Red-edge bands have the ability to capture and record variations pigment concentration between species, which enables their better discrimination. However, although they were not as good as the red edge, the visible green and red band were also good in discriminating between C3 and C4, especially during the winter fall, when C3 and C4 were more distinct. This indicates that the visible range has a limited temporal window to discriminate between C3 and C4 grasses, as they can perform better when the difference between species is most observable or if there are clear distinctions.

5.6. Conclusion

The present study performed an analysis of multi-temporal Sentinel 2 images for optimal discrimination of C3 and C4 grass species in the montane grasslands of KwaZulu-Natal, South Africa. Overall, image acquisition period has been found to significantly influence the spectral distinction, classification accuracy and spatial representation of C3 and C4 grass species. Images acquired in winter, when both grasses have reached their maximum maturity stage of development were the most favourable to discriminate C3 and C4 grass species, compared to those acquired in summer. Summer images also show an over estimation and spatial representation of the target species and this was also supported by associated higher classification errors. Thus early summer and late winter present less suitable periods for discriminating and mapping C3 and C4 grasses. The discrimination of the target grasses was most attributed to the outstanding performance of the red edge, NIR and the SWIR portions which were consistent, over time, compared to the visible portion.

This study has provided the optimal period for classifying and mapping C3 and C4 species, thereby providing a better spatial representation of their distribution. This is a fundamental basis for appropriate accounting of their productivity. Although the new generation sensors have shown potential in mapping the target species, their ability to characterize spatial variations in species AGB remains uncertain. In addition, the lack of sensors for characterizing species AGB was one of the key challenges identified in the remote sensing of C3 and C4 AGB. In this regard, the succeeding chapter sought to explore how these sensors estimate and spatially represent species AGB.

CHAPTERS SIX AND SEVEN

C3 AND C4 GRASSES ABOVEGROUND BIOMASS CHARACTERIZATION

6. Determining optimal new generation satellite for accurate C3 and C4 grass species aboveground biomass estimation

(Source: https://www.oneonta.edu/faculty/baumanpr/geosat2/RS%20History%20II/RS-History-Part-2.html)

This chapter is based on:

Shoko C, Mutanga O and Dube T. Determining optimal new generation satellite for accurate C3 and C4 grass species aboveground biomass estimation. *Remote Sensing*, 2018 (10)4: 564

Abstract

While satellite data has proved to be a powerful tool in estimating C3 and C4 grass species aboveground biomass (AGB), finding an appropriate sensor that can accurately characterize the inherent variations remains a challenge. This limitation has hampered the remote sensing community from continuously and precisely monitoring their productivity. This study assessed the potential of Sentinel 2 MultiSpectral Instrument, Landsat 8 Operational Land Imager and Worldview 2 sensors, with improved earth imaging characteristics, in estimating C3 and C4 grasses AGB in the Cathedral Peak, South Africa. Overall, all sensors have shown considerable potential in estimating species AGB; with the use of different combinations of the derived spectral bands and vegetation indices produced better accuracies. However, Worldview 2 derived variables yielded better predictive accuracies, (R^2 ranging between 0.71 and 0.83; RMSE values between 6.92 and 9.84%), followed by Sentinel 2, with R^2 between 0.60 - 0.79; and RMSE between 7.66% and 14.66%. Comparatively, Landsat 8 yielded weaker estimates, with R^2 ranging between 0.52 and 0.71 and high RMSE values, ranging between 9.07 and 19.88%. In addition, spectral bands located within the red edge (*e.g.* centred at 0.705 and 0.745µm for Sentinel 2), SWIR and NIR, as well as derived indices were found to be very important in predicting C3 and C4 AGB from the three sensors. The competence of these bands, especially of the free-available Landsat 8 and Sentinel 2 dataset was also confirmed from the fusion of the variables. Most importantly, the three sensors managed to capture and show the spatial variations in AGB for the target C3 and C4 grassland area. This work therefore provides a new horizon and a fundamental step towards C3 and C4 grass productivity monitoring for carbon accounting, forage mapping and modelling the influence of environmental changes on their productivity.

Keywords: forage, carbon pool, climate change, new generation sensors, grass productivity

6.1. Introduction

C3 and C4 grass species Aboveground Biomass (AGB) indicate the productivity of grasses with common phenological, physiological and morphological characteristics (Jin et al., 2013; Tieszen et al., 1997). The accumulation and availability of C3 and C4 grasses AGB offers a wide range of ecosystem goods and services, as well as influence varying environmental processes. For instance, they are forage sources for a vast of wildlife and livestock populations (Polley et al., 2014), provide fuel load (Everson and Everson, 2016), maintain biodiversity and are potential carbon pools (Adair and Burke, 2010). C3 and C4 grass species are however, facing considerable threats from environmental changes and these are anticipated to vary significantly, according to species functional types (Adjorlolo et al., 2012b; Bremond et al., 2012). Most importantly, as they have different environmental tolerances and requirements, C3 and C4 AGB will respond differently to environmental changes, anthropogenic pressure, management practices and invasion. Similarly, considerable uncertainties about the productivity of C3 and C4 grass species also exist under a carbon dioxide-enriched, warmer environment and the influence of local conditions (Chamaillé-Jammes and Bond, 2010). Consequently, there is need to identify robust methods, which have the ability to spatially and temporarily characterize these grasses AGB, with better and reliable accuracies. This is critical to improve the monitoring of C3 and C4 grasses productivity, and associated response to environmental and anthropogenic pressure.

Field measurements and experimental surveys have, so far, been the prominent approaches used to determine C3 and C4 grasses AGB for various applications (Everson and Everson, 2016; White et al., 2012; Winslow et al., 2003). However, these approaches are labour-intensive and very expensive, which has limited their full application, especially in the developing world. In addition, they lack spatial representation (Chen et al., 2009; Gao et al., 2012; Wand et al., 1999), which is insufficient for spatial and temporal monitoring. The use of remotely sensed data remains the feasible method to estimate and spatially characterize C3 and C4 grass species AGB, for large areas, in a cost effective manner (An et al., 2013; Chen et al., 2009). The review by Shoko et al. (2016a) has provided the much needed overview on the progress of remote sensing of C3 and C4 grass species AGB. The review identified detailed findings on the availability of sensors, their potential and limitations, as well as challenges and prospects for C3 and C4 grass species AGB monitoring. In summary, it was found that finding a cost-effective sensor, with sufficient spatial resolution, more and unique spectral bands, at large geographical coverage for estimating C3 and C4 grass species AGB is a major challenge that has discouraged the remote sensing community to continuously monitor these ecosystems. For examples, previously-used sensors, such as AVHRR had a very limited number of bands, which limits their spectral potential in differentiating C3 and C4 species characteristics, whereas their coarse spatial resolution misrepresent spatial variations in AGB.

It was also identified that new generation sensors, such as Landsat 8, RapidEye, Worldview 2 and Sentinel 2, with improved and unique characteristics provide an invaluable opportunity to detect and quantify variations in AGB across grassland composition of different photosynthetic types (Shoko et al., 2016a). These sensors present more advanced remotely-sensed data to the remote sensing community, which has been caught in between image acquisition cost, spatial coverage (which include spatial resolution and swath width), spectral capabilities and accuracy, in predicting species AGB. More spectral bands constituted by these sensors (*e.g.* 13 from Sentinel 2) provide wide spectral windows to capture C3 and C4 AGB variations. Similarly, more spectral bands with different capabilities, increases the sensitivity of the sensor to species phenological, physiological and morphological characteristics, which influence AGB. The unique red edge have been acknowledged in species AGB estimation, due to their sensitivity and ability in providing additional relevant species information (Clevers and Gitelson, 2013; Mutanga and Skidmore, 2004b). This is very important, especially considering the different physiological, morphological and phenological properties of C3 and C4 grasses and associated influence in AGB variations. For example, the phenological contrast between C3 and C4 has been documented. C3 grasses are typically cool season, most active under cool conditions and remain active throughout the year. C4 are warm season grasses mostly active during summer conditions and become dormant during winter. Similarly, the review by Adjorlolo et al. (2012b) has highlighted the morphological differences in leaf anatomy between C3 and C4 grasses, which influences their ability to scatter, reflect or transmit incoming radiation. Slaton et al. (2001), also noted that typically, C4 grass leaves are significantly thinner, with long palisade cells, which reflect more of radiation in the near infrared portion, compared to C3. On the other hand, C3 grass have thick walls, which are normally associated with short, cylindrical mesophyll cells. The review by Shoko et al. (2016a) have also reviewed the influence of these contrasts in estimating C3 and C4 grass species AGB. These contrasts in leaf anatomy require remote sensing variables which have the ability to differentiate for optimal AGB estimation. So far, the readily-available Sentinel 2 provides easy access of high resolution red edge bands, which are currently available in commercial satellites (Shoko and Mutanga, 2017a; 2017b). These bands have the ability to extract subtle differences between species; their inclusion will enhance AGB estimation accuracy.

The spatial properties of available sensors (*e.g.* 1 km^2 pixel resolution of AVHRR and MODIS), which have been the primary data sources for estimating C3 and C4 AGB have also been limiting the accurate quantification and mapping of these grasses AGB. The spatial resolutions of the Sentinel 2 (10m) and Landsat 8 (30m) are far much better for characterizing C3 and C4 grass species AGB. These pixel resolutions enable better spatial representation of species AGB, which might be under- or over-estimated at a 1 km pixel resolution. Also, considering the co-existence of C3 and C4 grass species, sensor spatial resolution becomes a critical concern to capture AGB variations from these grasslands. In addition, large swath width (*e.g.* 185 km for Landsat 8 and 290 km for Sentinel 2) allows monitoring at large geographical coverage, whereas the associated high spatial resolution for S-2 is indispensable; hence these sensors hold much appeal for C3 and C4 grass species AGB estimation. This study therefore assessed the performance of new generation sensors, with refined earth imaging properties in estimating and mapping C3 and C4 grasses AGB variations in the temperate region of KwaZulu-Natal, South Africa.

6.2. Methodological Approach

6.2.1. Grass species AGB data collection

The collection of AGB for *Festuca*, C3 and *Themeda* C4 grass species was conducted in February 2016, using 80 randomly generated points for each species. At each point, three quadrats measuring 50cm*50cm were randomly thrown within a 10 by 10 m plot. This quadrat has been regarded as providing representative samples for AGB prediction, especially in predominantly grassland areas (Price et al., 2002; Ramoelo et al., 2015c; Ren et al., 2011). In each quadrat, standing grass was harvested and its weight was determined *in situ*. The grass AGB samples were then transported and oven dried in grassland facilities, at the University of KwaZulu-Natal, to determine dry AGB which was then converted to kilograms per square metre (kg/m^2). A total of 240 AGB samples for each species were used for analysis. AGB sample x and y locations were also captured and recorded, using a handheld global position system (GPS), at sub-meter accuracy.

6.2.2. Remote sensing data characteristics and processing for AGB estimation

Three images were acquired each for Landsat 8, Sentinel 2 and Worldview 2 multispectral sensors. Landsat 8 images are delivered as raw digital numbers in Universal Transverse Mercator (UTM) system. The sensor acquires 12-bit images at a 16-day revisit time, using the visible range, NIR, SWIR and TIR, at a spatial resolution of 30m. The calibration of Landsat 8 images was performed as highlighted at the website (http://landsat.usgs.gov/). The image was also corrected for atmospheric effects to derive surface reflectance, using the Fast Line-of-sight Atmospheric Analysis of Spectral Hypercube (FLAASH) model in ENVI environment. Seven bands, from the Landsat 8 were used in AGB estimations and these correspond to coastal blue (0.435-0.451µm), blue (0.452-0.512µm), green (0.533-0.590µm), red (0.636-0.673µm), NIR (0.851-0.879µm) and the two SWIR (1.566-1.6512, 107-2294µm), which have been considered by previous studies, not only in monitoring C3 and C4 grasslands (Price et al., 2002; Shoko and Mutanga, 2017b), but in grassland areas (Sibanda et al., 2015a; 2016).

Sentinel 2 is an open and freely-accessible multispectral data source, acquiring 12-bit images, every 5-19 days, at 10 m, 20 m and 60 m spatial resolution, in 13 spectral bands. Four bands delivered at 10 m spatial resolution are centred at 0.49; 0.56, 0.665 and 0.842µm. The 20 m spatial resolution six bands are centred at 0.705; 0.74; 0.783; 0.865; 1.375 and 2.190µm, whereas three bands at 60 m resolution are centred at 0.443; 0.945; and 1.375µm. The Sentinel 2 image was provided in orthorectified top of atmosphere reflectance, with UTM system, associated with the World Geodetic ellipsoid 84. The atmospheric correction of the image was also performed using the Sen2Cor atmospheric correction toolbox, which is an inbuilt algorithm within the Sentinel Application Platform (SNAP) tool. The tool was developed primarily to work with Sentinel images. The three bands acquired at 60 m spatial resolution were excluded from the analysis, as they are primarily designated for atmospheric monitoring purposes (Drusch et al., 2012), whereas the 20 m spatial resolution bands were resampled to 10 m of the rest of the bands. The resampling was performed in SNAP using nearest neighbour resampling tool. Worldview 2 commercial image was purchased and it was delivered, after all the necessary corrections were performed by the supplier. The image was acquired at 2 m spatial resolution in 8 spectral range corresponding to coastal blue (0.4–0.45µm), blue (0.45–0.51µm), green (0.51–0.581µm), yellow (0.585–0.625µm), red (0.63–0.69µm), red edge (0.705–0.745µm), NIR (0.77–0.895µm) and NIR 2 (0.86–1.04µm) (Adjorlolo et al., 2014).

Detailed information on the remote sensing image acquisition dates and the field data collection of species AGB are tabulated in Table 6.1. It remains challenging to obtain three different remote sensing datasets, with the same acquisition date, due to their varying revisit time. For example, within a month, only two images are available from the Landsat 8, with a 16-day revisit time. However, for Sentinel 2, there are high possibilities of obtaining more images within a month, with its high revisit frequency of 5 days. In addition, the influence of cloud cover also hinders the acquisition of corresponding images, especially during the summer period. However, although the images had different acquisition dates, they were all collected within the same week and seasonal period, during summer. Although more images are required for better vegetation classification, the intention of the study was to compare the performance of newly-launched Sentinel 2 and Landsat 8. In addition, different studies elsewhere have yielded reasonable results in assessing the performance of different sensors, using a single image dataset, acquired within the same season. Secondly, it remains a challenge to acquire more images for Worldview 2 commercial data, due to its acquisition cost.

Table 6.1: Summary of remote sensing datasets acquired and used in this study

Remote sensing dataset	Acquisition date (dd/mm/yy)	Supplier/Source
Landsat 8	16/02/2016	USGS GloVis https://glovis.usgs.gov/
Sentinel 2	12/02/2016	Sentinels Scientific Data Hub archive https://scihub.copernicus.eu/
Worldview 2	16/02/2016	Purchased from Digital Globe, Longmont, Colorado, USA

To derive AGB maps for the target species, without other land cover or grass classes, image classification was performed. The classification was done using the species GPS points collected as training samples, whereas other land cover classes within the study area were masked out to show AGB variations for the target grass species only. In a separate study (Shoko and Mutanga, 2017a), the potential of Landsat 8, Sentinel 2 and Worldview 2 in discriminating the target species was done, using images acquired in summer, which were used to estimate AGB in this study. The detailed information for the classification procedure, associated variables and accuracy results are provided by Shoko and Mutanga (2017a). The final output map for the two grass species was derived using the standard NDVI, which showed great performance, when compared to other indices that were considered in the study.

6.2.3. Regression algorithm for predicting grass species AGB

This study used the Sparse Partial Least Square Regression (SPLSR)(Chun and Keleş, 2010) to predict AGB variations using Landsat 8, Sentinel 2 and Worldview 2 multispectral datasets. SPLSR is a robust and powerful algorithm for estimating vegetation biophysical properties using remote sensing data. So far, its high performance in predicting grass AGB across different environments has been reported (Abdel-Rahman et al., 2014; Sibanda et al., 2017; 2015b). The model builds estimation functions and associated variables using remote sensing datasets. The model achieves this through transformation of the remote sensing variables to a set of components and variables, which show their ability in estimating AGB (Sibanda et al., 2015a). To determine the number of components for optimal results in estimating species AGB, the leave-one-out cross-validation (LOOCV) approach was used. The cross validation was done using 30% of the AGB data collected from the field. The optimum number of components searched for each variable set were between 1 and 10, as recommended by Chun and Keleş (2010). The approach produced estimation errors, using Root Mean Square Error of Prediction (RMSEP) associated with a certain number of components. The component and associated variables with the lowest estimation errors was then considered for further analysis and AGB estimation. The same approach was used successfully for example, by Sibanda et al. (2015a), Abdel-Rahman et al. (2014) and Kiala et al. (2017).

The SPLSR was run using single species datasets separately and combined species dataset. The single species dataset comprised individual species AGB for *Festuca* and *Themeda* grasses, separately. Secondly, the model was run using pooled data, where *Festuca* and *Themeda* species dataset was combined. This was performed to produce integrated species AGB models for mapping. Before the model was run, the field-based AGB data samples were split into 70%, which was used to train the model, whereas the remaining 30% was used for validation. All the computations of the SPLSR model were run using R software. The model also provided the most optimal variables for estimating AGB, by means of variable scores, where variables with scores above 1 were regarded as the most important, while those below 1 were less important. The SPLSR output include a model that is used for AGB calculation with remote sensing images within a Geographic Information System environment. In this study, the AGB maps were produced using ARCGIS raster calculator function based on the based model derived using SPLSR.

6.2.4. Remote sensing variables for estimating grass species AGB

Three sets of variables derived from Landsat 8, Sentinel 2 and Worldview 2 sensors (Table 6.2) were used to predict AGB, using the SPLSR model. Vegetation indices that were used to predict AGB for the target grasses were chosen based on their performance in estimating AGB for C3 and C4 grass species compositions (Rigge et al., 2013; Tieszen et al., 1997; Xie et al., 2009). In addition, red edge-based simple ratio and NDVI, which were previously reported (Ramoelo et al., 2015c) to perform well across grassland ecosystems in general were adopted to predict AGB variations for C3 and C4 grass species. This provides more insight about the potential of the unique bands in deriving different indices, which have been primarily developed, using the visible portion of broad-band multispectral datasets. Sensors data fusion was also done, where all the variables from each sensor were combined and used in the model. This provides a more comprehensive insight of the competence of each sensor's variables across multispectral sensors in estimating C3 and C4 grass species AGB, than when the sensor variables are used in isolation.

Table 6.2: Remote sensing variables used to predict species AGB

Data type	**Details**	**Analysis set**
Landsat 8 Sentinel 2 Worldview 2	Seven spectral bands (CB, B, G, R, NIR, SWIR1, SWIR2) Ten spectral bands (B, G, R, RE1-3, NIR, RE4, SWIR1, SWIR2) Eight spectral bands (CB, B, G, Y, R, RE, NIR1, NIR 2)	i
Vegetation Indices (VIs)	EVI, SAVI, StNDVI, RDVI, SR, MSR (common to all sensors), NDVIRE1-4, SRRE1-4 (using Sentinel 2 red edge bands), NDVI2 and SR2, (using Worldview 2 NIR2 and R) NDVIRE1, SRRE1 (using Worldview 2 NIR1 and RE) NDVIRE2, SRRE2 (using Worldview 2 NIR2 and RE)	ii
Image spectral data + VIs	Combined image spectral bands and vegetation indices	iii

EVI: Enhanced vegetation index (Huete et al., 1997), SAVI: Soil adjusted vegetation index (Huete, 1988), StNDVI: standard NDVI (Tucker, 1979), RDVI: renormalized difference vegetation index (Roujean and Breon, 1995), SR: simple ratio (Jordan, 1969).

6.2.5. Species AGB estimation accuracy assessment

Statistical measures of AGB estimation accuracy using the different sensors and associated variables were determined, as well as the model performance in estimating species AGB. These measures included the coefficient of determination (R^2), root mean square error (RMSE) and RMSE%. The RMSE is a measure of the difference between the actual measured AGB values in the field and the estimated values. These are frequently used in prediction accuracy assessment using remote sensing data. The RMSE was calculated using the formula:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(X_{measured} - X_{predicted})^2}{n}}$$

Where: $X_{measured}$ is the measured AGB, $X_{predicted}$ is the predicted AGB and i is the predictor variable included (Dube and Mutanga 2015). The RMSE% was also calculated as:

$$RMSE(\%) = \frac{\sqrt{\frac{1}{n}\sum_{1=n}^{n}\left(y_i - \hat{y}_i\right)^2}}{\bar{y}} \times 100$$

Where n is the number of measured values; y_i is the measured value; $\hat{y}_i$ is the estimated values and $\bar{y}$ is the mean of the measured AGB (Dube and Mutanga 2015).

A better model using the different metrics was selected from each sensor based on the highest R^2 and lowest RMSE. The selected model and associated variable with the highest VIP score for each sensor was then used to produce AGB maps for the study area in ARCGIS 10.2. Significant difference tests were also performed to determine if the performances of the three sensors in estimating C3 and C4 grass species AGB were significantly different. In addition, it was also tested whether the estimation accuracies of *Festuca* was significantly different from that of *Themeda,* using the three sensors.

6.3. Results

6.3.1. Species AGB variations measured

Table 6.3 shows the descriptive statistics of measured *Festuca* and *Themeda* grass species AGB. It was found that in early February, *Themeda* C4 grass had higher AGB variations, when compared to *Festuca*. Measured AGB of *Themeda* varied from 0.6kg/m^2 to as high as 1.276kg/m^2, whereas for *Festuca*, it varied between 0.52kg/m^2 to 1.16kg/m^2.

Table 6.3: Descriptive statistics of the measured species AGB

Species	Minimum (kg/m^2)	Maximum (kg/m^2)	Average (kg/m^2)	Stdev. (kg/m^2)
Festuca	0.524	1.160	0.709	0.115
Themeda	0.600	1.276	0.884	0.125
Combined species	0.524	1.276	0.797	0.148

*N is the number of sampled plots

6.3.2. The performance of sensors' variables in predicting species AGB

The results in Table 6.4 provide the performance of the variables derived from the three sensors in estimating species AGB. Overall, all the variables showed considerable potential in predicting species AGB. However, Worldview 2 sensor produced the best prediction accuracies, with the least estimation errors (between 6.92 and 9.84%), followed by Sentinel 2 estimates, far much better than those obtained using the Landsat 8 sensor. Spectral bands from all the sensors also estimated species AGB with the lowest accuracies, when compared to the use of indices and combined variables. There were noticeable improvements in estimation accuracy, from using spectral bands, to the use of combined variables, for both individual species and combined species datasets. This was most evident for Landsat 8 and Sentinel 2. For instance, Landsat 8 derived spectral bands produced an R^2 of 0.55 (RMSE = 17.55% of the mean) when estimating *Festuca* AGB. When estimating for *Themeda,* an R^2 of 0.52 was produced, with an RMSE of 19.88%. Landsat 8 bands also estimated combined species with an R^2 of 0.52 and an RMSE of 18.19%. When using indices, R^2 improved to 0.68 for *Festuca*, 0.63 for *Themeda* and 0.65 for combined species, whereas the errors of estimation were reduced to 11.48%, 12.53% and 13.5% for *Festuca*, *Themeda* and combined species dataset, respectively.

Tests of significance according to the t-test also revealed that the three sensors had significant differences in estimation accuracies using the different variables. Significant differences ($\alpha < 0.05$) were only observed between sensors, as well as between the variables used. However, although slight differences between the two species were observed, the differences were not significant ($\alpha < 0.05$).

Table 6.4: Sensor AGB predictive accuracies for *Festuca*, *Themeda* and combined species

Remote sensing datasets	Festuca R^2	Festuca RMSE (g/m^2)	Festuca RMSE (%)	Themeda R^2	Themeda RMSE (g/m^2)	Themeda RMSE (%)	Combined species R^2	Combined species RMSE (g/m^2)	Combined species RMSE (%)
Bands									
L-8	0.55	164.42	17.55	0.52	175.73	19.88	0.52	150.63	18.91
S-2	0.61	145.85	13.11	0.60	129.59	14.66	0.61	122.74	15.04
WV-2	0.73	93.59	8.97	0.71	97.50	9.22	0.72	78.42	9.84
Indices									
L-8	0.68	101.39	13.48	0.63	110.76	12.53	0.65	107.59	13.51
S-2	0.76	91.19	10.49	0.74	93.62	9.46	0.71	84.80	10.64
WV-2	0.79	55.44	7.82	0.77	64.17	7.26	0.75	64.47	8.09
Combined variables									
L-8	0.71	94.30	9.07	0.69	91.14	10.31	0.71	97.63	12.25
S-2	0.79	64.16	7.64	0.77	66.83	7.56	0.74	81.85	10.27
WV-2	0.83	52.39	7.39	0.8	61.17	6.92	0.82	64.23	8.06

*These results were based on the 70% sample set

Figure 6.1 shows the predictive accuracies of species AGB using optimal variables from the three sensors. These graphs illustrate the relationships between measured and estimated AGB, using combined variables, which were found to have better estimation accuracies, when compared to the use of spectral bands or indices. The optimal variables include Landsat 8 NDVI, NIR and SWIR; Sentinel 2 red edge bands (centred at 0.705, 0.74 and 0.783µm) with derived indices, NIR and SWIR, whereas for the Worldview 2 it was NIR, red and red edge bands and derived indices.

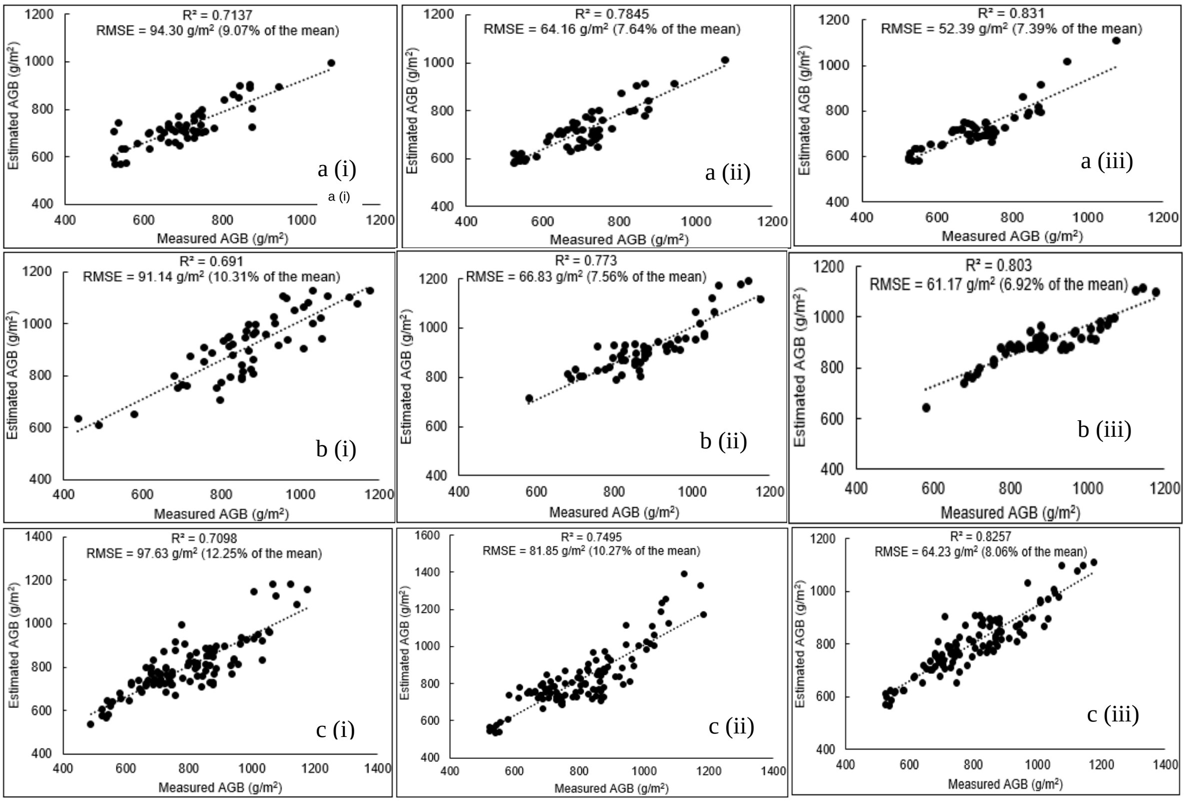


Figure 6.1: The relationship between measured and estimated AGB using the optimal variables of the three remote sensing datasets. a, b and c represent *Festuca*, *Themeda* and combined species datasets, respectively. i, ii and iii represent Landsat 8, Sentinel 2 and Worldview 2 datasets, respectively

6.3.3. Model validation results

Figure 6.2 provides the performance of the model in estimating species AGB using the independent 30% validation set. Overall the SPLSR performed well in estimating species AGB and the results were comparable to those produced using the 70% set. Therefore, only validation results for optimal variables for species pooled data was shown.

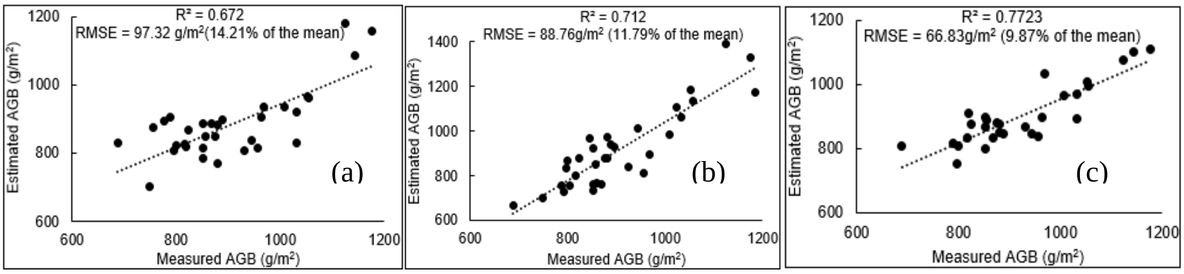


Figure 6.2: Model performance in estimating species AGB. a, b and c represents Landsat 8, Sentinel 2 and Worldview 2 remote sensing datasets

6.3.4. Sensors data fusion results in predicting C3 and C4 grass species AGB

When all the bands and indices from the three sensors were used separately for individual species dataset, the maximum numbers of components were 2. Therefore a report for the component with the lowest RMSEP and associated variables was provided. Figure 6.3 provides the most variables selected after fusing the three datasets, at individual species level and using species pooled data. Overall results indicated that the NIR, red edge and SWIR bands were the most important bands across sensors. When indices were used, the standard NDVI from Landsat 8 was found among Sentinel 2 and Worldview 2 most important indices, which included red edge-based indices. At individual species level, more variables were selected as important for estimating *Festuca* AGB, whereas for *Themeda* and pooled species dataset, a few variables were selected.

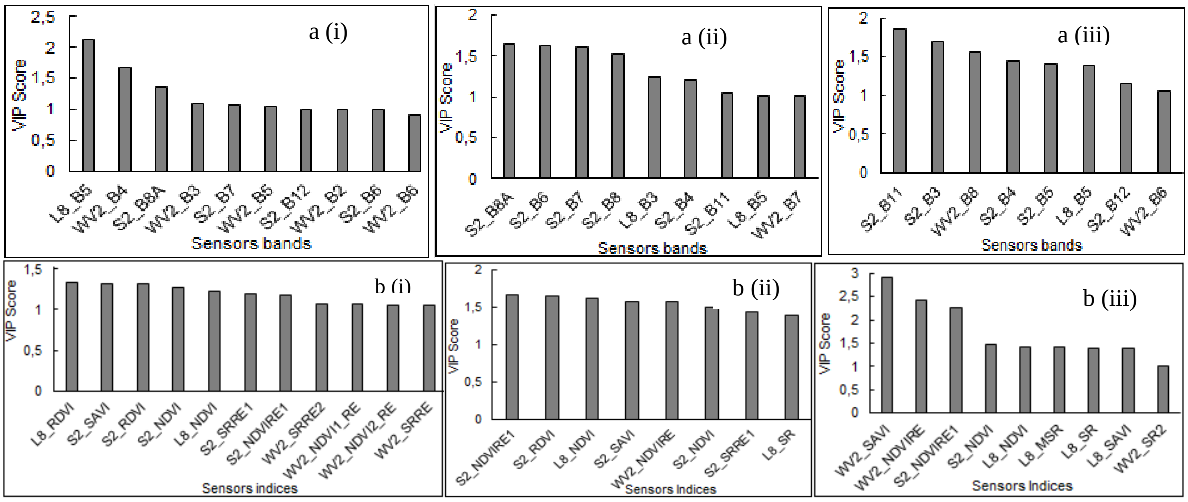


Figure 6.3: The most important (a) bands and (b) indices for estimating (i) *Festuca*, (ii) *Themeda* and (iii) combined species across sensors

6.3.5. The potential of the sensors in predicting and mapping C3 and C4 grasses AGB

Figure 6.4 shows the spatial variations of species AGB, estimated using optimal variables of the three multispectral sensors and species combined dataset. The combined species dataset has shown that NDVI was the most influential in estimating AGB. However, the index was derived using different sensors' spectral bands. For the Landsat 8, the AGB map was derived, using the standard NDVI, whereas for Sentinel 2, NDVI derived using red edge centred at 0.705µm was used and the NDVI using the red edge (centred between 0.705–0.745µm) was also used for Worldview 2. Thus NDVI derived using different spectral bands from the three datasets was used for species AGB mapping across the study area.

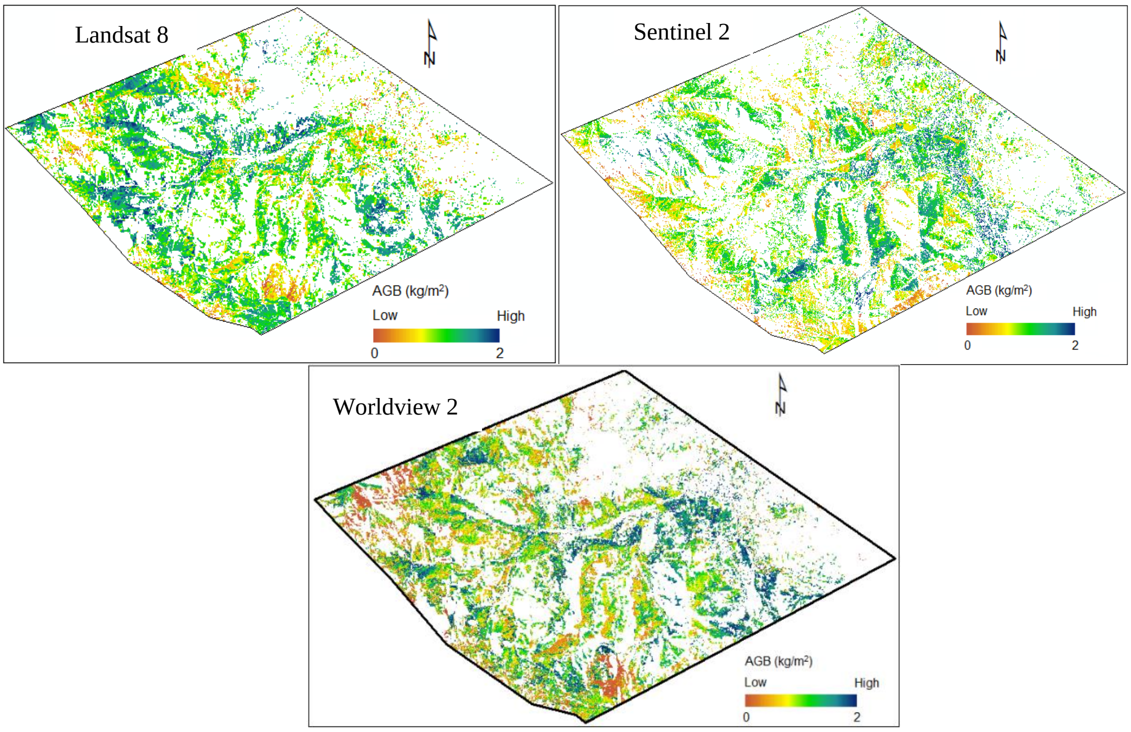


Figure 6.4: AGB variations in February 2016, derived using different remote sensing datasets

6.4. Discussion

Remote sensing of C3 and C4 grass AGB has remained a challenge, due to the lack of data sources, which have the capabilities to spatially characterize such subtle variations. The different physiological, morphological and phenological properties of C3 and C4 grasses influence AGB variations. Previous reviews (for example, Adjorlolo et al., 2012b; Shoko et al., 2016a) have noted the differences in leaf anatomy between C3 and C4 grasses, which influence their ability to scatter, reflect or transmit incoming radiation. Although these variations have been documented, not all sensors have the ability to discern such variations and estimate species AGB with optimal accuracy. This has resulted in lack of continuous monitoring of their productivity. It is therefore of much importance to identify remote sensing datasets to quantify and map the productivity of C3 and C4 dominated grasslands across vast scales. Current developments in remote sensing offer new perspectives for C3 and C4 AGB monitoring and modelling. It is also the focus of the remote sensing community to shift towards the use of freely-available new generation sensors, which have emerged with better capabilities for improved AGB estimation and monitoring. Similarly, the continuous monitoring of grassland areas is also a cause for research, especially in the light of climate change and its effects on food security, carbon cycle and biodiversity.

6.4.1. The performance of Landsat 8, Sentinel 2 and Worldview 2 variables in predicting species AGB

It can be observed that all sensors constitute variables which have the potential to estimate C3 and C4 grass species AGB. The availability of more bands from Sentinel 2 provides more spectral windows which are influential, as well as enabling the computation of different indices which have the potential to predict C3 and C4 grasses AGB. This has been reported by the findings of Addabbo et al. (2016) which highlighted that the novel spectral bands of the Sentinel 2 allows the computation of new indices, which offer additional information for vegetation analysis. The lower number of bands of the Landsat 8 sensor limits the number of variables with potential to estimate AGB. Among the most important variables for predicting C3 and C4 grasses AGB were spectral bands. For example, the Landsat 8 NIR and SWIR, as well as the red edge of Sentinel 2 and Worldview 2 contributed to species AGB estimation. Thus spectral bands of the new generation sensors have the capability to contribute to the estimation of C3 and C4 grasses AGB.

In addition, the important variables across the three sensors were mostly located within the NIR, red edge and the SWIR portions, as well as the corresponding indices. This was shown when individual sensors were tested, as well as from the fusion of the three datasets. However, for Landsat 8, only the NIR and derived indices and SWIR bands were competitive enough among Sentinel 2 and Worldview 2 variables. The potential of spectral bands of previously-used sensors have not been reported, as researchers were biased towards the use of derived indices, due to the broad spectral channels, which were perceived to be insensitive to species biophysical properties. However, a few studies reported the influence of NIR band in C3 and C4 grass species monitoring using previous Landsat data series, like the Thematic mapper 5 (Peterson et al., 2002). The study has highlighted significant differences in the NIR reflectance between C3 and C4 grass species using TM 5. In a different study, Lu et al. (2009) also reported the importance of NIR in estimating C3 and C4 grass species AGB using AISA Eagle hyperspectral imagery in Japan. The contribution of the SWIR portions in AGB predictions has been reported in grasslands ecosystems. The study by Chen et al. (2011) have reported the significance of SWIR bands in predicting AGB in the semi-arid rangelands of Idaho. This might also encourage future work to consider the use of SWIR-based indices, especially when using Sentinel 2 and Landsat 8 sensors.

Similarly, red edge bands and derived indices have been found to be sensitive to species biophysical properties, hence they boost the prediction of species AGB, when compared with the visible channels (Mutanga and Skidmore, 2004b; Sibanda et al., 2015a; Sibanda et al., 2017). The contribution of NIR, SWIR and red edge in this study might be attributed to the varying concentration of leaf pigments (*e.g.* chlorophyll and water) between C3 and C4. For example, NIR and red edge are closely related to chlorophyll (Delegido et al., 2011; Ramoelo et al., 2013), whereas SWIR to water content (Laurin et al., 2016). These bands have also been reported to be closely related to species AGB variations (Sibanda et al., 2015b), hence their important contribution in AGB estimation was observed in this study. This possibly indicates the variability in chlorophyll or water content between C3 and C4 species during the summer period, as indicated by a different study.

Spectral bands have low AGB predictive accuracy, when compared to the use of derived indices and a combination of variables. Improved prediction accuracies using indices have been acknowledged in estimating species AGB by previous studies (Lu et al., 2009; Schino et al., 2003; Sibanda et al., 2017). These variables have been perceived to be more sensitive to species characteristics, which improve their predictive accuracy, than individual bands. However, it should be noted that the performance of Landsat 8 spectral bands was weak, when compared to that of Sentinel 2 and Worldview 2. The slightly weaker performance of Landsat 8 bands in this study indicates the weaker performance of traditional bands in C3 and C4 dominated grasslands. In addition, Landsat 8 spectral settings lack unique bands like red edge, which weakens its potential to predict species AGB. On the other hand, the Sentinel 2 and Worldview 2 sensors constitute unique and important bands, which have the ability to extract the varying bio-physical characteristics of C3 and C4 species, which influence AGB. It should also be highlighted that the performance of traditional indices based on the traditional bands, such as visible or NIR were less important, when compared to those indices that were derived using additional unique bands, such as red edge and NIR. Substantial studies (that include Addabbo et al., 2016; Sharma et al., 2015) have studied the competence of indices derived from red edge or additional NIR, with those derived from traditional bands in characterizing species biophysical properties. For example, the study by Addabbo et al. (2016) which compared Landsat 8-based NDVI (using the red and NIR) with Sentinel 2 red edge NDVI for characterizing different vegetation.

Most interestingly, the improved performance using vegetation indices and combined variables was most apparent for Landsat 8, than Sentinel 2 or Worldview 2. This may be explained by the fact that Landsat 8 constitute broad traditional bands, which are not detailed enough to predict AGB, hence the inclusion of more than individual bands increases its prediction accuracy. In confirmation, vegetation indices have been the primary variables which have been preferred, over the use of individual bands, to estimate AGB variations between C3 and C4 grasses using broadband multispectral sensors (Grant et al., 2013; Guan et al., 2012; Pau and Still, 2014; Peterson et al., 2002). Broadband indices have been identified to be more sensitive to species AGB, which cannot be sensed by individual bands, thereby improving the model predictive accuracy. So far, the application of Landsat data series in estimating C3 and C4 grasses AGB has been very limited, except for a few studies which reported the derived indices. For example, the study by Davidson and Csillag (2001) in Canada reported the potential of the standard NDVI (R^2 = 0.64) from Landsat 5 TM-based Exotech Model radiometer, when compared to other indices. In a different study, in Kansas state of United States of America, Peterson et al. (2002) reported that although NDVI was influential in estimating C3 and C4 grass species AGB, the index failed to significantly differentiate variations in AGB between the two grass species. In this regard, mixed findings have been reported from previously-used Landsat datasets.

6.4.2. The potential of three sensors to predict and map C3 and C4 grassland AGB

One of the challenges faced by researchers in monitoring C3 and C4 AGB has been the ability of available sensors to map subtle AGB variations. This has been shown by the scarcity of the distributional maps of C3 and C4 AGB variations. Previously-used sensors were inadequate; they provided unsatisfactory predictions, because of their coarse spatial resolution and broad spectral channels. For example, the studies by Tieszen et al. (1997) and An et al. (2013) predicted C3 and C4 AGB with coefficient of determinations of 0.58 and 0.54 using AVHRR NDVI, whereas Rigge et al. (2013) reported AGB overlaps, using MODIS NDVI in the Prairies of the America. Findings from this study have shown improved estimations using the recently emerged multispectral sensors, than has been previously reported.

To the best of our knowledge, AGB maps for C3 and C4 grass species are rarely available. So far, few studies attempted to map C3 and C4 grasslands AGB using hyperspectral (Lu et al., 2009) and climatic variables (Epstein et al., 1997). However, the use of hyperspectral images, which are associated with high acquisition cost and climatic data proved unsuccessful and did not receive enough attention to understand the spatial variations of C3 and C4 AGB over large areas, especially in Africa, where climatic observation networks are very poor and financial resources are limited. This has limited the availability of AGB maps for C3 and C4 grasses. This study has therefore revealed a new opportunity for estimating and mapping AGB in C3 and C4 dominated grasslands over large areas in a cost effective manner, especially for the developing world, where the acquisition of commercial satellites is difficult. All three sensors showed great potential in mapping the spatial variations of species AGB. Researchers now have opportunities to use free-available Sentinel 2 and Landsat 8 or a combination of these datasets in monitoring the productivity of C3 and C4 grass species for a variety of applications.

Findings from this study also reveal the anticipated performance and potential of new generation sensors in mapping the AGB variations of C3 and C4 grassland areas (Shoko et al., 2016a). The sensors thus contain important abilities to monitor these grassland ecosystems, which was becoming almost impossible. Although it was not as good as the Worldview 2, Sentinel 2 was better than and Landsat 8. For example, Sentinel 2 predicted species AGB with better accuracy and showed better spatial variations, compared to Landsat 8. Recently, the study by Addabbo et al. (2016) reported the improved efficiency of the Sentinel 2, over that of Landsat 8. The study found statistical significance differences between the performances of the two sensors, using derived NDVI. They also reported that within a particular area, Sentinel 2 sampled 3015 pixels, when compared to 345 pixels from the Landsat 8. This confirms the magnitude of the Sentinel 2 10m spatial resolution, in representing spatial variability.

The Worldview 2 was also confirmed to remain critical in predicting more accurately and mapping C3 and C4 species AGB, than Sentinel 2 and Landsat 8. Within the same area, the potential application of Worldview 2 in estimating and mapping C3 and C4 grass species canopy nitrogen, with satisfactory accuracy has also been shown (Adjorlolo et al., 2014). The high spatial resolution and associated unique spectral bands thus enable the sensor to capture the spatial variability in canopy characteristics, such as leaf area index and pigment concentrations, which are related to species AGB variations; this improved its prediction accuracy. However, the operational application of the Worldview 2 might be hindered by its acquisition cost, this places Sentinel 2 and Landsat 8 as promising datasets for monitoring of C3 and C4 grasses AGB, especially in data scarce environments.

Although reasonable predictive results were produced from this study, especially in relation to those accuracies reported using broad-band multispectral datasets, the performance of the model in predicting C3 and C4 species AGB cannot be ignored. Overall, the SPLSR produced good predictive results for all the sensors, using different variables. However, results from this study might be considered inconclusive, since these sensors have been tested at a specific period. Snapshot AGB maps for C3 and C4 dominated grassland are inadequate; because AGB for these grasses vary over time, due to the influence of species phenology and more importantly changing climatic conditions. Decision making and implementation of policies require more details of species AGB variations. In relation with the performance of the sensors, the ability of the sensor to predict and spatially represent species AGB might also be influenced by the period considered. There is therefore the need to show how these sensors (particularly the free-available Sentinel 2 and Landsat 8 datasets) and the SPLSR model perform in predicting C3 and C4 grasses AGB, as well as their consistency over time.

6.5. Conclusion

The present study has shown the feasibility of using the new generation sensors to estimate and determine the subtle spatial variations of C3 and C4 grasses AGB in the temperate regions of South Africa. The most important finding from this study was the performance of the freely-available Sentinel 2 and Landsat 8 sensors in predicting and mapping species AGB. The sensors predicted species AGB with reasonable accuracy, which might be very useful in monitoring the productivity of C3 and C4 grasslands, for various applications. The sensors provide significant data sources to enable the monitoring of C3 and C4 grass species productivity, across different ecosystems.

For decades, the lack of appropriate remote sensing data sources compromised C3 and C4 grasses AGB estimation, over space and time, especially for the developing world, where the acquisition of commercial datasets is a major limitation. Results obtained from this chapter showed a new horizon for characterizing C3 and C4 grass species AGB using new generation sensors. This is encouraging for continuous monitoring of their productivity at large geographical coverage. Although Sentinel 2 produced lower accuracies, when compared to Worldview 2, its free availability becomes invaluable for characterizing C3 and

C4 grasses AGB over time. The sensor also showed better performance in relation to the freely-available Landsat 8, hence can optimally characterize AGB over time. Therefore, the next chapter used Sentinel 2 to characterize the seasonal spatial variations of C3 and C4 grasses AGB.

CHAPTER SEVEN

7. Characterizing the spatio-temporal variations of C3 and C4 dominated grasslands aboveground biomass in the Drakensberg, South Africa

This chapter is based on:

Shoko. C, Mutanga. O, Dube. T and Slotow. R. Characterizing the spatio-temporal variations of C3 and C4 dominated grasslands aboveground biomass in the Drakensberg, South Africa. 2018. *International Journal of Applied Earth Observations and Geoinformation*. 68:51-60.

Abstract

C3 and C4 grass species composition, with different physiological, morphological and most importantly phenological characteristics, influence Aboveground Biomass (AGB) and their ability to provide ecosystem goods and services, over space and time. For decades, the lack of appropriate remote sensing data sources compromised C3 and C4 grasses AGB estimation, over space and time. This resulted in uncertainties in understanding their potential and contribution to the provision of services. This study therefore examined the utility of the new multi-temporal Sentinel 2 to estimate and map C3 and C4 grasses AGB over time, using the advanced Sparse Partial Least Squares Regression (SPLSR) model. Overall results have shown the variability in AGB between C3 and C4 grasses, estimation accuracies and the performance of the SPLSR model, over time. Spectral bands information predicted species AGB with lowest accuracies and an improvement was observed when both spectral bands and vegetation indices were applied. For instance, in the month of May, spectral bands predicted species AGB with lowest accuracies for *Festuca* (R^2 = 0.57; 31.70% of the mean), *Themeda* (R^2 = 0.59; 24.02% of the mean) and combined species (R^2 = 0.61; 15.64% of the mean); the use of spectral bands and vegetation indices yielded 0.77; (18.64%), 0.75 (14.27%) and 0.73 (16.47%), for *Festuca*, *Themeda* and combined species, respectively. These results were comparable to those produced using 30% training dataset, with slight differences (+/- 5%), which indicated the potential of the model in estimating C3 and C4 grasses AGB over time. There were also noticeable variations in AGB between C3 and C4 grasses, where *Themeda* produced higher AGB from February to April, whereas from May to September, *Festuca* produced higher AGB. Both species also showed a decrease in AGB in August and September, although this was most apparent for *Themeda* than its counterpart. The red edge (at 0.705 and 0.74µm) and derived indices, NIR and SWIR 2 (2.19µm) were found to contribute more to grass species AGB estimation, over time. The AGB spatial variability maps produced in this study can be used to quantify C3 and C4 forage availability or accumulating fuel, over time, as well as for developing operational management strategies.

Keywords
Environmental changes, forage availability, red edge, seasonal variations, species functional types,

7.1. Introduction

C3 and C4 grass species Aboveground Biomass (AGB) represent a fundamental indicator of their productivity, which directly influences the ability of these ecosystems to provide ecosystem goods and services. Grass species productivity provides a wide range of ecological, economic and environmental services. For instance, these grasses are an important source of forage for livestock and wildlife populations (Diouf et al., 2015; Mansour et al., 2013), as well as a source of fuel load for fire occurrences, which is an important mechanism in their maintenance (Everson and Everson, 2016). Within the global carbon cycle, C4 grasses also store a substantial amount of carbon, compared to C3 grasses (Adair and Burke, 2010). Besides, the Intergovernmental Panel on Climate Change (IPCC) identified species AGB as one of the principal carbon pools of terrestrial ecosystems (Eggleston et al., 2006; Kumar and Mutanga, 2017; Vashum and Jayakumar, 2012). Most importantly, the phenological differences between C3 and C4 grass species, as determined by seasonal variations in climatic conditions influence their AGB over time. However, although a lot of studies have reported the phenological differences between C3 and C4, from a local scale, they tend to be more variable, due to the influence of local environmental conditions, such as topography. Consequently, the potential of these grasses to provide services is different and this may be more variable over space and time.

The current and projected environmental changes also threaten the spatial and temporal productivity of C3 and C4 grass species, with implications on AGB timing, accumulation and variations (Adjorlolo et al., 2012b; Bremond et al., 2012; Joubert et al., 2017; Morris, 2017). Compelling evidence have also reported substantial response of C3 and C4 grasses AGB to carbon dioxide (CO_2) fluctuations (Lee, 2011; Polley et al., 2014; White et al., 2012), water availability (Niu et al., 2008) and temperature changes (Auerswald et al., 2012; Still et al., 2014). Considerable uncertainties about the response of C3 and C4 grass species also exist under a CO_2-enriched, warmer environment and the influence of local conditions (Chamaillé‐Jammes and Bond, 2010). Nevertheless, environmental changes compromise the integrity of C3 and C4 grasses functional types and subsequently the provision of a range of services, such as forage and carbon storage. In this regard, the estimation of C3 and C4 grass species AGB over time provides detailed understanding of their productivity and response to environmental variability over time. This becomes a fundamental step to identify areas of low or high productivity, for example, in the case of forage availability, or determines vulnerable areas to environmental changes. This is required for developing proper management strategies to ensure sustainable provision of ecosystem goods and services.

Remote sensing remains a realistic and practical data source, for spatially explicit characterization of C3 and C4 grasses AGB over time and space. So far, AGB estimation for C3 and C4 grasses has been conducted or reported on specific seasonal period, using broadband multi-spectral datasets (Grant et al., 2013; Lu et al., 2009; Pau and Still, 2014). In a different study, Shoko et al. (2016a) conducted a detailed review on the progress of C3 and C4 grass species AGB estimation using remote sensing. The review found that the majority of studies which estimated C3 and C4 AGB were done using Moderate Resolution Imaging Spectroradiometer (MODIS), the Advanced Very High Resolution Radiometer (AVHRR), MEdium Resolution Imaging Spectrometer (MERIS) and Landsat multi-spectral datasets in the Prairies or Great Plains of the United States and in the temperate region of China. The challenges associated with using these datasets were also noted, which included lower estimation accuracies and spatial representation of AGB. This has been primarily attributed to mixed-pixel problem, due to their coarse spatial resolutions. These datasets also constitute limited number and strategically-positioned bands (*e.g.* red edge), which limit their spectral potential in differentiating C3 and C4 species characteristics associated with AGB variations. Their coarse spatial resolution (*e.g.* 1 km for MODIS and AVHRR) also misrepresent AGB spatial variations. With these challenges, other researchers (e.g. Lu et al., 2009) attempted to use hyperspectral datasets, with high spatial resolution and narrow spectral bands. These datasets have been reported to yield high predictive accuracies, compared to multispectral. However, their application did not receive enough attention from the research community, especially for AGB estimation at large geographical coverage over time. This has been due to their high acquisition cost; hence their application has been limited to small geographical coverage, especially in resource-constrained regions like Africa. The use of hyperspectral data sources becomes insufficient for the development of appropriate management strategies, especially considering the influence of climatic variations on C3 and C4 AGB over time. In this regard, AGB spatial and temporal variations for C3 and C4 grasses remains poorly documented. However, future prospects in understanding the productivity between C3 and C4 depend on the use of new generation freely-available sensors, such as the Sentinel 2.

Currently, the readily-available Sentinel 2 is perceived to provide a major key data source for estimating C3 and C4 grasses AGB over time, in a cost effective manner, at large geographical coverage. Although Sentinel 2 earth imaging characteristics are not as advanced as hyperspectral data (*e.g.* in terms of spatial resolution), the sensor might be considered as an intermediate dataset between the freely available broadband multispectral sensors and more advanced and commercialized hyperspectral sensors. The characteristics of Sentinel 2 overcome the major challenges associated with the operational application of broadband and medium resolution satellites, such as MODIS, AVHRR, MERIS and Landsat data series, which have been the primary data sources for AGB estimation, across C3 and C4 grasslands. The sensor is equipped with state-of-the-art instrumentation, which offers high resolution optical images, when compared to freely-available satellites on board optical or multispectral sensors, such as Landsat 8 or ETM 7 (Addabbo et al., 2016). Increased and unique spectral bands (13) at different and refined portions of the electromagnetic spectrum of Sentinel 2 free of charge provide more spectral windows sensitive to species morphological, physiological and phenological characteristics, which influence the production of AGB. This may improve the estimation accuracy of C3 and C4 grass species over space and time. In addition, these bands are only available in commercial datasets, such as hyperspectral, hence Sentinel 2 provide free access to the unique bands. The high revisit frequency (5-19 days), most importantly, captures the phenological variations of C3 and C4 grass, which influence AGB variations over time, as well as enabling the acquisition of cloud-free images. The 290 km swath-width also allows large geographic coverage, which is one of the major limitations of using hyperspectral data, whereas the 10 m spatial resolution captures AGB spatial variations at a finer scale, appropriate for mapping, especially considering the co-existence of C3 and C4 grass species, with varying characteristics.

Sentinel 2 sensor has so far proved a great potential in estimating and mapping crop quality (Clevers et al., 2017; Immitzer et al., 2016), vegetation health (Addabbo et al., 2016), wood cover mapping (Munyati, 2017), as well as C3 and C4 grass species discrimination and mapping (Shoko and Mutanga, 2017a). However, its applicability in C3 and C4 grass AGB estimation over time is still rudimentary despite the immediate need of information on rangeland productivity, in the face of the changing climate. This study therefore used time-series Sentinel 2 data to estimate and map C3 and C4 dominated grasslands AGB, in the Drakensberg, KwaZulu-Natal, over time. The study also aimed at determining the consistency of Sentinel 2 derivatives in estimating species AGB, over space and time.

7.2. Materials and methods

7.2.1. Data collection

The AGB data was collected for *Festuca,* C3 and *Themeda* C4 grass species. The collection of AGB for these species was conducted in early February, May, August and November 2016, using randomly generated points. At each point, three quadrats, measuring 50 cm by 50 cm were used to collect grasses AGB samples within a 10 by 10 m plot. In each quadrant, standing grass AGB was harvested and its weight was determined *in situ.* The grass AGB samples were then transported and oven dried at the University of KwaZulu-Natal grassland facilities, to determine dry AGB. The dry AGB was weighed and this was converted to kilograms per square metre (kg/m^2). A total of 80 plots, measured 10 by 10 m were used for each species, with three samples per plot. This resulted in a total of 240 AGB samples for each species, which were used for analysis during each acquisition period. AGB sample locations were also captured and recorded using a handheld global position system (GPS), with sub-meter accuracy.

7.2.2. Remote sensing data acquisition and processing

Sentinel 2A images are freely-available for download from the European Space Agency (ESA) website (https://scihub.copernicus.eu/), through the Sentinels Scientific Data Hub archive. Eight cloud-free Sentinel 2 MSI images (Table 7.1), covering the entire study area were selected and downloaded for AGB estimation over time. Sentinel 2 sensor acquires images using 13 spectral bands, four bands at 10m spatial resolution, featuring blue (0.49µm), green (0.56µm), red (0.665µm) and near-infrared (0.842µm), six bands at 20m, with four narrow bands in the vegetation red-edge spectral domain (0.705, 0.74, 0.783 and 0.865µm) and two SWIR, at 1.61 and 2.19µm. Sentinel 2 spectral range also offers cirrus (0.443µm), water vapour (0.945µm) and aerosol (1.38µm) bands, at 60m spatial resolution, which have been dedicated to atmospheric monitoring. For this study, ten bands were therefore used, with the exception of cirrus, water vapour and aerosol bands, and all bands at 20 m were resampled to 10 m spatial resolution using nearest neighbour resampling in Sentinels Application Platform (SNAP) environment. Sentinel 2 images are delivered orthorectified and geometrically corrected top of atmosphere reflectance in Universal Transverse Mercator projection and World Geodetic System (WGS) 84 ellipsoid. The images were therefore corrected for atmospheric effects using the Sen2Cor prototype processing tool in SNAP.

Table 7.1: Sentinel 2 image acquisition characteristics

Season	Acquisition period	Sun zenith angle (°)	Sun azimuth angle (°)
Summer	**07/02/2016**	41.57	44.02
	05/03/2016	46.94	36.32
	03/11/2016	24.59	60.95
	03/12/2016	22.41	77.97
Winter	**14/05/2016**	55.99	28.94
	26/06/2016	58.34	29.29
	25/08/2016	47.16	37.10
	29/09/2016	36.49	43.65

*Bolded acquisition periods are those months in which ground measurements of species AGB were collected, whereas those in regular format were the images that were used to predict using models developed from ground-based measurements

7.2.3. Regression algorithm for predicting grass species AGB

This study used the Sparse Partial Least Square Regression (SPLSR) to predict AGB variations between C3 and C4 grass species. SPLSR is one of the robust and powerful non-parametric model with reported potential in predicting vegetation biophysical properties using remote sensing data (Verrelst et al., 2012). It is the more advanced version of the normal PLSR and the study by Abdel-Rahman et al. (2014) revealed detailed differences between them. Compared to its predecessor, the SPLSR performs dimensionality reduction and variable selection simultaneously and when it transforms the data, the SPLSR enforces sparsity and picks out the most suitable remote sensing variables for estimation. This enabled the recent studies in grass AGB estimation to shift towards its adoption. For example, SPLSR has been reported to perform well in predicting AGB for grasses under different management practices (Sibanda et al., 2017; 2015b), with reliable accuracy, using different remote sensing datasets, including hyperspectral and multispectral imagery. SPLSR predicts AGB using the remote sensing variables and ground-based measurements. The model also provides the most optimal variables for predicting AGB, using the variable importance projection (VIP) scores, which are allocated to each variable. Variables with values above the VIP threshold of the SPLSR (*i.e.* VIP > 1) are regarded as significantly important, whereas those below the threshold are less important in estimating AGB. The VIP scores were therefore used to determine the frequency of each variable. Frequency in this regard was the number of occurrences of each important variable, when its value was above the threshold, in estimating species AGB over the period of study. The model was run four times, using ground measured AGB values collected in February, May, August and November with three sets of variables. This resulted in a total of 12 runs and variable frequency was reported when using (i) spectral bands only, (ii) vegetation indices only and (iii) spectral bands + vegetation indices. Before the model was run, the field-based AGB data samples were randomly split into 70%, which was used to train the model, whereas the remaining 30% was used for validation. Consequently, for each species 56 plots (*i.e.* 168 samples) were used for training, whereas 24 (*i.e.* 72 samples) were used for validation. This also resulted in 336 samples for training and 144 samples for validation, for species pooled dataset.

7.2.4. Sentinel 2 variables used to predict grass species AGB

Three sets of variables from the Sentinel 2 images were used to predict AGB using the SPLSR and these include: (i) image data (ii) derived vegetation indices (VIs) and (iii) a combination of indices and image data. All the Sentinel 2 derived variables that were used to predict AGB are provided in Table 7.2. VIs were chosen based on their performance in C3 and C4 grass species compositions AGB (Rigge et al., 2013; Tieszen et al., 1997). The indices chosen have been frequently used since the potential of remote sensing in C3 and C4 AGB estimation has been recognized and had shown great potential using different datasets. In addition, red edge-based simple ratio (SR) and normalized difference vegetation index (NDVI), which were previously reported (Ramoelo et al., 2015c) to perform well across grasslands ecosystems in general were adopted to predict AGB variations for C3 and C4 grass species. Red-edge based indices have not yet been fully utilised in estimating C3 and C4 grass species AGB. Previously used sensors for estimating C3 and C4 grasses AGB does not constitute red edge bands, the majority of studies have used red and NIR-based NDVI and SR. The inclusion of red edge-based indices in this study therefore provides more insight on the performance of these indices derived using different spectral bands and enlightens prospects for future AGB monitoring of these grasses. The indices were named based on the red edge band used; for example, NDVIRE1 and SRRE1 indices were derived using red edge band 1. A total of 24 variables were used in this analysis, with 12 analyses using each variable set (*i.e.* spectral bands, indices and bands + indices), for the whole study period.

Table 7.2: Sentinel 2 variables that were used to predict species AGB over time

Data type	Details	Analysis set
Original image data	Ten spectral bands Bands 2-8A (Blue, Green, Red, Red edge1-3, NIR, Red edge4) Bands 11 and 12 (Shortwave infrared bands)	i
Derived Vegetation Indices (VIs)	EVI, SAVI, NDVI, RDVI, SR, MSR, red edge-based NDVI (using red edge bands 1-4), red edge-based SR (using red edge bands 1-4),	ii
Image spectral data + VIs	Combined image spectral bands and vegetation indices	iii

EVI: Enhanced vegetation index (Huete et al., 1997), SAVI: Soil adjusted vegetation index (Huete, 1988), NDVI: normalized difference vegetation index (Tucker, 1979), RDVI: renormalized difference vegetation index (Roujean and Breon, 1995), SR: simple ratio (Jordan, 1969).

7.2.5. Species AGB accuracy assessment

Statistical measures of the estimation accuracy over time, using the different variables were determined. These measures were the coefficient of determination (R^2) and root mean square error (RMSE) and %RMSE. The RMSE is a measure of the difference between the actual measured AGB values in the field and the estimated values by the model, whereas %RMSE is its deviation from the measured values expressed as a percentage. By expressing the RMSE as a % (within a scale between 0 and 100%) more insight is provided on the magnitude of deviation of AGB estimates using the different Sentinel 2 variables. These accuracy measures are frequently used in prediction accuracy assessment, using remote sensing data, for example by Dube and Mutanga (2015a) and Adam et al. (2014). From each analysis using the field-based measurement, a better model was identified, and the selected model and associated variables was then used to produce AGB map for the study area.

7.2.6. Species AGB spatial predictions over time

Four AGB models were developed (two for summer and two for winter), which correspond with the field measured data. These models were used to produce AGB maps for the study area during the field data acquisition period, as well as for the subsequent months in which AGB measurements were not available. For instance, the model developed and associated VIP variable using AGB measurements collected in February 2016 was used to estimate AGB variations for March 2016. In addition, the predicted AGB maps were also used to extract species AGB, using the GPS points. The extracted AGB values were then used to derive descriptive statistics of the target grass species, over time.

7.3. Results

7.3.1. Measured species AGB over time

Figure 7.1 shows summary statistics, which include the maximum, minimum and average of the measured dry AGB for the two species, in kg/m^2, over time. The measured AGB shows temporal variations between the two grasses. For *Festuca* grass, the highest AGB was recorded in May, whereas for *Themeda*, the highest AGB was measured in November

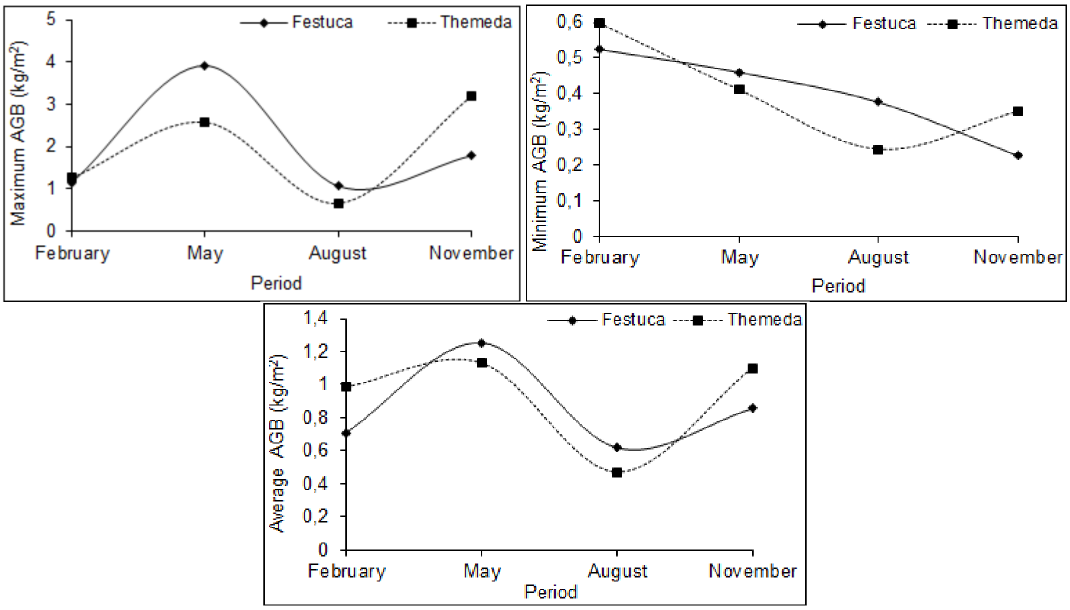


Figure 7.1: Maximum, minimum and average species AGB, based on field dataset

7.3.2. Performance of Sentinel 2 derived variables in predicting grasses AGB over time

Table 7.3 provides the statistical measures of accuracies for estimating *Festuca*, *Themeda* and combined species dataset AGB, using spectral bands, indices and spectral bands plus indices in February, May, August and November 2016. Overall, Sentinel 2 derived variables yielded reasonable accuracies and this was quite variable over time. Spectral bands predicted species AGB with lower accuracies and this increase when indices and a combination of spectral bands were used. For instance, in May, spectral bands predicted species AGB with lower accuracies for *Festuca* (R^2 = 0.57; 31.70% of the mean), *Themeda* (R^2 = 0.59; 24.02% of the mean) and combined species (R^2 = 0.61; 15.64% of the mean). Indices improved the prediction accuracies for *Festuca* (R^2 = 0.70; 22.05% of the mean), *Themeda* (R^2 = 0.69; 16.51% of the mean) and combined species (R^2 = 0.70; 23.15% of the mean). Comparably, spectral bands + indices yielded the highest accuracies for *Festuca* (R^2 = 0.77; 18.64% of the mean), *Themeda* (R^2 = 0.75; 14.27% of the mean) and combined species (R^2 = 0.73; 16.47%

of the mean). Similar pattern in the improvement of prediction accuracies from using spectral bands to the combination of bands and indices was found in February, August and November.

Results also clearly show that the performance of predictive variables varied with seasonal period. For instance, lowest prediction accuracies were found in May using spectral bands for *Festuca* (R^2 = 0.57; 31.70% of the mean), *Themeda* (R^2 = 0.59; 24.08% of the mean) and combined species (R^2 = 0.57; 28.11% of the mean). The highest predictive accuracies were found in August, for *Festuca* (R^2 = 0.85; 7.64% of the mean), *Themeda* (R^2 = 0.86; 7.56% of the mean) and combined species (R^2 = 0.84; 9.27% of the mean).

Table 7.3: Predictive accuracies using Sentinel 2 variables for estimating species AGB, over time

Variables/Period	Festuca			Themeda			Combined species		
	R^2	RMSE (g/m^2)	RMSE (%)	R^2	RMSE (g/m^2)	RMSE (%)	R^2	RMSE (g/m^2)	RMSE (%)
Bands									
February	0.61	145.85	13.11	0.60	129.59	14.66	0.61	100.74	15.64
May	0.57	346.68	31.70	0.59	352.13	24.08	0.57	320.62	28.11
August	0.66	132.80	12.29	0.67	102.11	20.75	0.69	231.66	23.42
November	0.62	225.27	21.80	0.62	251.62	20.29	0.63	364.39	26.26
Indices									
February	0.76	91.19	10.49	0.74	99.62	15.11	0.73	96.80	10.64
May	0.70	299.95	22.05	0.69	246.95	16.51	0.70	267.71	23.15
August	0.78	108.53	11.89	0.78	96.36	15.86	0.77	192.23	15.78
November	0.73	185.98	18.99	0.76	223.60	15.35	0.71	313.72	19.63
Bands + Indices									
February	0.82	74.16	9.84	0.78	66.83	9.46	0.74	81.85	10.59
May	0.77	244.38	18.64	0.75	178.86	14.27	0.73	221.05	16.47
August	0.85	99.98	7.64	0.86	89.10	7.56	0.84	135.20	9.27
November	0.79	166.14	16.07	0.81	201.36	12.89	0.76	247.83	12.06

Table 7.4 highlights the model performance using the 30% independent set, for individual species and pooled species dataset, based on variables, which only produced the best AGB estimation accuracies over time. Overall results indicate the potential of the SPLSR model in estimation accuracy, explaining above 70% of C3 and C4 species AGB variations over time. The model also produced highest estimation errors in May, compared to other periods. The results were also comparable to those produced using the 70% training dataset, with slight differences (+/- 5%) between them. For example, in February according to the 70% dataset, *Festuca* AGB was estimated with R^2 of 0.82 (9.84% of the mean); this was 0.79, with a RMSE of 13.32%. The performance of the model also varied over time using species individual species dataset, as well as for pooled data. For example, using AGB data acquired

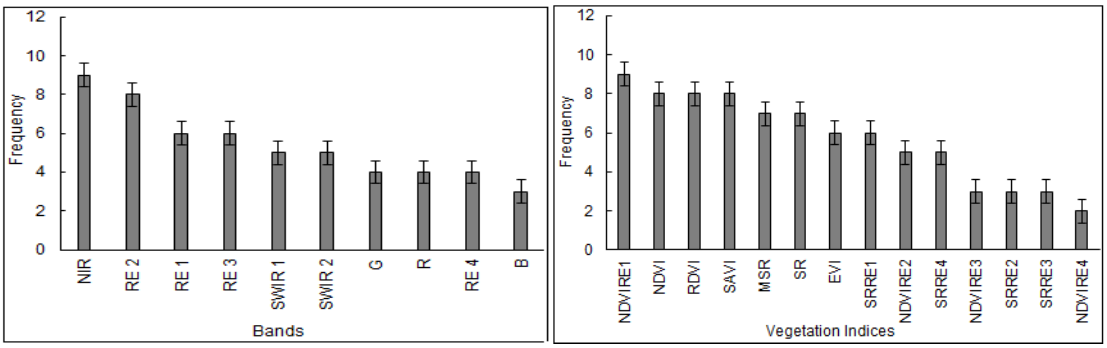
in May, which had the highest measured values, the model showed lower estimation accuracies, compared to other periods. In May, *Festuca* AGB was estimated with an R^2 of 0.71, which was 20.22% deviation, whereas for *Themeda*, it was 0.70 with a RMSE of 21.02%. On the other hand, in February, *Festuca* AGB was estimated with an R^2 of 0.82 (9.84% of the mean), whereas *Themeda* was estimated with 0.78 (9.46% of the mean).

Table 7.4: Model validation results, using combined Sentinel 2 derivatives

Period	**Festuca**			**Themeda**			**Combined species**		
	R^2	RMSE (g/m^2)	RMSE (%)	R^2	RMSE (g/m^2)	RMSE (%)	R^2	RMSE (g/m^2)	RMSE (%)
February	0.79	81.21	13.32	0.76	73.22	11.01	0.73	86.15	13.59
May	0.71	255.25	20.22	0.70	186.43	21.02	0.70	226.44	18.47
August	0.80	105.61	11.64	0.79	97.76	9.81	0.77	144.31	11.27
November	0.74	176.11	19.07	0.77	211.69	15.06	0.71	255.66	15.73

7.3.3. The importance of Sentinel 2 variables in species AGB estimation over time

The importance of Sentinel 2 variables in estimating species AGB, over time is graphically presented in Figure 7.2. The Figure shows the frequencies of each variable, using each variable set, for all the species dataset, over time. The use of spectral bands has shown that NIR (0.842µm) had the highest frequency, followed by RE 2 (0.74µm), whereas the visible blue had the lowest frequency. NDVIRE1 showed the highest frequency, followed by the standard NDVI, whereas RE4-derived NDVI had the lowest frequency, when indices were used. The combined use of bands + indices showed that RE 1 (0.705µm), RE 2 and the NIR had significantly the highest frequencies in their contribution in estimating AGB over time, whereas the simple ration derived using red edge 3 had the lowest frequency.



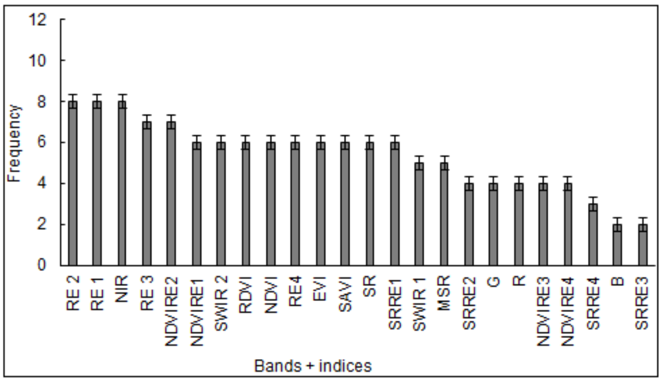


Figure 7.2: The frequency of Sentinel 2 variables in estimating species AGB, over time. Error bars show significant differences in variable frequency

7.3.4. Temporal variations in AGB using Sentinel 2 data

Figure 7.3 shows the derived AGB variations between the two species over time. The presented results are averaged AGB values, extracted using species GPS points. Overall, the two grass species showed variations in AGB over time. During the summer months of February, March, November and December 2016, higher AGB estimates were found for *Themeda* (C4), than *Festuca* (C3). There was however a shift in AGB variations between the two species, where higher estimates were found for *Festuca*, than *Themeda*, from May to September. Both species also showed a marked decrease in AGB, especially in August and September.

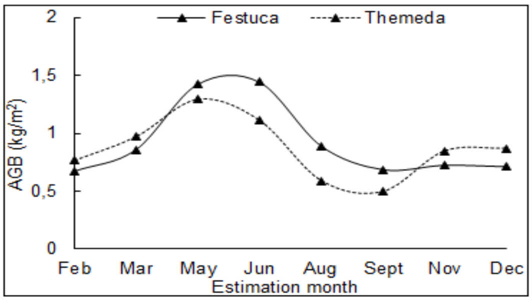


Figure 7.3: Average species AGB variations over time (2016)

7.3.5. The variability in AGB over time

Figure 7.4 illustrates the estimated variability in AGB over time for the study area during 2016, using Sentinel 2. Overall, AGB variations within the area exhibited temporal and spatial fluctuations and the sensor managed to capture these variations. Higher AGB were estimated in February, March, May, November and December, whereas during the midyear, low AGB estimates were produced. The beginning of winter (May) had the highest AGB, compared to other months, whereas lowest estimates were after the winter fall (September).

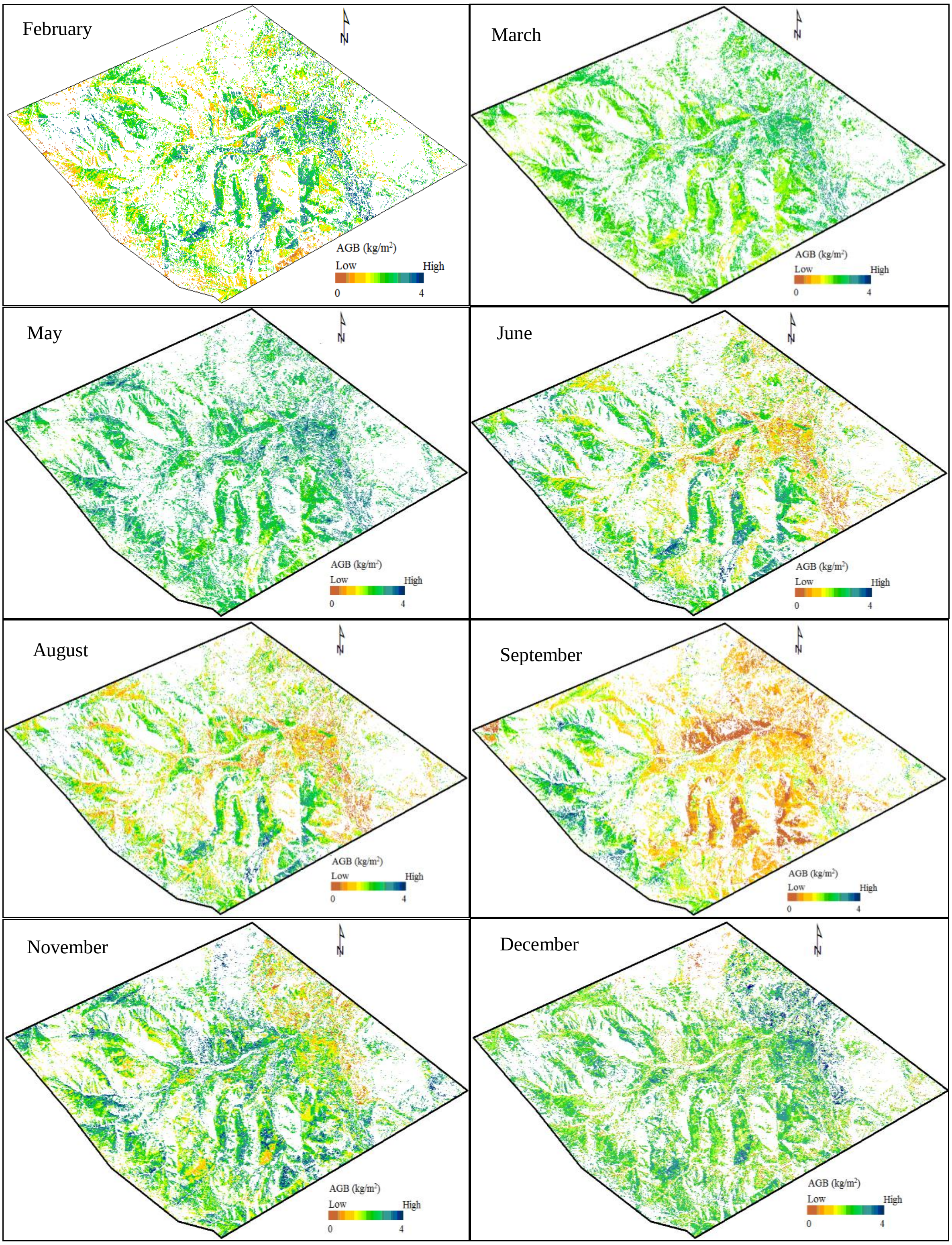


Figure 7.4: The spatial and temporal variability of C3 and C4 grass species AGB over time

7.4. Discussion

7.4.1. The frequency of Sentinel 2 variables in estimating species AGB over time

Sentinel 2 variables have shown great potential in predicting C3 and C4 grasses AGB variations, over time. Among the most important variables in estimating species AGB were the red edge centred at 705 and 740 nm, derived indices, the NIR and SWIR spectral bands. For instance, the NIR band showed the highest frequency in its importance in estimating AGB and was also competitive among indices, when indices + bands were used. In accordance with results from this study, compelling studies (Mutanga and Skidmore, 2004b; Ramoelo and Cho, 2014; Sharma et al., 2015) have reported the importance of red edge bands and derived indices in estimating AGB. It has been established that red edge variables are sensitive to species canopy AGB and chlorophyll concentration, when compared to other portions of the electromagnetic spectrum (Mutanga and Skidmore, 2004b). This improves the competence of red edge bands and derived indices in estimating species AGB, over time. However, not all the Sentinel 2 red edge and derived indices were found to be important in species AGB prediction in this study. For example, red edge centred at 865nm (band 8A) and derived indices have shown consistently poor importance in estimating species AGB, over time, with lower frequencies. The contribution of the SWIR may be attributed to its sensitivity to species water content, and this is variable between the two species, especially when *Themeda* (C4) becomes dormant, particularly in August. In consistence, Numata et al. (2008) revealed a significant correlation between grass AGB and water content, and suggested that the use of water related wavelength, improve AGB estimation accuracy. The study by Chen et al. (2011) also reported the importance of SWIR bands in estimating species AGB in the semi-arid rangelands of Idaho, using SPOT 5. In this regard, researchers might advocate for the development and use of Sentinel 2 SWIR-based indices in estimating C3 and C4 grass species AGB over time. The importance of NIR, as indicated by the highest frequency highlights its consistent, as well as its competence among indices in AGB estimation, over time. Previous studies (Lu et al., 2009; Price et al., 2002) also found NIR to be a very important spectral portion in C3 and C4 grasslands monitoring.

On the other hand, the visible portion had the lowest frequencies in estimating species AGB over time. This shows that the visible bands are inconsistent and have limited potential in estimating C3 and C4 grass species AGB over time. The limited potential of visible bands in estimating AGB has been previously attributed to their sensitivity, for example, the review by

(Lu, 2006). These bands were reported to be less sensitive to species biophysical characteristics and AGB variations; hence they become insignificant and less competitive.

7.4.2. Species AGB prediction accuracies

The use of indices showed a marked increase in species AGB prediction accuracy over time, when compared to the use of individual bands. Indices have been reported to have better AGB prediction accuracies, when compared to the use of spectral bands (Sibanda et al., 2015a; 2017). This is due to the combination of different bands which improve their sensitivity, thereby boosting AGB prediction accuracy, when compared to individual bands which have limited sensitivity capacity. In confirmation, across C3 and C4 grasslands, studies which estimated AGB used vegetation indices, particularly NDVI (An et al., 2013; Rigge et al., 2013; Tieszen et al., 1997). The broadband nature of the used sensors discouraged the use of spectral bands, which have been perceived to be insensitive to species biophysical properties, hence have low ability in estimating AGB. Thus Sentinel 2 extends the availability of variables for estimating C3 and C4 grasses AGB, which were previously limited to traditional indices.

Species AGB prediction accuracies was quite variable over time. For example, species AGB was predicted with relatively lower accuracies in May and November, than in February and August. This is a clear indication of the influence of seasonality on species AGB estimation accuracies, which might be associated with the amount of AGB available. In this study, lower AGB prediction accuracies in May are likely attributed to species phenology. Species phenology determines the accumulation of AGB and the subsequent estimation accuracy, using remote sensing data. This was also confirmed by the validation dataset, where the model showed lowest estimation accuracies in May. In May, *Themeda* had reached its peak, whereas *Festuca* was at its peak stage of growth, both species therefore had high density AGB. Field-based AGB measurements also confirmed that May had the highest AGB for both species. High AGB during peak stage of species phenology causes saturation problem and this might have challenged the estimation accuracy. Saturation due to high AGB at maximum productivity is one of the major problems associated with multispectral sensors in estimating species AGB. However, in February and November, although both species were active, they have not yet reached their peak, which implies limited saturation problem and therefore better accuracies, than in May. The influence of phenology and AGB variations on estimation accuracy was also noted by Ramoelo and Cho (2014) in north east South Africa, using Worldview 2 dataset. The study reported slightly higher prediction accuracies in July, which was characterized by lower AGB, when compared to March, which had higher species AGB. Similarly, the influence of high density AGB lowering estimation accuracy was also explored by Mutanga et al. (2012), using Worldview 2 dataset and random forest model.

Although the use of Sentinel 2 derived indices provided better estimation accuracies using data acquired during the study period, this study urges caution when estimating *Themeda* AGB during the winter fall, as the species and other C4 species starts to lose their vigour. Some of the indices used like NDVI are related to vegetation greenness and have been reported to have limited potential during low vegetation cover (for example, Butterfield and Malmström, 2009). In this regard, during February, May and November 2016, when both species were active, indices related to greenness remained applicable, despite saturation problems in May. However, in August, when C4 becomes less active, loses its greenness and there is less vegetation cover, soil reflectance interferes with species signal in *Themeda* dominated areas. Possibly, the use of other indices besides NDVI or the use of SWIR-based indices in estimating C4 AGB during low productivity stages is recommended.

7.4.3. Spatial variations in AGB over time

This study managed to depict the spatial variations of C3 and C4 dominated grassland AGB in KwaZulu-Natal, using Sentinel 2 multi-temporal dataset. The study confirms the potential of the Sentinel 2 sensor in estimating and mapping C3 and C4 AGB over time. This performance is the combined contribution of its spectral range, which constitute more and unique bands, as well as its 10 m spatial resolution. These characteristics are sensitive to C3 and C4 species physiological, morphological and phenological properties which improve the AGB prediction and variations. At a finer spatial resolution, subtle differences in AGB for different species are also better captured, with limited mixed pixel problem (Lu, 2006).

It was found that AGB across the study area exhibited spatial and temporal variations. This shows the influence of various factors governing AGB variations for C3 and C4 grass species across the area. The source of differences in AGB over time is contributed by the variations in species composition, growth, as well as climatic influence. For instance, reflecting on the distributional pattern of the grass species under study, the AGB variation maps are closely associated with the recognized distribution pattern of the target grass species (Figure 7.1) or species composition and associated biophysical properties over time. In the present study area, *Themeda* is predominantly within the central, north east and eastern parts of the study area, which showed higher AGB during the summer months, when the species is most active and productive. In winter *Themeda* dries, due to harsh unfavourable conditions. This was also noticed especially in August, during field data collection. *Festuca* on the other hand has been reported to be active for most parts of the year, which promotes AGB availability, and during the field data collection the grass remained active, although it will not be as active as during early winter. In agreement, the study by Rigge et al. (2013) reported the effect of grass composition within a landscape on the spatio and temporal patterns of AGB.

The spatial distribution of AGB also coincided with the characteristics of the study area. For example, the far north east and eastern parts include communal areas, characterized by livestock grazing, as well as human disturbances, whereas the majority of the area is under conservation. Similarly, the communal area has more of *Themeda,* a high palatable grass that is favourable to livestock (Coughenour et al., 1985; Danckwerts et al., 1983), when compared to *Festuca*. *Themeda* is also recognized as an important source of fodder, fibre for paper, thatching and basketry. Consequently, this contributes to the loss of *Themeda* within the communal area, thereby lowering its AGB. The area under conservation showed consistently higher AGB during most time of the year. This is due to limited grazing and human disturbances, as well as the predominance of *Festuca* grass, which has been reported to be green for most part of the year. *Festuca* has also been identified as unpalatable and therefore unfavourable to grazers, compared to *Themeda*. This reduces grazing pressure in *Festuca* dominated landscapes. However, although it is not comparable to communal area, the conserved area also provide forage to a few small ungulate wildlife grazers (Joubert et al., 2017).

AGB variations also highlighted inter and intra-annual variability in climatic conditions, such as the reported seasonal rainfall and temperature, influencing species the timing and amount of AGB accumulation. Although it was quiet variable across the study area, higher AGB was estimated during the summer months, whereas lower AGB was observed during winter months, particularly winter fall (August and September). Higher AGB may be primarily caused by the prevailing of favourable climatic factors, which boost species AGB production and accumulation. For instance, Morris et al. (2016) and Nel (2009) reported that the area receives summer rainfall, from November to March. This facilitates species growth and AGB production, during this period. This is most apparent for *Themeda,* which is most active in summer. In contrast, August and September showed a marked decrease in AGB across the area under study. This period is typically end of winter, associated with no rainfall (Everson et al., 1988), which limit plant growth, thereby lowering AGB production and accumulation for most parts of the area. This also indicates that the winter fall, present unfavourable conditions for AGB accumulation across the study area. A very limited number of studies have reported the AGB variations of C3 and C4 grass species within the area (Everson and Everson, 2016; Everson et al., 1985; 1988). These studies have reported high AGB during the summer months, compared to winter, using ground measurements. The influence of climate variability on C3 and C4 grasses AGB has been reported, for example, by the study done by Winslow et al. (2003) which reported significant response of C3 and C4 grass species AGB to water variability.

7.5. Conclusion

Findings presented in this study demonstrated the spatial productivity of C3 and C4 grass species over time. This is crucial in determining the potential of C3 and C4 dominated grasslands as forage sources, their carrying capacity and in predicting the effects of global change on their productivity. The study also demonstrated the potential and strength of using the readily available Sentinel 2 data as an invaluable source of C3 and C4 grasses AGB information, for the proper and well-informed management at large areas. This is critical, especially in sub-Saharan Africa, where high-resolution remote sensing data availability remains a challenge for monitoring vegetation productivity and its response to environmental changes, over time. Results also demonstrated that SPLSR is a useful and a robust model for estimating C3 and C4 grass species AGB over time.

The results from this chapter have highlighted the spatial and temporal variations of C3 and C3 grasses AGB, using Sentinel 2 dataset. These results are valuable in determining the contribution of these species as forage sources, fuel load and potential carbon pools over time. With anticipated climate change effects on the productivity of species functional types, it becomes critical to identify the environmental conditions that influence the productivity of these grass species, as well as how these species AGB respond over time. Environmental conditions control species biophysical processes and consequently determine their growth rates and productivity. Furthermore, the availability of multi-temporal Sentinel 2 and its potential in estimating C3 and C4 AGB allow the ability to examine the variability in species

AGB. Therefore, the succeeding chapter explored the response of C3 and C4 grass species AGB to seasonal climate and topography.

CHAPTERS EIGHT AND NINE

MODELLING AND SYNTHESIS

8. Remotely-sensed C3 and C4 grass species aboveground biomass variability in response to seasonal climate and topography

A view of the study area (Photographed by Terence Mushore; November 2016)

This chapter is based on:

Shoko. C, Mutanga. O and Dube. T. Remotely-sensed C3 and C4 grass species AGB variability in response to seasonal climate and topography. *Journal of Applied Geography* (Manuscript ID: 2018_117).

Abstract

Environmental conditions influence the productivity of C3 and C4 grass species. These conditions regulate biophysical processes, which determine plant growth and aboveground biomass (AGB). However, the anticipated climate change effects on species functional type are threatening the productivity of C3 and C4 grasses AGB. This emphasized the need to monitor the AGB for well-informed management strategies. Emerging new generation sensors present an opportunity to characterize C3 and C4 AGB variations over time. Their improved spatial, temporal and spectral capabilities enable multi-temporal analyses of dynamic phenomena in a spatially explicit manner. This has been difficult to achieve using conventional methods and available sensors. The present study therefore investigated the response of remotely-sensed derived C3 and C4 grasses AGB to seasonal climate and topography. Overall, the influence of seasonal climate and topography on species AGB was quite variable. For example, a marked increase in C4 AGB (*e.g.* in February and March) was associated with an increase in rainfall, whereas dry months were associated with a decrease in AGB. This was also supported by the highest significant positive relationship ($R^2 = 0.82$, $P < 0.005$) found between C4 AGB and rainfall. Spatial and temporal response of AGB variations were also evidenced across the study area. However, some areas showed unstable responses, whereas others showed stability, despite climatic changes over time. During the winter fall in August, AGB significantly responded to climatic conditions for most parts of the study area. For example, AGB significantly decreased from averages of 2.592 kg/m^2 and 1.101 kg/m^2 in May, to 0.718 kg/m^2 and 0.469 kg/m^2 in August, for C3 and C4 grasses, respectively. August and September produced the lowest AGB across the study area. This coincided with lowest rainfall, rise in temperatures and radiation. Elevation was the most influential topographic variable to determine species AGB, with the highest significant positive relationship ($R^2 = 0.84$) with C3 and highest negative ($R^2 = -0.77$) with C4. Findings from this study thus provide a key step in identifying vulnerable areas in C3 and C4 dominated ecosystems, for management purposes in light of climate changes. The results further demonstrated the potential of using multi-temporal Sentinel 2 for time series analyses of C3 and C4 AGB and their response to seasonal climate.

Key words: climatic effect, radiation, productivity, rainfall, temporal variability,

8.1. Introduction

C3 and C4 grass species aboveground biomass (AGB) directly reflects their level of productivity, structure and functioning. Globally, C4 grasses have been identified to account for 20 – 25% overall terrestrial productivity (Still et al., 2014) and covers large areas in Africa and Australia, when compared to C3. These grasslands also operate as agro-ecosystems, providing forage for variable populations of livestock (Woodward et al., 2004), which support millions of people, especially in Africa. C4 grasses have also been reported to have better palatability, highly suitable for animal production (Snyman et al., 2013), compared to C3. C3 and C4 also facilitate nutrient cycling and carbon sequestration. For example, C4 grasses store a substantial amount of carbon, than C3 grasses (Adair and Burke, 2010) and the Intergovernmental Panel on Climate Change (IPCC) has emphasized species AGB as one of the principal carbon pools of terrestrial ecosystems (Eggleston et al., 2006; Vashum and Jayakumar, 2012). C3 and C4 AGB also determines the occurrence and intensity of fire regimes (Everson et al., 1985) in the management of grassland ecosystems. Most importantly, the seasonal variations in climatic conditions influence C3 and C4 grasses AGB over time, thereby influencing their ability to provide ecosystem goods and services.

Climate and topography influence the spatial and temporal variability in C3 and C4 grasses AGB (Auerswald et al., 2012; Lee, 2011). These factors have been identified to regulate species biophysical processes and phenological response (Epstein et al., 1997; Ricotta et al., 2003; Saleem et al., 2009). At different phenological phases, these grasses exhibit variations in their exchange of energy, water and carbon fluxes, as well as in nutrient uptake, storage and release, throughout the growing season, influencing the productivity of AGB (Adair and Burke, 2010; Jin et al., 2013). The variability in AGB is therefore sensitive to any alterations of the phenological profiles of these grasses to climatic changes over time. The projected effects of climate change have also been anticipated to influence the productivity of C3 and C4 grass species, with significant implications on their AGB variability. For example, an increase in warming has been predicted to favour C4 grasses, such that they will improve in productivity, compared to C3 (Bremond et al., 2012). Climatic changes will therefore, cause significant challenges to the provision of ecosystem goods and services by C3 and C4 grasses. For example, declines in grazing capacity, with significant implications on livestock production and human livelihoods. This emphasized the need to monitor C3 and C4 AGB, to have a better understanding of their state and functioning over time.

Conventional methods have so far been the main sources of characterizing C3 and C4 grass species AGB (Auerswald et al., 2012; Epstein et al., 1997; Polley et al., 2014; Taylor et al., 2014). However, these studies were conducted at small geographical coverage (*i.e.* plot level), at a limited temporal scale. This has been mainly attributed to the high costs, time and labour associated with the use of these methods. Consequently, results obtained lack spatial and temporal aspects of species AGB; hence are insufficient for monitoring or understanding the dynamics of C3 and C4 AGB. This resulted in uncertainties in understanding the contribution of these species and the effects of climate change. This approach also hinders any prospects to predict the future of C3 and C4 grasses productivity, as well as formulating conclusive management strategies in a spatially explicit context.

Remote sensing provides critical data source for estimating, mapping and monitoring of grass species AGB (Lu, 2005; Zhao et al., 2014). The intrinsic spatial nature of remotely-sensed data allows spatial representation of species AGB, which could not be achieved using conventional methods. In addition, the spectral capability of remote sensing technology is also crucial in extracting species morphological and phenological characteristics, which influence their AGB variations. Most importantly, emerging sensors offer outstanding opportunities to monitor C3 and C4 grasses AGB (Shoko et al., 2016). For example, the high temporal resolution of emerging sensors (*e.g.* Sentinel 2 at 5 days) allows multi-temporal analysis of dynamic phenomena like species AGB in a spatially explicit manner. Its large geographical coverage, with a swath-width of 195 km at a refined spatial resolution (*e.g.* 10 m) offers data for large scale monitoring of AGB variations, at a finer spatial resolution. This is also suitable to identify areas in C3 and C4 grasslands, which are most vulnerable to climatic anomalies, under different climate change scenarios. Sentinel 2 is also the first optical sensor of its kind to provide more bands within the red edge domain, noted for extracting key information on vegetation biophysical characteristics (Bruzzone et al., 2017). This represents a substantial improvement, especially with respect to the past, thereby opening a wide range of innovative possibilities of multi-temporal analysis. The present study thus aimed at characterizing remotely sensed derived C3 and C4 grasses AGB. Specifically, the study intended to explore the response of C3 and C4 AGB to seasonal climate and topography.

8.2. Materials and Methods

8.2.1 Grass species AGB data

The present study assessed the response of C3 and C4 grass species. AGB samples were collected at different seasonal periods, which included summer and winter distinctive seasons. The summer period was represented by data collected in early February and early November, whereas for the winter period, it was early May and end of August 2016. AGB data was collected based on randomly generated points. During each AGB data collection, three quadrats, measuring 50 cm by 50 cm at each random point were used to collect samples, and these quadrats were demarcated within 100 m^2 (*i.e.* 10 * 10 m) plot. The standing green grass was clipped and weighed *in situ;* using a weighing scale and this was recorded as fresh AGB in kg/m^2. The collected AGB samples were also oven dried at the University of KwaZulu-Natal grassland facilities, to derive dry AGB and this was expressed as kg/m^2. A total of 240 AGB samples for each species were used for analysis during each field visit. AGB sampled locations were also captured using a Trimble GEO XH 6000 hand held global position system (GPS).

8.2.2. Climatic and Topographic variables

The climatic and topographic variables that were used in this study are provided in Table 8.1. For climatic variability over time, rainfall, temperature and radiation were used. Rainfall data was delivered as daily point values recorded at eight stations, sufficient for the Cathedral Peak catchment. For analysis purposes, the daily rainfall was aggregated to monthly totals and was also interpolated to obtain its spatial variability across the study area. This was performed using ordinary Kriging interpolation method in ArcGIS 10.2. Temperature recordings were available from a station within the study area and this data was insufficient for analysis; however, the data was used to show the general pattern of temperature variations within the study area. A digital elevation model (DEM) from the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) at a spatial resolution of 30 m was also used to derive topographical variables for the study area. The DEM was pre-processed to remove imperfections associated with the product and have a better spatial representation of topography. This was done in ARCGIS using the spatial analysist extension tool. The topographical derivatives used included elevation, aspect, slope and total wetness index (TWI). Elevation, aspect and slope indicate the surface terrain and these were derived using the surface extension spatial analyst tool. The TWI is a hydrological index that determines the variability in soil water conditions and was derived using the hydrological spatial analyst tool in ArcGIS 10.2. Solar radiation recordings were also not available; due to lack of routine observations, hence it was modelled from DEM using radiation modelling tool in ArcGIS 10.2. The use of radiation modelled from DEM has been widely accepted as a reliable data source in ecological modelling (Dube and Mutanga, 2016; Kumar et al., 1997; Ruiz-Arias et al., 2009). All derived maps were also standardized to the same resolution using nearest neighbour resampling technique in a GIS environment, to ensure their compatibility and consistency.

Table 8.1: Climatic and topographical variables that were used in this study

Variable	Definition	Source
Aspect	Slope direction measured in degrees (°) or compass direction clockwise from North (0) to North (360)	ASTER DEM
Elevation	Height above sea level, in meters (m)	ASTER DEM
Radiation	Insolation received from the sun, in Watts Hours per square meter (WH/m^2)	ASTER DEM
Rainfall	Monthly total, in millimeters (mm).	SAEON, SAWS
Slope	Elevation steepness, in degrees (°) from 0 (flat) to 90 (steep)	ASTER DEM
Temperature	Maximum, minimum and average, in degrees Celsius (°C).	SAEON, SAWS
TWI	Wetness condition, which determines the spatial variability of soil water (-)	ASTER DEM

*DEM: digital elevation model, SAEON: South African Earth Observation Network, SAWS: South African Weather Services, TWI: total wetness index, ASTER: Advanced Spaceborne Thermal Emission and Reflection Radiometer

8.2.3. Remotely sensed derived AGB over space and time

Remotely-sensed estimates of C3 and C4 grasses AGB over time were derived using the recently available Sentinel 2 multi-temporal images in a different study. This was achieved using derived variables, which were identified to optimally estimate species AGB, using the Sparse Partial Least Squares regression (SPLSR) model and ground-based measurements. The model is one of the robust and powerful with reported potential in estimating species AGB, using remote sensing variables (Abdel-Rahman et al., 2014; Sibanda et al., 2017). SPLSR predicts AGB and provides variable importance projection (VIP) scores, which indicates the potential of each variable in AGB estimation. Variables with the highest scores were then used to produce AGB maps for the study area.

8.2.4. Statistical Analysis

SPLSR was further used to relate seasonal climatic and topographic variables to C3 and C4 AGB using ground-based measurements collected in February, May, August and November 2016. Statistical tests were also performed to determine the significance of the derived relationships between ground-based AGB and the seasonal climatic and topographic variables. The tests were done using one-way Analysis of Variance (ANOVA) at 95% confidence interval.

8.3. Results

8.3.1. Descriptive statistics of data collected

Table 8.2 provides the descriptive statistics of AGB, climatic and topographic variations between C3 and C4 grasses. It was found that species AGB varied from a minimum of 0.244 in August (for *Themeda*, C4), to a maximum of 3.912 kg/m^2 in May (for *Festuca*, C3). The climatic conditions and topography associated with AGB collected also varied.

Table 8.2: Descriptive statistics of the data collected and extracted

Acquisition Month	Variables	Species	Min	Max	Avg.	Stdev
February	AGB	C3	0.524	1.160	0.709	0.115
		C4	0.600	1.276	0.984	0.125
	Aspect	C3	0.0 (N)	358.0 (N)	194.78 (S)	137.9
		C4	0.0 (N)	359.1 (N)	267.7 (W)	99.2
	Elevation	C3	1375.0	1462.0	1397.5	49.1
		C4	1296.0	1428.0	1302.8	21.7
	Radiation	C3	282.20	303.18	297.95	37.6
		C4	289.80	304.35	298.80	37.3
	Rainfall	C3	122.5	129.5	124.3	2.2
		C4	121.0	131.4	125.3	3.7
	Slope	C3	2.4	29.7	17.2	10.6
		C4	0.8	20.9	8.7	4.8
	Temperature	-	12.8	23.5	18.5	-
	TWI	C3	4.47	12.99	7.69	2.92
		C4	4.26	9.39	6.38	1.29
May	AGB	C3	0.460	3.912	1.253	0.719
		C4	0.412	2.592	1.101	0.418
	Aspect	C3	0.0 (N)	358.0 (N)	194.78 (S)	136.4
		C4	0.0 (N)	359.1 (N)	267.7 (W)	102.9
	Elevation	C3	1375.0	1462.0	1398.7	50.5
		C4	1328.0	1440.0	1302.1	19.0
	Radiation	C3	114.83	172.25	143.86	13.65
		C4	116.57	165.41	140.72	13.63
	Rainfall	C3	14.1	17.2	16.1	1.0
		C4	13.5	16.0	15.0	0.9
	Slope	C3	2.4	29.7	15.3	9.6
		C4	0.8	21.9	8.9	4.9
	Temperature	-	10.1	20.3	12.6	-
	TWI	C3	4.47	12.99	7.69	2.92
		C4	4.26	9.39	6.38	1.29
August	AGB	C3	0.376	1.072	0.718	0.306
		C4	0.244	0.668	0.469	0.182
	Aspect	C3	0.0 (N)	358.0 (N)	194.78 (S)	136.4
		C4	0.0 (N)	359.1 (N)	267.7 (W)	102.9
	Elevation	C3	1375	1462.0	1398.7	50.5
		C4	1328.0	1440	1302.1	19.0
	Radiation	C3	122.83	179.85	152.03	13.65
		C4	124.60	173.33	148.91	13.64
	Rainfall	C3	55.8	71.8	61.0	5.2
		C4	58.8	71.4	65.9	5.9
	Slope	C3	2.4	29.7	18.6	9.6
		C4	0.8	20.9	8.9	4.9
	Temperature	-	8.5	20.3	12.9	-
	TWI	C3	4.47	12.99	7.69	2.92
		C4	4.26	9.39	6.38	1.29
November	AGB	C3	0.226	1.784	0.855	0.355
		C4	0.352	3.208	1.163	0.607
	Aspect	C3	0.0 (N)	358.0 (N)	194.78 (S)	136.4
		C4	0.0 (N)	359.1 (N)	267.7 (W)	102.9
	Elevation	C3	1375.0	1462.0	1398.7	50.5
		C4	1328.0	1440.0	1302.1	18.9
	Radiation	C3	273.58	298.57	293.84	3.63
		C4	284.31	299.50	294.65	3.40
	Rainfall	C3	71.5	86.0	75.4	10.3
		C4	70.6	78.9	74.6	3.3
	Slope	C3	2.4	29.7	21.3	10.1
		C4	0.9	20.9	8.9	4.9
	Temperature	-	9.7	24	16	-
	TWI	C3	4.47	12.99	7.69	2.92
		C4	4.26	9.39	6.38	1.29

*Max: maximum, Min: minimum, Avg: average and Stdev: standard deviation. TWI: total wetness index. Aspect is also indicated in terms of directions, which are represented by N: North; W: West and S: South facing slopes.

8.3.2. Remotely sensed AGB variability over space and time

Figure 8.1 illustrates the estimated variability in AGB for the study area, using Sentinel 2 remote sensing dataset. Overall, the area produced noticeable spatial variations in C3 and C4 grass species AGB over time. However, much of AGB was produced during the summer months, where the majority of the area showed high AGB. Lower AGB variations were also noted, especially during the winter fall in August and September, where most of the study area showed a decrease in AGB. It was also found that May had the highest AGB accumulation across the area, whereas the lowest was produced in September. AGB changes across the study area were also found to be variable, where some areas experienced notable changes over time, while others remained almost stable, despite seasonal changes. For example, the central and eastern parts show notable changes in AGB over time, when compared to the southern tip and the south-western most parts of the study area.

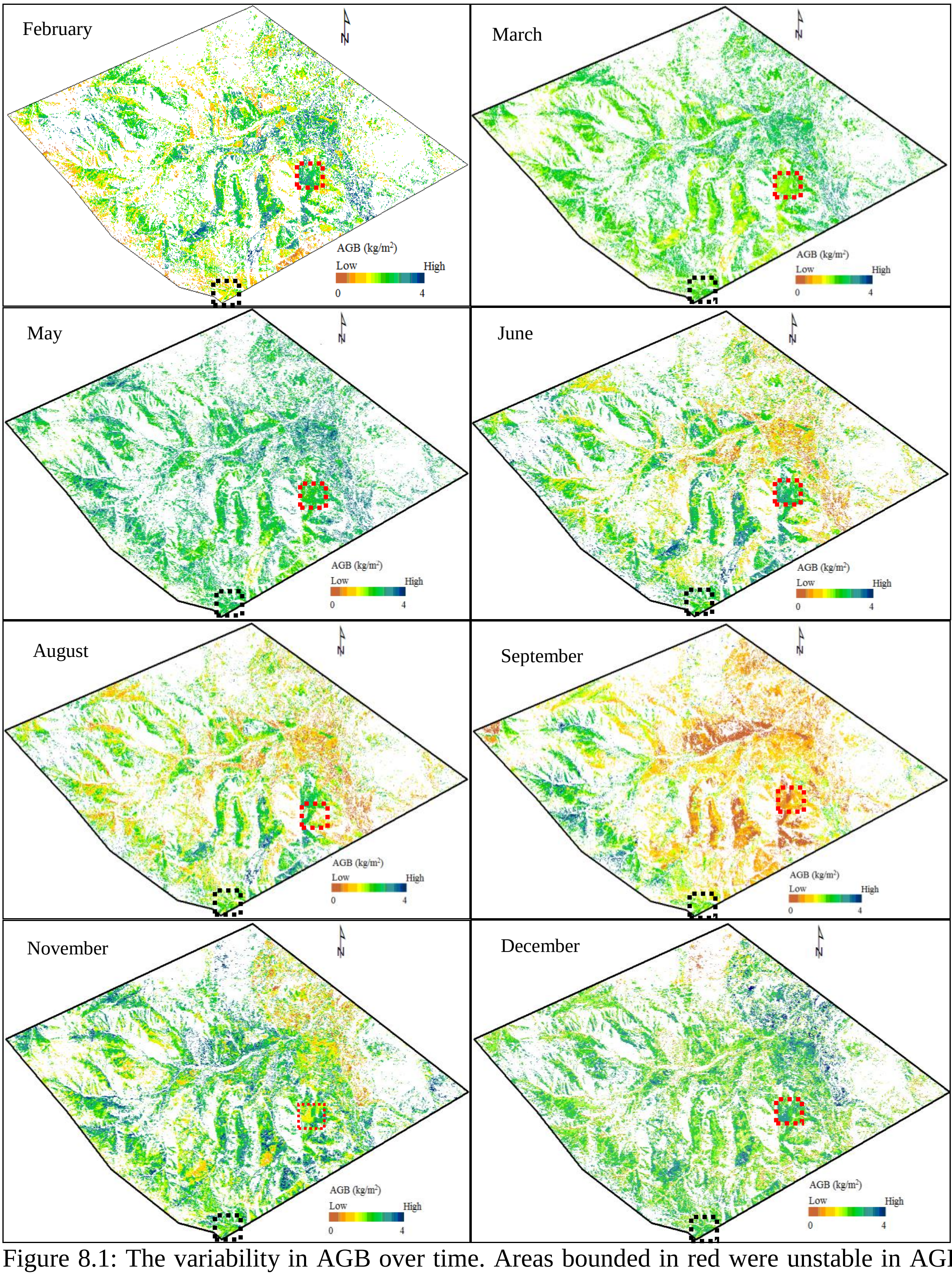


Figure 8.1: The variability in AGB over time. Areas bounded in red were unstable in AGB, whereas those in black remain stable

8.3.3. Climatic factors variability over time

Figure 8.2 shows the temporal variability in monthly rainfall, temperature and solar radiation descriptive statistics of the study area in 2016. The graphs illustrate the general pattern in climatic conditions under which AGB estimations for C3 and C4 grass species were derived using Sentinel 2. The variables include monthly total rainfall, maximum, minimum and average temperature, as well as monthly averaged solar radiation. Overall, climatic conditions across the study area showed a temporal variability. Lowest total rainfall (6.8mm) was recorded in July, whereas January received the highest amount (263.9mm). It was also found that maximum temperature (26°C) was recorded in December, whereas July experienced the lowest (6°C). In terms of solar radiation, the highest (185 KwH/m^2) was received in January, whereas the lowest (32.6 KwH/m^2) was received in June.

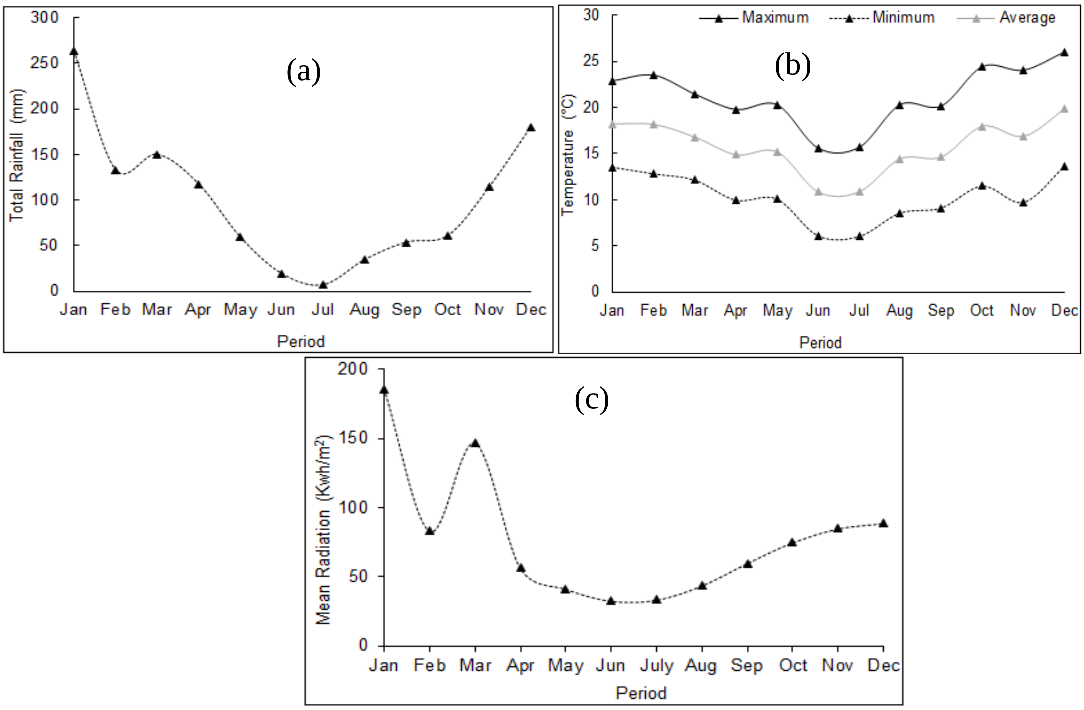


Figure 8.2: The general (a) rainfall, (b) temperature and (c) radiation variability of the study area, over time

Figure 8.3 (a and b) further displays the spatial variability in the modelled solar radiation and rainfall received across the study area in 2016. It was found that high rainfall (a) was received at the southern tip, compared to most parts of the area. The southern, western and eastern parts also received more radiation, compared to the central and north eastern parts.

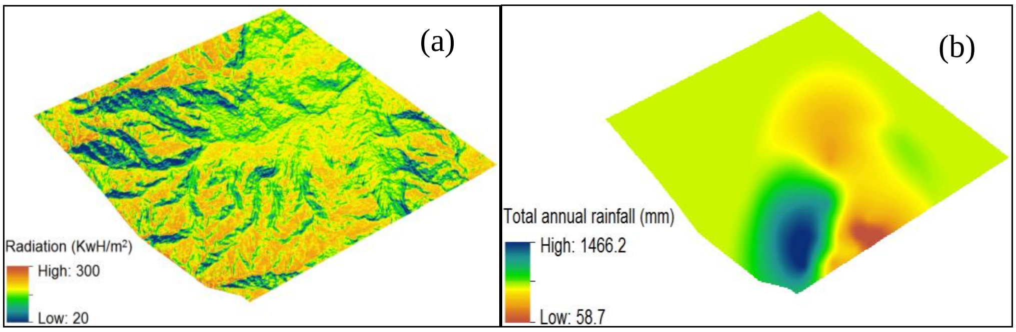


Figure 8.3: Spatial variability in annual average radiation and total rainfall received in 2016

8.3.4. Spatial variability of topography

Figure 8.4 shows the derived spatial variability of topography in terms of elevation, slope, aspect and TWI, within which C3 and C4 grass species AGB was explored. The elevation of the area (Figure 5a) was found to be quite variable, ranging between 1225, in the central and north eastern parts and 3034 m above sea level, in the western and southern parts. Similarly, slope (Figure 5b) varies from 0 to 70.4°, with high slopes for most parts of the area, except for the central and north eastern parts. The aspect (Figure 5c) of the area was found to be heterogeneous, constituting slopes facing different directions, whereas the TWI (Figure 5d) indicate that the majority of the area has low soil water potential, except for the central and north eastern parts.

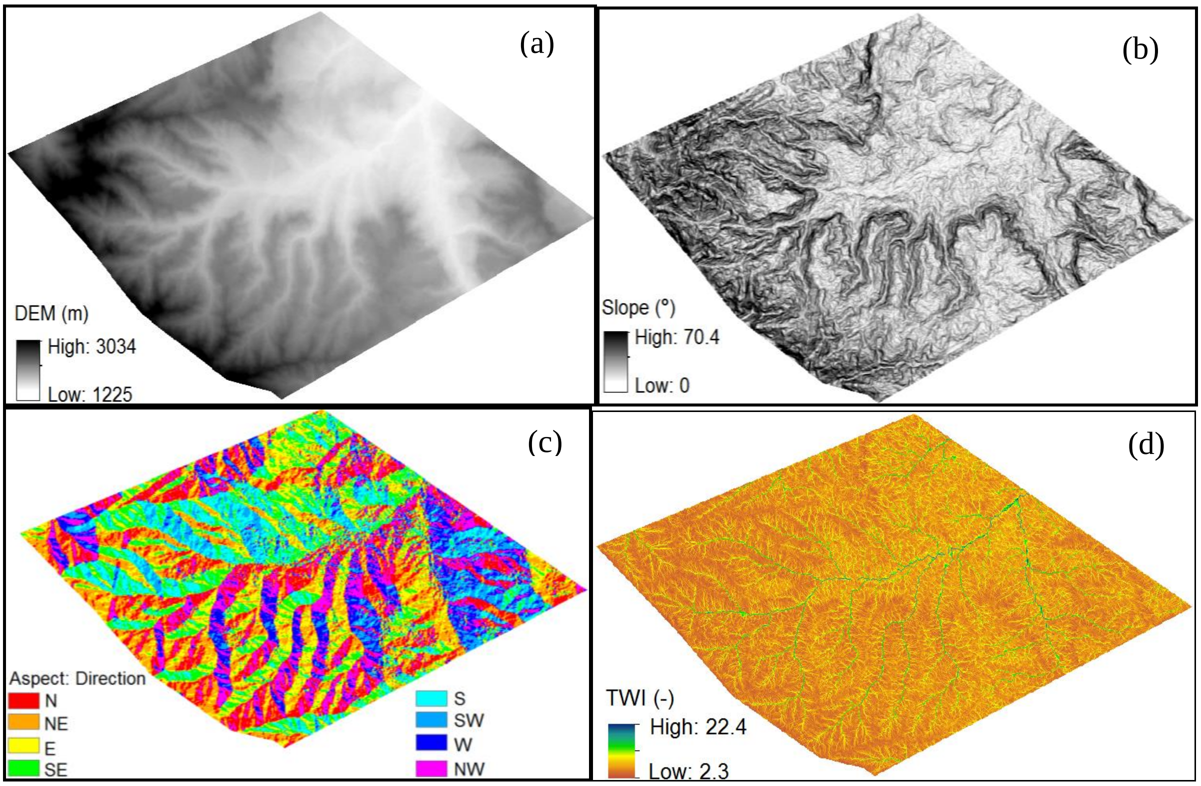


Figure 8.4: Topographical variability showing (a) elevation, (b) slope, (c) aspect and (d) TWI

8.3.5. The response of remotely sensed species AGB to climate variability over time

Figure 8.5 shows the response of estimated C3 and C4 grass species AGB to monthly (a) total rainfall, (b) average temperature and (c) average radiation, over time. The findings revealed that seasonal climatic factors had a significant influence on C3 and C4 AGB over time. For example, a marked increase in AGB (*e.g.* in February and March) was noted with an increase in total rainfall (Figure 6 (a)), whereas dry months were associated with a decrease in AGB. It was also found that during the summer months (February, March, November and December), species AGB showed a gradual increase with an increase in radiation. Between April and June, peak species AGB was reached; however, this period indicated a sharp decrease in radiation.

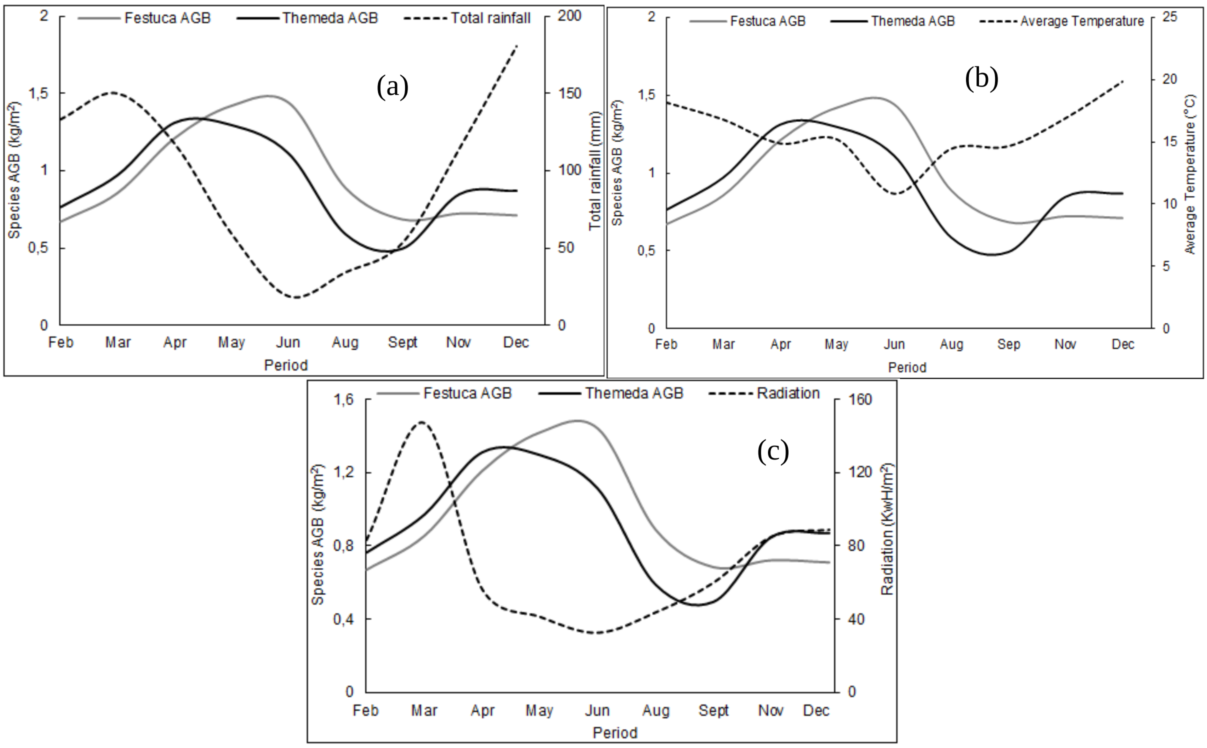


Figure 8.5: The response of individual species AGB to (a) rainfall, (b) temperature and (c) radiation over time

Figure 8.6 also zoomed in to highlighted areas (indicated in Figure 8.1) which show the spatial variations of AGB over time. These results were derived to show how the estimated AGB responded to rainfall and radiation variations over time. Generally, the unstable areas were mostly dominated by C4 (*Themeda*), whereas the stable tip was dominated by C3 (*Festuca*), although species co-existence occurs. In C3-dominated area, it was found that high radiation was associated with lower species AGB, for example in March (Figure 8.6 a (i)). High fluctuations in AGB were also observed for C3, despite rainfall and radiation changes over time. On the other hand, C4 (Figure 8.6 (b) showed sharp or immediate response (either decreasing or increasing) to rainfall (ii) and radiation (i) variations, especially in November and December.

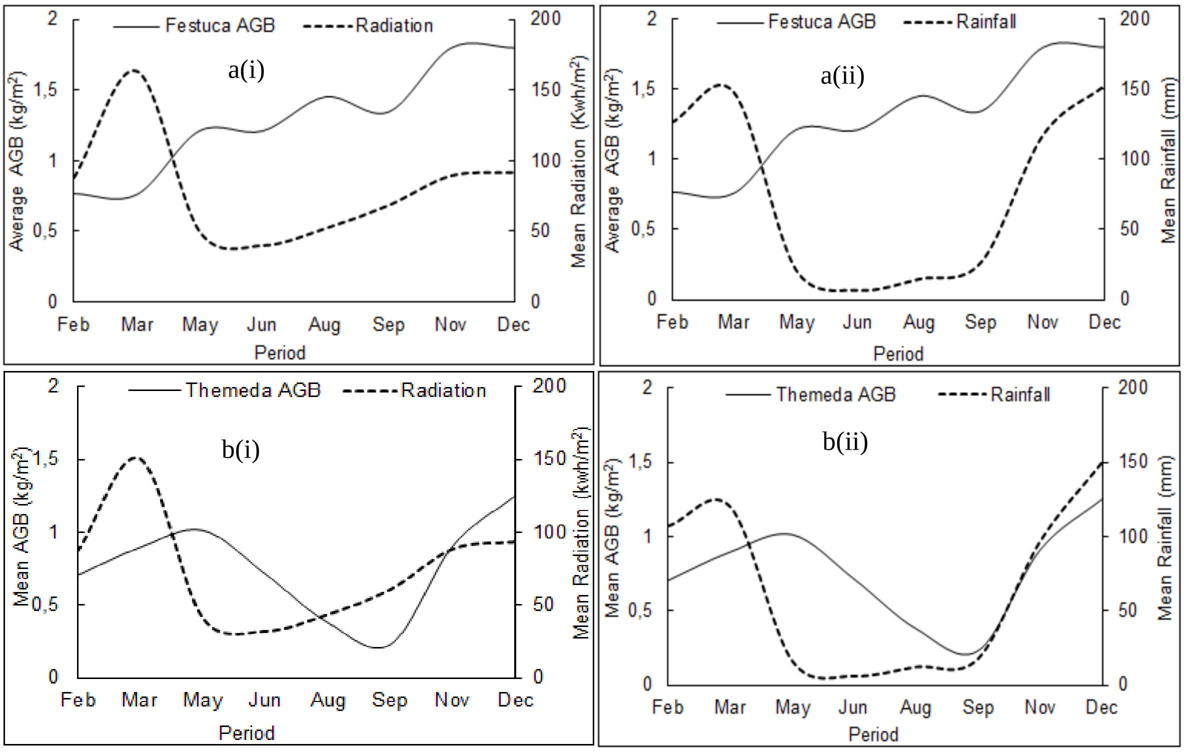


Figure 8.6: The response of (a) *Festuca* and (b) *Themeda* AGB to (i) radiation and (ii) rainfall variations over time

Tables 8.3 and 8.4 also illustrate the correlation between species AGB with climatic and topographical variables. Overall, C4 AGB showed better positive correlations with rainfall and radiation, than C3 AGB. C4 AGB also had the highest significant positive association with rainfall (R^2 = 0.82; P < 0.05). However, C3 AGB showed the highest significant positive correlation with elevation (R^2 = 0.84; P < 0.05). Positive correlations between C3 AGB and topographical variables were also shown, whereas for C4 AGB, mixed findings were found. For example, C4 was negatively correlated with elevation and slope, while responded positively to aspect and TWI. It was also found that elevation had the highest positive correlation with C3 AGB and highest negative correlation with C4.

Table 8.3: Correlation between species AGB and climatic factors over time

	Festuca (C3) AGB				Themeda (C4) AGB			
Climatic Variables	**Feb**	**May**	**Aug**	**Nov**	**Feb**	**May**	**Aug**	**Nov**
Radiation	0.44	0.49	0.42	0.54	0.63	0.54	0.46	0.79
Rainfall	0.57	0.52	0.31	0.59	0.79	0.61	0.70	0.82

Table 8.4: Correlation between C3 and C4 AGB and topography

Topographical Variables	Festuca (C3) AGB	Themeda (C4) AGB
Aspect	0.55	0.64
Elevation	0.84	-0.80
Slope	0.78	-0.77
TWI	0.74	0.69

*TWI: total wetness index

8.4. Discussion

Results from this study have revealed the spatial and temporal AGB variations as derived using multi-temporal Sentinel 2 remote sensing images. These findings indicate the potential of using freely-available emerging sensors for monitoring the dynamics of C3 and C4 AGB over time. This has been a limitation in monitoring C3 and C4 grass species, especially considering the anticipated climate change effects on their productivity. The spatial representation of AGB over time has shown that AGB distribution across the study area was varied. For example, summer months produced high AGB for most parts of the study area until May, whereas a decrease in AGB was noted from June until September, which showed the lowest AGB variations. The spatial and temporal variations observed in this study indicated not only the influence of seasonal climatic, but also that of spatial heterogeneity in terms of topography. Topographical derivative maps have shown that the area is predominantly high elevated, with steep slopes of varying aspects, facing all the different campus directions. These variations influence, for example, the intensity of radiation received, soil moisture and temperature. These topographical influence on species growth and AGB productivity have also been identified, for example by Måren et al. (2015).

Although significant spatial changes in AGB were observed, over time, it was noted that those changes were not uniform across the study area. Instead, some areas experienced rapid changes, whereas others remained almost stable, despite changes in climatic conditions. This possibly occurred because of the climatic and topographical heterogeneity of the area, which exert difference influence on C3 and C4 grasses AGB over time. However, in August and September, the majority of the study area showed a marked decrease in AGB. This is an indication that the period, which is winter fall, did not offer favourable conditions for both species AGB. For example, C3 grasses are active under cooler climatic conditions, particularly during winter. Possibly, during winter fall, rise in temperatures expectedly impacted negatively to C3 AGB. Studies (Adjorlolo et al., 2012; Auerswald et al., 2012) have also indicated that C3 grasses require higher moisture content, and this is not sufficient during the dry period of August and September, hence they become less active. Similarly, it is expected that rise in temperatures associated with dry conditions reduces the rate of activity of C4 negatively, impacting its AGB. C4 grasses prefer warm environments, with sufficient rainfall, hence as conditions becomes dry in August and September, their productivity is constrained and AGB is decreased. Possibly, the activity of C3 and C4 grasses and AGB production significantly decreases if the conditions are above their optimal or below their optimal requirements. For instance, August and September marked the end of winter, which is preferred by C3 and it does not fall within the summer period, which is favourable to C4.

It was also found that climatic factors considered in this study (*i.e.* rainfall, temperature and radiation) influence species AGB over time. This was also confirmed, for example, by positive correlation between rainfall and ground-based species AGB. C4 AGB had the highest correlation with rainfall, where high AGB values were observed with an increase in rainfall during the summer months. The same trend was also observed during dry winter months associated with lowest rainfall, where C4 AGB showed a sharp decrease. These trends can be considered intuitively sound. Rainfall within the study area is received during the summer period which coincided with the growth of summer or warm season C4 grasses, thereby influencing their AGB variations. In addition, the response of selected areas, predominated by C4 grass has indicated a close association between AGB and rainfall pattern over time. In agreement, it has been long established that summer rainfall typically benefits the growth of C4 grasses, thereby increasing their relative contribution to AGB accumulation (Carmel and Kadmon, 1999). This observation also concurs with previous studies (Epstein et al., 1997; Måren et al., 2015; Polley et al., 2014) which have indicated that rainfall boost the growth and AGB accumulation of C4 grasses. For example, the studies done during the summer period in United States by Epstein et al. (1997) found that mean annual rainfall explained 81% of C4 AGB in the great plains, whereas Polley et al. (2014) reported that C4 AGB increased significantly with an increase in rainfall in Texas. For C3 grass species, although a positive correlation was found with rainfall, its AGB remained high in winter, despite a noted decrease in rainfall. Similarly, the selected area predominated by C3, that showed almost stable response in AGB over time has indicated the same trend. It is likely that C3 AGB remained high in winter due to cool conditions, associated with winter period. In agreement with this notion, the results highlighted that June had the lowest average temperature and this corresponded with the highest estimated C3 AGB. As temperatures drop, cool conditions occur, which favour C3 grasses; hence their AGB remained stable despite a decrease in rainfall.

The influence of solar radiation was also detected on C3 and C4 AGB over time. C4 AGB responded positively with radiation variations over time; this was most apparent during the summer months, like February, March, November and December. C4 grass species have been identified to require high solar radiation (Adjorlolo et al., 2012), a condition that promotes their AGB production. Solar radiation is the primary source of energy that regulates physical, chemical and biological processes (*e.g.* photosynthesis and evapotranspiration) of terrestrial ecosystems (Dubayah and Rich, 1995; Ruiz-Arias et al., 2009). Consequently, it determines species growth rate and productivity of AGB. For C3 AGB, highest AGB was associated with low radiation, for instance, in winter (May and June). This is because C3 grass species prefer low radiation (Adjorlolo et al., 2012), which is received during the winter period.

Topography also influenced species AGB; however, this was variable between C3 and C4 species in this study. For instance, elevation had the highest positive correlation with C3 AGB. C3 AGB production favours conditions at high elevated and steep slopes, as well as with high potential of soil moisture. The influence of elevation on C3 AGB might be attributed to the fact that the study area forms part of the Drakensburg mountain range, which promote cool conditions favourable to the growth and AGB accumulation of C3, hence changes in elevation significantly result in AGB changes. In agreement, it is well accepted that high elevated areas are typically cool and C3 species generally favour cool conditions (Adjorlolo et al., 2012; Yan and de Beurs, 2016). Yan and de Beurs (2016) found the importance of elevation in the distribution and abundance of C3 grasses at three varying temporal scale, using random forest algorithm. For C4 species, high elevated and steep areas promote cool conditions, which do not favour their growth and AGB production. This explained why C4 AGB was negatively correlated with elevation and slope in this study. TWI was positively correlated with both C3 and C4 AGB. The index determines the spatial variability in soil moisture conditions (Wilson et al., 2016), which boost vegetation cover, growth and productivity; this possibly explains it had a positive association with species

AGB in this study. In this study, C3 AGB was positively associated with TWI most likely at low elevation areas. At low elevated areas, AGB for C3 will be enhanced by soil moisture, which has been identified as one of the favourable conditions for C3 grass species (Adjorlolo et al., 2012). For C4 grass species, wetness has been found to be very important under favourable warming and radiation conditions (Sage and Kubien, 2003).

Aspect was also found to positively influence C3 and C4 AGB in this study. Aspect determines radiation or light received at a particular location. North oriented slopes generally receives maximum radiation, followed by northeast and northwest slopes, whereas south facing slopes receives the lowest radiation, followed by southeast and southwest slopes. In association with this notion, the general variations in aspect and radiation has been detailed by Kumar et al. (1997). They indicated that in the southern hemisphere including South Africa, north facing slopes typically receives more radiation, whereas south facing receives the lowest radiation and they are typically cool and in shadow. In this regard, the positive association of aspect with C4 AGB was found on north oriented slopes, which receives more radiation. On the other hand, the association of aspect with C3 AGB is most likely on southwest slopes. Possibly, although C3 grasses prefer cool conditions with low radiation, few exceptions may exist, where their AGB is associated with high aspect. This might be the availability or contribution of other variables (*e.g.* moisture and elevation), which might be considered as most important for the productivity of these grasses. Although the study showed the influence of climatic variables and topography on the productivity of C3 and C4 grass species, the influence of CO_2 should not be ignored, future studies might consider exploring its influence.

8.5. Conclusion

This study examined the response of C3 and C4 grass species AGB to seasonal climate over time and topography, within the montane grasslands of South Africa. From the findings, it can be concluded that topographical and climatic variations exert considerable influence on C3 and C4 grasses AGB. C3 AGB variations were significantly influenced by elevation, whereas for C4, it was mainly rainfall variability. It was also noted that the changes in AGB over time were not uniform across the study area. Some areas experienced rapid changes, whereas others remained almost stable, despite changes in climatic conditions over time. This indicates the spatial and temporal heterogeneity of C3 and C4 dominated areas, which exert varying changes to AGB and ecosystem goods and services over time. However, additional research is required to quantify how AGB varies at different temperature variations at a finer scale. The study area lacked enough temperature data (*i.e.* it lacked spatial representation) for modelling in this study, which has been identified as one of the key climatic variables that influence the distribution of C3 and C4 grasses, hence it plays considerable role in their AGB response over time.

CHAPTER NINE

9. Synthesis

9.1. Introduction

C3 and C4 grass species offer a wide range of ecosystem services and goods, as well as influencing the functioning of these ecosystems at large. The co-existence of C3 and C4 grass species, due to local climate and topograpny also plays a considerable role in governing their biophysical processes, growth and productivity. This further implicates their ability to provide goods and services over space and time. The discrimination of these grass species therefore offer valuable information to understand their distribution and model their possible shift in the face of climate change effects. Their AGB is also an indicator of their productivity; hence characterizing it helps to understand their contribution to forage availability, veld fires and as potential carbon pools.

The use of ground-based methods offer the most accurate and reliable data source for characterizing C3 and C4 grass species and therefore remains the most applicable in understanding their distribution and AGB variations. However, this approach is spatially limited, strenuous and costly; consequently, its application becomes difficult for continuous monitoring over large geographical extent. Furthermore, it becomes difficult to apply the approach on a seasonal basis, due to challenges associated with its application. Remote sensing therefore offers an opportunity for the discrimination and AGB characterization of C3 and C4 grass species in a spatially explicit manner. Remote sensing overcomes the challenges associated with the use of ground-based methods.

Previous studies which attempted to discriminate or estimate C3 and C4 grass species AGB relied on broadband sensors. However, although these datasets were used, they were associated with poor results and uncertainties. This has been primarily attributed to their coarse spatial resolution and broadband spectral nature, with limited number of bands. Their operational use therefore became limited, especially in co-existing C3 and C4 dominated grasslands. Other researchers also attempted to use hyperspectral datasets, which were reported to produce high accuracies in C3 and C4 grass species discrimination and AGB estimation. However, high cost associated with the use of these datasets hinders their application, especially for large geographical coverage and time series analyses. In addition, high dimensionality problems associated with hyperspectral data also limits its wide application. Consequently, although remote sensing offers an invaluable means to discriminate and estimate AGB variations of these species, finding appropriate sensors, which have the potential to spectrally distinguish and spatially characterize these grasses, was the major challenge. This further hinders the possibility of time series analyses or continuous monitoring of these grass species, thereby resulting in uncertainties in their contribution to the provision of ecosystem goods and services, as well as their response to climate change.

The rise of new generation of multispectral sensors offers an indispenasble opportunity for the characterization of C3 and C4 grass species. These sensors have improved earth imaging characteristics, compared to the broadband sensors. The provision of data by these sensors at large geographical coverage, refined spatial resolution, more and unique spectral bands at high temporal frequency is considered a great improvement for the remote sensing of C3 and C4 grass species. These sensors overcome challenges associted with previously-used sensors; hence provide hope for monitoring of C3 and C4 grass species. In this regard, this study focused on the seasonal discrimination and characterization of AGB for C3 and C4 grass species, using new generation sensors. To achieve this task, the following objectives were considered:

1. Evaluate the prospects of the varying spectral configurations of the new generation sensors for the seasonal discrimination of C3 and C4 grasses functional types,
2. Examine the strength of the newly-launched Sentinel 2 MSI sensor in detecting and discriminating subtle differences between C3 and C4 grass,
3. Determine the optimal season for discriminating the eco-physiological distinction between C3 and C4 grass functional types using multi-date Sentinel 2 data,
4. Determine optimal new generation satellite derived metrics for accurate C3 and C4 grass species aboveground biomass estimation in a protected temperate eco-region,
5. Characterize the spatio-temporal variations of C3 and C4 dominated grasslands aboveground biomass in the Drakensberg, South Africa, and
6. To determine remotely-sensed C3 and C4 grass species AGB variability response to climatic factors and topography.

9.2. Seasonal discrimination of C3 and C4 grasses functional types: An evaluation of the prospects of the varying spectral configurations of the new generation sensors

Sensors spectral settings influnce their ability to detect or characterize the physiological, morphological and phenological characteristics of C3 and C4 species. This is very critical in mapping the spatial distribution of C3 and C4 grass species and their biophysical properties. One of the major limitation of the previously used sensors in discriminating C3 and C4 grass species was their limited number of bands and their broad-band settings. This resulted in lower classification accuracies, associated with over and under-representation of species, thereby limiting their application for species discrimination. Thefore, it was apparent to test the spectral prospects offered by the new generation sensors. This was achieved by conducting an experimental survey, using *in situ* hyperspectral measurements, which collect species spectra, using narrow band spectral settings that have the ability to extract and discriminate the finest details between species. The data used was collected in February (summer) and August (end of winter) 2016 and resampled to the spectral configurations of Landsat 8, Sentinel 2 and Worldview 2 sensors. The resampled data was also used to derive indices, that were tested for C3 and C4 grass species discrimination.

Overall results have shown the utility of hyperspectral data in exploring the applicability of different sensors' spectral settings for extracting species bio-physical properties. The spectral settings of new generation sensors were found to offer a potential for spectral discrimination of C3 and C4 grass species at selected different seasonal periods. High overall classification accuracies were produced during both periods. Data collected in February produced better discrimination than August data. Simulated Sentinel 2 spectral settings were also competent, especially when compared to Landsat 8. The G Chl index, EVI and the standard NDVI were the most influential indices in discriminating between the two species, with the standard NDVI identified as the most influential variable. This indicated the relevance and reliability of the long-serving NDVI in discriminating C3 and C4 grass species. However, although hyperspectral produced high overall accuracies, the applicability of the data is limited to plot level; it lacks the spatial aspect for C3 and C4 species mapping. Moreover, although February seems to provide the optimal discrimination window period, this data lacked the temporal variability. There is therefore a likelihood of inconclusive findings regarding the most suitable period for mapping the two species. There is a need to test the same objective using data collected across a couple of months per season (*i.e.* at most four months) to validate the above observation.

9.3. Examining the strength of the newly-launched Sentinel 2 MSI sensor in detecting and discriminating subtle differences between C3 and C4 grass

The significance of this study was to evaluate the performance of Sentinel 2, its spectral bands, derived indices and a combination of variables in discriminating and mapping C3 and C4 grasses. The new sensor has emerged with improved spatial resolution, more and unique spectral bands at large geographical coverage, compared to the previously-used sensors; this marks a great improvement for a better spatial representation of C3 and C4 grass species. Results obtained from using Sentinel 2 were therefore compared with those derived from the Worldview 2 commercial sensor and the Landsat 8. Sentinel 2-based results were comparable to Worldview 2, which produced slightly higher accuracies and far much better than those associated with Landsat 8. The classification accuracies using Sentinel 2 did not differ significantly (z = 1.34) from Worldview 2, when using standard bands; however, it was significantly (z > 1.96) different using indices and combined variables. When compared to Landsat 8, Sentinel 2 accuracies were significantly different (z > 1.96) using all variables. This paved a way for the applicability of Sentinel 2 in C3 and C4 grass species discrimination and mapping.

9.4. Determining the optimal season for discriminating the eco-physiological distinction between C3 and C4 grass functional types using multi-date Sentinel 2 data

Although Sentinel 2 provided the most appropriate data source for C3 and C4 grass species discrimination and mapping, the performance of the sensor is determined by image acquisition period. This is attributed to seasonal variations, which influence species phenological, physiological and morphological characteristics. Consequently, the use of single images acquired within a specific period (*e.g.* summer) becomes inconclusive. In this regard, this study was intended to optimise the discrimination of C3 and C4 grass species using Sentinel 2 multi-temporal images.

The results have revealed that the winter period presents a better temporal window for discriminating and mapping C3 and C4 target grass species, with higher overall classification accuracies, than summer. Lower classification errors (between 2.5 and 14.2%) were also observed, when discriminating using winter images. During the winter period, particularly in May and June, both species had reached their peak, with maximum productivity. Therefore, they become more distinct in morphology and biophysical characteristics, which facilitated their discrimination using remote sensing. Although high overall classification accuracies were produced in summer, these results were associated with high errors (between 4.7 and 22.2%). The winter fall, particularly in August was the least period to discriminate and map species. During this period, there is less biochemical activity with less AGB coverage. This resulted in soil background interference, thereby compromising the discrimination, especially of *Themeda* C4 grass. This study also managed to show that the majority of the area studied was occupied by *Festuca* (C3), when compared to *Themeda* (C4). Sentinel 2 derived species spectral curves have also revealed variations in the separability potential among the different spectral portions. For example, a close similarity (overlap) between the two species in the visible (*e.g.* blue, green and red) portion was observed, whereas the NIR and red edge portions showed separable spectral response. However, during early winter, separable species spectral curves were derived.

It is however, important to note that unlike the resampled hyperspectral data collected in February (summer) and August (end of winter), the use of multi-temporal Sentinel 2 images in winter (May, June, July and August) and summer (November, December, February and March) showed that May was the most suitable period for discriminating the two grass species and August remained the least period for species discrimination. It can be concluded that the use of hyperspectral data collected for two months was not enough for species discrimination as it does not capture the most possible variations in species physiological and morphological characteristics (Section 9.2). This was achieved by using Sentinel 2 images acquired at different months.

9.5. Determining optimal new generation satellite for accurate C3 and C4 grass species aboveground biomass estimation

The characteristics of new generation sensors are promising for monitoring of C3 and C4 grass species AGB. For example, these sensors have better spatial resolution (*e.g.* 30m for Landsat 8 and 10 m for Sentinel 2), which provide the spatial variability in species AGB at a much finer resolution than previously offered by sensors like MODIS, AVHRR and MERIS. These sensors, particularly MODIS and AVHRR offer remotely-sensed data at 1 km spatial resolution and have been the primary data sources for C3 and C4 grass species characterization. This study therefore tested the competence of Sentinel 2, against the freely available Landsat 8 and Worldview 2 commercial sensor. The potential of these sensors' variables were performed as isolated datasets in estimating C3 and C4 grass species AGB. Sensors data fusion was also done, where all the variables from each sensor were combined and used in the model to predict species AGB. Data fusion from the three sensors showed the most important bands or indices across multispectral sensors. It also showed a more comprehensive insight of the competence of each sensor's variables in estimating C3 and C4 grass species AGB, than when the sensor variables are used in isolation.

Findings from this study have indicated that Landsat 8, Sentinel 2 and Worldview 2 sensors can estimate and map the spatial variability of C3 and C4 AGB. Although the sensors show variations in spatial representation of AGB across the study area, some agreements were observed. In addition, their variables managed to estimate C3 and C4 grass species AGB with high accuracy especially in relation to those reported using broadband multi-spectral sensors. Specifically, the availability of more bands from Sentinel 2 offer additional information for vegetation analysis. More bands allowed the computation of new indices, which have the potential to predict C3 and C4 grasses AGB. On the other hand, the lower number of Landsat 8 bands limited the number of variables with potential to estimate species AGB. Overall, among the most important variables for predicting C3 and C4 grasses AGB were the Landsat 8 NIR and SWIR, the red edge of Sentinel 2 and Worldview 2.

9.6. Characterizing the spatio-temporal variations of C3 and C4 dominated grasslands aboveground biomass in the Drakensberg, South Africa

C3 and C4 grass species AGB indicate their productivity and ability to provide a wide range of ecosystem goods and services. The productivity of C3 and C4 grass species is variable over space and time. This is primarily due to the influence of climate, which regulates their phenology and AGB production. Although Landsat 8 variables, particularly NIR and SWIR were competitive against Sentinel 2, its 30 m spatial resolution, limits its operation for spatial representation of species AGB. In addition, its lower temporal frequency is also a challenge under the influence of cloud cover especially during summer. This limits its potential for temporal characterization of species AGB. Sentinel 2 therefore provides a key data source to determine C3 and C4 grass species AGB over time. This study therefore used the new multi-temporal Sentinel 2 to estimate and map C3 and C4 grasses AGB over time.

Findings have indicated the spatial variability in C3 and C4 species AGB, over time. Overall, high AGB across the area was noted during the summer months of February, March, November and December. This period coincided with the photosynthetically active stage of *Themeda* (C4), thereby facilitating AGB accumulation. This also explains why C4 produced higher AGB than *Festuca* (C3) during the summer months. On the other hand, C3 produced higher AGB from May to September. C3 prefers cool conditions and these occur in winter, which extends from May to August in the study site. This promoted C3 biological activity and AGB accumulation. May had the highest AGB; this period coincided with the peak stage of C3, whereas for C4, it had reached its maximum. This contributed to high AGB for most parts of the study area. The lowest AGB was also estimated during the winter fall in August and September, where most parts of the area showed a decrease in AGB. In addition, both species showed a decrease in AGB during this period although this was most apparent for C4 than its counterpart. This period coincided with the senescence stage of C4 grass, which is characterized by photosynthetic or biological inactivity. For *Festuca*, although it remained active, the conditions during the winter fall were not conducive enough for maximum AGB; this contributed to lower AGB across the area.

Considering the performance of Sentinel 2 variables over time, spectral bands predicted species AGB with lowest accuracies and an improvement was observed when both spectral bands and vegetation indices were applied. For instance, in May, spectral bands predicted species AGB with lowest accuracies for *Festuca* (R^2 = 0.57; 31.70% of the mean), *Themeda* (R^2 = 0.59; 24.02% of the mean) and combined species (R^2 = 0.61; 15.64% of the mean). The use of spectral bands and vegetation indices improved the prediction accuracies for *Festuca* (0.77; 18.64%), *Themeda* (0.75; 14.27%) and combined species dataset (0.73; 16.47%). Similarly, the estimation accuracy was variable over time. However, it was noticed that during the period of maximum AGB productivity in May, estimation accuracies were lower as compared to, for example, February, when species AGB was slightly lower. This indicated the influence of species phenology on estimation accuracy using remote sensing data. The red edge (at 0.705 and 0.74µm) and derived indices, NIR and SWIR 2 (2.19µm) of the Sentinel 2 contributed more to grass species AGB estimation, over time.

9.7. Remotely-sensed C3 and C4 grass species AGB variability in response to seasonal climate and topography

Climate and topography influence the productivity of C3 and C4 grass species. These conditions regulate biophysical processes, which determine species growth and the production of AGB. This study therefore explored the response of C3 and C4 grass species to seasonal climate and topography.

Spatial and temporal response of AGB variations were observed across the study area. For instance, AGB decreased from averages of 2.592 and 1.101 kg/m^2 in May, to 0.718 and 0.469 kg/m^2 in August, for C3 and C4 grasses, respectively. In addition, most parts of the study area also showed high AGB in May, whereas a significant decrease was noted in August and September. Although spatial and temporal changes occurred, the responses of species AGB over time were not uniform across the study area; some areas showed unstable response, whereas others showed stability in AGB, despite climatic changes over time. The observed changes in AGB was found to be influnced by rainfall, radiation and temperature. For example, a marked increase in C4 AGB (*e.g.* during summer months) was associated with an increase in rainfall, whereas low AGB (*e.g.* in August and September) were associated with dry months. Elevation was also the most influential topographical variable, with highest significant positive correlation (R^2 = 0.84) with C3 and highest negative (R^2 = -0.77) with C4 AGB.

9.8. Conclusion

C3 and C4 are an important component of grass species functional types, which influences their distribution, productivity, as well as their functioning within an ecosystem. The present study was therefore conducted to discriminate C3 and C4 grass species and characterize their AGB over time using remote sensing data. The study was also intended to optimise the discrimination and AGB characterization of C3 and C4 dominated grasslands. This has been stimulated by the need for information, which is increasingly becoming more relevant considering their roles in carbon accounting, forage supply and fire regimes, especially with the anticipated influence of climate change. Similarly, the emergency of new generation sensors, with improved earth imaging characteristics than previous-used sensors provides prospects for monitoring grass species according to functional types. Based on findings from this study, it can be concluded that:

- Sentinel 2 provides a key data source for landscape scale monitoring of co-existing C3 and C4 grass species functional types,
- The discrimination of C3 and C4 grass species was found to be most optimum in May and June, when both species reach their peak,
- When C3 and C4 grass species are at their early stages or inactive stages, their discrimination and mapping using remote sensing is compromised by surrounding vegetation and soil background reflectance,
- The winter fall, particularly in August was found to provide unfavourable climatic conditions for the productivity of C3 and C4 grass species, similarly, the same period was found to be least optimal for their discrimination,

- Seasonal climate and topography were also found to significantly influence C3 and C4 grass species AGB over time and space; however this was not uniform across the study site, and
- The advanced SPLSR and the DA algorithms have shown promising results for C3 and C4 grass species discrimination and AGB estimation, using different datasets and over time.

Overall results obtained from this study have demonstrated a new opportunity to monitor the spatial distribution and AGB variations of C3 and C4 grass species functional types, using the new Copernicus Sentinel 2 dataset. Most importantly, the study covered the seasonal aspect in discrimination and AGB estimation of these species; which was previously difficult to achieve. This study therefore marks a great improvement in discriminating, mapping and determining the productivity of C3 and C4 grass species functional types, over space and time. The findings provide new knowledge for optimal mapping of C3 and C4 grasses functional types and the basis for monitoring their potential shift in distribution and productivity. Furthermore, the seasonal characterization of C3 and C4 AGB allows for inferences on their contribution to forage availability and fire regimes over time; this thus contributes to the development of well-informed conservation strategies, which can lead to sustainable utilization of rangelands, especially in relation to the changing climate.

9.9. Recommendations

Overall, the present study provides valuable insight for the conservation, as well as optimal and sustainable utilization of rangelands according to species functional types. The study also demonstrated the potential of Sentinel 2 dataset in the discrimination and AGB estimation of C3 and C4 grass species over space and time. However, future studies need to take the following into consideration:

- It would be relevant for future work to consider the different Sentinel 2 derivatives in discriminating and AGB estimation of C3 and C4 grass species during winter fall, which has been characterized by the lowest AGB and least temporal window for the discrimination of C3 and C4 grasses,
- The study utilized climate data collected during the period under study (*i.e*. 2016); it also remains to be evaluated whether this was the typical climatic conditions, which influenced species AGB or there was a deviation. This will help in establishing the magnitude of extreme events (*e.g*. drought or floods) on C3 and C4 species productivity.

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