REMOTE SENSING GRASS QUANTITY UNDER DIFFERENT GRASSLAND MANAGEMENT TREATMENTS PRACTISED IN THE SOUTHERN AFRICAN RANGELANDS

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ABSTRACT

Grasslands productivity optimization has recently received considerable attention in rangeland management. Specifically, grassland management treatments, such as mowing, grazing, fertilizer application, burning as well as no-treatment have been practiced globally. Monitoring the effects of management treatments on grass quantity has remained one of the major challenges due to limited comprehensive frame works and lack of objective precedents. In southern Africa, for instance, this challenge has been aggravated by the lack of spatially explicit data, which could cover a large geographic areas at detailed scales and limited costs. Optical remote sensing, especially by new generation of multispectral remote sensors, has a high potential as a source of spatial information urgently required in discriminating grasses grown under different grassland management treatments and estimating its above-ground biomass. In that regard, the objective of this study was to assess the utility of earth observation data (i.e. field measured spectra, WorldView-3, simulated HyspIRI, Santinel-2 MSI) in discriminating and estimating biomass for native grasses grown across complex levels of management practices at Ukulinga Research Farm Pietermaritzburg, South Africa. This objective was accomplished by assessing the utility of earth observation data under three levels of investigation, namely Level 1: in-situ remote sensing, Level 2 use of new generation earth observation data and Level 3: utility of combining spectral and spatial techniques.

Results of this study showed that discriminant analysis (DA) outperformed partial least squares-discriminant analysis (PLS-DA) in discriminating complex combinations of ammonium nitrate, ammonium sulphate combined with lime and phosphorus, as well as unfertilized grasses based on field measured spectra. Specifically, four bands within the red edge (731nm and 737nm) and the mid-infrared (1310nm and 1777nm) regions of the electromagnetic spectrum demonstrated a high potential for discriminating the effect of fertilizer treatments on grasslands.

In assessing the potential of Sentinel-2 MSI spectral resolutions for quantifying above ground biomass across different fertilizer treatments relative to Landsat 8 OLI, results showed that Sentinel-2 MSI derived models satisfactorily performed (R square (R^2) = 0.81, root mean square error of prediction (RMSEP) = 1.07 kg/m^2, relative root mean square error of prediction ($RMSEP_{-}^{rel}$) = 14.97) relative to Landsat 8 OLI (Landsat 8 OLI: R^2 = 0.76, RMSEP = 1.15 kg/m^2,

RMSEP$_{-}^{rel}$ = 16.04). Meanwhile, hyperspectral data derived models exhibited better grass above ground biomass estimation across complex fertilizer combinations (R^2 = 0.92, RMSEP= 0.69 kg/m^2, RMSEP$_{-}^{rel}$ = 9.61).

Results of this study further showed that the spectral setup of HyspIRI, Sentinel-2 MSI, Venus and Landsat 8 OLI yielded overall accuracies of up to 92%, 82%, 83% and 75%, respectively in discriminating grass grown under different rangeland management practices. The high classification accuracies were exhibited by the use of vegetation indices and wavebands located in the red edge (HyspIRI: 700, 740 and 780nm and Sentinel-2 MSI: bands 5, 6, 7 and 8a) and NIR (HyspIRI: 700, 740 and 780nm and Sentinel-2 MSI: band 8a) spectra respectively. Results of this study illustrate that although simulated Sentinel-2 MSI data yields lower classification accuracies when compared to HyspIRI, it offers better classification accuracies with high agreements between training and testing data sets when compared to the HyspIRI data.

Meanwhile, HyspIRI data exhibited slightly higher grass above ground biomass estimation accuracies (RMSE =6.65 g/m^2, R^2 = 0.69) than Sentinel-2 MSI (RMSE = 6.79 g/m^2, R^2 = 0.58) across all rangeland management practices. Then the Student t test results showed that Sentinel-2 MSI exhibited a comparable performance to HyspIRI in estimating the biomass of grasslands under burning, mowing and fertilizer application. In comparing the RMSEs derived using wave bands and vegetation indices of HyspIRI and Sentinel-2 MSI, no statistically significant differences were exhibited (α = 0.05). Sentinel-2 MSI (Bands 5, 6 and 7) and HyspIRI (Bands 730 nm, 740nm, 750 nm, 710 nm), as well as their derived vegetation indices, yielded the highest predictive accuracies. The strength of red-edge spectral bands of new generation multispectral sensors such as the newly launched WorldView-3 improved the discrimination of grasses grown under different grassland management treatments from an overall accuracy of 65 % to 70%. Furthermore, overall accuracy was 73% when standard vegetation indices (Vis) were used and increased to 78% when the red-edge VIs were added. On the other hand, results of this study showed that red-edge indices improved above-ground grass biomass from an RMSEP of 0.83 kg/m^2 to an RMSEP of 0.55 kg/m^2. Texture models further improved the accuracy of grass biomass estimation to an RMSEP of 0.35 kg/m^2. The combination of texture models and red-edge derivatives resulted in an optimal prediction accuracy of RMSEP 0.2 kg/m^2 across all grassland management treatments.

Overall, the findings of this work comprehensively underscore that new generation of sensors, such as Sentinel-2 MSI and HyspIRI can be used to quickly and optimally model grass grown under different levels of grassland management treatments commonly practiced in southern Africa at limited costs. The red-edge wavebands of these new generation sensors and the derived texture models in conjunction with robust classification and estimation algorithms, improve grass quantity modelling, a previously challenging task, especially in data poor areas.

PREFACE

The research work detailed in this thesis was conducted in the School of Agricultural, Earth and Environmental Sciences, University of KwaZulu-Natal, Pietermaritzburg, South Africa, from January 2014 to November 2016, under the supervision of Professor Onisimo Mutanga and Professor Mathieu Rouget.

I would like to declare that the research work presented in this thesis has never been submitted in any form to any other institution. This work represents my original work except where due acknowledgements are made.

Mbulisi Sibanda Signed _______________ Date_______________

As the candidate's supervisors, We certify the aforementioned statement and have approved this thesis for submission.

Supervisor

Prof. Onisimo Mutanga Signed_______________ Date_______________

Co-supervisor

Prof. Mathieu. Rouget

DECLARATION 1-PLAGARISM

I, **Mbulisi Sibanda**, declare that:

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

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;
   b. where their exact words have been used, their writing has been placed in italics and inside quotation marks, and referenced;

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 sections.

Signed: ___________

DECLARATION 11-PUBLICATIONS AND MANUSCRIPTS

1. Sibanda, M., O. Mutanga, M. Rouget and J. Odindi (2015). "Exploring the potential of in situ hyperspectral data and multivariate techniques in discriminating different fertilizer treatments in grasslands." Journal of Applied Remote Sensing **9** (1): 096033-096033.

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Signed: _______________

DEDICATION

To Him who works in me to will and to do in order to fulfill His good purpose,

To my late father Paggy Hirrin Sibanda: Wish you were here to celebrate these achievements with me!

To my mother Magqu Rosemary Sibanda: You've always been my pillar of strength, thank you for your fervent prayers and love, I am greatly indebted to you!

To ithembalami: Thank you for your time I spent on this thesis

To "Zoë":

Here is the beginning of our lives!

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In deed all things work together for good to those who are called in His purpose! **[Rom 8:28]**....Who would have known that one day I will have the privilege to operate the ASD Spectrometer, workout publishable material from its data and earn myself a PhD? **Yes I did!** However **it was not by my might nor by my power**! It's through the grace of God! I wouldn't come to this far were it not for **Him**! **Thank you Lord!**

It's my pleasure to boldly acknowledge the support that I received from several people and institutions during the past three years of my PhD research.

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CHAPTER ONE:

GENERAL INTRODUCTION AND OVERVIEW

1. GENERAL INTRODUCTION

Figure 1.1 : Ukulinga Research Farm, University of KwaZulu-Natal, Pietermaritzburg, South Africa

1.1 Socio-economic and ecological importance of grasslands

Grasslands are an area of ecological and socio-economic importance which is characterized by perpetual conflicts between agricultural productivity and conservation endeavours (Franke *et al.* 2012). Grassland use intensity, propelled by anthropogenic activities, is the major driver that is threatening the numerous critical goods, services offered as well as roles played by such a biome (Franke *et al.* 2012). About 7.5% of the global grasslands have been reported as degraded, and about 16% under the threat of further degradation (O'Mara 2012). Literature suggests that agricultural practices, mining, as well as urban growth and development, due to rapid population increases and high food demands, are the main drivers of grasslands degradation (Bai *et al.* 2002, Zhihui *et al.* 2008, Andrade *et al.* 2015). More specifically, grasslands are one of the ecosystems with high species richness in the world (Wilson *et al.* 2012), covering 37% (500 million square kilometers) of the land surface with the exception of the Antarctica continent (O'Mara 2012) and currently under threat (Ali *et al.* 2016). Grasslands are critical carbon sinks that account for about 18% of the global terrestrial carbon (Conant *et al.* 2001). Furthermore, about 12% of the global organic matter content (Conant et al. 2001) created and stored by grasslands is currently under threat. Similarly, grassland degradation has also threatened the provision of multipurpose utilities to human activities. Grasslands support economic activities, such as smallholder and commercial livestock production systems, as well as tourism activities. In southern Africa, these grassland services have been reported to be significant in raising the income per capita of rural communities. In South Africa, grasslands have a total economic value of R9.7 billion, which includes a consumptive value of R1.59 million as well as an indirect value of about R8 million (de Wit *et al.* 2006).

In South Africa, about 3370 plants, 15 mammals, 13 reptiles and amphibians, and 10 bird species currently flagged under threatened species are affected by grassland use intensities (Birdlife South Africa 2016). Moreover, streamflow and flooding regulation, soil development and protection are amongst other critical ecological services offered by grasslands. Grassland use intensities threatening the ecological and socioeconomic values of grasslands have drawn the attention of all affected stakeholders to attempt drawing policies that will supersede these challenges and provide an equilibrium between conservation and development. Subsequently, precise and rapid methods that would offer the required critical information on grasslands are currently an important scientific issue of concern in rangeland ecosystem research frontiers (Hurt and Bosch 1991, Zhao *et al.* 2014). Furthermore, there is need for spatial representation of the levels of grassland degradation.

1.2 Grassland productivity and available management practices

The continued pressure on the grasslands, induced by the increase in population has resulted in their degradation. Faced with this challenge, the majority of rangeland managers, farmers and other grassland stakeholders resorted to different grassland management practices designed to restore, protect and maintain grassland productivity while facilitating their sustainable provision of ecosystems goods and services. In southern Africa, the dominant grassland management practices which have been utilized to improve grassland productivity include mowing/ grazing, fertilizer application, burning while some grasslands are left untreated (Mbatha and Ward 2010). These management practices have resulted in various levels of productivity and success. For instance, literature attests to an improvement in grass productivity of natural grasslands after the application of fertilizers, as well as after proper administration of grazing and fire treatments (Mbatha and Ward 2010, Trotter *et al.* 2014, Vogeler *et al.* 2014). For example, Johnson *et al.* (2001) noted that the application of nitrogen fertilizer increased grass mass by about 129%, when compared to unfertilized grasses. Mbatha and Ward (2010) demonstrated that administering burning treatments improved the phosphorus content of grasslands by 1.03% in the dry regions of South Africa. However, these management treatments often alter the biophysical and biochemical characteristics of the grasses. For example, mowing reduces the leaf area index and leaf angle distribution of the grass (Zhao *et al.* 2011). When grass properties are altered, storage of carbon, circulation of nutrients, palatability to livestock, soil development and protection, as well as the multi-purpose utilities to human activities will be compromised. As a result, grassland managers are often faced with a challenge of understanding the effect of these grassland management treatments on grass productivity at a larger geographic scale. To guarantee sustainable utilization of grasslands, information on the influence of these management treatments on grassland productivity, quality, and composition at local to regional scales, is essential. However, the major challenge has been the lack of appropriate spatial data sources, comprehensive frameworks and objective criterion for monitoring grasslands (Lehnert *et al.* 2013). In southern Africa, such critical information is scarce, due to the lack of resources, as well as the inaccessibility of those rangelands. During the previous decades, the impact of grassland management treatments were assessed based on bio-indicative vegetation analysis and visual tactile methods (Tainton 1988, Jordaan *et al.* 1997, Mueller *et al.* 2014). The challenge with these methods is that they often require expert knowledge. Furthermore, they are tedious, unrepeatable and associated with high expenses yet they are limited to local scales. The utility of traditional methods makes insights into the uncertainties of different management treatments on grass productivity at a regional scale to remain elusive. In that regard, there is still need for relatively accurate, timely, affordable and efficient methods of assessing grassland quantity, if sustainable management of these resources is to be achieved. Earth observation data facilities have a high potential as sources of spatial information required in the monitoring of grasslands. This is due to the fact that earth observation facilities provide spatially explicit grassland ecosystem pattern changes required for efficiently managing grasslands, when compared to other grassland inventorying methods. Earth observation data facilitates rapid, repeated and ongoing grassland ecosystem observations over various spatial and temporal scales.

1.3 Remote sensing of grassland productivity under different management treatments

Earth observation data have been successfully utilized to classify, predict and gain insights into different rangeland biophysical characteristics, such as foliar biochemical properties, leaf area index and degradation extent. For instance, hyperspectral data have been proven to be important in grassland mapping, exhibiting optimal accuracies (Thenkabail *et al.* 2002, Ling *et al.* 2014, Möckel *et al.* 2014, Schweiger *et al.* 2015, Möckel *et al.* 2016). For example, Ling *et al.* (2014) used in-situ and airborne hyperspectral data to estimate canopy nitrogen of grasses grown under different grazing and fire treatments with high accuracies. Möckel *et al.* (2016) illustrated that hyperspectral data can detect subtle spectral differences in vegetation amongst grassland plots under different treatments. This could be attributed to the numerous, narrow and contiguous spectral channels in hyperspectral data which provide detailed information on different vegetation characteristics. However, hyperspectral data is limited to small geograohical extents (i.e experimental plots) and it challenging to processing it. Despite its limitations, it is hypothesised that the robustness of hyperspectral data could better detect the subtle grass variations induced by different grassland management practices on grasses relative to other earth observation data sources at plot levels. Considering its ability to deduce detailed information on vegetation traits, hyperspectral data could also be used to develop efficient and robust estimation and discrimination algorithms required in characterizing grasslands under different management treatments. Hyperspectral data also offers a suitable platform for assessing the utility of other earth observation facilities when resampled based on the spectral configurations of a specific EO sensor of interest. This is a critical procedure that is essential in identifying optimal earth observation products that are appropriate for monitoring grasslands. Other than Hyperspectral data, there are broadband multi-spectral sensors that are also critical, credible and relatively cheaper sources of spatially explicit data for characterizing physiochemical traits of vegetation. Moderate resolution sensors, such as Landsat series have also been extensively used, with various successes, in discriminating grasses, as well as in estimating grass above-ground biomass (Fassnacht *et al.* 2015, Mutanga *et al.* 2015, de Beurs *et al.* 2016, Tarantino *et al.* 2016). For example, Fassnacht *et al.* (2015) used Landsat 8 operational land imager (OLI) to classify different levels of grassland degradation in the Tibetan Plateau, China and attained kappa statistics that ranged between 84% and 93%. Meanwhile, very high spatial resolution (VHR) earth observation facilities, such as WorldView, RapidEye, Ikonos, and QuickBird have also been reported to exhibit relatively optimal grass discrimination and estimation accuracies, when compared with moderate spatial resolution sensors such as Landsat series (Thenkabail *et al.* 2004, Thenkabail *et al.* 2013, Marshall and Thenkabail 2015, Tarantino *et al.* 2016). Tarantino *et al.* (2016), for example, noted that WorldView-2 based cross-correlation analysis had high overall accuracies of up to 96.45% in detecting changes in the area of the grasslands of Puglia region, southern Italy, when compared with Landsat data with overall accuracies of up to 76.7%. However, the spatial resolution of Landsat does not always capture the subtle variations of vegetation, such as those induced by different rangeland management treatments, relative to VHR and hyperspectral sensors. Landsat is also affected by saturation issues in areas with dense vegetation.

In southern Africa, the lack of cheap earth observation data with high temporal, spectral and spatial resolutions suitable for grassland monitoring activities, at a fine grain of detail, has been a major challenge in the management of rangelands (Dube and Mutanga 2015). Furthermore, the lack of robust assessment techniques that can be applied from local to regional scales, has retarded the use of remotely sensed data in southern Africa (Moran *et al.* 1997, Haboudane *et al.* 2002). The new generation of earth observation spatial data facilities could offer better prospects of detailed spatial information required for understanding the effect of grassland management treatments on grass quantity and composition both at local and regional scales.

1.4 Implications of remote sensing grass quality across different grassland management practices of southern African

Literature shows that only a few studies have been conducted in southern Africa to estimate grass quality and quantity (Mutanga and Skidmore 2004, Mutanga *et al.* 2004, Mutanga and Kumar 2007, Mansour *et al.* 2012, Ramoelo *et al.* 2012, Adjorlolo *et al.* 2013, Ramoelo *et al.* 2013, Ramoelo *et al.* 2013, Mutanga *et al.* 2015). For example, Mutanga *et al.* (2015) used WorldView-2 satellite images to estimate foliar nitrogen with RMSE % of 17% and 0.22% based field measured spectral and WorldView-2 data , respectively. This has been attributed to the limited availability of cheap earth observation data with high temporal, spectral and spatial resolutions suitable for grassland monitoring. Furthermore, work that has been conducted so far, covered only a few grassland management treatments. For instance, Brüser *et al.* (2014) sought to evaluate the differences between the communal grazing areas from the protected commercial farm grasslands. Dusseux *et al.* (2014) characterised leaf area index of grassland management practices such as mowing, grazing and mixed using time series data. To our knowledge no study has been conducted to assess the effect of different levels of various grassland management treatments in southern Africa.

The utility of data sets, such as radar and light detection and ranging (LIDAR) in grassland monitoring is still rudimentary in southern Africa. This is because LIDAR brings along challenges, such as exorbitant costs, enormous data volumes as well as unavailability to regions with limited resources. Earth observation data, such as field measured hyperspectral data, WorldView, and Landsat data have been successfully used in mapping grasslands growing under different management treatments (Adjorlolo *et al.* 2013). However, literature suggests that the utility of new and forthcoming generation of narrow and broad band multi-spectral data sets could improve mapping and monitoring the effect of grassland management treatments on grass quality and quantity (Delegido *et al.* 2013, Dube *et al.* 2016, Shoko *et al.* 2016, Tarantino *et al.* 2016).

The new and forthcoming earth observation sensors, such as Sentinel-2 multispectral imager (MSI), Landsat 8 operational land imager (OLI), hyperspectral infrared imager (HyspIRI), WorldView-3 (WV-3) could offer a better platform for mapping and detecting grasses grown under different grassland management treatments. The new generation of earth observation sensors (i.e. HyspIRI, Sentinel-2 MSI and WV-3) cover critical spectral sections of the electromagnetic spectrum that are important for vegetation mapping, such as the red-edge portion (Boochs *et al.* 1990, Curran *et al.* 1990, Delegido *et al.* 2013). The red-edge portion of the electromagnetic spectrum is crucial in mapping numerous vegetation characteristics, such as leaf area index, leaf angle distribution, chlorophyll and stress conditions of plants (Mutanga and Skidmore 2007, Mutanga *et al.* 2012, Schumacher *et al.* 2016). Furthermore, these sensors are characterized by bigger swath-widths (i.e. Sentinel-2 MSI has field of view of 190 km) which are suitable for monitoring grasslands at lager geographic scales. New earth observation will be freely available for various applications including rangeland management and monitoring activities. Furthermore, their spatial and spectral resolutions are suitable for mapping small matrices of different rangeland management treatments. For example, Sentinel-2 MSI has a minimum spatial resolution of 10 m while HyspIRI will have numerous narrow spectral channels with approximately 10 nm wide offering detailed information on grassland characteristics.

It is upon these observations that this work sought to evaluate the utility of five new generation earth observation facilities and possible optimal techniques for gaining insights on the impact of different rangeland management practices in southern African rangelands. This work also sought to identify an affordable spectral information source required in discriminating, mapping and monitoring above-ground biomass of native grasses grown under mowing, grazing, burning, fertilization and untreated conditions of southern Africa. Consequently, the conclusions of this work will be limited to the utility of new generation of optical sensors, such as Landsat 8 OLI, HyspIRI, Venµs, Sentinel-2 MSI and WorldView-3 sensors.

1.5 Aim

The aim of this study was to assess the utility of earth observation data including field measured spectra, WorldView-3, simulated HyspIRI, Santinel-2 MSI and Venµs in estimating biomass and discriminating native grasses grown across complex levels of management practices at Ukulinga research farm Pietermaritzburg, South Africa.

1.6 Objectives of the Study

The objectives of this thesis were:

1. to test the utility of hyperspectral data in (i) discriminating the effect of complex fertilizer combinations (i.e. eleven grass fertilizer combinations) on grass, and (ii) assessing the performance of PLS-DA compared with DA in discriminating grasses under different fertilizer treatments,
2. to explore the utility of the forthcoming new generation multispectral sensor Sentinel-2 MSI spectral configuration and indices in estimating grass above ground biomass across complex fertilizer treatments in relation to the simulated Landsat 8 OLI spectral band,
3. To test the strength of HyspIRI, Landsat 8 OLI, Sentinel-2 MSI and Venµs spectral configurations in discriminating grass species grown under different management practices including mowing, grazing, burning and fertiliser application,
4. to assess the robustness of the newly launched Sentinel-2 MSI spectral settings, in relation to those of HyspIRI in estimating grass biomass across mowing, burning and fertiliser application treatments,
5. to test the utility of the red-edge of the newly launched WV-3 in discriminating grasses grown under different management treatments,
6. to test whether the combined use of WV-3 optical texture models and red-edge can improve accuracies of predicting above-ground biomass of native grass grown under different levels of management practices using the sparse partial least squares regression algorithm.

1.7 Scope of the study

In addressing the limitations to monitoring grasses grown under different grassland management treatments in the southern African, the premise of this work is limited to the utility of new generation earth observation instruments in discriminating grasses grown under natural, mowing, grazing, burning and fertilizer applications. It also illustrates their spectral capabilities in estimating the grass above-ground biomass across these grassland management treatments.

Precisely, this study tested the utility of partial least squares discriminant analysis in comparison to discriminant analysis algorithm in distinguishing grass grown under different management treatments based on hyperspectral data. Consequently, discriminant analysis performed better hence it was then utilised to test the spectral settings of the newly launched and forthcoming sensors (i.e. Sentinel-2 MSI, HyspIRI, Venµs, WorldView-3, and Landsat 8 OLI). The sensors that exhibited optimal grass discrimination capabilities were further evaluated. The sparse partial least squares regression algorithm was utilised in assessing the accuracy of these sensors in estimating above-ground biomass of these native grasses.

1.8 Description of the study area

The study was conducted using experimental plots established by J.D. Scott in 1950(Morris and Fynn 2001) at Ukulinga (University of KwaZulu-Natal Research Farm) in Pietermaritzburg, South Africa, (29°24′E, 30°24′S). The initial aim of the experiment was to understanding the influence of different management practices on grass quantity and quality.In this study, only the grass growing seasons of October 2013 to April 2016 were considered. The dominant grass species in the experimental plots include *Themedatriandra, Heteropogoncontortus, Eragrostisplana, Panicum maximum, Setarianigrirostrosis and Tristachyaleucothrix*. The average height of theses grasses ranged between 25 and 40 cm. Generally, temperatures in Pietermaritzburg range from 23 - 33^0 C during summer and 16 - 25^0 C during winter. The soils at Ukulinga are grouped under the acidic Westleigh form (plinthic paleustalf) group which is relatively infertile (Fynn and O'Connor 2005).

1.8.1 Experimental design

In this study, 96 experimental plots with a length of 9 m and a width of 3 m were used. In all these plots, 11 fertilizer combinations and the “control” (untreated grass) were used to treat the grass in this experiment as shown in Figure 1.2 and 1.2. An amount of zero and 33.6 $g.m^{-2}$ of dolomite lime treatments were applied every fifth year, super phosphate applied every year at zero and 225 $g.m^{-2}$ as well as two ammonium fertilisers (ammonium nitrate and ammonium sulphate), each applied every year at four levels. In this experiment, ammonium nitrate was combined with lime and phosphorus but not with ammonium sulphate considering the fact that they are both nitrogenous fertilisers. All treatments were randomly assigned to each plot within the three replicates or blocks.

BURNING AND MOWING TRAILS

REPLICATE 3

B4	B5	B6	B9	B2	B10	B8	B11	B7	B3	B1
C1	C2	C6	C3	C7	C9	C4	C10	C11	C5	C8
D4	D1	D5	D7	D2	D3	D11	D10	D6	D9	D8
A2	A9	A1	A7	A3	A10	A8	A5	A6	A4	A11

REPLICATE 2

D2	D7	D6	D4	D10	D5	D11	D8	D1	D9	D3
A9	A8	A2	A11	A6	A7	A5	A4	A3	A10	A1
C5	C4	C10	C2	C11	C8	C6	C1	C9	C3	C7
B8	B5	B11	B7	B10	B6	B3	B1	B2	B4	B9

REPLICATE 1

B11	B6	B9	B8	B2	B10	B1	B3	B4	B7	B5
A1	A8	A11	A2	A6	A3	A9	A4	A7	A5	A10
C8	C2	C11	C9	C6	C4	C10	C3	C5	C1	C7
D1	D8	D10	D2	D4	D11	D7	D5	D3	D6	D9

18.3 m

13.7 m

FERTILIZER TRAILS

96 N1P	85 n1L	84 L	73 P	72 L	61 nP	60 N2P	49 n2	48 PL	37 N3P	36 n1	25 n2P	24 N3L	13 n2L	12 n3P	1 N1	REP 1
95 N2	86 n2PL	83 n3	74 N3PL	71P	62 N3	59 N1	50 n3PL	47 N1PL	38 n3L	35	26 N2L	23 N2P	14 PL	11	2 n1PL	
94 L	87 N3L	82 N2	75 P	70	63 n1P	58 N2P	51 n2L	46 N1	39 n2	34 n3L	27 N2PL	22 PL	15	10 N2L	3 N1P	REP 2
93 n1	88 N1PL	81 n2PL	76 n3P	69n3	64 N1L	57 PL	52N3PL	45 N3P	40L	33 P	28 n1PL	21 n1L	16 n2P	N 3	4 n3PL	
92 P	89 n2P	80 n1PL	77 L	68	65 n1L	56 N1P	53 N3L	44 n2L	41n3P	32 N2P	29 P	20 N2	17 N1L	8 n1P	5 n2PL	REP 3
91 N3PL	90n3	79 N1	78 N2L	67PL	66 n2	55 N2PL	54 n3P	43 N1PL	42L	32 N3	30 n2	19	18 n3L	7 N3P	6 PL	

3 m

9 m

Figure 1.2: Experimental setup and design at Ukulinga research farm.

1.9 Thesis Outline

This work is composed of six articles that have been submitted for peer review to international journals of geographic information system and remote sensing applications. All of these journal papers have been published online. Each of these articles is presented as chapter in this thesis. Accordingly, each article contributes in addressing the overall aim of this study. The format and content of these peer reviewed articles was preserved in compiling this thesis. Consequently, each chapter comprises of the introduction and conclusion which then links with the proceeding chapter. In that regard, it is inevitable that there are overlaps or repetition of theory within the ambit of the research. The reason being that there is a seamless flow of principles underpinning the entirety of the current scientific setting. This is considered to be trivial, because these articles were critically peer-reviewed by international journals. In that regard, these articles can be considered as stand-alone work without compromising the general context of the thesis. Ultimately, there are eight chapters which constitute this thesis. These chapters are categorized under four subdivisions (i) general overview and contextualization (ii) in-situ remote sensing (iii) use of new generation earth observation facilities (iv) utility of combined spectral and spatial techniques.

1.9.1 General overview and contextualization

1.9.1.1 Chapter One

This is an introductory chapter which unveils the essence of the study. Specifically, the objectives, scope and outline of the thesis are provided in this chapter. Furthermore, this chapter contextualizes the research questions addressed in this work from a local to regional outlook. It illustrates the significance of the methods, spectral settings of new generation sensors, and image techniques, such as grey-level co-occurrence texture models in mapping and monitoring grasslands, especially in regions that are ill-posed by the lack of resources, spatial data and expertise.

1.9.2 In-situ remote sensing

1.9.2.1 Chapter Two

In this chapter, the accuracy of two discrimination techniques, i.e. discriminant analysis and partial least squares discriminant analysis, are compared in distinguishing native grasses grown under complex fertilizer treatments. This chapter sought to identify a technique that could efficiently discriminate grasses grown under different levels of nitrogenous fertilizer treatments combined with dolomite and lime. Furthermore, the utility of hyperspectral remotely sensed data in discriminating grasses under various levels of composite fertilization treatments was also tested in this chapter.

1.9.2.2 Chapter Three

Having noted the utility of remotely sensed data and robust method of discriminating grasses grown under complex management practices, chapter three sought to evaluate the utility of new generation of broadband sensors in estimating the above-ground biomass of grass growing under different fertilizer treatments. Specifically, this chapter presents a comparison of the accuracies obtained based on the spectral settings of Landsat 8 OLI and Sentinel-2 MSI simulated from hyperspectral data using sparse partial least squares regression algorithm. Accordingly, the findings of this chapter unveil another challenge of testing the utility of remotely sensed data in discriminating, not only grasses grown under complex fertilizer treatments, but also the ultimate grassland management treatments practiced in southern Africa.

1.9.3 Use of new generation earth observation facilities

1.9.3.1. Chapter Four

Considering that, in chapter two discriminant analysis was noted to outperform partial least squares discriminant analysis, it was, therefore, used in this chapter to compare the spectral settings of the new and fourthcoming generation of earth observation facilities in distinguishing grasses grown under different management treatments practised in southern Africa such as, native grass (untreated/ 'control'), mowing, grazing, burning as well as fertilization treatments. The new generation sensors considered in this piece of work were HyspIRI, Landsat 8 OLI, Sentinel-2 MSI, and Venµs. This section was conducted in the premise of addressing the challenge of lack of spatial data sources required in for monitoring and management of grasslands in southern Africa. The findings deduced this section illustrate the prospects of regional grassland quantity monitoring required in the optimal management of southern African rangelands. Furthermore, HyspIRI and Sentinel-2 MSI, respectively, outperformed the other sensors, these two promising sensors were considered for the subsequent chapter.

1.9.3.2. Chapter Five

Having noted the prospects of Sentinel2 MSI sensor's spectral settings in discriminating and mapping and monitoring grasslands quantity across a wide range of grassland management treatments, it was inevitable to compare the magnitude of its error or accuracy in estimating grass quantity. This section, therefore, sought to assess the accuracy of Sentinel-2 MSI in estimating above-ground biomass of grass growing across all the typical grassland management treatments practices (i.e. mowing, grazing, fertilizer application, burning and no-treatment ('control') in southern Africa. The testing of Sentinel-2 MSI sensor's spectral settings specific section of the thesis was motivated by the optimal spectral and spatial characteristics of the sensor. However, during the period of study, Sentinel-2 MSI data was not yet available for testing. Consequently, the newly launched WorldView-3 satellite data was used instead of Sentinel-2 MSI in the subsequent chapters.

1.9.4 Utility of combined spectral and spatial techniques

1.9.4.1. Chapter Six

This segment of the thesis tested the spatial fidelity as well as the incorporation of critical wave bands such as the red-edge in discriminating native grasses thriving under multifaceted levels of grassland management treatments. As aforementioned, this chapter utilized the newly launched Worldview-3 satellite data instead of Sentinel-2 MSI because during the period of the study Sentinel-2 MSI was going through the testing phase. This chapter concludes by affirming the utility of the red-edge waveband as a critical portion of the electromagnetic spectrum for accurately discriminating mapping grasses influenced by different levels of grassland management treatments.

1.9.4.2 Chapter Seven

After noting that the red-edge wavebands from space-borne data are critical in mapping and monitoring grasses grown under different grassland management treatments, this chapter further sought to evaluate the combination of red-edge and image processing techniques in estimating grass quantity. Specifically, the utility of combining grey-level co-occurrence texture models was examined in predicting biomass of native grass grown under the aforementioned grassland management treatments.

1.9.5.1. Chapter Eight

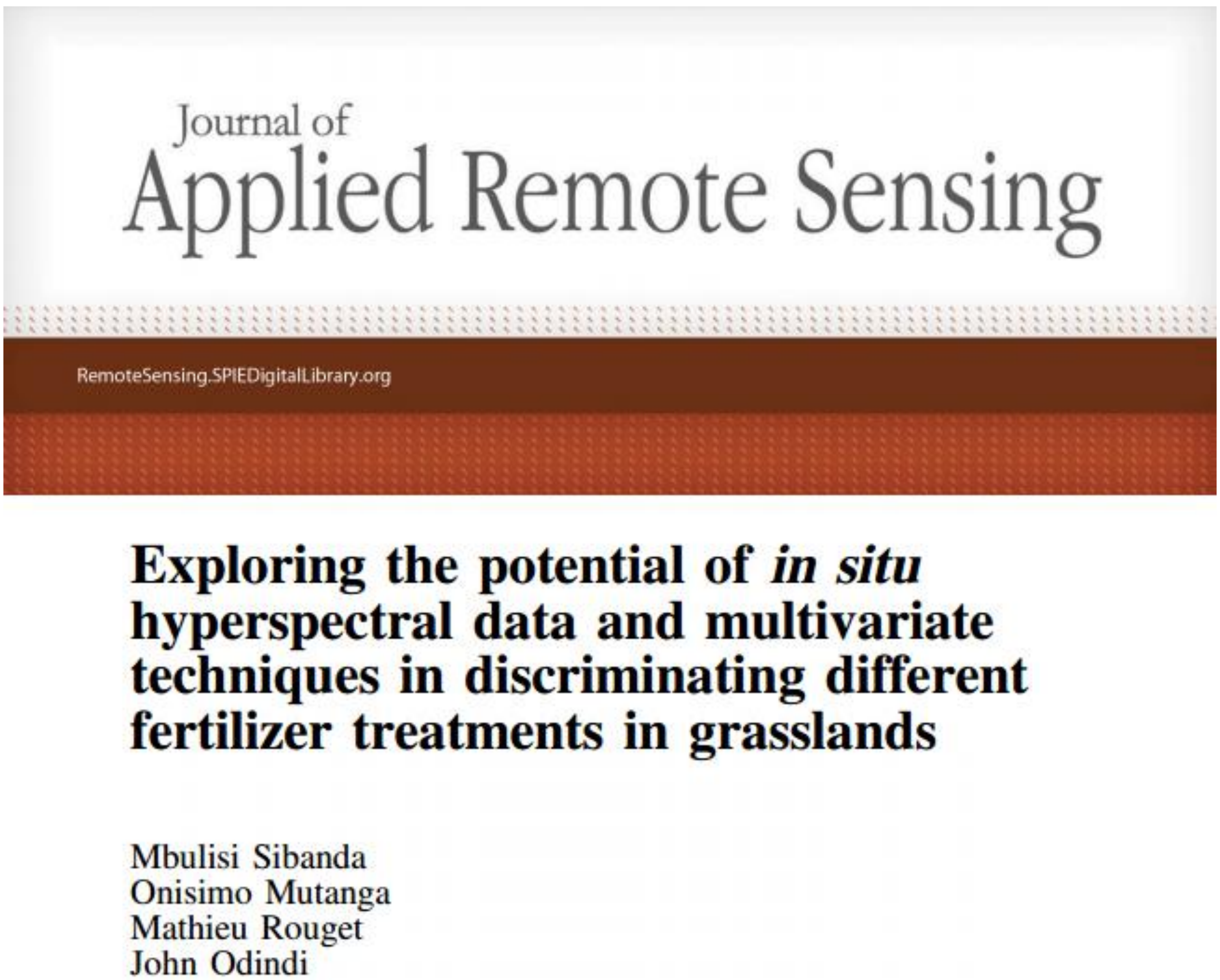
The final chapter presents a synthesis of the conclusions deduced from the findings of the six previous chapters of this work. This section sums up and evaluates the initial framework of the study against the insights drawn from the findings of the six chapters, despite certain limitations which are also outlined in this chapter. Consequently, this section points out the direction for future studies.

CHAPTER TWO AND THREE

IN-SITU REMOTE SENSING

2. EXPLORING THE POTENTIAL OF IN-SITU HYPERSPECTRAL DATA AND MULTIVARIATE TECHNIQUES IN DISCRIMINATING DIFFERENT FERTILIZER TREATMENTS IN GRASSLANDS

This chapter is based on:


Journal of Applied Remote Sensing

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Exploring the potential of *in situ* hyperspectral data and multivariate techniques in discriminating different fertilizer treatments in grasslands

Mbulisi Sibanda
Onisimo Mutanga
Mathieu Rouget
John Odindi

Sibanda, Mbulisi, Onisimo Mutanga, Mathieu Rouget, and John Odindi. 2015. "Exploring the potential of in situ hyperspectral data and multivariate techniques in discriminating different fertilizer treatments in grasslands." *Journal of Applied Remote Sensing* **9** (1):096033-. doi: 10.1117/1.JRS.9.096033.

Abstract

Optimizing the productivity of native rangelands has received considerable attention in range management. Rangeland fertilizer application has emerged as a popular intervention for improving rangeland quality. To achieve optimal range quality from such intervention, there is need for quick and accurate methods of assessing the effect of different fertilizer combinations. This study assesses the utility of *in-situ* hyperspectral data and multivariate techniques in distinguishing twelve complex ammonium nitrate, ammonium sulphate, lime and phosphorus fertilizer combinations on a grassland. Partial least squares regression discriminant analysis (PLS-DA) and discriminant analysis (DA) classification results derived using hyperspectral grass reflectance that were (i) fertilized using eleven combinations of ammonium sulphate, ammonium nitrate, phosphorus and lime and (ii) unfertilized experimental plots were compared. Results illustrate the strength of *in-situ* hyperspectral data and multivariate techniques in detecting and discriminating grasses with different fertilizer treatments. Specifically, four bands within the red edge (731nm and 737nm) and the shortwave infrared (1310nm and 1777nm) regions of the electromagnetic spectrum demonstrated a high potential for discriminating the effect of fertilizer treatments on grasslands. DA outperformed PLS-DA in discriminating complex combinations of ammonium nitrate, ammonium sulphate combined with lime and phosphorus, as well as unfertilized grasses. Overall, spectroscopy and DA offer great potential for discriminating complex fertilizer combinations.

Keywords

Tropical grass fertilization, discrimination, multivariate techniques, field spectroscopy

2.1 Introduction

Globally, grasslands occupy about 37% of the total land area and play a critical role in food security, biodiversity conservation, and greenhouse gas mitigation (Conant *et al.* 2001, Snyman 2003, Jungers *et al.* 2015). Grassland ecosystems are predominantly used for grazing (Boval and

Dixon 2012). Consequently, they are highly susceptible to degradation through overgrazing and inappropriate agricultural management practices (Xu *et al.* 2014). Grassland and rangeland degradation commonly occur when forage quality and quantity are reduced (Rook *et al.* 2004, Jungers *et al.* 2014). This adversely affects livestock production through increased expenses on stock feeds (Valkama *et al.* 2014). Grasslands, like fodder crops, are commonly rehabilitated through the application of fertilizers. For instance, application of organic or inorganic fertilization like ammonium nitrate ($(NH_4)(NO_3)$) or ammonium sulphate ($(NH_4)_2SO_4$), combined with lime and phosphorous fertilizers has been found to effectively restore the productivity of degraded grasslands, and therefore adopted as a common management practice (Conant *et al.* 2001, Liebisch *et al.* 2013, Messiga *et al.* 2013, Pan *et al.* 2014, Valkama *et al.* 2014). Black and Wight (Black and Wight 1979) for instance, note that N and P fertilization yields high forage quality, which may even persist long after fertilizer application. Kowaljow (2010) noted that due to the high N content, grasslands respond more to inorganic fertilizer than organic fertilizers. However, comprehensive frameworks and objective criterion for monitoring these grasslands and rangelands are largely absent (Lehnert *et al.* 2013).

Detailed and precise inventories of grassland quality are important for sustainable rangeland/grassland management (Conant *et al.* 2001, Rook *et al.* 2004, Messiga *et al.* 2013, Xu *et al.* 2014). Traditionally, Visual Soil Assessment (VSA), Muencheberg Soil Quality Rating (MSQR), visual-tactile methods, bio-indicative vegetation analyses and soil survey data have been used to characterize general physical, chemical and biological status of grasslands(Tainton 1988, Jordaan *et al.* 1997, Jordaan *et al.* 1997, Mueller *et al.* 2014). However, these methods cover limited spatial extents, require expert interpretation, are costly, tedious and time consuming. In this regard, there is need for more detailed, accurate, affordable, robust, timely and efficient methods of assessing grassland quality for sustainable grassland management.

Remotely sensed data offers spatially explicit patterns of ecosystem changes and variations. These datasets have been widely used to estimate rangeland biophysical characteristics, for instance Leaf Area Index (LAI) (Darvishzadeh *et al.* 2008), foliar nutrients (Mutanga and Kumar 2007, Mutanga *et al.* 2015) and chlorophyll or primary productivity estimation (Cho *et al.* 2007, Clevers *et al.* 2007, Cho and Skidmore 2009, Schweiger *et al.* 2014). The advent of hyper-spectral remote sensors, including *in-situ* remote sensing have been proven to be invaluable in discriminating vegetation characteristics (Mutanga *et al.* 2009). This can be attributed to their ability to acquire data in many narrow spectral channels that can distinguish subtle differences in target features that may otherwise be masked by the broadband sensors (Ullah *et al.* 2012). *In-situ* hyperspectral data collected using hand held spectro-radiometres have particularly proved to be valuable for calibrating models in estimating grass quality (Palacios-Orueta and Ustin 1996, Clevers 1999, Mutanga and Skidmore 2004, Mutanga and Skidmore 2007, Mutanga *et al.* 2009, Alonzo *et al.* 2014, Lehnerta *et al.* 2014). Such data has also been used to discriminate rangeland vegetation species and forms. Schmidt and Skidmore (2001) for instance demonstrated the utility of hyperspectral data in improving the mapping of grassland floristics in the African rangelands while Mutanga *et al.* (2015) evaluated the extent to which the resampled field spectra compared to the satellite image spectra of the multispectral WorldView-2 (WV-2) sensor. Whereas their results validated the relevance of field spectroscopy in assessing grassland quality, analysis due to high data dimensionality, particularly when using individual hyperspectral bands as variables remains a challenge (Sobhan 2007, Adam *et al.* 2012, Mutanga *et al.* 2015). Furthermore, the close hyperspectral bands are sometimes affected by multi-collinearity, which makes the variance-covariance matrix nearly singular, which leads to problems of matrix inversion and results in highly unreliable estimates of vegetation parameters.

Subsequently, the multi-collinearity of hyperspectral data has prompted the use of a number of data reduction techniques. In some instances, analysis of variance (ANOVA) has been used to reduce dimensionality prior to the use of classification algorithms (Adam and Mutanga 2009, Adelabu *et al.* 2014). Typically, ANOVA seeks to establish the wavelengths at which statistical differences amongst groups exist, without classifying the target groups. In this regard, if optimal rangeland quality and productivity is to be attained, robust algorithms that can reliably and efficiently classify the target groups are a necessity. In this study, we evaluated the use of two algorithms: discriminant analysis (DA) and partial least squares discriminant analysis (PLS-DA) in discriminating the complex combination of ammonium nitrate with lime and phosphorous as well as ammonium sulphate with lime and phosphorous. DA and PLS-DA provide an opportunity to assess and interpret the spectral patterns derived from grass samples. According to existing literature, these algorithms build a characteristic spectrum that represents the finger print of the sample and simplify the classification process better than other algorithms like K-nearest neighbors (Boulesteix 2004, Corbane *et al.* 2013). Lehnert *et al.* (2013), for instance, used PLS discriminant analysis to separate grass and non-grass species to evaluate the utility of hyperspectral imaging for predicting forage quality and quantity in the western Tibetan Plateau. Tong *et al.* (2014) demonstrated that remotely sensed data and PLS-DA can be used to classify grass age-classes with high overall classification accuracy using a set of wave bands in the Baltic island of Öland, South-east Sweden. Although both these algorithms have been noted to be robust in classification studies, the superiority between the two, especially, in discriminating complex ammonium nitrate and ammonium sulphate combinations with lime and phosphorus fertilizers in the tropical grasslands is yet to be established.

Remote sensing techniques have been used extensively for pasture and grassland nutrient planning. N and K have particularly received great attention in remote sensing related studies. Recent studies show a growing interest towards phosphorous and other plant minerals (Sanches *et al.* 2013, Zhai *et al.* 2013). Curran (1989), for instance, established an association amongst numerous absorption features in the near-infrared region and N concentrations. Sanches et al. (Sanches *et al.* 2013) investigated the ability of *in-situ* hyperspectral remotely sensed data in predicting N, P, and K concentrations in mowed and grazed grasslands during different seasons. Vickery et al. (Vickery *et al.* 1980) noted that remotely sensed grass reflectance can be utilized to discriminate and map areas of pastures that require additional N, P and K. Whereas a large body of literature exist on N and to a certain extent P, to our knowledge, no study has attempted to discriminate the grasses treated with either ammonium nitrate, ammonium sulphate, lime, or phosphorus, as well as the combinations of these fertilizer treatments using DA and PLS-DA based on hyperspectral data in a Southern Africa rangeland. Furthermore, there is no particular algorithm that has extensively been verified to be efficient in optimal feature selection in classification studies (Thenkabail *et al.* 2004, Adam and Mutanga 2009). In this study, therefore, we test the utility of hyperspectral data in (i) discriminating the effect of complex fertilizer combinations (i.e. eleven grass fertilizer combinations) on grass, and (ii) assessing the performance of PLS-DA compared with DA in discriminating grasses under different fertilizer treatments.

2.2. Methods and materials

2.1.1 Study area

The study was conducted based at the experimental plots established by J.D. Scott in 1950 (Morris and Fynn 2001) at Ukulinga (University of KwaZulu-Natal Research Farm) in Pietermaritzburg, South Africa, (29°24′E, 30°24′S) (Figure 2.1). In this study, only the grass growing season of October 2013 to April 2014 was considered. The grass species prevalent in the experimental plots include *Themeda triandra*, *Heteropogon contortus, Eragrostis plana, Panicum maximum Setaria nigrirostrosis and Tristachya leucothrix*. Generally, Pietermaritzburg has high temperatures in summers and slightly cold winters. Much of the annual precipitation (694 mm) occurs in summer, facilitating a grass growing season that stretches between October and April (Fynn and O'Connor 2005) Soils at Ukulinga are generally classified as a Westleigh form (plinthic paleustalf), acidic and comparatively infertile (Fynn and O'Connor 2005).

2.2.2 Experimental design

Ninety six experimental plots measuring 3m x 9m were used for the study. Eleven combinations of fertilization treatments and the control were used in all the plots as illustrated on Table 2.1. The Treatments levels of dolomitic lime were (0 and 225 $g.m^{-2}$) applied at five year intervals and two levels (0 and 33.6 $g.m^{-2}$), super phosphate applied every year at 0 and 225 $g.m^{-2}$ and two types of ammonium fertilisers NH_4NO_3 and $(NH_4)_2SO_4$ each applied yearly at four levels. NH_4NO_3 was not combined with $(NH4)_2SO_4$ but both were combined with either lime, P or both lime and P. The fertilisers are applied during the beginning of the growing season. Treatments were randomly assigned to each plot within the three replicates or blocks

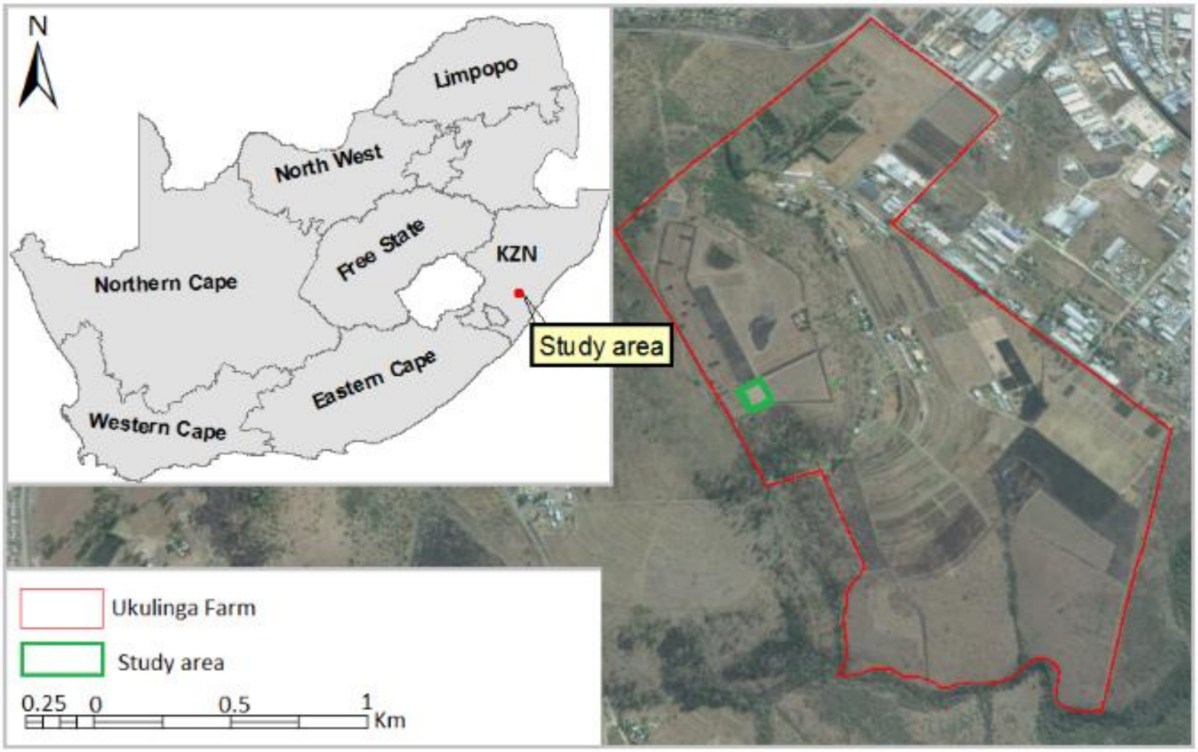

Figure 2.1: Study area at Ukulinga Farm (Source: Google Earth images).

2.2.3 Field data collection

An Analytical Spectral Device (ASD) FieldSpec instrument was used to measure the spectral reflectance of grasses within the 96 plots. The ASD spectrometer indexes radiation at 1.4 nm intervals for the 350 –1000 nm spectral region and 2 nm intervals for the 1000–2500 nm spectral region. The bare fiber-optic sensor connected to the hyperspectral spectro-radiometer was held at a nadir position approximately 1m directly above the grass canopies resulting in an acceptable ground view of approximately 0.45m in diameter, sufficient to capture the reflectance of grass canopy (Mutanga *et al.* 2015). The fiber optic sensor was held at an arm's-length from the observer so as to avoid their influence on the grasses reflectance. Spectrometer measurements were normalized after every 5-10 spectra measurements using a standard white panel to normalize any changes in the atmospheric condition and irradiance of the sun. Eight spectra were measured on each of the 96 plots resulting in a total of 768 samples. The grass canopy reflectance was measured under clear skies between 1000 to 1400hrs because this is the period of the day which has maximum net radiation from the sun critical for determining plant spectral characteristics. These spectra were collected after the green peak stage when the grasses were fully mature. The average reflectance of grasses treated with the twelve different fertiliser combinations and the control are shown on Figure 2.2 for exploratory purposes.

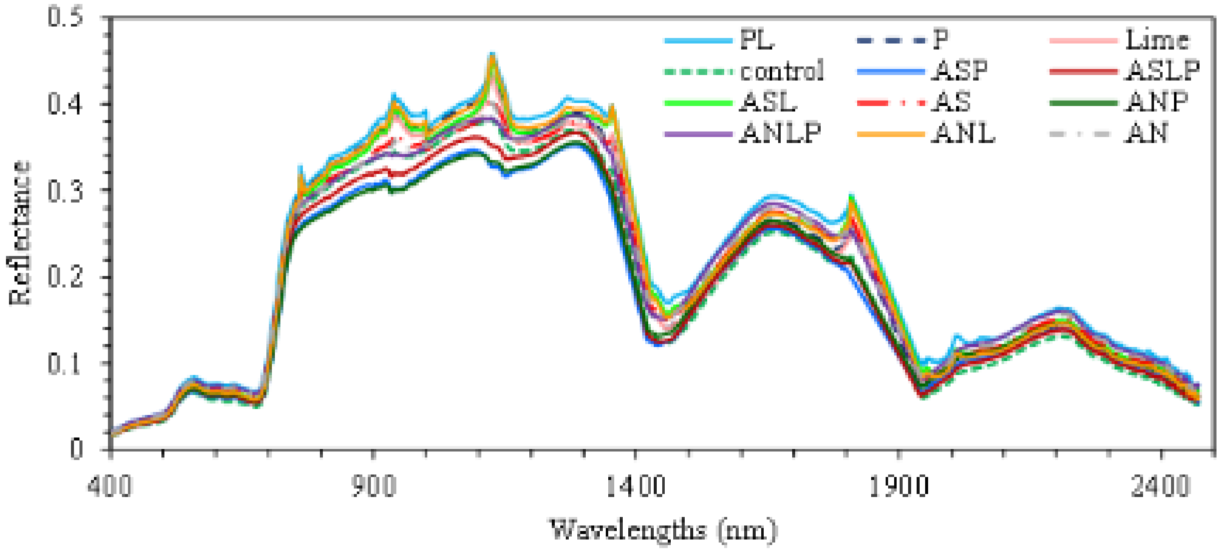

Figure 2.2: The average reflectance of grasses treated with the twelve different fertiliser combinations. AN = ((NH4)(NO3)); AS = ((NH4)2SO4); L = lime; and PL = P combined with lime.

2.2.4 Statistical data analysis

Two phases of statistical analysis were conducted to discriminate grasses fertilizing treatments as well as non-fertilized grasses. This was done to reduce high dimensionality that still remained even when one technique was used (Adam and Mutanga 2009, Carvalho *et al.* 2013, Prospere *et al.* 2014). In addition, Adelabu *et al.* (2014) demonstrated that pre-filtering of wavelengths using ANOVA in the classification process increases the probability of selecting the most important variables for classification algorithms. Consequently, in the first phase, an ANOVA test was conducted to filter out redundant wavelengths. In the second phase, a comparison of discrimination abilities of PLS-DA and DA in distinguishing grasses under different fertilizer treatments was conducted. The dataset was split into training and testing using a stratified random sampling technique based on the type of fertilizer treatment. As recommended by (Kohavi 1995, Ye *et al.* 2003, Riggins *et al.* 2009), seventy percent of the samples was used for training, while the remaining 30% was used as test samples per treatment (Table 2.1). This was done to first train the discrimination algorithms and then validate their accuracies, a prerequisite for all machine learning techniques (Adam and Mutanga 2009, Adelabu *et al.* 2014, Dube *et al.* 2014, Mutanga *et al.* 2015).

Table 2.1: Number of reflectance samples measured on each fertiliser treatments

Treatment Group	**Fertiliser combinations**	**No. of plots**	**No. of Samples**	**Testing Samples**	**Training Samples**
1	Control	6	48	14	34
2	$(NH4)_2SO_4$	9	72	22	50
3	$(NH4)_2SO_4$ + Lime	9	72	22	50
4	$(NH4)_2SO_4$ + P	9	72	22	50
5	$(NH4)_2SO_4$ + Lime + P	9	72	22	50
6	NH_4NO_3	9	72	22	50
7	NH_4NO_3+ Lime	9	72	22	50
8	NH_4NO_3 + P	9	72	22	50
9	NH_4NO_3 + Lime + P	9	72	22	50
10	P	6	48	14	34
11	Lime	6	48	14	34
12	Lime + P	6	48	14	34
Total		**96**	**768**	**230**	**538**

2.2.4.1 Analysis of variance and Dunnet post hoc test

An analysis of variance was conducted in Statistica 6 to test whether there were significant differences in mean reflectance among grasses fertilized with various treatments and those without treatment. Subsequently, a post hoc Dunnett test of significant differences was performed to compare the control group (unfertilized grasses) and the grasses from the 11 fertilizing treatments. Dunnett test accounts for type I errors by decreasing the significance level (α) of each test such that the type I error rate between the group and the control remains at the predefine level, in this case 0.05. The wavelengths with significant statistical differences ($p < 0.05$) were then selected and used as input variables for the second phase of statistical analysis. The twelve fertilizer treatments were categorized into five groups prior to discriminating their effect on tropical grass using multivariate techniques as illustrated on Table 2.2.

Table 2.2: Groups of fertilizer treatments considered for discriminant analysis and partial least squares discriminant analysis

Group	Fertilizer combinations		Fertilizer combinations
1	$(NH4)_2SO_4$		NH_4NO_3
2	$(NH4)_2SO_4$ + Lime		NH_4NO_3 + Lime
3	$(NH4)_2SO_4$ + P	VS	NH_4NO_3 + P
4	$(NH4)_2SO_4$ + Lime + P		NH_4NO_3 + Lime + P
5	Lime, Lime + P		P
6	Different fertiliser combination (1-5)		control

2.2.4.2 Partial Least squares discriminant analysis

PLS-DA improves data analysis of datasets where the independent variables are highly correlated and the amount of independent variables is more than the amount of samples. The utilization of a highly correlated independent variables may affect grass signal, which may result in overfitting of the model as well as low accuracies. Use of PLS-DA reduces the risk of model overfitting by merging the information derived from highly-correlated independent variables into numerous latent components. Latent variables are assessed based on loading weights of each independent variable that explain much of the covariance amongst the independent variables and the dependent variables. As latent variables increase in number, the classification capability of this algorithm generally improves because a combination of numerous independent variables provides much more data than less latent variables. However, because too many latent variables can overfit the model, the best quantity of latent variables has to be established (Boulesteix 2004). In this study, the number of latent variables that resulted in a lower misclassification error rate were utilized in discriminating the fertilizer groups. The training datasets related to that model were utilized to measure its accuracies discriminating grasses administered with different fertilizer treatments based on a discriminant analysis with a tenfold cross-validation. The validation datasets related to the models were utilized to assess them for the training datasets by fitting the final cross-validated PLS-DA models of the training datasets to the validation datasets.

2.2.4.3 Discriminant Analysis

PLS-DA was compared with DA in the second phase of discriminating grasses fertilized with different treatments based on the wavelengths derived using ANOVA. Discriminant analysis moderates the dimensionality of the hyperspectral data to numerous components that account for the variation within the dataset (Zhang *et al.* 2012). It utilizes a discriminant function to categorize targets into classes, using a measure of generalized squared distances. Discriminant analysis is grounded on the individual within-group covariance matrices. Individual observations are categorized to a group that it has the least generalized squared distance. Discriminant analysis produces both the classification and cross-validated results. In this study, we ran a backward feature selection method for cross-validation, producing eigenvalues which indicate how good a certain function discriminates the classes. Functions that can effectively discriminate variables are indicated by larger eigenvalues. For DA, five canonical variates were generated from canonical coefficients derived from training spectra. One of the five had a higher significant discrimination power. Using the Box test (Chi-square asymptotic approximation), Box test (Fisher's F asymptotic approximation), Mahalanobis distances, Wilks' Lambda test (Rao's approximation) and Kullback's test, we then tested whether within-class covariance matrices were equal. Each of these tests exhibited significant discriminating power ($\alpha = 0.05$). Both, PLS-DA and DA were conducted in XLSTAT for Microsoft Excel 2013 platform(XLSTAT 2013).

2.2.5 Accuracy assessment

Recent studies demonstrate limitations of using kappa statistic in classification accuracy assessment as it provides redundant and even misleading information for planning purposes. Pontius Jr. and Millones (Pontius Jr and Millones 2011) shows that kappa and its variants are difficult to calculate, comprehend, and even interpret. In countering this challenge, Pontius Jr. and Millones (Ullah *et al.* 2012) advocate for the abandonment of the use of kappa in accuracy assessment and comparing classified maps. They suggest summarizing the cross-tabulation matrix based on two parameters namely quantity disagreement and allocation disagreement.

Quantity disagreement is the sum of differences amongst the training dataset and testing dataset which is attributed to the least perfect matches in the proportions of the fertilizer treatment groups. Quantity disagreement ensues when the column total of a fertilizer class is not equivalent to the row total for that class in the confusion matrix. The remaining disagreement is allocation disagreement. To calculate the agreement between the testing and the training data we subtracted the two disagreement from a total of hundred percent. To contrast the correct group with that group allocated by the two classifying algorithms and to compute the overall accuracy (OA), User accuracy (UA) and Producer Accuracy (PA) a confusion matrix was generated. In addition, group-level assessments of agreement, omission disagreement and commission disagreement for the respective algorithms (i.e. DA and PLS DA) and fertilizer combinations were derived from the confusion matrices of the eight classification scenarios based on the confusion matrix proposed by Pontius Jr and Millones(Pontius Jr and Millones 2011).

To compare the classification abilities of the DA and PLS-DA, a McNemar test with α at 0.05 was used. McNemar, a non-parametric test, has demonstrated robustness as well as a higher precision in comparing accuracy assessments in classification studies. The test is based on a chi square (X^2) statistic which is calculated from two error matrices stated as

$$(X^2) = (f_{12} - f_{21})^2 / (f_{12} + f_{21}),$$

where f_{12} is the number of fertilizer classes that are incorrectly classified by the first algorithm and appropriately classified by the second algorithm while f_{21} is the number of fertilizer classes that are properly classified by the first algorithm and incorrectly classified by the second classifier algorithm. The null hypothesis tested in this instance is that there are no significant differences in fertilizer treatment classification abilities between DA and PLS-DA. The McNemar's test was implemented as explained in de Leeuw *et al.* (2006) and Manandhar *et al.* (2009).

2.3 Results

2.3.1 Level one: Analysis of variance test

The ANOVA test indicated significant differences ($\alpha < 0.05$) between the grasses administered with different combinations of $(NH_4)_2SO_4$, NH_4NO_3, lime as well as P. Fourteen treatments could be distinguished at both 725nm-750nm, and 1640nm -1720nm in 16 mid infrared wavelength regions based on ANOVA Dunnet post-hoc tests (Figure 2.3).

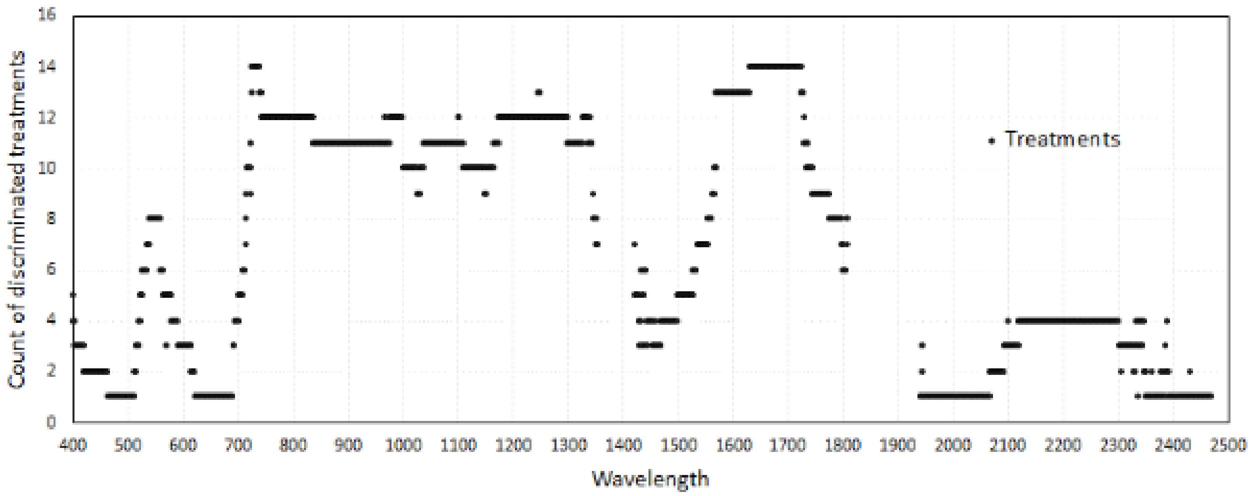

Figure 2.3: Fertiliser treatments discrimination ($p < 0.05$) from the control based on analysis of variance (post hoc Dunnett test).

Table 2.3 illustrates the incidence of significant bands adapted into the extensively used spectral domains (red edge, NIR, SWIR) adapted from. From Table 2.3, it can be observed that based on ANOVA pre-filtering, only 414 out of 2500 wavelengths were selected.

Table 2.3: Frequency of significant wavelengths selected based on analysis of variance, partial least squares-discriminant analysis (PLS-DA) and discriminant analysis (DA)

Reduction phase		**Fertiliser combination**	**Region**	**Wavelengths**	**Number of wavelengths**		**Total**
One	ANOVA		Red Edge	680-750	22		
			Near Infrared	700-1300	108		
			Shortwave Infrared	1300-2500	304		414
		Fertiliser combination	Region	Wavelengths	PLS DA	DA	Bands selected by both
Two	PLS-DA vs DA	$((NH_4)_2SO_4)$ vs $((NH_4)(NO_3))$ vs Control	Red Edge	680-750	7	2	2
			Near Infrared	700-1300	7	2	2
			Shortwave Infrared	1300-2500	67	18	10
			Total		74	20	12
		$((NH_4)_2SO_4)$ +Lime vs $((NH_4)(NO_3))$ + Lime vs Control	Red Edge	680-750	7	2	2
			Near Infrared	700-1300	7	2	2
			Shortwave Infrared	1300-2500	44	18	8
			Total		51	20	10
		$((NH_4)_2SO_4)$ + P vs $((NH_4)(NO_3))$ + P vs Control	Red Edge	680-750	7	2	2
			Near Infrared	700-1300	7	2	2
			Shortwave Infrared	1300-2500	34	17	9
			Total		41	19	11
		$((NH_4)_2SO_4)$ + P + Lime vs $((NH_4)(NO_3))$ + P + Lime vs Control	Red Edge	680-750	7	2	2
			Near Infrared	700-1300	7	2	2
			Shortwave Infrared	1300-2500	67	19	11
			Total		74	21	13
		PL vs P vs Lime vs Control	Red Edge	680-750	7	2	2
			Near Infrared	700-1300	7	2	2
			Shortwave Infrared	1300-2500	65	18	12
			Total		72	20	14

PLSDA = partial least squares discriminant analysis; DA = discriminant analysis.

2.3.2 Level two: Classification results

Figure 2.4 (A) shows the disagreement between the training and test data for PLS-DA and DA derived from classifying the five groups of fertilizers treatments. Both elements of disagreement are smaller for DA than for the other algorithm to discriminate the fertilizer treatments. The amount of agreement between the testing and the training data ranged from 83% to 93% for the DA and from 27% to 51% for PLS-DA. Overall, the total quantity disagreements for DA were lower than those of PLS-DA, meaning that there were similarities in the training and sample data for DA, hence higher accuracy in classifying fertilizer treatments, as compared to PLS-DA (Figure 2.4 B).

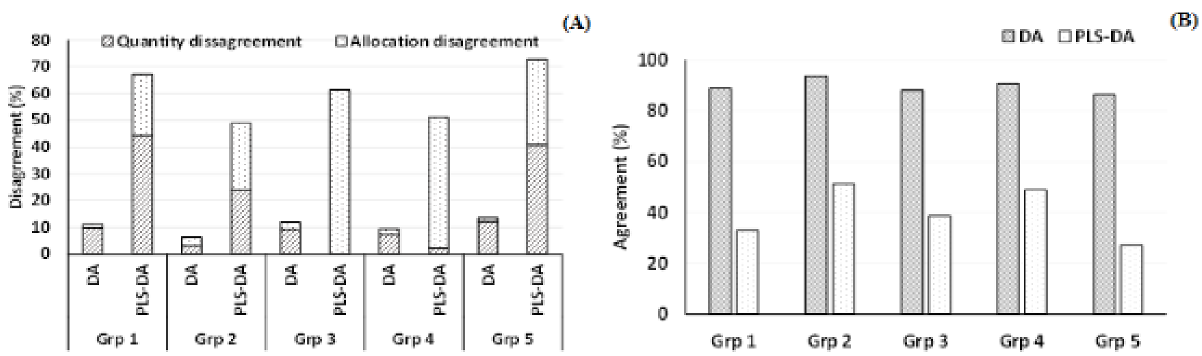

Figure 2.4: (A) Components of quantity disagreement between the reference training data and the the test data. (B) Quantity agreements for discriminant analysis (DA) partial least squares – discriminant anlysis (PLS-DA). Grp refers to the groups of fertilizer treatments considered for discriminant analysis and partial least squares discriminant analysis illustrated on Table 2.2.

In comparison to DA, PLS-DA showed inconsistent user's and producer's classification accuracies for each fertilizer treatment. Notable deviations are observed on Figure 2.5 (c and d), where PLS-DA attained distinctly low accuracies for the control, ammonium sulphate combined with phosphorus as well as ammonium sulphate combined with lime and phosphorous. In comparison, DA classification accuracies were generally constantly higher for each fertilizer treatment and combination. Secondly, the overall accuracy of DA's classification is relatively higher in discriminating all the fertilizer treatments, while that for PLS DA is low.

Based on the accuracy assessment, the allocations of agreement and disagreements for each classification are presented on Figure 2.6 (a-e). Generally, the PLS-DA had high percentages of allocation of disagreements (omission and commission) and low allocations of agreements in all the classifications. Conversely, DA demonstrated a pattern of relatively higher allocations of agreement and lower allocations of disagreements in all the classifications. In summary, the classification results of DA algorithm demonstrated a higher capability to reliably discriminate the grass fertilizer treatments in comparison to PLS-DA.

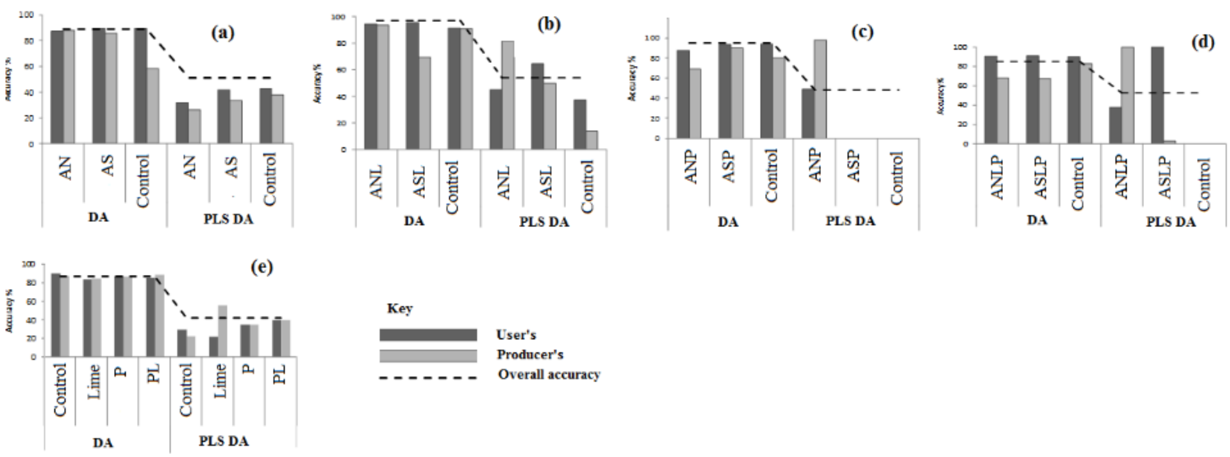

Figure 2.5: Classification accuracies obtained using partial least squares discriminant analysis (PLS-DA) and discriminant analysis (DA). AS is $((NH_4)_2SO_4)$; AN, $((NH_4)(NO_3))$; L, lime; P, phosphorous; ASP, a combination of $((NH_4)_2SO_4)$and P; ANP, the combination of $((NH_4)(NO_3))$ and P; ASLP, the combination of $((NH_4)_2SO_4)$, P and lime; ANLP, the combination of $((NH_4)(NO_3))$, P and lime; and PL is the combination of P and lime.

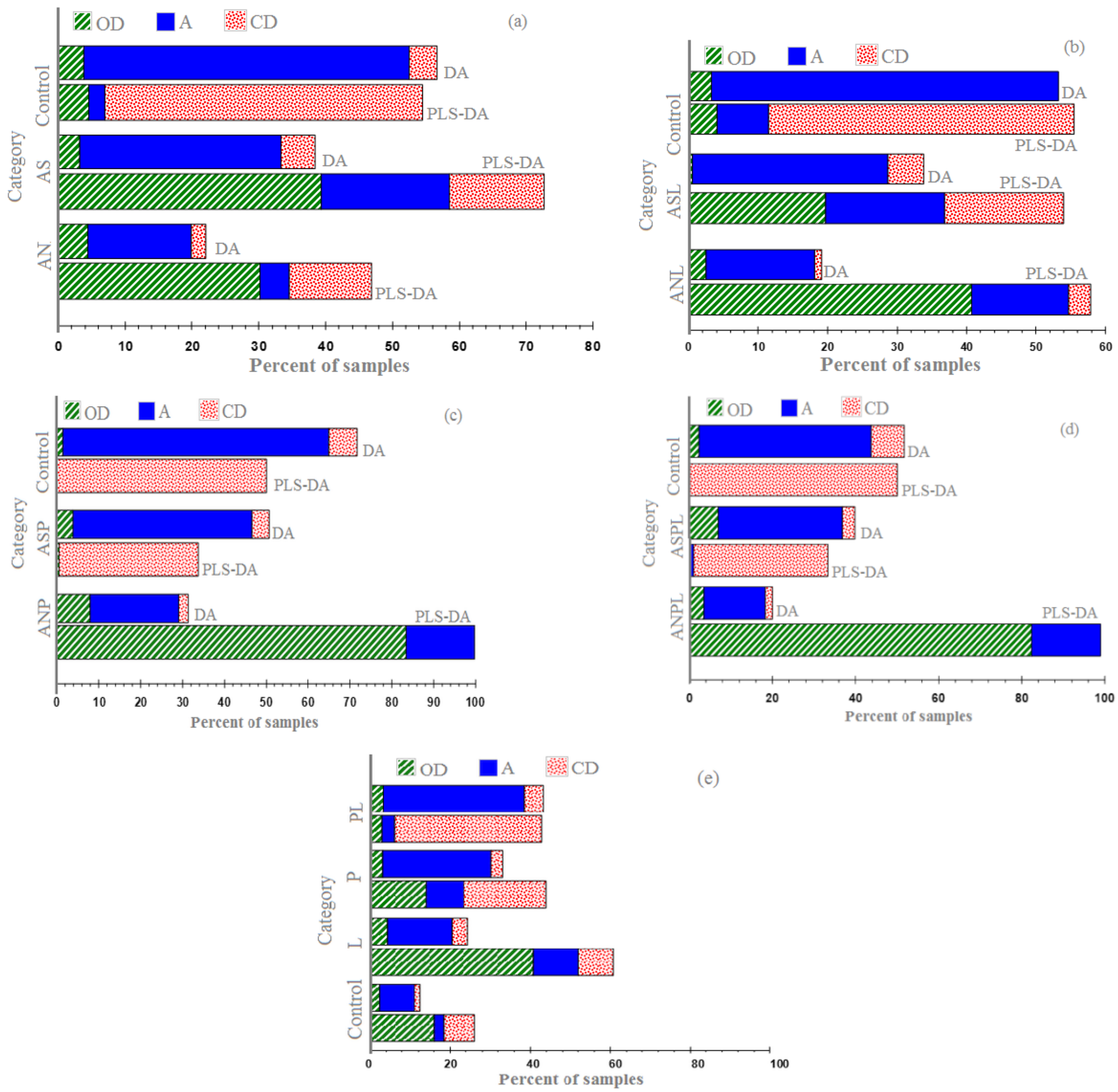

Figure 2.6: A comparison of the allocations of agreements and disagreements of partial least squares discriminant analysis (PLS-DA) and discriminant analysis (DA). OD is omission disagreement; A, agreement; and CD, commission disagreement. AS = ((NH4)2SO4); AN, = ((NH4)(NO3)); Lime; P = phosphorous; ASP = a combination of ((NH4)2SO4) and P; ANP = the combination of ((NH4)(NO3)) and P; ASPL = the combination of ((NH4)2SO4), P and lime; ANPL = the combination of ((NH4)(NO3)), P and lime; and PL = is the combination of P and lime.

A total of 59 bands were selected by PLS-DA while six were selected by DA. Two of the bands selected by DA were within the red edge region while the other four were in the shortwave infrared region. For the PLS-DA, six of the bands selected were from the red edge region while the rest were from the shortwave infrared region. The frequency of wavelengths selected by the two algorithms in the classification of the combined fertiliser treatments is shown in Table 2.5. It can be observed that PLS-DA was more generalising in selecting band combinations that could significantly distinguish the fertiliser treatments. Compratively, DA was generally conservative in selecting the best wavelenths for discriminating fertiliser treatments.

Table 2.4: Frequency of wavelengths selected in discriminant fertilizer combinations both by partial least squares- discriminant analysis and discriminant analysis applied to the five groups of fertilizer combinations and their relation with known absorption wavelengths.

Absorption feature centre	Wavelength of chemical influence	Known casual biochemical	Reference	All Selected bands	Frequency of bands selected -+of known wavelength		No of bands selected by PLS DA	No of bands selected by PLS DA
550-700	700-750	chlorophyll + N		**731**, 732, 733, 734, 735, 736, **737**	7		7	2
1634-1786	1690	N						
	Unattributed	N		**1310**, 1311, 1312, 1313, 1314, 1315, 1316, 1317, 1318, 1319, 1320, 1321, 1322, 1323, 1324, 1325, 1326, 1327, 1328, 1329, 1330, 1331, 1332, 1333, 1334, 1335, 1336, 1337, 1338, 1339, 1340, 1341, 1342, 1343	34		34	1
	1540	P	(Curran 1989),(Kumar *et al.* 2001),(Ramoelo *et al.* 2013)	1554, 1555,1556,1557,1558,	5		5	
	1780	P	(Curran 1989); (Kumar *et al.* 2001);(Sims and Gamon 2002)	1774, 1775, 1776,**1777**, 1778, 1779,1780, 1781, 1782, **1783**, **1786**,	11		11	4
TOTAL					57		57	7

The wavelengths selected by both classification algorithms are represented by bold numbers.

2.3.3 Comparison of the DA and PLS-DA in discriminating fertilizer treatments

Based on the data from the confusion matrices, we also tested whether the PLS-DA classification accuracy was significantly different from DA using the McNemar test. Results showed that there were significant differences ($p < 0.05$) between classification accuracies of both classification algorithms (DA and PLS-DA).

2.4 Discussion

The essence of this study was to assess the utility of hyperspectral data in (i) discriminating the effect of complex fertilizer combinations (i.e. eleven grass fertilizer combinations) on grass, and (ii) assessing the performance of PLS-DA compared with DA in discriminating grasses under different fertilizer treatments. Discriminating the effect of complex fertilizer treatments on the pastures is important for achieving optimal range quality, a necessity for high livestock productivity. Specifically, in this study, *in-situ* hyperspectral data and multivariate techniques, namely, partial least squares discriminant analysis (PLS-DA) and discriminant analysis (DA) were used to discriminate grasses under different fertilizer treatments as a rapid method of determining differences in rangeland intervention measures.

2.4.1 Discrimination of different fertilizer applications on the grasses

Results in this study demonstrate the capability and strength of *in-situ* hyperspectral data in detecting and distinguishing spectral variations in grasses with different fertilizer treatments. With reliable accuracy, the DA located wavelengths in the red edge (731nm and 737nm) and the mid infrared (1310nm and 1777nm**)** regions**.** For instance, $(NH_4)_2SO_4$ and NH_4NO_3 combined with lime and P as well as unfertilized grass (i.e. control treatment) could effectively be distinguished with plausible accuracies (85% overall accuracy). Spectral discrimination of NH_4NO_3, $(NH_4)_2SO_4$ combined with lime and phosphorous fertilized grasses as well as unfertilised grasses can be explained by the N concentrations that increase the chlorophyll content in the grasses (Sanches *et al.* 2013). Spectral discrimination of NH_4NO_3, $(NH_4)_2SO_4$ combined with lime and P fertilized grasses as well as unfertilised grasses in the red edge and the mid infrared regions can be explained by the N concentrations that increase the chlorophyll content in the grasses (Sanches *et al.* 2013).

It is known that the slope of the reflectance curve of plants with variations in the N content significantly varies with the increases in the chlorophyll content (Curran *et al.* 1990, Filella and Penuelas 1994, Dash and Curran 2004, Mutanga and Skidmore 2007, Delegido *et al.* 2013), with the spectral reflectance curves of those plants with high concentrations of N and chlorophyll moving towards longer wavelengths. Thus, the discrimination of these grasses at the red edge and the mid infrared wavelengths in this study may be also an effect of variations in the chlorophyll concentrations from different fertiliser treatment combinations.

The $(NH_4)(NO_3)$ has a N/P/K ratio of 33-0-0 and $(NH_4)_2SO_4$ has a 21-0-0 ratio, with 24% sulphur. The NH_4NO_3 combined with lime and phosphorous have a higher N content than $(NH_4)_2SO_4$ combined with lime and phosphorous. In these combinations, ammonium nitrate provides a rapid acting N plant nutrient, promoting healthy plant growth and rich green leaves (Calcino *et al.* 2000). In comparison, ammonium sulphate supplies plants with two vital nutrients for crop growth, N and sulphur. Sulphur lowers pH such that in some instances ammonium sulphate fertilization acidifies the soils due to the high sulphur content (24%) when compared to N (21%) content. This leads to stunted and unhealthy grasses, with altered biochemical components. In this study spectral signatures of such grasses are distinct from those of unfertilized, as well as those fertilized using ammonium nitrate, especially in the red edge (731nm and 737nm) and the mid infrared (1310nm and 1777nm) wavelengths thereby easing their classification. This could be explained by the effects of acidic conditions which initiate high water losses through transpiration facilitating discrimination of such grasses from those that are treated with $(NH_4)(NO_3)$, growing on less acidic conditions at mid infrared wavelengths. In comparison, N rich plants can be discriminated based on their reflectance from those that have a deficiency (Zhao *et al.* 2005). N content in foliar tissues is positively related to the chlorophyll content (Curran 1989, Yoder and Pettigrew-Crosby 1995, Gitelson *et al.* 2014). Thus, an increase in N content is directly linked to an increase in chlorophyll content (Blackburn 1999, Gamon and Surfus 1999, Daughtry *et al.* 2000, Sims and Gamon 2002, Gitelson and Merzlyak 2003, Tian *et al.* 2014), which affects the reflectance spectrum detected using remotely sensed data specifically in the red edge region, making N rich plants easy to be discriminated from those with a deficiency. In this study, the higher N content of NH_4NO_3 (33%) induces higher chlorophyll content than $(NH_4)_2SO_4$ (21%), facilitating their spectral discrimination in the red edge wavelengths. A large body of literature supports this claim that plants with different N contents can be easily discriminated using the red edge spectral signatures (Boochs *et al.* 1990, Gitelson and Merzlyak 2003, Zhao *et al.* 2005). For instance, work by Gitelson and Merzlyak (Gitelson and Merzlyak 2003), Mutanga et al. (Mutanga *et al.* 2003), Özyiğit and Bilgen(Özyiğit and Bilgen 2013) has demonstrated that nutrient variations in grasses induced by fertilisers influence spectral reflectance in the red edge amongst other regions, permitting spectral discrimination. Mutanga *et al.* (2003) illustrated that grasses treated with higher quantities of N were better discriminated from those with intermediate and low contents in the red edge region. In consistency with Mutanga et al.(2003), the discrimination between the grasses treated with ammonium nitrate and ammonium sulphate in this study can be attributed to variations in the N supplies after the ammonium fertilizers were combined with other chemical fertilizers such as phosphorous.

Generally, long-term N fertilizer application increase soil acidity (Pierre 1933, Nihlgård 1985). For instance $(NH_4)_2SO_4$ has a slightly higher acidity equivalent than NH_4NO_3 which results in the lowering of soil pH. Frequent application of $(NH_4)_2SO_4$ fertilizer may result in reduction of soil minerals more than NH_4NO_3 which in turn affects grass chemical components and reflectance in the mid infrared and the red edge regions. In this regard, the discrimination of $(NH_4)(NO_3)$ and $(NH_4)_2SO_4$ combined with lime and P fertilized grasses can also be explained by the accumulation of acid from persistent application of fertilizers, especially $(NH_4)_2SO_4$ with a higher acid level in the experimental plots dating back to the 1950s. The acidic conditions from $(NH_4)_2SO_4$ combinations with a higher sulphur content could explain the discrimination of these grasses in the mid infrared region (1310, 1321, 1335, 1331, 1332 1342, 1343, 1554, 1560 and 1777nm). According to Mengel *et al.* (1989) plants that are exposed to high acidic conditions tend to transpire more than those that are in tolerable conditions. In that regard, the high loss of water in grasses with acidic conditions from sulphur may be attributed to high dehydration which then leads to a distinction between these grasses in the water absorption bands of the mid infrared region from those fertilized with NH_4NO_3 which have relatively low acidity levels. Moreover, high water losses or dehydration in grasses with high acid conditions may also result in the reduction of chlorophyll concentrations resulting in red edge and the mid infrared spectral signatures that are different from those of grasses treated with NH_4NO_3 (Saneoka *et al.* 2004). These findings are consistent with Kowaljow et al. (Kowaljow *et al.* 2010) and Everitt et al. (Everitt *et al.* 1989). Everitt et al. (1989) noted that high yields of fertilised grasses were associated with the mid infrared reflectance and Kowaljow et al. (2010) reported a higher grasslands response to inorganic fertilizers, characterized by higher concentration of N, than organic fertilizers. Although costs are prohibitive to large scale fertilisation of rangelands, these results indicate that fertiliser application improves the quality of the rangeland (Power 1972, Korfanta *et al.* 2015). For instance the study by Mutanga et al. (Mutanga *et al.* 2005) has demonstrated that fertiliser application optimizes rangeland quality. Furthermore, findings of this study are also consistent with earlier grassland management studies that used hyperspectral remotely sensed data (Schmidt and Skidmore 2001, Messiga *et al.* 2013).

This study further indicates that lime, P and a combination of lime and P can be successfully discriminated using hyperspectral data. The principal wavelengths that discriminated lime, P and a combination of lime and P were from the red edge (731, 732, 733, 734, 735, and 737 nm) and the mid near infrared regions (1310, 1321, 1335, 1331, 1332 1342, 1343, 1554, 1560 and 1777 nm). Again this can be attributed to the increase in soil acidity due to fertilizers like super-phosphate, which retards the growth of grass on long-term application i.e. (1950 to 2014). Consequently, lime is commonly added into the soil to reduce soil acidity and to promote grass growth (Moschler *et al.* 1960, Materechera and Mkhabela 2002). The reduction of pH by lime results in healthier grasses, making them distinctive in the red edge and the mid infrared wavelengths from those fertilized using acidic fertilizers, enabling discrimination. These results are consistent with Fynn and O'Connor (2005) who used a similar experimental setup. Their results showed that P yielded acidic conditions while lime as well as the combination of lime with P resulted in a soil higher pH thereby enhancing the growth of healthier grasses, which facilitates discrimination. However, the results of Fynn and O'Connor (2005) showed that liming improved the yield when combined with ammonium sulphate. Thus, in the present study, the discrimination of fertilizer treatments which were combined with lime in the red edge and mid infrared wavelengths, may be explained by the above stated effect of lime (i.e. increasing soil pH and enhancing the health growth of some grass species).

2.4.2 A comparison of the partial least squares discriminant analysis and discriminant analysis in discriminating different fertilizer applications

Comparison of allocation of agreement as well as allocation disagreements between PLS-DA and DA showed that the latter yielded higher accuracy. Furthermore, the McNemar test for all the analyses indicated significant differences between the two algorithms. However, it is worth noting that in this study, PLS-DA did not perform well in detecting and distinguishing the spectral variations between grasses with different fertilizer treatments. PLS-DA is generally known to perform better than renowned machine learning algorithms, such as K-nearest neighbors (Corbane *et al.* 2013, Peerbhay *et al.* 2013). However, PLS-DA was unable to distinguish grasses with different fertilizer treatments, as the model failed to explicitly eliminate unnecessary wavebands or choose the ideal set of wavebands valuable for distinguishing grasses under different fertilizer treatments. This confirms the assertion by Corbane *et al.* (2013) on PLS-DA's limitation in handling enormous datasets with numerous redundant predictors. Conversely, DA has been successfully used in discrimination studies, in some cases combined with principal components analysis (Filella *et al.* 1995, Guang and Maclean 2000, Karimi *et al.* 2005, Pu and Liu 2011, Capuano *et al.* 2014, Vítková *et al.* 2014). However, in the present study the DA performed well in discriminating different fertilizer treatments. Specifically, results of Pu and Liu (2011) illustrated the effectiveness of dimension reduction and feature extraction of DA in discriminating species with a comparatively limited amount of training samples. In consistency with our findings, their results showed that DA performed better than the segmented PCA methods and had the most premier accuracies.

Overall, the enhanced classification results from both methods illustrates the capability and strength of high spectral resolutions of *in-situ* hyperspectral data in detecting and distinguishing grasses with different fertilizer treatments. Specifically, this study demonstrated that the spectral wavelengths 731,737, 1310 and 1777nm are very important in discriminating grasses under different fertilizer treatments. These findings are in consistency with those of Ramoelo *et al.* (2013) who observed that short wavelengths amongst other wavelengths can be used to map rangeland foliar N and P. Therefore, this information is critical for future sensor development specifically for rangeland management.

2.5 Conclusion

This study sought to assess the utility of hyperspectral data and multivariate techniques in discriminating fertilized grasses from unfertilized grasses. Specifically, this study tested the utility of hyperspectral bands in (i) discriminating the influence of different fertilizer applications on the grasses; and (ii) comparing the utility and robustness of PLS-DA and DA in discriminating the influence of fertilizer applications on the grasses. Based on the results, we conclude that:

- remotely sensed data, specifically wavelengths located at 731,737, 1310 and 1777nm, could be effectively used to discriminate the influence of different fertilizer applications on the grasses.
- DA performs better than PLS-DA in discriminating the influence of fertilizer applications on the grasses.

This study shows that hyperspectral data and DA offer quick, accurate and effective approaches for monitoring grasslands and rangeland quality. The findings of this work are a significant platform at which comprehensive landscape assessments of quality of grass/forage treated with complex fertilizer combination can be conducted, which is valuable in the dairy and beef industry. Furthermore, these findings are valuable for the assessment of other grass characteristics influenced by different rangeland management practices, such as fertilizer application. In comparing the utility and robustness of PLS-DA and DA in discriminating the influence of fertilizer applications on a Southern African rangeland, our findings indicated that DA outperformed PLS-DA. Nevertheless, we suggest that the ability, robustness and reliability of discriminant analysis in distinguishing phenomena should be tested using vegetation indices and other band combinations. Although the findings in this study need to be tested at landscape scale, this study provides a basis for quick, accurate and efficient assessment of grassland quality. The red-edge and shortwave near infrared optimal wavelengths identified in this study present a great potential in the design and development of a sensor that is suitable for rangeland resources monitoring and management.

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This chapter identified discriminant analysis as an optimal algorithm for effectively discriminating grasses grown under different levels fertilizer treatments. The results underscored the high influence of red edge wavebands in discriminating grasses grown under different fertilizer treatments. Having noted that remotely sensed data could be used to optimally characterize grasses grown under different levels of fertilizer treatments, the succeeding chapter sought to examine whether optical remotely sensed data could also be used to estimate above-ground biomass grown across different levels of complex fertilizer applications.

3. EXAMINING THE POTENTIAL OF SENTINEL-2 MSI SPECTRAL RESOLUTIONS IN QUANTIFYING ABOVE GROUND BIOMASS ACROSS DIFFERENT FERTILIZER TREATMENTS

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Examining the potential of Sentinel-2 MSI spectral resolution in quantifying above ground biomass across different fertilizer treatments

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Abstract

The major constraint in understanding grass above ground biomass variations using remotely sensed data are the expenses associated with the data, as well as the limited number of techniques that can be applied to different management practices with minimal errors. New generation multispectral sensors such as Sentinel-2 Multispectral Imager (MSI) are promising for effective rangeland management due to their unique spectral bands and higher signal to noise ratio. This study resampled hyperspectral data to spectral resolutions of the newly launched Sentinel-2 MSI and the recently launched Landsat 8 OLI for comparison purposes. Using Sparse partial least squares regression, the resampled data was applied in estimating above ground biomass of grasses treated with different fertilizer combinations of ammonium sulphate, ammonium nitrate, phosphorus and lime as well as unfertilized experimental plots. Sentinel-2 MSI derived models satisfactorily perfomed (R^2 = 0.81, RMSEP = 1.07 kg/m^2, RMSEP-^{rel} = 14.97) in estimating grass above ground biomass across different fertiliser treatments relative to Landsat 8 OLI (Landsat 8 OLI: R^2 = 0.76, RMSEP = 1.15 kg/m^2, RMSEP-^{rel} = 16.04). In comparison, hyperspectral data derived models exhibited better grass above ground biomass estimation across complex fertilizer combinations (R^2 = 0.92, RMSEP= 0.69 kg/m^2, RMSEP-^{rel} = 9.61). Although Sentinel-2 MSI bands and indices better predicted above ground biomass compared with Landsat 8 OLI bands and indices, there were no significant differences (α = 0.05) in the errors of prediction between the two new generational sensors across all fertilizer treatments. The findings of this study portrays Sentinel-2 MSI and Landsat 8 OLI as promising remotely sensed datasets for regional scale biomass estimation, particularly in resource scarce areas.

Keywords

Field spectroscopy, new generation multispectral sensors, rangeland fertilization, spectral resampling.

3.1 Introduction

Optimizing the productivity of natural rangelands through fertilization has become a global norm especially in sub-Saharan Africa where livestock farming is limited by the lack of quality forage resources (Vickery *et al.* 1980, Valentin *et al.* 2014). Fertilizer application is critical in restoring the quality and quantity of native rangelands or pastures for high livestock production (Vogeler *et al.* 2014, Quan *et al.* 2015). Moreover, the higher the grass quantity, the greater the potential of supplementary carbon sinks and soil protection mechanism amongst other factors (Prado *et al.* 2014). There is ample literature that indicates an increment in the productivity of natural grasslands or pastures after the application of fertilizers (Ghani *et al.* 2014, Trotter *et al.* 2014, Vogeler *et al.* 2014). However, there are remarkable discrepancies in the extent of productivity reported by these studies. This is largely due to great variations in the methods used, fertilizer type, soil fertility, amount of rainfall, temperature variations, differences in grass species, management practices (Wight and Godfrey 1985, Jørgensen *et al.* 2014) and most importantly the lack of reliable primary spatial data sources (Jørgensen *et al.* 2014, Porter *et al.* 2014).

Remote sensing is an alternative primary data source that can contribute to a better understanding of the effect of fertilizer application on grass productivity since it offers instantaneous and spatially explicit patterns of ecosystem changes and variations (Abbasi *et al.* 2014). Specifically, attention has been focused on the use of nitrogen for pasture or grassland fertilization (Richardson *et al.* 1983, Wight and Godfrey 1985, Kooistra *et al.* 2010, Ramoelo *et al.* 2013, Ling *et al.* 2014, Yahdjian *et al.* 2014, Mutanga *et al.* 2015). For instance, Ling et al. (2014) used hyperspectral datasets to estimate canopy nitrogen of prairie tall grass and concluded that empirical methods based on hyperspectral data can be used to optimally estimate grass canopy nitrogen. Similar studies were also done to estimate grass biomass using hyperspectral data (Mutanga and Skidmore 2004, Mutanga and Adam 2011). However, hyperspectral data is very expensive and spatially restricted (Tong *et al.* 2014). There is therefore, a need to identify cheap data sources that would permit regional estimation.

An increasing body of contemporary literature shows the potential of multispectral remotely sensed data in rangeland studies (Serrano *et al.* 2002, Ramoelo *et al.* 2012, Ullah *et al.* 2012). The major motivation for their usage is their free availability to resource constrained regions (Lu 2006). Besides, most multispectral remotely sensed datasets are characterised with high temporal resolutions and wide swath widths making them suitable for regional applications (Lu 2005, Li *et al.* 2014). In spite of these advantages, some studies discredited the utility of multispectral data in remote sensing plant biomass and biochemical properties (Broge and Mortensen 2002). The broad bandwidths and low spectral resolutions of multispectral data were often cited to be insensitive to differences in plant characteristics (Elvidge and Chen 1995, Broge and Leblanc 2001, Curran 2001, Hansen and Schjoerring 2003, Mutanga and Skidmore 2004, Underwood *et al.* 2007).

The upcoming space borne multispectral sensors with improved bandwidths and spectral resolutions are hypothesized to have a great potential in a wide range of vegetation mapping applications (Oumar and Mutanga 2013). For instance, the forthcoming Sentinel-2 Multi-Spectral Imager (MSI) is perceived to have a great potential of facilitating the development of a variety of applications including assessing the effect of plant fertilizer applications. The advent of Sentinel-2 MSI coincides with the growing interest from the agricultural sector of coming up with accurate and affordable spatial datasets and techniques for assessing different agricultural management practices at regional scales (Moran *et al.* 1997, Haboudane *et al.* 2002). The forthcoming Sentinel-2 MSI is a polar orbiting sensor comprised of two satellites, each carrying a MSI characterized by 290-km swath width, potentially suitable for regional mapping in rangeland management. This sensor offers a multipurpose design of 13 spectral bands traversing from the visible and near infrared up to the shortwave infrared. In total, Sentinel-2 MSI has four bands (2, 3, 4 and 8) with a spatial resolution of 10m, six bands (5, 6, 7, 8a, 11 and 12) at 20m and the final three bands (1, 9 and 10) at 60m. Amongst the thirteen Sentinel-2 MSI bands, there are three novel bands in the red-edge region positioned at 705, 740 and 783nm, a component that previous multispectral sensors lacked. These bands are presumed to have a high potential for mapping various vegetation characteristics. For instance, Ramoelo *et al.* (2014) successfully demonstrated the potential of Sentinel-2 MSI's red edge bands in estimating grass nutrients. The sensor is expected to provide data acquired over land and coastal zones. Consequently, the three new Sentinel-2 MSI bands in the red edge region could be useful in estimating grass productivity particularly in data scarce regions of the sub-Saharan Africa.

To ascertain the full potential of Sentinel-2 MSI sensor in estimating grass above ground biomass, there is need to compare its performance to other satellite datasets particularly the Landsat 8 and hyperspectral. A comparison of grass above ground biomass estimation accuracies of Sentinel-2

MSI with those of the newly launched Landsat 8 operational land imager can illustrate the utility and the predictive strength of this sensor in sustainable rangeland management particularly in resources scarce areas as Southern Africa. Landsat 8 OLI is one of the two instruments on board Landsat 8 satellite offering nine bands with a great potential of estimating grass above ground biomass. Although this sensor has not been fully utilized in grassland studies, so far its application in forests has demonstrated that it is more robust in predicting above ground biomass (Dube and Mutanga 2015). Considering that no study has sought to evaluate the utility of Sentinel-2 MSI in estimating rangeland grass above ground biomass across different fertiliser applications, a comparative study of this sensor and other readily available sensors such as Landsat 8 OLI is critical in evaluating its utility for regional scale rangeland management applications.

The use of these remotely sensed datasets in conjunction with efficient and robust prediction algorithms could provide critical tools for assessing rangeland condition across different management practices at regional scales. One of the renowned prediction algorithms that contemporary remote sensing scientists (Abdel-Rahman *et al.* 2014) advocate for is the Sparse Partial Least Squares Regression (SPLSR) algorithm (Chun and Keleş, 2010). This algorithm has a capacity to screen greatly correlated data without over-fitting its prediction models (Lee *et al.* 2011). In addition, SPLSR has the capacity to select best predictor variables as compared to its predecessor, partial least squares regression analysis (PLSR) (Abdel-Rahman *et al.* 2014). The aforementioned robustness of SPLS makes it an ideal algorithm for assessing the productivity of native grasslands treated with complex fertilizer treatments. The aim of this study was to explore the utility of the forthcoming new generation multispectral sensor Sentinel-2 MSI bands and indices in estimating grass above ground biomass across complex fertilizer treatments. To explore the utility of Sentinel-2 MSI in estimating grass above ground biomass, this study compared the results of Sentinel-2 MSI resampled data with those of hyperspectral and the simulated Landsat 8 OLI spectral bands. The simulated Landsat 8 OLI spectral bands were also used because of the sensor's spatial fidelity and the improved signal to noise ratio (Dube and Mutanga 2015).

3.2 Materials and methods

3.2.1 Study area

The study was conducted using experimental plots established by J.D. Scott in 1950 (Morris and Fynn 2001) at Ukulinga (University of KwaZulu-Natal Research Farm) in Pietermaritzburg, South Africa, (29°24′E, 30°24′S). In this study, only the grass growing season of October 2013 to April 2014 was considered. The grass species prevalent in the experimental plots include *Themeda triandra*, *Heteropogon contortus*, *Eragrostis plana*, *Panicum maximum*, *Setaria nigrirostrosis and Tristachya leucothrix*. The height of the grasses ranged between 25 and 30cm. Generally, temperatures range from 23 - 33^0 C during summer and 16 - 25^0 C during winter in Pietermaritzburg. The soils at Ukulinga are grouped under the, acidic Westleigh form (plinthic 2 paleustalf) group which is relatively infertile (Fynn and O'Connor 2005).

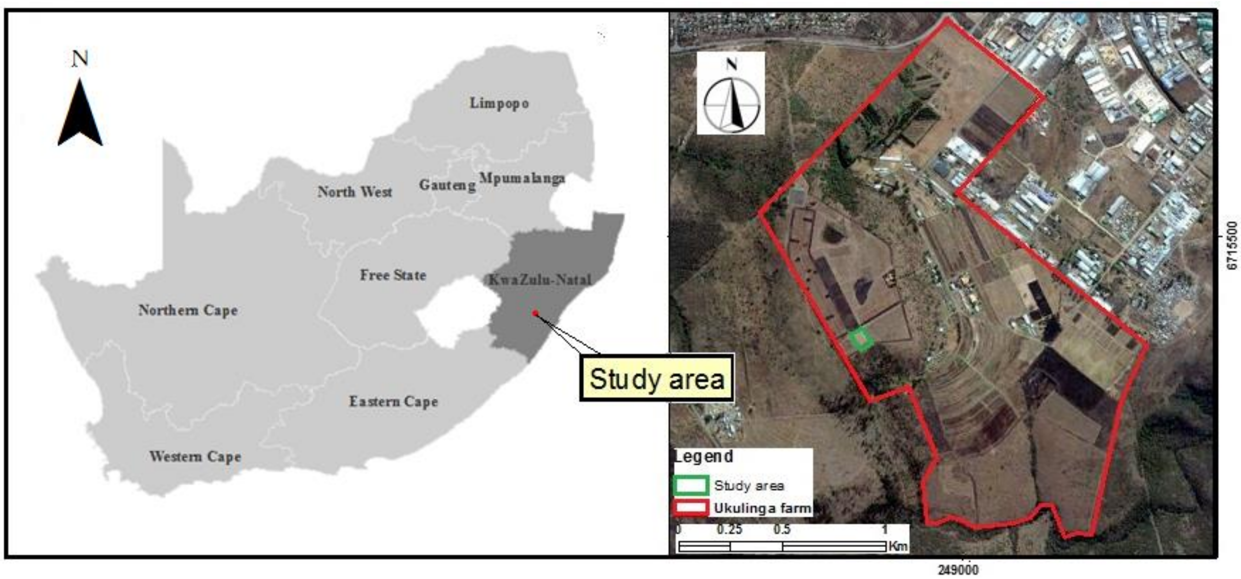

Figure 3.1: Ukulinga grassland trails, UKZN farm, Pietermaritzburg, South Africa (Image source: Google Earth).

3.2.2 Experimental design

In this study, 96 experimental plots with a length of 9m and a width of 3m were used. In all these plots, 11 fertilizer combinations and the "control" (untreated grass) were used to treat the grass in this experiment as shown in Table 3.1. An amount of zero and 33.6 g.m^{-2} of dolomite lime treatments were applied every fifth year, super phosphate applied every year at zero and 225 g.m^{-2} as well as two ammonium fertilisers (ammonium nitrate and ammonium sulphate), each applied every year at four levels. In this experiment, ammonium nitrate was combined with lime and phosphorus but not with ammonium sulphate considering the fact that they are both nitrogenous fertilisers. All treatments were randomly assigned to each plot within the three replicates or blocks.

3.2.3 Grass above ground biomass data

To derive grass above ground biomass, the fertilized grasses in the 96 plots were harvested at the end of the grass growing season in April 2014. After harvesting, representative samples were selected from each plot, oven dried and reweighed to derive the dry biomass. These measurements were then transformed to derive total above ground biomass for each plot in kilograms per plot (kg/plot).

3.2.4 Remotely sensed data

For this study, hyperspectral data as well as Sentinel-2 MSI and Landsat 8 OLI data resampled from hyperspectral data were used to estimate grass above ground biomass. Field grass spectral reflectance was measured using an Analytical Spectral Device (ASD) FieldSpec instrument within the 96 plots, treated with different fertiliser treatments. In each of the 96 plots, eight spectra were measured resulting in a total of 768 samples (Table 3.1). The ASD spectrometer records radiation at 1.4 nm intervals for the spectral region 350 –1000 nm and 2 nm intervals for the spectral region 1000–2500 nm. Spectral measurements were conducted under clear sky conditions between 10 am and 2pm because this is the period of day with the maximum radiation from the sun. In measuring grass reflectance, bare fiber-optic sensor connected to the hyperspectral spectro-radiometer was held at a nadir position approximately 1m above grass canopies (Abdel-Rahman *et al.* 2014, Mutanga *et al.* 2015). Consequently a ground view of approximately 0.45m in diameter, ample to capture the reflectance of grass canopy was covered (Abdel-Rahman *et al.* 2014). When measuring the spectra, fiber optic cable was held at an arm's length away from the person recording so as to avoid the influence of the recorder's shadow and clothing on the registered grass canopy spectra. Moreover the spectra were collected after the green peak stage when the grasses were mature. Spectrometer measurements were standardized after every 5-10 spectra measurements using a standard spectral on to regulate possible atmospheric condition changes and sun irradiance (Abdel-Rahman *et al.* 2014).

Table 3.1: Field measured reflectance samples

Treatment Group	Fertiliser combinations	Abbreviation	No. of plots	No. of Samples
1	“Control” (C)	C	6	48
2	Ammonium Nitrate (AN)	AN	9	72
3	AN + Lime	ANL	9	72
4	AN + Phosphorous (P)	ANP	9	72
5	AN + Lime (L) + P	ANLP	9	72
6	Ammonium Sulphate (AS)	AS	9	72
7	AS+ L	ASL	9	72
8	AS + P	ASP	9	72
9	AS + L + P	ASLP	9	72
10	P	P	6	48
11	L	P	6	48
12	L + P	LP	6	48
Total			96	768

AN = ammonium nitrate; AS = ammonium sulphate; L = lime; and PL = phosphorus combined with lime

To simulate Sentinel-2 MSI, 768 grass reflectance samples measured in the 96 plots treated with different fertilizer combinations were then resampled based on the bandwidths of the thirteen bands illustrated in Table 3.2 as in Delegido *et al.* (2011) and Ramoelo *et al.* (2014). The two instruments from the European Space Agency (ESA), Sentinel-2A launched on the 23 of June and Sentinel-2B yet to be launched in 2016, are dedicated to monitor land and coastal areas (Lachérade *et al.* 2014, Laurent *et al.* 2014, van der Meer *et al.* 2014). According to ESA, the two sensors will have a revisit time of 5 days, placed at an orbital angular distance of 180^0 with a field of view of 290km (Cole *et al.* 2014). It is expected that it would acquire all its images at a nadir position at thirteen spectral wavelengths ranging from visible through the most promising red edge bands to the short wave infrared wavelengths as listed in Table 3.2 with a high spatial resolution ranging from 10 to 60 m.

To simulate the spectral resolution of Landsat 8 OLI, hyperspectral data, measured in the 96 plots treated with different fertiliser combinations was averaged based on the bandwidths of the seven bands illustrated on Table 3.2. Launched in 2013, the operational land imager (OLI) and the thermal infrared sensor (TIRS) are the two instruments on board Landsat 8 satellite. These two instruments capture images of the earth at 16 day temporal resolution with a scene size of about 170km by 183km, suitable for regional vegetation mapping applications. Although the spectral bands of OLI sensor are similar to those of Landsat 7 ETM+, OLI sensors has two new bands and an advanced signal to noise radiometric performance which gives it a great potential for agricultural applications.

Table 3.2: Spectral and spatial resolutions of Sentinel-2 MSI and Landsat 8 OLI

Sentinel-2 MSI				Land sat 8 OLI	
Spectral bands	Band centre (nm)	Bandwidth (nm)	Spatial resolution (m)	Band range (nm)	Spatial resolution (m) (m)
B1	443	20	60	0.435-0.451	30
B2	490	65	10	0.452-0.512	30
B3	560	35	10	0.533-0.590	30
B4	665	30	10	0.636-0.673	30
B5	705	15	20	0.851-.879	30
B6	740	15	20	1.566-1.651	30
B7	783	20	20	2.107-2.294	30
B8	842	115	10	0.503-0.676	15
B8a	865	20	20		
B9	945	20	60	1.363-1.384	30
B10	1375	30	60	10.60-11.19	100
B11	1375	30	20	11.50-12.51	100
B12	2190	180	20		

3.2.5 Variables for predicting grass above ground biomass

To test the utility of sentinel-2 MSI in estimating grass above ground biomass relative to Landsat OLI and hyperspectral sensors, raw bands and several vegetation indices were used. Table 3.3 shows the specific calculated broad and narrow band vegetation indices. The vegetation indices used in this study were selected based on their performance in previous grass biomass and grass nutrients estimation studies (Anderson *et al.* 1993, Broge and Leblanc 2001, Mutanga and Skidmore 2004, Liu *et al.* 2007, Cho *et al.* 2008, Agapiou *et al.* 2012, Thenkabail *et al.* 2013).

3.2.6 Statistical analysis

Prior to statistical analysis, exploratory data analysis was conducted to understand the data. Descriptive statistics were generated in Statistica 6 by testing for normality based on the Lilliefors test, prior to regression analysis. The null hypothesis we tested was that the data does not significantly ($\alpha = 0.05$) deviate from the normal distribution.

3.2.6.1 Sparse partial least squares regression (SPLS)

Sparse partial least squares regression (SPLSR) proposed by Chun and Keles (2010) was used in this study. Similar to partial least squares regression, SPLSR transforms the variables to new orthogonal factors (components) in order to overcome multicollinearity and over-fitting challenges. When SPLSR is transforming the data, it enforces sparsity and picks out suitable variables for estimating the item of interest. This capability makes SPLSR a unique technique for evaluating highly correlated hyperspectral data. The hypothesis tested was that, the forthcoming new generation Sentinel-2 sensor can estimate above ground biomass with a higher accuracy than the Landsat 8 OLI and can yield comparable results to those obtained using hyperspectral data. Our interest in this study was to use SPLS to derive universal bands and indices that could optimally predict grass above ground biomass across different fertilizer treatments.

3.2.6.2 Evaluation of grass above ground biomass predictions

To evaluate the SPLSR models, a leave-one-out cross validation (LOOCV) method was used as explained in literature (Abdel-Rahman et al. 2014 and Richter et al. 2012). The cross validation method is efficient in cases where the available data samples are limited. In performing the LOOCV method, the data was divided into *n* samples (which are 768 in the present study) which were then eliminated one by one. Prediction errors related to a certain number of SPLSR latent components were computed from the predictions attained from the leave-one-out cross validation. These were then used to ascertain the number of components to be used in estimating grass above ground biomass. To assess and evaluate the accuracy and performance of the models, the LOOCV root mean square error of prediction (RMSEP), relative root mean square error ($RMSEP_{-}^{rel}$), coefficient of determination (R^2) as well as Bias were computed. The use of raw spectral bands and vegetation indices that yielded the lowest RMSEP in all the stages of the analysis were then used in stage three (i.e. combination of optimal bands and indices) of the analysis. To test whether there were significant differences ($\alpha = 0.05$) between prediction errors of all the sensors, we calculated and used the confidence intervals of RMSEP. The RMSEP were derived using the selected raw spectral bands and vegetation indices that could optimally estimate grass above ground biomass across all fertiliser treatments. Models which resulted from components that yielded the lowest RMSE of prediction (RMSEP), higher R^2 and low levels of bias were selected and used for predicting grass above ground biomass. To evaluate the contribution of wavelengths to the selected components, loadings or variable importance (VIP) scores derived using SPLSR algorithm were used. Wavelengths that had a loading or VIP score greater than one were deemed to be highly influential and were selected while those with values less than zero were discarded (Abdel-Rahman et al. 2014).

3.2.7 Grass above ground biomass prediction stages

In comparing the spectral resolution robustness of Sentinel-2 MSI to Landsat 8 OLI and hyperspectral data, statistical analysis was conducted at three stages illustrated on Table 3.3 as follows;

i. Raw bands of Sentinel-2 MSI and Landsat 8 OLI, resampled from hyperspectral data as well as the original hyperspectral data were regressed with field measured grass biomass using SPLSR. The component or latent variable that yielded the least possible estimation error (RMSEP) was selected as the best above ground biomass predictor. The SPLSR algorithm selected very important (VIP) variables that optimally estimated grass above ground biomass based on the loading or contribution of each band to the latent variable with the least estimation error.

ii. Vegetation indices derived from Sentinel-2 MSI and Landsat 8 OLI resampled from hyperspectral data and the original hyperspectral data were also regressed with field measured grass above ground biomass using SPLSR. The vegetation indices that were selected as the best above ground biomass predictors were again selected based on the criteria explained in item one above.

iii. The bands and indices selected in stages two and three as optimal variables were then combined together and regressed using SPLSR to further select the variables that could optimally estimate above ground biomass across all fertilizer treatments following the criteria explained in item one.

Table 3.3: Variables used in predicting above ground biomass of grasses treated with different fertilizer.

Analysis Stage	Variables	Sensor	Spectral bands
1	Raw bands	Hyper spectral	Band 400-1355, 1421-1809,1941-2469 (1326 bands)
		Sentinel-2 MSI	visible (band 1, 2, 3, 4,), red edge(band 5,6,7,8,8a), shortwave infrared (band 9 and 12)
		Landsat 8 OLI	Visible (band 1 2 3 4) near infrared (bands 5) shortwave infrared (6 7 8) (8bands)
2	Vegetation Indices	Hyper spectral	NDVI, PSRI SR3 VOG MCARI MTVII MTVI SAVI RDVI MSR REP_Guy, VREI MRESR MTVI RDVI MSR TCARI
		Sentinel-2 MSI	NDVI
		Landsat 8 OLI	NDVI
3	Bands and indices	combination of optimal bands and Indices	

NDVI :Normalized Difference Vegetation Index, PSRI:Plant Senescent Reflection Index, SR: Simple Ratio, VOG: Volgaman Index, MCARI: Modified Chlorophyll Absorption Ratio Index, MTVI: Modified Triangle Vegetation Index, REP Guy: Red edge position Guyot, SAVI: Soil Adjusted Vegetation Index, VRIE: Volgman Red Edge Index, MRESR: Modified Red Edge Simple Ratio, MTVI: Modified Triangle Vegetation Index , RDVI: Renormalized Difference Vegetation Index, TCARI: Transformed chlorophyll Absorption in Reflectance Index. The vegetation indices used in this study were selected based on their performance in previous grass biomass and grass nutrients estimation studies (Anderson *et al.* 1993, Broge and Leblanc 2001, Mutanga and Skidmore 2004, Liu *et al.* 2007, Cho *et al.* 2008, Agapiou *et al.* 2012, Thenkabail *et al.* 2013).

3.3. Results

3.3.1 Grass above ground biomass descriptive statistics and analysis of variance test

Exploratory analysis showed that the average grass above ground biomass from the 96 plots was 7.17 kg, with a minimum of 2.07 kg and a maximum of 15 kg. Following the normality test, grass above ground biomass data did not significantly deviate from the normal distribution (Figure 3.2). Analysis of variance test results exhibited significant differences in the amount of grass above ground biomass across different fertilizer treatments. Based on post hoc test, there were no significant differences ($\alpha = 0.05$) in the amount of grass above ground biomass amongst plots treated with Ammonium nitrate, Ammonium sulphate, Phosphorus, Lime Ammonium sulphate combined with lime fertilisers and the “control” (Table 3.4).

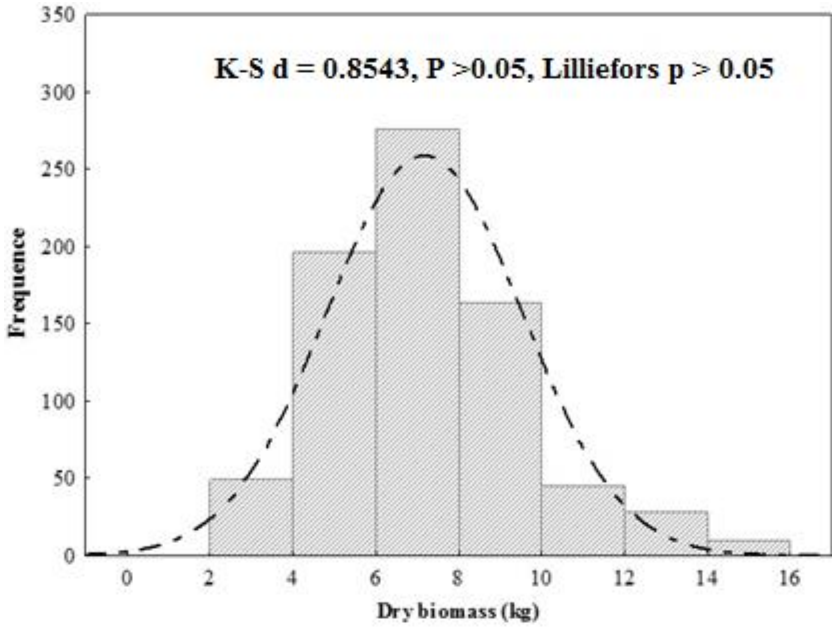

Figure 3.2: Dry grass above ground biomass data is not significantly (α > 0.05) deviating from the normal distribution based on the Lilliefors and Kolmogorov Smirnov tests of normality.

Table 3.4: Analysis of variance test results based on Fisher's Least significant difference post hoc test of dry grass above ground biomass

	"Control"	AN	AS	P	Lime	ANL	ASL	PL	ANLP	A_S_L_P	A_P	ASP
"Control"		-	-	-	-	*	*	*	**	**	**	**
AN	-		-	-	-	-	**	*	**	**	**	**
AS	-	-	-		-	-	*	*	**	**	**	**
P	-	-	-		-	-	*	*	**	**	**	**
Lime	-	-	-	-		-	*	*	**	**	**	**
ANL	*	-	-	-	-		-	-	**	**	**	**
ASL	**	**	*	*	*	-		-	**	**	**	**
PL	**	**	*	-	*	-	-		**	**	**	**
ANLP	**	**	**	**	**	**	**	**		*	-	-
ASLP	**	**	**	**	**	**	**	**		*	-	-
ANP	**	**	***	**	**	**	**	**	-	**		-
ASP	**	**	**	**	**	**	**	**	-	-		

*denote significant differences α at 0.05 and ** denote significant differences α at 0.01 based on the Fisher's Least Significant Difference post hoc test. AN = ammonium nitrate; AS = ammonium sulphate; L = lime; and PL = phosphorus combined with lime

3.3.2 Performance of Sentinel-2 MSI in grass above ground biomass estimation relative to Landsat OLI and hyperspectral data. .

Figure 3.3 is a correlogram illustrating the correlation between various Sentinel-2 MSI wavebands and grass biomass. Strong correlations between grass biomass and red edge bands (band 5, 6,and

7) as well as NIR (8) bands can be observed in the correlogram. It can be obsevered from the correlogram that bands from the visible region exhibited geberally poor coreelations to grass biomass. Figure 3.4 (a & c) shows that generally, Sentinel-2 MSI optimally estimated above biomass better than Landsat 8 OLI and performed somewhat comparable to hyperspectral bands. For example, using Sentinel-2 MSI raw bands, it can be osberved that grasses treated with ammonium sulphate (R^2 =0.67, RMSEP = 0.90 kg/m^2 RMSEP$_{-}^{rel}$ = 15.41), “control” (R^2 =0.64, RMSEP = 0.65 kg/m^2 RMSEP$_{-}^{rel}$ = 12.1), ammonium nitrate (R^2 =0.58, RMSEP = 0.8809 kg/m^2 RMSEP$_{-}^{rel}$ = 15.29) and ammonium sulphate (R^2 =0.69, RMSEP = 0.9005 kg/m^2 RMSEP$_{-}^{rel}$ = 15.41) fertilisers exhibited the least prediction errors. On the other hand, when using raw Landsat 8 OLI bands, “control” (R^2 =0.43, RMSEP = 0.6442 kg/m^2 RMSEP$_{-}^{rel}$ = 11.93), ammonim nitrate (R^2 =0.22, RMSEP = 1.0422 kg/m^2 RMSEP$_{-}^{rel}$ = 23.7), ammonium nitrate combined with lime (R^2 =0.47, RMSEP = 1.13 kg/m^2 RMSEP$_{-}^{rel}$ = 19.09) and ammonium sulphate combined with lime (R^2 =0.37, RMSEP = 1.14 kg/m^2 RMSEP$_{-}^{rel}$ = 16.90) had the least prediction errors. Based on hyperspectral data, the grasses treated with ammonium nitrate combined with phosphorous (R^2 =0.60, RMSEP = 0.1712 kg/m^2 RMSEP$_{-}^{rel}$ = 2.2), ammonium sulphate combined with phosphorous (R^2 =0.69, RMSEP = 0.52 kg/m^2 RMSEP$_{-}^{rel}$ = 6.1), “control” (R^2 =0.66, RMSEP = 0.52 kg/m^2 RMSEP$_{-}^{rel}$ = 9.43) and lime (R^2 =0.65, RMSEP = 0.6391 kg/m^2 RMSEP$_{-}^{rel}$ = 11.6) had the least prediction errors. When the treatments were pooled together, hyperspectral data yielded the lowest errors of prediction. (R^2 = 0.73, RMSEP = 1.1837kg/m^2, RMSEP$_{-}^{rel}$ = 16.51) relative to Landsat 8 OLI (R^2 = 0.56, RMSEP = 1.39 kg/m^2, RMSEP$_{-}^{rel}$ = 21.36) and Sentinel-2 MSI (R^2 = 0.65, RMSEP = 1.45 kg/m^2, RMSEP$_{-}^{rel}$ = 20.18) (Figure 3.4a & c). Although hyperspectral bands optimally estimated above grass biomass, overall, it can be observed that its prediction errors are comparable to those of new generation sensor bands.

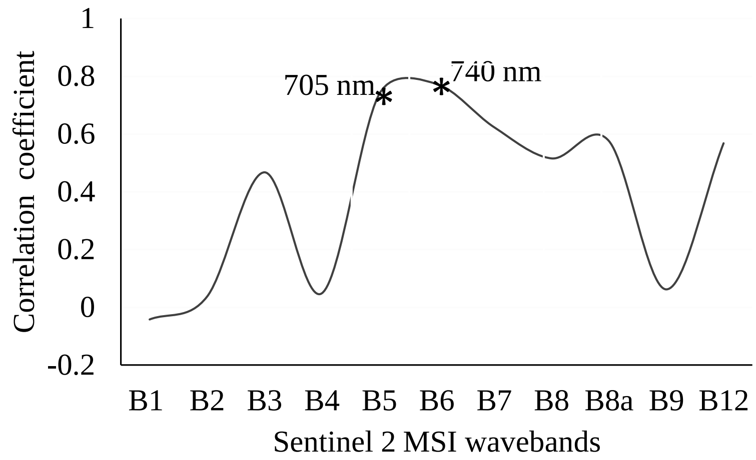

Figure 3.3: Relationship between Sentinel-2 MSI bands and grass biomass using the entire dataset, with bands 5 (centered at 705nm) and 6 (centered at 740nm) showing the highest correlation coefficient.

3.3.3 Performance of the resampled Sentinel-2 MSI derived vegetation indices in grass above ground biomass estimation relative to the perfomance of Landsat 8 OLI and hyper spectral derived vegetation indices.

Figure 3.4 (b & d) illustrates accuracies attained in estimating grass above ground biomass using vegetation indices derived using Sentinel-2 MSI, Landsat 8 OLI, and hypesrpectral data. It can be noted that Sentinel-2 MSI derived vegetation indices optimally estimated above ground biomass of grasses treated with different fertiliser treatments relative to the Landsat 8 OLI. Specifically, the fertiliser treatments that were best estimated using hyperspectral derived vegetation indices were “control” with a RMSEP of 0.4 kg/m^2 (R^2 = 0.70, RMSEP$_{-}^{rel}$ = 7.35), 0.44 kg/m^2 (R^2 = 0.87, RMSEP$_{-}^{rel}$ = 4.88) for ammonium sulphate combined with lime, 0.51 kg/m^2 for ammonium sulphate (R^2 = 0.79, RMSEP$_{-}^{rel}$ = 8.72), and 0.47 kg/m^2 for Phosphoros (R^2 = 0.85, RMSEP$_{-}^{rel}$ = 8.13). When using Sentinel-2 MSI derived vegetation indices, “control” had a RMSEP of 0.89 kg/m2 (R^2 = 0.68, RMSEP$_{-}^{rel}$ = 16.42), 0.51 kg/m^2 (R^2 = 0.78, RMSEP_rel = 10.23) for ammonium sulphate combined with phosphorous, 0.7112 kg/m^2 (R^2 = 0.79 RMSEP$_{-}^{rel}$ = 12.17) for amonium sulphate and 0.8963 kg/m^2 (R^2 = 0.84, RMSEP$_{-}^{rel}$ = 15.47) for phophorous. When using vegatation indices derived from Landsat 8 OLI bands, the amonium nitrate had a RMSEP of 0.66kg/m^2 (R^2 = 0.42, RMSEP$_{-}^{rel}$ = 17.78), 0.79 kg/m^2 (R2 = 0.56, RMSEP$_{-}^{rel}$ = 17.64) for “control”, 0.84 kg/m^2 (R^2 = 0.57, RMSEP$_{-}^{rel}$ = 17.25) for ammonium sulphate combined with phosphorous (ASP), and 0.8741 kg/m^2 (R^2 = 0.74, RMSEP$_{-}^{rel}$ = 15.09) for phophorous. When all the fertiliser treatment were pooled together, vegetation indices derived from the new generation sensors (Sentinel-2 MSI: R^2 = 0.76;RMSEP = 1.19 kg/m^2; $RMSEP_{-}^{rel}$ = 18.62 and Landsat 8 OLI: R^2 = 0.65; RMSEP = 1.17 kg/m^2; $RMSEP_{-}^{rel}$ = 19.41) and hyperspectral data (R^2 = 0.92; RMSEP = 1.18 kg/m^2; $RMSEP_{-}^{rel}$ = 12.14) optimally estimated grass above ground biomass .

Figure 3.5 and Table 3.5 illustrate the detailed frequence and location of each hyperspectral, Sentinel-2 MSI, and Landsat 8 OLI and vegetation indices within the electromagnetic spectrum that were used in comparing the utility of new generation sensors in estimating above ground biomass of grass treated with different fertiliser combinations. It can be observed that the optimal bands and indices that have a potential to estimate grass above ground biomass across all fertiliser treatments are mainly from the red edge and near infrared sections for all the sensors.

Although this study did not seek to evaluate the utility of new generation sensors in estimating the effect of specific fertiliser combination treatments on grass above ground biomass , it can be observed that ammonium nitrate as well as the “control” treatments were optimally estimated both when using raw bands and indices derived from the three sensors. In addtition, results of this study also showed that red edge and near infrared vegetation indices derived from the three sensors better estimated grass above ground biomass across different fertiliser combinations when compared with raw bands.

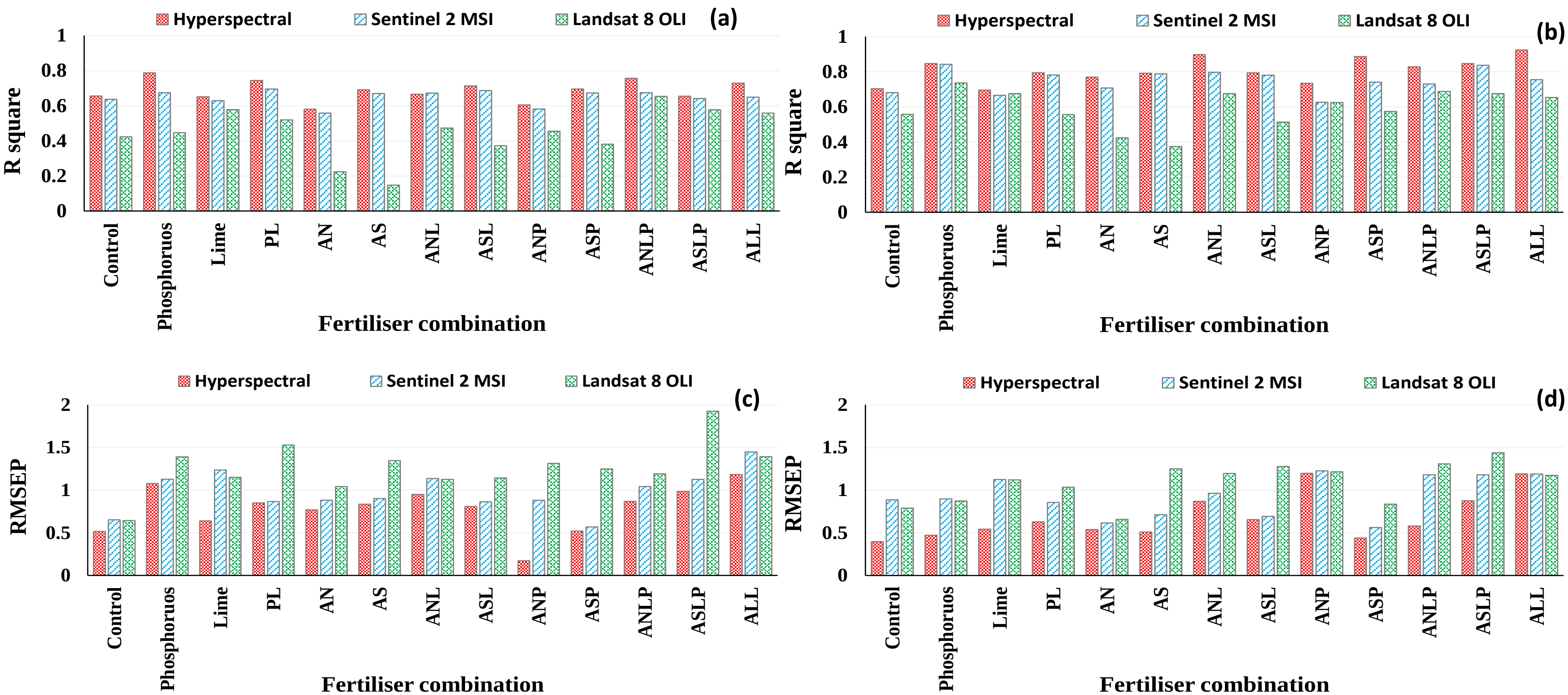

Figure 3.4: Accuracy of Sentinel-2 MSI bands and indices in predicting above ground biomass across different fertiliser treatments in relation to accuracies of Hyperspectral, Landsat 8 and indices. (a & b) represent the R-square obtained from the using spectral bands and indices, respectively in estimating grass above ground biomass, (c & d) represent root mean square errors of grass above ground biomass prediction derived from raw bands and indices respectively. ALL = all treatments pooled. AN = ammonium nitrate; AS = ammonium sulphate; L = lime; and PL = phosphorus combined with lime

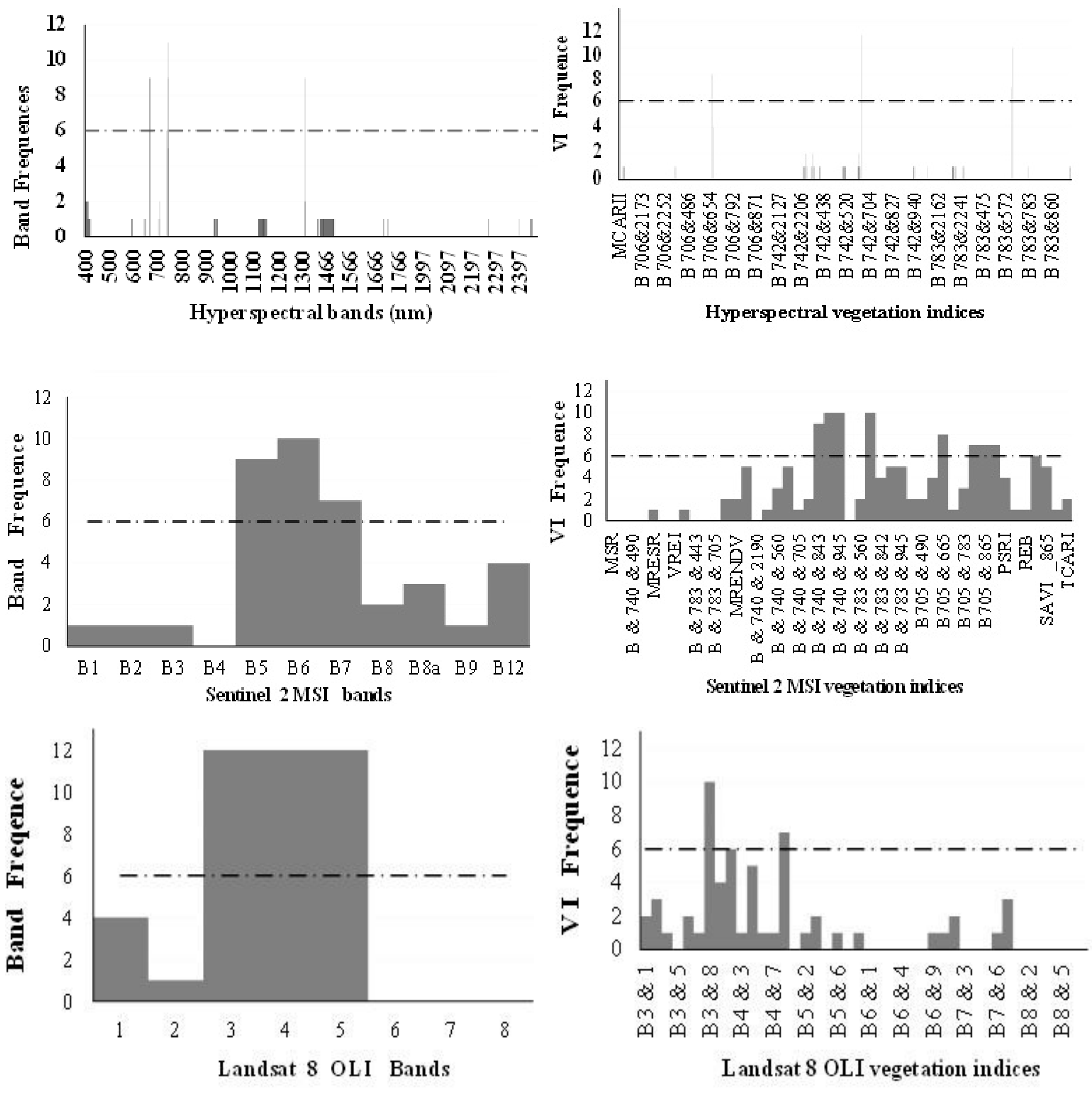

Figure 3.5: Frequency of raw Hypespectral, Sentinel-2 and Landsat bands in estimating above ground biomass across different fertiliser treatments. The dotted line shows the otpimal number of treatments estimated by bands or indices . The optimum number six is the half of the twelve fertiliser treatment combinations

Table 3.5: Frequence of seleted bands that optimally estimate above ground biomass of grasses treated with different fertiliser treatments.

Treatment	**Visible** 390-679			**RE** 680-750			**NIR** 700-1300			**MID_IR** 1300-2500			**Total bands**		
	ASD	***Sentinel-2 MSI***	***Landsat 8***	***ASD***	***Sentinel-2 MSI***	***Landsat 8***	***ASD***	***Sentinel-2 MSI***	***Landsat 8***	***ASD***	***Sentinel-2 MSI***	***Landsat 8***	***ASD***	***Sentinel-2 MSI***	***Landsat 8***
"Control"	0	0	3	1	1	0	1	3	1	5	0	0	6	3	4
Phosphorous	0	1	3	3	2	0	3	3	1	2	0	0	5	4	4
Lime	13	0	2	5	1	0	5	3	1	1	1	0	19	3	3
PL	2	0	2	2	2	0	2	3	1	8	0	0	12	3	3
AN	2	0	2	6	2	0	6	2	1	1	1	0	9	3	3
AS	24	0	3	1	2	0	1	3	1	5	0	0	30	3	4
ANL	2	0	2	4	2	0	4	3	1	0	1	0	6	4	3
ASL	2	0	3	5	2	0	5	3	1	1	0	0	8	3	4
ANP	6	0	2	5	0	0	55	3	1	67	1	0	128	4	3
ASP	2	0	3	4	2	0	4	3	1	1	0	0	7	3	4
ANLP	7	1	2	3	2	0	3	2	1	0	0	0	10	3	
ASLP	2	1	2	2	1	0	2	3	1	2	0	0	6	3	3
All treatments	0	0	3	2	2	0	2	3	1	1	0	0	3	3	4
Combined Bands & indices	0	0	4(1B&3 I)	4(2B&4I)	5 (2B & 2I)	0	7(2B&5I)	5(2B & 4I)	3(1B&2I)	1	0	1I	8	9	7

Table 3.6: Selected bands and indices that can be used to optimally estimate grass above ground biomass across different fertilizer combinations and their relation to known biomass related wavelengths.

Absorption feature centre	**Wavelength of chemical influence**	**Known casual Biochemical**	**Reference**	**All Selected Bands**	**Frequency of Bands/indices selected of known wavelength**
550-700	Red Edge 700-750 680/670	chlorophyll + nitrogen Foliage, Biomass carotenoids	(Barnes *et al.* 2000) (Blackburn and Steele 1999) (Gitelson and Merzlyak 2003) (Sims and Gamon 2002, Adam *et al.* 2014) (van Deventer *et al.* 2015)	*Sentinel-2 MSI:* B5_705, **B6_740**, NDVI705_665, ndvi705_945, **ndvi740_945**, *Landsat 8***:** B4, **B5**, ndvi B4_5, ndviB4_8, **ndviB5_4**, ndviB5_8 *ASD:* ***B740***, ***B741***, ndvi706_437, ndvi742_935, **ndvi742_665**,	5 7 5
	860	Leaf water content	(Blackburn and Steele 1999) (van Deventer *et al.* 2015)	*Sentinel-2 MSI*: **B8a_865**, SAVI_865, *ASD:* ndvi783_665, **ndvi783_667**, B1310,	4 3
TOTAL					26

*The similar optimal wavelengths across the three sensors are represented in bold.

3.3.4 Combination of optimal bands and indices derived from Hyperspectral, Sentinel-2 MSI and Landsat 8 OLI.

Table 3.6 shows number of selected bands and indices when using Sentinel-2 MSI, Landsat 8 OLI and hyperspectral data. A total of 9 Sentinel-2 MSI bands and indices were selected. The bulk of the bands and indices that could optimally estimate above ground biomass are close to the chlorophyll absortption regions of the red edge (700-780nm). In particular, B5, B6, NDVI705 and 665, B8a & 865, B8a SAVI were selected from Sentinel-2 MSI whereas for the hyperspectral data 740, 741, 1310nm, ndvi742_665, 706_437 and 742_935nm were selected as the best. For Landsat 8 OLI, the selected bands were B4, B5, ndvi B4_5, ndviB4_8, ndviB5_4, ndviB5_8. Based on the combination of the best bands and indices derived in this study, it can be noted that Sentinel-2 MSI perfomed slighty lower (R^2 = 0.81, RMSEP = 1.07 kg/m^2, $RMSEP_{-rel}$ = 14.97; than hyperspectral data (R^2 = 0.92, RMSEP= 0.69 kg/m^2, $RMSEP_{-rel}$ = 9.61). Sentinel-2 MSI performed relatively better than Landsat 8 OLI (R^2 = 0.76, RMSEP = 1.15 kg/m^2, $RMSEP_{-rel}$ = 16.04). Although Landsat 8 OLI has a slightly higher RMSEP than Sentinel-2 MSI, no significant differences ($p < 0.05$) were observed in terms of accuracy between the two new generation sensors (Figure 3.6).

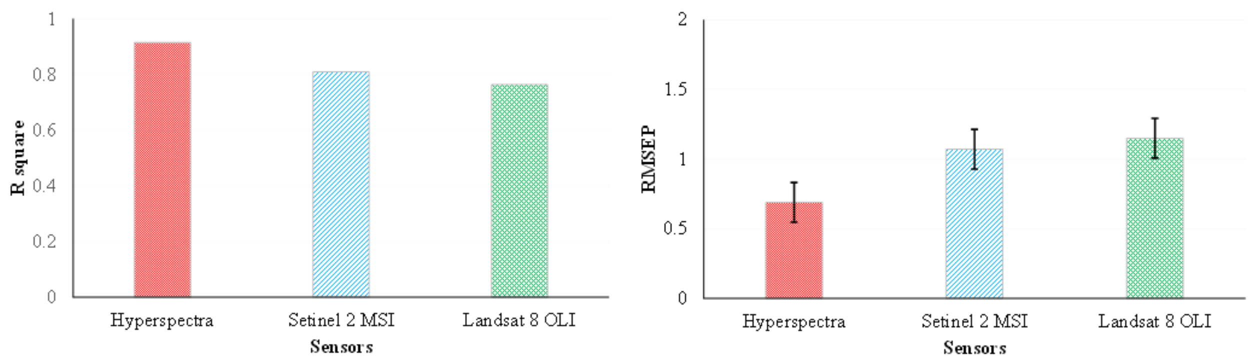

Figure 3.6: Comparison of new generation and traditional sensors in estimating grass above ground biomass across all (pooled) fertiliser treatments using a combination of the selected best bands and vegetation indices derived from hyperspectral data, Sentinel-2 MSI and Landsat 8. Error plots represent the upper and the lower confidence intervals of each sensor's prediction error.

3.4 Discussion

This study sought to explore the utility of the new generation multispectral sensor, Sentinel-2 MSI in estimating biomass across different fertilizer treatments. We then compared findings with those obtained using Landsat 8 OLI simulated data, and hyperspectral data in order to understand the productivity of native grasslands treated with different fertiliser combinations.

3.4.1 Combination of optimal bands and indices derived from Hyperspectral, Sentinel-2 MSI and Landsat 8 OLI.

The present study has shown that the best Sentinel-2 MSI bands and indices that optimally estimated grass above ground biomass across the twelve fertiliser combinations are from the red edge (bands 4, 5 and 8a), similar to those of hyperspectral (705,706,740 and 741). Relatively, the optimal bands that were selected for Landsat 8 OLI (bands 4 and 5) were in the near infrared region. All these selected bands are within wavelength regions that are known to relate well with biomass (Curran 1989, Mutanga *et al.* 2005, Ramoelo *et al.* 2013). As in other earlier related studies (Curran *et al.* 2001, Mutanga and Skidmore 2004, Mutanga and Skidmore 2007), the high influence of near infrared bands at the canopy level can be explained by the high nitrogen concentration in the ammonium fertilizers (33% in ammonium nitrate and 21% in ammonium sulphate fertiliser), which increased biomass density, leaf area Index (LAI) and leaf area distribution (LAD). For instance, nitrogen stimulates rapid growth and plant healthy (Fichtner and Schulze 1992, Bassegio *et al.* 2013) and the red edge/NIR region is sensitive to such changes. Clevers and Gitelson (2013), demonstrated the significance of Sentinel-2 MSI red edge bands centred at 705 and 740nm in optimally estimating chlorophyll and nitrogen in grasslands and crops. The results of this study are consistent with those of Delegido *et al.* (2011) who also indicated a strong influence of Sentinel-2 MSI's new red edge bands as well as the derived normalised difference vegetation indices in estimating the leaf area and chlorophyll of crops. In a related study, Ramoelo *et al.* (2014) also noted that Sentinel-2 MSI red edge bands could optimally estimate leaf nitrogen in the north eastern part of South Africa.

3.4.2 Evaluating the performance of Sentinel-2 MSI in estimating grass above ground biomass relative to other sensors

Although hyperspectral data outperformed the new generation sensors, its utility is prohibited by the high cost, area coverage, multi-collinearity and dimensionality (Adjorlolo *et al.* 2015).

This study has shown that Sentinel-2 MSI and Landsat 8 OLI, which are freely available and cover large swath widths, can still yield acceptable biomass estimation accuracies. The variations in prediction accuracies among sensors can be explained by the differences in the bandwidths. Specifically, hyperspectral data is measured at 1.4nm intervals at region 350–1000 nm and at 2 nm intervals within the wavelength region 1000–2500 nm (Abdel-Rahman *et al.* 2014). Comparatively, the bandwidths of the new generation sensors are marginally different from those of traditional sensors. Sentinel-2 MSI has a bandwidth ranging from 50 to 180nm for its 12 bands (Delegido *et al.* 2011), hyperspectral has bandwidths that range from approximately 1nm. In that regard, it was implicit that hyperspectral sensor derived bands and indices would perform somewhat better than the new generation sensors. However, the findings of this study underscore the potential of new generation sensors, Sentinel-2 MSI and Landsat 8 OLI, in estimating grass above ground biomass at a regional scale despite their intermediate spectral resolutions. Results of this study are comparable to the results of Numata *et al.* (2007) who also estimated grass above ground biomass with plausible accuracies ($R^2 = 0.72$) similar to those presented in this study. Although Landsat 8 OLI data may be used as an alternative to Sentinel-2 MSI, the red edge bands on Sentinel-2 MSI sensor offer great potential for biomass estimation, a component that previously limited the utility of multispectral sensors. Moreover, in resource scarce regions where costs of data over ride the need for optimal spectral resolutions in remote sensing above ground biomass (Lu 2006, Dube and Mutanga 2015, Dube *et al. In press*), the high costs of hyperspectral sensors hails high the potential of Sentinel-2 MSI in rangeland ecology. Proper rangeland management techniques require cheap, timely and accurate data that is repeatedly collected at regional scales (Mansour *et al.* 2012). Considering the expenses associated with hyperspectral sensors as well as their limitation to a local scale, hyperspectral sensors are, to some extent, inappropriate for rangeland management activities in sub Saharan Africa (Mansour *et al.* 2012). In view of this study’s findings, there is still a need to compare and understand the utility of these sensors, paying particular interest to the variations in terms of spatial fidelity in estimating grass above ground biomass at a regional scale.

Results of this study also point out that ammonium nitrate and “control” treatments were the best treatments that could be optimally predicted constantly across the three sensors, both using the raw bands as well as the derived vegetation indices. As mentioned above, the nitrogen/ phosphorous/ potassium ratio of ammonium fertiliser is 33-0-0. Considering the fact that nitrogen has been proven to be one of the fertilisers that results in rapid plant growth rate, LAI, LAD and more importantly high accumulation of biomass density, the relatively high nitrogen content could therefore explain optimal estimation of biomass using the three sensors.

Finally, the results of this study indicated that vegetation indices out performed raw spectral bands in estimating grass above ground biomass across all fertiliser treatments. A large body of literature has demonstrated the utility and robustness of vegetation indices in estimating above ground biomass (Mutanga and Skidmore 2004, Clevers and Gitelson 2013, Helman *et al.* 2014, Ren and Feng 2014). The plausible performance of vegetation indices could be attributed to their ability to reduce background effects much better than individual spectral bands. In addition, vegetation indices are more sensitive to plant biochemical and biophysical differences. This could be explained by that vegetation indices are a product of two or more bands that are more sensitive to vegetation traits as compared with single bands that may be tainted by background effects hence poorly estimate biomass (Bannari *et al.* 1995). For instance, normalised vegetation index used in this study is a result of the red and red edge bands as well as near infrared bands. The visible red radiation is absorbed by plants' chlorophyll while the near infrared radiation is highly reflected by vegetation leaves. Thus a combination of these two portions of the wavelengths results in a much robust index that can optimally estimate plant biomass than singular bands that are susceptible to back ground effects hence their unsatisfactory performance in this study.

3.5 Conclusion

This study sought to explore the utility of the forth coming new generation multispectral sensor Sentinel-2 MSI performance in estimating grass above ground biomass across different fertiliser treatments in relation to the performance of new Landsat 8 OLI and hyperspectral. Grounded on the results of this study, we conclude that the red edge bands 4, 5 and 8a of Sentinel-2 MSI could be effectively used to optimally and consistently estimate biomass across all fertiliser combinations compared to hyperspectral data (bands 705,706,740 and 741nm).
This study demonstrates the potential of new generation multispectral sensors in effectively estimating above ground biomass for optimal rangeland management purposes. The findings of this study are a footing for regional grass quantity evaluation which is essential in the livestock industry. Despite the fact that the findings of this study need to be tested at a regional

scale to compare the spatial fidelity of these sensors, this work provides a basis for efficient evaluation of grass quantity at a regional scale. The red edge and near infrared wavelengths established in this work underscore the potential of the new multispectral sensor bands in rangeland resource monitoring and management.

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This chapter presented a comparison of the accuracies obtained based on the spectral settings of Landsat 8 OLI and Sentinel-2 MSI simulated from hyperspectral data using sparse partial least squares regression algorithm. The results of this study indicated the optimal influence of red edge spectral wavebands in estimating above grass biomass. Consequently, the findings of this chapter prompted an attempt to comprehensively evaluate the potential of newly launched as well as forth coming new generation earth observation sensors such as HyspIRI, Landsat 8 OLI, Sentinel-2 MSI, and Venµs in characterising the quantity of grasses grown under complex fertilizer and grassland management practice treatments in southern Africa, such as mowing grazing burning and no treatment of native grasslands. In that regard, chapter four and five comprehensively sought to assess the potential and capabilities of new generation earth observation facilities in characterising native grass quantity across grassland management treatments practiced in southern Africa. Taking into cognizance the fact that in chapter two DA was identified as a better algorithm for discriminating grasses grown under different fertilizer treatments, chapter four used DA to evaluate the spectral settings of the new generation sensors in characterising grass grown under different management treatments.

CHAPTER FOUR AND FIVE:

USE OF NEW GENERATION EARTH OBSERVATION FACILITIES

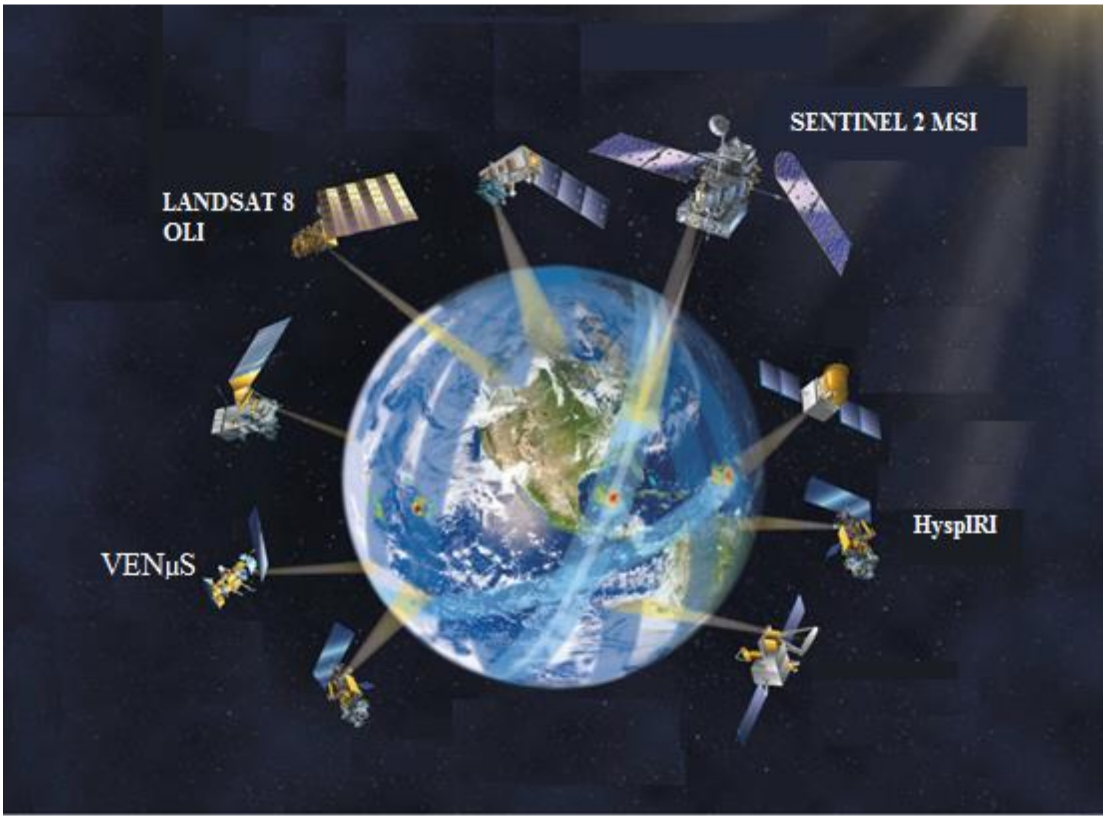

Figure 4.0: The new generation of earth observation facilities. (Adapted from: https://www.google.co.za/search?q=satellites&bih=613&biw=1366&espv=2&source=lnt&tbs=cdr%3A1%2Ccd_min%3A2011%2F01%2F01%2Ccd_max%3A2016%2F11%2F04&tbm=isch#tbm=isch&q=nasa+satellite&imgrc=tt1hw5fNeoQ7VM%3A)

4. DISCRIMINATING RANGELAND MANAGEMENT PRACTICES USING SIMULATED HYSPIRI, LANDSAT 8 OLI, SENTINEL-2 MSI AND VENμS SPECTRAL DATA

This chapter was based on:

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Discriminating Rangeland Management Practices Using Simulated HyspIRI, Landsat 8 OLI, Sentinel 2 MSI, and VENμS Spectral Data

Mbulisi Sibanda, Onisimo Mutanga, and Mathieu Rouget

Abstract

This study sought to spectrally discriminate grasses grown under different management practices (i.e. mowing, grazing, fertiliser application and burning), using field spectrometer data resampled to hyperspectral Infrared Imager (HyspIRI), Landsat 8 Operational Land Imager (OLI), Sentinel-2 Multi-Spectral Instrument (MSI), and Vegetation and Environment monitoring on a new MicroSatellite (Venµs).The study is inspired by the long standing challenge of lack of suitable satellite data with high temporal, spectral and spatial resolutions for rangelands monitoring. Specifically, this study spectrally discriminated grasses grown under (i) different rangeland management practices as well as (ii) different levels of application of each practice. Results of this study show that the spectral setup of HyspIRI, Sentinel-2 MSI, Venµs and Landsat 8 OLI yielded high accuracies of up to 92%, 82%, 83% and 75% overall accuracy respectively in discriminating grass grown under different rangeland management practices. The high classification accuracies were exhibited by the use of vegetation indices and wavebands located in the red edge (HyspIRI: 700, 740 and 780nm and Sentinel-2 MSI: bands 5, 6, and 7 8a) and NIR (HyspIRI: 700, 740 and 780nm and Sentinel-2 MSI: band 8a) spectra respectively. Results of this study illustrate that although simulated Sentinel-2 MSI data yields lower classification accuracies when compared to HyspIRI, it offers better classification accuracies with high agreements between training and testing data sets when compared to the HyspIRI data. Overall, the findings of this study underscore the potential of upcoming satellite missions in ensuring informed rangeland monitoring and management applications.

Keywords

classification, discriminant analysis, field spectroscopy, rangeland management practices, remote sensing

4.1 Introduction

In rangeland studies, information on the effect of different grass management practices is essential for rangeland restoration, sustainable planning and management purposes (Dusseux *et al.* 2014). Grasses are one of the four major vegetation classes in the world (Guo *et al.* 2000, Briggs *et al.* 2005), with tropical grasslands covering an area of 15 million km^2 globally (Osborne 2000). Rangeland grasses are an important ecosystem element as they facilitate carbon cycling and storage, soil development and protection and also save a multipurpose utility to anthropogenic activities (Guo *et al.* 2000, Smith *et al.* 2015). For example, grasslands support numerous livelihood strategies from the goods and services they provide (McGranahan and Kirkman 2013, Ling *et al.* 2014, Smith *et al.* 2015). Specifically, grasslands in Southern Africa sustain economic activities, such as tourism, commercial and smallholder livestock production systems (Naidoo *et al.* 2013, Reed *et al.* 2015). These economic activities significantly increase the per capita income of the communities. In South Africa, for example, these activities provide approximately ZA Rands (R) 1200 (approximately USD$120) per household per annum and an aggregated value per annum of R 2.88 billion (approximately USD$200 million) (Shackleton *et al.* 2001). However, continued pressure on this important resource due to increased population growth patterns has led to over utilisation and in other instances degradation of rangelands (McGranahan and Kirkman 2013).

Faced with this challenge, the majority of farmers, rangeland managers and other interested stakeholders have now adopted various rangeland management practices, which include fertilisation, mowing and burning to increase grass productivity (Dyer *et al.* 1991, Rahman and Gamon 2004, Schweiger *et al.* 2015). All these management practices often change grass biophysical and biochemical properties (Bastin *et al.* 2012, Xu *et al.* 2014). For instance, the application of fertilisers as one of the rangeland management practices, improve grass quality and quantity (Messiga *et al.* 2013, Valkama *et al.* 2014). The study by Johnson *et al.* (2001) observed that grass fertilization with 78 kg of nitrogen increased grass forage mass by approximately 129% when compared to grass with no fertiliser application. Mowing and burning rangeland management practices significantly affect grass quality. For instance Mbatha and Ward (2010) illustrated that rangeland burning increased phosphorus content in pastures by 1.03% in semi-arid savanna, South Africa. Mowing, which is similar to grazing on the other hand alters the grass plant structure. When rangeland grass properties are altered, palatability to livestock, soil development and protection, storage of carbon, circulation of nutrients as well as their multipurpose utility to anthropogenic activities is generally compromised (Guo *et al.* 2000, Ling *et al.* 2014, Xu *et al.* 2014). Often, rangeland managers are faced with a challenge in understanding the influence of these management practises on the grasses at a regional scale (Lü *et al.* 2012). To ensure a prolonged provision of such services, information on the effect of the different management practices on grass quality and composition is necessary both at local and regional scales. In sub-Saharan Africa, such key information is scarce due to lack of resources as well as the inaccessibility of those rangelands. Optical remote sensing has a high potential as a source of spatial information on grass properties in the rangelands (Ullah *et al.* 2012, Marabel and Alvarez-Taboada 2013, Barrett *et al.* 2014, Schweiger *et al.* 2015). From the available sensors, the application of hyperspectral data has been dominant in grass discrimination studies because it exhibits high accuracies ranging from 70 to 99 % (Yamano *et al.* 2003, Shen *et al.* 2008, Marabel and Alvarez-Taboada 2013, Schweiger *et al.* 2015), when compared to broadband multispectral sensors. However, the application of over large spatial extents is often inhibited by high costs, particularly in resource constrained regions. This has resulted in a shift towards the use of new generation multispectral sensors in management and monitoring of tropical rangelands (Price *et al.* 2002, Mariotto *et al.* 2013, Zillmann *et al.* 2014, Barrachina *et al.* 2015, Kong *et al.* 2015). The principal motivation for the utilisation of multispectral data in discriminating various rangeland management practices stems from their low-cost and accessibility (Lu 2006). Above all, the majority of multispectral sensors have wide swath widths, which makes them suitable for wall-to-wall applications (Li *et al.* 2014). Also, some of these sensors are characterised by strategically positioned spectral bands, such as the red edge, which has been proved to be critical for vegetation mapping and biomass estimation (Ramoelo *et al.* 2012, Adelabu *et al.* 2014, Vaglio Laurin *et al.* 2014). Hence, the absence of the red edge spectral region in previous sensors has been pointed to be one of the factors limiting their potential (Mutanga *et al.* 2009). Furthermore, previous generation of sensors (i.e. Landsat 7) have been discredited for consisting of relatively broader, averaged wavebands which are disjunctive (Mutanga *et al.* 2009). These characteristics could make broadband sensors to be insensitive to variations in reflectance of vegetation characteristics (Adam *et al.* 2014) such as those of mowed, grazed and fertilised native rangeland grasses. Nonetheless, the synoptic views of the rangelands acquired by the newly launched and forthcoming space borne multispectral and hyperspectral sensors are expected to provide valuable data at spatial and temporal scales unattainable by old generation of broadband sensors.

The forthcoming HyspIRI, for example, will be amongst the first space borne sensors (similar to the forthcoming EnMAP hyperspectral imager) to provide high spectral resolution data (213 bands ranging from 400-2500nm, including the red edge region) at landscape scale (swath width of 145km and footprint of 60m) as well as a revisit time of 19 days (Palacios *et al.* 2015). Studies conducted using narrow wave bands obtained from space and airborne sensors (i.e. Worldview 2, Airborne Imaging Spectrometer for Applications (AISA) Eagle), although critical for vegetation mapping e.g. discriminating various vegetation biochemical (i.e. chlorophyll) as well as biophysical structures (i.e. biomass), they are relatively costly . On the other hand, the Vegetation and Environment monitoring on a New MicroSatellite (Venµs) which will provide a twelve refined bands, of which five will be covering the red edge region, at a 27 km swath width and a spatial resolution of 5.3m (Herrmann et al. 2011, EOportal.org 2015) is expected to provide a great potential for detecting subtle differences in grasses grown under different management practices. The application of newly launched sensors, such as Sentinel-2 MultiSpectral Imager (MSI) as well as the Landsat 8 Land Operational Imager (OLI) is also promising in rangeland management. Like HyspIRI and Venµs, Sentinel-2 MSI with a 290 km swath width, 13 spectral bands also covering the red edge region (at band centres 705, 740 and 783nm) is also expected to be suitable for regional scale rangeland management applications (Delegido *et al.* 2011, Herrmann *et al.* 2011, van der Meer *et al.* 2014). In addition, Landsat 8 OLI, relative to its predecessors, is characterised by a push broom scanner technology which increases signal to noise ratios (Roy *et al.* 2014, Dube and Mutanga 2015). The increased signal to noise ratio, as well as other sensor improvements on Landsat 8 OLI, have the potentially for better discriminating grasses at a landscape scale when compared to its predecessors. Overall, the spectral characteristics of the four sensors are conceived to offer a platform for landscape scale discrimination of subtle grass differences. Despite the fact that the performance of HyspIRI and Venµs spectral settings have not been tested in rangeland applications, current research based on the spectral setup of these sensors that has been conducted in mapping phytoplankton (Palacios *et al.* 2015), minerals (Kruse *et al.* 2011), forests (Roberts *et al.* 2012) and crop monitoring (Herrmann *et al.* 2011) indicates their robustness in estimation and discrimination scenarios. Since there is no study, that has attempted to assess the utility of these sensors in discriminating grasses under different management practises, there is need for a comparative study to assess the utility of these sensors with other newly launched sensors, i.e. Landsat 8 OLI and Sentinel-2 MSI, in regional scale rangeland management applications. It is hypothesised that their availability and robustness might improve the monitoring as well as the management of rangelands in Southern Africa. This study, therefore, evaluates the strength of HyspIRI, Landsat 8 OLI, Sentinel-2 MSI and Venµs spectral configurations in discriminating grass species grown under different management practices i.e. mowing, grazing, burning and fertiliser application. A number of vegetation indices derived from the simulated sensors were also evaluated.

4.2 Methods and Materials

4.2.1 Study area

The study was conducted at Ukulinga Research Farm in Pietermaritzburg, University of KwaZulu-Natal, South Africa, (29°40′ 05.95” E, 30°24′ 22”S). Generally, Pietermaritzburg has high mean monthly temperatures of approximately 27°C in summer and slightly cold winters with a minimal mean monthly temperature of 6°C (Richard *et al.* 2004, Sibanda *et al.* 2015). *Themeda triandra*, *Heteropogon contortus*, *Eragrostis plana*, *Panicum maximum*, *Setaria nigrirostrosis* and *Tristachya leucothrix* are the dominant grass species at the research farm. The average height of these grasses was approximately 40cm across all the plots. Ukulinga soils are relatively infertile, acidic and of the Westleigh type (Fynn and O'Connor 2005).

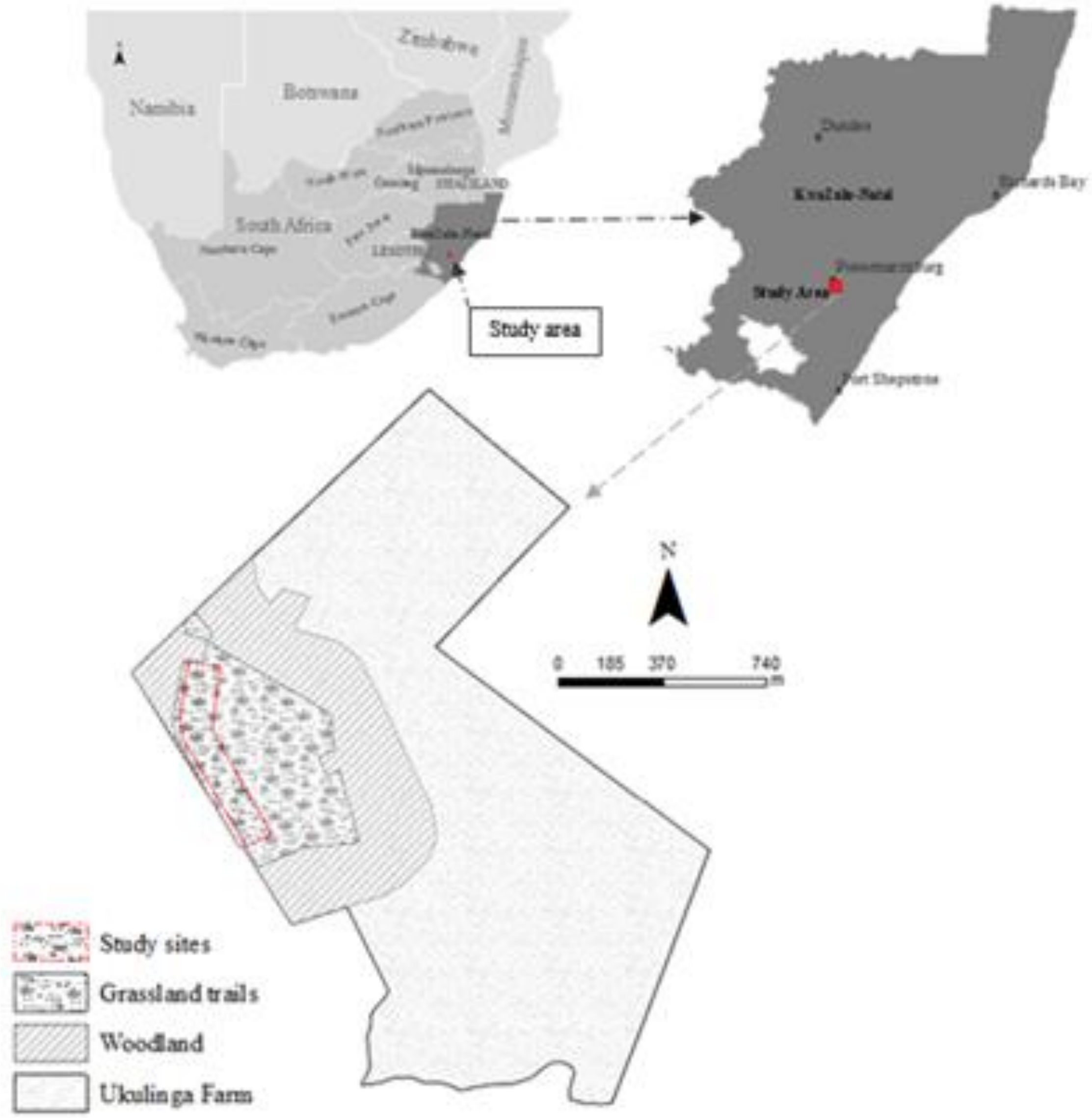

Figure 4.1: Ukulinga grassland trials, UKZN farm, Pietermaritzburg, South Africa.

4.2.2 Experimental design

Burning and mowing, as well as the fertiliser treatment plots were established by J D Scott in 1950 (Morris and Fynn 2001) with the objective of understanding the influence of different management practices on grass quantity and quality. Seventy-two plots measuring 13.7 x 18.3 m with native grasses under mowing, burning, and no-treatment ('control'), as well as three plots measuring 3 x 9 m with native grasses treated with a combination of fertilisers were used in this study (Table 4.1). Grass burning treatments in the experimental plots were conducted at three levels annually (after 1yr), triennially (after 2 yrs) and biennially (after 3 yrs). Mowing on the other hand, is conducted at three levels (i.e. level 1: no mowing, level 2: mowing once in August and level 3: mowing twice in August and after the 1st spring rain). For fertilization treatments, Ammonium nitrate (NH_4NO_3) was applied at four levels combined with dolomitic lime (lime) and super phosphate (Phosphorus: P). Fertiliser treatments were applied at the beginning of the growing season. Although biomass and canopy morphological factors were not measured in this study, there is need for future studies to embark on understanding their influence in grass discrimination especially when different rangeland management treatments are considered.

4.2.3 Simulated remotely sensed data

HyspIRI, Landsat 8 OLI, Sentinel-2 MSI and Venµs data used in this study were resampled from spectral measurements and used to discriminate rangeland grasslands in Environment for visualizing images, Research Systems, Inc (ENVI) as in Oumar and Mutanga (2010). Broge and Mortensen (2002), Adam *et al.* (2012) and Mansour *et al.* (2012) successfully demonstrated the strength and ability of simulating the spectral characteristics of selected sensors using a field ASD spectroradiometer as conducted in this study. Although factors such as the spatial resolution, angle of view variations, different radiometric resolutions and signal-to-noise-ratios determine the performance of these four sensors, in this study we held these factors constant in order to evaluate the performance as well as robustness of the spectral configurations of these four sensors in rangeland management applications. In that regard, field grass' spectral reflectance measurements were done using an Analytical Spectral Device (ASD) FieldSpec instrument within plots under different rangeland treatments. Eight spectra were recorded in each fertiliser plot and 30 spectra were recorded from the burning and mowing trials summing up to a total of 2052 samples (Table 4.1).

The ASD spectrometer records radiation at 1.4nm intervals for the spectral region 350 –1000 nm and 2nm intervals for the spectral region 1000–2500nm. Spectral measurements were conducted under clear sky conditions between 10am and 2pm because this is the period of day which receives maximum sun radiation. In measuring grass reflectance, bare fiber-optic sensor connected to the spectro-radiometer was held at a nadir position approximately 1m above grass canopies to capture reflectance of grass canopies (Abdel-Rahman *et al.* 2014, Mutanga *et al.* 2015). Consequently a ground view of approximately 0.45m in diameter, ample to capture the reflectance of grass canopy was covered (Abdel-Rahman *et al.* 2014). When measuring the spectra, the fiber-optic cable was held at an arm's length, to avoid the recorder's shadow and clothing influence on the registered grass canopy spectra. Moreover, the spectra were collected after the green peak phenological stage when the grasses were mature (on the day of the year 150 of 2015). Spectrometer measurements were standardized after every 5-10 spectra measurements using a standard spectralon to regulate possible atmospheric condition changes and sun irradiance (Abdel-Rahman *et al.* 2014). To discriminate native grass growing under different treatments, ground reflectance not radiance or raw DN values were used in this study. Furthermore, the visible spectral region refers to wavebands ranging between 380 to 700nm, red edge refers to wavebands ranging from 680-750nm, near infrared (NIR) refers wavebands from 700-1300nm, and short wave infrared (SWIR) refers to wavebands between 1300-2500nm in this study.

Table 4.1 Reflectance samples measured on each rangeland management treatment.

Management practice	No. of plots	No. of Samples
Annual burn	12	360
Biennial burn	18	540
Triennial burn	18	540
Mowing	12	360
Grazing	3	90
Fertiliser Application	9	72
Native ('control')	3	90
Total	75	2052

To simulate HyspIRI, Landsat 8 OLI, Sentinel-2 MSI and Venµs data, 2052 grass reflectance samples measured in 75 plots under different rangeland management practices were resampled accordingly.

In the present study, spectral measurements were resampled to Sentinel-2 MSI as in Delegido *et al.* (2011). Specifically, Sentinel-2 MSI has 12 wavebands which include the Red/edge region (bands 5, 6 and 7), a 5 day revisit time, placed at an orbital angular distance of 1800 with a field of view of 290km (Cole *et al.* 2014). Sentinel-2 MSI acquires all its images at a nadir position at thirteen spectral wavelengths ranging from visible through the red edge bands to the short wave infrared wavelengths with a high spatial resolution ranging of 10, 20 and 60 m.

To simulate the spectral resolution of Landsat 8 OLI, spectral measurements, measured in the 75 plots with different grass management practices was resampled based on the bandwidths of the bands illustrated in Dube and Mutanga (2015). Launched in 2013, OLI and the thermal infrared sensor (TIRS) are the two instruments on board Landsat 8 satellite. These two instruments capture images of the earth at 16 day temporal resolution with a scene size of about 170km by 183km, suitable for regional vegetation mapping applications. Although the spectral bands of OLI sensor are similar to those of Landsat 7 ETM+, OLI sensor has two new bands and an advanced signal to noise radiometric performance which gives it a great potential for agricultural applications (Dube and Mutanga 2015).

The third sensor simulated in this study is the Hyperspectral Infrared imager. On board the HyspIRI are two instruments i.e. visible shortwave infrared (VSWIR) and the thermal infrared (TIR) multispectral scanners. VSWIR will be offering between the visible to short wave infrared (i.e. 0.38 and 2.5um) at a spatial scale of 60 m with a swath width of 153 km. Meanwhile, the TIRS will range from 4 and 12um at a spatial scale of 60m with a swath width of 600 km. VSWIR is expected to record radiation between 380 - 2500nm in 10 nm contiguous. Both the VSWIR and TIR instruments have a spatial resolution of 60 m at nadir. The VSWIR will have a revisit of 19 days and the TIR will have a revisit of 5 days.

On the other hand, Venµs will acquire multispectral images after two days. Venµs will acquire data in a near polar sun-synchronic orbit at an altitude of 720km with a two day revisit time. The Venµs sensor will acquire images at a swath width of 27km consisting of 12 narrow spectral bands from the visible through the red edge to the near infrared. The radiometric resolution of Venµs will be 10 bits while the spatial resolution will also be at 10 m (https://directory.eoportal.org/web/eoportal/satellite-missions/v-w-x-y-z/venus).

4.2.4 Statistical data analysis

To discriminate grasses treated with different management practices, four stages of analysis were conducted based on the spectral setup of the four sensors. Table 4.2 shows the specific analysis stages conducted, the treatments discriminated as well as the algorithms used at each stage.

Stage 1: Analysis of variance (ANOVA) was used to test for significant differences in grasses reflectance across all rangeland management practises. Literature shows that ANOVA is a useful algorithm for reducing excess wave bands in discrimination studies (Adam and Mutanga 2009, Adelabu *et al.* 2014, Sibanda *et al.* 2015). At this stage, grass reflectance collected across all treatments were compared with the untreated grass (‘control’). The wavebands that optimally discriminated the grass under different management practices at this stage were selected and used in the second stage.

Stage 2: Discrimination of grasses was conducted within groups of fertilisation, mowing, grazing and burning levels. In the fertiliser group we discriminated grasses treated with the four levels of NH4NO3 (level 1: 0 kg/ha/season (control), 2: 210 kg/ha/season, level 3: 421 kg/ha/season and level 4: 632 kg/ha/season) combined with L and P. We also discriminated grasses under the three mowing levels (1: grasses that are not mowed (‘control’), 2: grasses mowed once and 3: grasses mowed twice a year). Finally, we discriminated grasses amongst non- burnt (‘control’), annual, biennial and triennial burning management practises. Wavebands that could optimally discriminate grasses growing under different levels of the four rangeland management practices were selected

Stage 3: Discrimination was conducted across grasses under mowing, grazing, burning and fertiliser application. Reflectance of grasses at various levels of different rangeland management treatments were pooled at this level of discrimination.

Stage 4: Best performing sensors in discriminating rangeland management practices were selected based on their classification accuracies. All possible vegetation indices, were then computed and used in discriminating grasses grown under different rangeland practices. The performance of these indices was then assessed based on their classification accuracies.

Table 4.2 Stages followed, variables and algorithms used in classifying grasses under different rangeland management practices

Analysis	Algorithm	Analysis	Treatment	Description	No
1	ANOVA	Across all treatments	All treatments	All treatments vs control	27
2	Discriminant analysis	Within groups	Fertilisation	AN[1]PL vs AN[2]PL vs AN[3]PL	3
			Mowing	1/yr vs 2/yr	2
			Grazing	Burning vs Control	2
			Burning	Annual vs triennial vs Biennial	3
3	Discriminant analysis	Across all groups	All treatments (pooled)	Mowing vs Fertilisation vs Burning vs Grazing vs Control	5
4	Discriminant analysis	Across all groups (Using vegetation Indices)	All treatments (pooled)	Mowing vs Fertilisation vs Burning vs Grazing vs Control	5

4.2.5 Analysis of Variance

We tested whether there were significant differences between mean reflectance of grasses under different management practices (i.e. mowing, burning, fertilisation and grazing practices and those that were not treated (‘control’) using the ANOVA tests. We then used the Dunnett post hoc test to evaluate whether there were statistically significant ($\alpha = 0.05$) differences between the untreated native grasses and the grasses under different rangeland management treatments illustrated in Table 4.1. The Dunnett post hoc tests were used to pre-filter excess wave bands prior to discriminating grasses using a multivariate classification algorithm. Thus, all wavebands that yielded significant differences between the reflectance of grasses under different rangeland management treatments and the reflectance of those that were untreated were selected and used as input in stages 2 to 4.

4.2.6 Discriminant Analysis (DA)

Discriminant analysis is a multivariate classification algorithm that has been demonstrated to be robust in classifying tropical grasses treated with complex management practices (Sibanda *et al.* 2015). Its robustness lies in its ability to moderate the similarities of wavebands to numerous components which can then account for variations within grasses grown under different rangeland management practices. DA utilises a discriminant function in categorising targets into classes using a measure of squared class distances (Adam and Mutanga 2009). This algorithm provides cross validated results with Eigen values that indicated the strength of a specific function in discriminating grasses under different rangeland management practices. Eigen vectors also known as variable scores were produced by DA and used in this study to evaluate the relative contribution of each waveband to the DA function that optimally discriminated grasses under different management practices. The Box test (Chi square asymptotic approximation), Box test (Fisher's F asymptotic approximation), Mahalanobis distances, Wilks's Lambda test (Rao's approximation) and Kullback's test were used to test whether within-class covariance matrices were equal (Sibanda *et al.* 2015). These tests exhibited significant classification power ($\alpha < 0.05$). Classification was conducted using XLSTAT for Microsoft Excel 2013 platform (XLSTAT 2013), and confusion matrices were derived. In each confusion matrix, the columns represented the test data while the rows represented the classes to which each sample was allocated to by the DA classifier.

4.2.7 Accuracy assessment

To evaluate the classification accuracy, quantity disagreement and allocation disagreement were used as suggested by Pontius Jr and Millones (Pontius Jr and Millones 2011). Quantity disagreement is a sum of least perfect matches between the training (70%) and the testing (30%) grass reflectance datasets of each rangeland management practice. Specifically, the quantity disagreement follows when the column total of a management practice class deviates from the row total of that class in a confusion matrix. The remnant disagreement is allocation disagreement. To compute the agreement between the training and testing datasets, we deduct the two disagreements from 100%. To compare the correctly classified rangeland management practice groups with that allocated by DA and to compute overall, producer, user accuracies, we generated confusion matrices of the classification scenarios based on the confusion matrix proposed by Pontius Jr and Millones (2011). Finally, a McNemar test ($\alpha = 0.05$) was used to compare the classification accuracies derived using HyspIRI, Landsat 8 OLI, Sentinel-2 MSI and Venµs data. The McNemar test was used in this study following its robustness and higher precision in comparing accuracy assessments in classification studies. The details of conducting the McNemar test are well explained in literature (de Leeuw *et al.* 2006, Manandhar *et al.* 2009, Sibanda *et al.* 2015). As such, the null hypothesis tested using the McNemar test implied that there was no significant difference in discriminating grasses treated under different rangeland management practices when using HyspIRI, Landsat 8 OLI, Sentinel-2 MSI or Venµs data.

5.2.8 Discrimination of grassland management practices using vegetation indices derived from the best performing sensors.

Two sensors that best discriminated grasses grown under different management practices were selected for calculating vegetation indices (VI). The two sensors were chosen because they yielded high classification accuracies (i.e. overall classification accuracy, allocation of agreement, and low allocations of disagreements). All possible 2 band hyperspectral and multispectral vegetation indices (VIs) were computed and used to discriminate grasses in this study as in Mariotto *et al.* (2013). VIs minimise background effects such as atmospheric conditions, soil background and sun view angles in detecting vegetation biochemical and biophysical properties, when compared with raw bands, hence they were used in this study (Mutanga and Skidmore 2004, Tillack *et al.* 2014, Bendig *et al.* 2015). The hyperspectral and multispectral vegetation indices were computed based on the formula:

$VIs = \frac{b_i - b_j}{b_i + b_j}$ where *i* and *j* are bands and *b* represents reflectance of the respective bands.

4.3 RESULTS

4.3.1 Level 1: ANOVA

Figure 4.2 shows the differences amongst rangeland management treatments based on ANOVA. Using Landsat 8, it can be observed that mowing cannot be discriminated from untreated grasses using the visible spectrum bands. Furthermore, grass under mowing cannot be discriminated from that under fertiliser application (Figure 4.2). On other hand, when using the Sentinel-2 MSI spectral settings, all rangeland management treatments could be discriminated amongst one another except for burning and untreated, as well as mowing and grazing which could not be discriminated in the red edge and NIR sections (Figure 4.2). Based on the dunnet post hoc test, grasses under different rangeland management practices could be discriminated from those that were not treated using remotely sensed data (Figure 4.2). It can be observed that the bulk of grasses under different rangeland management practices were better discriminated using the red-edge (by HyspIRI, Sentinel-2 MSI and Venµs) and near infrared regions (by HyspIRI, Landsat 8 OLI, Sentinel-2 MSI and Venµs), followed by the visible region of the electromagnetic (EM) spectrum across the four simulated sensors (Figure 4.3). Moreover, it can be observed that when using HyspIRI data, grasses from a few rangeland management practices were discriminated from the 'control' grasses in the red edge region when compared with the shortwave infrared region. However, when using Sentinel-2 MSI data, more grasses under different rangeland management practices were discriminated from the 'control' grasses in the red edge region as compared with the shortwave infrared region. When using Venµs simulated data, the majority of treatments were discriminated from the untreated grasses in the visible portion of the EM spectrum through the red-edge to the NIR regions (Figure 4.3). On the other hand, when using Landsat 8 OLI, the bulk of the grasses under various rangeland management practices were differentiated from the control grasses in the near infrared regions of the EM spectrum (Figure 4.3).

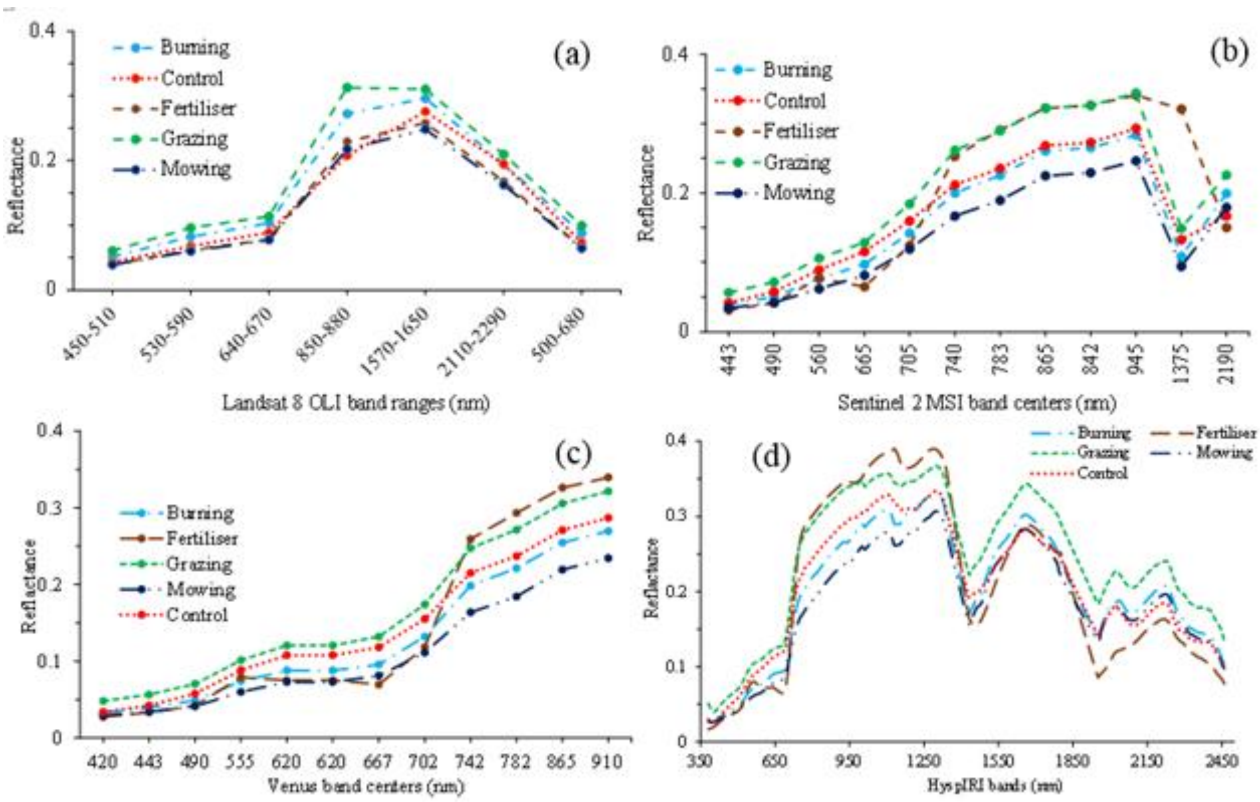

Figure 4.2: Average reflectance of grasses under burning, grazing, mowing and fertiliser treatments and untreated grasses (control) using hyperspectral data resampled to (a) Sentinel-2 MSI (b) Landsat 8 OLI and (c) and Venus (d) HyspIRI. Makers represent multispectral sensors and some Landsat 8OLI bands were excluded.

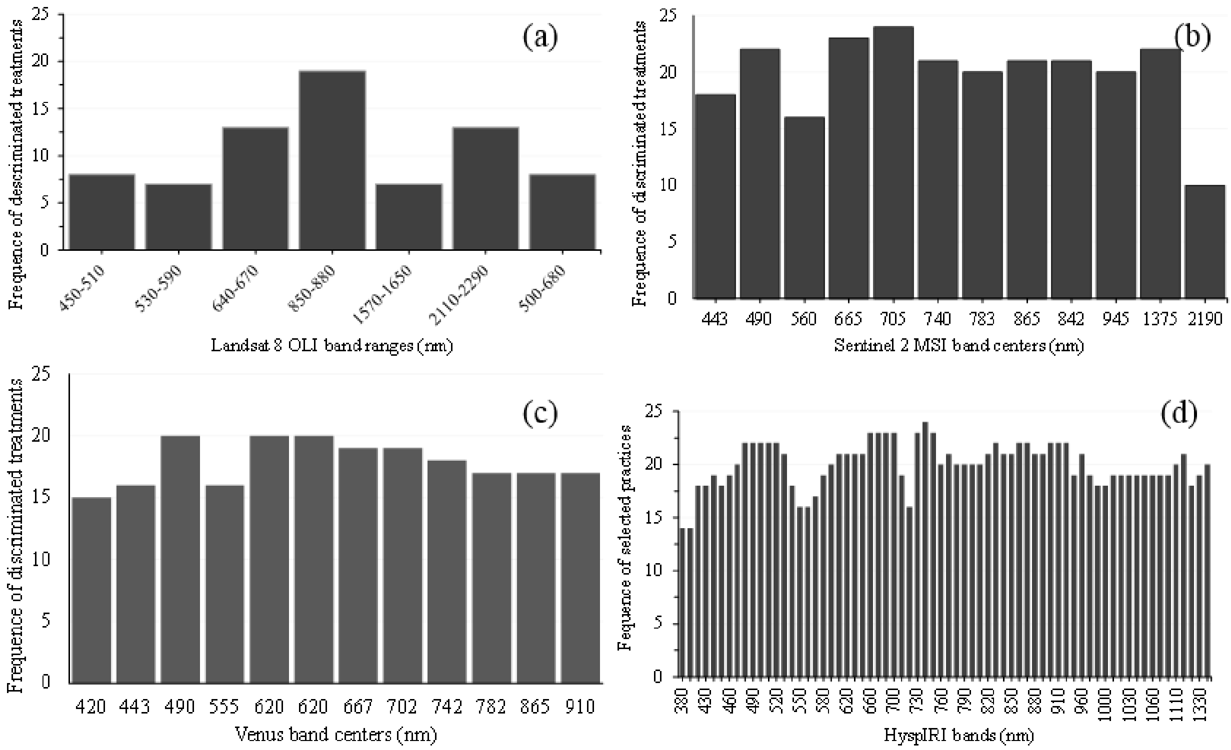

Figure 4.3: Discrimination of grasses under burning, grazing, mowing and fertiliser treatments from those that are untreated (control) based on Analysis of variance (Dunnett post hoc tests) using hyperspectral data resampled to (a) Landsat 8 OLI (b) Sentinel-2 MSI, (c) Venµs and (d) HyspIRI.

4.3.2 Level 2: Classification within rangeland management groups

Classification accuracies obtained based on the spectral setup of HyspIRI, Landsat 8 OLI, Sentinel-2 MSI and Venµs are illustrated on Table 4.3. Generally, it can be observed that HyspIRI exhibits higher classification accuracies (overall: 73-91%, producer: 66-96% and user accuracies: 68-98%), followed by Sentinel-2 MSI in relation to the other sensors across all levels of rangeland management practices. Although classification accuracies of Sentinel-2 MSI are higher compared to Venµs, however, no marginal differences can be observed between the classification performances of the two sensors. Furthermore, when classifying the mowing levels, Sentinel-2 MSI yielded relatively higher user (up to 95 %) and producer (up to 94%) accuracies than HyspIRI (up to 78 % user, 87% producer accuracies) and the other sensors. In addition, it can be observed that the simulated Landsat 8 OLI classification accuracies (overall: 52%, user: up to 70%, and producer: up to 62%) are the lowest across all levels of rangeland management practices (Table 4.3).

Importantly, a significant number of treatments were discriminated using wavebands in the visible (Sentinel-2 MSI: 7 and Venµs: 10), red edge (Sentinel-2 MSI: 8 and Venµs: 8) and NIR (Sentinel-2 MSI: 11 and Venµs: 9) regions. In that regard, the visible, red edge and NIR bands were identified as the best in discriminating reflectance of grasses under various levels of mowing, grazing, fertiliser application and burning practice when using Sentinel-2 MSI and Venµs resampled data. The (SWIR) region from HyspIRI and Landsat 8 OLI exhibited better accuracies (i.e. HyspIRI: 96, Landsat 8 OLI: 9 discriminated practices), NIR region (HyspIRI: 24, Landsat 8 OLI: 4 discriminated practices) and the visible region (HyspIRI: 20, Landsat 8 OLI: 7 discriminated practices) .

4.3.3 Level 3: Discriminating all grass treatments

It was observed that grasses under mowing burning grazing and fertiliser management practices could be optimally discriminated using the spectral setup of HyspIRI with overall accuracies of 0.86, and producer and user accuracies ranging from 0.32-0.96 (Table 4.3). The untreated ('control') and fertilised grasses are the only treatments that exhibited the highest user and producer accuracies when discriminating amongst all other rangeland management treatments based on the spectral setup of HyspIRI. The second performing sensor illustrated in Table 4.3 is Sentinel-2 MSI with overall accuracy of 0.79, as well as user and producer accuracies ranging up to 0.96. Comparatively, Landsat 8 OLI was the least preforming sensor with critically low user and producer accuracies of less than 0.2 were in discriminating burning and mowing grassland treatments (Table 4.3). Moreover, Table 4.3 shows that reflectance of grasses growing under mowing could not be effectively discriminated from that of other rangeland management practices as illustrated by low accuracies.

It can be observed that all the sensors could optimally discriminate treatments using bands located in the NIR (700-1300), red edge (680-750nm) and the visible (380-700nm) regions. Furthermore, when using HyspIRI more treatments were discriminated in the SWIR region.

Table 4.3: Classification of grasses grown under different rangeland management practices based on the spectral setup of Landsat, Sentinel-2 MSI, HyspIRI and Venµs sensors.

Analysis Stage	Classification	Treatment	Landsat 8 OLI User	Landsat 8 OLI Producer	Landsat 8 OLI Overall	Sentinel-2 MSI User	Sentinel-2 MSI Producer	Sentinel-2 MSI Overall	HyspIRI User	HyspIRI Producer	HyspIRI Overall	Venus User	Venus Producer	Venus Overall
		N1LP	0.50	0.45		0.98	0.82		0.67	0.80		0.47	0.57	
	Fertiliser	N2LP	0.41	0.44	**0.44**	0.57	0.67	**0.70**	0.88	0.70	**0.73**	0.47	0.37	**0.51**
		N3LP	0.40	0.43		0.50	0.60		0.63	0.71		0.60	0.56	
		Annual	0.41	0.55		0.42	0.51		0.75	0.77		0.40	0.52	
2	Burning	Biennial	0.61	0.49	**0.55**	0.59	0.5	**0.72**	0.81	0.76	**0.79**	0.54	0.50	**0.55**
		Triennial	0.59	0.62		0.56	0.59		0.79	0.84		0.65	0.62	
		C10	0.44	0.50		0.95	0.73		0.66	0.69		0.66	0.60	
	Mowing	C11	0.43	0.4		0.71	0.94		0.68	0.66		0.56	0.62	**0.64**
		D10	0.70	0.62	**0.52**	0.54	0.79	**0.73**	0.78	0.87	**0.75**	0.62	0.71	
		D11	0.50	0.45		0.78	0.56		0.88	0.78		0.72	0.63	
	Grazing	Grazing	0.74	0.77		0.89	0.88		0.91	0.96		0.88	0.85	
		Control	0.77	0.75	**0.76**	0.88	0.89	**0.89**	0.98	0.96	**0.912**	0.85	0.86	**0.87**
	Burning vs Mowing	Burning	0.76	0.52		0.83	0.64		0.93	0.84		0.88	0.67	
		Mowing	0.19	0.05		0.13	0.18		0.35	0.56		0.01	0.22	
		control	0.17	0.44	**0.51**	0.85	0.83	**0.69**	0.98	0.99	**0.84**	0.82	0.81	**0.69**
	Burning vs Grazing	Burning	0.80	0.59		0.82	0.80		0.90	0.89		0.85	0.81	
		Grazing	0.29	0.55		0.64	0.73		0.88	0.88		0.34	0.49	
		control	0.05	0.68	**0.58**	0.77	0.79	**0.78**	0.88	0.88	**0.89**	0.73	0.80	**0.79**
	Burning vs Fertilisation	Burning	0.81	0.67		0.84	0.82		0.87	0.89		0.88	0.85	
		Fertilisation	0.62	0.63		0.83	0.85		0.88	0.85		0.78	0.80	**0.85**
3		Control	0.20	0.58	**0.66**	0.72	0.79	**0.82**	0.88	0.89	**0.90**	0.72	0.82	
	Mowing vs Grazing	Mowing	0.68	0.60		0.85	0.82		0.90	0.90		0.79	0.87	
		Grazing	0.84	0.91		0.81	0.84		0.90	0.90		0.79	0.89	
		Control	0.64	0.68	**0.72**	0.83	0.83	**0.83**	0.88	0.89	**0.930**	0.78	0.87	**0.79**
	Mowing vs Fertilisation	Mowing	0.74	0.63		0.85	0.82		0.90	0.90		0.80	0.76	
		Fertilisation	0.08	0.33		0.83	0.85		0.90	0.89		0.76	0.78	
		Control	0.69	0.71	**0.66**	0.82	0.85	**0.83**	0.89	0.90	**0.89**	0.75	0.90	**0.77**
	Grazing vs fertilisation	Grazing	0.90	0.46		0.83	0.82		0.90	0.90		0.85	0.81	
		Fertilisation	0.02	0.43		0.83	0.85		0.90	0.89		0.81	0.85	
		Control	0.88	0.67	**0.75**	0.82	0.82	**0.83**	0.89	0.90	**0.89**	0.85	0.83	**0.83**
	All treatments	Burning	0.95	0.60		0.96	0.75		0.94	0.83		0.92	0.74	
	(pooled)	Control	0.13	0.77		0.89	0.91		0.96	0.98		0.76	0.74	
4		Fertilisation	0.00	0.00		0.98	1.00		1.00	1.00		0.49	0.55	
		Grazing	0.45	0.69		0.78	0.87		0.98	0.98		0.00	0.00	
		Mowing	0.00	0.00	**0.61**	0.00	0.25	**0.79**	0.30	0.57	**0.86**	0.83	0.89	**0.74**

The best selected wave bands for discriminating reflectance of grasses under mowing, grazing, fertiliser application and burning practices are presented on Figure 4.4. It can be observed that using discriminant analysis, reflectance of grasses under mowing, grazing, fertiliser application, grazing and 'control' could be optimally discriminated using the red edge spectral setup (of HyspIRI, Sentinel-2 MSI and Venus), near-infrared (HyspIRI, Sentinel-2 MSI, Venus and Landsat 8 OLI) as well as the shortwave infrared of HyspIRI, Sentinel-2 MSI and Venus. Table 4.4 shows the most performing wavebands in relation to known absorption regions. It can be observed that the best wavebands that contributed most in yielding optimal classification accuracies are located close to known chlorophyll (700-750nm), protein (1634-1786nm) and cellulose (2350nm) absorption regions. Accuracy assessments of classifying reflectance of grasses under mowing grazing, fertiliser application and burning rangeland practices are presented on Figure 4.5. Although Venµs simulated spectral setup exhibited higher classification accuracies, high allocations of disagreement were observed (Figure 4.5c). A similar trend of high allocations of commission and omission disagreements were observed using Landsat 8 OLI and Venμs data. Following the observation that the spectral setup of HyspIRI and Sentinel-2 MSI better performed as compared to that of Venμs and Landsat 8 OLI, data from these two sensors was used in assessing the utility of vegetation indices.

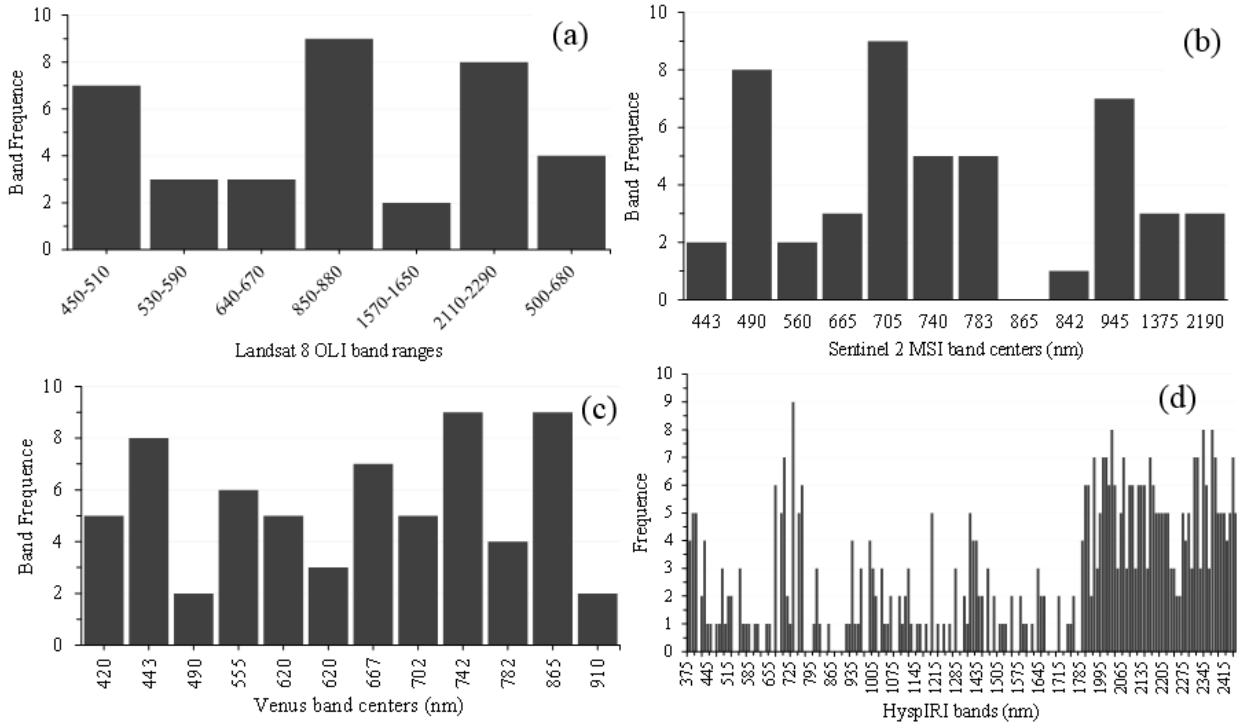

Figure 4.4: Discrimination power of wavebands in classifying grass grown under different rangeland management practices using resampled (a) Landsat 8, (b) Sentinel-2 MSI, (c) Venμs and (d) HyspIRI data

Table 4.4: Frequency of wavelengths selected in classifying grasses grown under different rangeland management practices using resampled Landsat 8, Sentinel-2 MSI and HyspIRI data in relation to known absorption wavelengths

Absorption feature centre	Wavelength of chemical influence	Known casual biochemical	Reference	Bands selected close known wavelengths			
				Landsat 8 OLI	Sentinel-2 MSI	HyspIRI	Venµs
Unattributed							
						370	Band 2 (@ 443nm)
550-700	700-750	chlorophyll + nitrogen	Curran (1989) , Mutanga and Skidmore (2007), Sims and Gamon (2002) , Sibanda *et al.* (2015)	**Band 5 (0.851-0.879µm)**	band 5 (705 nm) **band 7 (@ 783nm)**	**710, 740 nm**	Band 9 (@ 742nm)
							Band 7 (@ 865nm)
1634-1786	1690	Lignin, protein and starch	(Barton et al. 1992)				
2350		Cellulose, nitrogen, protein	(Barton *et al*. 1992, Daughtry *et al.* (2005))			**2375 nm**	
Unattributed						**2445 nm**	

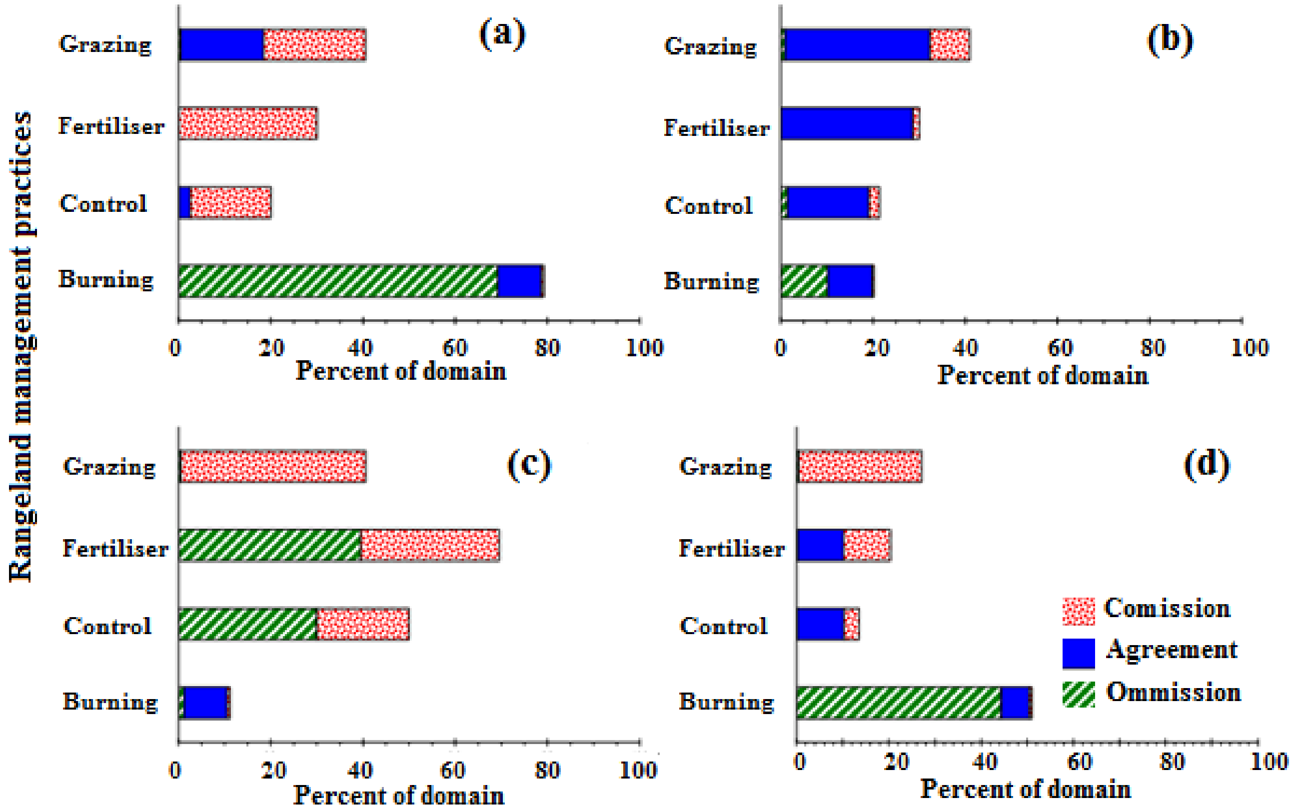

Figure 4.5: Comparing allocations of agreements and disagreements (omission disagreement and commission disagreement) between the training and testing data used in classifying grass reflectance under mowing grazing fertiliser application and burning rangeland management practices using hyperspectral data resampled to (a) Landsat 8 OLI, (b) Sentinel-2 MSI, (c) HyspIRI and (d) Venµs resampled data.

4.3.4 Level 4: Classification based on indices derived from best performing sensors

Table 4.5 shows the classification accuracies of vegetation indices derived from HyspIRI and Sentinel-2 MSI. The majority of best performing vegetation indices derived from both HyspIRI and Sentinel-2 MSI data were associated with red edge bands (HyspIRI: 700, 740 and 780nm, Sentinel 2 MSI: bands 5, 6, 7 and 8a) illustrated on Table 4.5. It can be observed that vegetation indices improved the discrimination of grasses growing under mowing, grazing, fertiliser application and burning rangeland management treatments. When using Sentinel-2 MSI derived normalised difference vegetation indices associated with the red edge, an increase of up to 85% overall accuracy was obtained. Comparatively, when using HyspIRI normalised difference vegetation indices in discriminating grasses under the five rangeland management practices, overall accuracy increased up to 89 %. In addition, the majority of the bands that yielded high overall classification accuracies which also exhibited relatively higher allocations of agreement in comparison to allocations of disagreement on Figure 4.6 were from the red edge region. These red edge bands (HyspIRI: 700, 740 and 780nm, Sentinel-2 MSI: bands 5, 6, and 7) were close to the chlorophyll absorption regions (700-750) as well as cellulose and starch (2280nm). In spite of the increases in accuracies, grasses under mowing were still not well classified from those under burning

Table 4.5 : Classification accuracies obtained using vegetation indices derived from Sentinel-2 MSIand HyspIRI

	Sentinel-2 MSI			HyspIRI		
Practice	User accuracy	Producer accuracy	Overall accuracy	User accuracy	Producer accuracy	Overall accuracy
Burning	0.95	0.88		1.00	0.80	
Fertilisation	0.91	0.49		0.82	1.00	
Grazing	0.60	0.77		0.87	0.93	
Mowing	0.07	0.32		0.13	0.37	
Native	0.99	0.99	0.85	0.93	0.84	0.89
Selected vegetation indices	Band 8a and 11, Band 1 and 7, Band 1 and 4, Band 6 and 2, Band 10/11 and 3, Band 7 and 5			Band 740 and 6, Band 1291 and 682, Band 2290 and 700, Band 780 and 690, Band 690 and 690, Band 730 and 690, Band 740 and 687,		

NB for HyspIRI the units are [nm] while for Sentinel-2 MSI they are band numbers

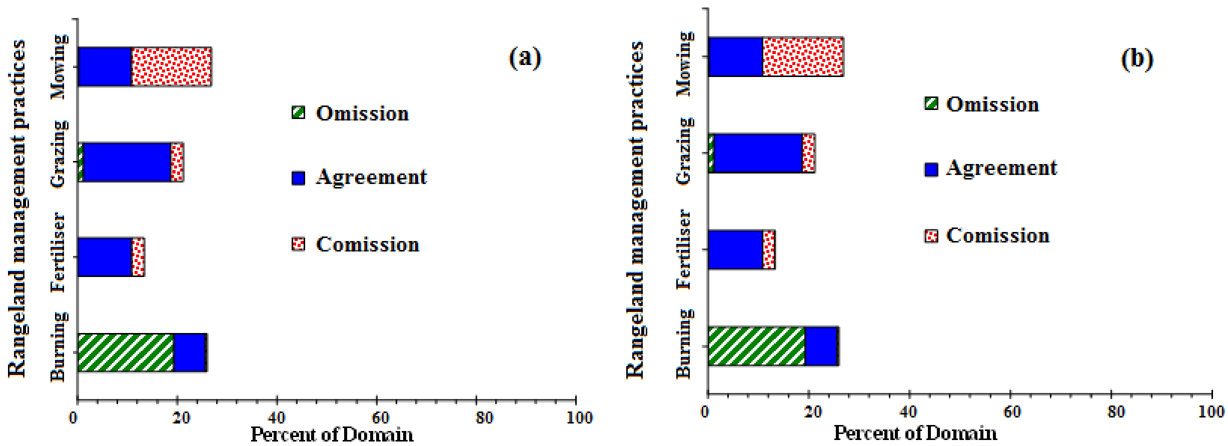

Figure 4.6: Comparing allocations of agreements and disagreements (omission disagreement and commission disagreement) between the training and testing data used in classifying grass reflectance under, mowing, grazing, fertiliser application and burning rangeland management practices using vegetation indices derived from (a) HyspIRI and (b) Sentinel-2 MSI

4.4 Discussion

In rangeland monitoring and management the challenge of discriminating grassland management practices has been lurking for quite a while from a remote sensing standing point

(Booth and Tueller 2003, Kong *et al.* 2015, Pellissier *et al.* 2015). This is because of the lack of sensors that have a high revisit frequency, bandwidths that traverse across the renowned spectral regions for characterising vegetation properties. Thus, this study sought to compare the robustness of the forth coming HyspIRI and Venµs as well as the recently launched Landsat 8 OLI and Sentinel-2 MSI sensors in discriminating grasses under different management practices i.e. mowing, grazing, fertiliser application and burning.

4.4.1 Comparison of HyspIRI, Landsat 8 OLI, Sentinel-2 MSI and Venµs data in discriminating grass under different rangeland management practices

Results demonstrated that reflectance of grass under different levels of mowing, grazing fertiliser application and burning practices can be spectrally discriminated with relatively high accuracies using simulated bands of the forth coming HyspIRI data. This could be explained by the fact that the upcoming HyspIRI sensor will provide numerous narrow spectral bands that will be sensitive to subtle differences between reflectance of grasses at different levels and different rangeland management practices that are otherwise masked out by the bands of multispectral sensors, such as Landsat 8 OLI. These results are consistent with those of Samiappan *et al.* (2010) who noted that HyspIRI simulated data retained its robustness in classification, even in adverse scenarios of discriminating mixed pixels. Although, the results of this study indicated that the spectral configurations of HyspIRI optimally discriminate different rangeland management treatments, our results also indicate a comparable performance of the spectral settings of the newly launched Sentinel-2 MSI sensor. Sentinel-2 MSI, therefore, will be a better substitute to the forthcoming hyperspectral sensor, especially to regions such as southern Africa with limited resources as well as spatial data suitable for management and monitoring of abundant grasslands.

Also, the results of this present study demonstrated that the Venµs sensor will have robust spectral settings, comparable to those of Sentinel-2 MSI considering. As in Sentinel-2 MSI, this could be explained by the 4 wavebands that are strategically located in the red edge portion of the EM spectrum. These Venµs wavebands (band 7, 8, 9 and 10) are very sensitive to chlorophyll dynamics resulting from mowing, grazing, fertiliser application and burning activities at varied levels facilitating optimal spectral classifications. In addition, the band widths of these two sensors cover approximately the same spectral regions, making their potentials in rangeland applications similar. These results are consistent with research work by Nguy-Robertson and Gitelson (2015) which demonstrated a comparable performance of the

Venµs spectral setup data to simulated Sentinel-2 and 3 sensors in mapping vegetation leaf area index. In spite of a comparable performance illustrated by the simulated Venµs data, the fact that it is micro-satellite that will provide commercial data makes it the least suitable source of spatial data for the southern African grasslands when compared to the freely available Sentinel-2A MSI data.

The results further indicated that Landsat 8 OLI simulated data was the least performing sensor in spectrally discriminating grass under mowing, grazing, fertiliser application and burning management practices. This could be attributed to Landsat 8 OLI's limited spectral resolution with broader band widths covering only the visible, NIR, and SWIR regions of the EM spectrum (Mariotto *et al.* 2013). Landsat 8 OLI has about 6 six spectral bands which could provide useful spatial information on land surface / vegetation properties, such as that of different rangeland management treatments (http://landsat.gsfc.nasa.gov/?page_id=5377). Furthermore, the bandwidths of these wavebands are too coarse (approximately 0.02mµ) to capture the subtle variations in grass reflectance grown under mowing, grazing, fertiliser and burning management practices, when compared to the other three sensors. Landsat 8 OLI does not cover the red edge portion of the EM spectrum which is known for discriminating biochemical and biophysical characteristics of vegetation. In that regard, the lack of information from the red edge region could also explain the unsatisfactory performance of Landsat 8 OLI in this study. However, work by Guo *et al.* (2003) demonstrated the utility and robustness of the Landsat 8 OLI data in spectrally discriminating biophysical and spectral properties of two types of grass under three land management practices in Kansas, which is contrary to our findings. Despite the optimal classification accuracies in discriminating two types of grasses under three land management practices in Kansas by Guo *et al.* (2003) it is important to note that the environment (precipitation, temperatures and soils) of Kansas in America where their study was conducted is different from that of Ukulinga grassland research trials in KwaZulu Natal, South Africa. Furthermore, the differences in the results obtained in this study when compared to those of Guo *et al.* (2003) could be explained by the fact that the former used Analysis of Variance (ANOVA) and Multiple Analysis of Variance (MANOVA) tests whereas in our case discriminant analysis was also utilised. Finally, the number of management practices considered in the study by Guo *et al.* (2003) were fewer when compared to those in the present study, hence the satisfactory performance of Landsat in their study. Above all, the simulated HyspIRI, Landsat 8 OLI, Sentinel-2 MSI and Venµs data demonstrated agreements in spectrally discriminating the reflectance of grasses within management practices as well as across rangeland management practices. Least performance of Landsat 8 when compared to other sensors in this study concurs with the findings of related studies, such as those of Mariotto *et al.* (2013) and Thenkabail *et al.* (2013) which indicated that the ability to detect biophysical characteristics of vegetation is lost at coarser spectral resolutions.

4.4.2 Discrimination of grasses across different rangeland management practices using simulated data

Results of this study indicate that tropical grasses subjected to different management practices can be optimally discriminated using the red edge and NIR bands (HyspIRI: 700, 740 and 780nm, and Sentinel-2 MSI: bands 5, 6, 7 and 8a). The red edge and the NIR spectral regions are known to be sensitive to high chlorophyll, biomass and cellulose concentrations (Curran *et al.* 1990, Filella and Penuelas 1994, Dash and Curran 2004, Filella *et al.* 2009, Sibanda *et al.* 2015). Grasses treated with a combination of NH4NO3 and other fertilisers could be spectrally distinguished from those that are untreated, mowed and grazed due to the higher nitrogen concentration from the fertiliser. This higher nitrogen concentration induces higher chlorophyll concentrations, leaf area index and leaf area distribution which facilitates their distinction from grasses of other rangeland management practices (Sibanda *et al.* 2015). Moreover the variations in the nitrogen contents of three levels of grass fertilisation in this study also explains the spectral discrimination of grasses under those levels. In a related study Mutanga and Skidmore Mutanga and Skidmore (2007) demonstrated that an increase in nitrogen supply to vegetation increases the shift of the red edge position towards the longer wavelengths which makes grasses with higher nitrogen concentrations to be differentiated spectral from those with less nitrogen concentrations.

Moreover, grasses that were administered with fire were also spectrally discriminated from those under mowing, and grazing. This could be explained by the post-fire high concentration of foliar nutritients, such as P and N. As mentioned above, the high concentration of chlorophyll associated with N concentrations from the ashes enables spectral discrimination of grasses under burning practices. Ferwerda *et al.* (2006) and Knox *et al.* (2011) demonstrated that although fire reduces the grasses density, it increases foliar nutrients, such as N, which also increase chlorophyll concentrations. If chlorophyll concentrations are increased in vegetation, then the discrimination of that vegetation from that with limited concentrations is inevitable (Mutanga and Skidmore 2007, Nguy-Robertson and Gitelson 2015).

Grasses grown under mowing could not be spectrally discriminated from those under grazing, fertiliser application, burning and those that are untreated ('control'). This could be attributed to a mixture of old and new grass tissues after mowing which tends to be classified as reflectance of grasses under burning and untreated native grass ('control') treatment. However our results are consistent with those of Guo *et al.* (2003) who also noted that mowed/hayed grasses could not be spectrally discriminated with high accuracies from the burning and native grasses reflectance. Contrary to our expectation, the reflectance of grasses under grazing practices were higher than grasses under mowing, burning as well as untreated ones facilitating spectral discrimination amongst the rangeland management practices. This could be explained by the fact that when livestock graze, they do not completely eat the entire plant but rather leave some stumps and stems re-sprout faster into healthier plants in comparison to grasses under other rangeland management practices aiding to their spectral discrimination at high accuracies.

Results of this study demonstrated that the grasses under various levels of mowing, grazing, fertiliser application and burning practices could be spectrally discriminated with high accuracies across all the sensors. Specifically, the spectral discrimination of grasses under the two levels of grazing and mowing in this study could be attributed to the removal of grass canopy (old mature stems and leaves) in annual and biennial burning as well as in those grasses that are mowed twice a year. This changes the grass characteristics, such as leaf angle distribution, leaf area index, which influence the grasses reflectance (Sangbum and Lathrop 2006). Mowing also alters growth and development of grass and increases its vulnerability to other stresses (Socher *et al.* 2013). On the other hand, fire administration on the grasses is a recommended tool that restores and maintains rangeland by removing moribund grasses paving way for fresh and healthier grass stems (Lü *et al.* 2012). The fresh and younger grasses on annual burning trails can then be spectrally differentiated from older ones, i.e. from triennial burning, which have a high influence of dry and dead matter. In triennial burning there is high accumulation of biomass, a higher cover of mature grass and moribund, which enables optimal spectral discriminations of grasses under this treatment from others. These results are consistent with work by Lü *et al.* (2012) which demonstrated that long term burning reduces nitrogen concentrations in grasses which then resulted in high foliar chlorophyll variations in their study conducted in China. The variation in chlorophyll concentrations due to variations in fire administration in this study could also explain the spectral discrimination of reflectance of grass under annual, biennial and triennial burning practices in this study.

4.4.3 Performance of HyspIRI and Sentinel-2 MSI derived vegetation indices in discriminating grasses under different rangeland management practices

Results of the present study, illustrate that vegetation indices performed better than individual wavebands in discriminating grass under different rangeland practices in comparison to raw bands. This may be explained by the fact that vegetation indices suppress background effects as well as atmospheric conditions which cause variability in raw wavebands (Byrd *et al.* 2014). This can result in clear and unique signals of grasses under different rangeland management practices facilitating their classification. In related studies, Thenkabail *et al.* (2013) as well as (Mutanga and Skidmore 2004) demonstrated that vegetation indices improve plant detection in vegetation studies. The results of work by Thenkabail *et al.* (2013) demonstrated that red edge and NIR vegetation indices could optimally be used to discriminate eight major world crops in various agro-ecological zones better than other indices which is consistent with the results of this study in the rangeland management.

4.5 Conclusion

Based on our results, we conclude that:

- Sentinel-2 MSI offers better classification accuracies with high agreements between training and testing data sets when compared to the HyspIRI data. We therefore conclude that the new generation spaceborne multispectral sensors (e.g., Sentinel-2 MSI) with a high spatial resolution have the potential to satisfactorily predict grass biomass across different grassland management practices.

- Mowed, grazed, fertilised as well as grasses under burning practice can be spectrally discriminated using vegetation indices and wavebands located in the red edge (HyspIRI: 700, 740 and 780nm and Sentinel-2 MSI: bands 5, 6, 7 and 8a) and NIR (HyspIRI: 700, 740 and 780nm and Sentinel-2 MSI: bands 5, 6, 7 and 8a) spectra respectively. Specifically, normalised difference vegetation indices associated with red edge significantly improve discrimination of grassland management practices.

This study indicates that the upcoming multispectral and hyperspectral sensors have a high potential of improving discrimination of grass management practices essential for optimal rangeland management purposes, a component that was lacking in the previous optical sensors. In addition, the findings of this study are an important foundation on which the longstanding challenge of understanding the influence of different management practises on the grasses at a regional scale could be attempted. Despite the need for assessing the actual data derived from these forthcoming sensors, using the simulated data our results indicate spectral information that could be useful in rangeland management. Future studies need to assess the performance of these sensors taking into account the influence of the signal-to-noise ratio, as well as the radiometric calibrations of these sensors. Furthermore, there is also need to evaluate the influence of factors, such as grass height and canopy volume in discriminating different rangeland management practices, using remotely sensed data. Overall, the given the variations in biomass across different management practices, the cheaper new multispectral sensors will be a better alternative for the accurate estimation of biomass in data scarce regions.

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Results of this study indicated that HyspIRI and Sentinel-2 MSI spectral settings optimally discriminated grasses grown under different levels of grassland management treatments. Once more, the optimal influence of red edge spectral wavebands in discriminating grasses was indicated by this study. Consequently the subsequent chapter sought to assess the performance of HyspIRI and Sentinel-2 MSI as cheaper and accurate alternative sources of spatial data for predicting grass biomass in regions limited spatial data sources such as southern Africa.

5. COMPARING THE SPECTRAL SETTINGS OF THE NEW GENERATION BROAD AND NARROW BAND SENSORS IN ESTIMATING BIOMASS OF NATIVE GRASSES GROWN UNDER DIFFERENT MANAGEMENT PRACTICES

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Comparing the spectral settings of the new generation broad and narrow band sensors in estimating biomass of native grasses grown under different management practices

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Abstract

The challenge of assessing and monitoring the influence of rangeland management practices on grassland productivity has been hampered in southern Africa, due to the lack of cheap earth observation facilities. This study, therefore, sought to evaluate the capability of the newly launched Sentinel-2 multispectral imager (MSI) data, in relation to Hyperspectral infrared imager (HyspIRI) data in estimating grass biomass subjected to different management practices, namely, burning, mowing and fertiliser application. Using sparse partial least squares regression (SPLSR), results showed that HyspIRI data exhibited slightly higher grass biomass estimation accuracies (RMSE =6.65 g/m^2, R^2 = 0.69) than Sentinel-2 MSI (RMSE = 6.79 g/m^2, R^2 = 0.58) across all rangeland management practices. Student t test results then showed that Sentinel-2 MSI exhibited a comparable performance to HyspIRI in estimating the biomass of grasslands under burning, mowing and fertiliser application. In comparing the RMSEs derived using wave bands and vegetation indices of HyspIRI and Sentinel-2 MSI, no statistically significant differences were exhibited (α = 0.05). Sentinel (Bands 5, 6 and 7) and HyspIRI (Bands 730 nm, 740nm, 750 nm, 710 nm), as well as their derived vegetation indices, yielded the highest predictive accuracies. These findings illustrate that the accuracy of Sentinel-2 MSI data in estimating grass biomass is acceptable when compared with HyspIRI. The findings of this work provide an insight into the prospects of large-scale grass biomass modelling and prediction, using cheap and readily-available multispectral data.

Keywords

Grass productivity, rangeland management, native tropical grass, remote sensing

5.1. Introduction

Grasslands biomass is vital for regulating the circulation of greenhouse gases, such as carbon, and facilitating soil development, ecosystem energy exchange and other biogeochemical cycles (Smith *et al.* 2015, Jansen *et al.* 2016). Moreover, grasslands harbour the highest number of vegetation species at a fine spatial grain. Covering an areal extent of 37% of the total land on earth and contributing about 20% of overall terrestrial productivity (Jin *et al*. 2014), grasslands are also an important stock feed, as well as a source of livelihood to a considerable population globally (Mbatha and Ward 2010, Pellissier *et al.* 2015, Sibanda *et al.* 2015). Specifically, the livelihoods of pastoralists, ranchers, livestock farmers, and rural communities hinge predominantly upon grassland health and productivity. These economic activities significantly contribute to the per capita incomes of the people. For instance, in South Africa, grasslands services produce approximately ZA R2.88 billion (Mbatha and Ward 2010). Consequently, grasslands in the semi-arid and arid areas, such as southern Africa, are being subjected to high pressure from the increased demand by escalating human, livestock and wildlife populations. The increased demand for grassland services has resulted in their degradation, as well as the disturbance of the ecosystems (Mbatha and Ward 2010). For instance, literature shows that 4.8% of South Africa has been degraded by anthropogenic activities (Fairbanks *et al.* 2000, Wessels *et al.* 2004).

Both commercial and rural farmers, as well as grassland scientists, have resorted to adopting rangeland management practices, such as mowing, burning and fertiliser application, to optimise grasslands productivity. However, these grass management treatments often alter the physical and chemical state of the grass. For instance, the frequent administration of fire on rangelands removes the moribund, increases soil nutrients and results in healthy greener grasses, with unique leaf angle distribution, leaf area index, as well as relatively lower biomass turnover. A study by Nepolo and Mapaure (2012) indicated that shorter fire regimes do not significantly influence grass biomass, but have an effect on the physio-chemical properties of grass. The fertilisation of native grasses, on the other hand, significantly affects the physio-chemical properties of grass, specifically the chlorophyll content, leaf area distribution, leaf area index, biomass, as well as forage quality. A study by Mbatha and Ward (2010) in the semi-arid savanna of South Africa showed that fertiliser application increased grass biomass from 68.9 to 79.57gm^{-2}. On the other hand, mowing and or grazing practices change grass structure and biomass content (Sibanda et al. in press). This deteriorates the palatability of grass to livestock, biogeochemical cycles, soil development and the provision of services for various anthropogenic activities (Snyman 2003, Conant 2010, Schuster et al. 2015). Consequently, farmers, rangeland managers and other stakeholders often seek new technologies, better methods and data to understand the periodical regional impact of these rangeland management practices on native grasses. Information on the effect of these grassland treatments on native grasses is vital for optimising productivity, as well as ensuring the continuous availability of the afore-mentioned grassland services. Due to limited resources, especially in the sub-Saharan Africa, such information is scarce. As a result, the effect of long-term burning mowing/grazing and fertiliser application on native grassland productivity is poorly understood (Pellegrini et al. 2015).

Remote sensing technologies, especially the cheap and readily-available space-borne sensors, offer vital information in rangeland management (Propastin 2013). For instance, it is conceived that space-borne sensors, with strategically positioned red edge wavebands, will enhance the estimation of above-ground biomass of grasses under various management practices. This is because the red edge region of the electromagnetic spectrum is critical for vegetation mapping. Specifically, the red edge region is highly sensitive to plant properties, such as chlorophyll, leaf area index and leaf angle distribution, which are all linked to biomass (Curran 1989, Clevers *et al.* 2002, Mutanga and Skidmore 2007, Ramoelo *et al.* 2014). However, previous studies that sought to estimate biomass, based on space-borne sensors in rangeland applications, used multispectral sensors, such as Moderate Resolution Imaging Spectroradiometer (MODIS), Systéme Pour l'Observation de la Terre Vegetation (SPOT VGT), normalized difference vegetation index (NDVI) (Liu *et al.* 2015) and Landsat (Archer 2004, Peterson 2005, Mundava *et al.* 2014, Xu *et al.* 2014). The spectral resolution of such sensors does not cover the red edge region of the electromagnetic spectrum, which is critical for vegetation mapping. For example, all the Landsat missions (1-8) and MODIS do not cover the red edge band of the electromagnetic spectrum. Although there are a considerable number of studies that have been conducted, based on other sensors that also cover the red edge region, such as RapidEye (Mutanga *et al.* 2015), the costs associated with these commercial sensors inhibits their utility for regional scale applications.

The remote sensing fraternity recently witnessed the launching of the space-borne Sentinel-2 A multispectral imager (MSI) (on 23rd of June 2015). The Sentinel-2 MSI has spatial resolutions of 10, 20 and 60 m. Furthermore, the 13 spectral wavebands of Sentinel-2 MSI cover the red edge region (Bands 5, 6 and 7) acquired at a swath width of 290 km. This sensor is conceived to be suitable for wall-to-wall rangeland applications (Delegido *et al.* 2011, van der Meer *et al.* 2014), such as estimating biomass of native grass species, because it is relatively cheaper. To understand the effectiveness of Sentinel-2 MSI in estimating the biomass of grass under different rangeland management treatments, there is need to compare it to other new generation sensors, such as the forthcoming Hyperspectral infrared imager (HyspIRI). HyspIRI is anticipated to offer relatively higher spectral data (i.e. 213 bands covering the red edge region) at a spatial resolution of 60 m from space. HyspIRI will offer spatial information at a larger scale (i.e. a swath width of 145 km) and at a temporal resolution of 19 days, which is conceived to be optimal for rangeland monitoring (Pellissier *et al.* 2015). Although it is widely recognised that hyperspectral sensors best estimate vegetation biomass when compared with multispectral sensors, there is a need to evaluate and compare the accuracy of cheaper new multispectral sensors with a wider swath widths, such as Sentinel-2 MSI relative to the expensive hyperspectral sensors such as HyspIRI. This will help in providing spatial data required for the effective management of rangelands in southern Africa, as well as offsetting the costs associated with remotely sensed data. The essence of this study was, therefore, to assess the robustness of the newly launched Sentinel-2 MSI spectral settings, in relation those of HyspIRI in estimating grass biomass across mowing, burning and fertiliser application treatments. Hyperspectral data from ASD field spectra were resampled to the spectral settings of Sentinel-2 MSI and HyspIRI sensors, respectively, for this study. Concisely, the objective of the study was to compare the capability of Sentinel-2 multispectral imager's (MSI) spectral settings, to those of Hyperspectral infrared imager (HyspIRI), in estimating grass biomass subjected to burning, mowing and fertiliser application.

5.2. Methods and materials

5.2.1 Study area

This study was implemented at the University of KwaZulu-Natal research farm in Pietermaritzburg, South Africa (29°24′E, 30°24′S) (Figure 5.1). The study area is characterised by a temperature range of 23 to 33^{0}C in summer and 16 to 25^{0} C in winter. Pietermaritzburg has an annual precipitation of about 694 mm, received mainly in summer. This precipitation sustains grasses, such as *Themeda triandra, Heteropogon contortus, Eragrostis plana,* *Panicum maximum Setaria nigrirostrosis* and *Tristachya leucothrix* at the farm research. The soils are generally infertile and acidic (Fynn and O'Connor 2005).

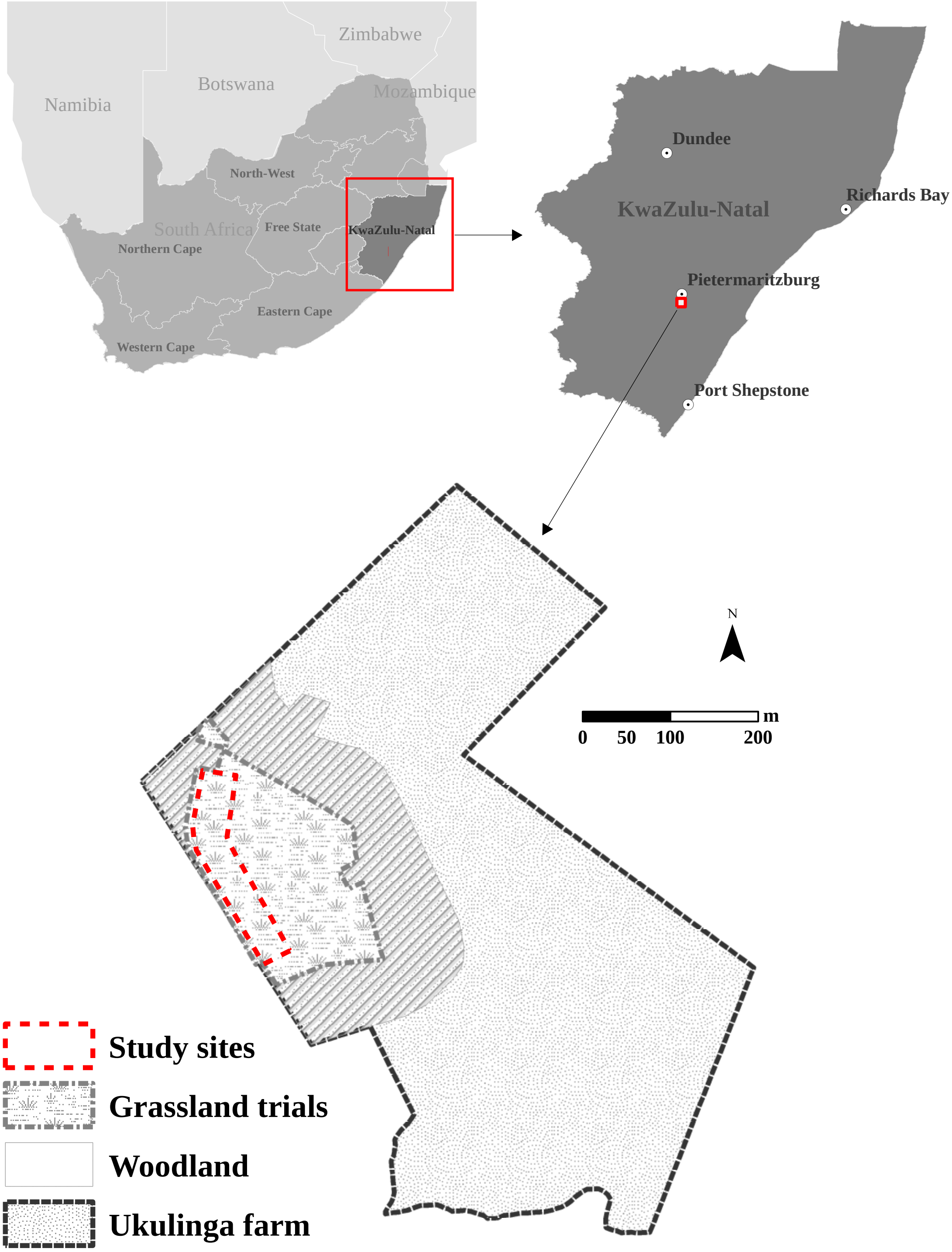

Figure 5.1: Location of the area under study

5.2.2 Grassland treatments

This study was conducted on grassland management experimental plots, established in 1950 by DJ Scott, to understand the effects of utilization and fertilisation on native grasslands (Morris and Fynn 2001). In this study, a total of 75 plots were subjected to fertiliser application, burning and mowing (Table 5.1). The mowing and burning plots were 13.7 × 18.3 m, while the fertiliser plots were 3 × 9 m in size. All the plots, (i.e. 72 plots were subjected to burning and mowing, while three plots were subjected to fertiliser applications), were occupied by native grass. In the fertiliser trials, nitrogen fertilisers were applied at three levels, combined with dolomitic lime fertiliser (lime), as well as super phosphate fertiliser (phosphorus). Specifically, ammonium nitrate [$(NH_4)(NO_3)$] was applied at 21, 42.1 and 63.2 g.m-2 (Fynn and O'Connor 2005). The initial objective of this experiment was to evaluate the effect of different rangeland management treatments on grass quality and quantity. In the burning treatments, fire is administered at three Levels. At Level one, burning is conducted in the first week of August, while at Level two, burning is done after the first spring rains and, at Level three, burning is conducted in autumn. Ultimately, fire administration in these experimental plots is conducted at annual, triennial and biennial intervals. Mowing is done at three Levels (i.e. Level one: no mowing, Level two: mowing once in August, and Level three: mowing twice in August, as well as after the first spring rain). On the other hand, in the fertiliser plots, ammonium nitrate is combined with dolomitic lime and super phosphate fertilizers and applied at four Levels. Grass fertilisation is conducted at the beginning of the growing season. To measure above-ground grass biomass, the grass was clipped and weighed in the field and a sample was taken from each plot. The samples were then taken to the laboratory for oven drying. The samples were weighed after drying, to determine the moisture content, and ultimately the dry grass biomass, referred to as ‘above-ground biomass’ in this study.

5.2.3 Remotely sensed data

To estimate the effect of burning, mowing and fertiliser application on above-ground biomass of native southern African grass, the hyperspectral data were resampled to the spectral settings of HyspIRI and Sentinel-2 MSI in this study. The grass spectral reflectance were measured in each of the experimental plots, using an Analytical Spectral Device (ASD) FieldSpec instrument. In the mowing and burning trials, 30 spectra per plot were measured, while in the fertiliser trials, 8 spectra per plot were measured, adding up to 1512 samples (Table 5.1). The ASD spectrometer measures radiation at 1.4 nm intervals, within the spectral ranges of 350 to

1000 nm, and it then measures radiation at 2 nm intervals for the region 1000 – 2500 nm. Considering that maximum radiation from the sun occurs between 10am-2pm, all reflectance were measured at this period, under clear skies. In measuring the grass reflectance, the bare fiber optic sensor connected to the ASD device was held at a nadir position approximately 1 m above the grass canopies (Abdel-Rahman *et al.* 2014, Mutanga *et al.* 2015). This resulted in a ground view of about 0.45 m in diameter, for capturing the grass reflectance at each plot. During the reflectance measurement sessions, the fiber optic cable was held away from the recorder, to avoid the effect of their clothes and a shadow on the measured grass canopy spectra. The spectral measurements were standardised at five to ten scans, using a customary white spectralon, to normalise possible variations of atmospheric conditions and irradiance (Abdel-Rahman *et al.* 2014).

Table 5.1: Reflectance samples measured on each rangeland management treatment (Sibanda et al *in press*)

Management practice	No. of plots	No. of Samples
Annual burn	12	360
Biennial burn	12	360
Triennial burn	12	360
Mowing	12	360
Fertiliser Application	9	72
Total	57	1512

A total of 1512 grass reflectance samples measured in the 57 plots were resampled to the spectral settings of Sentinel-2 MSI and HyspIRI, based on the conventional breadth of these sensors' wavebands. To derive Sentinel 2 MSI spectral bands in this study, hyperspectral data were resampled, as illustrated by Delegido *et al.* (2011). Sentinel-2 was recently launched by the European Space Agency (ESA) in June 2015, primarily for monitoring land and coastal areas (Lachérade *et al.* 2014, Laurent *et al.* 2014, van der Meer *et al.* 2014). Sentinel-2 MSI is characterised by 12 spectral wavebands, which also cover the red edge section of the electromagnetic spectrum (Wavebands 5, 6 and 7). Sentinel-2 MSI has a temporal resolution of 5 days and a swath width of 290 km, which makes it suitable for regional scale applications. The image products are scaled at a spatial resolutions of 10, 20 and 60 m, traversing through the short wavelengths region.

As mentioned earlier, Sentinel-2 MSI's spectral settings were compared to those of the National Aeronautics and Space Administration's Hyperspectral Infrared imager (HyspIRI).

HyspIRI is an upcoming mission of a space-borne satellite. This satellite is anticipated to have two instruments on board (i.e. the visible shortwave infrared (VSWIR) and the thermal infrared (TIR) multispectral scanner). The VSWIR will capture data from 0.38 to 2.5 µm (i.e. visible to the shortwave infrared) at a spatial resolution of 10, 20 and 60 m from a swath width of 153 km. Then the TIR will measure data from 4 to 12 µm at a spatial resolution of 60 m and a swath width of 600 km. The temporal resolution of VSWIR will be 19 days, while that of TIR will be five days. The high revisit frequency, broader swath width and high spectral resolution are suitable for rangeland applications at a regional scale.

5.2.4 Above-ground biomass modelling

To compare the utility of Sentinel-2 MSI in estimating the above-ground biomass of grass, relative to HyspIRI, raw bands and vegetation indices were computed in this study. Table 5.2 shows the specific calculated broad and narrow-band vegetation indices. The vegetation indices that were computed and used to estimate above-ground grass biomass in this study were chosen based on their performance as reported in literature (Anderson *et al.* 1993, Broge and Leblanc 2001, Mutanga and Skidmore 2004, Liu *et al.* 2007, Cho *et al.* 2008, Agapiou *et al.* 2012, Thenkabail *et al.* 2013).

5.2.5 Statistical analysis

First, we conducted an exploratory analysis, followed by descriptive statistics. These were conducted in Statistica version 6. Specifically, we tested whether grass biomass data significantly ($\alpha = 0.05$) deviated from the normal distribution, using the Lilliefors test. We then used analysis of variance test to establish whether above-ground grass biomass under mowing, mowing and fertiliser treatments were significantly ($\alpha = 0.05$) different. We also used the Turkeys HSD post hoc tests to explore whether there were significant differences between pairs of different grassland management practices with alpha at 0.05.

5.2.5.1 Sparse partial least squares regression (SPLSR)

Chun and Keleş's (2010) sparse partial least regression (SPLSR) was used in this study to assess the accuracy of Sentinel-2 MSI in estimating above-ground grass biomass, when compared with HyspIRI, resampled from field hyperspectral data. SPLSR transforms the variables (i.e. wavebands) into new orthogonal factors, in order to surpass multicollinearity and overfitting issues. During the transformation process, SPLSR implements sparsity and chooses out the variables (i.e wave bands and vegetation indices) that relate better to above-ground biomass. This ability makes this algorithm suitable for application on data with high collinearity, such as the HyspIRI wavebands. Furthermore, the implementation of sparsity and the selection of optimal variables make SPLSR different and better than partial least squares regression (PLSR), which does not have that capability (Chun and Keleş 2010, Abdel-Rahman *et al.* 2014). The known asymptotic consistency of the PLSR predictor changes, when the predictor variables are more than the predicted variables, whilst the opposite is true for SPLSR (Chun and Keleş 2010). In this study, our objective was to compare the accuracy of Sentinel-2 MSI remotely sensed data in estimating the above-ground biomass of grass grown under different rangeland management treatments, relative to HyspIRI data, using the SPLSR algorithm. Moreover, this study sought to identify optimal bands and indices that could be utilised in estimating biomass across all the general grassland management treatments in southern Africa. Thus, SPLSR was selected and applied in this study due to the capability of selecting optimal wavebands for estimating above-ground grass biomass.

5.2.5.2 Assessing the accuracy of above-ground grass biomass models

Leave-one-out cross-validation (LOOCV) was conducted in this study to assess the accuracy of the SPLSR models derived from Sentinel-2 MSI and HyspIRI data, as detailed in Richter *et al.* (2012). When conducting the LOOCV, the 1512 spectra samples from the 57 plots were eliminated one by one. Above-ground grass biomass estimation errors associated with specific latent components were derived through the LOOC validation procedure. The latent components that had the least estimation errors were considered to be the optimal estimation models for estimating above-ground biomass grass from different rangeland management practices. Specifically, the calculated coefficient of determination (R^2), bias, relative root mean square error (RRMSE), as in Frazer *et al.* (2011), and root mean square error (RMSE) were used in this study to evaluate the models derived, based on raw bands, as well as indices. The models of components that produced small RMSEs, high R^2 and low bias were then selected, combined and used in the final stage of above-ground grass biomass estimation. A Student's t-test was then conducted to evaluate the performance of Sentinel-2 MSI in predicting above-ground grass biomass, in relation to that of HyspIRI data. The rationale of using a Student t test was to compare the magnitude of variation in terms of performance (RMSE) between the two sensors, HyspIRI and Sentinel-2 MSI. Specifically, we tested the null hypothesis stating that there were no significant differences between the RMSEs of HyspIRI and Sentinel-2 MSI data. To identify important wavebands and indices that were most influential in estimating above-ground grass biomass, we used the loadings or variable importance (VIP) scores produced by SPLSR. Specifically, wavelengths and indices that yielded high VIP scores were selected as the most influential variables from each model, whereas those with less than zero were not selected (Abdel-Rahman *et al.* 2014). We then computed and utilised the confidence intervals of RMSEs, to test and illustrate the differences between the accuracies of the models derived from the optimal bands and indices of the two sensors.

5.2.5.3 Stages followed in modelling grass above-ground biomass

Statistical analysis for evaluating the performance of Sentinel-2 MSI's spectral resolution in estimating above-ground grass biomass relative to that of HyspIRI was conducted, based on three Levels illustrated in Table 5.2. In Level one, raw bands were used to estimate above-ground grass biomass and optimal bands identified by SPLSR were selected and used on the third Level. In the second Level, derived vegetation indices were used to estimate above-ground grass biomass and indices that produced better estimations were also selected. In the final stage, we combined the selected bands and indices from the previous Levels and estimated above-ground biomass. Figure 5.2 summarises the logic and stages followed in conducting this study.

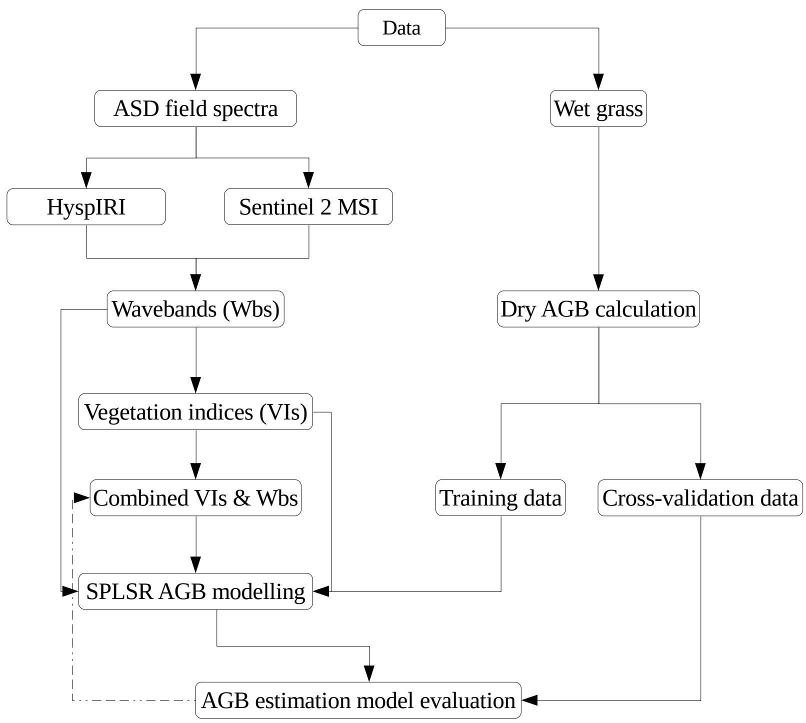

Figure 5.2: Flowchart illustrating stages followed in estimating above-ground (ABG) grass biomass in this study.

Table 5.2: Variables used in predicting above-ground grass biomass treated with different grassland management practices

Level of analysis	Data type	Sensor	Bands and indices
i	Raw bands	Hyper spectral	Band 400-1355, 1421-1809,1941-2469 (1326 bands)
		Sentinel-2 MSI	visible (Band 1, 2, 3, 4,), red edge(Band 5,6,7,8,8 a), shortwave infrared (Band 9 and 12)
ii	Vegetation Indices	Hyper spectral	NDVI, PSRI, SR 3, VOG, MCARI, MTVI, MTVI, SAVI, RDVI, MSR, REP_Guy, VREI, MRESR, MTVI, RDVI, MSR, TCARI
		Sentinel-2 MSI	NDVI
iii	Bands and indices	combination of optimal bands and Indices	

NDVI :Normalized Difference Vegetation Index, PSRI:Plant Senescent Reflection Index, SR: Simple Ratio, VOG: Volgaman Index, MCARI: Modified Chlorophyll Absorption Ratio Index, MTVI: Modified Triangle Vegetation Index, REP Guy: Red edge position Guyot, SAVI: Soil Adjusted Vegetation Index, VREI: Volgman Red Edge Index, MRESR: Modified Red Edge Simple Ratio, MTVI: Modified Triangle Vegetation Index , RDVI: Renormalized Difference Vegetation Index, TCARI: Transformed chlorophyll Absorption in Reflectance Index. The vegetation indices used in this study were selected based on their performance in previous grass biomass and grass nutrients estimation studies (Anderson *et al.* 1993, Broge and Leblanc 2001, Mutanga and Skidmore 2004, Liu *et al.* 2007, Cho *et al.* 2008, Agapiou *et al.* 2012, Thenkabail *et al.* 2013)

5.3. Results

5.3.1 Grass above-ground biomass exploratory analysis

Descriptive statistics of grass above-ground biomass derived from native grass plots, treated with different rangeland management treatments, showed that the minimum and maximum weight of grass biomass was 4.65 and 76.61 g, respectively, whereas the mean was 46.27 g. The Lilliefor test of normality results showed that above-ground grass biomass did not significantly (*p-value* > 0.05) deviate from the normal distribution. Generally, there were statistically significant differences in above-ground biomass of grass growing among different mowing, burning and fertiliser applications (*p-value < 0.05*). Turkeys HSD post hoc tests also showed that there significant differences between pairs of different grassland management treatments. For example, significant differences (α = 0.05) were observed between mowing/grazing, fertiliser application and burning treatments, based on the analysis of variance test, coupled with Tukeys HSD post hoc tests (Table 5.3).

Table 5.3: Significant differences (α =0.05) in the quantity of biomass amongst plots administered with different mowing, grazing and fertiliser treatments derived using ANOVA and Turkey's HSD post hoc test.

	D2	D3	D4	D5	D7	D8	D10	D11	C1	C2	C3	C4	C5	C7	C8	C10	C11	N1PL	N2PL	N3PL
D2	0.00																			
D3	0.98	0.00																		
D4	1.00	0.00	1.00																	
D5	0.00	0.04	0.00	0.00																
D7	0.99	0.00	0.10	0.81	0.01															
D8	0.05	0.00	0.00	0.01	0.87	0.94														
D10	0.20	0.00	0.00	0.04	0.53	1.00	1.00													
D11	0.00	0.02	0.00	0.00	1.00	0.02	0.95	0.71												
C1	1.00	0.00	0.83	1.00	0.00	1.00	0.20	0.52	0.00											
C2	0.75	0.00	1.00	0.98	0.00	0.01	0.00	0.00	0.00	0.39										
C3	1.00	0.00	0.74	1.00	0.00	1.00	0.28	0.64	0.00	1.00	0.28									
C4	0.67	0.00	0.01	0.25	0.13	1.00	1.00	1.00	0.24	0.93	0.00	0.97								
C5	0.00	0.00	0.50	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.91	0.00	0.00							
C7	0.02	0.00	0.00	0.00	0.97	0.80	1.00	1.00	0.99	0.08	0.00	0.13	1.00	0.00						
C8	1.00	0.00	0.66	1.00	0.00	1.00	0.35	0.72	0.00	1.00	0.22	1.00	0.98	0.00	0.17					
C10	1.00	0.00	0.19	0.92	0.00	1.00	0.84	0.99	0.01	1.00	0.03	1.00	1.00	0.00	0.63	1.00				
C11	0.01	0.00	0.00	0.00	0.99	0.71	1.00	1.00	1.00	0.06	0.00	0.09	0.99	0.00	1.00	0.12	0.53			
N1PL	0.00	0.95	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00		
N2PL	0.00	0.67	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	
N3PL	0.00	1.00	0.00	0.00	0.03	0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	1.00

LEGEND
0.00 Significant (α = 0.05)
1.00 Non-Significant

Note dark cells represent significant differences between pairs of treatments, while white cells illustrate non-significant differences (α =0.05). D and C1 to 11 represent different levels of burning and mowing, while N1PL- N3PL show different levels of ammonium nitrate [$(NH_4)(NO_3)$] fertiliser application.

5.3.2 Modelling grass above-ground biomass using raw bands

Prior to above-ground grass biomass estimation, correlation test results indicated that there was a strong correlation between field-measured above-ground grass biomass and Sentinel-2 MSI wavebands (Figure 5.3 (a)). There were strong correlations between grass biomass and wavebands from the visible, red edge, as well as the shortwave infrared regions covered by Sentinel-2 MSI. However, no significant (*p-value > 0.05*) correlations were established between Band 10 and above-ground biomass in this study. Similarly, when using simulated HyspIRI data, significant relationships between the wavebands from the visible, red edge, mid-infrared and shortwave sections of the electromagnetic spectrum were established (Figure 5.3 (b)).

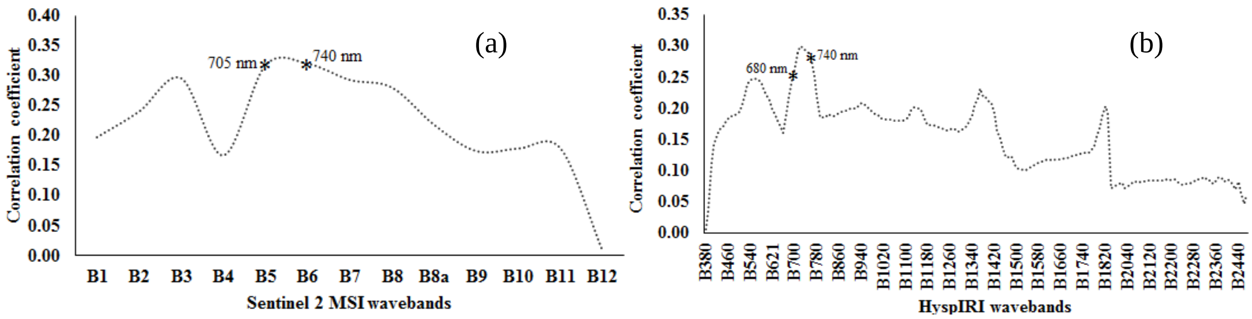

Figure 5.3: correlation coefficients derived using, (a) Sentinel-2 MSI, and (b) HyspIRI spectral settings.

Table 5.4 shows accuracies derived from estimating the biomass of native grasses under different rangeland management practices. Generally, it can be observed that the performance of simulated Sentinel-2 MSI in estimating native grass biomass was comparable to that of the simulated hyperspectral infrared imager, both when using raw bands and derived vegetation indices. For instance, it can be observed from Table 5.4 that grasses grown under biennial burning treatments (D4: RMSE = 3.92 g/m^2, R^2 = 0.67 and D5: RMSE = 4.97, R^2 = 0.61) exhibited the least estimation errors, when using Sentinel-2 MSI. On the other hand, when using HyspIRI, biennial burning treatments also showed least estimation errors (D4: RMSE = 2.74 g/m^2, R^2 = 0.84 and D5: RMSE = 3.84, R^2 = 0.77). It can be observed in Table 5.4, that the accuracies of HyspIRI were slightly less than those derived, based on Sentinel-2 MSI raw spectral bands. The most influential bands in estimating the above-ground biomass of native grass grown under different rangeland management treatments were from the red edge (Bands 5, 6 and 7), as well as shortwave infrared regions (Band 9) of the electromagnetic spectrum, based on Sentinel-2 MSI data resampled from hyperspectral data (Figure. 5.3(b)). Based on HyspIRI data simulated from hyperspectral data, the most influential bands in estimating above-ground grass biomass derived from plots treated with different rangeland management practices, were from the red edge (B710, B720, B730, B740 and B750) and the mid-infrared regions (i.e. B1660, B1670, B1680, B1690, B1700 and B1710) (Figure. 5.3(a)).

Table 5.4: Accuracies obtained in predicting above-ground biomass of grass grown under mowing, burning and fertiliser treatments

	Raw bands				Vegetation Indices			
	Sentinel-2 MSI		HyspIRI		Sentinel-2 MSI		HyspIRI	
Grass treatment	RMSE	R^2	RMSE	R^2	RMSE	R^2	RMSE	R^2
D1	6.49	0.79	4.59	0.90	4.84	0.89	3.21	0.95
D2	4.27	0.80	4.11	0.81	3.20	0.84	3.14	0.89
D3	3.97	0.73	4.00	0.72	2.52	0.76	2.77	0.87
D4	0.70	0.52	0.39	0.85	0.47	0.80	0.34	0.88
D5	1.24	0.76	0.74	0.91	1.07	0.82	0.69	0.96
D7	4.09	0.75	4.86	0.65	2.43	0.84	4.48	0.70
D8	4.16	0.87	5.04	0.81	3.81	0.84	4.89	0.82
D10	4.44	0.53	4.28	0.57	1.36	0.93	2.87	0.81
D11	6.75	0.73	6.06	0.79	4.58	0.80	5.82	0.80
C1	7.22	0.79	5.09	0.89	2.77	0.96	3.63	0.95
C2	5.42	0.90	3.06	0.96	2.94	0.96	3.91	0.95
C3	4.30	0.79	3.96	0.82	3.28	0.82	3.36	0.87
C4	3.92	0.67	2.74	0.84	2.48	0.62	2.59	0.85
C5	4.97	0.61	3.84	0.77	2.47	0.59	2.23	0.92
C7	4.33	0.55	3.58	0.69	0.78	0.67	2.92	0.85
C8	3.90	0.79	3.78	0.75	1.63	0.92	3.44	0.94
C10	3.93	0.69	2.40	0.89	3.65	0.51	3.08	0.81
C11	5.91	0.88	5.41	0.87	4.11	0.91	5.75	0.86
N1PL	6.91	0.80	5.13	0.89	5.51	0.84	2.65	0.97
N2PL	5.45	0.63	4.22	0.87	1.32	0.97	2.74	0.91
N3PL	7.75	0.67	4.41	0.89	1.93	0.97	1.05	0.96

5.3.3 Modelling grass above-ground biomass using vegetation indices

Table 5.4 shows that, when using vegetation indices derived from both Sentinel-2 MSI and HyspIRI, grass above-ground biomass estimation improved significantly, compared with the performance of the raw bands. It can also be observed from Table 5.4 that when using vegetation indices to estimate above-ground grass biomass, biennial burning treatments had the least prediction errors, compared to all other treatments. The accuracy of biennial treatment D4 improved to an RMSE of 2.48 g/m^2 and R^2 of 0.62 (RRMSE:1.09 Bias :1.369), whereas D5 also improved to an RMSE of 2.47 g/m^2 and R^2 of 0.59 (RRMSE:1.03, Bias :1.20), based on Sentinel-2 MSI derived normalised difference vegetation indices. Again, when vegetation indices derived from HyspIRI were used, the above-ground grass biomass of biennial burning treatments exhibited the least estimation errors and improved to an RMSE of 2.59 g/m^2 (R^2 = 0.85, RRMSE=0.81, Bias = -0.13) for D4, whereas D5 improved to an RMSE of 2.233 g/m^2 (R^2 = 0.92, RRMSE= 2.23 Bias = 1.37) (Table 5.4).

Results of this study showed that the optimal vegetation indices that were selected by the SPLSR algorithm, derived from Sentinel-2 MSI data were from the visible and red edge regions (B5B4 and B6B4), illustrated in Figure 5.4 (d). Again, when using HyspIRI resampled data, the optimal vegetation indices that were extracted by the SPLSR algorithm were from the red edge and the mid-infrared regions (i.e. B750B650, B730B650, B1660B710, B1660B720, B1660B730, and B1660B740), as shown in Figure 5.4 (c).

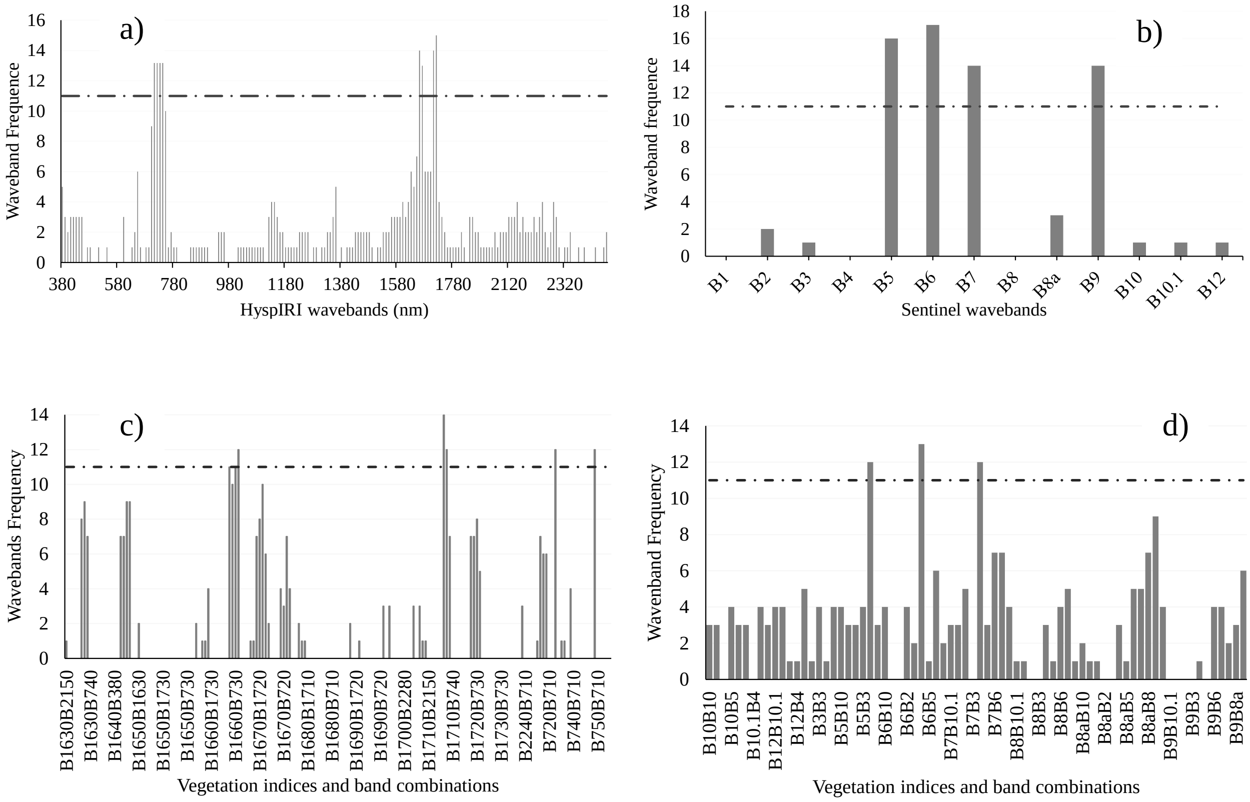

Figure 5.4: Frequency of raw wavebands and indices selected by SPLSR as optimal bands for estimating above-ground grass biomass of native grass growing under different rangeland management treatments. (a) and (b) show the frequency of HyspIRI and Sentinel-2 MSI, respectively, while (c) and (d) illustrate the frequency of vegetation indices derived, based on HyspIRI and Sentinel-2 MSI, respectively.

5.3.4 Modelling grass above-ground biomass using selected raw bands combined with selected vegetation indices, across all rangeland management practices

Prior to combining Sentinel-2 MSI and HyspIRI's optimal wavebands and indices, we tested whether the accuracies derived, using resampled Sentinel-2 MSI, were significantly ($\alpha = 0.05$) different from those derived, using HyspIRI. Figure 5.5 (a and b) illustrates that there were no statistically significant differences (*p-value* > 0.05) in terms of accuracies between using HyspIRI and Sentinel-2 MSI resampled data to estimate grass above-ground biomass, although HyspIRI's RSMEs were slightly lower than those of Sentinel-2 MSI.

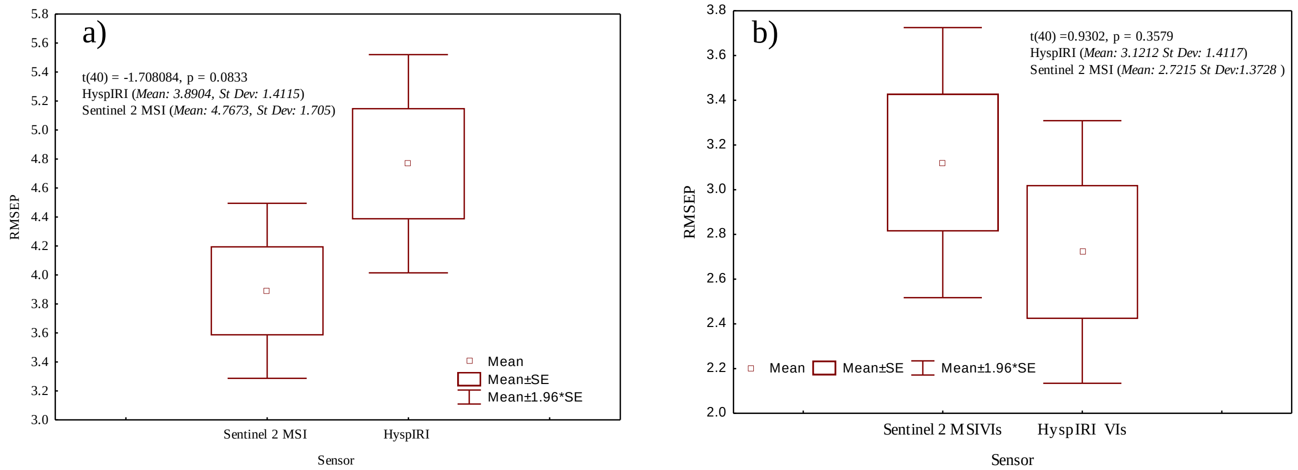

Figure 5.5: Root mean square errors from above-ground grass biomass predictions, based on (a) raw HyspIRI and Sentinel-2 MSI bands, as well as (b) vegetation indices (VIs) derived from the HyspIRI and Sentinel-2 MSI wave bands simulated from field hyperspectral data.

When bands and indices were combined, it was observed that the performance of HyspIRI and Sentinel-2 did not significantly (*p-value* > 0.05) differ. Sentinel-2 MSI had an RMSE of 6.79 g/m^2 (R^2 = 0.58 RRMSE = 61.3186 and Bias = 12.2248), whereas HyspIRI had an RMSE of 6.65 g/m^2 (R^2 = 0.69, RRMSE = 62.42 and Bias =15.67). Table 5.5 illustrates the selected optimal bands and indices for estimating above-ground grass biomass across areas with native grasses under different rangeland management treatments. Specifically, bands and indices from the visible (HyspIRI: B650), red edge (Sentinel-2 MSI: B5, B6 and HyspIRI: B730, B740, B750, B710), as well as mid-infrared (HyspIRI: B1660, B1710) portions of the electromagnetic spectrum were selected. Our results suggest an agreement between the Sentinel-2 MSI and HyspIRI. The majority of bands identified in this study, based on both HyspIRI and Sentinel-2 MSI are close to the chlorophyll absorption sections of the red edge (650-780 nm) (Table 5.5).

Table 5.5: Optimal bands and indices selected by the SPLSR algorithm in estimating grass biomass across different rangeland management treatments and their association to wavelengths with a known relationship to biomass

Centre of absorption feature	Wavelength associated with chemical influence	Chemical influence	Reference	Data	Sensor	Selected wavebands
640	Visible 640 and 660	Chlorophyll a and b				B650
550-700	Red edge 680-750	Chlorophyll a and b nitrogen, Foliage, Biomass		Raw bands	HyspIRI Sentinel-2 MSI	B730,B740,B750,B710 B5,B6
				Vegetation Indices	HyspIRI Sentinel-2 MSI	B1660B740, B1660B740,B750B650,B1710B720 B6B4
unattributed	unattributed	unattributed				B1660, B1710

5.4. Discussion

Farmers, rangeland managers and other interested stakeholders are often faced with the need to optimise the productivity of grasslands, due to their degradation and the high demand from various anthropogenic activities. Consequently, the lack of appropriate data sources that could cover a lager areal extent has been a long-standing challenge in rangeland management. In that regard, we sought to assess the utility of the new multispectral sensors (i.e. Sentinel-2 MSI) in estimating aboveground grass biomass from areas treated with different rangeland management practices, in relation to the performance of the forthcoming space-borne hyperspectral sensors, such as HyspIRI in this study.

5.4.1 Performance of Sentinel-2 MSI in estimating grass above-ground biomass, relative to the forthcoming HyspIRI

Results of this study indicated that, although the grass above-ground biomass estimations derived, based on both the raw wavebands, and vegetation indices derived from the HyspIRI sensor, were relatively higher than those derived based on Sentinel-2 MSI simulated data, the performance of Sentinel-2 MSI in this study was comparable to that of HyspIRI. Specifically, results of this study indicated that there were no statistically significant differences between above-ground grass biomass estimation accuracies (RMSE) derived from both the raw wavebands and vegetation indices of the simulated Sentinel-2 MSI and HyspIRI data. This could be attributed to the fact that both sensors cover the most strategic region, such as the red edge bands (Sentinel-2 MSI: Bands 5, 6 and 7, as well as HyspIRI band 680-780 nm), which are critical for mapping vegetation properties (Pellegrini *et al.* 2015, Sibanda *et al.* 2015). The red edge region is highly associated with numerous leaf optical properties, such as leaf angular distribution (LAD), leaf area index (LAI), chlorophyll concentration, biomass etc. (Curran *et al.* 1990, Mutanga and Skidmore 2004, Delegido *et al.* 2011, Ramoelo *et al.* 2014, Marshall and Thenkabail 2015). According to Marshall and Thenkabail (2015) and Lee *et al.* (2004), remote sensors characterised by wavebands, which cover the red edge section of the electromagnetic spectrum, perform better than those sensors without the red edge region.

On the other hand, the slightly higher accuracies exhibited, when using HyspIRI data, compared with those derived using Sentinel-2 MSI data, were expected. compared with the fewer number (13) of Sentinel-2 MSI wavebands This could be explained by the higher number (213) of wavebands from HyspIRI spectral data, when compared with the fewer number (13) of Sentinel-2 MSI wavebands (Verrelst *et al.* 2015). Furthermore, HyspIRI has a shorter band width of 10 nm, when compared to Sentinel-2 MSI (Mariotto *et al.* 2013). In that regard, narrower wave bands can detect better the subtle differences of vegetation characteristics induced by mowing, fertiliser application and burning. Hence, HyspIRI performed slightly higher than Sentinel-2 MSI. Despite the slightly higher accuracies derived using the hyperspectral sensor, specifically HyspIRI in this study, our results indicate a comparable performance from the new generation multispectral sensors, such as Sentinel-2 MSI in rangeland management applications. In a related study of evaluating Sentinel-2 MSI for Lakeshore Habitat Mapping Based on Airborne Hyperspectral Data, Stratoulias *et al.* (2015) concluded that Sentinel-2 MSI has great promise in effective vegetation mapping. Overall, these results underscore the importance of Sentinel-2 MSI as a cheaper alternative, which covers a larger swath width yet yields comparable results to HyspIRI, a commercial hyperspectral sensor.

5.4.2 Optimal bands and indices for modelling grass biomass derived from different rangeland management treatments

In the present study, raw red edge bands and red edge derived vegetation indices, from both Sentinel-2 MSI and HyspIRI were selected as optimal bands for estimating the grass above-ground biomass of native grasslands under different rangeland management treatments. Specifically, Sentinel-2 MIS's Bands 6, 5 and 7, as well as Bands B730, B740, B750, and B710 (in respective order of importance) were the most influential wavebands in estimating above-ground grass biomass in the present study. The influence of the red edge wavebands and their vegetation indices on grass biomass estimation could be attributed to the effect of rangeland management treatments on the grass. Such treatments often alter the grass optical properties, such as leaf area index, leaf angle distribution etc (Pellissier *et al.* 2015), which are linked to other physiochemical plant properties, such as biomass and chlorophyll, which are sensitive to this region of the electromagnetic spectrum. For example, the administration of nitrogenous fertiliser on native grasslands increases chlorophyll content in plants (Mutanga and Skidmore 2007). On the other hand, it is common knowledge that the red edge bands are sensitive to chlorophyll concentrations (Curran *et al.* 1990, Filella and Penuelas 1994, Cho and Skidmore 2006, Mutanga and Skidmore 2007) which, in this case, were induced by fertiliser applications, as well as plant nutrients released through burning activities. A study by Filella and Penuelas (1994) demonstrated that plants with high nitrogen fertiliser concentrations had higher chlorophyll concentrations. They also illustrated that plants with higher chlorophyll concentrations had higher LAIs and were associated with high biomass, when compared with those that were not fertilised with low chlorophyll concentrations. In a related study of tropical grass fertilisation, Johnson *et al.* (2001) illustrated that the administration of 78 kg of nitrogen fertiliser on the grass, increased forage quality by 129%, when compared to the control in their experiment.

On the other hand, mowing (grazing) reduces the leaf angular distribution, leaf area index, as well as plant moisture, which then results in a unique spectral signature in the red edge region of the electromagnetic spectrum (Pellissier *et al.* 2015). This explains the influence of red edge bands associated with optimal above-ground grass biomass estimation in the present study. Our results are consistent with those of Trenholm *et al.* (2000), which demonstrated that red edge bands, amongst others, could plausibly be used to detect chlorophyll concentration decreases associated with mowing and other stress-related features on turf grasses.

The administration of fire on native grasslands, as a rangeland management treatment, results in the reduction of biomass, as well as moribund, the rapid mineralisation of nitrogen, and an increase in phosphorus, which facilitates an increase in growth after the administration of fire (Rieske 2002, Skidmore *et al.* 2010). Specifically, Skidmore *et al.* (2010) noted that grass areas that were frequently administered with fire did not only have higher above-ground biomass, but also had high nitrogen concentrations. They also noted the influence of red edge bands (710 nm), where the grasses were administered with fire, nitrogen and chlorophyll concentrations were also high. In a related study, Rieske (2002) also illustrated the increase in grass biomass associated with high chlorophyll concentrations during the post-fire re-growth. Furthermore, Rieske (2002) noted that the post-fire regrowth grass was more sensitive to the red edge bands, when compared to other bands.

Results of this study showed that normalised difference vegetation indices, derived from Sentinel-2 MSI and HyspIRI red edge regions, greatly improved the accuracy of estimating above-ground grass biomass derived from native grass plots under different rangeland management treatments. This could be explained by the fact that the vegetation indices are derived on wavebands that are sensitive to chlorophyll levels, which are directly linked to the optical properties of grass leaves, such as the LAD, LAI, as well as biomass (Mutanga and Adam 2011, Adelabu *et al.* 2014, Marshall and Thenkabail 2015). In a related study, Marshall and Thenkabail (2015) also noted that vegetation indices derived from the red edge bands and/or region (722 nm and 758 nm, amongst others) were highly associated with crop chlorophyll, as well as the above-ground wet biomass of crops in the central valley of California, United States of America. Our results are consistent with those of Lunagaria *et al.* (2015), who also noted that vegetation indices derived from the red edge wavebands 733-736 nm were the most sensitive to leaf optical properties of two wheat varieties in Anand, India. Mutanga and Skidmore (2004), in another related study also demonstrated that red edge derives vegetation indices estimated above-ground grass biomass of tropical grasses better than other indices.

In addition, results from this work have shown that remote sensing offers a platform upon which the monitoring and management of grasslands in semi-arid and arid areas, such as southern Africa could hence be achieved, at a relatively cheaper cost. This is an important step towards grassland carbon accounting, something that is currently elusive in regions where data remains a challenge (Munyati *et al.* 2011, Kumar *et al.* 2015) .

5.5 Conclusion

This research assessed the effectiveness of the Sentinel-2 MSI spectral resolutions, compared to that of HyspIRI, the new and forth coming generation space-borne sensor, in estimating the effect of long-term burning, mowing and fertiliser application on native southern African grass biomass. The importance of red edge region coverage by a sensor, as opposed to the band width of the waveband channels of a sensor, is brought out by the results of this study. Based on the results of this study, we conclude that:

- Sentinel-2 MSI spectral resolution can estimate the above-ground biomass of grasses under different rangeland management treatments with optimal accuracies, comparable to those of HyspIRI data
- Red edge bands (Sentinel-2 MSI Bands 5, 6 and 7, as well as HyspIRI bands B730, B740, B750, and B710) and derived vegetation indices, are optimal variables for estimating the above-ground biomass across grassland areas treated with different rangeland management treatments at plausible accuracies.

However, there is still need to assess the spatial fidelity of the two sensors evaluated in this study, in the light of wall-to-wall rangeland monitoring and management applications. The established resemblances in the performance between the spectral settings of Sentinel-2 MSI and HyspIRI data suggest a great opportunity for solving the long-standing issue in rangeland management applications of limited space-borne sensors that could effectively be utilized to monitor grasslands. In that regard, the results of the present study are a foundation for coming up with an effective means of attaining spatially explicit coverage in the monitoring and management of southern African grasslands, considering the limited resources and the prevalent data scarcity. The optimal performance of these sensors is a step towards assessing the interaction between the different phenological stages of grass, long-term burning, mowing/grazing and fertiliser applications on the optical properties of native rangelands.

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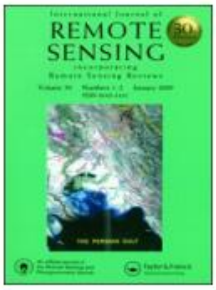
This study showed that simulated HyspIRI data outperformed the simulated Sentinel-2 MSI data in estimating grass above ground biomass of grass grown under different grassland management treatments. This study further indicated that Sentinel-2 MSI spectral resolution can estimate the above-ground biomass of grasses with optimal accuracies, comparable to those of HyspIRI data. The wavebands that exhibit higher above-ground grass biomass estimations were derived from the red edge. The findings of all the preceding chapters comprehensively underscored the optimal performance of red edge wavebands simulated from field measured spectra. However, the question of the influence of spatial fidelity in remote sensing grass quantity under complex grassland management treatments of southern Africa remained untested. Furthermore, considering the optimal performance of the Sentinel-2 MSI's spectral settings in the previous chapters, still there was a lurking need for testing the spatial fidelity and performance of the actual Sentinel-2 MSI satellite image in characterising the spatial distribution of grass quantity across the different grassland management treatment practices of southern Africa. However, during the period of study the newly launched Sentinel-2 MSI was still going through the testing phase, hence the newly launched Worldview-3 satellite data was used instead of Sentinel-2 MSI data to map the spatial distribution of different levels of mowing grazing burning fertilizer application and un-treated grasses. The preceding two chapters, therefore, test the utility of combined spectral and spatial attributes of the newly launched WorldView-3 satellite data in characterising the grass quantity.

CHAPTER SIX AND SEVEN:

UTILITY OF COMBINED SPECTRAL AND SPATIAL TECHNIQUES

6. .TESTING THE CAPABILITIES OF THE NEW WORLDVIEW-3 SPACEBORNE SENSOR'S RED-EDGE SPECTRAL BAND IN DISCRIMINATING AND MAPPING COMPLEX GRASSLAND MANAGEMENT TREATMENTS

This chapter is based on:



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Testing the capabilities of the new WorldView-3 space-borne sensor's red-edge spectral band in discriminating and mapping complex grassland management treatments

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Abstract

The majority of grasslands are overused and poorly managed, globally. The overuse of these grasslands has resulted in the adoption of numerous management treatments as interventions for optimizing their productivity. However, there are limited comprehensive frameworks and objective precedents for monitoring these grasslands and rangelands. In that regard, understanding the effect of such rangeland management treatments on grassland productivity is, therefore, a critical step towards their effective conservation and sustainable management. This study sought to test the capabilities of the WorldView-3 (WV-3) satellite data derivatives in characterizing grasslands administered with different rangeland management treatments (i.e. mowing, grazing, burning, fertilizer application, and control: no-treatment), using discriminant analysis. We compared the accuracies obtained based on WV-3 standard visible and near-infrared bands and vegetation indices (VIs), excluding and including the red-edge. Results illustrate that incorporating the strategically positioned red-edge band improves the classification accuracy of the four different rangeland management treatments from 65% to 70%. Furthermore, the overall accuracy was 73% when standard VIs were used and it increased to 78% when the red-edge VIs were added to standard VIs. Other than the red-edge derivatives, the results of this study showed that the yellow, red, NIR-1, and NIR-2 bands were the most influential. The utility of fine spatial resolution sensors such as the newly launched WV-3, with strategically positioned bands (red-edge), could offer detailed information essential for the sustainable management of grasslands.

Keywords: WorldView-3, grass biomass, SPLSR, texture, vegetation indices, grassland management treatments

6.1 Introduction

Discriminating grasslands subjected to different management practices is a critical step towards understanding the effect of grassland management treatments on grass productivity, as well as its sustainable management. However, robust frameworks and objective outlines for monitoring these grasslands are largely limited in data poor areas. In that regard there is, therefore, a growing interest and need for inventorying these grasslands, in order to obtain refined records essential in drawing effective grassland conservation policies. The typical grassland management treatments prevalent in southern Africa include mowing, burning, fertilizer application and grazing, while some are left pristine. However, discriminating such grassland management treatments is still a challenging task (Dusseux *et al.* 2014, Lehnert *et al.* 2013), due to limited expertise and financial resources (Dube *et al.* 2016). This is because grassland management treatments are characterized by small spatial extents with high similarities in a highly diverse matrix of vegetation composition. In this context, grassland management treatments inventorying efforts are hampered by limited data resources with high spatial and temporal coverage to cover the expanse grassland ecosystems yet detecting their subtle variations. Furthermore, the land partitions and multi-party ownership limit the accessibility of these grasslands for inventorying. There is, therefore, need for accurate, repeatable techniques and data sources that could offer unlimited spatial information on remote grasslands.

Earth observation (EO) data could offer valuable, timely synoptic and relatively cheap data required for effectively monitoring grasslands under heterogeneous management treatments at various scales (Robinson *et al.* 2016). This is because of the fact that earth observation sensors are sensitive to various chemical and physical plant characteristics, such as, leaf area index (LAI), leaf angle distribution (LAD) and chlorophyll content which are induced by different management treatments on the grass (Sibanda *et al.* 2015). These chemical and physical plant characteristics directly interact with the incident energy there by resulting in unique spectral signature of grasses growing under these varying management treatments. For instance, nitrogenous fertilizer application on grass increases its chlorophyll content which could make it distinct from that which is untreated based on earth observation data. Mowing alters the leaf angle distribution and leaf area index of grass, which also could make mown grasslands to be differentiated from that which is not mown, when detected using earth observation data. However, the capability of discriminating different grassland management treatments, using

Earth observation data, is not well documented despite its perceived efficiency and wide coverage when compared to field sampling techniques (Schuster *et al.* 2015).

Amongst the few studies that have been conducted based on earth observation data to map grasslands (Dusseux *et al.* 2014, Schuster *et al.* 2015, Sibanda *et al.* 2015). Franke *et al.* (2012) used RapidEye data to discriminate native grassland use intensities with overall accuracies of 86% at the foot hills of the Bavarian Alps in southern Germany. Sibanda *et al.* (2015), discriminated native grasslands under complex fertilizer applications with overall accuracies of up to 90% based on hyperspectral data in southern Africa. Although recent attempts of mapping grasslands under different management treatments have been successful, discriminating different levels of each grassland management treatment is still a challenge (Sibanda *et al.* 2015). Furthermore, a growing body of literature demonstrates that hyperspectral data has the most robust means of discriminating subtle plant variations, making it the best earth observation data for discriminating different rangeland management treatments (Adam *et al.* 2012, Adelabu *et al.* 2014, Rajah *et al.* 2015, Sibanda *et al.* 2015). However, the utility of such earth observation data is associated with numerous limitations such as high costs, unavailability, limited spatial coverage, and challenges in processing and analysis due to lack of skills, especially in sub-Saharan Africa. Hyperspectral data has high redundancy, because of its high inter-band correlations, making its analysis quite a daunting task (Dube *et al.* 2014, Gao *et al.* 2015).

Literature also shows that there has been numerous attempts of utilizing airborne (Vohland *et al.* 2005, Cho *et al.* 2007, Atzberger *et al.* 2015, Schweiger *et al.* 2015), as well as satellite-borne sensors (Ullah *et al.* 2012, Nestola *et al.* 2016) in mapping grassland ecosystems. Airborne sensors are relatively costly when compared to satellite-based platforms. This explains the current shift from in-situ and airborne sensors towards satellite-borne earth observation data in vegetation mapping. Despite a high and growing interest on the utility of satellite remotely sensed data in grassland monitoring, the characterization of different grassland management treatments based on remotely sensed data is still hampered by the coarse spatial resolution of sensors with higher temporal resolution, as well as a low temporal resolution of sensors with higher spatial resolutions. For instance, Moderate Resolution Imaging Spectroradiometer (MODIS) has a high revisit frequency of one day but it has a coarse spatial resolution of 250m and 1000m suitable only for regional applications. However, the coarse spatial resolution sensors do not capture the variability in the reflectance of different grassland management treatments at their different levels of application (Franke *et al.* 2012). Thus to date, the utility of EO data for characterizing Intra and inter variations amongst grassland management treatments at local scales is barely understood. In that regard, there is a need for high accurate earth observation data with higher spatial resolutions to detect subtle variations of grasslands under various management treatments at local levels.

Broad spectral band sensors, such as QuickBird, GeoEye and Ikonos with fine spatial resolutions less than 3m could provide spatial data required to discriminating subtle vegetation characteristics, a concept that was previously achievable based on the costly airborne and ground-based platforms only. Worldview sensors are amongst the new generation of commercial space-borne sensors with the capability of discriminating subtle vegetation characteristics at a plot management level, due to their fine spatial resolutions (Mutanga *et al.* 2015, Ramoelo *et al.* 2015, Tarantino *et al.* 2016). Specifically, Worldview sensors provide spatial data with a high spatial resolution of 2 m, and a robust spectral information (i.e. red-edge bands) critical for discriminating vegetation characteristics. For example, Marshall *et al.* (2012) tested the capability of WV-2 in discriminating the invasive Buffel grass (*Cenchrus ciliaris*) in the arid areas of Australia and obtained an overall accuracy of 60%. However, the prospects of high spatial resolution sensors in discriminating different grassland treatments remain untested and unknown.

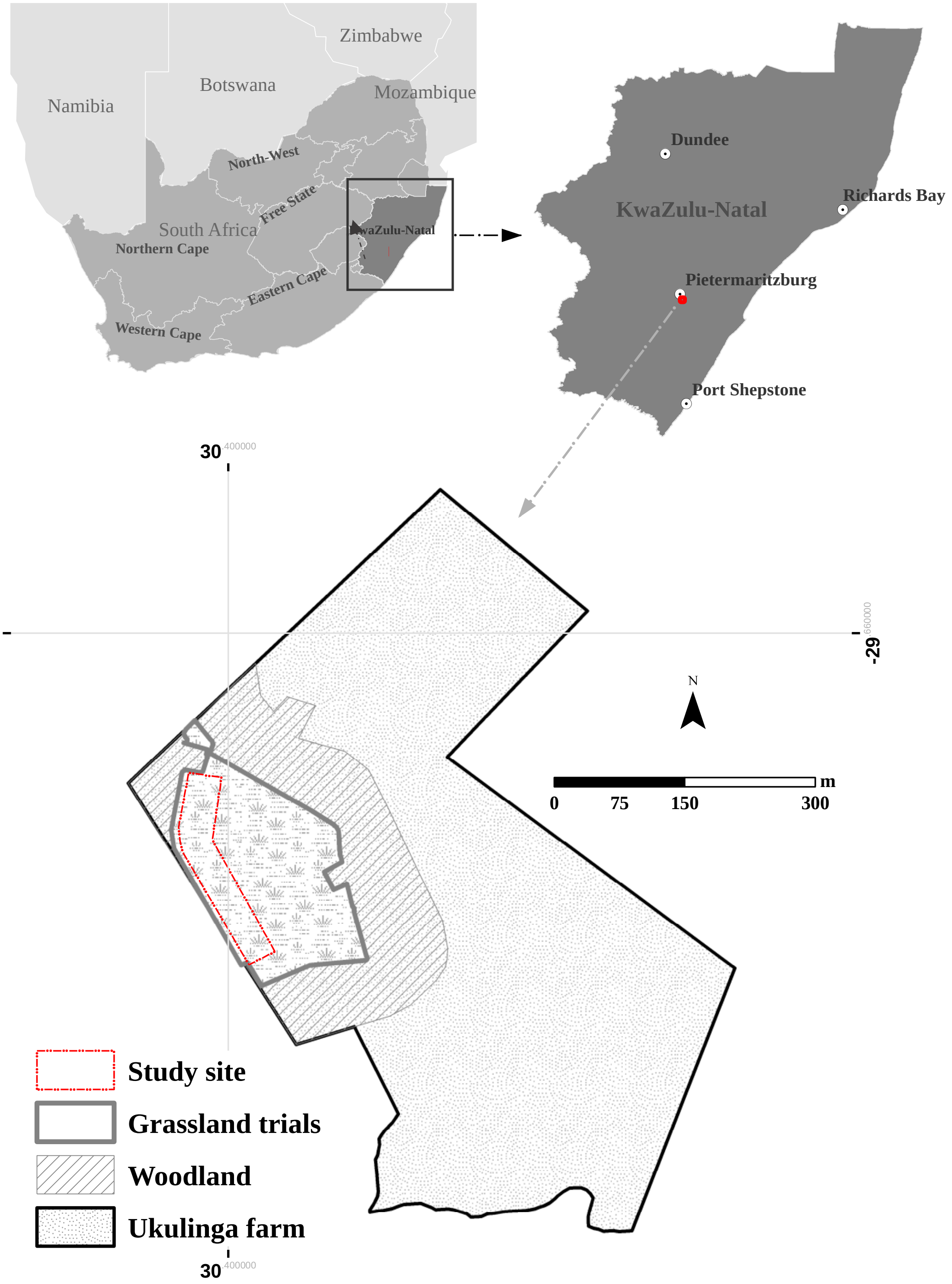
The opportunities and the promise of fine spatial resolution EO facilities with critical spectral information that could be used in discriminating different grasslands and their management treatments further increased after the successful launching of Worldview-3 (WV-3) on August 13, 2014 (Asadzadeh and de Souza Filho 2016). WV-3, a sun-synchronous sensor with a swath width of 13.1 km could be useful in discriminating different grassland management treatments at local scales. Similar to its predecessor WV-2, the newly launched WV-3 has four standard wavebands (red, green, blue and near infrared), as well as four additional multispectral bands namely the coastal, yellow, red, red-edge, and near-IR2. These additional bands have a great potential of improving vegetation mapping activities, at a management plot level. Specifically, the red-edge waveband has been renowned for its potential in vegetation discrimination activities (Curran *et al.* 1995, Mutanga *et al.* 2012, Oumar and Mutanga 2013, Peerbhay *et al.* 2014, Robinson *et al.* 2016, Tarantino *et al.* 2016). WV-3 also has eight shortwave infrared bands within a spectral range of 1195-2365nm, and twelve Clouds, Aerosols, Vapors, Ice, and Snow (CAVIS) bands which are critical in providing information for estimating atmospheric phenomena, such as aerosols and water vapor required in atmospheric correction of satellite remotely sensed data. The other advantage of WV-3 is its super spatial resolution of 0.31m for panchromatic and 1.24m for 8 bands which are critical in detecting fine differences in vegetation characteristics, such as those produced by different management treatments on grasslands. The strength of this new generation sensor lies in its 8 spectral bands coupled with a high spatial resolution that surpasses that of Aster and Landsat 8 operational land imager, which could potentially aid in accurate vegetation discrimination (Marshall and Thenkabail 2015, Asadzadeh and de Souza Filho 2016, Tarantino *et al.* 2016). It is perceived that WV-3's fine spatial spectral data, as well as derived vegetation indices could offer detailed and valuable information that will significantly improve the characterization of complex grassland management treatments and their levels of application at a farm level. Literature shows that vegetation indices also improve the detection and discrimination of vegetation characteristics such as those induced on the native grass by different management treatments (Thenkabail *et al.* 2013, Sibanda *et al.* 2015). This study, therefore, compared the accuracies of discriminating grasses grown under mowing, grazing, burning as well as fertilizer application based on the standard visible, near infrared and shortwave infrared bands and vegetation indices excluding and including red-edge of the newly launched high spatial resolution WV-3.

6.2 Methods

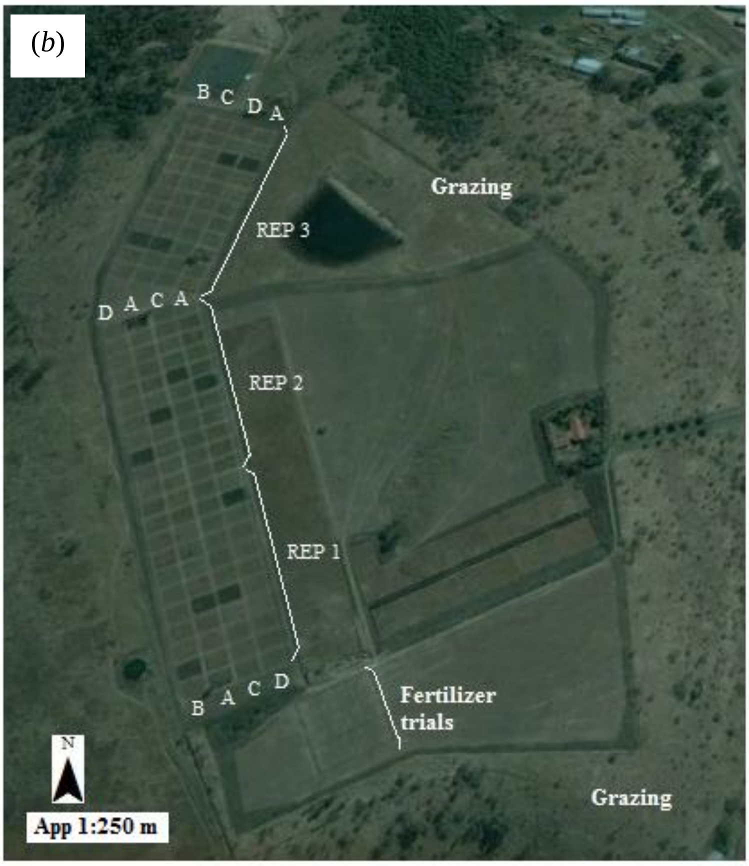
6.2.1 Study area

This study was conducted using an experiment that was initiated by JD Scott in 1950 at the University of KwaZulu-Natal research farm in Pietermaritzburg, South Africa. This experiment is still running. This experiment was intended to evaluate the impact of grass removal (burning), utilization (mowing and grazing) as well as fertilizer application on grass quality and quantity. The dominant native grass species that are prevalent in the study area are *Themeda triandra, Heteropogon contortus, Eragrotis plana, Panicum maximum, Setaria nigrirostrosis and Trystachya leaucothrix*. These grasses had an average height of approximately 40cm across all the plots. The study area is characterized by soils categorized under the acidic Westleigh group which is generally infertile. Mean monthly temperatures of approximately 27°C in summer and slightly cold winters with a minimum mean monthly temperature of 6°C are experienced in the study area.

(*a*)



Zimbabwe
Namibia
Botswana
Mozambique
North-West
Free State
South Africa
Northern Cape
KwaZulu-Natal
Eastern Cape
Western Cape
Dundee
KwaZulu-Natal
Richards Bay
Pietermaritzburg
Port Shepstone
30
-29
N
0
75
150
300
m
Study site
Grassland trials
Woodland
Ukulinga farm
30



BURNING AND MOWING TRIALS

REPLICATE 3

B4	B5	B6	B9	B2	B10	B8	B11	B7	B3	B1
C1	C2	C6	C3	C7	C9	C4	C10	C11	C5	C8
D4	D1	D5	D7	D2	D3	D11	D10	D6	D9	D8
A2	A9	A1	A7	A3	A10	A8	A5	A6	A4	A11

REPLICATE 2

D2	D7	D6	D4	D10	D5	D11	D8	D1	D9	D3
A9	A8	A2	A11	A6	A7	A5	A4	A3	A10	A1
C5	C4	C10	C2	C11	C8	C6	C1	C9	C3	C7
B8	B5	B11	B7	B10	B6	B3	B1	B2	B4	B9

REPLICATE 1

B11	B6	B9	B8	B2	B10	B1	B3	B4	B7	B5
A1	A8	A11	A2	A6	A3	A9	A4	A7	A5	A10
C8	C2	C11	C9	C6	C4	C10	C3	C5	C1	C7
D1	D8	D10	D2	D4	D11	D7	D5	D3	D6	D9

18.3 m

13.7 m

FERTILIZER TRIALS

96 N1P	**85 n1L**	**84 L**	**73 P**	**72 L**	**61 n1P**	**60 N2PL**	**49 n2**	**48 PL**	**37 N3P**	**36 n1**	**25 n2P**	**24 N3L**	**13 n2L**	**12 n3P**	**1 N1**	**REP 1**
95 N2	**86 n2P**	**83 n3**	**74 N3PL**	**71 P**	**62 n3**	**59 N1L**	**50 n3PL**	**47 N1PL**	**38 n3L**	**35**	**26 n2L**	**23 N2P**	**14 PL**	**11**	**2 N1PL**	
94 L	**87 N3L**	**82 N2**	**75 P**	**70**	**63 n1P**	**58 N2P**	**51 n2L**	**46 N1**	**39 n2**	**34 n3L**	**27 N2PL**	**22 PL**	**15**	**10 N2L**	**3 N1P**	**REP 2**
93 n1	**88 N1PL**	**81 n2P**	**76 n3P**	**69 n3**	**64 n1L**	**57 PL**	**52 N3PL;**	**45 N3P**	**40 L**	**33 P**	**28 n1PL**	**21 n1L**	**16 n2P**	**9 N3**	**4 n3PL**	
92 P	**89 n2P**	**80 n1PL**	**77 L**	**68**	**65 n1L**	**56 N1P**	**53 N3L**	**44 n2L**	**41 n3PL**	**32 N2P**	**29 P**	**20 N2**	**17 N1 L**	**8 n1P**	**5 n2PL**	**REP 3**
91 N3PL	**90 n3**	**79 N1**	**78 N2L**	**67 PL**	**66 n2**	**55 N2PL**	**54 n3P**	**43 N1PL**	**42 L**	**31 N3**	**30 n1**	**19**	**18 n3L**	**7 N3P**	**6 PL**	

Figure 6.1: (*a*) Location of Ukulinga research farm in Pietermaritzburg, KwaZulu-Natal province, (*b*) illustrates the experimental setup and design at Ukulinga research farm (Image source: Google Earth)

This study is based on one hundred and thirty-sixty 13 x 18.3m plots with native grasses growing under mowing, burning, grazing and no-treatment ('Control'), as well as six plots measuring 3 x 9m with native grasses administered with complex fertilizer treatments (Table 6.1). Native grasses in this study were fertilized at the beginning of the growing season.

Ammonium nitrate (NH4NO3) was applied at four levels (‘control’, N1LP, N2LP and N3LP) combined with dolomitic lime (Lime: L) and super phosphate (Phosphorus: P). In the removal treatments, grasses are burnt at three levels that is annually (after 1 year), triennially (after 2 years and biennially (after 3 years) while mowing is conducted at three levels (i.e. level 1: no mowing, level 2: mowing once in August and level 3: mowing twice in August and after the 1st spring rain).

6.2.2 Field surveys

To test the capability of the newly launched WV-3 we conducted a field survey on 10 February 2016. During the field campaigns, a total of 142 plots (Table 6.1) with native grasses growing under mowing, grazing, burning, fertilizer application, as well as no-treatment were surveyed. Prior to conducting the field survey, we created a shapefile of all the plots where the experiment was conducted. The plots-shapefile was then used in a geographic information system (ArcGIS 10.2) to randomly generate twenty sampling points per plot (Figure 6.1 (*b*) and Table 6.1). The minimum distance between each sampling was set to 2m. A minimum distance of two meters was chosen following the spatial resolution of the WorldView-3 satellite image. A hand-held Trimble GeoXH 6000 global positioning system with a sub-meter accuracy was used to navigate to these sample points prior to the classification process. The point map was later overlaid with the remotely sensed data to derive spectral signatures of each grassland management practice at each point.

Table 6.1: Descriptive statistics of the sampled plots

Treatment	Plot description	No. of Samples	No. of plots
Control	A1, B1, C1 & D1	240	12
Burning	A2-9, B2-9, C2-9 & D2-9	1920	96
Mowing	A10-11, B10-11, C10-11 & D10-11	480	24
Fertiliser	Fertiliser	120	6
Grazing	Grazing	80	4
Total		2840	142

6.2.3 Remotely sensed data

A cloudless level-1 WV-3 image acquired on 16 February 2016 was used in this study to evaluate the strength of this earth observation instrument in discriminating grasses growing under complex management treatments. The sensor of the WV-3 satellite is characterized by eight multispectral bands (i.e. costal blue at 400-450nm, blue at 450-510nm, green at 510-580nm, yellow at 585-625, red at 630-690nm, red-edge at 705-745nm) and two near infrared bands which are overlapping at 770-895nm and 860-1040nm. All these bands had a spatial resolution of 1.24 m. Prior to any analysis, the atmospheric correction was conducted based on the Fast Line of Sight Atmospheric Analysis of Spectral Hypercubes (FLAASH) using parameters that were provided with the image. The FLAASH analysis was conducted after converting the image into radiance (Envi 2009). Then after, the image was geometrically corrected, using ten locations measured using hand-held Trimble GeoXH 6000 global positioning system with a sub-meter accuracy. The first order polynomial transformation and nearest-neighbor resampling technique was then used to resample the image. As highlighted before, the preprocessed image was then overlaid with the point map to derive spectral signatures that were used for statistical analysis. The spectral signatures were saved in a table format and exported to Microsoft excel. Specifically, standard WV-3 bands and possible normalized difference vegetation computed from all the wavebands (including the red-edge computed Normalized Difference Indices (NDVIre)) were used to discriminate spectral reflectance of grasses growing under different management treatments.

6.2.4 Statistical data analysis

6.2.4.1 Analysis of variance

Prior to any statistical analysis, the data was tested for normality based on the Kolmogorov Simonov test. The null hypothesis tested was that the data did not significantly ($\alpha = 0.05$) deviate from the normal distribution. Specifically, spectra and vegetation indices data from each grassland management treatments were tested for normality, while those that significantly deviated from the normal distribution were log-transformed. Consequently, analysis of variance test was conducted to test whether there were significant differences in the reflectance of grasses growing under different management treatments. Tukey's honest significant differences post hoc test was used to establish the influence of different management treatments on the reflectance of native grasses.

6.2.4.2 Discriminant Analysis

The Discriminant Analysis algorithm was utilized in assessing the capability of WV- 3 in discriminating reflectance of grasses grown under different rangeland management treatments. Prior to the application of discriminant analysis, the data was randomly split into training (70%) and testing (30%) data. More specifically, we randomly split the samples within individual treatments considering the minimal distances (> 5 m) between samples in order to avoid the potential problem of spatial autocorrelation. Discriminant analysis aggregates wavebands into components also known as latent factors. The impact of these latent factors is measured using scores known as Eigen vectors or variable scores. Consequently, the most effective latent factors in discriminating grass reflectance in this study were those that had the highest scores. Furthermore, we conducted Box test (Chi-square asymptotic approximation), Box test (Fisher's F asymptotic approximation), Mahalanobis distances, Wilks's Lambda test (Rao's approximation) and Kullback's test to examine the magnitude of variation within class covariance matrices as in Sibanda *et al.* (2016) . All discriminant analysis computations were conducted using XLSTAT embedded on Microsoft Excel 2013 platform. The most important results that are derived from discriminant analysis in XLSTAT are confusion matrices that are cross-validated based on the testing data (30%).

6.2.4.3 Accuracy assessment

To assess the accuracy in this study, we employed summary parameters proposed by Pontius Jr and Millones (2011), as well as classification overall accuracies. These parameters are the quantity disagreement and allocation disagreement. The quantity disagreement is the sum of mismatches between the training (70%) and the testing (30%) data of each grassland management practice while allocation disagreement is the quantification of mismatches between the column-total of a class and its row total on the confusion matrix derived from XLSTAT. We then compared the quantity and allocation disagreements, as well as the overall accuracies derived using (ii) standard bands excluding and including red-edge bands (ii) vegetation indices derived using standard bands excluding and including red-edge bands and (iii) combined bands and indices of the newly launched WV-3.

6.3 Results

6.3.1 ANOVA results

The mean spectral signatures exhibited by grasses growing under different grassland management treatments derived from WV-3 using ANOVA are illustrated in Figure 6.2. It can be observed that based on WV-3, the spectral signatures of grasses could be significantly (α = 0.05) differentiated across the entire multispectral bands except for the red-edge band (Table 6.2). However, WV-3 wavebands 5 (red at 630-690nm) and 7 (NIR1 at 770-895nm) exhibited highest significant differences (α = 0.01) across all WV-3's multispectral wavebands.

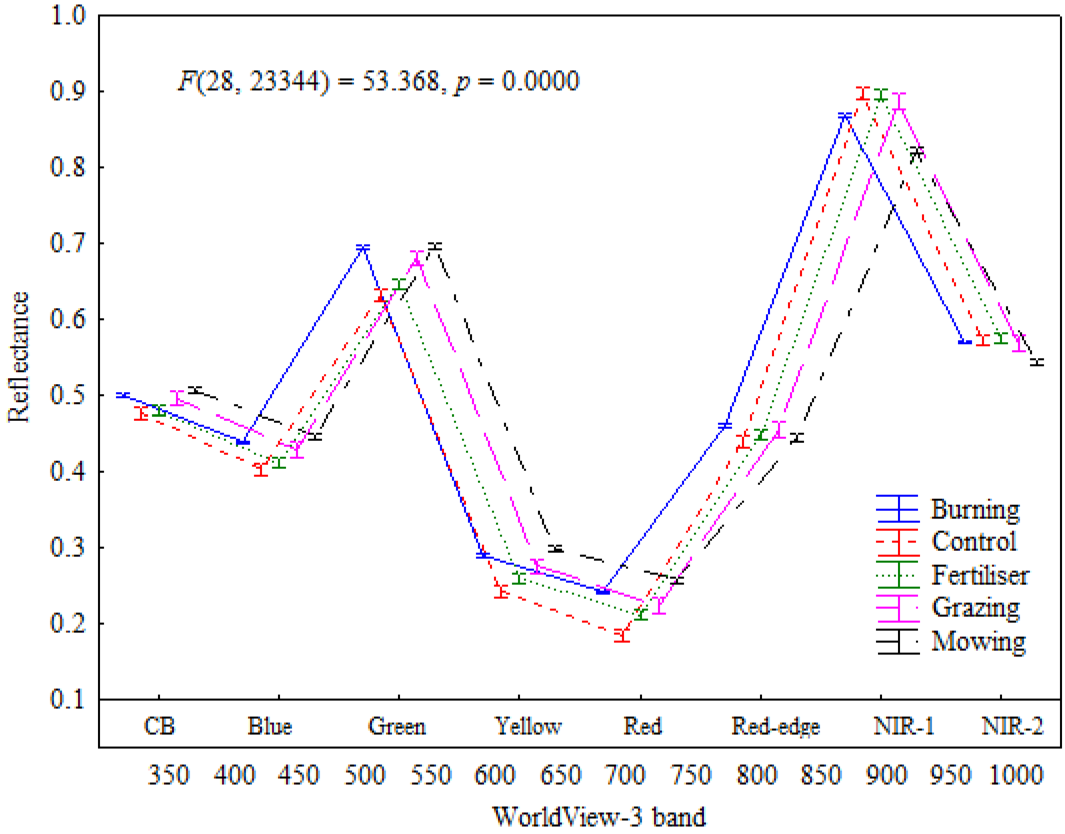


Figure 6.2: WorldView-3 derived mean reflectance of grasses treatments grown under different management treatments. CB means Coastal blue and NIR means near infrared

Table 6.2: Significant differences between spectral signatures of grass growing under different grassland management treatments based on ANOVA and Tukey's HSD post hoc test

	Treament	Burning	Burning	Burning	Burning	Burning	Burning	Burning	Burning	Control	Control	Control	Control	Control	Control	Control	Control	Fertiliser	Fertiliser	Fertiliser	Fertiliser	Fertiliser	Fertiliser	Fertiliser	Fertiliser	Grazing	Grazing	Grazing	Grazing	Grazing	Grazing	Grazing	Grazing	Mowing	Mowing	Mowing	Mowing	Mowing	Mowing	Mowing	Mowing
Treatment	**Band**	1	2	3	4	5	6	7	8	1	2	3	4	5	6	7	8	1	2	3	4	5	6	7	8	1	2	3	4	5	6	7	8	1	2	3	4	5	6	7	8
Burning	1		0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.63	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Burning	2	0.00		0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.60	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.42	0.00	0.00	0.00	0.21	0.00	0.00	0.00	0.72	0.00	0.00
Burning	3	0.00	0.00		0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.70	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00
Burning	4	0.00	0.00	0.00		0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.68	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.38	0.00	0.00	0.00	0.00
Burning	5	0.00	0.00	0.00	0.00		0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.37	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Burning	6	0.00	0.00	0.00	0.00	0.00		0.00	0.00	0.06	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.32	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Burning	7	0.00	0.00	0.00	0.00	0.00	0.00		0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.15	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Burning	8	0.00	0.00	0.00	0.00	0.00	0.00	0.00		0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Control	1	0.00	0.00	0.00	0.00	0.00	0.06	0.00	0.00		0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.43	0.00	0.00	0.00	0.00	0.30	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Control	2	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00		0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Control	3	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00		0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.57	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Control	4	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00		0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.24	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.69	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.20	0.00	0.00	0.00
Control	5	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00		0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Control	6	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00		0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.93	0.00	0.00	0.00	1.00	0.00	0.00	0.00	1.00	0.00	0.00
Control	7	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00		0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Control	8	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00		0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Fertiliser	1	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00		0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.79	0.00	0.00	0.00	0.00	0.03	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Fertiliser	2	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00		0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.68	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Fertiliser	3	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.57	0.00	0.00	0.00	0.00	0.00	0.00	0.00		0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Fertiliser	4	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.24	0.00	0.00	0.00	0.00	0.00	0.00	0.00		0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.89	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00
Fertiliser	5	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00		0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.99	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Fertiliser	6	0.00	0.60	0.00	0.00	0.00	0.32	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00		0.00	0.00	0.00	0.37	0.00	0.00	0.00	1.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	1.00	0.00	0.00
Fertiliser	7	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00		0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Fertiliser	8	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00		0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Grazing	1	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.43	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.79	0.00	0.00	0.00	0.00	0.00	0.00	0.00		0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Grazing	2	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.68	0.00	0.00	0.00	0.37	0.00	0.00	0.00		0.00	0.00	0.00	0.16	0.00	0.00	0.00	0.43	0.00	0.00	0.00	0.66	0.00	0.00
Grazing	3	0.00	0.00	0.70	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00		0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.57	0.00	0.00	0.00	0.00	0.00
Grazing	4	0.00	0.00	0.00	0.68	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.89	0.00	0.00	0.00	0.00	0.00	0.00	0.00		0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.04	0.36	0.00	0.00	0.00
Grazing	5	0.00	0.00	0.00	0.00	0.37	0.00	0.00	0.00	0.00	0.00	0.00	0.69	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.99	0.00	0.00	0.00	0.00	0.00	0.00	0.00		0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Grazing	6	0.00	0.42	0.00	0.00	0.00	1.00	0.00	0.00	0.30	0.00	0.00	0.00	0.00	0.93	0.00	0.00	0.03	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.16	0.00	0.00	0.00		0.00	0.00	0.00	1.00	0.00	0.00	0.00	1.00	0.00	0.00
Grazing	7	0.00	0.00	0.00	0.00	0.00	0.00	0.15	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00		0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Grazing	8	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00		0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01
Mowing	1	0.63	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00		0.00	0.00	0.00	0.00	0.00	0.00	0.00
Mowing	2	0.00	0.21	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.43	0.00	0.00	0.00	1.00	0.00	0.00	0.00		0.00	0.00	0.00	1.00	0.00	0.00
Mowing	3	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.57	0.00	0.00	0.00	0.00	0.00	0.00	0.00		0.00	0.00	0.00	0.00	0.00
Mowing	4	0.00	0.00	0.00	0.38	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.04	0.00	0.00	0.00	0.00	0.00	0.00	0.00		0.00	0.00	0.00	0.00
Mowing	5	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.20	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.36	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00		0.00	0.00	0.00
Mowing	6	0.00	0.72	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.66	0.00	0.00	0.00	1.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00		0.00	0.00
Mowing	7	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00		0.00
Mowing	8	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	

Legend

0.90	Non-Significant
0.04	Significant (alpha = 0.05)

Note: White cells illustrate nonsignificant differences ($\alpha = 0.05$), while dark cells portray significant differences between the spectral signatures of mowing grazing fertilizer application burning and control treatments (untreated).

6.3.2 Classification using WV-3 traditional bands.

Table 6.3 illustrates the performance of WV -3 selected standard bands (excluding red-edge), all wavebands (including red-edge), vegetation indices derived from the two categories as well as a combination of wavebands and indices in classifying grass growing under different management treatments. In general, when using standard wavebands, the spectral discrimination between burning and mowing exhibited an overall accuracy of 0.73, while discriminating between different levels of burning exhibited the lowest overall classification of 0.34. In comparison, the highest overall accuracies derived using standard bands combined with the red-edge band were obtained in discriminating grass grown under mowing from those grown under fertilizer applications (0.85) while spectral discrimination of grass under different burning levels exhibited the lowest overall accuracy of 0.51. It can be observed that when red-edge bands were included in classifying grasses growing under different management treatments, classifications considerably improved. For example, discrimination of grasses growing under different levels of fertilizer application, burning and mowing when the red-edge band was included increased from an overall accuracy of 0.64 to 0.76, 0.34 to 0.51, 0.44 to 0.56, respectively (Table 6.3). In addition, when the red-edge band was included the overall accuracy slightly improved from 0.65 to 0.70. The most frequently selected wave bands derived from latent factors with the highest Eigen values in this section of analysis included wave band 4 (yellow), 5 (red), 7 (NIR1), 8 (NIR2) and (6 red-edge). The inclusion of the red-edge band contributed an average of 14% increase in the overall classification accuracies from those derived using only the standard bands.

6.3.3 Comparing classification based NDVI compared NDVIre

When standard band vegetation indices were used, the discrimination between grass under mowing and fertilizer application attained the highest overall accuracy of 0.88, while classification between different levels of burning exhibited the lowest over accuracy of 0.54. In contrast, the highest overall classification accuracies were obtained in discriminating between grass growing under mowing and fertilizer application (0.96) treatments, based on red-edge and standard wavebands derived vegetation indices. It can also be observed that when WV-3 NDVIre was used, overall classification accuracies improved by an average of 4%. For instance, it can be observed in Table 6.3 that the overall accuracies obtained in discriminating between reflectance of grass growing under burning and grazing, burning and fertilizer application, as well as grazing and fertilizer application increased from 0.83 to 0.91, 0.87 to 94 and 0.69 to 0.78 respectively, based on the vegetation indices derived, using all wavebands (including the red-edge). In summary, all discriminations based on WV-3 vegetation indices (excluding red-edge) increased by an average of ~3% from accuracies obtained using wavebands only. A considerable increase of ~7% was also observed when red-edge indices were included. Consequently, the frequently selected indices were derived using the red-edge, the NIRs and the red wavebands in this study.

6.3.4 Classification of rangeland management treatments using a combination of optimal vegetation indices and bands

Figure 6.3 illustrates the sensitivity of WV-3 bands and vegetation indices to the variation in the reflectance of grass growing under different grassland management treatments. The variables that were highly sensitive were red-edge and yellow wave bands as well as their derived vegetation indices (Figure 6.3). When the optimal WV-3 bands and indices were combined, grasslands were better discriminated to higher accuracies, when compared to those derived using only vegetation indices or wavebands. The overall accuracies obtained in discriminating between grass growing under burning and grazing, burning and fertilizer application, as well as grazing and fertilizer application based on combined data increased from 0.91 to 0.92, 0.94 to 96 and 0.78 to 0.81 using vegetation indices derive using all (red-edge included) wavebands. The combination of optimal bands and vegetation indices including red-edge bands increased the overall accuracies by an average of 1%.

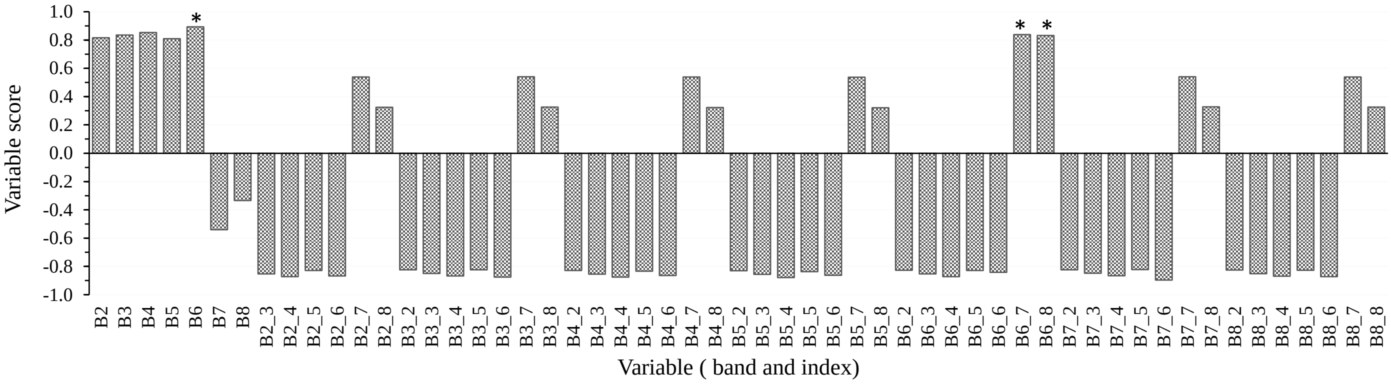


Figure 6.3: Sensitivity of WV-3 derived vegetation indices and bands in discriminating grazing, mowing, burning, fertilizer application treatments. Variables scores that are lower (closer to zero and below) are the least sensitive to the grass under different treatments, while those with positive scores are the most influential. The asterisk indicates the most influential variables, while B2 or B4_2 represents band 2 or index derived from band 4 and 2.

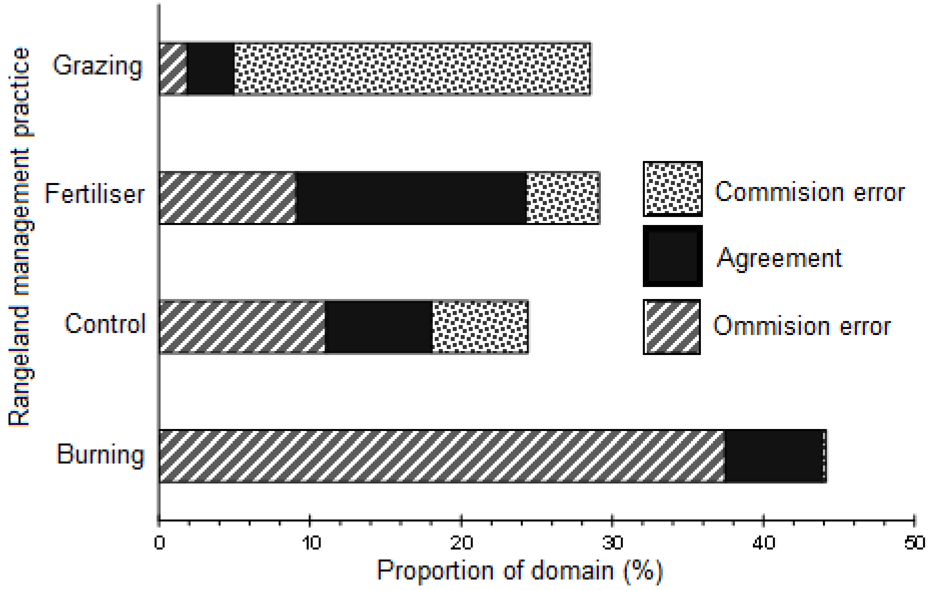
Table 6.3: Classification accuracies of grasses grown under different rangeland management treatments based on the Worldview-3 bands and vegetation indices. UA means User's accuracy, PA represents Producer's accuracy while OA represents Overall accuracy.

Analysis Stage	Classification	Treatment	**Standard bands No Red-edge**			**Standard bands & Red-edge**			**Standard bands No Red-edge VIs**			**Standard bands & Red-edge VIs**			**All Bands and All VIs**		
			UA	PA	OA	UA	PA	OA	UA	PA	OA	UA	PA	OA	UA	PA	OA
		N1LP	0.68	0.74		0.71	0.83		0.80	0.92		0.78	0.97		0.81	1.00	
	Fertiliser	N2LP	0.50	0.56	**0.64**	0.71	0.69	**0.76**	0.61	0.70	**0.77**	0.69	0.71	**0.80**	0.74	0.78	**0.84**
		N3LP	0.71	0.82		0.83	0.75		0.83	0.75		0.90	0.75		0.86	0.76	
		Annual	0.16	0.15		0.34	0.43		0.24	0.38		0.38	0.49		0.35	0.48	
2	Burning	Biennial	0.39	0.42	**0.34**	0.60	0.52	**0.51**	0.57	0.56	**0.54**	0.67	0.56	**0.56**	0.67	0.55	**0.57**
		Triennial	0.46	0.34		0.52	0.54		0.70	0.58		0.56	0.61		0.56	0.60	
		C10	0.34	0.29		0.39	0.47		0.42	0.47		0.44	0.46		0.57	0.47	
	Mowing	C11	0.55	0.51		0.70	0.63		0.72	0.67		0.65	0.64		0.65	0.75	
		D10	0.41	0.43	**0.44**	0.49	0.53	**0.56**	0.44	0.49	**0.57**	0.49	0.59	**0.58**	0.61	0.62	**0.65**
		D11	0.55	0.49		0.63	0.57		0.65	0.58		0.70	0.59		0.74	0.64	
	Grazing	Grazing	0.88	0.59		0.99	0.69		0.99	0.70		0.99	0.74		0.89	0.77	
		Control	0.21	0.75	**0.60**	0.21	0.92	**0.71**	0.22	0.87	**0.72**	0.40	0.94	**0.75**	0.57	0.76	**0.77**
	Burning vs Mowing	Burning	0.87	0.72		0.87	0.83		0.93	0.85		0.94	0.85		0.95	0.88	
		Mowing	0.80	0.78		0.24	0.79		0.40	0.61		0.49	0.69		0.64	0.75	
		control	0.22	0.72	**0.73**	0.81	0.81	**0.79**	0.86	0.98	**0.83**	0.88	0.98	**0.86**	0.89	0.99	**0.89**
	Burning vs Grazing	Burning	0.88	0.75		0.88	0.85		0.99	0.96		1.00	0.96		0.99	0.96	
		Grazing	0.58	0.16		0.68	0.15		0.21	0.44		0.17	0.33		0.23	0.36	
		control	0.10	0.50	**0.60**	0.12	0.63	**0.80**	0.74	0.74	**0.83**	0.73	0.74	**0.91**	0.73	0.76	**0.92**
	Burning vs Fertilisation	Burning	0.68	0.66		0.88	0.87		0.86	0.96		0.99	0.97		1.00	0.97	
		Fertilisation	0.26	0.49		0.69	0.63		0.80	0.91		0.80	0.89		0.84	0.95	
3		Control	0.51	0.32	**0.61**	0.47	0.64	**0.81**	0.85	0.73	**0.87**	0.79	0.84	**0.94**	0.86	0.88	**0.96**
	Mowing vs Grazing	Mowing	0.80	0.74		1.00	0.94		0.89	0.94		0.99	0.96		1.00	0.97	
		Grazing	0.02	0.17		0.02	0.17		0.27	0.48		0.37	0.58		0.37	0.58	
		Control	0.75	0.58	**0.61**	0.95	0.68	**0.82**	0.85	0.72	**0.84**	0.85	0.75	**0.89**	0.85	0.74	**0.91**
	Mowing vs Fertilisation	Mowing	0.70	0.70		0.90	0.90		0.95	0.93		0.99	0.99		1.00	1.00	
		Fertilisation	0.55	0.61		0.79	0.94		0.91	0.95		0.93	0.94		0.90	0.96	
		Control	0.58	0.51	**0.62**	0.83	0.76	**0.85**	0.84	0.83	**0.88**	0.93	0.91	**0.96**	1.00	0.88	**0.97**
	Grazing vs fertilisation	Grazing	0.10	0.35		0.10	0.50		0.19	0.59		0.20	0.92		0.27	0.88	
		Fertilisation	0.72	0.63		0.84	0.76		0.89	0.78		0.92	0.90		0.95	0.87	
		Control	0.64	0.48	**0.56**	0.76	0.58	**0.67**	0.73	0.51	**0.69**	0.92	0.65	**0.78**	0.91	0.72	**0.81**
	All treatments (pooled)	Burning	0.77	0.69		0.81	0.70		0.88	0.82		0.91	0.83		0.91	0.84	
		Control	0.52	0.54		0.51	0.60		0.71	0.72		0.76	0.70		0.74	0.74	
4		Fertilisation	0.68	0.60		0.70	0.68		0.77	0.79		0.75	0.91		0.84	0.90	
		Grazing	0.12	0.24		0.13	0.25		0.21	0.32		0.23	0.32		0.31	0.42	
		Mowing	0.21	0.59	**0.65**	0.25	0.61	**0.70**	0.43	0.60	**0.73**	0.45	0.58	**0.78**	0.46	0.59	**0.80**

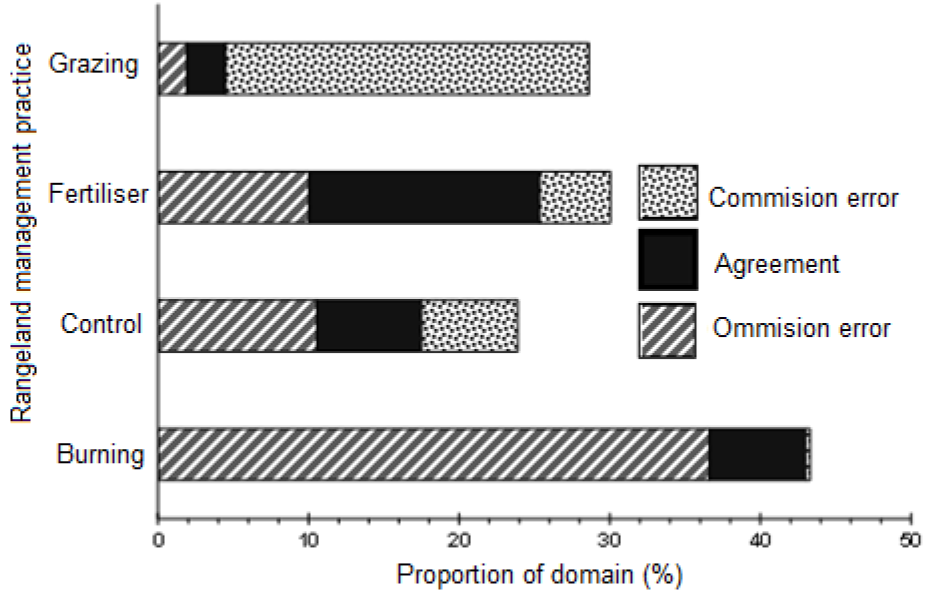
NB N1LP, N2LP, N3LP represents Nitrogen (Ammoniun nitrate) fertiliser at three levels combined with dolomitic lime (L) and super phosphorus (P) fertilisers,while C10 and C11 as

Figure 6.4 shows a comparison of allocations of agreement and disagreement between the testing and training data. It can be observed that when using combined data, the allocations of agreement are higher than when discriminations are conducted using only optimal wavebands *a* and vegetation indices. Figure 6.5 illustrates the spatial distribution of different rangeland management treatments derived using the red-edge and other selected optimal bands and NDVI indices. It can be observed that based on WV-3 red-edge, yellow and NIR wavebands bands and indices, the spatial variation of different grassland management treatments was well detected (overall accuracy 80%). The fertilization treatments located on the southern portion of the grassland trials were optimally detected relative to all the other treatments (Figure 6.5). Overall, the spatial distribution of grazing, burning, mowing and 'control' treatments were fairly detected as illustrated in Figure 6.5.

(*a*)



(b)



(c)

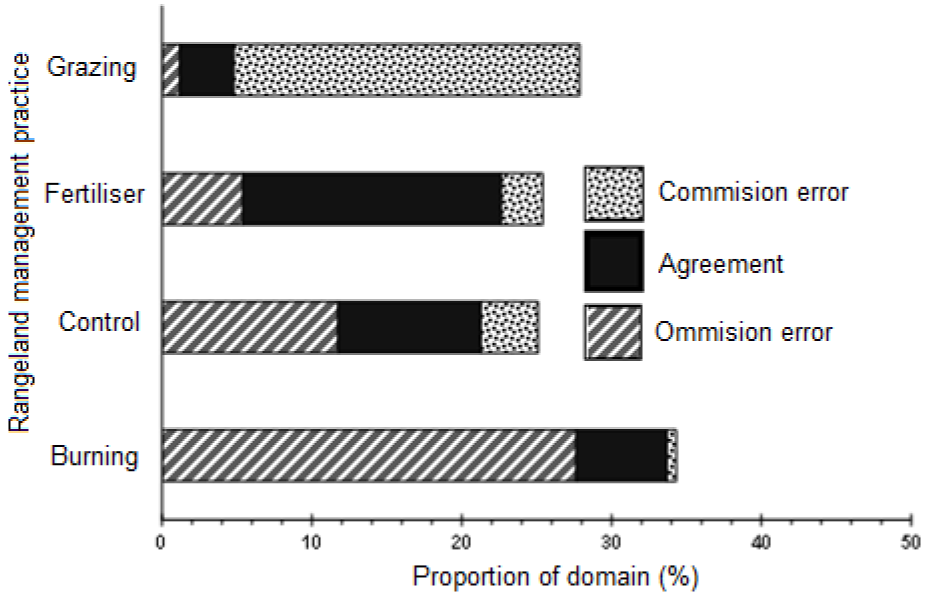


Figure 6.4: A comparison of allocations of agreements and disagreements between training and testing data used in classifying reflectance of grasses growing under mowing, grazing fertilizer and burning rangeland treatments using Worldview 3 data (*a*) without red-edge bands (*b*) with red-edge bands included and (*c*) a combination of raw bands and vegetation indices.

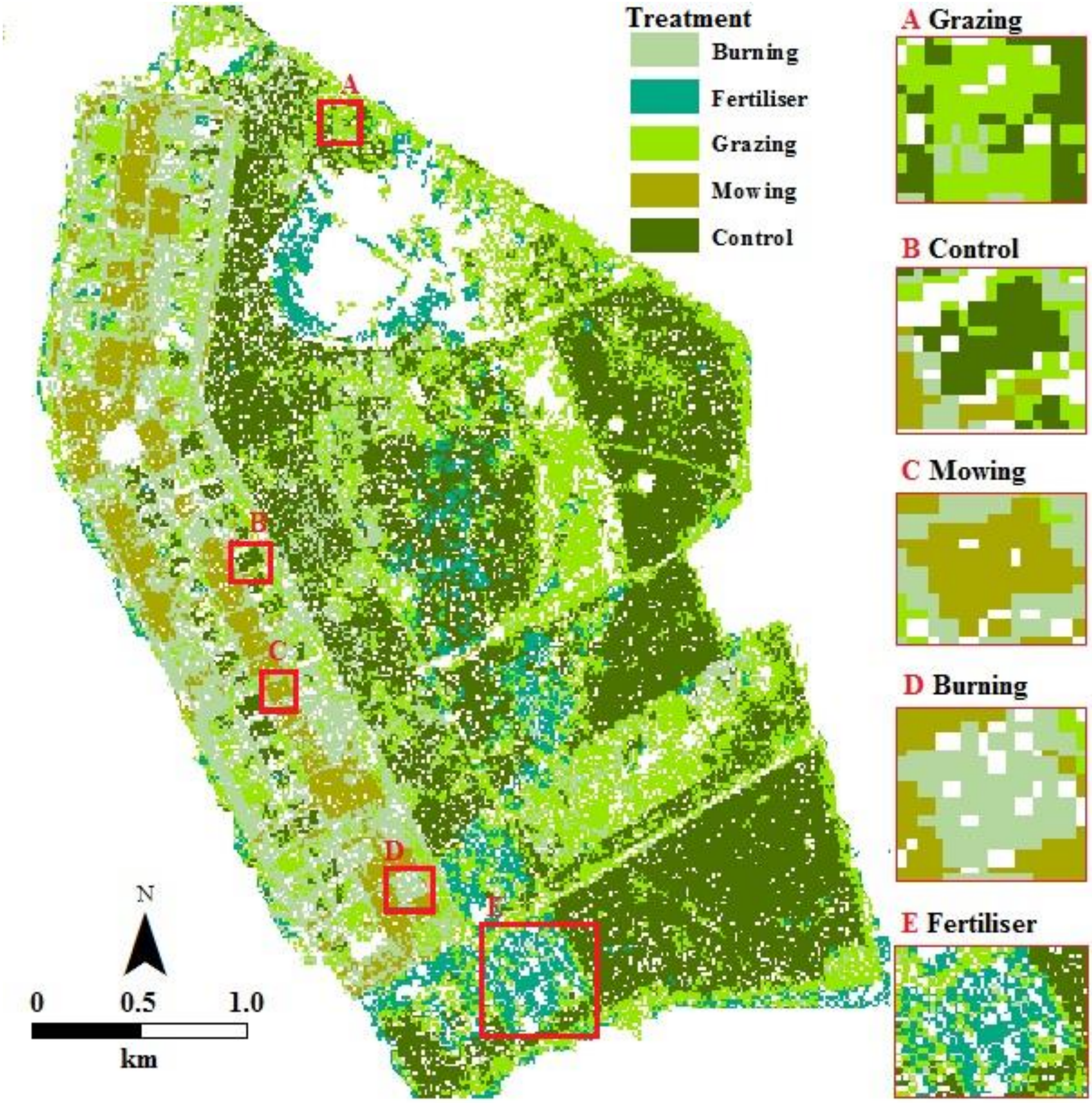


Figure 6.5: A map of the various grassland management treatments at Ukulinga farm, University of KwaZulu-Natal, South Africa. Mapping was done using the model selected optimal bands and indices. *White spaces illustrate other land cover types irrelevant to this study.

6.4 Discussion

The challenge in remote sensing rangeland grasses is often about the lack of spatial and spectral data that could best discriminate between different grassland management treatments and their different application levels. In that regard, this study sought to evaluate the utility of the newly launched worldview-3 sensor's spectral robustness in discriminating grass growing under different management treatments.

6.4.1 The influence of the red-edge wave band in grass discrimination

The results of the present study have indicated the utility of the red-edge band of the newly launched WV-3 in spectrally discriminating between grass plots grown under different grassland management treatments. When red-edge bands were included, the overall classification accuracies improved and were comparably higher than those derived using only standard bands.

The red-edge is insensitive to the soil background effect (Vane *et al.* 1993, Clevers *et al.* 2000, Datt and Paterson 2000, Schumacher *et al.* 2016)., this then makes it to optimally perform in discriminating grasslands treated with different rangeland management treatments when compared to the standard bands. Furthermore, Literature shows that the red-edge region of the electromagnetic spectrum is highly associated with plant characteristics, such as chlorophyll and Leaf Area Index (LAI) which directly affect the reflectance of vegetation (Curran *et al.* 1990, Clevers and Gitelson 2013, Delegido *et al.* 2013). In this study grass growing under natural conditions (no-treatment), fertilizer treatments, mowing, grazing and burning were satisfactorily discriminated at optimal overall accuracies based on the red-edge waveband. The influence of the red-edge in discriminating different management treatments could be attributed to the increase in chlorophyll concentrations associated with some grassland management treatments, such as ammonium nitrate fertilizer application, and burning (Wicklein *et al.* 2012). More specifically, it is widely known in the remote sensing community that nitrogenous fertilizers increase chlorophyll content in green plants (Blackburn 1999, Daughtry *et al.* 2000, Sims and Gamon 2002, Gitelson and Merzlyak 2003, Kalacska *et al.* 2015). Meanwhile, burning grassland management treatment has also been associated with post-fire nutrients which increase the nitrogen and chlorophyll content (Ferwerda *et al.* 2006, Knox *et al.* 2011). When the chlorophyll content is high, the red-edge position shifts towards the longer wavelengths, whereas, plants that are untreated have red-edge positioned towards the shorter wavelengths (Curran *et al.* 1995). Consequently, the spectral signature of grass characterized by high chlorophyll levels, due to post fire nutrients and fertilization, can then be optimally discriminated using the red-edge band from those with less concentrated chlorophyll (Delegido *et al.* 2013) as noted in this study. Similar to the findings of this study, Clay *et al.* (2006)

demonstrated that the spectral signature of nitrogen fertilized plants can be optimally discriminated from those that are untreated based on the red-edge portion of the electromagnetic spectrum. In another related study, Dunham and Price (1996) demonstrated that the structural features induced by mowing, grazing and no-treatment on grasslands facilitated their successfully discrimination based on remotely sensed data.

On the other hand, grassland management treatments, such as the mowing and grazing alter the physiological structure of grass specifically its LAI and LAD. Mowed and grazed grasses have relatively reduced LAI, as well as LAD when compared to grass growing under fertilization, burning and natural (untreated) conditions. In that regard, the spectral signatures of grasses with compromised LAI and LAD then become more distinct in the red-edge region when compared to standard band regions of the electromagnetic spectrum. More specifically, a decrease in the LAD, leaf angle inclination caused by mowing results in the shift of the red-edge from the longer wavelengths to the shorter wavelength positions in a similar way to increases in chlorophyll (Van der Meer and De Jong 2011). Conversely, an increase or higher LAD, leaf angle inclination associated with untreated and fertilized grasses is linked with a red-edge position's shift towards the longer wavelengths (Pu *et al.* 2003, Cho *et al.* 2006, Van der Meer and De Jong 2011, Zou *et al.* 2014). Consequently, the grasslands under mowing and grazing treatments are then optimally discriminated from those that are fertilized, burnt regularly or even those that are untreated. The findings of this study are consistent with those of Zou *et al.* (2014) who also noted significant variations in the red-edge spectral signatures of erectophile crops leaves relative to the planophile crop leaves characterized by different LAD.

Furthermore, several studies have also indicated that when physiological elements of plants are compromised, either through being cut, grazed or defoliated by insects, they respond by altering their photosynthesis which also increases and decreases their chlorophyll content in some instances (Boochs *et al.* 1990, Filella and Penuelas 1994, Curran *et al.* 1995, Trenholm *et al.* 2000, Adelabu *et al.* 2014, Pellissier *et al.* 2015, Sibanda *et al.* 2015). When their chlorophyll is changed, the red-edge position shifts towards shorter wavelengths resulting in the spectral signature of those plants being distinguishable based on the shifts in the red-edge region of the electromagnetic spectrum (Pu *et al.* 2003). This premise could also explain the successful discrimination of the spectral signature of grass growing under grazing and mowing from the other grassland management treatments based on the inclusion of the red-edge band.

Results of this study are consistent to those attained Adelabu *et al.* (2014) in discriminating different levels of mopane leaf defoliation by insects based on RapidEye remotely sensed data. Work by Adelabu *et al.* (2014) indicated that red-edge band increased discrimination between undefoliated, partly defoliated and defoliated leaves by 20%. Results of this study are consistent with those of Pellissier *et al.* (2015) also noted the influence of wavebands from the red-edge region of the electromagnetic spectrum in estimating nitrogen content in the grass under different management strategies in New Hampshire, United Kingdom.

6.4.2 Performance of vegetation indices in grass discrimination

In addition, a significant improvement was also observed when different grassland management treatments were discriminated using vegetation indices derived based on standard bands and red-edge wavebands when compared to the utility of only the standard bands derived vegetation indices. The improvement of classification accuracy obtained when vegetation indices were used could be explained by the fact that they are results of two or more wavebands which are more sensitive to vegetation traits when compared to bands only. Furthermore, vegetation indices are highly sensitive to vegetation spectral and temporal characteristics while reducing the sensitivity to noise from atmospheric noise, view/sun angle soil background and topographic effects when compared to individual bands (Thenkabail *et al.* 2011). In that regard, the satisfactory performance of vegetation indices in discriminating grasses growing under different rangeland management strategies could be attributed to their ability to reduce noise while being sensitive to the effect of treatment strategies on grass's spectral signatures. Then, the plausible performance of red-edge associated vegetation indices could be attributed to the fact that these indices are derived from a region in the electromagnetic spectrum that is highly sensitive to variations in grass chlorophyll content by nitrogen from fertilizers, as well as variations in LAD and LAI from grazing and mowing.

Finally, our results indicated that when all optimal wavebands and vegetation indices were combined, the overall accuracies slightly increased, contrary to our expectations. In other similar studies, the combination of bands and indices greatly increases the discrimination power of vegetation. However in this study, the combined data resulted in an average increase less than 3% in overall classification accuracies. In that regard, future studies have to attempt to understand the combined influence of the grass phenological stages as well as the grassland management strategies in discriminating the grass.

The optimal performance noted in this study after integrating the red-edge waveband and its derived vegetation indices in grass discrimination could also be explained by the variability of grass species that have been growing under these grassland management treatments for a long period of time (for 66 years). In a study conducted based on a similar experiment, Richard *et al.* (2004) noted high species diversity in frequently mown/grazed and burnt grasslands, when compared to those that are not disturbed. In a related study, Sims and Gamon (2002) demonstrated that red-edge is a critical wavelength in estimating species diversity. In that regard, the optimal spectral discrimination of grass growing under natural conditions from that growing under mowing, grazing, burning and fertilizer application management treatments could then be attributed to the high species diversity in the latter treatments (Richard *et al.* 2004). Furthermore, Fynn and O'Connor (2005) noted a high concentration of highly diverse nitrophilous grass species in the experimental plots of this study that were treated with ammonium nitrate combined with dolomitic lime fertilizers, when compared to other plots. In this regard, an optimal discrimination of the highly diverse grass species in the fertilized plots from those that are not fertilized (mown, grazed and burnt) is inevitable. Meanwhile, mowing depletes the available nutrients required for plant growth, making the spectral signature of nutrient deficient grass to be better discriminated from that of healthy fertilized grasses, especially in the red-edge wavelength of the electromagnetic spectrum. In related studies, Magiera *et al.* (2013), Feilhauer *et al.* (2011) and Feilhauer and Schmidtlein (2011) demonstrated that the physiological plant characteristics induced by different management practices in a nutrient-poor grassland, a wet heath, and a floodplain meadow near Cologne, Germany affected the spectral signature of grasses facilitating their discrimination.

6.5 Conclusion

Results of the study showed that:

- WV-3’s red-edge spectral information is invaluable in discriminating different grassland management treatments at a farm scale with plausible accuracies when compared to the visible and near infrared bands,
- WV-3 normalized difference vegetation indices derived based on the red-edge significantly improve the discrimination of grass growing under complex grassland management strategies

Results of the present study are important for deriving detailed information on the spatial distribution of different grassland management treatments especially in instances where moderate spatial resolution sensors, as well as in-situ hyperspectral data, are not suitable. Comprehensive maps of grasslands with high details on different management strategies, such as those derived using WV-3, have numerous potential applications with respect to land management. Considering the fact that grasslands are related to a number of critical socio-economic human activities, such as livestock production and tourism, fine details are a necessity for planning and management of these important natural resources. Specifically, the ability to discriminate different grassland management strategies could help in rehabilitation and optimization of pastures for livestock productivity, prevention of soil erosion, as well as storage of carbon. Furthermore, there is still need to evaluate the utility of such high resolution data as WV-3 in estimating biomass across complex rangeland management treatments in a southern African context. Despite the high overall accuracies associated with high spatial resolution earth observation facilities, such as WV-3, their application in regions with limited resources are limited by costs. In that regard, there is a need for evaluating alternative sensors such as Sentinel-2 MSI data in discriminating different grassland management treatments at regional to landscape scales. Discriminating these grassland treatments is critical in understanding their influence as sustainable management techniques, at a regional scale.

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This study affirmed the utility of the red-edge waveband as a critical portion of the electromagnetic spectrum for accurately mapping grasses grown under different levels of grassland management treatments as noted in the preceding chapters. Consequently, it was hypothesized that image processing techniques such as grey level co-occurrence matrix could improve the accuracies of estimating above ground biomass of grass grown under different *grassland management treatments. The succeeding chapter therefore sought to test integration of the red edge spectral bands with grey level co-occurrence matrices in estimating grass above ground biomass.*

7. .ESTIMATING BIOMASS OF NATIVE GRASS GROWN UNDER COMPLEX MANAGEMENT TREATMENTS USING WORLDVIEW-3 SPECTRAL DERIVATIVES

This chapter is based on:

remote sensing

MDPI

Article

Estimating Biomass of Native Grass Grown under Complex Management Treatments Using WorldView-3 Spectral Derivatives

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Abstract

The ability of texture models and red-edge to facilitate the detection of subtle structural vegetation traits could aid in discriminating and mapping grass quantity, a challenge that has been longstanding in the management of grasslands in southern Africa. Subsequently, this work sought to explore the robustness of integrating texture metrics and red-edge in predicting the above-ground biomass of grass growing under different levels of mowing and burning in grassland management treatments. Based on the sparse partial least squares regression algorithm, the results of this study showed that red-edge vegetation indices improved above-ground grass biomass from a root mean square error of prediction (RMSEP) of 0.83 kg/m^2 to an RMSEP of 0.55 kg/m^2. Texture models further improved the accuracy of grass biomass estimation to an RMSEP of 0.35 kg/m^2. The combination of texture models and red-edge derivatives (red-edge derived vegetation indices) resulted in an optimal prediction accuracy of RMSEP 0.2 kg/m^2 across all grassland management treatments. These results illustrate the prospect of combining texture metrics with the red-edge in predicting grass biomass across complex grassland management treatments. This offers the detailed spatial information required for grassland policy-making and sustainable grassland use and management in data-scarce regions such as southern Africa.

Keywords: grass biomass; SPLSR; vegetation indices; estimation accuracy

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7.1. Introduction

Understanding above-ground grass biomass variations at various scales has become increasingly critical among stakeholders, such as farmers, ecologists and scientists, amongst others. Grasslands are significant carbon sinks, accounting for 18% of the global terrestrial carbon sinks (Kumar *et al.* 2015). Furthermore, in South Africa grasslands are one of the biodiversity hot spots harbouring a wide variety of plants and animals (Wilson *et al.* 2012), while facilitating soil formation and preservation. From an agricultural perspective, native grasses are the cheapest source of stock feed available. Moreover, grasslands are also a significant source of livelihood, especially to rural communities in southern Africa, where natural disasters and socio-economic hardships are frequent. Collectively, these factors drive the growing interest of accurately monitoring grassland biomass variations for developing optimal management regimes.

A total of 7.5% of the world's grasslands have been degraded, while about 16% are currently being degraded (O'Mara 2012). Tropical grasslands, specifically, are often at risk of degradation because of increasing pressure from human activities due to population increase (Suttie et al. 2005, Andrade et al. 2015). For instance, infrastructural development, crop farming and overgrazing have been cited as the major causes of tropical grassland degradation (Suttie *et al.* 2005, O'Mara 2012). Livestock farming has been considered as the fastest growing agricultural sector due to the demand for meat and milk products. Consequently, overstocking and overgrazing have been reported, as drivers of grassland degradation. To optimise productivity, while preserving native grasses, numerous grass management practices have been introduced (Conant *et al.* 2001). These include burning, mowing, fertiliser application, as well as controlled grazing (Conant *et al.* 2001). However, insights on the effectiveness of these grass management treatments on grass productivity are limited. This is because there are no cost-effective monitoring systems that have hitherto been developed. Furthermore, the use of existing methods has not been comprehensively evaluated across space and time to the extent that is sufficient for meaningful decision-making and management in data-scarce regions, such as southern Africa.

To acquire comprehensive quantitative information on grass biomass, the utility of earth observation data has recently become more popular and feasible with an increase, as well as advances, in the available sensors (Bastin *et al.* 2014). Earth observation (EO) data have been renowned for facilitating rapid, repeated and ongoing biomass observations over various spatial and temporal scales. This is because EO enables comparatively convenient data acquisition dating back over several years, while offering satisfactory ranges of accuracy on above-ground biomass estimation over larger spatial scales. Despite the fact that numerous EO methodologies have been evaluated in quantifying above-ground biomass, no study has hither to illustrated an operational technique that is consistent, precise and repeatable for estimating biomass at local to continental scales. This is caused by the variations in the biophysical, environmental and topographic traits of vegetation in space and time (Rosenqvist *et al.* 2003, Sarker and Nichol 2011). A growing body of literature illustrates that the common approach for estimating biomass, based on EO data, has been to examine the possible association between the ground measured biomass and the EO data, since biomass quantities cannot be directly derived from remotely sensed data (Lu 2006, Al-Hamdan *et al.* 2014, Hansen *et al.* 2015, Lu *et al.* 2016, Meng *et al.* 2016). Landsat data is the most widely used earth observation data in vegetation above-ground biomass estimation studies due to its limited costs. However, the majority of the studies have used Landsat for forest inventories (Anderson *et al.* 1993, Schino *et al.* 2003, Dube *et al.* 2016, Jansen *et al.* 2016, Lu *et al.* 2016, Wu *et al.* 2016). The few studies that have been conducted on grass productivity have focused only on a limited number of grass management treatments (Griffith et al. 2001, Munyati and Makgale 2009, Xie et al. 2009, Mbatha and Ward 2010). Furthermore, primary vegetation indices (VI), such as the normalised difference vegetation index (NDVI), have been widely used for estimating above-ground grass biomass (Griffith *et al.* 2001, Xie *et al.* 2009, Prabhakara *et al.* 2015, Zhu and Liu 2015). VI have been widely used because they tend to supersede the influences of the soil background, atmospheric impurities and the viewing and zenith angle effects, while magnifying the signature of vegetation (Huete 1986, Bannari *et al.* 1995). However, these have attained only moderate success in the tropical and subtropical regions, (Mutanga and Skidmore 2004, Nichol and Sarker 2011) characterised by complex management treatments, with high spatial heterogeneity. This is due to the lack of strategically located wavebands (Ramoelo et al. 2012, Ngubane *et al.* 2014, Ramoelo *et al.* 2014), such as the red-edge (i.e. in the Landsat data series). Furthermore, these indices are affected by saturation, soil background and the coarse spatial resolutions for application in grass grown across different grassland management treatments, which still remains a challenge (Broge and Leblanc 2001, Mutanga and Skidmore 2004, Zhao *et al.* 2016). This is aggravated by the lack of a clear criterion on the appropriateness of specific EO sensors, proxies, as well as repeatable operational techniques that could provide accurate biomass information from a variety of grass management treatments.

After examining literature, red-edge (680-740nm) and texture models seem to offer better proxies, which suppress the soil-background effect, saturation issues (Thenkabail *et al.* 2000, Mutanga and Skidmore 2004, Bannari and Staenz 2016, Li *et al.* 2016) and high spatial heterogeneity. Literature shows that the red-edge is sensitive to chlorophyll, as well as leaf structure reflection (i.e. leaf area index, leaf angle distribution), thereby providing more information for the characterisation of vegetation (Guyot et al. 1992, Pu *et al.* 2003, Delegido *et al.* 2015, Wang *et al.* 2016). More specifically, when the concentration of foliar chlorophyll increases, it results in the bulging of the optical chlorophyll absorption feature, shifting away from the long wavelength margin, and thereby shifting the red-edge to longer wavelengths (Curran *et al.* 1990, Curran *et al.* 1995). Meanwhile, the concentration of leaves of a certain vegetation canopy, as well as the angular nature of those leaves, directly affects the spectral reflectance of that vegetation, especially in the red-edge portion of the electromagnetic spectrum (Asner 1998). Subsequently, the biomass of vegetation with a high chlorophyll concentration or leaf area index can then be detected from that with less concentration, based on these shifts. In this regard, it is perceived that the red-edge waveband and its derivatives can better estimate above-ground biomass, when compared to primary bands and vegetation indices (Mutanga and Skidmore 2004). On the other hand, literature indicates that grey level co-occurrence optical texture models also relate better with field measured above-ground vegetation biomass when compared with vegetation indices (Lu 2005, Lu and Batistella 2005, Sarker and Nichol 2011). For instance, work by Cutler *et al.* (2012) indicated that integrating texture metrics data improved biomass estimation from R^2 of 0.05,0.23 and 0.16 to 0.79, 0.79 and 0.84 in Thailand, Malaysia and Brazil, respectively, when compared with multispectral data. Furthermore, texture models offer information that could characterise the subtle structural characteristics of the vegetation canopy, such as those induced by different grassland management treatments. Texture metrics i.e. the grey level co-occurrence matrix, distinguishes minute, but critical, vegetation details, based on a local spectral variation in the image (Bastin *et al.* 2014). This is due to the fact that texture models can also suppress the influence of atmospheric effects, the sensor view-angle and the sun view angle, which improve the vegetation spectral signature required for the accurate estimation of above-ground grass biomass (Sarker and Nichol 2011, Eckert 2012, Dube and Mutanga 2015). It is, therefore, important to note that texture variables can optimise the discrimination of vegetation spatial information independently from the tone, while spectral features, i.e. the red edge, provides detailed vegetation tonal variations that are paramount for accurate vegetation mapping. Based on the above premise, the combination of optimal texture models and red-edge wavebands has a high potential for improving above-ground biomass estimation across different grassland management treatments, superseding the saturation effect of spectral data. To our knowledge, very few studies, if any, have been conducted, based on texture models, to predict above-ground grass biomass. The majority of the studies that utilised texture metrics were focused on forest above ground biomass (Ozdemir and Karnieli 2011, Rodriguez-Galiano *et al.* 2012, Sarker *et al.* 2012, Bastin et al. 2014, Dube and Mutanga 2015, Meng *et al.* 2016, Salas et al. 2016, Wallis *et al.* 2016, Zhao *et al.* 2016). In addition, most of these studies utilised the moderate resolution Landsat data, which does not capture the minute variations that could be induced by different grass treatments in a grassland landscape that is characterised by high spatial heterogeneity (Kumar *et al.* 2015). Considering the lack of suitable specific proxies for accurate biomass information in southern African grasslands, due to limited resources and data scarcity (Dube and Mutanga 2015), there is a need to evaluate the performance of possible sources of spatial information, such as texture models and red-edge wavebands. The advent of new generation multispectral sensors, such as the newly launched Sentinel-2 multispectral imager and WorldView-3, offers an opportunity to improve the accuracy of above-ground grass biomass estimation in southern Africa. This is because of their spectral regions, such as red-edge, which are crucial for vegetation mapping, as well as their optimal spatial resolution, could offer the critical spatial information that is required in well-informed grasslands management practices.

Despite the relatively high costs associated with high spatial resolution earth observation data, these data sources offer abundant texture information, which could better characterise the spatial distribution of different grassland management treatments (Eckert 2012). For example, the new WorldView-3 sensor, characterised by a fine spatial resolution of 2m, as well as the strategically positioned red-edge waveband, offers better spatial information, when compared to other sensors, such as Landsat, which has a moderate spatial resolution and lacks the red-edge waveband. In that regard, Worldview-3 texture models, combined with red-edge band derivatives, could have better spectral responses to grass above-ground biomass estimation with complex grass management treatments.

The aim of this study, therefore, is to test whether combining WV-3 optical texture models with red-edge can improve the accuracies of predicting above-ground biomass of native grass grown under different levels of mowing, burning and fertiliser treatments using the sparse partial least squares regression algorithm. To achieve the above objective we tested the strength of (i) WV-3 wavebands with that of broadband VIs, (ii) of WV-3 standard wavebands combined with broadband VIs compared with that of red-edge derived VIs, (iii) WV-3wavebands, broadband and red -edge VIs combined compared to single band texture models, (iv) all variables combined compared to that of all texture models in estimating above-ground biomass of grass grown under different grassland treatments.

7.2. Methods and Materials

7.2.1. Study area description

This study was undertaken at the Ukulinga Research Farm in Pietermaritzburg, KwaZulu-Natal, South Africa (29°24′E, 30°24′S) (Figure 7.1). The weather at Pietermaritzburg is characterised by cold dry winters and hot wet summers, with a minimum mean monthly temperature of 6^0C, as well as a maximum mean monthly temperature of ± 27^0C. Ukulinga is 228 ha farm that is situated on a plateau, hence it is characterized by a generally flat terrain with an altitude ranging between 838 to 847 m above sea level (Fynn and O'Connor 2005). The major grass species at the grassland trials on the University farm are Themeda triandra, *Heteropogon contortus*, *Eragrostis plana*, *Panicum maximum*, *Setaria nigrirostrosis* and *Tristachya leucothrix*. The mean height of these grasses was about 40 cm. The soils at the research farm are generally infertile, acidic and of the Westleigh type (Fynn and O'Connor 2005). The experimental site at Ukulinga was established by JD Scott in 1950, with the aim of understanding the influence of different management practices on grass quantity and quality.

7.2.2. Experimental design

The experiment consisted of grass burning, mowing and fertilisation treatments at timely intervals. A total of fifty four plots measuring 13.7 × 18.3 m, with native grass growing under mowing, burning, were utilised in this study (Table 7.1). Burning treatments were undertaken at three levels, namely: (i) annually, (ii) biennially (after two years) and (iii) triennially (after three years). Mowing was also implemented at three levels. At Level 1, there was no mowing, at Level 2 grass was mown once in August, and at Level 3, grass was mown twice in August and after the first spring rains.

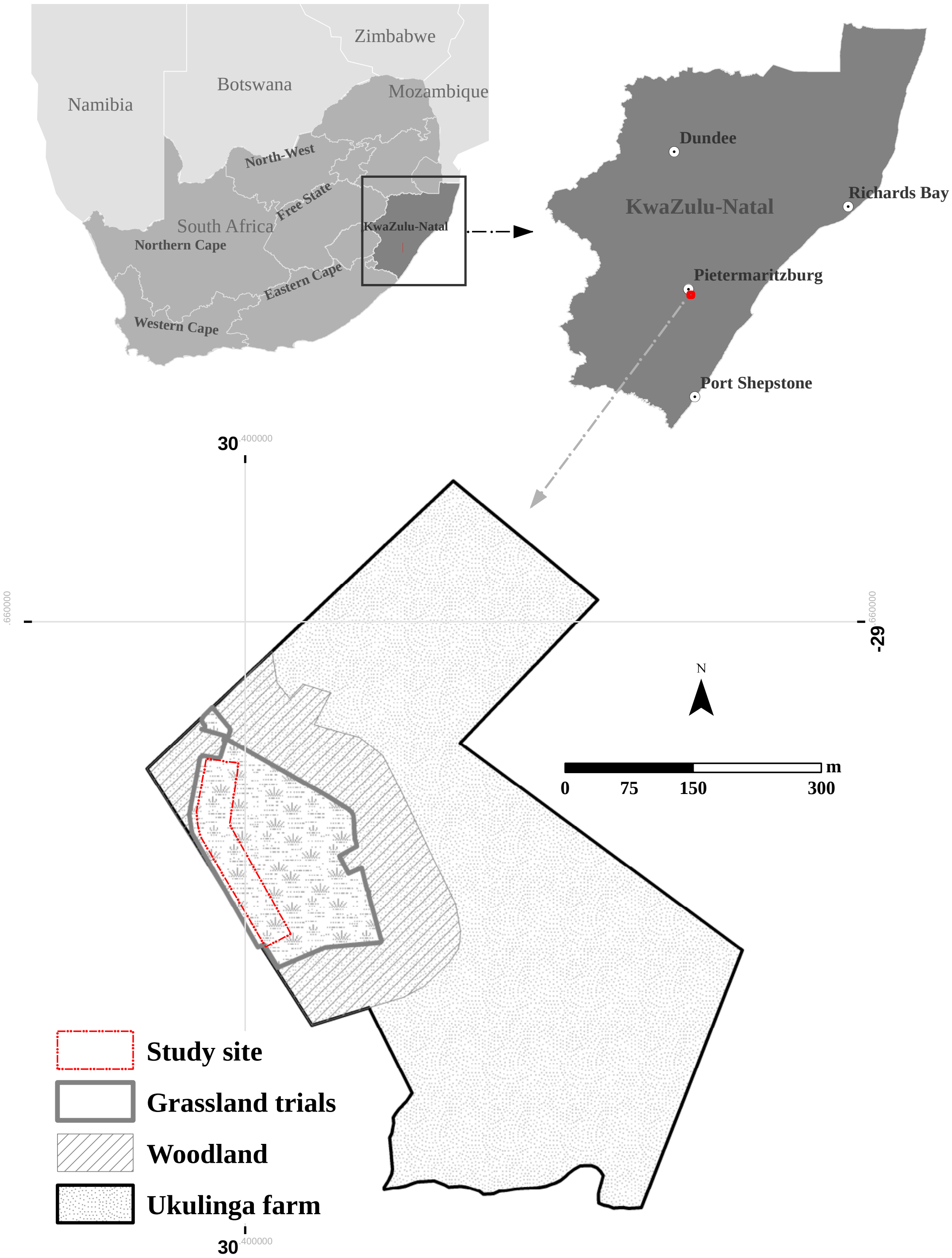


Figure 7.1: Location of the grassland sites at Ukulinga University of KwaZulu-Natal experimental Farm, Pietermaritzburg, South Africa

7.2.3. Field Campaign

To extract spectra from each plot, 20 points were randomly generated in a Geographic Information System (GIS) environment. Ultimately, 1080 points were derived from 54 plots and used to extract all WV-3 variables, using an overlay function in a GIS (Table 7.1). To test the capability of the combined red-edge and texture models in estimating above-ground grass biomass, we conducted a field survey on the 10th of February 2016. During the field campaigns, plots with native grasses grown under mowing, burning, as well as no-treatment, were surveyed and the grass biomass clipped. The wet biomass of grass from each level of treatment was derived after cutting, during the field survey. The samples were then taken to the laboratory, where moisture content was determined and dry grass biomass, hereafter referred as above-ground grass biomass, was derived.

Table 7.1: Reflectance samples measured on each rangeland management treatment

Treatment level	**Treatment**	**Samples**	**Plots**
C1	Control	60	3
C2	Annual burn (in August)	60	3
C3	Annual burn (after Spring rain)	60	3
C4	Biennial burn (in August)	60	3
C5	Biennial burn (after Spring rain)	60	3
C7	Triennial burn (in August)	60	3
C8	Triennial burn (after Spring rain)	60	3
C10	Mowing (in August)	60	3
C11	Mowing (after Spring rain)	60	3
D1	Control	60	3
D2	Annual burn (in August)	60	3
D3	Annual burn (after Spring rain)	60	3
D4	Biennial burn (in August)	60	3
D5	Biennial burn (after Spring rain)	60	3
D7	Triennial burn (in August)	60	3
D8	Triennial burn (after Spring rain)	60	3
D10	Mowing (in August)	60	3
D11	Mowing (after Spring rain)	60	3
Total		1080	54

Note*: Grass on C treatments are removed end of February, while those in D are removed Twice in February and December.

7.2.4. Remotely sensed data

A Worldview-3 image, acquired on a cloudless day of the 16th of February 2016, was used in this study to evaluate the strength of red-edge, combined with texture models, in predicting above-ground biomass. The WV-3 image has eight multispectral bands i.e. coastal blue at 400-450nm, blue at 450-510nm, green at 510-589nm, yellow at 585-625, red at 630-690nm, red-edge at 705-895nm and two near infrared bands, which overlap, at 770-895nm and 860-1040nm, respectively. The spatial resolution of all wavebands was 2 m. The image was first pre-processed to correct for the influence of atmospheric effects, using the Fast Line of Sight

Atmospheric Analysis of Spectral Hypercubes (FLAASH), based on the parameters that were provided with the image. The FLAASH analysis was conducted after converting the image into radiance in Envi 5.2. Subsequently, the WorldView-3 image was geometrically corrected, based on ten locations measured using hand-held Trimble GeoXH 6000 global positioning system with a sub-meter accuracy. The image was then resampled using the first order polynomial transformation and nearest-neighbor resampling technique as in Sibanda *et al.* (2017). As mentioned earlier, the atmospherically corrected image was used in an overlay analysis, in conjunction with the point map, in order to derive spectral signatures of grass growing under different levels of grassland management treatments.

7.2.5. Modelling above-ground grass biomass

Single wavebands, broadband and red-edge vegetation indices, as well as grey level co-occurrence single-band and band-ratio texture models, were derived in Envi ®4.3 from the pre-processed WV-3 image. The vegetation indices used in this study were chosen based on their optimal performance in literature (Anderson et al. 1993, Broge and Leblanc 2001, Mutanga and Skidmore 2004, Liu et al. 2007, Cho et al. 2008, Agapiou et al. 2012, Thenkabail et al. 2013). Formulae for computing vegetation indices are detailed in Schumacher *et al.* (2016). The window sizes for deriving the grey-level co-occurrence texture models used in this study were 3 x 3, 5 x 5 and 7 x7 pixels (Chica-Olmo and Abarca-Hernandez 2000, Chen *et al.* 2004, Wang *et al.* 2004). These window sizes were selected because their area was not bigger than that of a single plot of grass used in this study. The co-occurrence shifts considered in this study were 0:1, 1:1, 1:0, -1:1, 1;-1 which were chosen based on literature (Dube and Mutanga 2015, Safari and Sohrabi 2016) and a quantization level of 64 was used in this study. The texture models computed in this study were mean, variance, homogeneity, contrast, dissimilarity, entropy, second moment and correlation. More details about the formulae for computing these texture models are summarised in Dube and Mutanga (2015), as well as Schumacher et al. (2016). All the variables used in this study, and the formulae used to compute them, are detailed in Table 7.2. The derived spectral signatures were saved in a table format and exported to Microsoft Excel as comma separated values. These were then imported into STATISTICA ®Version 7 and R statistical software for statistical modelling.

7.2.5.1. Statistical modelling of above-ground grass biomass

The initial step was to conduct exploratory analysis and to derive descriptive statistics in Statistica Version 7. Under the exploratory data analysis procedure, we tested whether above-ground grass biomass data measured in the field significantly deviated ($\alpha = 0.05$) from the normal distribution, based on the Lilliefors Test. We then tested whether there were significant difference in the amount of above-ground biomass of grass, grown under mowing and burning based analysis of variance and Tukey honest significant difference post hoc tests.

7.2.5.2. Regression modelling

In this study, we used Chun and Keleş's (2010) sparse partial least regression (SPLSR) algorithm. The SPLSR algorithm converts the variables into new orthogonal factors to circumvent multicollinearity and overfitting issues, considering the large number of variables used in this study. In converting the variables into orthogonal factors, SPLSR imparts sparsity into the models and then selects the optimal variables that correlate better to grass above-ground biomass. Because of these capabilities, SPLSR is appropriate for application on data with multicollinearity issues, such as the texture models of this study, relative to other algorithms (i.e. partial least squares regression (PLSR)) (Chun and Keleş 2010, Abdel-Rahman *et al.* 2014). In this study, the aim was to test whether combining WV-3 optical texture models with red-edge derivatives improves accuracies. Therefore, SPLSR was chosen and utilised because of its ability to select optimal variables.

7.2.5.3. Assessing the accuracy of above-ground grass biomass models

To evaluate the accuracy of above-ground grass biomass models in this study, a leave-one-out cross-validation (LOOCV) procedure was followed, as detailed in (Abdel-Rahman *et al.* 2014). In implementing the LOOCV procedure, 1080 samples, derived from 54 grassplots, were eliminated one by one and above-ground grass biomass estimation errors for each latent variables were derived. The latent variables that exhibited the least root mean square errors were considered as the optimal models for estimating above-ground grass biomass across different levels of grassland management treatments. We computed the coefficient of determination (R^2), root mean square error (RMSEP) as well as the relative root mean square error ($\text{RMSEP}_{-}^{\text{rel}}$), as in Frazer et al. (2011), to evaluate the models derived using band indices, as well as texture models. Models that exhibited small RMSEPs and a high R^2 were considered to be best in estimating above-ground biomass. Considering that SPLSR has the capability of identifying and selecting optimal variables, we then used the variable importance (VIP) scores allocated for each of the selected variables by SPLSR, to distinguish the most influential ones from the best models (Abdel-Rahman et al. 2014).

Finally, an analysis of variance was used to test whether there were significant differences between the accuracies (RMSEP) of: (i) WV-3 wavebands, (ii) broadband VIs, (iii) Wavebands combined with broadband VIs, (iv) red-edge VIs, (v) combination of all VIs and wavebands, (vi) single band texture models, (vii) combination of single band and band ratio texture models, and (viii) all variables combined in predicting above-ground biomass. These combinations were derived in literature (Dube and Mutanga 2015, Schumacher et al. 2016). Analysis of variance (ANOVA) was used after the normality test and it indicated that the data did not significantly deviate from the normal distribution.

7.2.5.4. Phases of estimating above-ground grass biomass

Table 7.2 summarises the four phases that were followed. In Phase one, the strength of WV-3 wavebands was compared with that of broadband vegetation indices. In the second phase, wavebands were combined with broadband vegetation indices and then compared with the performance of red-edge vegetation indices. In the third phase the wavebands, broadband and red-edge vegetation indices were combined and compared to the performance of single band-texture models. Lastly, the combination of all variables were then compared with the performance of all texture models. The optimal bands, indices and texture models that are derived, using the variable selection capability of SPLSR, were then used to estimate above-ground biomass across all grassland management treatments in this study. Figure 7.2 conceptually illustrates the phases followed.

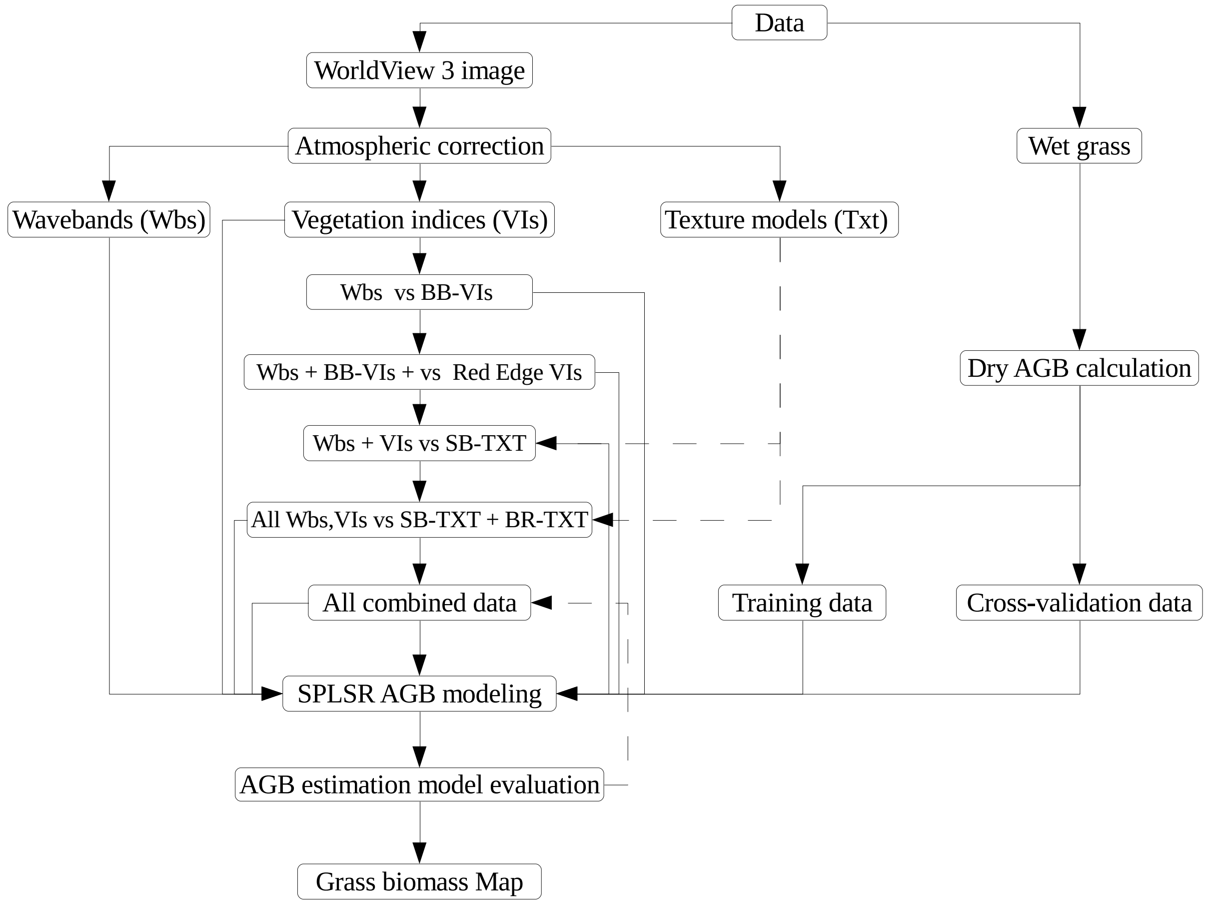


Figure 7.2: Flowchart illustrating stages followed in estimating above-ground (ABG) grass biomass in this study. Wbs represents WV-3 wavebands, Vis are vegetation indices, BB-Vis are broadband vegetation indices, SB-TXT represents single band texture models and BR-TXT represents band ration texture models

Table 7.2. Variable categories used in this study.

Phase	Analysis	Variable	Description	Reference
1	Bands vs Broadband VIs	***WV-3 B2-B8***	Single bands-reflectance values	
		Broad band VIs		
		Chlorophyll Index Green	$CGM = \frac{NIR}{G} - 1$	Kang et al (Kang *et al.* 2016),Gitelson et al(Gitelson and Merzlyak 1997)
		Green normalised difference VI	$GNDVI = \frac{NIR - G}{NIR + G}$	Fernández-Manso et al (Fernández-Manso *et al.* 2016)
		Green blue normalised difference VI	$GBNDVI = \frac{NIR - (G + B)}{NIR + (G + B)}$	Santoso et al (Santoso *et al.* 2011)
		Normalised difference VI	$NDVI = \frac{NIR - R}{NIR + R}$	Tucker (1980)
		soil adjusted vegetation index	$SAVI = \frac{NIR - R}{NIR + R + 0.5} * (1 + 0.5)$	Huete (Huete 1988)
		Enhanced vegetation index	$EVI = \frac{2.5 * NIR - R}{NIR + 6 * R - 7.5 * B + 1}$	Cabezas et al (Cabezas *et al.* 2016)
2	Broadband VIs +bands vs Red-Edge Vis	***Red-edge Indices***		
		Browning reflectance index	$BRI = \frac{\frac{1}{G} - \frac{1}{RE}}{NIR}$	Merzlyak et al., (Merzlyak *et al.* 2003)
		Canopy chlorophyll content index	$CCCI = \frac{\frac{NIR-RE}{NIR+RE}}{\frac{NIR-R}{NIR+R}}$	El-Shikha et al., (El-Shikha *et al.* 2008)
		Normalised difference near infrared red-edge index	$NDNRE = \frac{NIR - RE}{NIR - RE}$	
		Normalised difference red-edge index	$NDRE = \frac{RE - R}{RE + R}$	Fitzgerald et al (Fitzgerald *et al.* 2010)
		Tasseled cap: soil brightness Index	$TCSBI = 0.332 * G + 0.0603 * R + 0.675 * RE - 0.262 * NIR$	Cabezas et al. (Cabezas *et al.* 2016)
		Anthocyanin reflectance Index		Gitelson et al. (Gitelson *et al.* 2001)
3	All VI + Bands vs Single band textures	***Single band Textures windows (3 and 5)***		
		Texture type:		
		Mean	$Mn = \sum_{i,j=0}^{N-1} (P_{i,j})$	Wallis (Wallis *et al.* 2016) Kelsey et al (Kelsey and Neff 2014)

		Variance	$Var = \sum_{i,j=0}^{N-1} Pi,j(i - ME)^2$	Schumacher et al (Schumacher *et al.* 2016) Ouma et al (Ouma *et al.* 2008) Salas et al.(Salas *et al.* 2016) Zhao et al (Zhao *et al.* 2016)
		Homogeneity	$Hom = \sum_{i,j=0}^{N-1} \frac{Pi,j}{1 + (i.j)^2}$	
		Contrast	$Con = \sum_{i,j=0}^{N-1} Pi,j\ (i - j)^2$	
		Dissimilarity	$Dis = \sum_{i,j=0}^{N-1} Pi,j\lvert i - j\rvert$	
		Entropy	$Ent = \sum_{i,j=0}^{N-1} Pi,j\left(-, \ln P_{i,j}\right)$	
		Second moment	$Sec = \sum_{i,j=0}^{N-1} P^2 i,j$	
		Correlation	$Cor = \sum_{i,j=0}^{N-1} Pi,j\left[\frac{(I - ME)(j - ME)}{\sqrt{VA_I}VA_J}\right]$	
		*Note $Pi,j = \sum_{I,J=0}^{N-1} Vi,j$ where Vµ is the value in cell *i,j* and N is the number of rows or columns		
4	Band texture variables vs All combined data	***Band ratios*** texture	B2/B3, B2/B5,B2/B7, B2/B8, B3/B5, B3/B7, B3/B8, B5/B7, B5/B8, B2/B6, B3/B6, B6/B7, B6/B8, B6/B8, B8/B7,	

3. Results

7.3.1. Descriptive statistical analysis and ANOVA tests

Normality test results based on the Lilliefors Test, showed that above-ground grass biomass did not significantly deviate from the normal distribution ($\alpha = 0.05$), as illustrated in Figure 7.3 (a). Consequently, ANOVA and SPLSR were then conducted. Figure 7.3(a) illustrates other descriptive statistics of grass above-ground biomass. The mean of 3.158 kg and a median of 3.149 kg were derived from the field-measured above-ground biomass of grass growing under different levels of burning and mowing treatments. Significant differences in the amount of above-ground biomass were observed amongst grasses growing under different grassland treatments (Figure 7.3 (b)). Furthermore, Tukey's HSD post hoc test showed that there were significant differences in the quantity of grass biomass between different pairs of burning and mowing grass treatments, as illustrated in Table 7.3 (p-value < 0.05).

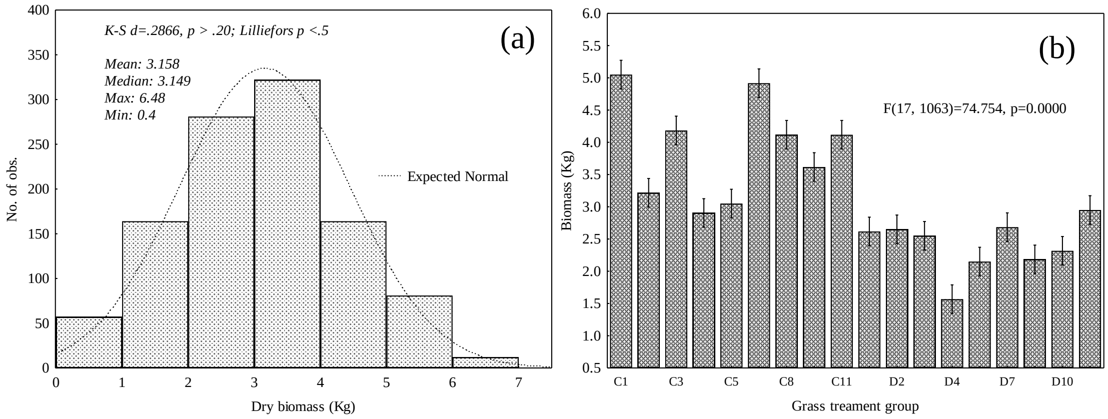


Figure 7.3: (a) Descriptive statistics of measured grass above ground biomass, (b) significant difference amongst different levels of mowing and burning grassland management treatments based on analysis of variance test. Bars represent mean biomass of each management treatment level while whiskers represent confidence intervals of means at 95%

Table 7.3: Significant differences between different pairs of grass above-ground biomass grown under different levels of mowing and burning treatments, based on the Tukey's HSD test

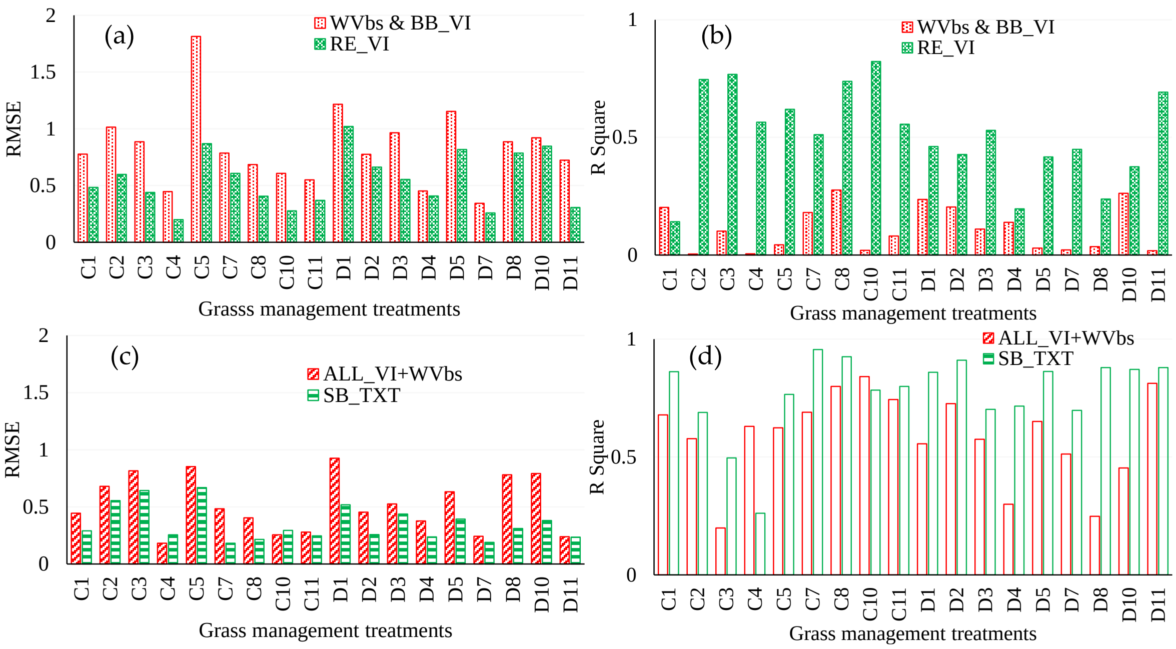
Treatment	C1	C2	C3	C4	C5	C7	C8	C10	C11	D1	D2	D3	D4	D5	D7	D8	D10
C2	0.00																
C3	0.00	0.00															
C4	0.00	0.89	0.00														
C5	0.00	1.00	0.00	1.00													
C7	1.00	0.00	0.00	0.00	0.00												
C8	0.00	0.00	1.00	0.00	0.00	0.00											
C10	0.00	0.53	0.04	0.00	0.04	0.00	0.14										
C11	0.00	0.00	1.00	0.00	0.00	0.00	1.00	0.14									
D1	0.00	0.02	0.00	0.94	0.37	0.00	0.00	0.00	0.00								
D2	0.00	0.04	0.00	0.98	0.53	0.00	0.00	0.00	0.00	1.00							
D3	0.00	0.00	0.00	0.73	0.14	0.00	0.00	0.00	0.00	1.00	1.00						
D4	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00					
D5	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.24	0.14	0.53	0.03				
D7	0.00	0.08	0.00	1.00	0.69	0.00	0.00	0.00	0.00	1.00	1.00	1.00	0.00	0.08			
D8	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.37	0.24	0.69	0.01	1.00	0.14		
D10	0.00	0.00	0.00	0.03	0.00	0.00	0.00	0.00	0.00	0.92	0.83	0.99	0.00	1.00	0.69	1.00	
D11	0.00	0.97	0.00	1.00	1.00	0.00	0.00	0.00	0.00	0.83	0.92	0.53	0.00	0.00	0.97	0.00	0.01

0.00 Significant (α = 0.05)
1.00 Non-Significant

* Note light grey cells illustrate significant differences between pairs of treatments, while dark grey cells represent non-significant differences (α =0.05). D1 to D 11 and C1 to 11 represent different levels of burning and mowing treatments illustrated in table one.

7.3.2. Comparing the performance of WV-3 wavebands combined with broadband VIs and red-edge VIs in estimating above-ground grass biomass

Exploring the possibility that WV-3 wavebands could better estimate above-ground biomass in relation to broadband VIs resulted in very small and very high RMSEP indicating poor model fitting. In that regard, those results were not presented. It can be observed from Figure 7.4 (a) and (b) that the red-edge derived vegetation indices performed better than broadband vegetation indices combined with band reflectance values. Red-edge derived VIs resulted in higher accuracies (lower RMSEP), when compared with combined broadband VIs and band reflectance values. Specifically, triennial burning treatment D7 (R^2 = 0.45, RMSEP = 0.26 kg/m^2, $\text{RMSEP}^{-\text{rel}}$ = 12.83) exhibited the lowest prediction error, when red-edge derived vegetation indices were used. Meanwhile, the highest prediction errors obtained, based on the red-edge vegetation indices, were observed in C5 (R^2 = 0.62, RMSEP = 0.87 kg/m^2, $\text{RMSEP}^{-\text{rel}}$ = 28.49). Red-edge derived vegetation indices improved the accuracies of above-ground grass biomass estimation. However, relatively high prediction errors were observed from the triennial burn treatment D7 (R^2 = 0.2, RMSEP = 0.34 kg/m^2, $\text{RMSEP}^{-\text{rel}}$ = 13) and C5 (R^2 = 0.04, RMSEP = 1.81 kg/ m^2, $\text{RMSEP}^{-\text{rel}}$ = 92.21), when WV-3 bands were combined with broadband vegetation indices in estimating above-ground grass biomass. The optimal red-edge indices that were selected were the normalized difference near infrared red-edge index, the normalized difference red-edge index, the canopy chlorophyll content index, the tasseled cap: soil brightness index, and the anthocyanin reflectance index, in order of influence.



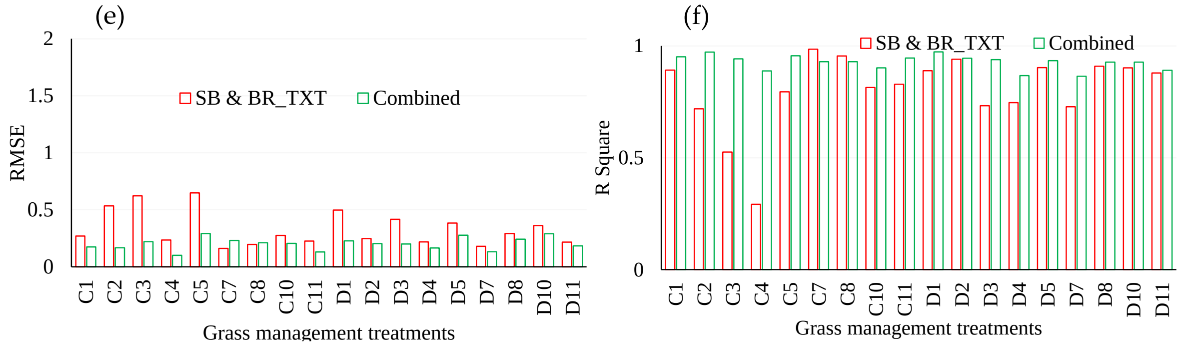


Figure 7.4: A comparison of estimating accuracies derived using different WV-3 satellite data and its derivatives. RMSEP and R squares obtained in comparing (a and b) WV-3 combined BB_VIs and red-edge vegetation (RE_VIs) (c and d), all VIs combined with WVbs and single-band texture models (SB_TXT) and (e and f) SB_TXT) and All data combined. C1-11 and D1-11 are illustrated on table

7.3.3. Comparing the performance of single-band texture models with all WV-3 VIs and bands reflectance values in estimating above-ground grass biomass

The results of this study showed that the single band texture models derived using the SPLSR algorithm predicted above-ground grass biomass better than all vegetation indices and wavebands combined. Figure 7.4 (c and d) shows accuracies derived from using single-band texture models, as well as combined vegetation indices and wavebands. Based on single-band texture models, triennial burn treatments C7 (R^2 = 0.51, RMSEP = 0.18 kg/m^2, RMSEP$_{-}^{rel}$ = 5.56) had the least prediction errors. The single-band texture predictions had relatively lower estimation errors, when compared with all vegetation indices, combined with wavebands (C7 R^2 = 0.18, RMSEP = 0.48 kg/m^2, RMSEP$_{-}^{rel}$ = 9.83). When, single band texture models were used, the optimal window sizes were 3 ×3 and 5 × 5 at [0:1] and [1:1] offsets. The mean, dissimilarity, homogeneity entropy, correlation, variance and second moment texture model types were frequently selected as optimal variables at this stage, based on the SPLSR algorithm. In this study, the single-band texture and band-ratio texture models did not perform significantly differently, hence those results were not included in this study.

7.3.4. Comparing the performance of combined single band and band ratio texture models with the combination of all WV-3 VIs, band reflectance values and single band texture models in estimating above-ground grass biomass

Results of this work also showed that all data combined (texture indices, vegetation indices and spectral wavebands), outperformed the texture models (i.e. single band and band ratio texture). Texture models individually exhibited slightly higher prediction errors when compared to the combination of single band texture models vegetation indices and wavebands. Based on all variables combined, biennial burn treatments C4 (R^2 = 0.89, RMSEP = 0.1 kg/m^2, $RMSEP_{-}^{rel}$ = 3.45) had the lowest estimation errors. The combination of texture models resulted in comparatively lower accuracies with higher errors (C4: R^2 = 0.29, RMSEP = 0.22 kg/m^2, $RMSEP_{-}^{rel}$ = 5.61) (see Figure 7.4 (e) and (f)).

7.3.5. Estimating above-ground grass biomass across different levels of grassland management treatments, using WV-3 derived texture models combined with optimal vegetation indices selected by the SPLSR algorithm.

When all data were combined and all treatments pooled, a comparatively lower prediction error was obtained, as illustrated in Figure 7.5. Further analysis (Figure 7.5(b)) illustrated that the stray points on Figure 7.5(a) were induced by those variables which exhibited low correlation coefficients such as B6, B6/B7 and NDRRE. However, the overall influence of stray points on error was minimal as indicated by an R^2 of 0.90 and RMSEP of 1.67 kg/m^2 were observed. It was also observed that the red-edge derived texture and vegetation indices were the most influential variables that produced relatively lower accuracies (Figure 7.6). From the selected variables, the 5×5 second moment and variance simple band ratio texture models derived from Band 6 and 7 exhibited the highest scores in this study.

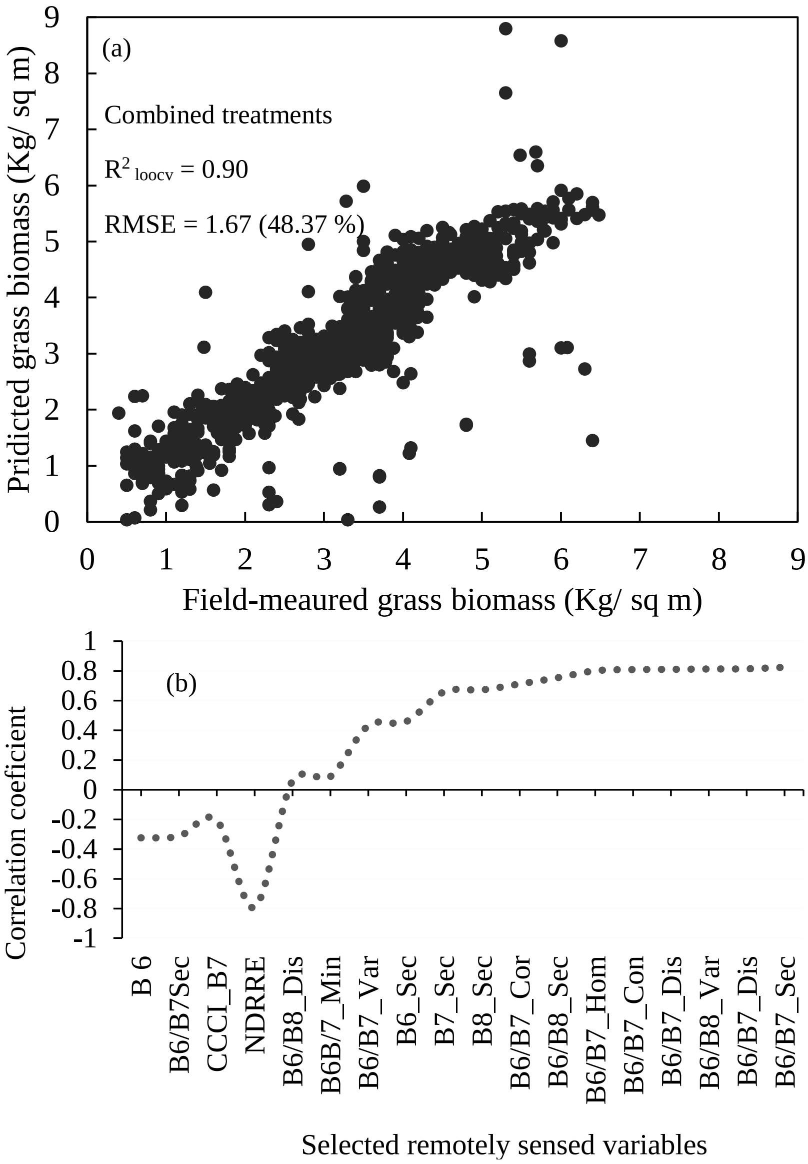


Figure 7.5: (a) Relationship between the field-measured and estimated grass above-ground biomass across all grass management treatments for validating SPLSR models, based on the leave-one-out cross-validation procedure. Note that the relative root mean square error is presented as a percentage, (b) illustrates the relationship between all the optimal variables and grass biomass across all treatments.

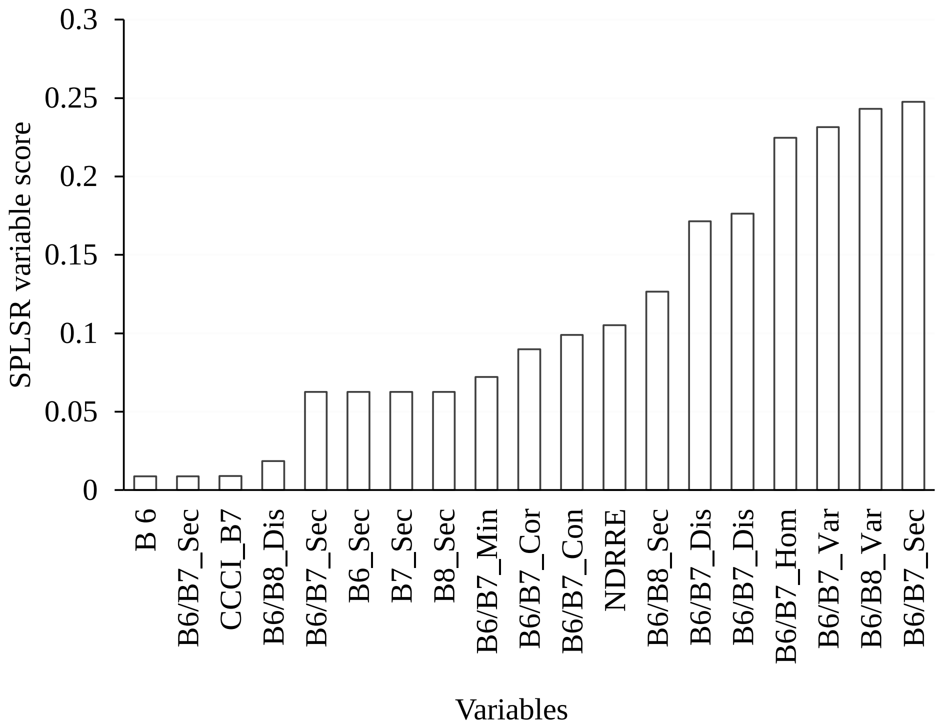


Figure 7.6: Best variables selected, using SPLSR, in estimating above-ground grass biomass across different grassland management treatments. Note that on 'B6/B7_Dis' Dis represents the texture type, B6 and B7 represent the ratio of WV-3 Bands 6 and 7, and NDRE is the normalised difference red-edge index

Figure 7.7 illustrates the spatial distribution of above-ground biomass (ABGB) across different levels of mowing and burning treatments. It can be observed that the triennial (C8) and biennial C5) treatments accumulate more biomass, compared to the annual burn (D3). On the other hand, the mowing treatments (C10) show less ABGB accumulation, due to the high removal of grass.

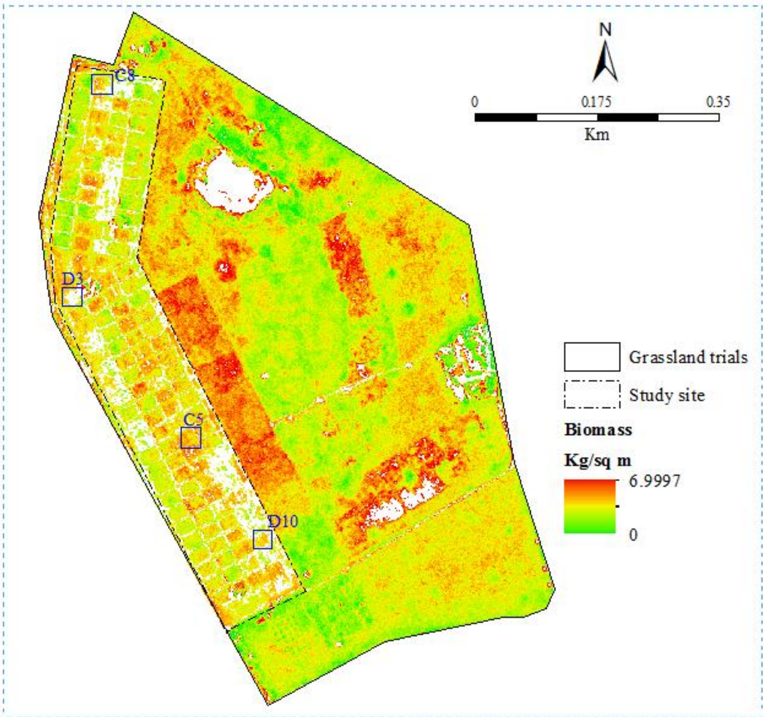


Figure 7.7: Spatial distribution of biomass across different grassland management treatments

Figure 7.8 summarises the accuracies obtained, using single wavebands, broadband vegetation indices, red-edge vegetation indices, single band and band ratio texture models, in predicting ABGB across different levels of mowing and burning treatments. When single wavebands were used in estimating above-ground grass biomass, an average RMSEP of 1.02 kg/m^2 was obtained. These variables had the highest RMSEP and were the least accurate predictors for estimating grass ABGB in this study. The accuracy of estimating ABGB slightly improved to an average RMSEP of 0.83, 1.02 kg/m^2, when broadband vegetation indices were used. However, combining the broadband vegetation indices did not significantly improve the accuracy of ABGB estimation, as illustrated in Figure 7.8. The red-edge vegetation indices significantly improved the accuracy of ABGB estimation to average RMSEP: 0.55 kg/m^2. The combination of red-edge vegetation indices with broadband vegetation indices, as well as single wavebands, did not significantly improve the accuracy of estimating grass ABGB in this study. When, single band grey level co-occurrence texture matrices were used the ABGB prediction accuracy significantly improved (average RMSEP: 0.35 kg/m^2). In comparison, the combination of single-band and band-ratio texture models did not significantly improve the accuracy of estimating ABGB. When all variables were combined (red-edge and texture models), optimal accuracies (average RMSEP: 0.2 kg/m^2) were obtained in this study.

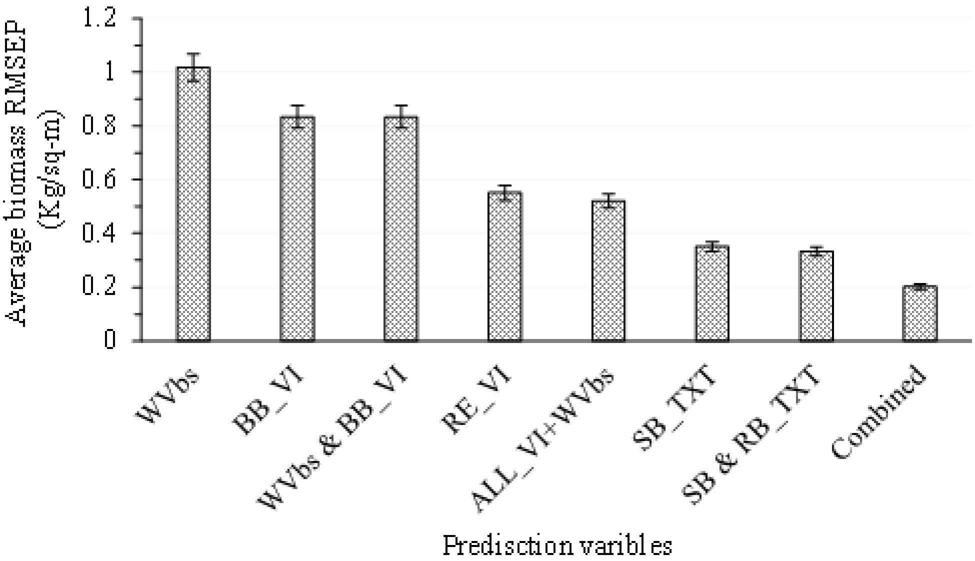


Figure 7.8: Average RMSEPs derived in predicting above-ground biomass, using WV-3 wavebands (WVbs) broadband (BB_VI), red-edge (RE_VI), single-band (SB_TXT), band ratio texture (BR_TXT) indices and all combined data across different rangeland management treatments. Whiskers represent the upper and lower confidence intervals of the mean.

7.4. Discussion

This study tested the robustness of combining texture models with red-edge in estimating the ABGB across different rangeland management treatments, based on the recently launched WorldView-3 Earth observation data. This study specifically sought to find out whether the integration of the red-edge with grey level co-occurrence texture models, extracted at different window sizes and offsets, could improve the accuracy of models for predicting grass above-ground biomass across different levels of mowing and burning treatments in the context of southern African grasslands.

7.4.1. Combining texture models with red-edge in predicting above-ground grass biomass

The findings of this study suggest that combining texture metrics and red-edge derived vegetation indices has relatively higher prospects of improving the estimation accuracy of ABGB growing across different levels of grassland management treatments, when compared to the performance of texture metrics as stand-alone data.

This could be attributed to the sensitivity of the red-edge section of the electromagnetic spectrum to the variations in LAI and LAD changes (Cho et al. 2007, Van der Meer and De Jong 2011, Zhao et al. 2011), as well as foliar chlorophyll variability caused by different levels of mowing, and the influx of post-fire nutrients (Rieske 2002, Skidmore et al. 2010). During the mowing process, grass twigs and leaves are reduced, according to different mowing treatment levels. This results in the alteration of the grass LAI as well as LAD across different levels of mowing. Accordingly, the spectral reflectance from these mowing different levels is better detected by the red-edge section of the electromagnetic spectrum, augmenting the performance of texture models. Furthermore, the red-edge is also sensitive to the variability in chlorophyll content, which accumulates after the burning treatment of grass. This also facilitates an improvement in the accuracy of the estimation of grass biomass, when the red-edge is combined with texture models.

Meanwhile, the textural variables are sensitive to the geographical distribution of minute, but crucial, tonal grass variations in the image induced by the reflectance of different levels of grassland management treatments on certain spectral bands, such as the red-edge and its derived band ratios (Haralick and Shanmugam 1973). This boosts the robustness of texture models and red-edge variables in estimating ABGB. Furthermore, texture is also sensitive to the variations in LAI and LAD induced by mowing, as well as the high chlorophyll content from post-fire nutrients in those grasses grown under different levels of burning and mowing treatments. Subsequently, high estimation accuracies of above-ground grass biomass are realised when texture models are combined with the red-edge derivatives. In addition texture optimises the characterisation of spatial information independently of the tone, while increasing the range of biomass to optimal levels (Rosenqvist et al. 2003). This facilitates robustness and a plausible performance, when texture metrics are combined with red-edge waveband derivatives, optimising the accurate estimation of ABGB across complex grassland management treatments in this study. Our results are consistent with those of Zhang *et al.* (2015), who noted that the models derived from a combination of spectrum and texture models of the Chinese high-resolution remote sensing satellite Gaofen-1, increased the estimation accuracies of Populus euphratica forest when compared with the performance of reflectance or texture models. In another similar study, Takayama and Iwasaki (2016) showed that the combination of the spatial and spectral information from spectral responses and texture models optimally improved the estimation accuracies of tropical vegetation biomass from a RMSE of

66.16 t/ha to a RMSE of 62.62 t/ha in Hampangen, Central Kalimantan, Indonesia, based on WV-3 satellite data. Kelsey and Neff (2014) also demonstrated that texture models improved the estimation of vegetation biomass at the San Juan National Forest in southwest Colorado, USA, from a RMSE of 56.4 to a RMSE of 45.6, based on Landsat data.

Results of this study also indicated that the single band texture metrics improved the accuracy of ABGB estimation relative to red-edge and broadband VI, combined with single wave bands. This is because texture metrics are renowned for accurately capturing the heterogeneity of vegetation structural traits when compared to vegetation indices as a stand-alone dataset (Ozdemir and Karnieli 2011, Eckert 2012). The local variance within pixels at a defined neighbourhood, induced by different levels of mowing and burning treatments in this study, is better distinguished by the texture variables when compared with their spectral signature variations at various WorldView-3 wavelengths. Specifically, the spectral responses of vegetation are computed on a pixel basis, while texture is computed from a desired neighbourhood of pixels that is adjustable, increasing the prospects of texture in credibly predicting biomass better than broadband and spectral reflectance (Kelsey and Neff 2014).

Furthermore, the optimal performance of texture variables, in relation to red-edge and other wavebands and indices in this study, could be explained by the fact that the saturation levels of texture metrics in estimating biomass are considerably higher when compared to those of vegetation indices, such as (NDVI), which saturate at lower levels of biomass (Fujiki et al. 2016, Shen *et al.* 2016). This results in the underestimation of ABGB. In addition, the distinctive performance of texture models could also be attributed to the fact that the band ratio textures are an amalgamation of strengths derived from different spectral wavebands, combined with image tone variations. This increases the sensitivity of texture and red-edge models to the spatial characteristics of different grass canopies, hence facilitating a comparatively higher estimation accuracy of ABGB, a mammoth challenge when using vegetation indices.

Our results are consistent with those of a growing body of literature that attests the optimal performance of grey level texture models, when compared to all vegetation indices (Kuplich et al. 2005, Ozdemir and Karnieli 2011, Fu *et al.* 2014, Barbier and Couteron 2015, Kross *et al.* 2015, Thapa *et al.* 2015, Fujiki *et al.* 2016). For example, Zhang et al. (Zhang *et al.* 2015) noted that when texture models from a high spatial resolution (2 and 16 m) GoaFen-1 optical EO data were integrated, the accuracy of above-ground of the Populus euphratica forest. In a related study, Sarker and Nichol (2011) concluded that the spectral reflectance and traditional vegetation indices have low prospects for estimating biomass, when compared with texture models. Specifically, Sarker and Nichol (2011) noted that texture models derived from ALSO AVNIR-2 improved the vegetation biomass estimation from a RMSE of 64 t/ha, based on traditional vegetation indices and spectral reflectance to a RMSE of 46 t/ha, as noted in this study. However, Sarker and Nichol's results showed that band ratios further improved the accuracy of estimating biomass to a RMSE of 32 t/ha. Their results are contrary to those of this study, which indicated that band ratios and single band texture models did not perform significantly differently when predicting ABGB across different levels of grassland management treatments.

Furthermore, results of this study showed that the red-edge waveband derivatives improved the accuracy of the models for predicting ABGB at different grassland management treatments, when compared to broadband vegetation indices combined with wavebands. Based on the results of this study, the red-edge bands outperformed the broadband vegetation indices, combined with raw wavebands. These results were somewhat expected, as this has been noted in literature. This can be explained by the fact that the red-edge portion of the electromagnetic spectrum is highly sensitive to changes in the grass chlorophyll (Filella and Penuelas 1994), induced by disturbances such as mowing and burning. Post-fire foliar nutrients, which are rich in nitrogen and phosphorus, induce high chlorophyll concentrations in the grass, which is then detected by the red-edge waveband derivatives in this study.

Meanwhile, the decreases in the leaf area distribution and LAI, due to mowing activities, induces a variation in the signature of grass, which is then detected better by the red-edge derivatives, when compared with the single wavebands and broadband vegetation indices. Our results are consistent with those found in a growing body of contemporary literature (Eitel *et al.* 2011, Mutanga *et al.* 2012, Sibanda *et al.* 2015, Gara *et al.* 2016, Sibanda *et al.* 2016) . For instance, Fernández-Manso et al. (2016) noted that red-edge derivatives detected the fire activities better and with higher accuracies (Modified Simple Ratio red-edge narrow R^2: 0.69), when compared to single wave bands and broadband vegetation indices (Red band R^2: 0.093, NIR ^{R2}: 0.63, and NDVI R^2: 0.43) in Sierra de Gata (central-western Spain), based on Sentinel-2 MSI data. (Gara *et al.* (2016)) also noted that the inclusion of red-edge derivatives also improved the estimation of carbon stocks from an explained variance of 63%, based on NDVI, to 70% in the savanna dry forest of Zimbabwe.

7.4.2 Biological behavior of grasses at Ukulinga research farm based on literature review.

As highlighted earlier, mowing through defoliation reduces grass LAI as well as LAD. This markedly reduces the relative abundance of the dominant Themeda triandra, (which is a highly palatable grass species), overall grass basal cover as well as the biomass (Tainton *et al.* 1977). The changes in grass species composition and dominance then could explain the spatial variability of grass biomass noted in this study. Furthermore, mowing at Ukulinga increased sward productivity in the season following the removal treatment when compared to burning which promotes growth of grasses with higher protein content (Tainton *et al.* 1977, Tainton and Mentis 1984). This is illustrated by high estimates of biomass in some mowing (C10 and 11as well as D10 and 11) treatments in relation to other burning treatments (C2 and 3 as well D2 and 3) in the results of this study through high biomass. Treatments with frequent fire administration would yield a variety of short grasses dominated by a Themeda triandra, Hyparrhenia hirta and Tristachya leucothrix as shown by Kirkman et al (Kirkman *et al.* 2014) which could also explain some of the variabilities observed in treatments such as C1 and 2 with annual burning relative to other treatments. Kirkman *et al* (Kirkman et al. 2014) reported that there is a high replacement rate of the dominant grass species between annually burned and unburned treatments at Ukulinga. These findings by Kirkman et al (Kirkman *et al.* 2014) are in agreement with the results of this study which indicate a variability in the estimated ABGB between annually burned and the control treatments. Furthermore research shows that biennially burnt treatments tend to produce more biomass, on average, than treatments burnt less frequently or mown annually in winter (Mentis and Tainton 1984). Above all, the effects of mowing and burning, as well as their interaction on native grasses still requires further studies (Van-Wyk 1998) especially from a remote sensing context.

7.5. Conclusions

The objective of this study was to assess the accuracy of combining red-edge derivatives with texture models in predicting the above-ground biomass of grass growing under different levels of grassland management treatments. Based on the findings of this study, we conclude that:

- combining texture models with red-edge derivatives provides a more accurate approach in estimating the above-ground biomass of grass grown under complex grassland management treatments. To our knowledge, this is the first study to evaluate the utility of texture models and red-edge in estimating above-ground grass biomass, across a multitude of grassland management treatment levels,

- the best predictor in estimating ABGB grown under complex grassland management treatments was derived using all data combined,
- texture models perform better than the red-edge vegetation indices in estimating grass above-ground biomass, and
- as expected, the red-edge spectrum derived vegetation indices outperformed the broadband indices.

In testing specific objectives, our results suggests that (i) broad band vegetation indices such as NDVI, EVI and SAVI are comparatively better predictors of ABGB, (ii) red-edge derived vegetation indices are better predictors than standard wave bands combined with broadband vegetation indices, (iii) texture models are better predictors of ABGB in relation to red-edge, broadband VIs combined with all WV-3 bands (iv) band texture ratios are better predictors of ABGB across different treatments when compared to all variables combined. Ultimately when all variables were combined a red-edge VIs, texture and band ratio texture exhibited optimal ABGB predictions in this study. The results of this work give insights into the estimation of grass biomass in complex grassland management treatments of arid tropical region grasses. The bulk of the studies that have demonstrated the utility of texture variables in above-ground biomass estimation have been on the forests and crops of America and Europe. Therefore, to our knowledge, the results of this study demonstrate, for the first time, the utility of texture models combined with red-edge waveband derivatives in estimating above-ground grass biomass across the complex grassland management treatments of the arid tropics, characterised by a high soil background effect. These results are an important footstool upon which critical spatial information required for grassland policy-making and sustainable grassland management in southern Africa could be derived.

CHAPTER EIGHT: SYNTHESIS

8. REMOTE SENSING GRASS QUANTITY UNDER DIFFERENT GRASSLAND MANAGEMENT TREATMENTS PRACTISED: A SYNTHESIS

8.1 Introduction

Precise prediction of grass above ground biomass and its dynamics is critical for gaining an insight not only into the variations in biogeochemical patterns but also for its sustainable management. Occupying 37% of the earth's surface, grasslands offer a role of paramount importance to numerous stakeholders, such as farmers, ecologists and other scientists. Grasslands account for approximately 20% of total terrestrial productivity (Jin *et al.* 2014). They are a very critical biodiversity hot spot, safeguarding a wide variety of flora and fauna. Grasslands facilitate the soil formation process and its protection from erosive agents, such as water and wind (Conant *et al.* 2001, Boval and Dixon 2012, O'Mara 2012). From an agricultural viewpoint, grasslands are the cheapest source of stock feed for livestock available and a graze for wildlife. Besides, they are a source of livelihood, particularly to the rural communities, especially in southern Africa. Grasslands support economic activities, such as commercial and domestic livestock production systems, and tourism activities. Specifically in South Africa, grasslands have total economic value of R 9.7 billion, which includes a consumptive value of R1.59 million as well as an indirect value of about R 8 million (de Wit *et al.* 2006). However, the increasing pressure on these critical resources, due the ever increasing human population growth, has resulted in overutilization and in some case degradation of grasslands.

However, the increasing pressure on these critical resources, due the ever increasing human population growth, has resulted in overutilization and in some case degradation of grasslands.

Entangled by such challenges, the mainstream stakeholders have embraced and implemented numerous grassland management practices, such as fertilization, burning, mowing and monitored grazing to optimize grass productivity (Dyer *et al.* 1991, Rahman and Gamon 2004). However, these management treatments tend to alter grass biophysical and biochemical components. The alteration of native grasslands properties often compromises their palatability to livestock, soil development and protection, carbon storage, nutrients cycling and other various utilities for human activities (Mbatha and Ward 2010, O'Mara 2012). Meanwhile, rangeland managers are often encountering a challenge of understanding the influence of these management treatments on native grasses at a landscape scale. To guarantee a long-term provision of grassland ecosystem services, there is an urgent need of information detailing the influence of different management practices on grass quality and quantity at local to landscape scales. In regions, such as southern Africa such information is limited, due to the limited resources and the inaccessibility of those rangelands.

The advent of space borne multispectral sensors, their advancement and the increase in the number of those offering data freely, could provide better spatial data required in facilitating a comprehensive understanding of the influence of different grassland management treatments on grass productivity. Specifically, the new generation sensors, such as Sentinel-2 MSI characterized by a relatively short re-visit frequency are potentially suitable for understanding the impact of grassland management treatments on grass productivity. This is because such earth observation facilities such as Sentinel-2 MSI offer critical spectral channels of the electromagnetic spectrum such as the red edge of which are urgently required for effective vegetation characterization and mapping (Boochs *et al.* 1990, Curran *et al.* 1990, Delegido *et al.* 2013). The wider swath-widths of these sensors, i.e. Sentinel-2 MSI's 185 km, makes them to be more suitable for local to regional application on grassland management. Sentinel-2 MSI, for example, has a minimum spatial resolution of 10 m while HyspIRI will have numerous narrow spectral channels with approximately 10nm wide which will offer detailed information on grassland characteristics. However, the discrimination of grasslands grown under different management practices and the estimations of their productivity at a regional scale are limited by the variability as well as the scarcity of quantitative uncertainty analyses. Therefore, the objectives of the study were:

1. to test the utility of hyperspectral data in (i) discriminating the effect of complex fertilizer combinations (i.e. eleven grass fertilizer combinations) on grass, and (ii) assessing the performance of PLS-DA compared with DA in discriminating grasses under different fertilizer treatments,
2. To test the strength of HyspIRI, Landsat 8 OLI, Sentinel-2 MSI and Venμs spectral configurations in discriminating grass species grown under different management practices i.e. mowing, grazing, burning and fertiliser application,
3. to explore the utility of the forthcoming new generation multispectral sensor Sentinel-2 MSI spectral configuration and indices in estimating grass above ground biomass across complex fertilizer treatments in relation to the simulated Landsat 8 OLI spectral band,

4. to assess the robustness of the newly launched Sentinel-2 MSI spectral settings, in relation those of HyspIRI in estimating grass biomass across mowing, burning and fertiliser application treatments,
5. to test the utility of the red-edge of the newly launched WV-3 in discriminating grasses grown under different management treatments,
6. to test whether combining WV-3 optical texture models with red-edge can improve accuracies of predicting above-ground biomass of native grass growing under different levels of mowing, burning and fertiliser treatments using the sparse partial least squares regression algorithm.

8.2 Testing the utility of hyperspectral data in (i) discriminating the effect of complex fertilizer combinations (i.e. eleven grass fertilizer combinations) on grass, and (ii) assessing the performance of PLS-DA compared with DA in discriminating grasses under different fertilizer treatments

Predominantly, native grasslands are the cheapest readily available feeds for both commercial and subsistence livestock farming. Considering the high demand for meat and dairy products, due to increased population growth, grasslands often get degraded through over grazing and over stocking of livestock, especially in native grasslands with a limited carrying capacity. Consequently, the availability, as well as the palatability of the grass is compromised. To optimize quality and quantity, as well as rehabilitation, native grasses are usually fertilized. The major setback of native grass fertilization is the dearth of comprehensive frameworks and objective criterion for monitoring these grasslands, which are largely not in place. Tedious, time consuming, and spatially limited methods, such as the visual-tactile methods and bio-indicative vegetation analyses methods have been used to evaluate the influence of different fertilizer treatments on native grasses. The advent of remotely sensed data has brought about a spatial explicit method with high prospects for accurately characterising grass growing under different rangeland management treatments. Literature illustrates that hyperspectral remote sensors have been proven to be invaluable in characterising vegetation characteristics (Clevers 1999, Mutanga *et al.* 2009, Ullah *et al.* 2012, Lehnerta *et al.* 2014). Furthermore, recent studies have indicated that hyperspectral remote sensing applications including the in-situ sensors, have been successfully implemented in mapping macroplant nutrients such as N, P and K. Although there is a significant amount of literature on N, to our knowledge, no study has so far sought to discriminate the grasses growing under ammonium nitrate/sulphate, lime, phosphorus, as well as these fertilizers treatments combined, using on the DA and PLS-DA based on hyperspectral data in a southern African rangeland. In addition, that there is no specific algorithm that has been comprehensively proven to be efficient in selecting optimal variables for classification purposes. This chapter, therefore, sort to test the utility of hyperspectral data in discriminating grass growing under eleven complex fertilizer combinations and to compare the performance of PLS-DA with DA in characterising grasses growing under different fertilizer combinations.

Results of this chapter illustrate the strength of in-situ hyperspectral data and multivariate techniques in discriminating grasses growing under different levels of complex fertilizer applications. The red edge bands 731 and 737nm, as well as shortwave infrared bands 1310 and 1777nm demonstrated high prospects for classifying grasses growing under complex blends of ammonium nitrate ammonium sulphate integrated with lime and phosphorus. Furthermore, results of this chapter illustrate that DA outperformed PLS-DA in detecting grasses growing under different fertilizer combinations. As a conclusion of this chapter, these results implied that spectroscopy and DA provide great prospects for classifying grasses grown under different levels of complex fertilizer combinations in the rangelands of southern Africa.

8.3 Examining the potential of Sentinel-2 MSI spectral resolutions in quantifying above ground biomass across different fertilizer treatments.

The principal constraints to a comprehensive understanding on the variability of grass above ground biomass based on remotely sensed data are the costs associated with such datasets, as well as the lack of efficient and repeatable estimation techniques. Considering the increase in the number of available earth observation facilities, the new generation of multispectral sensors i.e. Sentinel-2 MSI are perceived to have great prospects in a variety of mapping applications, such as examining the effect of rangeland grass fertilization. Subsequently, this chapter compared the performance of the Sentinel-2 MSI bands and indices in estimating grass above ground biomass across complex fertilizer treatments in relation to Landsat 8 OLI data resampled from field measured spectra. Results of this chapter showed that Sentinel-2 MSI models better estimates above ground biomass (R^2 = 0.81, RMSEP = 1.07 kg/m^2, RMSEP$_{-}^{rel}$ = 14.97) when compared to those of Landsat 8 OLI (Landsat 8 OLI: R^2 = 0.76, RMSEP = 1.15 kg/m^2, RMSEP$_{-}^{rel}$ = 16.04). Meanwhile, hyperspectral data optimally estimated above ground biomass of grass grown under different fertilizer applications, when compared with the two newly multispectral sensors (R^2 = 0.92, RMSEP= 0.69 kg/m^2, RMSEP_^{rel} = 9.61). Results of this chapter, illustrated that red edge bands 4, 5 and 8a of Sentinel-2 MSI could be effectively used to optimally and consistently estimate biomass across all fertilizer combinations in relation to hyperspectral data (bands 705,706,740 and 741nm). Furthermore, this chapter's results illustrated that there were no statistically significant difference between the estimation accuracies of Sentinel-2 MSI and Landsat 8 OLI. The results of this study indicate that Sentinel-2 MSI and Landsat 8 OLI are promising sensors that could optimally estimate above ground biomass in resource scarce regions such as southern Africa.

8.4 Discriminating Rangeland Management Practices Using Simulated HyspIRI, Landsat 8 OLI, Sentinel-2 MSI, and VENµS Spectral Data

The long standing challenge of limited earth observation facilities characterized by optimal temporal spatial and spectral resolutions suitable for rangeland monitoring inspired this chapter. Specifically, this chapter aimed at spectrally discriminating grass growing under various levels of different grassland management treatments using HyspIRI, Landsat 8 OLI, Sentinel-2 MSI and Venµs simulated using hyperspectral data. Considering that on chapter one DA was noted to perform better in discriminating grasses growing under different levels of complex fertilizer treatments, it was also adopted in this chapter to discriminate grasses growing under different levels of mowing, grazing, burning, fertilizer application and untreated (control). Specifically, this study examined the robustness of HyspIRI, Landsat 8 OLI, Sentinel-2 MSI and Venµs spectral settings in distinguishing grass species growing under mowing, grazing, burning and fertiliser application. Results of this chapter illustrated that the spectra configurations of HyspIRI, Sentinel-2 MSI, Venus and Landsat 8 OLI exhibited favorable overall accuracies of up to 92%, 82%, 83% and 75%, respectively. Best classification accuracies were achieved. using vegetation indices and wavebands locate in the red edge (HyspIRI: 700, 740 and 780nm and Sentinel-2 MSI: bands 5, 6, and 7 8a) and NIR (HyspIRI: 700, 740 and 780nm and Sentinel-2 MSI: band 8a) regions of the electromagnetic spectrum, respectively. Furthermore, the results of this chapter showed that even if the simulated Sentinel-2 MSI data exhibited lower classification accuracies in relation to HyspIRI, it provides satisfactory classification performance with high agreements between training and testing data sets in relation to the performance of HyspIRI data. The findings of this chapter underscore the prospects of the new generation of earth observation facilities in guaranteeing comprehensive rangeland monitoring and management applications.

8.5 Comparing the spectral settings of the new generation broad and narrow band sensors in estimating biomass of native grasses grown under different management practices

Monitoring the influence of rangeland management treatments on grass productivity has been limited by the lack of cheap and readily available earth observation facilities. Furthermore, the preceding chapters (3 and 4) indicated that the freely available Sentinel-2 MSI and the forthcoming HyspIRI will offer the best spectral settings for charactering grasses growing under different levels of grassland management treatments at limited costs. This chapter, therefore, aimed assessing the capability of the newly launched Sentinel-2 MSI data in relation to HyspIRI data in estimating grass biomass subjected to different rangeland management treatments. Based on the sparse partial least algorithm findings of this chapter illustrated that HyspIRI achieved slightly higher estimation accuracies of (RMSE =6.65 g/m^2, R^2 = 0.69) grass above ground biomass when compared with Sentinel-2 MSI (RMSE = 6.79 g/m^2, R^2 = 0.58). Furthermore, the student t-test indicated that there were no statistically significant difference between the estimation accuracies obtained using Sentinel-2 MSI and those obtained using HyspIRI (α = 0.05). The highest predictive models were yielded by Sentinel-2 MSI's Bands 5, 6 and 7 as well as HyspIRI's Bands 730 nm, 740nm, 750 nm and 710 nm as well as indices derived from these wavebands. These findings suggested that Sentinel-2 MSI exhibited a comparable performance to HyspIRI data in estimating above ground biomass of grass growing under burning, mowing and fertiliser application. Overall, these results demonstrate that the accuracies of Sentinel-2 MSI in estimating grass above ground biomass are within acceptable when compared with HyspIRI. The results of this chapter offer an understanding into the potential of large scale grass biomass estimation based on freely available multispectral data.

8.6 Testing the capabilities of the new WorldView-3 spaceborne sensor in discriminating and mapping complex grass management treatments.

Currently the geographical extent of arid and semi-arid grasslands that have been transformed into agricultural lands is largely unknown. The intensification of agricultural activities is the major driver behind the degradation of tropical grasslands. This has resulted in the advent of different grassland management treatments, such as burning and mowing, meant to optimize grass productivity. This has resulted in a mounting interest for inventorying the areal extent. as well as assessing the condition of grasslands so as to attain refined records essential in the process of drawing up effective grassland conservation policies. Despite the growing interest on grasses on the impact of grassland management treatments on grass productivity, the challenge has been the lack of objective frameworks and comprehensive precedents for monitoring these grasslands. A paramount stride towards an effective conservation and sustainable management of grass in arid and semi-arid areas will be, therefore, an attainment of comprehensive insights on the effect of grassland management treatments on grass productivity. Earth observation facilities with critical spectral information, such as the red edge have been perceived to perform better in discriminating structural characteristics of vegetation such as those induced by different grassland management treatments. This chapter, therefore, sought to test the robustness of the spectral resolution of the newly launched Worldview-3 sensor in discriminating grasses growing under different grassland management treatments (i.e. mowing grazing, burning, fertilizer application and control (no-treatment)) based on the discriminant analysis algorithm. Specifically, we compared the performance of red-edge and reflectance of other spectral bands, as well as their respective indices in discriminating grasses growing under different management treatments. Results of this chapter showed that integrating the red-edge band with other wavebands improved the discrimination of grass growing under different grassland management treatments from an overall accuracy of 65% to 70%. More so, the integration of red-edge vegetation indices with standard vegetation indices improved the discrimination of grass from an overall accuracy of 73% to 78%. Some of the most optimal wavebands identified in this chapter were the yellow red NIR-1 and NIR-2 Bands. Having noted the optimal performance of the red-edge and its derivatives, we sought evaluate the combination of red-edge derivatives and the image processing techniques, such as texture variables, which are renowned for estimating better vegetation productivity.

8.7 Examining the robustness of WorldView-3 texture models, combined with red-edge, in predicting the biomass of native grass growing under complex grassland management treatments in southern Africa.

The use of texture metrics combined with red-edge wave band derivatives of the new generation of earth observation facilities could be very instrumental in obtaining comprehensive spatial information on vegetation productivity. In that premise, this chapter sought to evaluate the robustness of Worldview-3 texture models combined with red-edge in predicting above ground biomass of grass growing under various levels of different management treatments in the context of grasslands of southern Africa. Using the sparse partial least squares regression algorithm, results of this study showed that the red-edge vegetation indices improved the estimation models of predicting grass biomass across different grassland management treatments from an RMSEP of 0.83 kg/m^2 to 0.55 kg/m^2. In addition, texture models further improved the accuracy of grass above-ground biomass estimation models from an RMSEP of 0.55 to 0.35 kg/m^2. Overall the combination of red-edge and texture models exhibited an optimal RMSEP of 0.2 kg/m^2 across all grassland management treatments.

Conclusion

This work mainly sought to assess the accuracy of new generation sensors, as well as image processing techniques. such as grey level texture models in discriminating and estimating above-ground biomass of grasses growing under different levels of complex grassland management treatments practices in southern Africa. The findings of this work have comprehensively indicated that new generation of sensors, such as Sentinel-2 MSI and HyspIRI can cheaply and optimally model the grass grown under different levels of grassland management treatments commonly practiced in southern Africa. The red-edge wavebands of these new generation sensors and the derived texture models in conjunction with robust classification and estimation algorithms, improve grass quantity modelling, a previously challenging task, especially in data poor areas.

Grounded on the findings deduced from each chapter and or objective, it is conclude that:

1. spectral information, located at 731,737, 1310 and 1777nm, could be effectively used to discriminate the influence of different fertilizer applications on the grasses. DA performs better than PLS-DA in discriminating the influence of fertilizer applications on the grasses.
2. red edge bands 4, 5 and 8a of Sentinel-2 MSI could be effectively used to optimally and consistently estimate biomass across all fertiliser combinations compared to hyperspectral data (bands 705,706,740 and 741nm).
3. Sentinel-2 MSI offers better classification accuracies with high agreements between training and testing data sets when compared to the HyspIRI data. We therefore conclude that the new generation spaceborne multispectral sensors (e.g., Sentinel-2 MSI) with a high spatial resolution have the potential to satisfactorily predict grass biomass across different grassland management practices. Mowed, grazed, fertilized, as well as grasses under burning practice can be spectrally discriminated using vegetation indices and wavebands located in the red edge (HyspIRI: 700, 740 and 780nm and Sentinel-2 MSI: bands 5, 6, 7 and 8a) and NIR (HyspIRI: 700, 740 and 780nm and Sentinel-2 MSI: bands 5, 6, 7 and 8a) spectra respectively. Specifically, normalised difference vegetation indices associated with red edge significantly improve discrimination of grassland management practices.
4. Sentinel-2 MSI spectral resolution can estimate the above-ground biomass of grasses under different rangeland management treatments with optimal accuracies, comparable to those of HyspIRI data. Red edge bands (Sentinel-2 MSI Bands 5, 6 and 7, as well as HyspIRI bands B730, B740, B750, and B710) and derived vegetation indices, selected for

estimating the above-ground biomass across grassland areas treated with different rangeland management treatments at plausible accuracies.

5. WV-3's red-edge spectral information is invaluable in discriminating different grassland management treatments at a farm scale with plausible accuracies when compared to the visible and near infrared bands. WV-3 normalized difference vegetation indices derived based on the red-edge significantly improve the discrimination of grass growing under complex grassland management strategies
6. combining texture models with red-edge derivatives provides a more accurate approach in estimating the above-ground biomass of grass grown under complex grassland management treatments. To our knowledge, this is the first study to evaluate the utility of texture models and red-edge in estimating above-ground grass biomass, across a multitude of grassland management treatment levels. Texture models perform better than the red-edge vegetation indices in estimating grass above-ground biomass, and as expected, the red-edge spectrum derived vegetation indices outperformed the broadband indices.

The future

The results of this work underscore the importance of the newly launched and forthcoming sensors that are and will be freely available in effectively monitoring and management of grasses growing under different rangeland management practices, a component that was lacking in the previous optical sensors. More so, the new generation of earth observation facilities, such as Sentinel-2 MSI and HyspIRI with a relatively fine spatial resolutions of ± 10 m, critical wavebands, such as the red-edge as well as optimal swath widths of ±185 km suitable grassland management applications at local to regional scales. The findings of the study are comprehensive foundation upon which the future studies could resolve the longstanding challenge of understanding the influence of different management practices on rangelands grass productivity at a regional scale. Grounded on the findings of this study, we recommend that future studies should;

1. assess the performance of the new generation sensors such as Sentinel-2 MSI in discriminating grass growing under different grassland management practices, as well as estimating their productivity at a regional scale,

2. to evaluate the influence of factors, such as grass height and canopy volume in discriminating different rangeland management practices, using remotely sensed data
3. test the utility of combining image processing techniques such as grey level co-occurrence matrices and red-edge waveband derivatives in discriminating and estimating above-ground grass biomass at a regional scale.

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